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Individual Claim Reserving e Machine Learning per la valutazione della riserva sinistri

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Introduction

- This presentation is a **guide** for actuaries about **Machine Learning** (ML) in non-life **claim reserving**
 - *It highlights new possible new methodologies for tackling actuarial challenges*
 - *Understanding these concepts helps actuaries maintain a competitive edge and adapt to changing industry norms*
 - *The presentation also sheds light on the **ethical** considerations and regulatory frameworks surrounding ML, crucial for responsible practice*
 - *For actuaries aiming to **blend traditional skills with modern technology**, this presentation could be a resource for staying relevant and innovative*
 - *By nature this presentation is educational*

Agenda

- Machine Learning
 - Actuarial Data Science
 - State of the Art - Literature
 - State of the Art – Actual Practice
 - Final Remarks
-

Machine Learning

What is Machine Learning?

- **Machine learning** is about the development and use of computer systems that learn and adapt without following explicit instructions. **And it uses algorithms and statistical models to analyze and yield predictive outcomes from patterns in data.**

How are Artificial Intelligence (AI) and ML connected?

- While AI and ML are not quite the same thing, they are closely connected. The simplest way to understand how AI and ML relate to each other is:
 - AI is the broader concept of enabling a machine or system to sense, reason, act, or adapt like a human
 - ML is an application of AI that allows machines to extract knowledge from data and learn from it autonomously.

One helpful way to remember the difference between machine learning and artificial intelligence is to imagine them as umbrella categories. Artificial intelligence is the overarching term that covers a wide variety of specific approaches and algorithms. Machine learning sits under that umbrella, but so do other major subfields, such as deep learning, robotics, expert systems, and natural language processing.

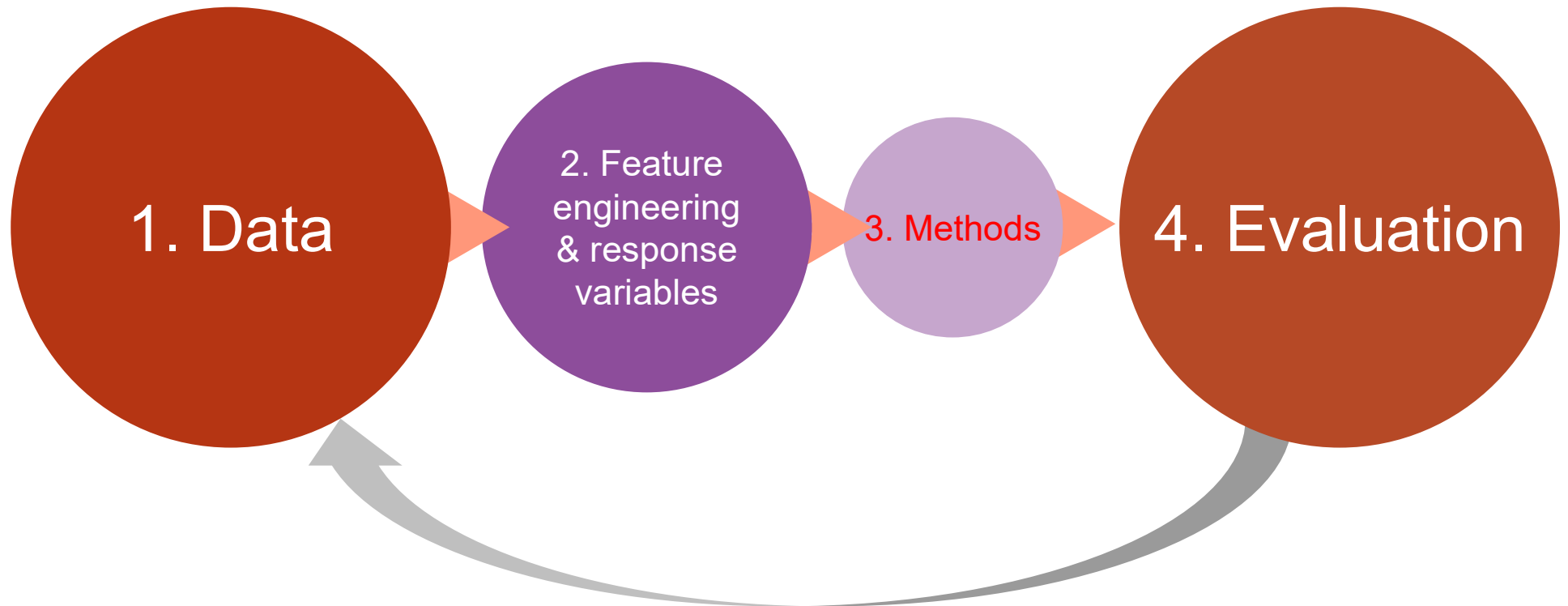
Machine Learning

- Much of what propels generative AI comes from machine learning in the form of large language models that analyze vast amounts of input data to discover patterns in words and phrases.
- Many of AI's unprecedented applications in business and society are supported by machine learning's wide ranging capabilities, whether it's analyzing mammograms or digesting Instagrams, assessing risks or predicting failures, navigating the roadways or thwarting the cyber attacks we never hear about. Machine learning's omnipresence impacts the daily business operations of most any industry, including e-commerce, manufacturing, finance, insurance services and pharmaceuticals.

Walk along the machine learning timeline

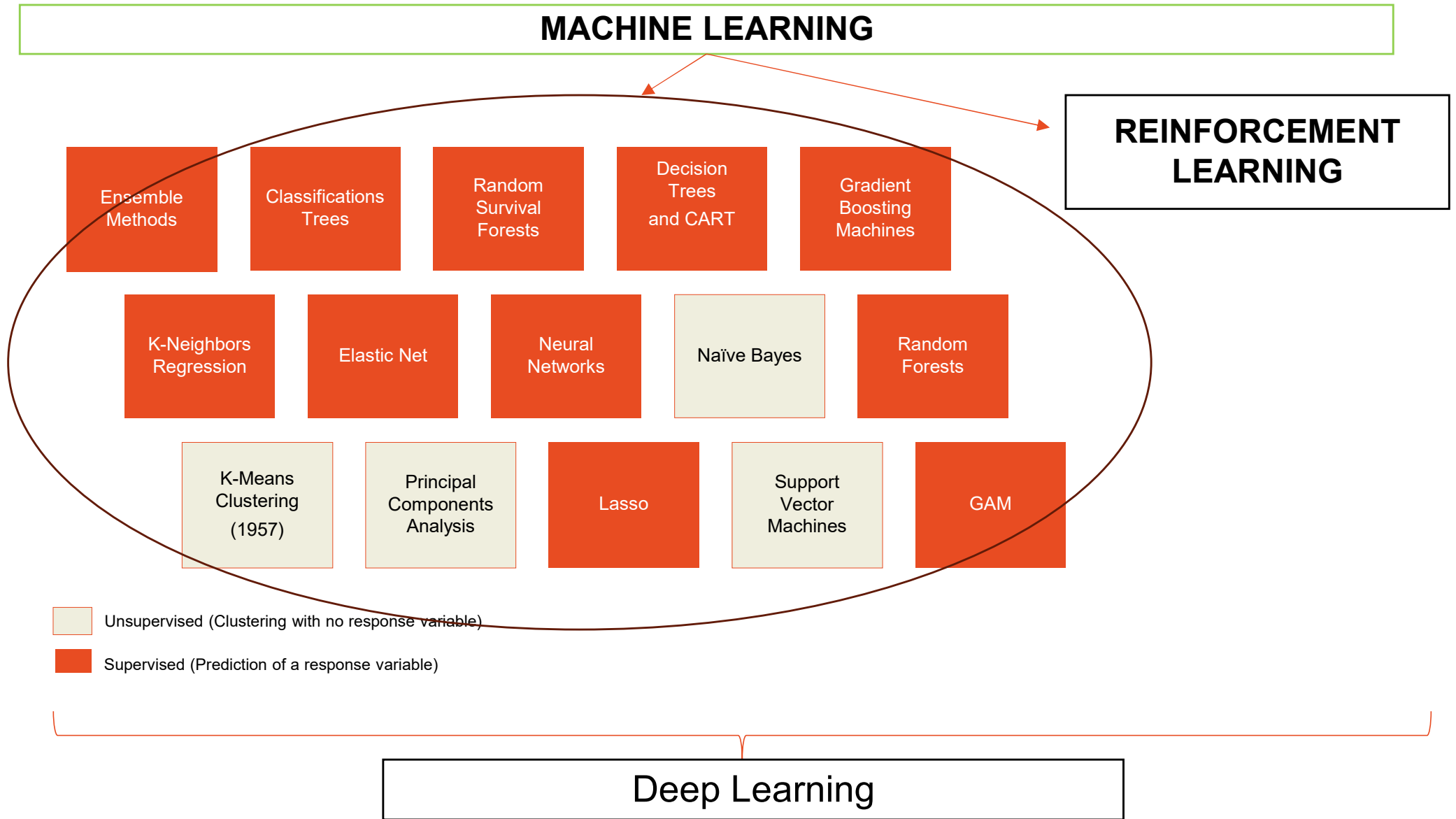
- Through the decades after the 1940s, the evolution of machine learning includes some of the more notable developments:
 - Pioneers named **Turing, Samuel, McCarthy, Minsky, Edmonds and Newell** dotted the machine learning landscape in the 1950s, when the Turing test, first artificial neural network, and the terms artificial intelligence and machine learning were conceived.
 - The **Stanford cart video-controlled remote vehicle, Eliza the first chatbot, Shakey the first mobile intelligent robot**, and the **foundations of deep learning** were developed in the 1960s.
 - Programs that recognize patterns and handwritten characters, solve problems based on natural selection, seek appropriate actions to take, create rules to discard unimportant information, and **learn like a baby learns to pronounce words highlighted the 1970s and 1980s**.
 - Programs capable of **playing backgammon and chess threatened** the domains of top-tier backgammon players and the reigning world chess champion in the 1990s.
 - **generative adversarial networks**, facial recognition, deepfakes, motion sensing, autonomous vehicles, and content and image creation have emerged so far in the 2000s.

Machine Learning - Workflow



3. Methods – What do we mean by Machine Learning algorithm?

ML Paradigm – feed data to the machine and let it figure out what is important from the data!



Remark 1 - What is training a model in machine learning?

- **Training a model** in machine learning is the process of teaching a machine learning algorithm to make predictions or decisions based on data
- **Model training is the heartbeat of machine learning.** Its significance cannot be overstated, and here's why it matters:
 - **Generalization:** Training enables a model to generalize from the data it has seen to make accurate predictions on new, unseen data
 - **Pattern Recognition:** Through training, models learn to recognize complex patterns, relationships, and trends within the data
 - **Automation:** Trained models can automate decision-making processes, saving time and resources
 - **Continuous Learning:** Machine learning models can be retrained with new data

How to train a machine learning model?

1. Gathering and Preparing **Data**
2. Choosing the Right **Algorithm** (see next slides)
3. Splitting Data for Training and Evaluation (**training** data, **validation** data, **testing** data)
4. Training the Model/ **Hyperparameter** Tuning:
 - The selected ML algorithm learns how to make **predictions or categorize data** using the training set. In this phase, **the model refines its internal settings to best match the training set of data.**
 - Finding the optimal values for hyperparameters (**parameters that govern the learning process**) that are not learned from the data is known as "**hyperparameter tuning**"
 - In order to enhance the performance of the model, **you must experiment with various hyperparameter settings using the validation set**
 - This process often involves iterative training and **validation** until you achieve a **satisfactory level of performance on the validation set.**

Loss Function: measures the dissimilarity between the model's predictions and the actual target values. During training, the model strives to minimize this loss, effectively improving its accuracy

Remark 2 – Hyparameters tuning

- One can draw a parallel between choosing parameters for the Benktander or Bornhuetter-Ferguson method and what in the **machine learning literature is referred to as hyperparameter tuning**.
- **Hyperparameters are parameters that determine the particular structure of the final model**, e.g., the *number of hidden layers* for a deep neural network or the *number of estimators* for a gradient boosting machine, and **cannot be estimated directly from the data**:
 - A **parameter** can be considered to be **intrinsic** or internal to the model and can be obtained after the model has learned from the data. Examples of parameters are **regression coefficients in linear regression**, and weights in neural networks.
 - A **hyperparameter** can be considered to be **extrinsic** or external to the model and can be set arbitrarily by the practitioner. Examples of hyperparameters include the k in k-nearest neighbors, **number of trees and maximum number of features in random forest**, learning rate in neural networks.

```
1 from sklearn.tree import DecisionTreeRegressor
2 # https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeRegressor.html
3
4 # Define Decision tree
5 model = DecisionTreeRegressor(
6     # function to measure the quality of a split.
7     criterion='mse', # or gini, mae, L2 mse, L1 mse
8     # The strategy used to choose the split at each node.
9     splitter='best', # or random
10    # The maximum depth of the tree.
11    max_depth=2,
12    # The minimum number of samples required to split an internal node
13    min_samples_split=2,
14    # The minimum number of samples required to be at a leaf node.
15    min_samples_leaf=1,
16    # The number of features to consider when looking for the best split
17    max_features=None, # None means use all features
18    # A node will be split if this split induces a decrease of the impurity
19    # greater than or equal to this value.
20    min_impurity_decrease=0.0,
21    # Threshold for early stopping in tree growth. A node will split
22    # if its impurity is above the threshold, otherwise it is a leaf.
23    min_impurity_split=None,
24    # seed
25    random_state=1234,
26 )
27
28 # fit
29 model.fit(x_train, y_train)
30
31 # predict
32 y_pred = model.predict(x_test)
```

Decision Trees

- Typical decision trees learn a set of rules from **training data** represented as a tree. Each level of a tree *splits* the tree to create a branch using a feature and a value (or range of values).
- **Nodes** are split into sub-nodes based on a **threshold value** of an attribute. The **root node** is taken as the training set and is split into two by considering the best attribute and threshold value. Further, the subsets are also split using the same logic. This continues till the last pure sub-set is found in the tree or the maximum number of **leaves** possible in that growing tree.

The top figure is the standard representation for trees.

The bottom figure offers an alternative view of the same tree. The feature space is partitioned into numerous rectangles, which is another way to view a tree, representing its nonlinear character more explicitly

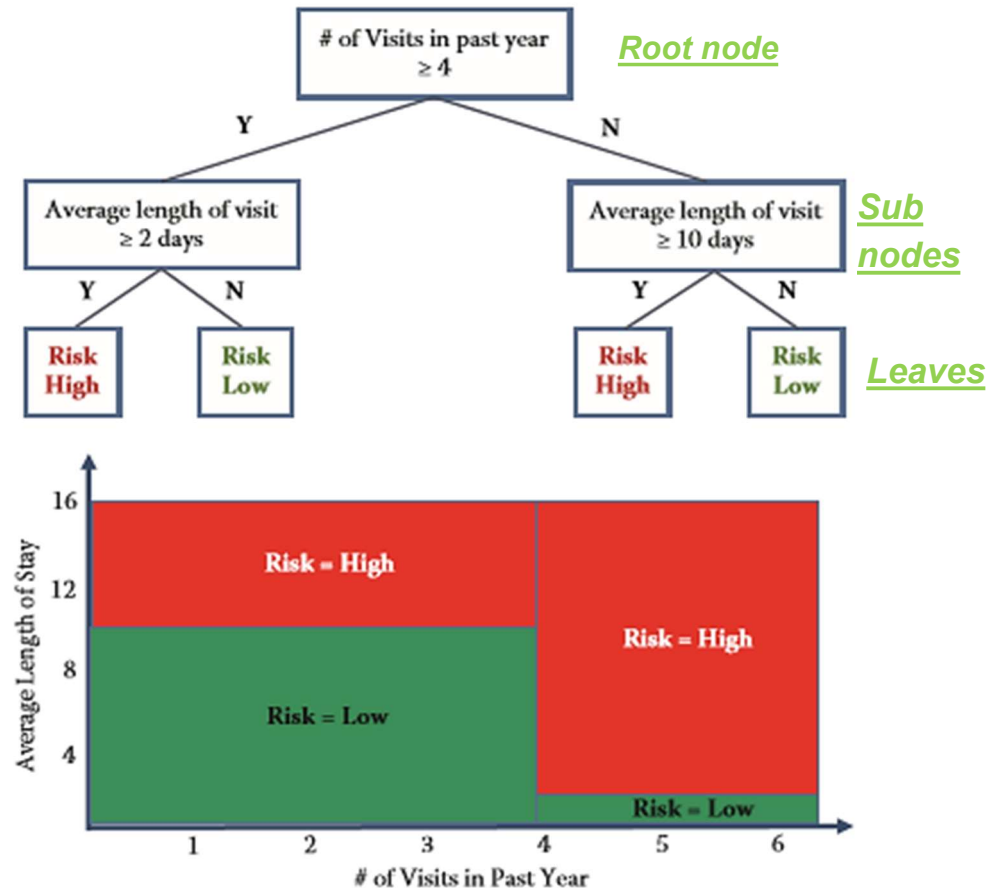
Pros

- No need of probability distribution assumptions
- Easy to explain to people, with a really intuitive graphical representation
- Be able to capture high non-linearity and complex relationships between dependent and independent variables

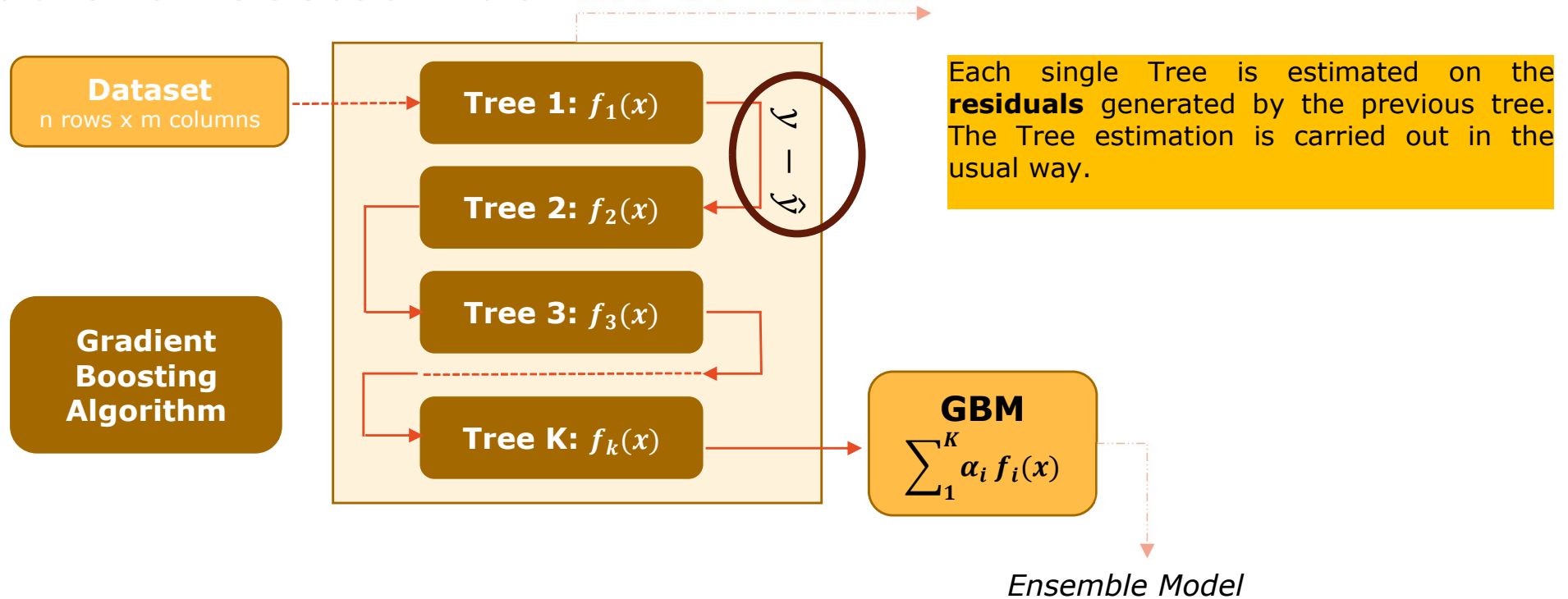
Cons

- Risk to overfitting data
- Instability with respect to the data; small change in data might result in a very different tree structure, making interpretation somewhat precarious.

CART (Classification And Regression Trees) is a variation of the decision tree algorithm. CART algorithm uses Gini Impurity to split the dataset into a decision tree. It does that by searching for the best homogeneity for the sub nodes, with the help of the Gini index criterion.



Gradient Boosted Machine or “GBM”



↑ Pros

- No need of probability distribution assumptions
- Excellent accuracy with modest use of memory

↓ Cons

- Very difficult to interpret
- Hard to tune: many hyper parameters, which leads to overfit the data
- The training process requires lot of computations

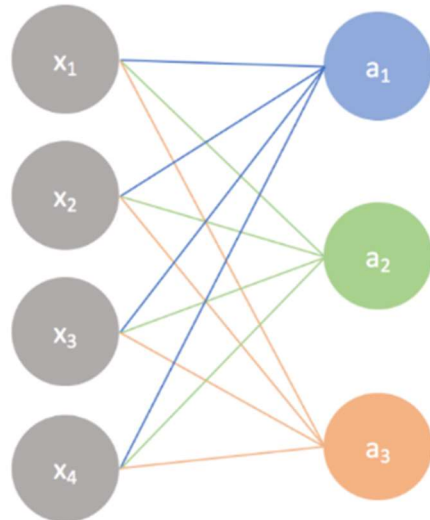
- **Extreme Gradient Boosting:** XGBoost is a scalable system for learning tree ensembles. It provides an implementation of distributed gradient boosting (GBM,GBT,GBDT) designed for speed and performance. XGboost uses a more regularized model formalization to control over-fitting, which gives it better performance.

Neural networks

- A **(Artificial) Neural Network (ANN or NN)** is a computer program that operates similarly to the human brain. The objective of neural networks is to perform those cognitive functions our brain can perform like problem-solving and being teachable.
- **Neural networks** are statistical models inspired by biological neural networks and their learning process. An ANN is built by a collection of connected simple units called “*artificial neurons*” and each connection (*synaptic weights*) between neurons can transmit a signal to another one.
- A nonlinear activation function will assess the activity of each neurons and a transfer function will produce an **output signal** to the connected neurons.
- Typically, ANN are organized in **layers**. There is an input layer to match the feature space, followed by a single or multiple *hidden* layers (**deep learning**) and at the end an output layer that match the overcome space.
- **The learning ability of a neural network is determined by its architecture and by the algorithmic method chosen for training.**

Neural networks

- A neuron is a (non)-linear function of a linear combination of inputs and weights
- Given a network architecture, the model is fit by identifying the neurons' weights that minimize a given loss;
- Numerical algorithms are used at this purpose



A simple Zero Layer (Feed Forward) Neural Network

$$\begin{bmatrix} w_1 & w_2 & w_3 & w_4 \\ w_1 & w_2 & w_3 & w_4 \\ w_1 & w_2 & w_3 & w_4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} b \\ b \\ b \end{bmatrix} = \begin{bmatrix} w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + b \\ w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + b \\ w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + b \end{bmatrix} \xrightarrow{\text{activation}} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}$$

Lets play: <https://playground.tensorflow.org>

Pros

- Be able to capture high non-linearity and complex relationships between dependent and independent variables
- Easy to update with new data
- ...

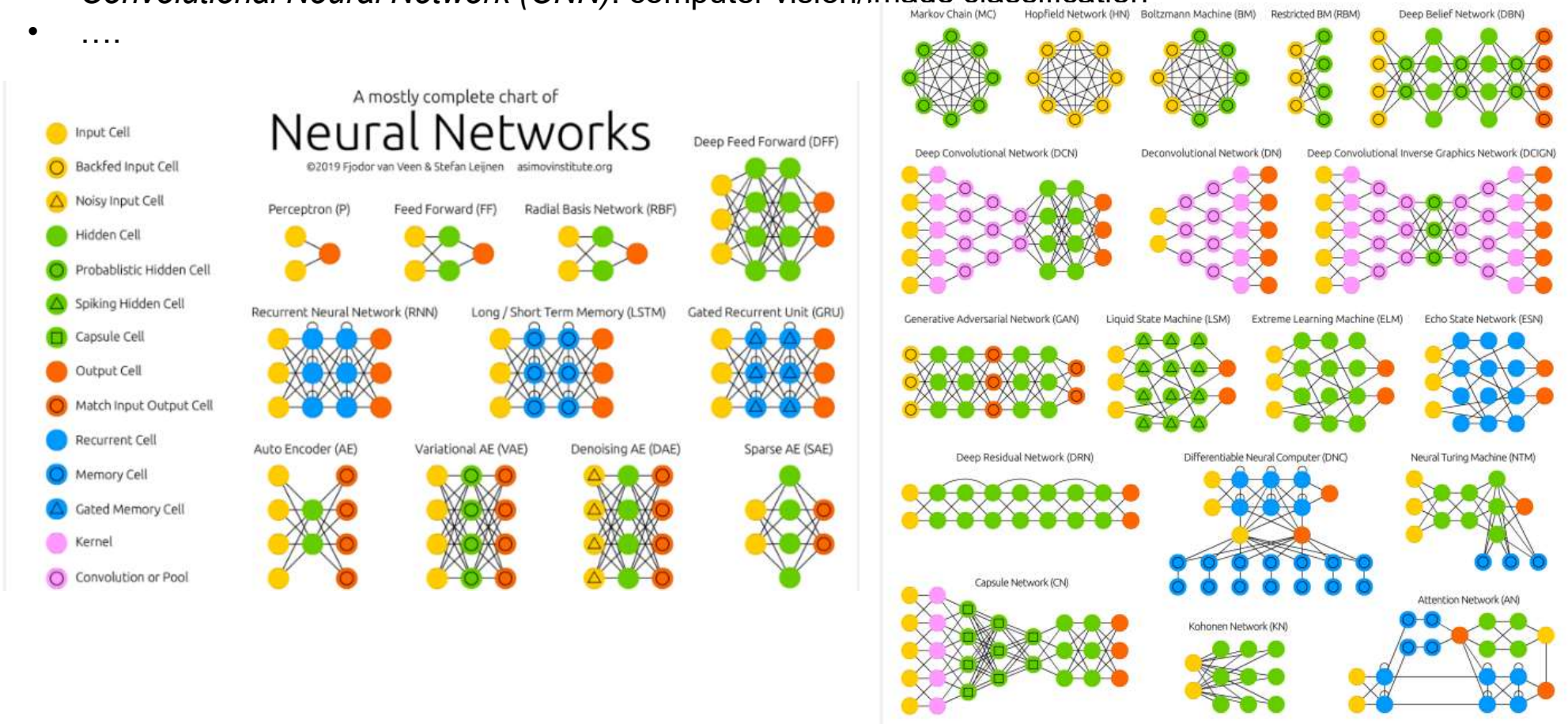
Cons

- Not easy to explain to people;
- Risk to overfitting data;
- Computational time (training, etc.)
- ...

The Neural Network Zoo

There are many types on *Neural Networks*:

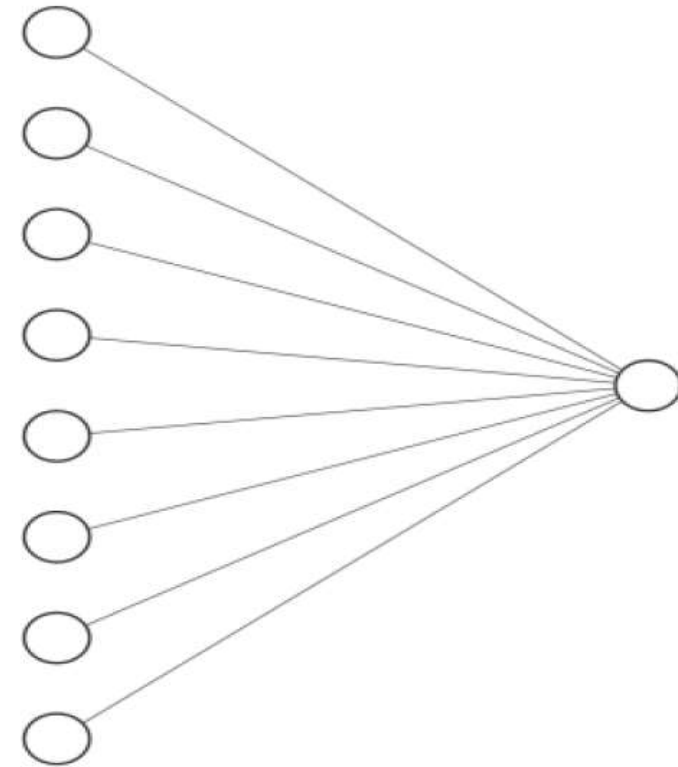
- *Feed Forward Neural Network*: regression classification basic tasks
- *Kohonen Self Organizing Neural Network*: unsupervised tasks
- *Recurrent Neural Network (RNN)*: sequence models
- *Convolutional Neural Network (CNN)*: computer vision/image classification
-



Neural networks

Single Layer NN = Linear Regression

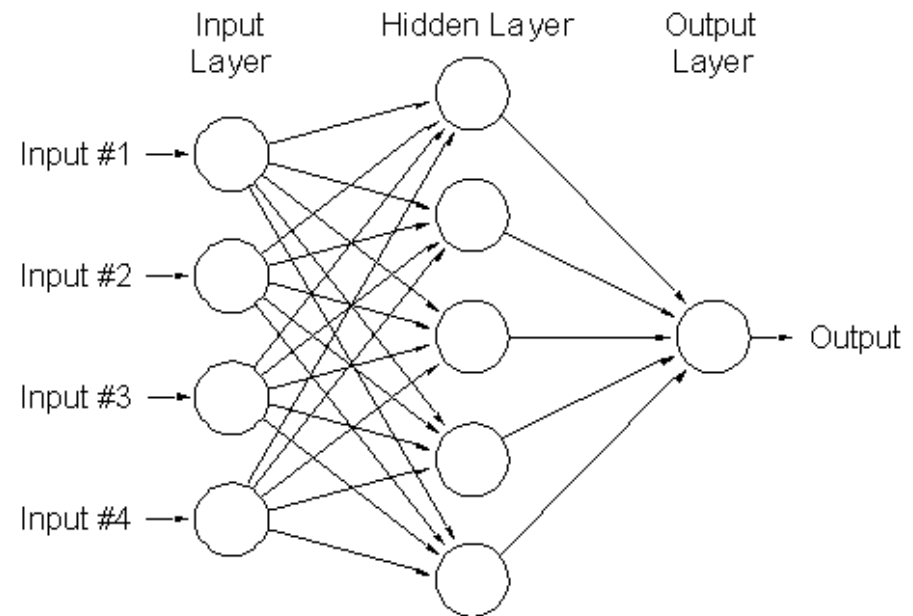
- **Single layer neural network**
 - Circles = variables
 - Lines = connections between inputs and outputs
- **Input layer holds the variables that are input to the network...**
- **... multiplied by weights (coefficients) to get to result**
- **Single layer neural network is a GLM!**



Input Layer $\in \mathbb{R}^8$

Deep Feedforward Net

- **Deep = multiple layers**
- **Feedforward = data travels from left to right**
- **Fully connected network (FCN) = all neurons in layer connected to all neurons in previous layer**
- **More complicated representations of input data learned in hidden layers - subsequent layers represent regressions on the variables in hidden layers**



Deep Learning (DL)

- **Deep Learning = representation learning technique that automatically constructs hierarchies of complex features to represent abstract concepts**
 - Features in lower layers composed of simpler features constructed at higher layers => complex concepts can be represented automatically
- Deep learning models consist in structured (layered) architecture of neurons, meaningfully connected
- The recent hype on DL is given by increasing availability of **big data**, computing power and new methodologies that permit to avoid over - fitting
- DL input data can be not only numeric tabular data, but also **mixed and non structured ones** like images, sequences (text, sound, categorical ones) that are internally encoded in matrix forms;
- Often computing power is essential for training DL models
- **The principle: Provide raw data to the network and let it figure out what and how to learn.**
- Desiderata for AI by Bengio (2009): **“Ability to learn with little human input the low-level, intermediate, and high-level abstractions that would be useful to represent the kind of complex functions needed for AI tasks.”**

Specialized Architectures

- **Most modern examples of DL achieving state of the art results on tasks rely on using specialized architectures i.e. not simple fully connected networks**
- Key principle - Use architecture that expresses useful priors (inductive bias) about the data => Achievement of major performance gains
 - Embedding layers – categorical data (or real values structured as categorical data)
 - Autoencoder – unsupervised learning
 - Convolutional neural network – data with spatial/temporal dimension e.g. images and time series
 - Recurrent neural network – data with temporal structure
 - Skip connections – makes training neural networks easier
- Recently, specialized architectures have begun to be applied to **actuarial problems** (see next slides)

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Walk along the “Actuarial Data Science” timeline

Traditionally, actuaries responsible for statistical and financial management of insurers

- Today, actuaries, data scientists, machine learning engineers and others work alongside each other

• Actuaries focused on specialized areas such as pricing/reserving

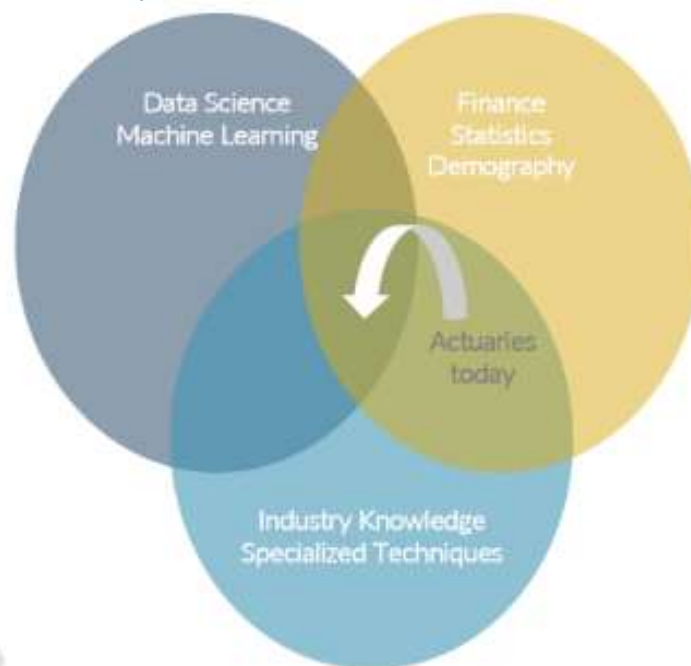
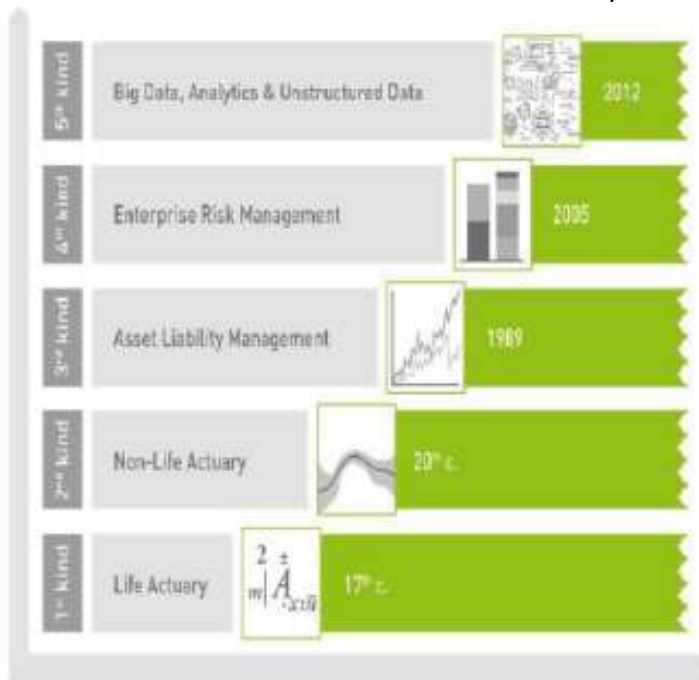
- Many applications of ML within insurance but outside of traditional areas

Actuarial science merges statistics, finance, demography and risk management

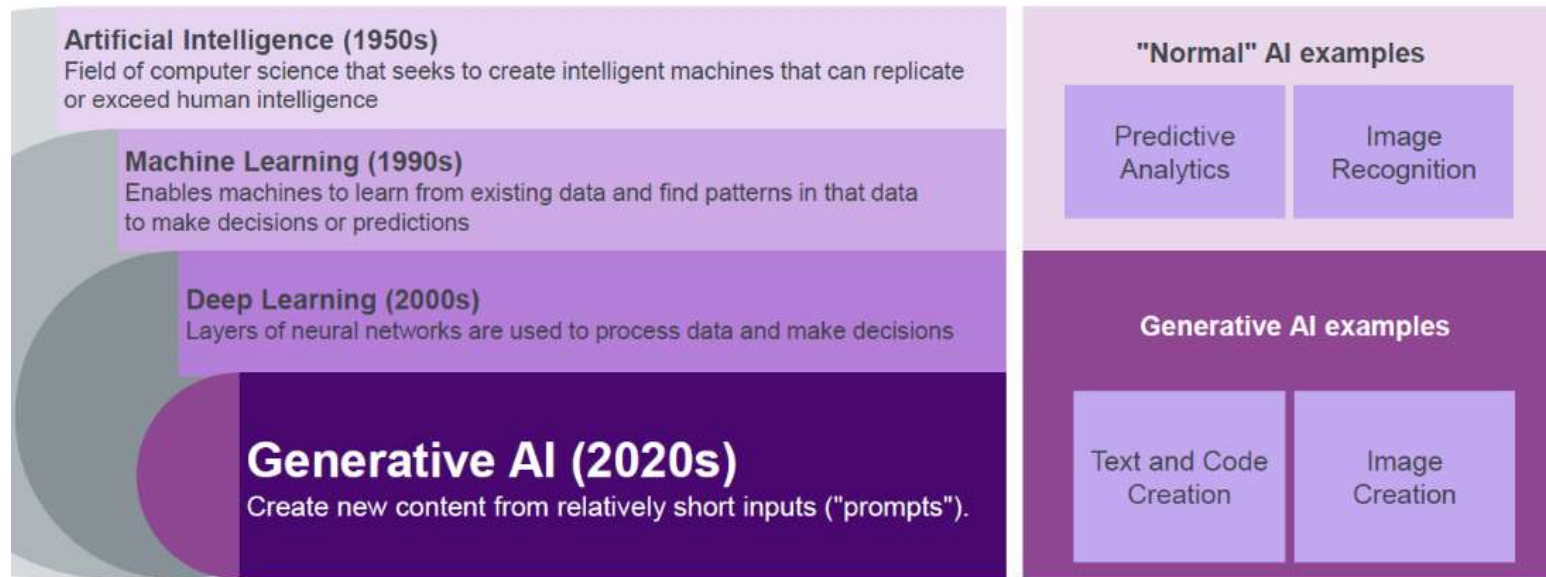
- Currently evolving to include ML

According to Data Science working group of the SAA:

- Actuary of the fifth kind - job description is expanded further to include statistical and computer-science
- Actuarial data science - subset of mathematics/statistics, computer science and actuarial knowledge



Walk along the “Actuarial Data Science” timeline



Source: Edwards et al. (2023)

Use case #1: Using AI to assist with coding

Use case #2: AI for expert systems

Use case #3: using AI for legacy model automation

Use case #4: AI for data validation

Use case #5: AI for automated model reconciliation

Generative AI can help streamline the claims process and optimize risk management for P&C insurers

Large language models (LLMs)

- “Large Language Models” are the engines which power text and code-based Generative AI
- LLMs are based on neural networks – 80 years old!
- These are connected layers of idealized neurons
- Each node calculates a simple numerical function based on input from the layer above, adjusted by a ‘weight’ parameter
- e.g. $output = \text{sum.product}(inputs, weights)$
- Parameters tuned to optimize output by seeing many correct examples
- Requires us to convert words (and their positions in text) into representative numbers (“tokens”)

Explaining or Predicting?

Which of the following are an ML technique?

- Linear regression and friends (GLM/GLMM)
- Generalized Additive model (GAM)
- Exponential Smoothing
- Chain-Ladder and Bornhuetter-Ferguson
- ...

It depends on the goal:

- Are we building a causal understanding of the world (inferences from unbiased coefficients)?
- Or do we want to make predictions (bias-variance trade-off)?

Distinction between tasks of predicting and explaining, see Shmueli (2010). Focus on predictive performance leads to:

- Building algorithms to predict responses instead of specifying a stochastic data generating model (Breiman, 2001)...
- ... favouring models with good predictive performance at expense of interpretability.
- Accepting bias in model coefficients if this is expected to reduce the overall prediction error.
- Quantifying predictive error (i.e. out-of-sample error)

ML relies on a different approach to building, parameterizing and testing statistical models, based on statistical learning theory, and focuses on predictive accuracy.

Actuarial Problems

Actuarial problems are often supervised regressions

If an actuarial problem can be expressed as a regression, then machine learning can be applied.

Obvious areas of application:

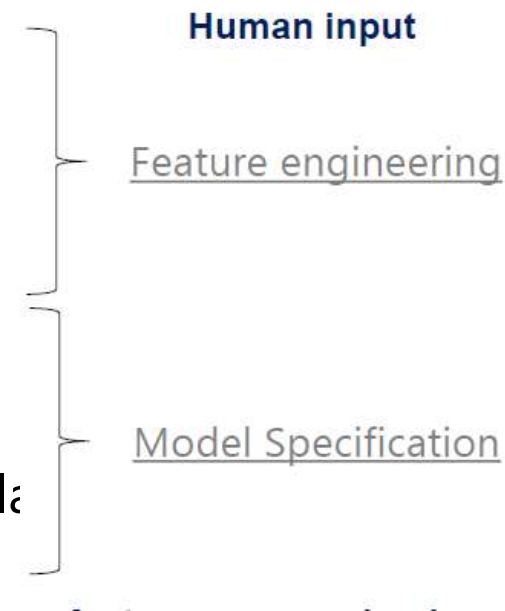
- P&C pricing
- IBNR reserving
- Experience analysis
- Mortality modelling
- «Lite» valuation models (Gan and Lin, 2015)

But don't forget about unsupervised learning either!

Actuarial Modelling

Actuarial modelling tasks vary between:

- **Empirically/data driven**
 - NL pricing
 - Approximation of nested Monte Carlo
 - Portfolio specific mortality
- **Model Driven**
 - IBNR reserving (Chain-Ladder)
 - Life experience analysis (AvE)
 - Capital modelling (Log-normal/Clayton copula)
 - Mortality forecasting (Lee-Carter)



Feature engineering = data driven approach to enlarging a feature space using human ingenuity and expert domain knowledge

- Apply various techniques to the raw input data – PCA/splines
- Enlarge features with other related data (economic/demographic)

Model specification = model driven approach where define structure and form of model (often statistical) and then find the data that can be used to fit it

Issues with Traditional Actuarial Modelling

In many domains, including actuarial science, traditional approach to designing machine learning systems relies on human input for feature engineering or model specification.

Three arguments against traditional approach:

- *Complexity* –which are the relevant features to extract/what is the correct model specification? Difficult with very high dimensional, unstructured data such as images or text. (Bengio 2009; Goodfellow, Bengio and Courville 2016)
- *Expert knowledge* –requires suitable prior knowledge, which can take decades to build (and might not be transferable to a new domain) (LeCun, Bengio and Hinton 2015)
- *Effort* –designing features is time consuming/tedious => limits scope and applicability (Bengio, Courville and Vincent, 2013; Goodfellow, Bengio and Courville, 2016)

Within actuarial modelling, complexity is not only due to **unstructured data**. Many difficult problems of model specification arise when performing actuarial tasks at a large scale (e.g. **Multi-LoB IBNR reserving**)

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Limitations of the traditional methods of reserving

- The current reserving practice consists of using method based on **claim development triangles** organised by origin period (e.g., accident, underwriting) and development period used for point estimate
- **Deterministic and stochastic unpaid claim reserving models based on triangles** have been a great success, such as Chain Ladder, Bornhuetter-Ferguson, GLM, etc
- These techniques have worked been in the past, but they have **several potential limits**, mainly:
 - **Over/under-estimation of the distribution** when back-testing realised amounts with forecast
 - **Huge estimation error** for the latest development periods due to the lack of observed aggregate amounts
 - **Uncertainty about the ability of these models to properly capture the pattern of claim development**, combined with the limited interpretative and predictive power of the accident and development period parameters
- These limits **are due to a loss of information when aggregating the original individual claim data** details (e.g., time of occurrence, reporting delay, time and amounts of payments, ...) into basic origin and development blocks in the triangle

Individual Claim Reserving (ICR)

- **Individual Claim Reserving (“ICR” or “Microreserving” or “Granular models” or “micro-models”)** is a claim reserving method based on individual (not aggregated) data using e.g. a Generalized Linear Model (“GLM”) and/or ML
- Granular models (GM) are not especially well-defined. **The general idea is that they endeavour to extend modelling into some of the detail that underlies the aggregate data in a claim triangle.** For example, a granular model may endeavour to model individual claims in terms of the detail of the claim process (Hachemeister’s, 1978, 1980) - [Model description](#)
- The early statistical **case estimation** models used in industry were also granular. See, for example, Taylor and Campbell (2002) for a model of workers compensation claims in which claimants move between “active” and “incapacitated” states, receiving benefits for incapacity and other associated benefits, such as medical costs

Individual Claim Reserving (ICR)

- The history of granular models is generally regarded as having commenced with the papers of Norberg (1993, 1999) and Hesselager (1994). These authors represented individual claims by a model that tracked a claim process through a sequence of key dates, namely accident date, notification date, partial payment date, partial payment date, final payment date, and closure date. **The process is a marked process in the sense that each payment date is tagged with a payment amount.**
- This type of model has been implemented by Pigeon et al. (2013, 2014) and Antonio and Plat (2014).
- Distinction is sometimes made between aggregate and granular models, but it is debatable. **The literature contains models with more extensive data inputs than just claim payment triangles.** For example, the payment triangle might be supplemented by a claim count triangle, as in the Payments per Claim Incurred model described in Taylor (2000), or in the Double Chain Ladder of Miranda et al. (2012).

Individual Claim Reserving (ICR)

- These models certainly use more extensive data than a simple claim amount triangle, **but the data are still aggregated**. It is more appropriate to regard claim models as forming a spectrum that varies from a small amount of conditioning data at one end (e.g., a chain ladder) to a very large amount at the other (e.g., the individual claim models of Pigeon, Antonio and Denuit).

Individual Claim Reserving (ICR)

- About Italian Researchers, it is worth mentioning Giovanna Ferrara (2003), Gigante et al. (2004), Parodi (2014) and Cavastracci e Tripodi (2018)
- In regards of recent papers with Italian Researches contribution, Bladt and Pittarello (2024):
 - propose an individual claims reserving model based on the conditional **Aalen–Johansen (AJ) estimator**, as developed in Bladt and Furrer ((2023a) arXiv:2303.02119.)
 - formulate a multi-state problem, where the *underlying variable is the individual claim size, rather than time*
 - propose a solution ⁽¹⁾ for modelling the IBNR (*incurred but not reported*) and RBNS (*reported but not settled*) reserves separately.
 - The model is compared with the chain ladder in two case studies, one using simulated data and the other using a recent dataset from a Danish non-life insurer. In both the simulation case study and the real data case application, they have access to the total future claims costs and can thus compare the predicted amount with the target amount. The predicted curve for the cumulative density function of claims size is compared with the empirical cumulative density function using the continuously ranked probability score (CRPS), first proposed in Gneiting and Raftery (2007)
 - show how the CRPS can be used to perform model selection by answering the natural question of how to select the number of states in the state space S

(1) The code at <https://github.com/gpitt71/conditional-aj-reserving> complements the results of this manuscript.

Individual Claim Reserving (ICR)

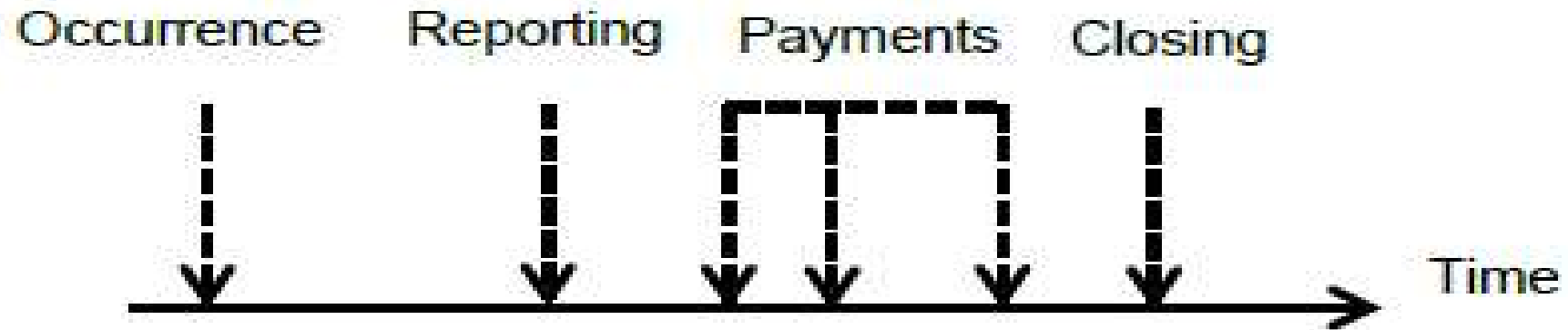
- **In next slides, we'll deal:**
 - **Section A) First of all, ICR with a GLM framework (without ML techniques)**
 - **Section B) Secondly, ICR with ML techniques**

Remarks - 1

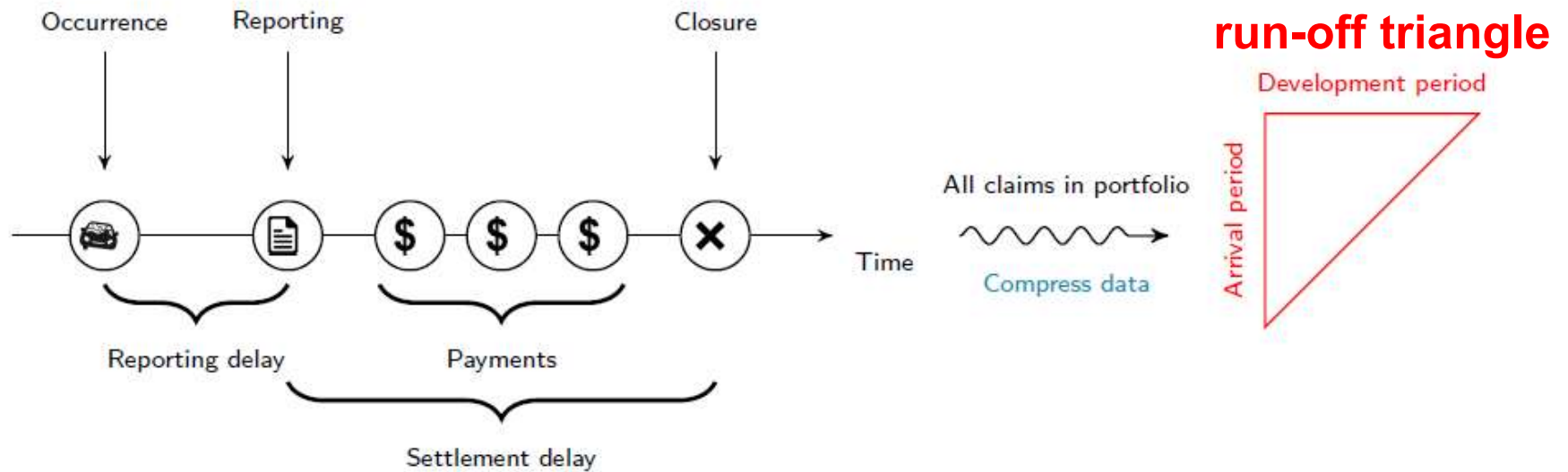
- It's crucial, in this context of rising demand for more accurate reserving approaches, to implement more flexible models to account for key effects, such as:
 - Capturing the **specific development pattern** of claims
 - Taking into account possible changes in the **product mix, the legal context of the claims processing over time**, to avoid potential biases in estimation and forecasting
 - Performing an advanced **risk assessment and monitoring**
 - Implementing a separate and consistent treatment of **IBNyR claims (Incurred But Not yet Reported → Pure IBNR)**
 - Including the key claim characteristics to allow for claims heterogeneity and to take advantage of **additional large datasets combined with big data and analytics technologies**
 - Gathering such features in a rigorous statistical framework allowing for **goodness of fit analysis and model checking**
- **A proper use of the information embedded in individual claims data combined with appropriate individual claims development models represent a promising future.**

Remarks – 2

- The individual claims point of view requires methodologies which are able to capture the detailed individual claim development, such as:
 - Occurrence (Accident Year – AY)
 - Reporting (Reporting Year – RY)
 - Payments (PY)
 - Closing (CY)



Remarks – 3



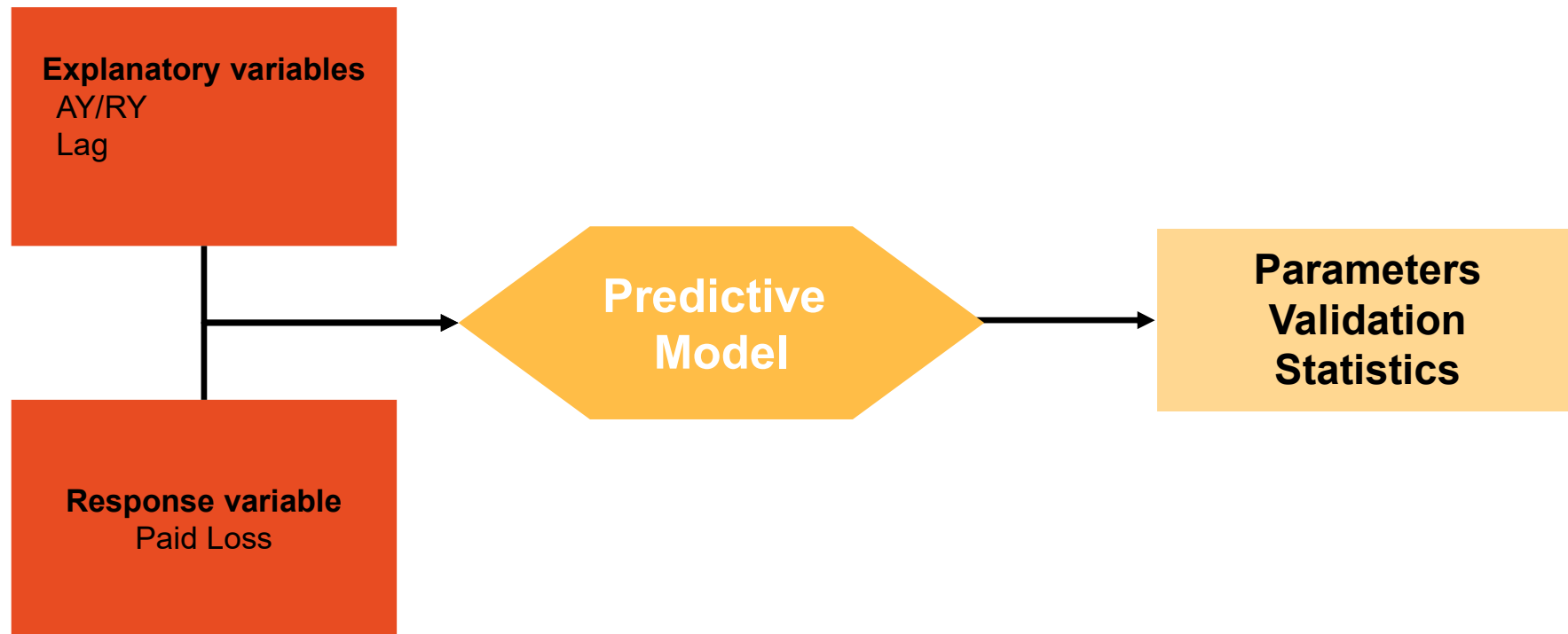
We typically aggregate the data from the time line into a **run-off triangle**

A) Individual Claim Reserving (ICR) and GLM

- Historically, the GLMs have been proposed by J. Nelder and R. Wedderburn in 1972 and in the field of non-life reserving, Renshaw et al. (1994, 1998) have studied log-Poisson model reproducing results of the Chain Ladder method while generating a full empirical distribution of future payments.
- The power of the GLM models may allow an improved estimate of the individual claim's case estimate using not only the individual claim's specific information, but also the information arising from **policy information and details captured at the time the claim was reported**. The advantages of these techniques are related to the ability to create an important link between individual behavior and future claims of policyholders.
- Some possible advantages:
 - Provides management information regarding the characteristics that contribute to changes in the claim status/cost and their underlying trends
 - IBNeR (Incurred But Not enough Reported) attribution to single risk unit
 - Building a more coherent process with other business functions (reserving, risk management, etc.), in the light of **Solvency 2 and IFRS17** as well.

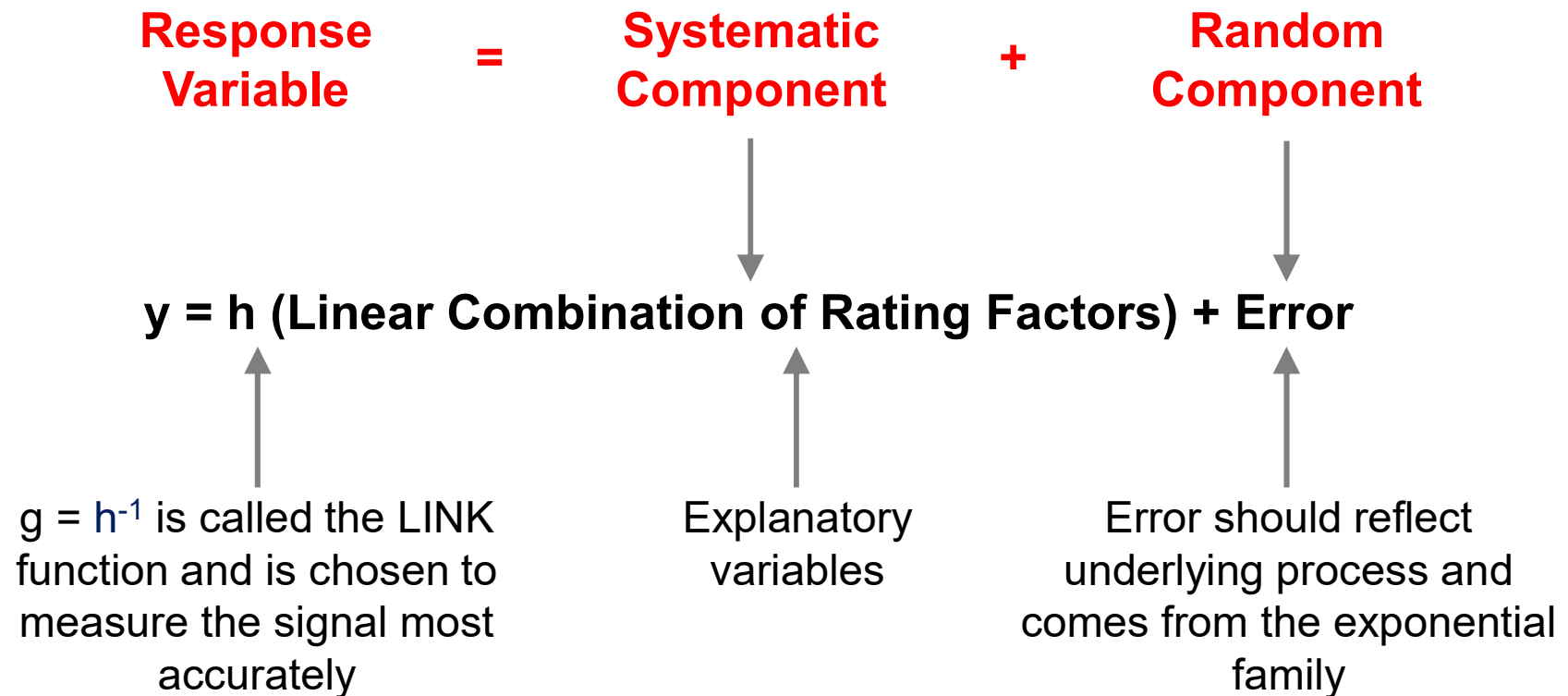
Predictive Models and GLM

- **Definition:** Statistical model to predict a response variable using a series of explanatory variables



Predictive Models and GLM

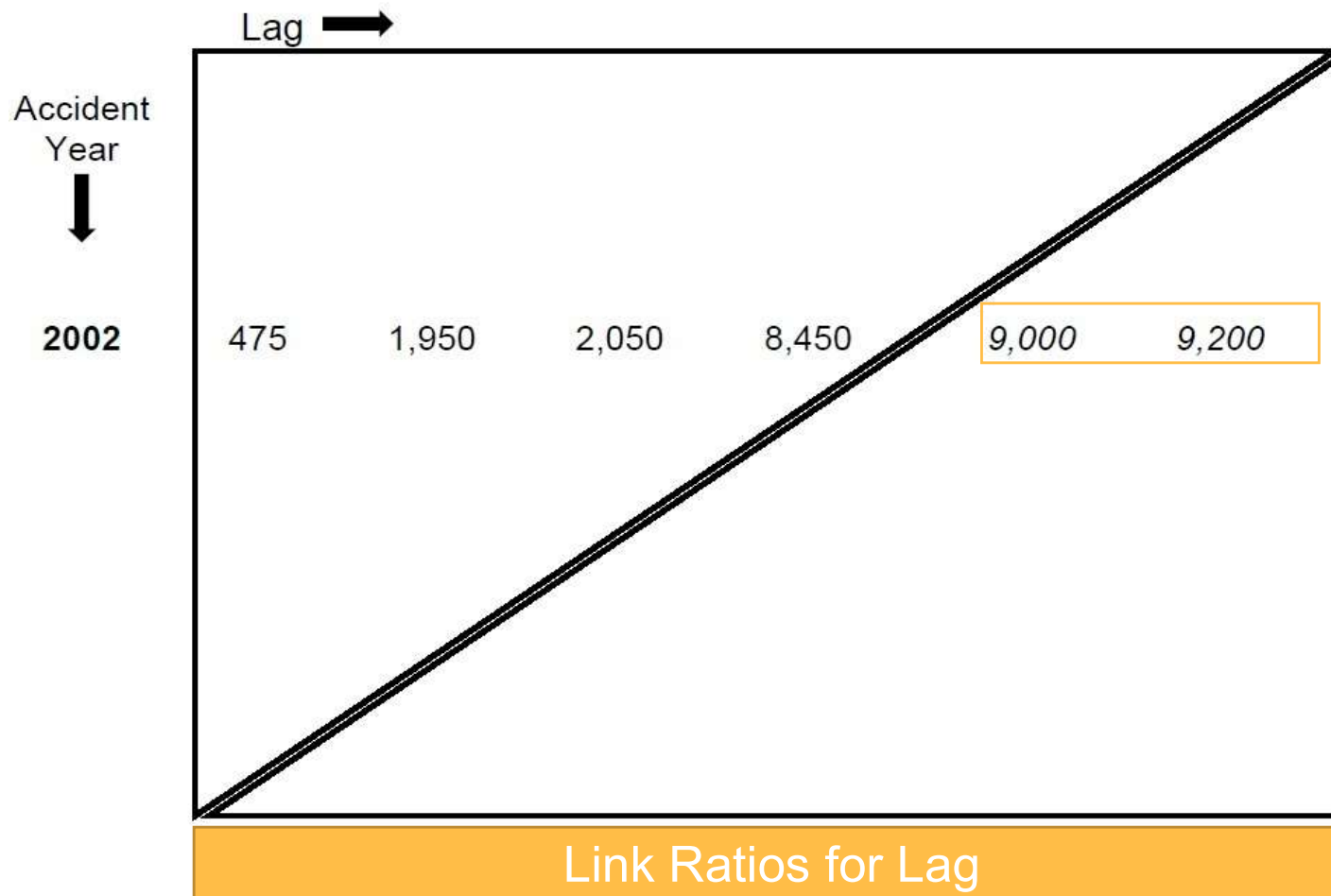
- GLMs are a flexible and sophisticated predictive modeling technique



The application of GLM to individual claims data by using multiple explanatory variables would be a kind of **bridge** between traditional methods and Machine Learning

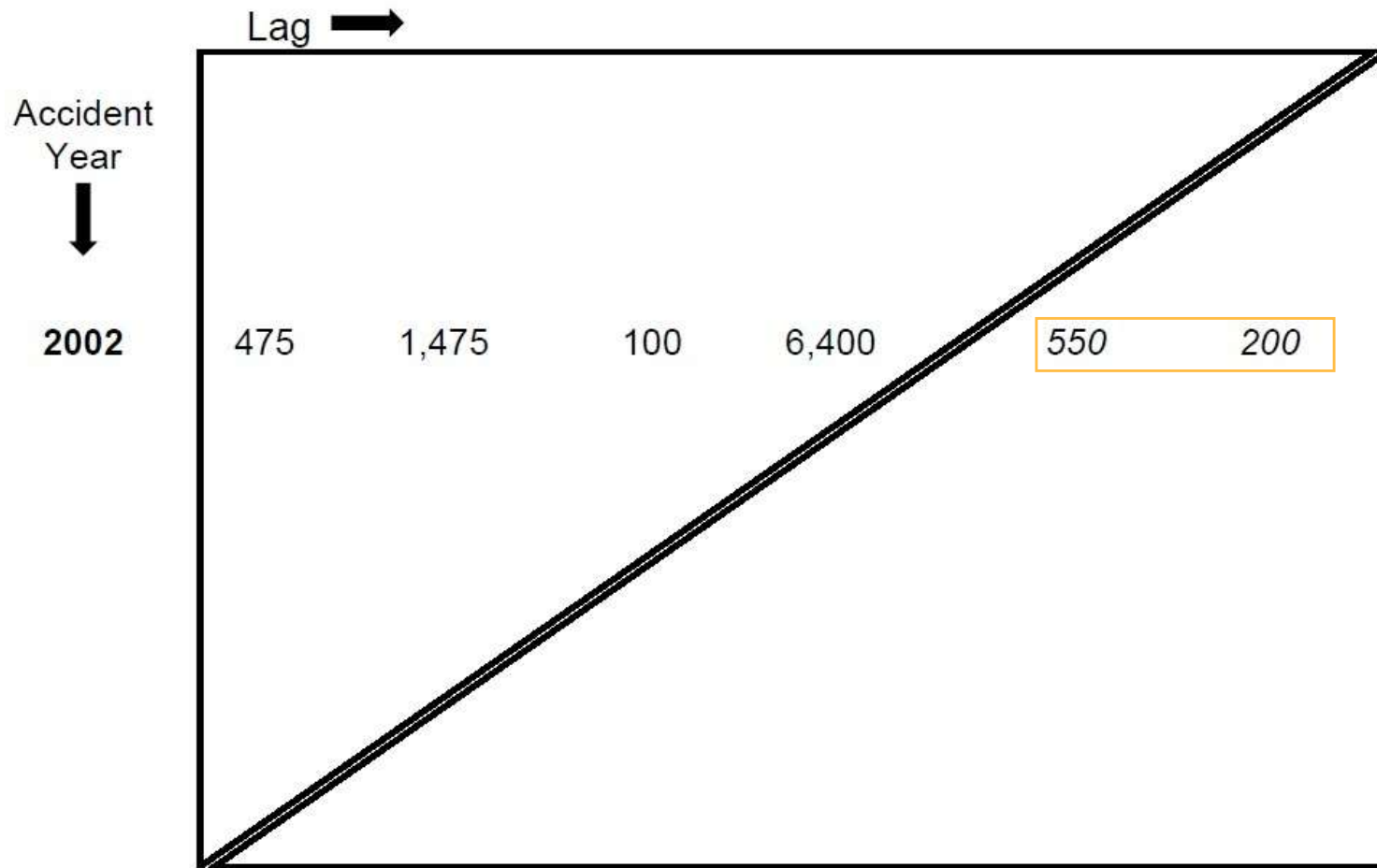
From the traditional to the ICR – Loss Development Method

- Goal: square up the triangle



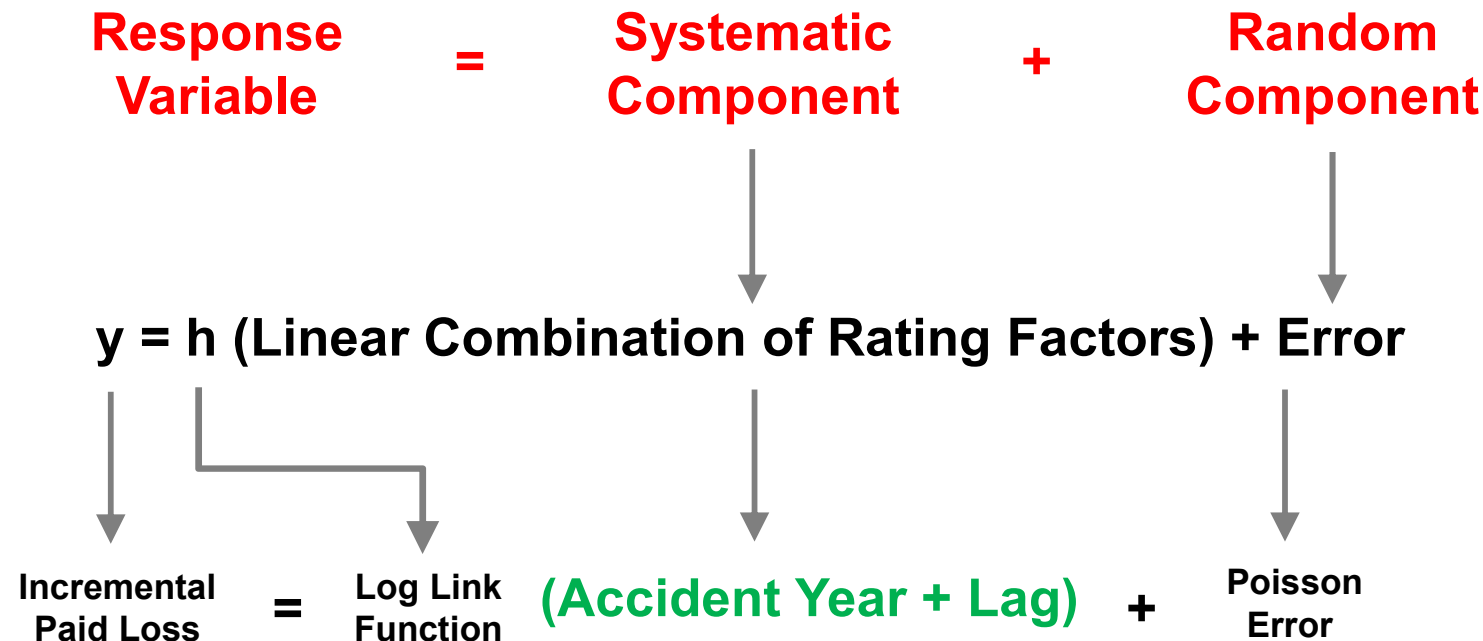
From the traditional to the ICR – GLM Aggregate Loss Development

- Goal of GLM is the same: square up the triangle using **more and new explanatory variables**. Difference is that GLM triangle is set to an **incremental** basis



From the traditional to the ICR – GLM Aggregate Loss Development

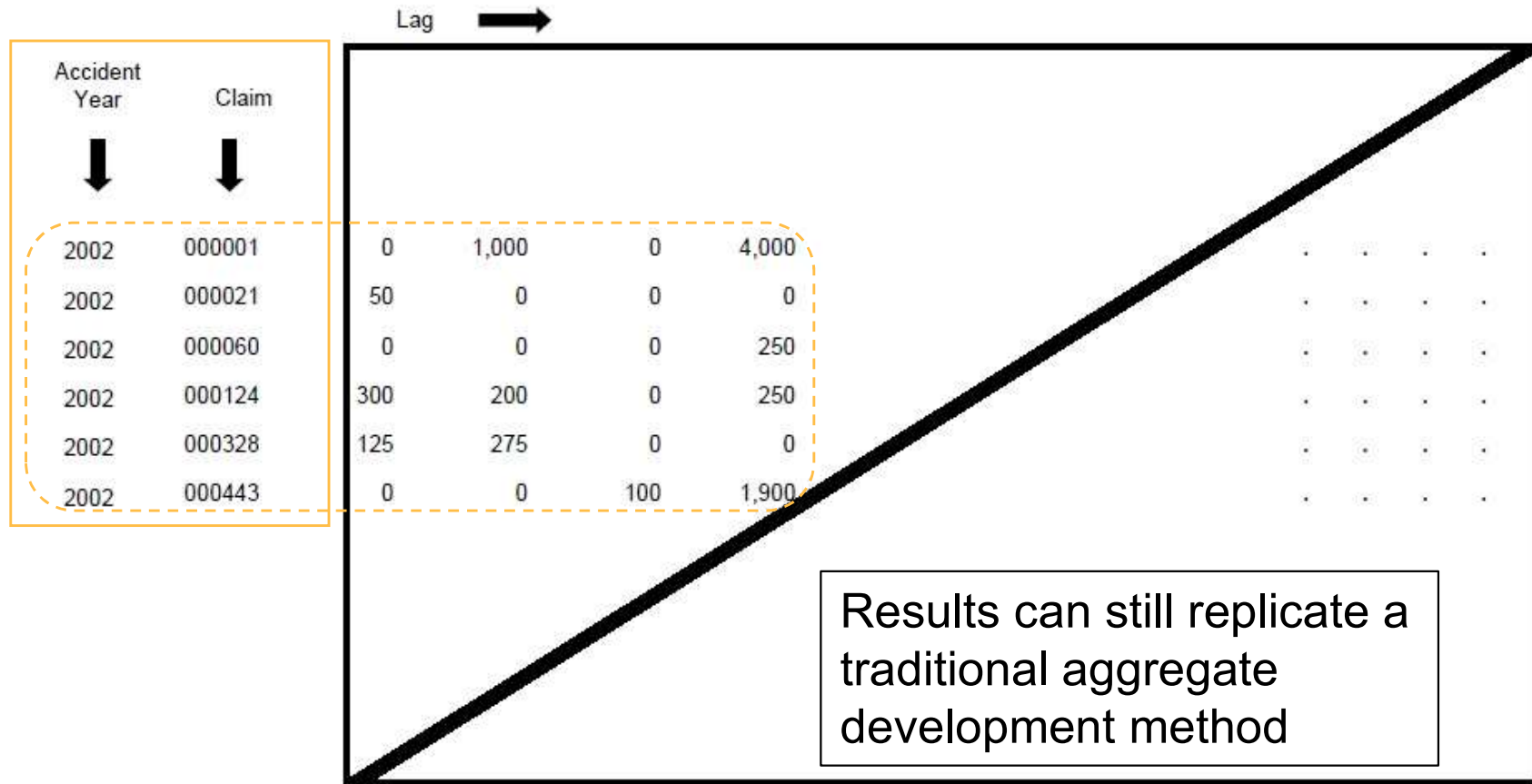
- GLMs are a flexible and sophisticated predictive modeling technique



GLM is a (analytical) stochastic methods. So it is possible to determine the **standard deviation** in **1-year** or **run-off approach** of the estimation (*prediction error*). See Cavastracci S, Tripodi A (2018)

From the traditional to the ICR– the ICR

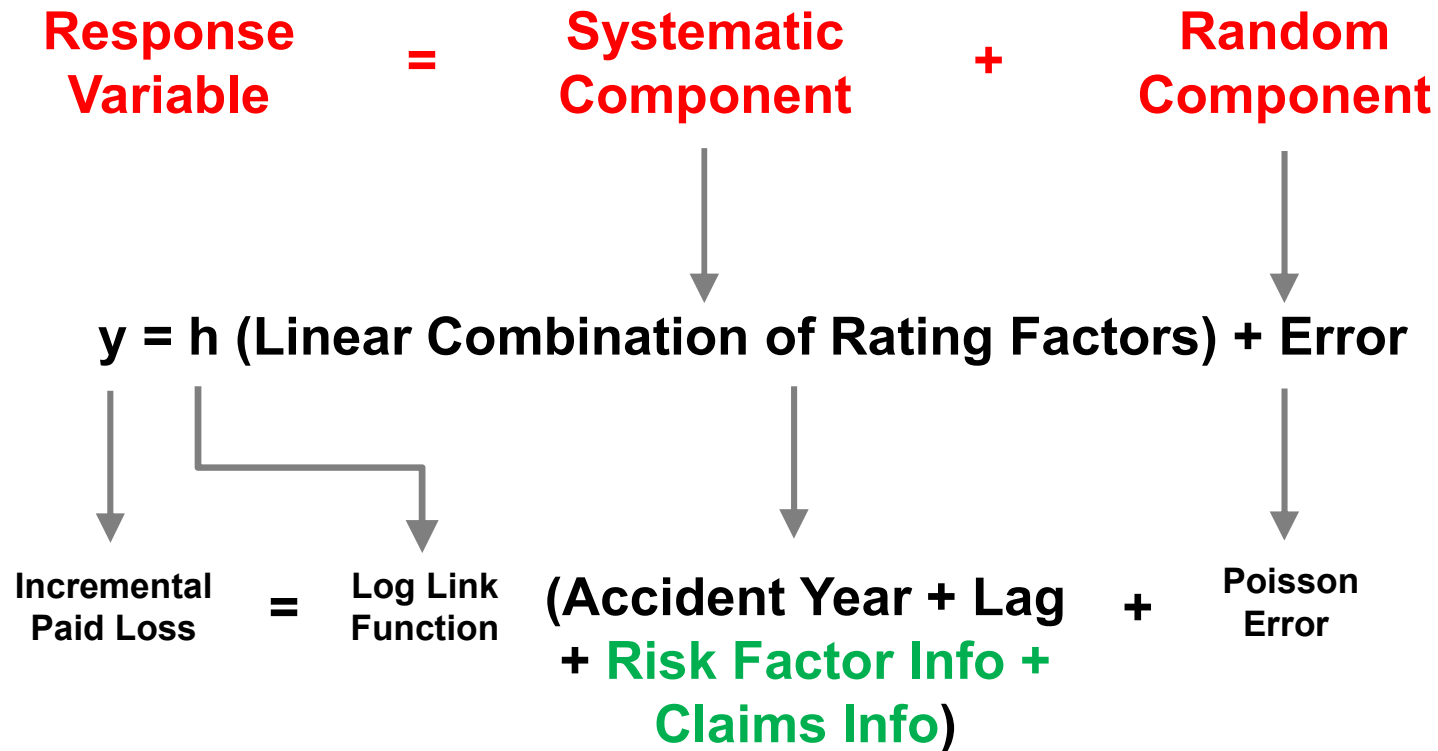
GLM triangle is set to an **incremental** basis



To square up the triangle, **the claim amount** will be projected using the relativities of the GLM

From the traditional to the ICR– the ICR

As shown before



Why we use the ICR for Reserving

- A GLM model will replicate a traditional development method using a volume weighted average of all years (for “Loss development method”):
 - With **aggregated** data, the GLM estimation can't take into account the prediction power of the individual information



ICR → Outstanding claims reserve (“OCR”) are estimated “claim by claim”

- Claims information:
 - Accident Year, Development Year, Calendar Year
 - Personal Damage or Bodily Injury damage
 - Geo-demographic
 - Direct Indemnity System (“CARD”)
- Risk profile information:
 - Insured: age, address, etc.
 - Vehicle: power, HP, type of fuel, Tariff sector, etc

ICR

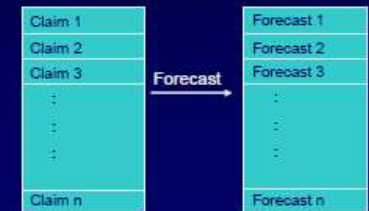
Why individual claim loss reserving ?

- What is meant by individual claim loss reserving ?
 - Or let's call it micro-reserving

Conventionally



Micro-reserving



TAYLOR FRAY
CONSULTING ACTUARIES

5

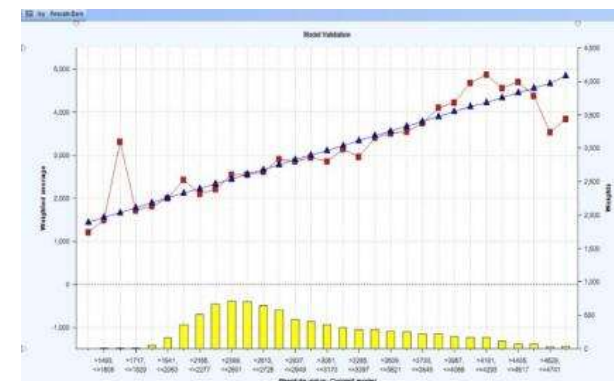
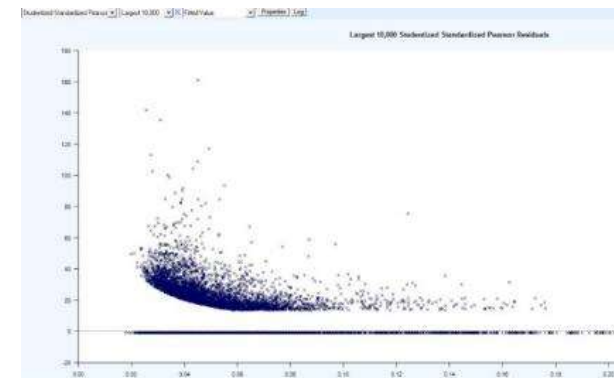
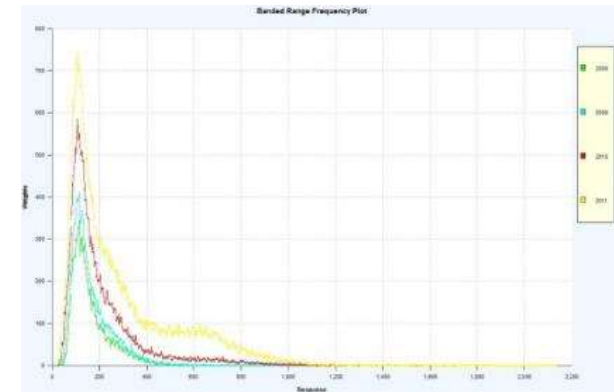
ASTIN, AFIR/ERM and IACA Colleges • Innovation & Invention

Implementing the ICR method

- Additional options available:
 - Choice of the periodicity
 - Years, half-years, quarters, months
 - Application of reinsurance
 - Excess of loss by stoping the projection for a claim once a threshold is crossed
 - Segmentation of claims using Initial reserves
 - And compute the parameters separately for each category
 - And many more

Why we use the ICR for Reserving

- ICR method could adjust the cost of claim for the IBNeR at single claim level
- The OCR will be estimated:
 - Explorative Data Analysis (e.g. one-way analysis, test of the error distribution, etc.).
 - Significancy of the explanatory by the GLM tools
 - Chose the “best” model: Deviance criterion, Chi-Squared statistic, Akaike’s test (c.d. “AIC”), Akaike’s corrected test (c.d. “AICc”) and/or the Bayesian’s one (c.d. “BIC”).
 - Residuals analyses (Pearson, Deviance, etc.).
- Sinergy between Pricing and Reserving Offices

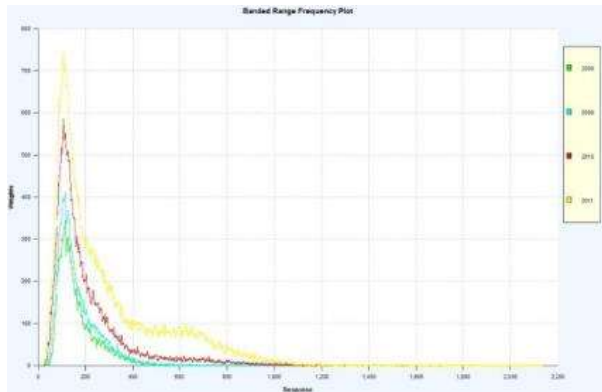


Solvency II – ICR and one-year view of reserve risk

- In Boumezoued et al. 2011 paper (“One-year reserve risk including a tail factor: closed formula and bootstrap approaches”) two adaptations of GLM, generating samples of the CDR in a one-year view, have been developed:
 - **First approach:** this approach has been proposed by Lacoume (2008) and Boisseau (2010). This method is applied to the residuals of the incremental payments of the loss development triangle. Two disadvantages:
 - 1) Independence of the random variables: Step 4 provides expected values in the sub-diagonal starting from the GLM parameters estimated on the upper triangle. Thus, at step 6 of re-estimation of the GLM parameters on the trapezoid by maximum likelihood, the random variables of the upper triangle and those of the sub-diagonal are not independent. The framework of maximum likelihood estimation, in which total probability breaks up into product of probabilities of the incremental payments, is thus not verified.
 - 2) Estimation error: This method estimates the GLM parameters twice (steps 3 and 6): first to obtain incremental payments in the sub-diagonal and second to calculate the expected future payments (lower triangle). **This approach tends to significantly increase the estimation error compared to the result of Wüthrich et al. (2008), and thereafter the total variance.**
 - **Second approach:** The second approach thereafter suggested makes it possible to overcome these limits. This improvement has been proposed by Boisseau (2010). In each iteration of this new approach, the residuals of the original triangle are resampled on the trapezoid containing the upper triangle and the sub-diagonal.

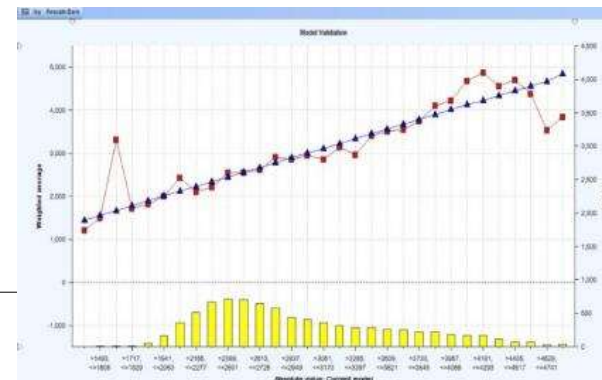
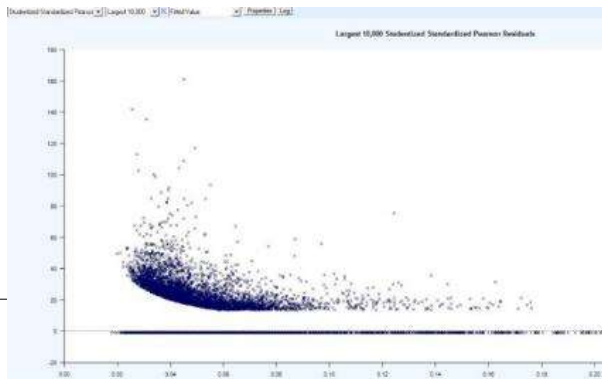
Solvency II – ICR and one-year view of reserve risk

- A GLM with an Over-Dispersed Poisson distribution → pdf of claim provision (e.g. package Chain ladder of R by Carrato et al.).



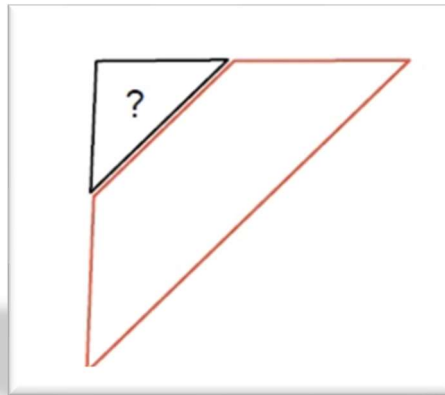
Practical Challenges – One Year Reserve Risk vs. Ultimate Reserve Risk (cfr. Han Chen, 2016):

- The one year reserve risk from Merz –Wüthrich method is often very close to the ultimate reserve risk from Mack method*
- In many cases, one year paid out loss is 30% to 70% of total reserve, but one year reserve risk is more than 90% of ultimate reserve risk*
- Merz -Wüthrich one year CV is 97% of Mack ultimate CV in Han Chen example*
- GLM and bootstrapping are other possible solutions for one year risk*



Some remarks

- Partial triangles under this approach discussed today will not reconcile to traditional methods
 - Alternative approaches need to be explored



- Essentially the ICR creating a development method on a Report Year basis which produces estimate of IBNeR, excluding the Pure IBNR (IBNyR):
 - Advantage or Disadvantage?
 - Is the Pure IBNR influenced by the claims and/or risk profile information?
- Other potential limitations are discussed by Parodi (2014) and F. Siegenthaler (2024) - <https://ssrn.com/abstract=4985826>
- Further discussions about IBNyR in next slides

B) Individual Claim Reserving (ICR) and Machine Learning

- The Actuary IFoA - <https://www.theactuary.com/> - July 2020:
 - *Individual claims reserving is gaining **popularity** across many actuarial associations and will most likely replace current models based on aggregate data.*
 - ***The claims reserve is the largest number on the liability side of the balance sheet** of a typical non-life insurance company, and reserves are essential for the financial strength of the company.*
 - ***Machine learning may help to improve the accuracy of claims reserving, and individual claims features can lead to model improvements and more accurate risk assessment.***
- Machine Learning Reserving Working Party – IFoA (to which I belong): “*Given the ready availability of and the great familiarity with loss development data, it is important to explore how machine learning (ML) could be applied to triangle data:*
 - *To produce estimates of ultimate values; and*
 - *Be used for diagnostic analyses”*

ML techniques and ICR

Machine learning techniques are very popular in data analytics and offer highly configurable and accurate algorithms that can deal with any sort of structured and unstructured information.

There are many researches with applications of ML techniques in the ICR:

- **Wüthrich (2016)** proposes a contribution to illustrate how the **regression trees** can be used for individual claims reserving.
 - He estimates the regression functions in a non-parametric way using classification and regression tree (**CART**) techniques (e.g. *classification trees for the frequency and regression trees for the severity*).
 - One of the main advantages of CART methods is the large modeling flexibility (for aggregate claims reserving methods with a good degree of model flexibility though not using machine learning, see **Pešta and Okhrin, 2014** and **De Felice and Moriconi, 2019**).
 - CARTs can deal with any sort of structured and unstructured information, an underlying structural form of the prediction function can be learned from the data, many explanatory variables can be used, both quantitative and qualitative and observed at different dates.
 - Moreover, the interpretability of results is generally allowed. As methods for providing expectations, CARTs can also be referred to as *prediction trees*.
 - **These regression trees are fully flexible and allow us to consider (almost) any kind of feature information, but aren't known to be very robust towards changes in observations.**

ML techniques and ICR

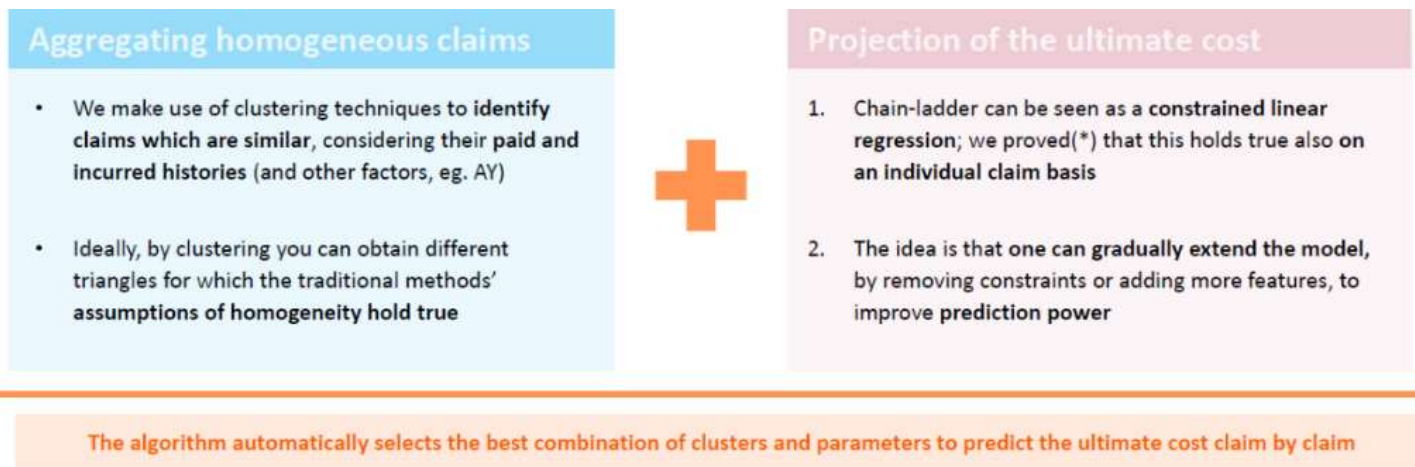
- **Wüthrich (2017)** proposes an application of the **Neural Network** model for the Chain Ladder factors to apply it in the ICR. The extended model used in this paper has the advantage that you can
 - analyze reserves on individual claims
 - capture changing portfolio mixes and
 - detect trends and business cycles in the insurance claims, but
 - *also this technique isn't free to defects, mainly the execution times.*
 - **Baudry et al. (2017)** proposes a **non-parametric approach** to estimate individual IBNyR and RBNS claims reserves using **ExtraTree algorithm**. They put emphasis on the impact of using micro-level information on the **variances of the prediction errors**. The method provides almost unbiased estimators of the **claims reserves with very small standard deviations** (in this paper five times smaller than the Mack chain-ladder standard deviation).
 - **McGuire et al. (2018)** modelled an earlier version of a data consisted of a unit record file in respect of about 60,000 Auto Bodily Injury finalised claims, each tagged with its accident quarter, development quarter of finalisation, calendar quarter of finalisation, Operational Time (OT) at finalisation and season of finalisation (quarter). **Prior GLM analysis** of the data set over an extended period had been carried out **by Taylor and McGuire (2004)**, and they found that claim costs were affected in a complex manner by the factors listed there. The **Artificial Neural Network (ANN)** was able to identify these effects. For example, **it identified**:
 - **an accident quarter effect (row effect) on claim sizes corresponding to the legislative change that occurred in the midst of the data (e.g. Milan Tables impact on MTPL and TPL in Italy);**
 - **superimposed inflation (a diagonal effect) that varied dramatically over time (finalization) and also over OT.**
-

ML techniques and ICR

- **Kuo (2019)**: proposed the Deep-Triangle as a novel approach for loss reserving based on deep neural network. DeepTriangle is a multi-task network utilizing a sequence-to-sequence architecture (**Sutskever et al., 2014**) simultaneously predicting paid losses and claims outstanding. The underlying **ANN** has multiple hidden layers (feed-forward network with fully connected layers) and does not pre-suppose a model structure.
-
- **Gabrielli (2021)** present a claims reserving technique that uses claim-specific feature and past payment information in order to estimate claims reserves for individual reported claims. He design one single **ANN** allowing to estimate expected future cash flows for every individual reported claim. He introduces a consistent way of using dropout layers in order to fit the neural network to the incomplete time series of past individual claims payments. A proof of concept is provided by applying this model to **synthetic as well as real insurance data** sets for which the true outstanding payments for reported claims are known.
-

ML techniques and ICR

- **Wang and Wuthrich (2022)** explain the individual claims generator “data simulation.R”. They use the statistical computing software R to design this individual claims generator. It may be used for developing and **back-testing individual claims reserving methods in non-life insurance**. They give a descriptive analysis of the generated data, and they provide Mack’s chain-ladder results as a benchmark.
- **Carrato (ICA 2023)** shows how to move from Chain Ladder to ICR using ML techniques by **k-means algorithm (clustering)** in order to group the claims in similar “pockets” and predicting his trajectory using its similarity to more developed claims
-



The model can be extended even further using popular/recent ML techniques(**), but this will result in a lack of model interpretability

Remark: the above can be applied only to reported claims, ie. to derive the IBNER component of the reserve. The IBNYR component is automatically estimated via a traditional approach

(*) Carrato, Visintin (2019) - „From Chain Ladder to Individual Claims Reserving with Machine Learning“ [ASTIN Colloquium]

(**) Traditional Machine Learning approach defines $C_j = f(\mathbf{X}_{j-1}) + \epsilon_{j-1}$, where f is found via gradient boosting or neural networks

ML techniques and ICR

There are many other machine learning techniques that can be used for this purpose (random forests, bagging, boosting, ...):

- **Ensemble methods:** meta-algorithms that combine several machine learning techniques into one predictive model in order to decrease variance (**bagging**), bias (**boosting**), or improve predictions (**stacking**) of decision trees for example:
 - **Boosting and Bagging can be used for prediction uncertainty. Bootstrap** can be used to get **some confidence interval** around the estimations
 - **Bagging is also a useful method for reducing the variance** in the resulting parameter estimates.

ML techniques and ICR – The IBNR issue

Note: We remark that claims reserves can be split into an RBNS (reported but not settled - which consist of estimated expected future payments for claims that have already been reported) part and an IBNyR (incurred but not reported) part. Main of these papers focus on modeling RBNS reserves. Usually, the biggest share of the claims reserves are due to such RBNS claims. For IBNyR some proxies (or traditional methods) is still used.

- **Delong, Lindholm and Wüthrich (2021):** This paper builds on a previous work (Delong & Wüthrich 2020) on individual claims reserving. There are two essential new parts here. **First, they derive an estimate of claims reserves for both reported (RBNS) and incurred but not reported (IBNR) claims.** The latter reserves are not considered in Delong & Wüthrich (2020), and they propose a conceptually new approach to deal with this part of the claims. **The second contribution is to come up with a smaller architecture compared to Delong & Wüthrich (2020).** Using this reduced architecture, **they benefit from improved run times** which is essential in practical applications. This improved run times allow us to consider finer time scales, and they verify that this smaller model provides accurate reserves by benchmarking it with the well-known chain-ladder (CL) method. **Finer time scales are important for capturing seasonal patterns and, for instance, sensitivities in insurance product features such as waiting periods in accident and health insurance.** *The price they pay by this reduction is that, in contrast to Delong & Wüthrich (2020), they no longer have a full simulation model, but they only design an optimal architecture to receive accurate claims reserves.*

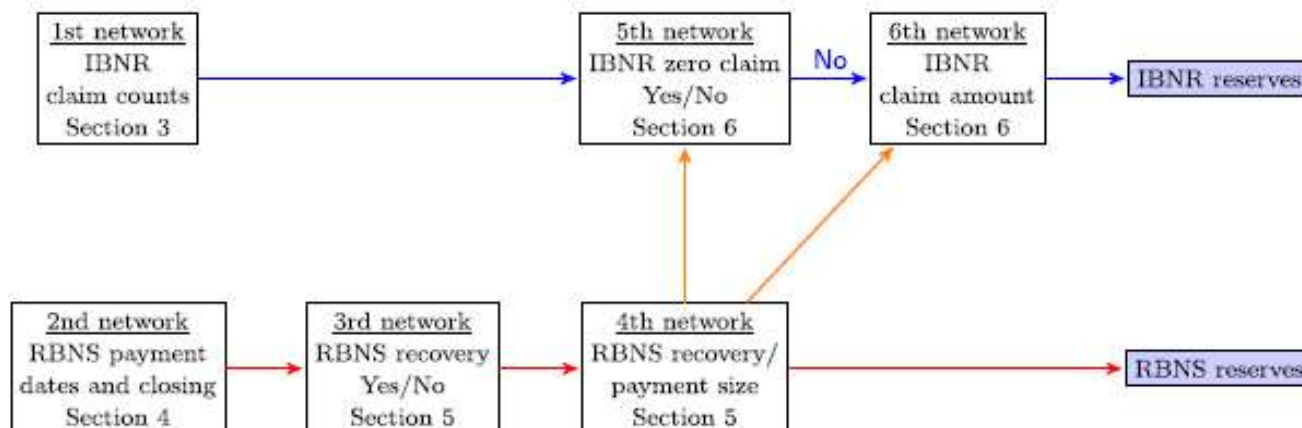


Figure 1. Claims reserving architecture used consisting of six networks.

ML techniques and ICR - The IBNR issue

Note: We remark that claims reserves can be split into an RBNS (reported but not settled - which consist of estimated expected future payments for claims that have already been reported) part and an IBNyR (incurred but not reported) part. Main of these papers focus on modeling RBNS reserves. Usually, the biggest share of the claims reserves are due to such RBNS claims. For IBNR some proxies (or traditional methods) is still used.

- **Jakobsen (ICA 2023):** *Risk managers and auditors might also be skeptical about productionizing models such as neural networks, although there is already some work done to address these concerns.* A way one might consider avoiding the issues with machine learning models is to instead **apply machine learning techniques to standard methods**. In this paper, they further develop the approach by **Balona and Richman (2020)** to handle real monthly claims data **for the problem of IBNyR reserving**. In particular, they consider auto collision and homeowners insurance. These are relatively short-tailed and high-frequency Line of Businesses (LoBs), **making it easier to validate the performance of their method on newer data**.

Summary sections A and B

Surveys of recently developed claims reserving techniques can be found in Boumezoued and Devineau (2017) and Taylor G (2019).

Here is a broad classification into ICR models with and without the use of machine learning Methods (taking into account only last 20 years papers).

ICR without ML	ICR with ML
Antonio K, Plat R (2014)	Baudry M, Robert CY (2019)
Bladt M., Pittarello G. (2024)	Carrato (2023)
Crevecoeur J, Antonio K (2019)	De Felice M, Moriconi F (2019)
Hiabu M, Margraf C, Martínez-Miranda MD, Nielsen JP (2016)	DeLong L, Lindholm M, Wüthrich MV (2020)
Jessen AH, Mikosch T, Samorodnitsky G (2011)	DeLong L, Wüthrich MV (2020)
Larsen CR (2007)	Duval F, Pigeon M (2019)
Martínez-Miranda MD, Nielsen JP, Verrall RJ, Wüthrich MV (2015)	Kuo K (2020)
Pigeon M, Antonio K, Denuit M (2013)	Lopez O, Milhaud X, Thérond P-E (2019)
Taylor G, McGuire G, Sullivan J (2008)	Wüthrich MV (2018)
Zhao XB, Zhou X, Wang JL (2009)	

(Some) Actuarial Applications of Deep Learning

	Pricing	Reserving	Telematics	Mortality Forecasting	Quantitative Risk Management
Feed-forward Nets	<ul style="list-style-type: none"> Ferrario, Noll and Wüthrich (2018) Noll, Salzmann and Wüthrich (2018) Wüthrich and Buser (2018) 	<ul style="list-style-type: none"> Castellani, Fiore, Marino et al. (2018) Doyle and Groendyke (2018) Gabrielli and Wüthrich (2018) Hejazi and Jackson (2016, 2017) Wüthrich (2018) Zarkadoulas (2017) 	<ul style="list-style-type: none"> Gao and Wüthrich (2017) Gao, Meng and Wüthrich (2018) Gao, Wüthrich and Yang (2018) 		<ul style="list-style-type: none"> Castellani, Fiore, Marino et al. (2018) Hejazi and Jackson (2016, 2017)
Convolutional Neural Nets			<ul style="list-style-type: none"> Gao and Wüthrich (2019) 		
Recurrent Neural Nets		<ul style="list-style-type: none"> Kuo (2018a, 2018b) 		<ul style="list-style-type: none"> Nigri, Levantesi, Marino et al. (2019) 	
Embedding Layers	<ul style="list-style-type: none"> Richman (2018) Schelldorfer and Wüthrich (2019) Wüthrich and Merz (2019) 	<ul style="list-style-type: none"> Gabrielli, Richman and Wüthrich (2018) Gabrielli (2019) 		<ul style="list-style-type: none"> Richman and Wüthrich (2018) 	
Autoencoders			<ul style="list-style-type: none"> Richman (2018) 	<ul style="list-style-type: none"> Hainaut (2018) Richman (2018) 	

Deep Learning for Actuarial Modelling

Actuarial tasks vary between Empirically/data driven and Model Driven

- Both approaches traditionally rely on manual specification of features or models
- Deep learning offers an empirical solution to both types of modelling task – feed data into a suitably deep neural network => learn an optimal representation of input data for task
- Exchange of model specification for a new task => architecture specification
- Opportunity – improve best estimate modelling
- Deep learning comes at a (potential) cost – relying on a learned representation means less understanding of models, to some extent

Selected Applications

- Following examples chosen to showcase ability of deep learning to solve the issues with the traditional actuarial (or ML) approaches.
 - In most of these instances, deep learning solution outperforms the traditional actuarial or machine learning approach
- Complexity –which are the relevant features to extract/what is the correct model specification?
 - Multi-population mortality forecasting
 - **Multi LoB IBNR reserving**
 - Non-life pricing
- Expert knowledge –requires suitable prior knowledge, which can take decades to build
- Lite valuation models

Multi LoB IBNR reserving (1)

- Even using triangles, most reserving exercises are more data rich than assumed by traditional (widely applied) methods (CL/BF/CC):
 - Incurred/Paid/Outstanding
 - Amounts/Cost per Claim/Claim Counts
 - Multiple LoBs
 - Multiple Companies
- Traditional solutions:
 - Munich Chain Ladder (Quarg and Mack, 2004) reconciles Incurred and Paid triangles (for single LoB) by adding a correction term to the Chain Ladder formula based on regression
 - Credibility Chain Ladder (Gisler and Wüthrich, 2008) derives LDFs for sub-portfolios of a main LoB using credibility theory
 - Double Chain Ladder (Miranda, Nielsen and Verrall, 2013) relates incurred claim count triangles to payment triangles
 - **Multivariate Chain Ladder (Zhang Y., 2010)**
- Would assume that multi-LoB methods have better predictive performance compared univariate methods, but no study (yet) comparing predictive performance of multi-LoB methods (Meyers (2015) compares several univariate reserving models)

Multivariate Chain Ladder

- Support USP validation/approval in case of M&A
- Analysis of correlation between segments of the same company or correlation between the segments of the group companies

CHAIN LADDER MULTIVARIATE - CHOOSE TRIANGLES

Choose triangles

Company

- Company One
- Company Two
- Company Three

Choose

Segment label

- FDP
- GLI
- MVL

Choose

Data classification

1

Choose

Type

DL

Choose

Deselect

Triangles selection

Tail development periods to be excluded from multivariate analysis

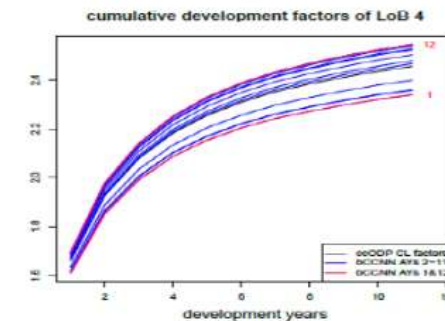
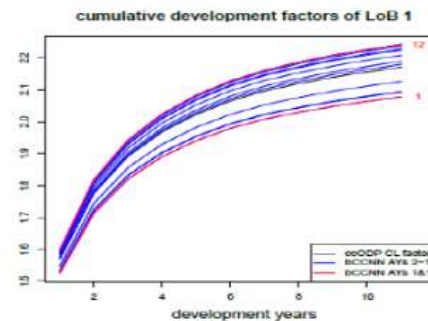
TRIANGLE NUMBER	COMPANY NAME	SEGMENT LABEL	DATA CLASSIFICATION	TYPE	YEAR MIN	YEAR MAX	TRIANGLE DIMENSION	Starting Year Selection
1	Company One	GLI	1	DL	2010	2018	9 x 9	
2	Company Two	GLI	1	DL	2009	2018	10 x 10	
3	Company Three	GLI	1	DL	2009	2018	10 x 10	
								2011
								2012
								2013
								2014

The image shows a software interface for 'US Prediction Studio Attuariale Cerchiana'. It features a main menu with icons for 'Import Data', 'Consistency Checks', 'Create Evaluation', 'RUN USP', 'USP ORSA', 'SCENARIO ANALYSIS', and 'Multivariate Chain Ladder'. There are also 'Developer' and 'EXIT' buttons at the bottom.

Multi LoB IBNR reserving (2)

- Recent work embedding the ODP CL model into a deep neural network (multi-LoB solution)
- 6 Paid triangles generated using the simulation machine of Gabrielli and Wüthrich (2018)**
 - Know true reserves
 - Relatively small data (12*12*6=478 data points)
- Gabrielli, Richman and Wüthrich (2018) use classical ODP model plus neural boosting on 6 triangles simultaneously**
 - Dramatically reduced bias compared to ODP model
 - Model learns smooth development factors adjusting for accident year effects
- Gabrielli (2019) extends model to include both paid and count data**
 - Further reduction in bias versus the previous model

	LoB 1	LoB 2	LoB 3	LoB 4	LoB 5	LoB 6
true reserves R_m^{true}	39,689	37,037	16,878	71,630	72,548	31,117
CL reserves R_m^{CL}	38,569	35,460	15,692	67,574	70,166	29,409
bCCNN reserves R_m^{LoB} (LoBs individually)	39,233	35,899	15,815	70,219	70,936	30,671
bCCNN reserves R_m^+ (multiple LoBs)	40,271	37,027	16,400	70,563	73,314	30,730



		LoB 1	LoB 2	LoB 3	LoB 4	LoB 5	LoB 6
(i)	true claims reserves R_m^{true}	39'689	37'037	16'878	71'630	72'548	31'117
(ii)	CL reserves R_m^{CL}	38'569	35'460	15'692	67'574	70'166	29'409
(iii)	single NNDODP reserves R_m^{ind}	39'407	36'283	16'123	70'547	71'873	31'092
(iv)	multiple NNDODP reserves R_m^{joint}	40'403	37'172	16'434	70'727		

Agenda

- Machine Learning
 - Actuarial Data Science
 - State of the Art - Literature
 - State of the Art – Actual Practice
 - Final Remarks
-



EXPLORING DIGITAL REGULATION

ANIA

- European Parliament introduced Regulation (EU) no. 2022/2554 on digital operational resilience for the financial sector, so-called “DORA” (“**Digital Operational Resilience Act**”).
- Starting from January 17, 2025, DORA sets forth an harmonized legal framework within the EU, applicable to financial entities (including insurance and reinsurance companies), **aimed at mitigating risks deriving from the increasing use of information and communication technologies (ICT)** in financial markets.
- In this perspective, **DORA requires financial entities to implement comprehensive capabilities to enable a strong and effective ICT risk management**, as well as specific mechanisms and policies for handling and reporting ICT-related incidents.
- This will have a strong impact on the Regulation’s recipients, including under a **corporate governance, organizational and operational perspective**.
- **Competent Authorities** (such as **IVASS** for the insurance sector) will need to harmonize reporting models, contributing to the **creation of a single European hub for notifications**.
- Additionally, financial entities will be required to conduct digital operational **resilience tests** and implement mechanisms for sharing information and analyzing cyber threats among themselves.
- Failure to comply with the Regulation's provisions will result in **administrative and criminal sanctions**, with details left to the Member States.

Si veda anche il sito dell’IVASS – sezione
Regolamenti Europei in merito all’ultimo
aggiornamento del **20 gennaio 2025**

Regolamenti europei

pagina 1 di 4

1. **Regolamento Delegato (UE) 2024/1774 della Commissione del 13 marzo 2024**
Regolamento (UE) 2024/1774 riguardante le norme tecniche di regolamentazione che specificano gli strumenti, i metodi, i processi e le politiche per la gestione dei rischi informatici e il quadro semplificato per la gestione dei rischi informatici
13 marzo 2024
2. **Regolamento Delegato (UE) 2024/1773 della Commissione del 13 marzo 2024**
Regolamento delegato (UE) 2024/1773 riguardante le norme tecniche di regolamentazione che precisano il contenuto dettagliato della politica relativa agli accordi contrattuali per l'utilizzo di servizi TIC
13 marzo 2024
3. **Regolamento Delegato (UE) 2024/1772 della Commissione del 13 marzo 2024**
Regolamento (UE) 2024/1772 riguardante le norme tecniche di regolamentazione che specificano i criteri per la classificazione degli incidenti connessi alle TIC e delle minacce informatiche
13 marzo 2024
4. **Regolamento Delegato (UE) 2024/1505 della Commissione del 22 febbraio 2024**
Regolamento delegato (UE) 2024/1505 che determina l'importo delle commissioni per le attività di sorveglianza che l'autorità di sorveglianza capofila addebita ai fornitori terzi critici di servizi TIC e le relative modalità di pagamento
22 febbraio 2024
5. **Regolamento Delegato (UE) 2024/1502 della Commissione del 22 febbraio 2024**
Regolamento Delegato (UE) 2024/1502 della Commissione del 22 febbraio 2024 che specifica i criteri per la designazione dei fornitori terzi di servizi TIC come critici per le entità finanziarie
22 febbraio 2024

<https://www.ivass.it/normativa/internazionale/internazionale-ue/regolamenti-europei/index.html>

Survey on the use of Machine Learning algorithms by insurance companies in their relations with policyholders

IVASS 2023

In late 2022, IVASS conducted a survey on the use of Machine Learning (ML) algorithms by insurance companies in processes impacting customers.

The survey supports IVASS' strategic goal of analysing the evolution and impact of InsurTech issues, promoting digital development in a modern consumer protection system.

Further developments may emerge following experimentation and evaluations of the added value of ML to business and with the full definition of the relevant regulatory framework, particularly at the European level: reference is made to the EU Commission Proposal for a “Regulation of the European Parliament and of the Council laying down harmonised rules on artificial intelligence and amending certain Union legislative acts” (**AI Act**) and to the Directive on a civil liability regime for artificial intelligence (**AILD**).



English

Home > ... > Doing business in the EU > Contract rules > Digital contracts > Liability Rules for Artificial Intelligence

Liability Rules for Artificial Intelligence

The European approach to artificial intelligence (AI) will help build a resilient Europe for the Digital Decade where people and businesses can enjoy the benefits of AI.

Survey on the use of Machine Learning algorithms by insurance companies in their relations with policyholders

IVASS 2023

Home > ... > Doing business in the EU > Contract rules > Digital contracts > Liability Rules for Artificial Intelligence

Liability Rules for Artificial Intelligence

The European approach to artificial intelligence (AI) will help build a resilient Europe for the Digital Decade where people and businesses can enjoy the benefits of AI.

PAGE CONTENTS

Documents

In its [White Paper on Artificial Intelligence](#), the Commission undertook to promote the uptake of artificial intelligence and to address the risks associated with certain of its uses.

The Commission proposed a [legal framework for artificial intelligence](#) which aims to address the risks generated by specific uses of AI through a set of rules focusing on the respect of fundamental rights and safety.

At the same time, the Commission intends to make sure that persons harmed by artificial intelligence systems enjoy the same level of protection as persons harmed by other technologies.

In the [Report on Artificial Intelligence Liability](#), the Commission identified the specific challenges posed by artificial intelligence to existing liability rules.

In October 2020, the European Parliament adopted a [legislative own-initiative resolution](#), based on Article 225 TFEU, on civil liability for AI and requested the Commission to propose legislation.

On 28 September 2022, the Commission delivered on the objectives of the White Paper and on the European Parliament's request with the Proposal for an Artificial Intelligence Liability Directive (AILD).

The purpose of the AI Liability Directive proposal is to improve the functioning of the internal market by laying down uniform rules for certain aspects of non-contractual civil liability for damage caused with the involvement of AI systems.

The proposal addresses the specific difficulties of proof linked with AI and ensures that justified claims are not hindered.

Survey on the use of Machine Learning algorithms by insurance companies in their relations with policyholders

IVASS 2023

Executive Summary

- Insurance companies report that they are **at an early knowledge-gathering stage** regarding the use of ML algorithms, adopted **mainly for the optimization of internal processes** and, **only in limited cases, in the relations with policyholders**.
 - 27% of companies use at least one ML algorithm in processes with direct impact on customers, for a market share of
 - 78% in non-life and
 - 22% in life business.
 - The **main areas** of use of ML algorithms, mainly in **motor liability**, relate to
 - **fraud prevention and**
 - **claims management,**and to the **identification of customer intention to churn (churn patterns)**, including for pricing purposes at policy renewal.
 - As regards the **governance of new ML tools** - crucial for their informed and responsible use –
 - only **one company indicates that it has defined a specific policy;**
 - other 19 companies are defining it;
 - 5 state that they have not yet addressed this issue.
 - It should be noted, however, that 56% of undertakings using ML algorithms say they have internal mechanisms in place to assess fairness to policyholders and detect unwanted exclusions or discrimination of customers.
-

Survey on the use of Machine Learning algorithms by insurance companies in their relations with policyholders

IVASS 2023

The use of new technologies is accelerating change in the insurance industry, leading to the development of products and services to intercept the demand from increasingly digital consumers and implement new ways of dealing with customers. Among the various technologies investigated by IVASS, an in-depth study was carried out on insurance companies' use of ML algorithms, with particular reference to those uses with direct effects on policyholders, such as customer profiling, policy pricing and claims management. The survey involved **93 insurance companies** (all the Italian companies and 4 non-EU companies), and was conducted between June (<https://www.ivass.it/normativa/nazionale/secondaria-ivass/lettere/2022/lm-06-06/index.html>) and September 2022.

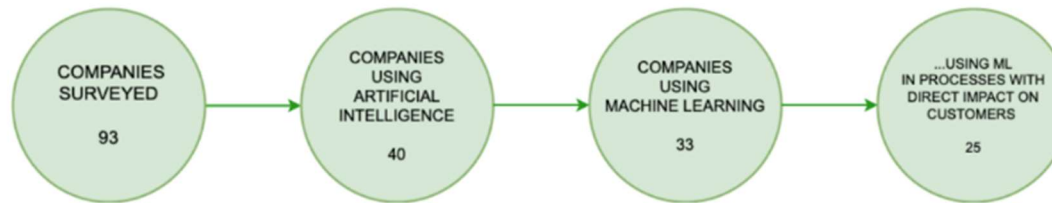
The questionnaire included a general section on the use of Artificial Intelligence (AI), ML and other technologies and specific sections on the following aspects, related to ML algorithms :

- Governance
- Security
- Explainability
- Fairness
- Outsourcing
- Main ML algorithms used by undertakings

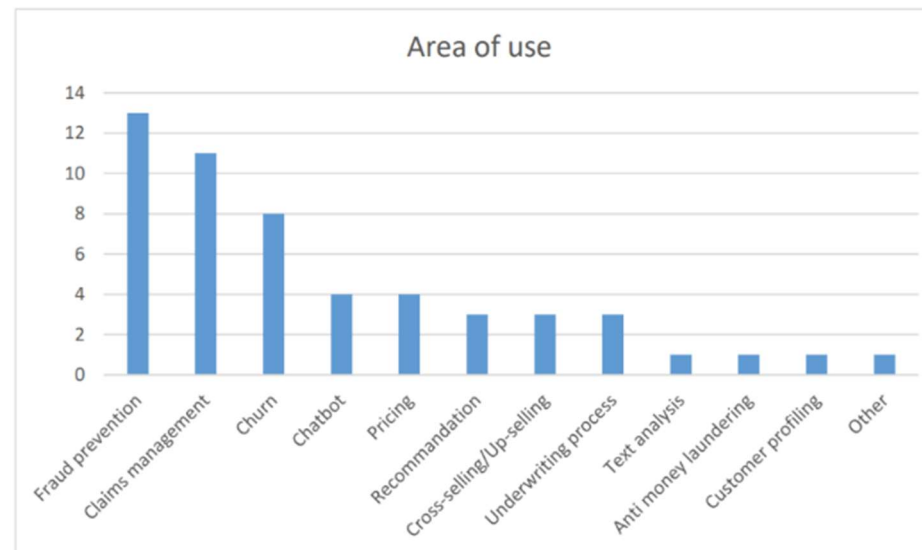
Survey on the use of Machine Learning algorithms by insurance companies in their relations with policyholders

IVASS 2023

- 43% (In a Europe-wide sample survey conducted by EIOPA in 2019, it was found that 31% of European insurance companies were using ML algorithms and 24% had ongoing trials) of surveyed undertakings use some form of AI;
- 27% use at least one ML algorithm in processes with direct impact on customer, for a market share of 78% in non-life and 25% in life business;



- The main areas of use of ML algorithms (some undertakings use the same algorithm for multiple areas of use) in retail processes relate to fraud prevention and claims management, mainly in motor liability, and the identification of customer intention to churn (churn patterns)



Survey on the use of Machine Learning algorithms by insurance companies in their relations with policyholders

IVASS 2023

- in the prevention of **MTPL fraud**, algorithms are mostly used to support predictive models, consisting of rules generated on the basis of the analysis of a sample of claims, aimed at drawing the human operator's attention to potential fraud indicators and to assess the relationships between the parties involved in claims, e.g. *drivers, witnesses, and loss adjusters*;

- ML is used to

- optimize the times for handling motor liability claims, for example, through the **assessment of the damage** by means of photos taken and sent by the injured party, compared with a database of photos of similar damages already settled;
- in other cases, it provides a **priority assessment for claims handling**, identifies cases where the client might have an advantage in bearing the cost so as not to incur the malus, and
- in general, even in **areas other than MTPL, ML is used to make the handling of non-complex claims more efficient through the analysis of documentation**;

- in underwriting processes, we note the use of ML algorithms for **facial recognition** of the customer in the case of remote contact and, in **health policies, for the prediction of diseases** that are most likely to affect the customer, to be brought to the attention of underwriters, based on the customers' biographical and medical history;

Survey on the use of Machine Learning algorithms by insurance companies in their relations with policyholders

IVASS 2023

- in the area of pricing, the following algorithms are used in motor insurance:

- to optimize the predictive accuracy of estimates of the probability of customer churn at renewal. **The probability calculated with ML is compared with that determined through traditional Generalised Linear Models (GLMs) and, together with an estimate of the expected profitability of the policy, helps to define a possible discount at contract renewal;**
- to **construct risk clusters** into which to classify vehicles and geographical areas, to determine rate coefficients in premium calculation;

- with respect to the governance of algorithms, one company has indicated that it has defined a **specific policy** while 19 companies stated that they have one in the process of being defined and 5 that they have not yet planned anything in this regard;

- **no major impacts** on other corporate policies, e.g., risk management, compliance, internal auditing or IT, are found as **a result of the use of ML algorithms**; most undertakings (19) have not changed these policies and 7 indicate that they are "in the process of adjusting them", 5 of these companies are engaged in data governance review;

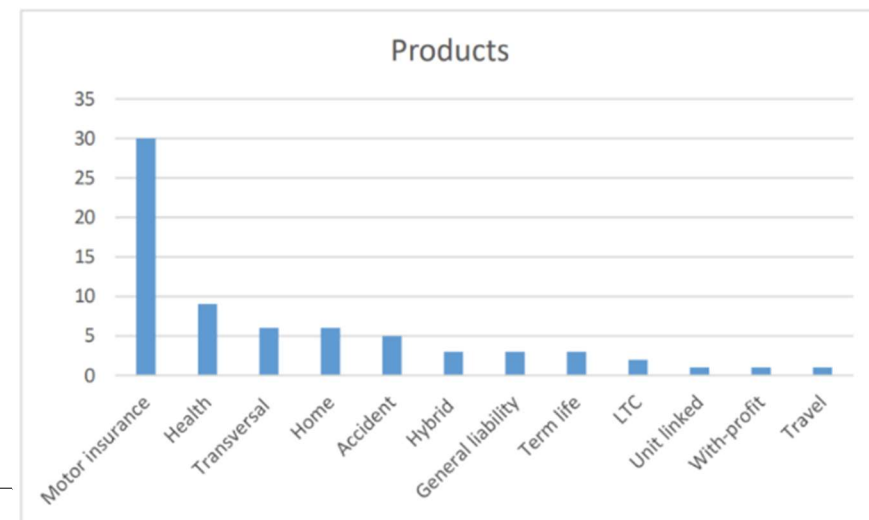
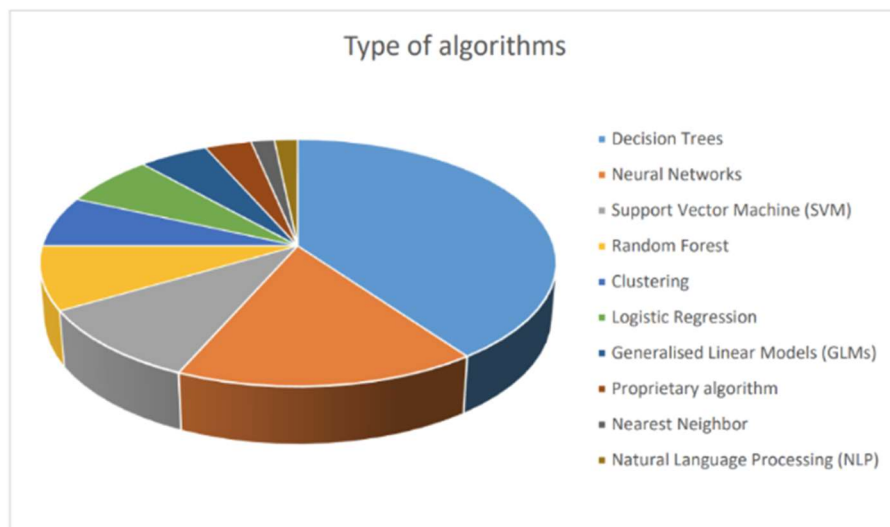
- 56% of undertakings using ML algorithms say they **have internal mechanisms in place to assess fairness to policyholders and detect unwanted exclusions or discrimination of customers**. Companies that have not equipped themselves with these tools say they do not need them due to the nature of the algorithms and data, which would not impact the policyholder fair treatment.

Survey on the use of Machine Learning algorithms by insurance companies in their relations with policyholders

IVASS 2023

Furthermore:

- among other technologies used by undertakings in conjunction with AI models,
 - 1% of undertakings indicate that they employ blockchain-related technologies,
 - 37% use cloud computing,
 - 16% adopt IoT - Internet of Things, and
 - 27% exploit information from big data;
- **decision trees** emerge as the most widely used type of ML algorithm, **followed by neural networks**.
- **20%** of algorithms are managed in **outsourcing**, while **the remainder are developed inhouse** or in collaboration with technology partners;
- with regard to **insurance products**, the motor insurance segment is the one in which ML algorithms are currently most widely used in **retail processes**;



Survey on the use of Machine Learning algorithms by insurance companies in their relations with policyholders

IVASS 2023

- all the companies that make use of ML algorithms **use a human-in-the-loop approach**, with human oversight to verify the results and make the final decision on the process;
- ML algorithms have undergone **specific validation processes or auditing (internal or external) in 18 out of 25 cases**;
- among the companies using ML, **70% of those pursuing business in the non-life sector and 22% in the life sector say they use specific KPIs/KRIs** (key performance indicator/key risk indicator) in relation to the algorithms, to evaluate the performance of the models; the indicators are not yet applied to the business functions involved;
- **some models** are characterized as a **black-box that is not accessible or modifiable by undertakings** (e.g., *neural networks in computer vision or natural-language processing*).

Undertakings have stated that they use such closed models together with tools that help explain their logic and internal functioning.



Survey on the use of Machine Learning algorithms by insurance companies in their relations with policyholders



February 2023

Market Conduct Supervision Directorate
by Claudio Vergati, Mariagrazia Rositano ed Eleonora Laurenza

Institute and Faculty of Actuaries Working Party – IFoA WP Machine Learning in Non-Life Reserving

Chair: Sarah McDonnell - Cerchiara R. R. member of the WP

The last blog in our Practical Introduction to Neural Networks series is now live: [Neural Network Hyperparameters](#)

When we started out in 2019, our premise was to find out why, whilst machine learning techniques are widespread in pricing, they are not being adopted 'on the ground' in reserving (certainly in the UK). Since then we have been working to help GI reserving actuaries develop data science skills, and are looking at ways that machine learning can be incorporated into reserving practice.

We have a [website](#) and regularly publish on our [blog](#).

General Insurance Machine Learning in Reserving Working Party

Our blog posts

Looking for our posts about machine learning and reserving? Check out our recent and older [blog posts](#) on research, issues, literature.

MLRWP book

Check out our new [online book](#), a collection of most of our blog posts over the last 4 years, organised by topic.

Looking for a particular topic? Check out:

- Our [posts](#)
- Our [workstreams](#)
- Our [FAQ](#)

Learn more about the working party

Check out our [About](#) page for

- information on the working party
- how to join us

MLR WP Year to Dec 2024

- 1 presentation (1)
 - IFoA Spring Conference
 - Practical introduction to using Neural Networks (Sarah and Jacky)
- 6 Blogs/articles (4)
- 3+ active workstreams/research projects (4+)
- 10 monthly meetings, many more breakout meetings: Journal Club, NNs in ICR Research
- ~90 members/196 LinkedIn members (74/167)
- Collaboration with wider IFoA data science community; AI research forum, debate and specific projects, Advent of Code

2023 figures shown in (blue brackets)

IFoA WP – ML in Non-Life Reserving Blog

Over the last years we have published material in a number of areas. We gather much of this material together in this book, organised by workstream:

- **Foundations:** *to provide useful educational resources, including sharing of code*
- **Data:** *to collate and promote sources of data that are available to help further research*
- **Literature Review:** *to review and promote relevant papers (and help us bring together the best ideas that are out there)*
- **Research:** *to undertake our own research projects*
- **Practical Considerations:** *to understand practical issues facing reserving actuaries implementing ML in their work*
- **Survey:** *to understand what is currently being done on the ground, and identify any barriers*

Machine Learning in Non-Life Reserving

Preface

1 Introduction

Foundations

2 Getting started

3 Introduction to R

4 My Top 10 R Packages for Data Analysis

5 The tidyverse for actuaries

6 R's data.table - a useful package for actuaries

7 Reserving with GLMs in R

8 Self-assembling claim reserving models using the LASSO

9 ML modelling on triangles - a worked example

10 Getting to grips with GLM, GAM and XGBoost

Data

11 simulationmachine engine for simulating data

12 SPLICE

Literature review

13 Non-parametric individual claim reserving in insurance

14 A brief history of papers looking at using neural networks in reserving

15 Probabilistic Forecasting with Neural Networks Applied to Loss Reserving

Research

16 Machine learning: Reserving on triangles - Q & A after GIRO 2021

17 Modelling Five Scenarios using the SynthETIC Dataset - Diagnostic from GIRO 2021

18 From Chain Ladder to Individual Mixture Density Networks on SPLICE Data

Practical Considerations

19 Practical Considerations Part 1: Time & Resource Limitations

Surveys

20 2020 Surveys of the use of ML in reserving

21 Summary

IFoA WP – ML in Non-Life Reserving

Practical Remarks

- “My Top 10 R Packages for Data Analysis”: https://mlrwp.github.io/mlrwp-book/Foundations/03_top_ten_r_packages.html
- SPLICE - Machine Learning in Non-Life Reserving - 12 SPLICE (mlrwp.github.io): The R data simulation package SynthETIC has been overtaken by an updated version, SPLICE (Synthetic Paid Loss and Incurred Cost Experience). SPLICE, whilst still based on SynthETIC, has now been extended to simulate case estimates, and hence incurred claims. It can be accessed on CRAN, along with other relevant resources including a reference manual. SPLICE is a useful tool for producing simulated datasets for testing out various reserving, including machine learning, methods. It generates datasets of triangles, as well as individual claims transactions, showing paid and incurred developments by occurrence as well as notification and settlement times.
- Practical Considerations: Machine Learning in Non-Life Reserving - 19 Practical Considerations Part 1: Time & Resource Limitations (mlrwp.github.io)

IFoA WP – ML in Non-Life Reserving

Practical Remarks - R or/and Python?

- Python and R are both open-source programming languages with huge selections of libraries and the support of large communities. But there are key differences between them.
 - **Libraries:** R has a larger variety of packages specifically for statistics because of its origins in statistical models.
 - **Syntax:** Python has an easy-to-read syntax, while R, on the other hand, is known for having difficult syntax. R programming can have a steeper learning curve.
 - **Graphics and visualization:** While visualization libraries are available in Python, R was made to present and visualize data with graphics, which means it's much faster than Python for graphics and statistical analysis. R's base graphics module lets you create simple charts and plots, and with packages like ggplot2 you can make more advanced displays, such as complex scatter plots with regression lines.
 - **Integrations:** R is also challenging to integrate in engineering environments compared to Python, although this is improving. Since R is limited to statistical analysis and visualization, it's not an ideal choice for an ML program that needs to be integrated with a large-scale environment that fulfills a range of operations.
- At a glance, *Python's versatility makes it seem like a winner for ML*. While it's a great choice, R is quite useful for statistical analysis, and *so many organizations use both languages*. While you might start with just one, it could be worth learning both. For instance, *you can do initial data analysis and exploration with R to take advantage of its speed, then switch to Python for shipping data products*. (Python supports R functionality with the RPy2 package)

IFoA WP – ML in Non-Life Reserving Posts

Order By ▼


Filter

Oct 31, 2023
Adam Stanley

My Machine Learning in Reserving Journey

FOUNDATIONS R LASSO XGBOOST RANDOM FOREST
MLR3

An ML beginner recounts his first steps into using Machine Learning for reserving



AUTHOR
Adam Stanley

PUBLISHED
October 31, 2023

Categories

- All (29)
- GLM (2)
- R (18)
- canada (1)
- data (8)
- deep learning (3)
- foundations (14)
- gam (1)

Introduction

The Foundations Workstream's aims are to:

- Create a roadmap for learning machine learning
- Gather the relevant learning materials
- Develop notebooks of example code in R and Python

In this blog I will be detailing the steps I have taken to upskill myself in the basics of machine learning in reserving and hence provide the roadmap mentioned above, with references to the relevant learning materials along the way.

The journey will mostly be based on previous [blogs written by the working party](#), which I will link throughout this blog. Note that a number of these blogs have been put together in an easy-to-follow format in a [living book](#) published by the working party as well as in the [Actuarial Analytics Cookbook](#), a collection of articles that was put together by the Young Data Analytics Working Group, a working party with the Actuaries Institute, the Australian actuarial body, with the relevant blogs being under the General Insurance section.

The first blog to look at is [Introducing the foundations workstream and articles](#). Here, we introduce the initial steps we will be going through:

- Choice of programming language
- What data to use
- What machine learning methods are available:
- GLMs (not machine learning but a good starting point)
- Regularised GLMs (LASSO method)
- Decision trees, random forest and XGBoost
- Neural networks, which we don't cover in this blog, but has been covered by the working party

I have decided to base my work within this blog on R. The reason for this is that I have some experience in R (as is standard for anyone who has studied for the IFoA actuarial exams), whereas I have none in Python, and many of the relevant previous blogs are also based in R. The blog states that

On this page

- [Introduction](#)
- [Deciding Data](#)
- [Reserving with GLMs](#)
- [Reserving with LASSO](#)
- [Machine Learning](#)
- [Triangles](#)

IFoA WP – ML in Non-Life Reserving

2024 research priorities and FAQ

Main Priorities:

- Use of RMSE/what error terms to use
- How to compare/measure model success/effectiveness

Frequently Asked Questions

When presenting our work we often find the same questions keep coming up. Hence we have collated them here in one place, not least to redirect people to in the future. The answers are not often straightforward, and people can have different, yet valid, perspectives. The answers shown have been written by a range of members of the working party, and as such reflect some of this mix of views.

Questions

Order By	Filter
Question	
1. Using machine learning for reserving	
2. Explaining ML models to stakeholders and auditors	
3. Incorporating expert judgement	
4. Practical advice for managers	
5. Data	
6. Learning ML	

IFoA WP – ML in Non-Life Reserving

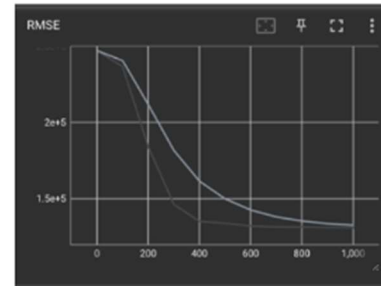
News since January 2024

Apr 29, 2024
Sarah MacDonnell

Neural Network Diagnostics

RESEARCH DEEP LEARNING NEURAL NETWORKS PYTHON
TALKS

Sample diagnostics and output graphs and how to produce them

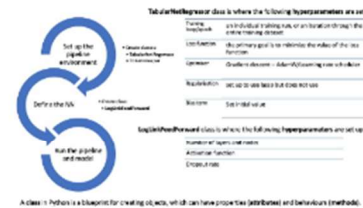


Apr 28, 2024
Sarah MacDonnell

How to run a basic neural network in Python: code explainer

RESEARCH DEEP LEARNING NEURAL NETWORKS PYTHON
TALKS

An explainer document to accompany the neural network code provided.



Apr 27, 2024
Sarah MacDonnell

A practical introduction to using neural networks in reserving on individual claims data

RESEARCH DEEP LEARNING NEURAL NETWORKS PYTHON
TALKS

An introduction to our series of blogs designed to get you up and running with a neural network

IFoA WP – ML in Non-Life Reserving

News since January 2024

Order By

Filter

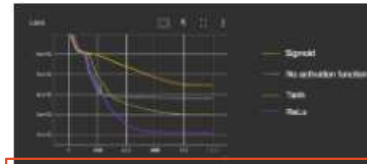
Oct 20, 2024
Sarah MacDonnell

Neural Network Hyperparameters

RESEARCH DEEP LEARNING NEURAL NETWORKS PYTHON

TALKS

A practical introduction to some of the main hyperparameters



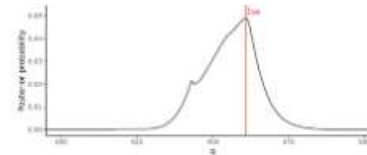
<https://institute-and-faculty-of-actuaries.github.io/mlr-blog/post/research/icnn-2024-04-hyperparameters/>

Aug 11, 2024
Grainne McGuire

Measuring loss reserving uncertainty with machine learning models

LASSO RESEARCH UNCERTAINTY R

Leveraging machine learning hyperparameters and bootstrapping to estimate uncertainty



<https://institute-and-faculty-of-actuaries.github.io/mlr-blog/post/research/20240811-model-error/>

IFoA WP – ML in Non-Life Reserving

Survey 2020

In 2020 Sarah MacDonnell and Jacqueline Friedland conducted surveys on the use of ML in reserving in the UK and Canada respectively.

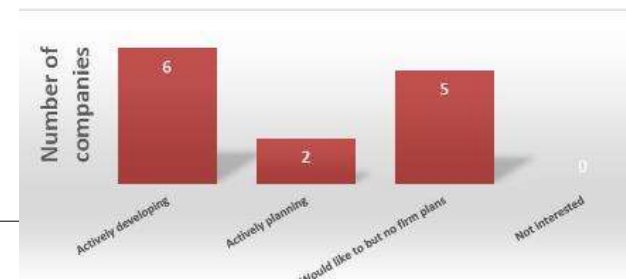
20.1 UK

Enthusiasm from reserving actuaries but stakeholder engagement low

In 2020 undertook a survey to find out to what extent machine learning is currently being used in reserving in the UK.

- **We found that there was near universal enthusiasm for developing techniques amongst reserving actuaries.**
- This contrasts starkly with the [GIROC 2014 reserving survey](#) which found that “*triangles and chain ladder and Bornhuetter-Ferguson type techniques are still the methods of choice and there is very little appetite for new methodologies to be found.*”
- There certainly appears to have been quite a sea change in attitudes towards new reserving techniques since then.
- Despite this enthusiasm **only a very small number of companies have actually applied machine learning to reserving so far.** It seems a gap is opening up in the motor insurance industry - will these companies gain an advantage over their competitors?
- One of the key differentials seems to be stakeholder engagement: with a key barrier for reserving teams **being time and resource limitations, investment and support from management is vital.** Developing the necessary knowledge is not something that can be learned in an afternoon. To quote one respondent “***it is complicated and is a lot of work***”.
- It is interesting to note that many of the companies **already use machine learning for pricing**, so will have a lot of the skills within their organisation, but they are not necessarily turning their attention to applying these to reserving.

Please note, the UK survey comprised **personal lines companies** only.



IFoA WP – ML in Non-Life Reserving

Survey 2020

In 2020 Sarah MacDonnell and Jacqueline Friedland conducted surveys on the use of ML in reserving in the UK and Canada respectively.

20.2 Canada

On behalf of the working party, Jacqueline Friedland conducted a survey among Canadian actuaries on the use of machine learning (ML) in reserving. The survey respondents consisted of:

- Nine insurers including
 - Canadian and global companies
 - One reinsurer
- Six consulting firms including
 - Canadian and global firms
 - Three of the big 4 accounting firms
- Three telephone interviews and twelve email responses

Overall there was enthusiasm for the potential of ML to assist with setting reserves,

- with four insurers currently using ML in the reserving process.
- For three of these insurers, ML was used for additional insights, **but, significantly, the final insurer used ML to book reserves.**

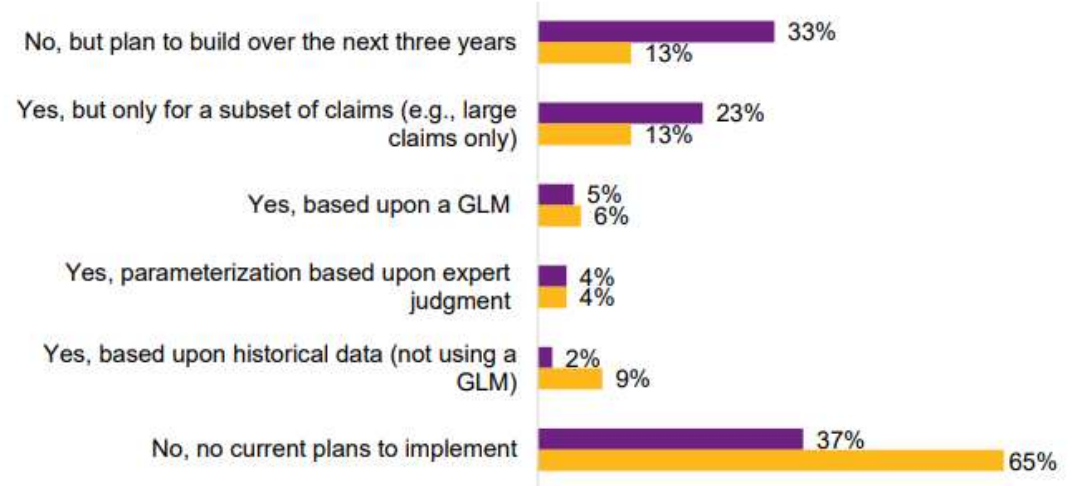
The full findings of the survey can be found [here](#).

Survey WTW 2020

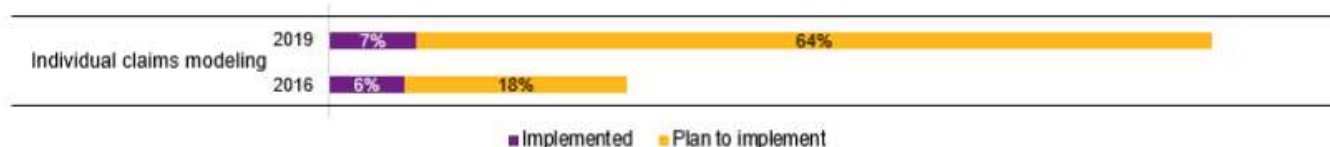
Individual Claim Reserving

The interest in individual claims modeling has doubled since our last survey

Do you utilize individual claims reserving methodologies?



Which techniques do you employ or plan to employ in your stochastic reserving?



IFoA WP – ML in Non-Life Reserving

Survey 2023 – Italy

In 2023 (and 2020) we conducted surveys on the use of ML in reserving in Italy. Quota share of Non Life Italian Market:

- 81% of total premiums
- 17% of total number of companies

Main findings

- More enthusiasm from reserving actuaries but stakeholder engagement low (as compared to 2020 survey)
- Only a very small number of companies (around 13%) have actually applied machine learning and/or ICR methods to reserving so far
- 27% of the respondents are applying stochastic methods in claim reserving
- Some companies are not using ML in any area of the business (20%). Other companies are using ML in Pricing and/or Marketing and/or Claims Management
- 31% of the companies are planning to introduce, or develop further ML techniques for reserving
- One of the key differentials seems to be stakeholder engagement: with a **key barriers** for reserving teams being
 - **Data Quality (50%)**
 - **Time and resource limitations (15%)**
 - **No support from management/headquarter (10%)**
 - **Lack of best practice (10%)**
 - **Developing the necessary knowledge is not something that can be learned in an afternoon (15%)**

IFoA WP – ML in Non-Life Reserving

Survey 2023 – Italy

In 2023 (and 2020) we conducted surveys on the use of ML in reserving in Italy. Quota share of Non Life Italian Market:

- 81% of total premiums
- 17% of total number of companies

Main findings

- The respondents proposed some ideas on how to help developing the knowledge or use of ML in reserving:
 - More courses on ML and Reserving / Better understanding of ML technique / Case studies
 - Generative AI
 - How to integrate ML models into reserving processes
 - Supervisor view and selection of ML techniques admitted for reserving
 - More survey
- Organization's attitude to using open source software such as R or Python:
 - High → 27%
 - Medium → 53%
 - Low → 20%

IFoA WP – ML in Non-Life Reserving

How can the IFoA WP help about Data (and best practice)?

5. Data

AUTHORS

Nigel Carpenter
Isabelle Williams
Jacky Poon
John McCarthy

PUBLISHED

November 22, 2022

What data is available to develop ML techniques on?

We have split this question into two parts:

- What data can you use while learning or benchmarking ML techniques?
- What internal and external data should you use when applying ML in your organisation?

Q5a: What data can you use while learning or benchmarking ML techniques?

First you can use the data available to your organisation - it's always motivational to use real data that is relevant to you when learning new methodology.

Saying that, if the data available to you is limited or not at the right level of granularity then there are some publicly available options that may be helpful. Collections of public insurance data like [R's insurance data](#) or more general data from websites like kaggle or the [UCI Machine Learning repository](#) may be useful in your learning journey.

Using synthetic data can be a good way of benchmarking different machine learning approaches and increasingly researchers are using simulated data in their publications and making the data available. Reading the papers and trying the code can be a good way to build and understanding of what data can be useful and how it can be incorporated into the machine learning algorithm. Examples of papers with published data and code, sometimes synthetic, include:

- DeepTriangle: A Deep Learning Approach to Loss Reserving | [Paper](#) [Code](#)
- An individual claims reserving model for reported claims | [Paper](#) [Code](#)
- Stochastic loss reserving with mixture density neural networks | [Paper](#) [Code](#)
- Individual data in [Reserving using machine learning - an advanced example in R \(Part 1\)](#)
- Triangular data in [ML modelling on triangles - a worked example](#)

The working party has reviewed several data simulation packages that can be helpful to create data for use in machine learning:

- One of our [GIRO 2022 talks](#) discusses a number of options
- [SPICE](#) (the successor to [SynthETIC](#))
- [simulationmachine](#)

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[Q5a: What data can you use while learning or benchmarking ML techniques?](#)

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Agenda

- Machine Learning
 - Actuarial Data Science
 - State of the Art - Literature
 - State of the Art – Actual Practice
 - Final Remarks
-

Final Remarks

Model	Advantages	Drawbacks
Aggregate	<ul style="list-style-type: none">• Cases may easily be identified in which a model as simple as the chain ladder works perfectly, and no other approach is likely to improve forecasting with respect to either bias or precision.• Robustness and reliability over time Significant and rich academic literature• Understandable by non-actuaries (accountant, auditor)• Easy to implement and do not necessitate a huge IT volume	<ul style="list-style-type: none">• These simple models are characterised by very simple assumptions and, when a data set does not conform to these assumptions, the performance of the simple models may be seriously disrupted.• Archetypal deviations from the simple model structures are the existence of structural breaks in the sequence of average claim sizes over accident periods, or variable claim settlement rates.• Subjective choice of development factor and sometimes of the tail factor/extrapolation method• Misalignment with pricing approach for the same underlying contracts (pricing focus on homogenous group of policies)• Difficulty to link potential changes in reserves to specific contracts• Non proportional reinsurance cannot be included in loss reserves estimation as it is related to specific claims• Large and attritional claims should be separate in some cases

Final Remarks

Model	Advantages	Drawbacks
GLM	Great flexibility in model structure	<ul style="list-style-type: none">• The fitting of these models requires considerable time and skill, and is therefore laborious and costly• One possible response to this is the use of regularised regression, and the lasso in particular. This latter model may be viewed as a form of ML in that it automates model selection, and also provides a powerful guard against over-parameterisation.

Final Remarks

Model	Advantages	Drawbacks
GM/ICR (and GLM)	<ul style="list-style-type: none">• The GMs are not a competitor of the GLM• Rather, they attempt to deconstruct the claim process into a number of components and model each of these• GLMs may well be used for the component modelling	<ul style="list-style-type: none">• However, there will often be considerable difficulty in modelling some dependencies in the data, and failure to do so may be calamitous for predictive accuracy.• Most GMs are also cascaded models and, indeed, some are extreme cases of these. The complexity of cascaded models, largely reflected in the number of sub-models, comes with a cost in terms of enlarged predictive error (MSEP). They are therefore useful only when the failure to consider sub-models would cause the introduction of prediction bias worse than the increase in prediction error caused by their inclusion.• The increased computing power of recent years has enabled the recruitment of larger data sets, with a greater number of explanatory variables for loss reserving, or lower-level, such as individual claim, data. This can create difficulties for GMs and GLMs. The greater volume of data may suggest greater model complexity. It may, for example, necessitate an increase in the number of sub-models within a GLM.• If a manually constructed GLM were to be used, the challenges of model design would be increased. It is true, as noted above, that these are mitigated by the use of a lasso (or possibly other regularisation), but not eliminated.

Final Remarks

Model	Advantages	Drawbacks
GM/ICR (and GLM)	<ul style="list-style-type: none">• This approach may extract valuable information about the claim process that would otherwise be unavailable	<ul style="list-style-type: none">• Automation of such a model requires a selection of the basis functions. It is necessary that the choice allow for interactions of all orders to be recognised in the model. As the number of potential covariates if the model increases, the number of interactions can mount very rapidly, possibly to the point of unworkability. This will sometimes necessitate the selection of interaction basis functions by the modeler, at which point erosion of the benefits of automated model design begins.

Final Remarks

Model	Advantages	Drawbacks
ML	<ul style="list-style-type: none">• Some Machine Learning algorithms such as trees models (decision trees, random forests, etc.), are easy to explain to unfamiliar users of those techniques. Decision trees, in particular, offer graphical outputs that help to see how individuals are associated to the nodes of the tree and thus facilitate the interpretation of their results.• Are able to capture high non-linearity and complex relationships between variables• Do not requires to separate large and attritional claims• Do not need to have assumption for extrapolation/tail factor Have an intrinsic ability to minimize the variance of the model• Trees models are able to adapt to missing data	<ul style="list-style-type: none">• Risk of overfitting data (linked to the sampling method, and to specific features of the models such as the size of a tree in terms of number of nodes, etc.)• Time-consuming either in designing or in implementation If implemented in R• Decision trees are instable with respect to the data: often a small change in the data can result in a very different series of splits, making interpretation somewhat precarious. This means that a single tree has a high variance. This problem can be addressed by aggregating the models (bagging, boosting)

Final Remarks

Model	Advantages	Drawbacks
ANNs (ML)	<ul style="list-style-type: none">• ANNs endeavour to address the last situation of GM and GLM. Their very general structure renders them sufficiently flexible to fit a data set usually as well as a GLM, and to identify and model dependencies in the data. They represent the ultimate in automation, since the user has little opportunity to intervene in feature selection.• They are specified also by their parcimonial abilities. It means that once the model parameters properly initialized, the network adjusts itself its weights (according to the selected learning algorithm) to reach its purpose (explaining a target variable or describing the space of data).• Many ML techniques are able to adapt to heterogeneous (numerical and categorical) data: support vector machine, neural networks, trees models, etc.	<ul style="list-style-type: none">• This flexibility comes at a price. The output function of the ANN, from which the model values are fitted to data points, becomes abstract and inscrutable. While providing a forecast, the ANN may provide the user with little or no understanding of the data. This can be dangerous, as the user may lack control over extrapolation into the future (outside the span of the data) required for prediction.• The literature contains some recent attempts to improve on this situation with xNNs, which endeavor to provide some shape for the network's output function, and so render it physically meaningful. For example, the output function may be expressed in terms of basis functions parallel to those used for a lasso. However, experience with this form of lasso indicates that effort may still be required for interpretation of the model output expressed in this form.

Final Remarks

The GM posits individual claim data, and generates individual claim loss reserves. **However, the parameters controlling these individual reserves are not individual-claim-specific.** So, the model appears to lie somewhere between an individual claim model and an aggregate model. This does not appear to be a case of a GM producing predictive efficiency superior to that of an aggregate model. **Rather, it is a case of a cascaded model producing efficiency superior to that of uncascaded models.**

De Felice and Moriconi (2019): Remark 1. *A model with such a structure can be also referred to as a cascaded model, see Taylor (2019) for a discussion of this kind of models. This model structure also bears some resemblance to Double Chain-Ladder (DCL), see Martínez-Miranda et al. (2013). In DCL a micro-model of the claims generating process is first introduced to predict the reported number of claims. Future payments are then predicted through a delay function and a severity model. In DCL, however, individual information is assumed to be “(in practice often) unobservable” and the micro-model is only aimed to derive a suitable reserving model for aggregate data. In this paper, instead, extensive individual information is assumed to be always available and each individual claim is identifiable. Moreover, we are interested in both claim watching and individual claims reserving, aggregate reserving being a possible byproduct of the approach.*

8.1. Cascaded Models

A cascaded model consists of a number of sub-models with the output of at least one of these providing input to another. An example is the Payments per Claim Finalized model discussed by Taylor (2000). This consists of three sub-models, as follows:

- claim notification counts;
- claim finalisation counts; and
- claim finalisation amounts.

The sub-models are configured as in Figure 4.

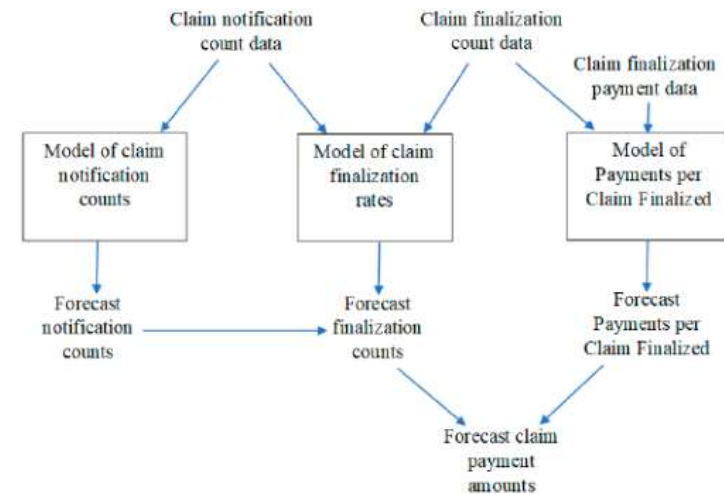


Figure 4. The Payments per Claim Finalized model and its sub-models.

Source Taylor (2019)

Final Remarks

- The tendency of GMs (**watchmaking**) is to increase the number of cascaded models (relative to aggregate models) to dissect the available data in ever greater detail, to increase the number of model components and the complexity of their connections, and then assemble an integrated model from all the tiny parts.
- If this can be achieved, **it will provide powerful understanding of the claim process in question.** However, the **process is fraught with difficulty.** The final model may be over-simplified and **over-parameterised**, with unfavourable implications for predictive efficiency. In addition, **the issue of modelling complex stochastic dependencies may be difficult, or even impossible, to surmount.**
- **One may even discover that all sub-models pass goodness-of-fit tests, and yet the integrated model, when assembled, does not.** This can arise because of inappropriate connections between the sub-models or overlooked **dependencies.**

Final Remarks

There is one other major characteristic of GMs that requires consideration:

Example. Recall [Antonio and Plat \(2014\)](#), where a GM endeavours to model individual claims in terms of the detail of the claim process., tracing individual claims through the process of occurrence, notification, partial payments and closure. Claim payments occur according to a distribution of delays from notification but, conditional on these, the severities of individual payments in respect of an individual claim are **equidistributed and stochastically independent**. In some lines of business, perhaps most but especially in **Liability lines, this assumption will not withstand scrutiny**.

The payments of a medium-to-large claim typically tend to resemble the following profile:

- a series of relatively small payments (fees for incident reports, preliminary medical expenses),
- a payment of dominant size (settlement of agreed liability),
- followed possibly by a smaller final payment (completion of legal expenses).

Consequently, if a large payment (say \$500 K) is made, the probability of another of anywhere near the same magnitude is remote. **In other words, the model requires recognition of dependency between payments.**

Final Remarks

- The behaviour of the **ANN** is **Oracle-like** (Taylor, 2019). It is presented with a question. **It surveys the available information, taking account of all its complexities, and delivers an answer, with little trace of reasoning.**
- **It confers the benefit of bypassing many of the challenges of granular modelling, but the price to be paid for this is an opaque model. This is the interpretability problem. Individual data features remain hidden within the model.** They may also be sometimes poorly measured without the **human assistance** given to more structured models. For example, **diagonal effects might be inaccurately measured**, but compensated for by measured, but actually nonexistent, row effects. **Similar criticisms can be levelled at some other MLMs, e.g., Lasso** ([Machine Learning in Non-Life Reserving - 8 Self-assembling claim reserving models using the LASSO \(mlrwp.github.io\)](#)).
- **The ANN might be difficult to validate.** Cross-validation might ensure a suitably small MSE overall. However, if a poor fit is found in relation to some subset of the data, one's recourse is unclear.
- The abstract nature of the model does not lend itself easily to **spot-correction**.

Final Remarks

Incurred Model and Case estimates:

- Case estimates are estimates of the ultimate cost of a claim that are created externally to an actuarial or statistical team in an insurance company. Consequently, they are based on an anecdotal rather than a statistical basis (Taylor, McGuire and Sullivan, 2008).
- This has its own advantages and disadvantages
- Namely, the case estimates are able to incorporate the experience of the claims assessor, and hence may incorporate information that is unable to be summarised into data to be used in statistical models.
- However, with the rise of natural language processing, even data trapped in written claims statements and police reports can potentially be accessed by statistical models. The main disadvantage of case estimates stems from their lack of verifiability and potential bias, although this bias can be corrected (Taylor, 2000).
- Case estimates are typically constructed at the notification of a claim, and are periodically updated as new information becomes available. Therefore, the case estimates will eventually converge to their true cost once enough information is gathered. ***This also means that the development of case estimates can be viewed as a time series, which is especially suitable for use in an RNN.***
- **While the case estimates are likely to be reasonably accurate in the later stages of a claim's lifetime, there can be considerable room for improvement on these estimates towards the beginning of the lifetime of a claim → effectively combine statistical and machine learning procedures with the information implicitly contained within the case estimates.**

Final Remarks

- In summary, the case is still to be made for both GMs and MLMs. Particular difficulties are embedded in GMs that may prove insurmountable. MLMs hold great promise but possibly require further development if they are to be fully domesticated and realise their loss-reserving potential.
- **A tantalising prospect is the combination of GMs and ANNs to yield the best of both worlds (Taylor, 2019).**

Final Remarks

Opportunities and further researches

- Open new possibilities for actuarial modelling by solving **difficult model specification problems**, especially those involving large scale modelling problems
- Enhance **the predictive power** of models built by actuaries
- Insurers have a remarkable opportunity to create substantial value and realize the potential of **Gen AI** by making well-thought-out investments aligned with their respective business strategies. By focusing on three key value dimensions—**profitability and growth**, **cost savings** and **efficiency**, and **operational intelligence**—insurers can drive transformative results.
- More research is needed on several issues:
 - Stability of results
 - **Interpretability methods**
 - Uncertainty intervals
- To benefit fully from machine and deep learning, the goals of actuarial modelling, and implications for practice, need to be clarified.

Final Remarks

Generative AI

Strengths and limitations of generative AI

This infographic is divided into two main color-coded sections: a light grey section for strengths and a purple section for limitations. Each point is accompanied by a small icon.

- Strengths (Light Grey):**
 - Icon: Two people talking. Text: "LLMs excel at generating text that closely resembles text written by humans"
 - Icon: Speech bubble with gear. Text: "These models are competent at solving novel unseen problems"
 - Icon: Document with pencil and arrow. Text: "LLMs make use of additional context to inform their responses"
 - Icon: Funnel. Text: "LLMs can be fine-tuned for specific tasks and behaviors"
- Limitations (Purple):**
 - Icon: Alarm bell. Text: "LLMs can be biased based on the data it has been trained on"
 - Icon: Document with circular arrow. Text: "LLMs can very confidently generate incorrect answers"
 - Icon: Brain with gear. Text: "LLMs can struggle with arithmetic and computational tasks"

Strengths and limitations of generative AI (2)

This infographic is divided into two main color-coded sections: a light grey section for strengths and a purple section for limitations. Each point is accompanied by a small icon.

- Strengths (Light Grey):**
 - Icon: Person at a laptop with code symbols. Text: "Incredibly powerful at writing code (and adjacent areas)"
 - Icon: Stack of books. Text: "Incredibly powerful at reading and 'digesting' large volumes of text"
- Limitations (Purple):**
 - Icon: Alarm bell. Text: "Can be biased"
 - Icon: Document with circular arrow. Text: "Can be incorrect"
 - Icon: Brain with gear. Text: "Can struggle with arithmetic"



- Generative AI is not the answer to everything!
- Outsourcing to plugins, such as WolframAlpha
- Explainability of LLMs is a growing research area, but we may never truly understand how these models work

Final Remarks

Responsible ML

- It is worth mentioning Meyer et al. (2023) about the «black-box»: «*This tutorial gives an overview of **SHAP (SHapley Additive exPlanation)**, one of the most commonly used techniques for examining a black-box machine learning (ML) model. Besides providing the necessary game theoretic background, we show how typical SHAP analyses are performed and used to gain insights about the model. The methods are illustrated on a simulated insurance data set of car claim frequencies using different ML models and different SHAP algorithms*»
- The basic idea of SHAP is to decompose a model prediction into additive contributions of the features in a fair way, and repeating this process for many observations provides a powerful method for explaining the model as a whole. The roots of the method (fair additive decomposition) go back to a classical result on **cooperative game theory** by Shapley

Responsible ML

See the link: [Material for the lecture Responsible ML](#)

GitHub - lorentzenchr/responsible_ml_material

Why **responsible**? Common risks are:

- ▶ Model does not solve the original goal or task.
- ▶ Missing understanding of the given data.
- ▶ Bias (model & data).
- ▶ Wrong claims about the ability of a model.

“Statistics is about the honest interpretation of data.” (Prof. Simon N. Wood)

This lecture aims to provide a toolbox.

- ▶ Model Comparison and Calibration
- ▶ Explainability

Not in this lecture:

- ▶ Data protection law
- ▶ Ethical questions
- ▶ (AI) Fairness

About other approaches, see also: [Cascarino et al. \(2022\) – XAI methods](#)

Final Remarks

Constraints

Constraints, according to the purposes, with regard to the types of algorithms used:

- The **auditability requirements** relating to certain processes (calculation of technical provisions and pricing in particular) imply that certain algorithms cannot be used to their full potential.
- It is thus possible to use them for the identification of **discriminatory variables**, but the final calibration must ultimately be carried out using algorithms allowing greater **auditability** (generalized linear model, for example).
- Thus, random forests or gradient boosting algorithms, while providing convincing prediction results, **cannot generally be used for reserving or risk management purposes (?)**
- These constraints partly explain the **delay** in the adoption of data science in insurance.

Final Remarks

Generative AI

Potential risks and regulatory implications

Though the opportunities and value created by **Generative AI** are impressive, artificial intelligence also introduces potential risks into the insurance industry. Insurance industry leaders would be wise to consider the following when scaling:

- **Malicious hallucinations and deep fakes, phishing and prompt injections, and ambivalent actors** can expose the attack surface and erode customer trust.
- Generative AI is prone to mimicking biases and **propagating discriminatory behavior** if implemented without guardrails and continuous monitoring.
- Models will be trained on a corpus of proprietary and often private **data, requiring regulatory compliance, node isolation, and source traceability.**
- **Customer servicing and engagement** within insurance companies requires a **heightened sense of empathy and softer human interaction skills**, especially during claim processing. Overemphasis on AI-driven automation may result in a lack of human touch, potentially leading to reduced customer satisfaction and loyalty.
- **Insurance regulators** want oversight on insurers' AI models and expect insurers to manage AI risk. AI oversight activity at the state level is forging ahead, with laws in place or contemplated, to bulletins from insurance commissioners asserting authority under multiple state and federal laws.

References

- AAE: What should an actuary know about artificial intelligence? <https://actuary.eu/memos/aae-discussion-paper-what-should-an-actuary-know-about-artificial-intelligence/what-should-an-actuary-know-about-artificial-intelligence/> (2024)
- ANIA: Exploring Digital Regulation Focus on artificial intelligence, digital finance and cybersecurity, [ANIA Exploring Digital Regulation - ANIA Exploring Digital Regulation - ANIA - Welcome](#) (2023)
- Antonio K., Plat R.: Micro-level stochastic loss reserving for general insurance. Scandinavian Actuarial Journal 2014/7, 649-669 (2014)
- Baudry M., Robert C.Y., Dami C.: Non parametric individual claims reserving, Workshop on «Data science in Finance and Insurance», ISBA (UCL), (2017)
- Bergstra J., Yamins, D., Cox D.: Making a Science of Model Search: Hyperparameter Optimization in Hundreds of Dimensions for Vision Architectures. Proceedings of the 30th International Conference on Machine Learning (Atlanta, 2013)
- Bladt M., Pittarello G.: Individual claims reserving using the Aalen–Johansen estimator. ASTIN Bulletin, First View , pp. 1 – 21, (2024) DOI: <https://doi.org/10.1017/asb.2024.28>
- DOI: <https://doi.org/10.1017/asb.2024.28>
- Boumezoued A., Devineau L., Taillieu F.: The future of (individual) reserving, Milliman, (2017)
- Breiman, L.: Random Forests. Journal Machine Learning archive 45(1), 5–32 (2001)
- Cavastracci S.: Dal chain ladder al modello di Merz e Wüthrich: derivazione completa del modello di volatilità della riserva sinistri in un orizzonte annuale, Quaderno n. 3 IVASS (2015)
- Cavastracci S., Tripodi A.: Modello overdispersed Poisson: formula chiusa per la stima GLM della volatilità one year della riserva sinistri. Quaderno IVASS n.9, Roma, (2018)
<https://www.ivass.it/pubblicazioni-e-statistiche/pubblicazioni/quaderni/2017/iv9/ivassq0022.pdf>

References

- Cascarino G., Moscatelli M. and Parlapiano F.: Explainable artificial intelligence: interpreting default forecasting models based on machine learning, *Questioni di Economia e Finanza*, Banca d'Italia (2022)
- Cerchiara R.R., Jain S., Scarth R.: A Practitioner's Introduction to Stochastic Reserving The One-Year View, IFoA (2020) - <https://www.actuaries.org.uk/system/files/field/document/A-Practitioners-Introduction-One-Year-View.pdf>
- Cerchiara R.R., Invernizzi, L., Magatti, V.: *Data Science, Big Data e Data Analytics*. Corso SIA (2020)
- Charpentier A.: *Computational Actuarial Science with R* (2016)
- Chen C., Guestrin: XGBoost: A Scalable Tree Boosting System. arXiv:1603.02754 [cs.LG] (2016)
- Corlosquet-Habart, Janssen: *Big Data for Insurance Companies, Volume 1*, Wiley (2018)
- D'Agostino L., De Felice M., Montanucci G., Moriconi F., Salciarini M.: *Machine learning per la riserva sinistri individuale. Un'applicazione R.C. Auto degli alberi di classificazione e regressione*. Alef Technical Report (2018)
- De Felice M., Moriconi F.: *Claim Watching and Individual Claims Reserving Using Classification and Regression Trees*. Risks (2019)
- Edwards, Ramsay, Carreon: *Generative AI : the biggest transformation since desktop computing*, IFoA congress 22-24 November (2023)
- Faculty and Institute of Actuaries: *Claims Reserving Manual* (1997)
- Foster, Rayid Ghani, Ron S. Jarmin, Frauke Kreuter, Julia Lane, *Big Data and Social Science: A Practical Guide to Methods and Tools*, 1st Edition, Chapman & Hall (2016)
- Friedman, J.: Greedy Function Approximation: A gradient Boosting Machine. *The Annals of Statistics* 29(5), 1189–1232 (2001)
- Friedman, J.: Stochastic Gradient Boosting. *Journal Computational Statistics & Data Analysis - Nonlinear methods and data mining archive* 38(4), 367–378 (2002)

References

Gabrielli A., Wüthrich M.V.: An individual claims history simulation machine. Risks 6/2, 29, (2018)

Gabrielli A., Richman R., Wüthrich M.V.: Neural network embedding of the over-dispersed Poisson reserving model, SSRN Manuscript, ID 3288454 (2018)

Gabrielli A.: An individual claims reserving model for reported claims, EAJ (2021)

Gigante P., Sigalotti L.: Valutazione della riserva sinistri con i GLM nel contest dei nuovi standard contabili. Quaderni del Dipartimento di Matematica Applicata alle Scienze Economiche Statistiche e Attuariali "B.deFinetti",n.6 (2004)

Golfin D., Kuo K.: A Machine Learning Framework For Loss Reserving, Casualty Loss Reserving Seminar and Workshops, September 18-20, 2016.

Guha R., Manjunath S., Palepu K.: COMPARATIVE ANALYSIS OF MACHINE LEARNING TECHNIQUES FOR DETECTING INSURANCE CLAIMS FRAUD, 2015, <http://www.wipro.com/documents/comparative-analysis-of-machine-learning-techniques-for-detecting-insurance-claims-fraud.pdf>

Hachemeister C.A.: A stochastic model for loss reserving. Transactions International Congress of Actuaries (1980)

Hastie T., Tibshirani R., Friedman J.: The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer Series in Statistics, New York (2009)

Hejazia S.A., Jacksona K.R.: Efficient Valuation of SCR via a Neural Network Approach (2016)
<ftp://www.cs.toronto.edu/na/reports/CAM-Paper3.pdf>

IIA ASTIN WP: Report on Individual Claim Development with Machine Learning (2018)

Invernizzi L., Magatti V.: A Standardized Machine Learning based approach to Conversion Rate Estimation, ASTIN Colloquium (2019)

References

- IVASS: Survey on the use of Machine Learning algorithms by insurance companies in their relations with policyholders (2023) - [Esiti Indagine Algovernance.pdf \(ivass.it\)](#)
- Larsen C.R.: *An Individual Claim Reserving Model*», Astin Bulletin, volume 37, issue 1 (2007)
- Landry: GBM & Random Forest in H2O – slides H2O (2015) <https://www.slideshare.net/0xdata/h2o-world-gbm-and-random-forest-in-h2o-mark-landry>
- Lee S.C.K., Lin S. & Antonio K.: DELTA BOOSTING: A BOOSTING APPLICATION IN ACTUARIAL SCIENCE (2015)
- Llaguno L., Bardis M., Chin R., Gwilliam T., Hagerstrand J., Petzoldt E.: Reserving with Machine Learning: Applications for Loyalty Programs and Individual Insurance Claims, CAS FORUM, (2017), https://www.casact.org/pubs/forum/17sforum/01-Llaguno_Bardis_Chin_Gwilliam_Hagerstrand_Petzoldt.pdf
- Lundberg S.M., Erion G. G., Su-In L.: Consistent Individualized Feature Attribution for Tree Ensembles. arXiv:1802.03888 [cs.LG] (2018)
- Mayer, Meier, Wüthrich: SHAP for Actuaries: Explain any Model: [SHAP for Actuaries: Explain any Model by Michael Mayer, Daniel Meier, Mario V. Wuthrich :: SSRN](#) (2023)
- Martnez-Miranda M.D., Nielsen J.P., Verrall R.J., W uthrich M.V.: The link. between classical reserving and granular reserving through double chain ladder and its extensions. Scandinavian Actuarial Journal 2013/5, 383-405 (2013)
- Merz M., Wüthrich M. V.: Statistical Foundations of Actuarial Learning and its Application (2023)
- McCullagh P., Nelder J.A.: Generalized Linear Models, Second edition. Chapman & Hall/CRC Monographs on Statistics & Applied Probability (1989)

References

McGuire G., Taylor G. , Miller H.: Self-Assembling Insurance Claim Models Using Regularized Regression and Machine Learning (2018) Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3241906

Milhaud X., Lopez O., Théron P.: Weighted decision trees applied to reserving in insurance, EAJ Conference - ISFA Lyon, LSAF, 6-8 September (2016)

Parodi P.: Triangle-free reserving A non-traditional framework for estimating reserves and reserve uncertainty. British Actuarial Journal 19:168-218 (2014)

Peters G.W.: Statistical Machine Learning and Data Analytic Methods for Risk and Insurance (2017)
https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3050592

Pigeon M., Antonio K., Denuit M.: Individual loss reserving with the multivariate skew normal framework. ASTIN Bulletin 43/3, 399-428 (2013)

Prokhorenkova, Gusev, Vorobev, Dorogush, Gulin: CatBoost: unbiased boosting with categorical features. arXiv:1706.09516 [cs.LG] (2017)

Savelli N.: IPER-PERSONALIZZAZIONE NELLA TARIFFAZIONE ASSICURATIVA Vs MUTUALITA' E SOLIDARIETA': POTENZIALITA', RISCHI E COMPORTAMENTI ETICI (2023)

Snoek J., Larochelle H., Adams R.: Practical Bayesian Optimization of Machine Learning Algorithms. arXiv:1206.2944v2 [stat.ML] (2012)

SOA: Machine-Learning Methods for Insurance Applications: <https://www.soa.org/globalassets/assets/files/resources/research-report/2019/machine-learning-methods.pdf>, (2019)

Srivastava N, Hinton G, Krizhevsky A, Sutskever I, Salakhutdinov R, Dropout: a simple way to prevent neural networks from overfitting. J Mach Learn Res 15:1929–1958 33 (2014)

Taylor G., McGuire G.: «Loss reserving with GLMs: a case study», Spring 2004 Meeting of the Casualty Actuarial Society, Colorado Springs, Colorado (2004)

References

Taylor, G., McGuire G., Sullivan, J.: «Individual claim loss reserving conditioned by case estimates», Taylor Fry Consulting Actuary, Australia, Sidney (2006)

Taylor G.: Loss reserving models: granular and machine learning forms. Risks 7(3):82, (2019)

Tibshirani, Hastie, James, Witten: An introduction to statistical learning, [Springer Texts in Statistics](#), 2013

Tibshirani, Hastie, Friedman: The elements of statistical learning – Data mining, Inference, Prediction, 2009, <https://web.stanford.edu/~hastie/Papers/ESLII.pdf>

Wright T.S.: Probability distribution of outstanding claim payments from individual payments data, Faculty and Institute of Actuaries, Claim Reserving Manual, Vol. 2., (1997)

Wüthrich V. M.: Machine Learning in Individual Claims Reserving, Swiss Finance Institute Research Paper No. 16-67. Available at SSRN: <https://ssrn.com/abstract=2867897> or <http://dx.doi.org/10.2139/ssrn.2867897> (2016)

Wüthrich M.V.: Machine Learning in Individual Claims Reserving, Swiss Finance Institute Research Paper Series N°16-67 (2016)

Wüthrich M.V.: Neural Networks Applied to Chain-Ladder Reserving (2017)

Wüthrich M. V.: Machine learning in individual claims reserving. Scand Actuar J (6):465–480 (2018)

Wüthrich M. V.: Yes, we CANN! The AIFR_ERM Colloquium (2019)

Zhang Y.: A general multivariate chain ladder model. Insurance: Mathematics and Economics, 46:588-599 (2010)



Rocco Roberto Cerchiara Actuary (IOA) – PhD – Adjunct Professor of Financial Reporting at CISA

- ❖ MSc in Statistical and Actuarial Sciences with honors at the University of Rome “La Sapienza” in 1999
- ❖ Full Qualified Actuary (IOA) since 2000 and volunteer at IFoA since 2018
- ❖ PhD in Actuarial Sciences at University of Rome “La Sapienza” in 2006
- ❖ He has been board member of the Italian Institute of Actuaries
- ❖ Since 1999 to 2003 he has been serving at Arthur Andersen (Deloitte Consulting)
- ❖ From 2005 to 2021 he was Assistant Professor of Risk Theory and Non-Life Insurance Mathematics at the Department of Economics, Statistics and Finance, University of Calabria in Italy
- ❖ Since 2007 to 2017 he was Senior Consultant with Willis Towers Watson in Rome
- ❖ From 2017 he is an independent actuary with consultancy for several Italian insurance companies on several. His experience covers the full range of actuarial services, including: Actuarial Function, Economic capital modelling, USP, Appointed Actuary, Pricing Support, Reserve review, IFRS 17, Pension Funds, Life Insurance, NAT CAT pricing, Machine Learning (in partnership with ESPLORES and SIR)
- ❖ He has been teaching at various Universities as adjunct professor at University of Rome “La Sapienza”, University of Sannio, LUISS and CISA «Scuola di Attuariato». He is lecturer at MIB School of Management in Trieste
- ❖ His main topics of research are: Risk Theory models for pricing and reserving risk, Individual Claim Reserving, Machine Learning, Extreme Value Theory, Solvency II and IFRS17. He had published a large number of works and presented in many national and international congress on these topics

APPENDIX 1





Artificial Intelligence: a case study on the estimation of CO₂-emission due to the claim management of a Non-Life insurance company

Rocco Roberto Cerchiara, PhD – Actuary (IOA)

Executive Summary



- At the UN Climate Change Conference (COP21) in Paris, on 12 December 2015, Parties to the United Nations Framework Convention on Climate Change (UNFCCC) reached a **landmark agreement to combat climate change** and to accelerate and intensify the actions and investments needed for a sustainable low carbon future. The Paris Agreement builds upon the Convention and – for the first time – brings all nations into a common cause to undertake ambitious efforts to combat climate change and adapt to its effects, with enhanced support to assist developing countries to do so. As such, it charts a new course in the **global climate effort**.
- The **transport sector** is responsible for about **a quarter of Europe's total CO₂ emissions, 71.7% of which come from road transport**, according to the European Environment Agency. In an effort to limit CO₂ emissions, the EU has set a **target** of reducing transport emissions by 60% from 1990 levels by 2030.
- The EU aims to achieve a 90% reduction in **GreenHouse Gas (GHG)** emissions from transport by 2050 compared to 1990 levels. This forms part of efforts to reduce CO₂ emissions and **achieve climate neutrality** by 2050 under the European Green Deal roadmap.

Executive Summary



- **Mediolanum Assicurazioni**, in its path of environmental sustainability, intends to **provide its Loss Adjusters operating in "non-motor" segments (Italian market) with a tool for measuring the carbon footprint** produced in the performance of their assignments
- The goal of this joint project (work in progress) with **All Consulting** is twofold:
 - **Quantify CO₂ emissions in claims management and define a scoring system of Loss Adjusters**
 - **Introduce Traditional AI, Operational AI and Generative AI in this process** in order to improve the sustainability framework of the Company as a starting point of a wider project
- The data were provided by All Consulting



International Overview

Claim Process and the contribution of Artificial Intelligence

- **AS IS:** work involved in managing the areas of the claims process requires
 - extensive human resources,
 - manual and repetitive tasks that are prone to duplication and error.
- **To Be:** AI will help close the skill gaps due to
 - an ageing insurance workforce
 - less skilled claims handlers involved in the claims process
 - **Operational AI:** Triage of messages, automatic responding, Entity Recognition, ...

Milliman “Industry survey: Tackling claims department challenges with AI,” March 19, 2024: *the top 5% to 10% of claims often account for 80% of total costs, emphasizing the significance of early identification and intervention. For large enterprises, AI-driven cost reductions can add up to millions annually. In fact, AI-enabled claims triage can reduce claim severity 3% to 10%.*

Benefits:

- IOT/telematics capabilities in order to alert insurers via smart phones, home assistants or smart cars when a potential claim has occurred and to **get initial information**
- Investigation by AI **reducing cycle times** (computer vision, etc.) and improve **Data Quality**
- Using GenAI in combination with LLM for claim adjustment, **automating largely the claims process for certain types of claims**
- Classification of similar claims and determining claim’s value by ML (e.g. **CART**) creating **automatic estimates and KPIs/Benchmarking**
- **Improvement of settlement rates and reduction in average costs** (and potentially claim reserves/premium rates)
- **reduction in CO₂ emission** (see next slides)

Adopting AI in insurance’s value chain ensures consistency in decision-making



The loss adjusting process and the tool developed by Mediolanum Assicurazioni

A) Measurement/Assessment

- **LCA** of the Loss Adjuster's work:
 1. assignment of the claim management by the Insurance Company
 2. activities to be carry out (data download, policy analysis, damage inspection, agreement of the loss compensation, etc.) using
 - Traditional assessment (e.g. on-site inspection) and/or
 - Sustainable assessment (e.g. video appraisal)
 3. preparation and sending the report to the Insurance company
- For each claim managed, the **tool** requires the entry of: a) **recurring data** (e.g. LA's car, etc.), b) **specific data** of the assigned claim, c) **other sources** by the model (survey and analysis by regulators, etc.), d) **assumption/Expert Judgement** when data are not available
- The total result, in terms of CO₂ per claim, will lead to a **numerical index consistent with the rating system** chosen by MA, representing an **emission performance**





The loss adjusting process and the tool developed by Mediolanum Assicurazioni

B) Mitigation/Management

- **The total result will be disaggregated into different components:** the analysis of the impact of each component on the overall value will allow the construction of **management actions and strategies** capable of orienting the Loss Adjusting company towards the sustainability target set by MA
- The **specific reduction measures** (limitation of pages printed, use of environmentally sustainable means of transport where possible, utilization of vegetable-derived inks, etc.) may be integrated with **interventions for the carbon neutrality** that the company will eventually put in place through activities aimed at offsetting emissions themselves with economically efficient actions
- This is to enable **to fall within the limits imposed by MA, with adequate carbon management.**

C) Carbon Audit

- The system also makes it possible to customize the reporting tools, so as **to allow MA to provide checkpoints** and any other moments of discussion with its Loss Adjusters.





Case study: Data, sources and assumptions

In order to calculate the total impact of a claim assessment, firstly it is necessary to calculate the CO₂ emission for each step: phone calls, energy consumed by desktop, laptop, monitor, pages printed, transport, etc. :

- Calculation of emissions for **transport** → Data obtained as an average of the best-selling cars in the country with emission data found from sources such as <https://www.terraup.it/> and "Ministero dell'Ambiente e della Sicurezza Energetica"
- Calculation of emissions for **Personal Computer** → Data obtained as an average of hourly energy consumption among the best-selling laptops, desktops, and monitors, multiplying by ISPRA's 2022 consumption/emission conversion factor
- Calculation of emissions for **papers printed** → see Arroja and Dias (2012)
- Calculation of emissions for **emails** → Data based on BBC research "*Why your internet habits are not as clean as you think*"
- Calculation of emissions for **phone calls** → Data based on Mike Berners-Lee (2022) "*What's the carbon footprint of... using a mobile phone?*"
- **Computer usage time** to handle the entire claim file: 3 hours (assumption)

Case study: Draft Results – 5 claims and 5 LAs

- Five different practices with comparable distance assigned to five Loss Adjusters (LAs)
- Common parameter => 25 km to get to the claim assessment location
- CO₂ emissions for each LA/Claim were then calculated
- The results were compared to show the best and worst performance in terms of sustainability (gCO₂)

gCO ₂	Claim 1	Claim 2	Claim 3	Claim 4	Claim 5	Total
Loss adjuster A	570.17	3495.30	3539.03	2197.95	2847.15	12649.60
Loss adjuster B	3090.00	1918.55	3027.33	3308.55	4103.30	15447.73
Loss adjuster C	3082.35	1469.00	2765.31	4168.13	4181.15	15665.94
Loss adjuster D	5969.00	1833.86	2632.25	3442.03	2121.25	15998.39
Loss adjuster E	3493.30	2687.55	2340.68	4595.56	5622.90	18739.99

- LA A had the lowest total environmental impact: the video call tool for viewing and assessing damages limits the emissions
- Claims number 2 and 3: LA A turns out to be the worst from the environmental impact. We can infer that video assessment can be said to be sustainable for long distances, but the shorter the distance between the starting point and the event location, the less beneficial the effect of video assessment will be

Case study: Focus on Claim 1 and Final Score

Loss Adjuster A - INPUT				OUTPUT	
Parameter (LCA)	Quantity	UoM	gCO2	570.17	gCO2 Total
Desktop	0	n	0.00	0,00	gCO2 Transport
Monitor	1	n	15.12	3113.00	gCO2 Saved
Laptop	1	n	18.05	2.00	Bonus points
Email	10	n	40.00	4.20	Final score **
Pages Printed	50	n	225.00		
Phone Call time	25	min	75.00		
Video assessment (AI)	Yes	(Yes/No)	-		
Video ass. duration	20	min	147.00		
Distance	25	km	3260.00		

LA A used video assessment, scoring a 4.2 with 2 bonus points due to emission savings (no use of car)

LA E didn't use video assessment, scoring 4.0 due to sustainable behaviours such as fewer printed pages, etc. without getting bonus points for video assessment

Loss Adjuster E - INPUT				OUTPUT	
Parameter (LCA)	Quantity	UoM	gCO2	3493.30	gCO2 Total
Desktop	0	n	0.00	3260.00	gCO2 Transport
Monitor	2	n	30.24	0.00	gCO2 Saved
Laptop	1	n	18.05	0.00	Bonus points
Email	5	n	20.00	4.00	Final score *
Pages Printed	20	n	90.00		
Phone Call time	15	min	75,00		
Video assessment (AI)	No	(Yes/No)	-		
Video ass. duration	0	min	0.00		
Distance	25	km	3260.00		

* Final score depends on bonus points and other parameters (distance, desktop, etc.)

APPENDIX 2



Additional survey – IFRS17



TERMS OF REFERENCE

ASTIN WORKING PARTY ON
IFRS 17 ACTUARIAL BEST PRACTICES

Specific Aims

The aim of the ASTIN Working Party on IFRS 17 Actuarial Best Practices is to:

- Design a survey to be sent to several (re)insurance companies, directly or through insurance regulators, insurance associations, actuarial associations and/or auditors. The survey will cover (non-exhaustive list):
 - classification of contracts under IFRS 17 (namely, statistics on the measurement model used or the OCT);
 - statistics on amounts used, such as the split of attributable and non-attributable expenses;
 - information on the interest rates used on a current and on a locked-in basis, as well as methods of discounting;
 - estimation of risk adjustment;
 - estimation of reinsurance coverage levels.

The survey will also include a “blank” field where entities will have the possibility to propose improvements to the standard, as well as to ask questions. The questions will have to be treated through subsequent working parties.

DEADLINE: 23RD January 2025

Additional survey – IFRS17



TERMS OF REFERENCE

ASTIN WORKING PARTY ON
IFRS 17 ACTUARIAL BEST PRACTICES

The screenshot shows an Excel spreadsheet titled "ASTIN WP - Survey on Actuarial Best Practices for IFRS 17.xlsm". The ribbon is set to "Home". A security warning is visible: "RISCHIO PER LA SICUREZZA Microsoft ha bloccato l'esecuzione delle macro perché l'origine del file non è attendibile." The spreadsheet content includes:

- Survey** (Section Header)
- This survey focuses only on the actuarial aspects of the work developed when applying the IFRS 17 standard.
- As mentioned in worksheet Introduction, there are several groups whose opinion may be considered when performing IFRS 17 valuations. This survey is thus divided not only per subject within the IFRS 17 standard, but also per addressee of the questionnaire.
- The survey should be kept anonymous in relation to naming the entities and individuals involved. It should however name the jurisdictions involved and it can also name the associations participating within each jurisdiction.
- Introduction** (Section Header)
- PART A: Perspective of Actuaries performing IFRS 17 Valuations** (Section Header)
- PART B: Perspective of Local Regulators or Insurance Associations** (Section Header)
- PART C: Perspective of Auditors** (Section Header)
- PART D: Perspective of Local Actuarial Associations** (Section Header)

A "Start" button is located in the top right corner of the survey content area.

Grazie

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