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Introduzione alle tecniche di Machine Learning applicate alla riservazione dei rami danni

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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*

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https://actuary.eu/memos/aae-discussion-paper-what-should-an-actuary-know-about-artificial-intelligence/what-should-an-actuary-know-about-artificial-intelligence

Agenda

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

Artificial Intelligence (1/5)

Obvious question: <u>What is AI?</u>

- Programs that behave externally like humans?
- Programs that operate internally as humans do?
- Computational systems that behave intelligently?
- Rational behavior?

Turing Test

- *Human beings are intelligent*
- *To be called intelligent, a machine must produce responses that are indistinguishable from those of a human*

Artificial Intelligence (2/5)

AI has uncountable applications:

- Autonomous planning and scheduling of tasks aboard a spacecraft
- Beating Gary Kasparov in a chess match
- Steering a driver-less car
- Understanding language
- Robotic assistants in surgery
- Monitoring trade in the stock market to see if insider trading is going on

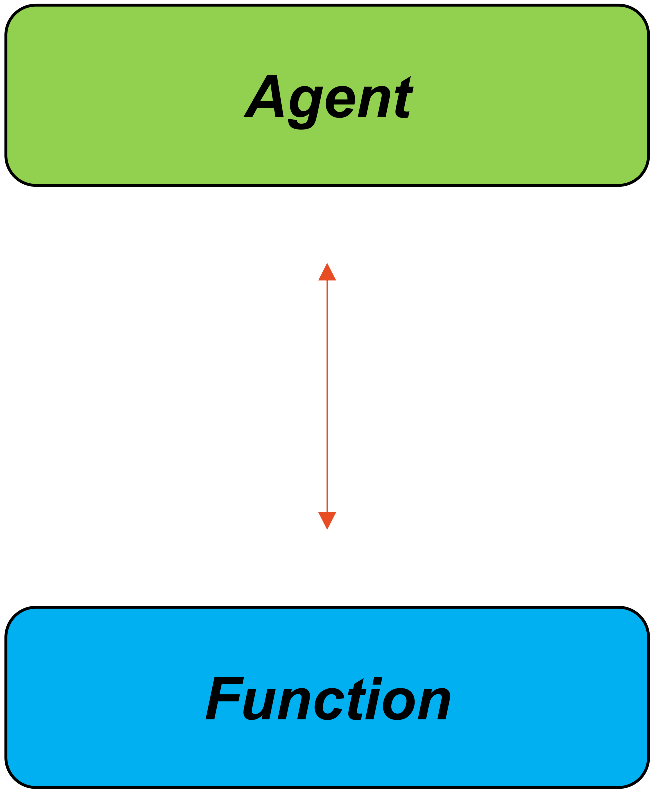
AI has a rich history:

Philosophy	*Mathematics*	*Economics*
Neuroscience	*Psychology*	*Control Theory*

→ **Coined by John McCarthy in 1950's**

Artificial Intelligence (3/5)

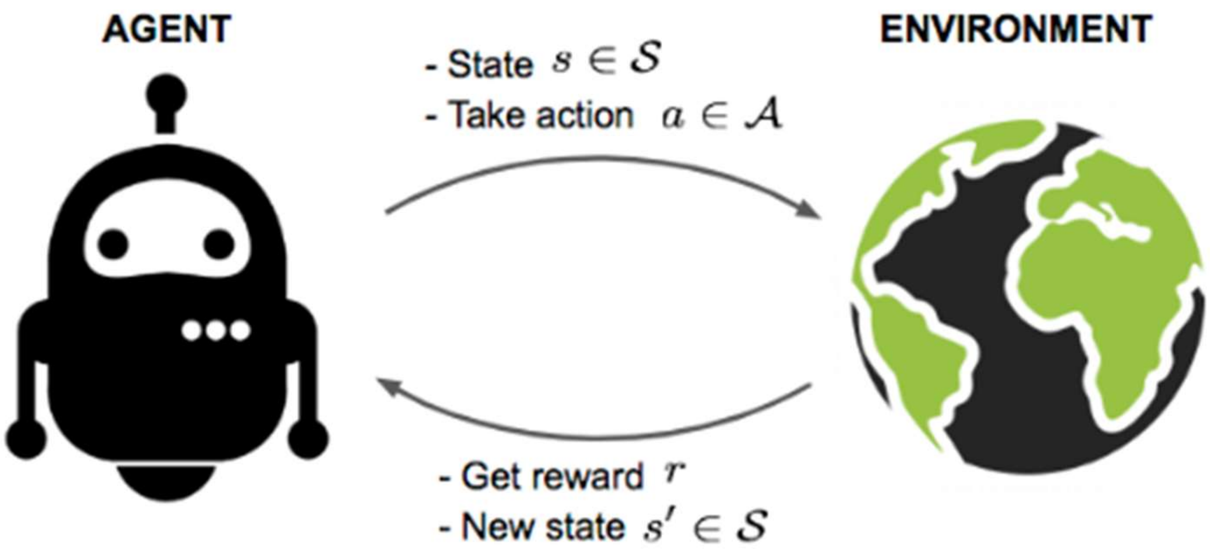
AI can be thought of as one of the following two concepts:



Artificial Intelligence (4/5)

*What is an **Agent?***

'Anything' that can gather information about its environment and take action based on that information, affecting the environment state

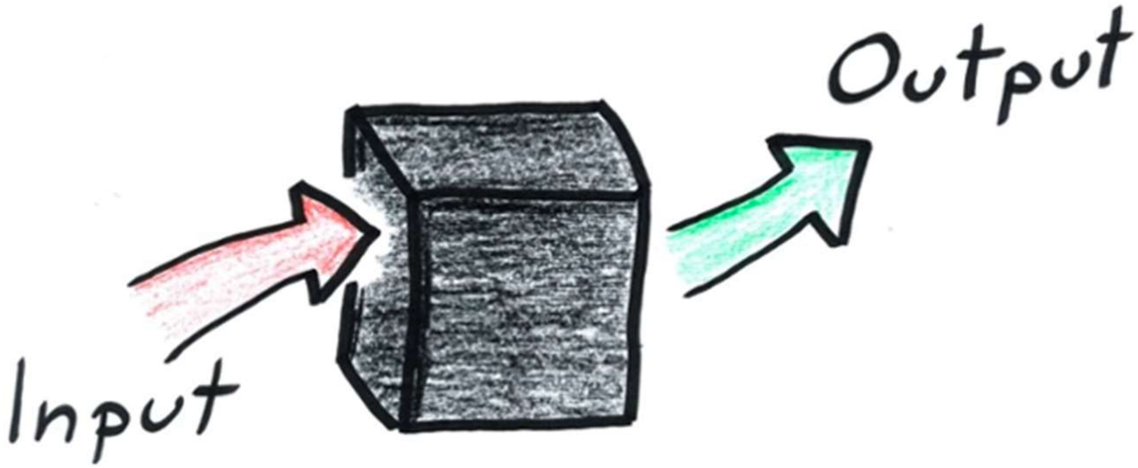


Artificial Intelligence (5/5)

*What is a **Function**?*

Given a sample set of inputs and corresponding outputs, find a function to express this relationship.
Such as:

- *Pronunciation: Function from letters to sound;*
- *Diagnosis: Function from lab results to disease categories*



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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 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.

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https://cloud.google.com/learn/artificial-intelligence-vs-machine-learning

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.

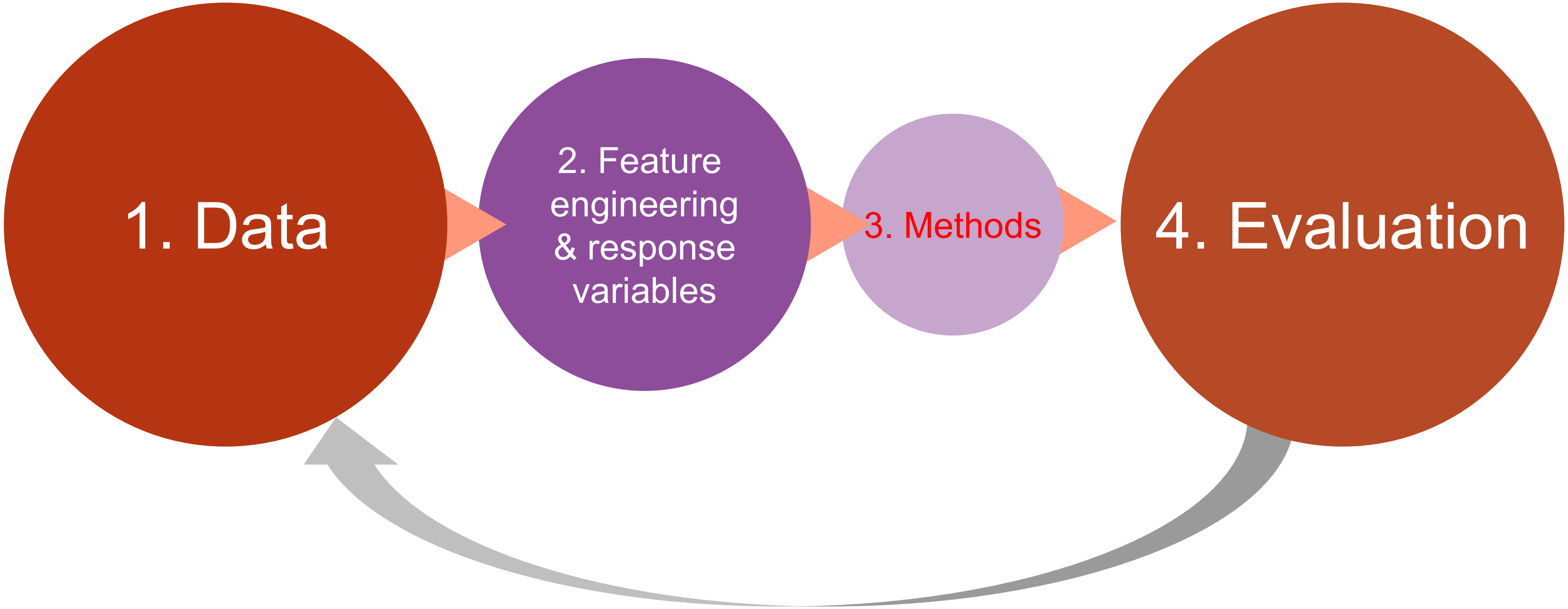
- Many of AI's unprecedented applications in business and society are supported by machine learning's wide ranging capabilities, whether it's analyzing mammograms or digesting Instagrams, assessing risks or predicting failures, navigating the roadways or thwarting the cyber attacks we never hear about. 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.

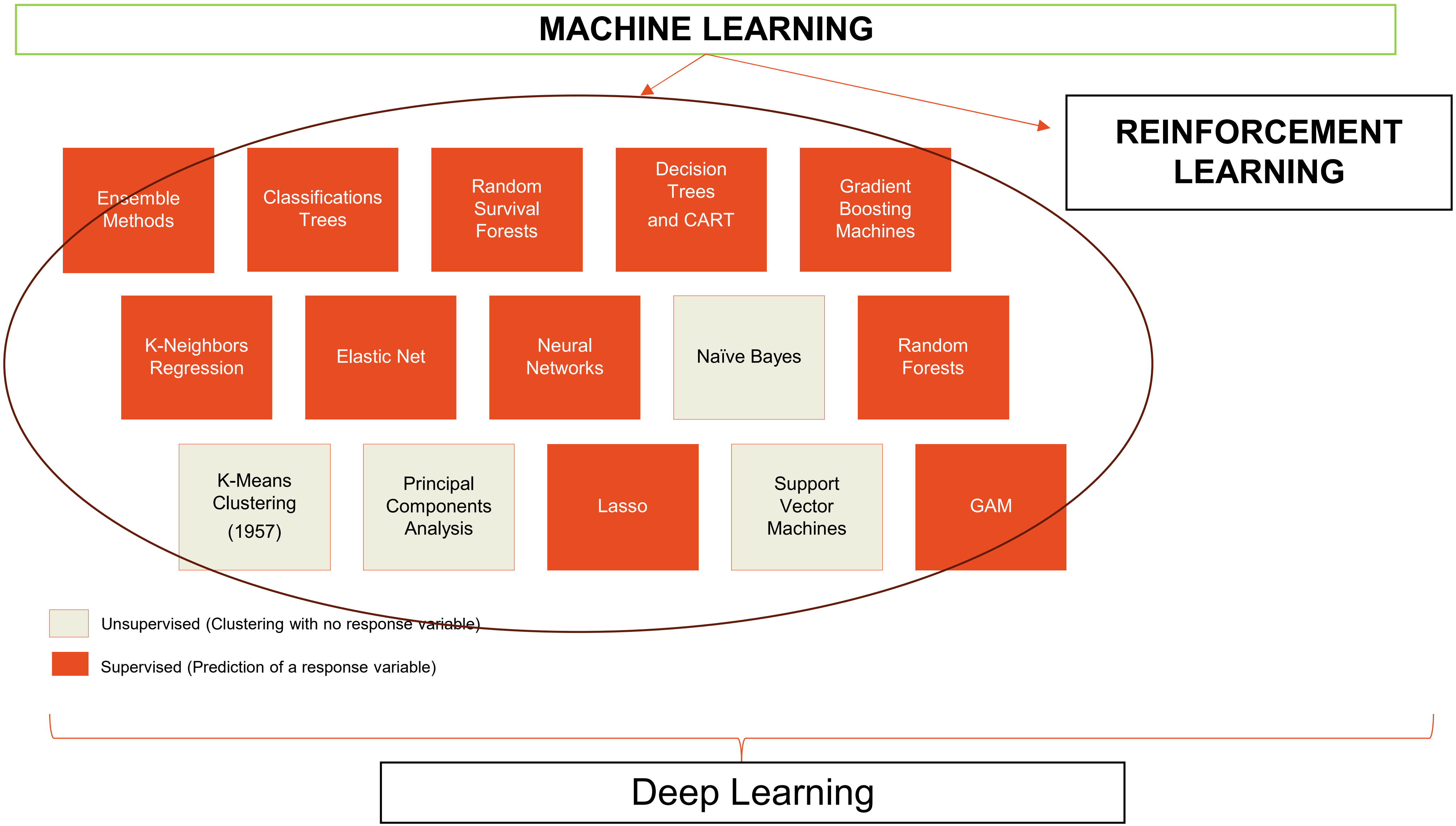
https://www.techtarget.com/whatis/A-Timeline-of-Machine-Learning-History

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.

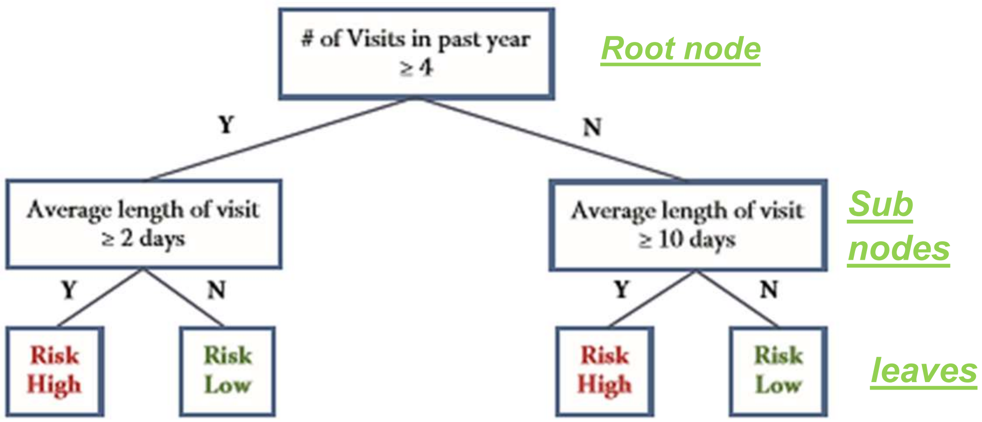
Remark 2 – Hyparameters tuning

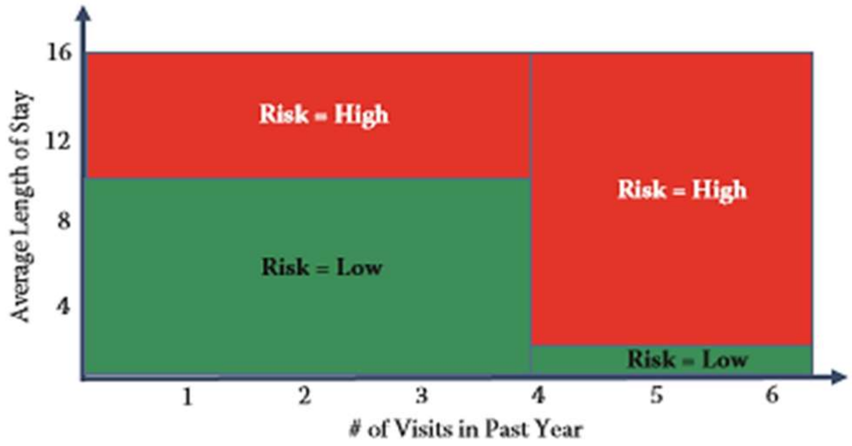
- One can draw a parallel between choosing parameters for the Benktander or Bornhuetter-Ferguson method and what in the **machine learning literature is referred to as hyperparameter tuning.**
- **Hyperparameters are parameters that determine the particular structure of the final model**, e.g., the *number 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.

```python
from sklearn.tree import DecisionTreeRegressor
# https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeRegressor.html

# Define Decision tree
model = DecisionTreeRegressor(
    # function to measure the quality of a split.
    criterion='mse', # or gini, mae, L2 mse, L1 mse
    # The strategy used to choose the split at each node.
    splitter='best', # or random
    # The maximum depth of the tree.
    max_depth=2,
    # The minimum number of samples required to split an internal node
    min_samples_split=2,
    # The minimum number of samples required to be at a leaf node.
    min_samples_leaf=1,
    # The number of features to consider when looking for the best split
    max_features=None, # None means use all features
    # A node will be split if this split induces a decrease of the impurity
    # greater than or equal to this value.
    min_impurity_decrease=0.0,
    # Threshold for early stopping in tree growth. A node will split
    # if its impurity is above the threshold, otherwise it is a leaf.
    min_impurity_split=None,
    # seed
    random_state=1234,
)

# fit
model.fit(x_train, y_train)

# predict
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

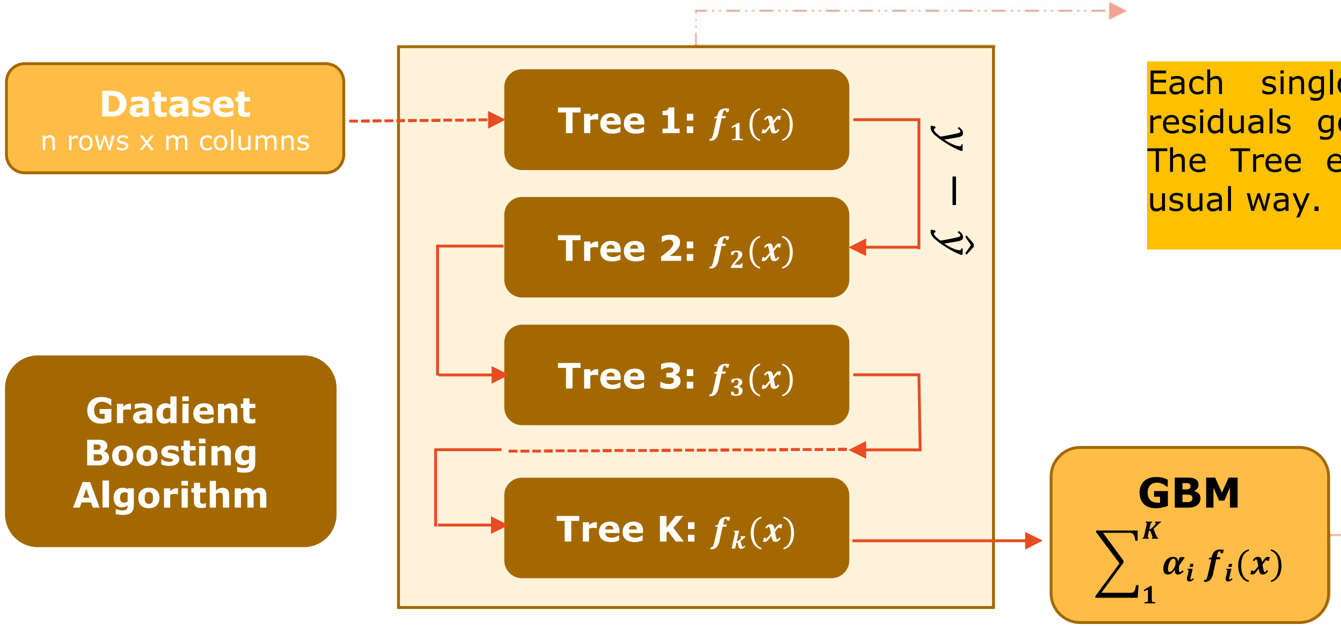
- *No need of probability distribution assumptions*
- *Easy to explain to people, with a really intuitive graphical representation;*
- *Be able to capture high non-linearity and complex relationships between dependent and independent variables.*

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"



Each single Tree is estimated on the residuals generated by the previous tree. The Tree estimation is carried out in the usual way.

Ensemble Model

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.

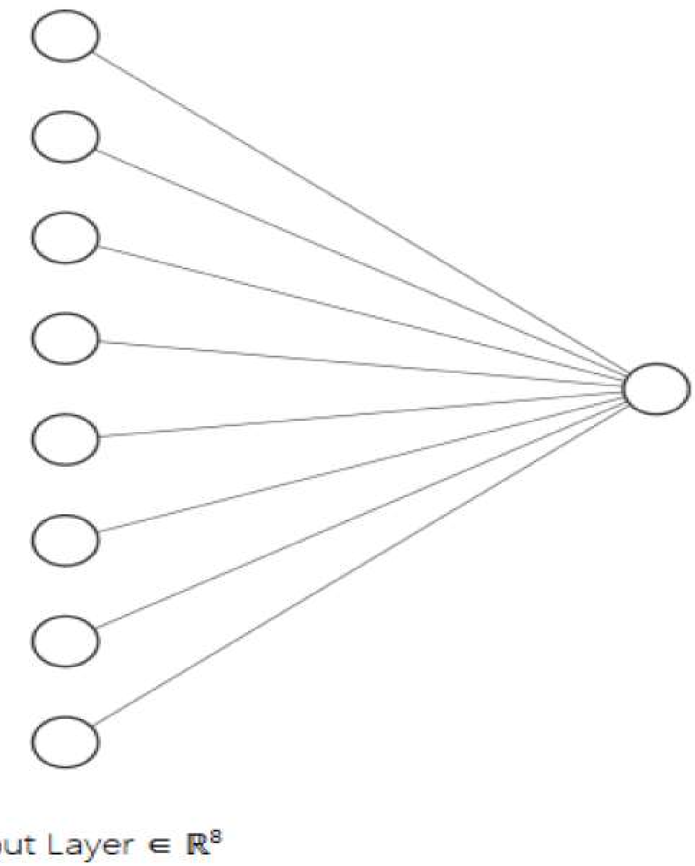
- Typically, ANN are organized in ***layers***. There is an input layer to match the feature space, followed by a single or multiple *hidden* layers (***deep learning***) and at the end an output layer that match the overcome space.

- **The learning ability of a neural network is determined by its architecture and by the algorithmic method chosen for training.**

Neural networks

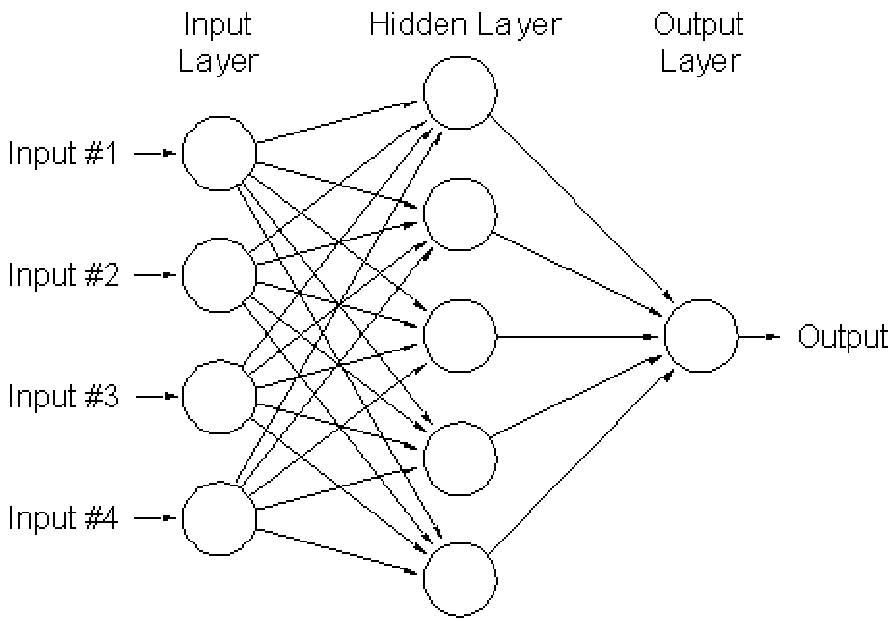
Single Layer NN = Linear Regression

- **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!**



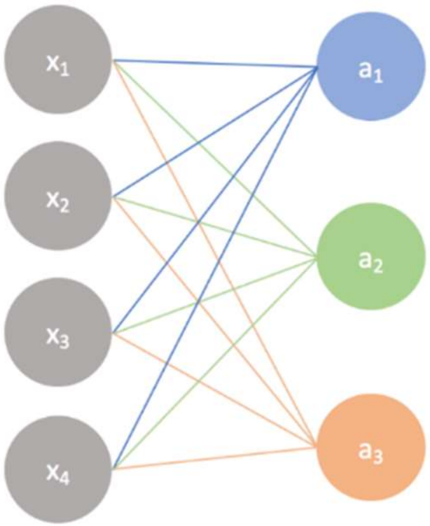
Deep Feedforward Net

- 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



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 identify the neurons' weights that minimize a given loss;
- Numerical algorithms are used at this purpose



A simple Zero Layer (Feed Forward) Neural Network

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

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*
- *…*

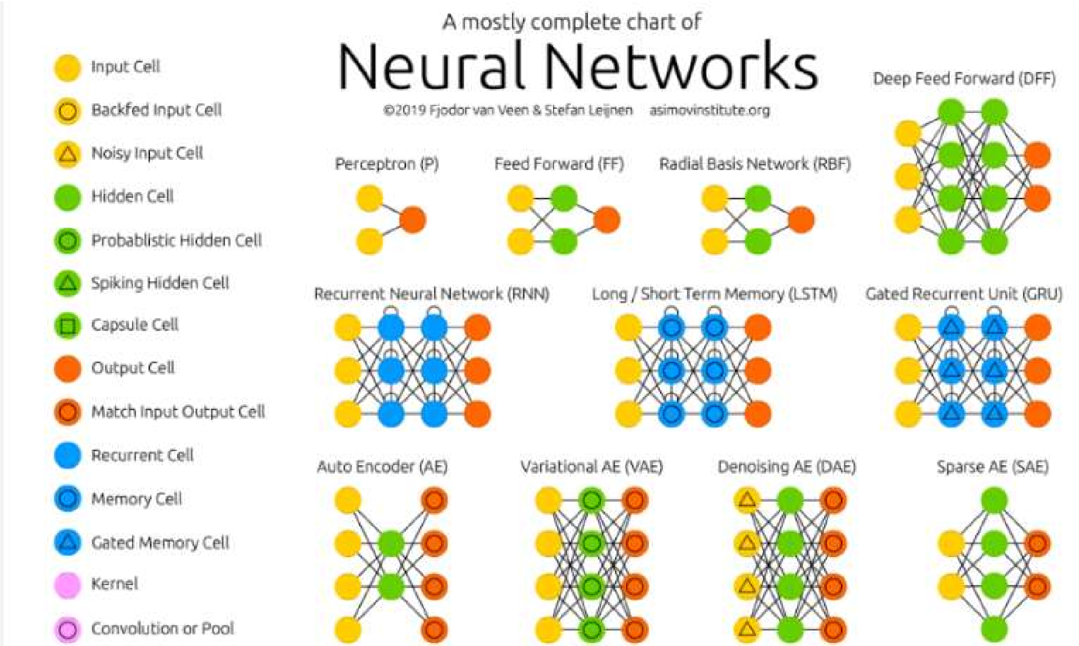
Cons

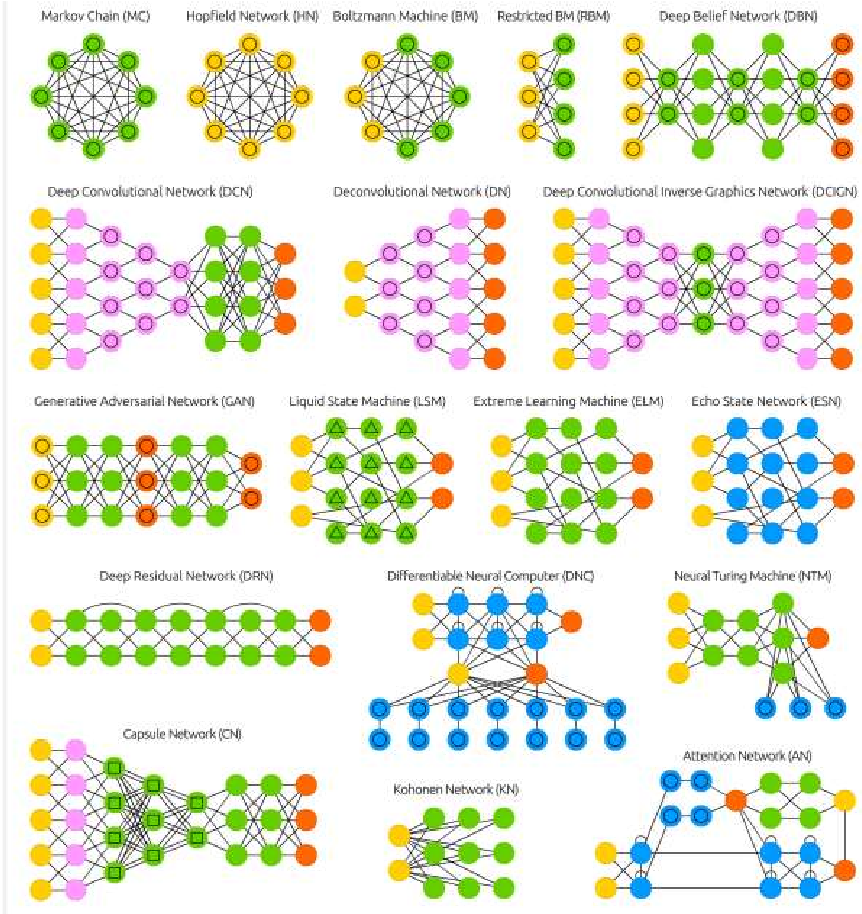
- *Not easy to explain to people;*
- *Risk to overfitting data;*
- *Computational time (training, etc.)*
- *…*

Neural networks

There are many types on *Neural Netwoks*:

- *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
- ….





Source https://www.asimovinstitute.org/neural-network-zoo/

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**

Indice del corso

- Artificial Intelligence
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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

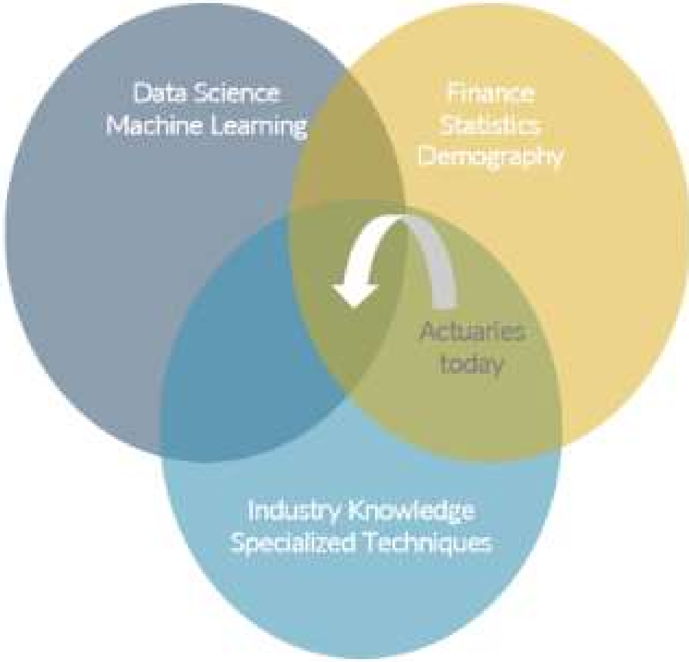
- Many applications of ML within insurance but outside of traditional areas

Actuarial science merges statistics, finance, demography and risk management

- Currently evolving to include ML

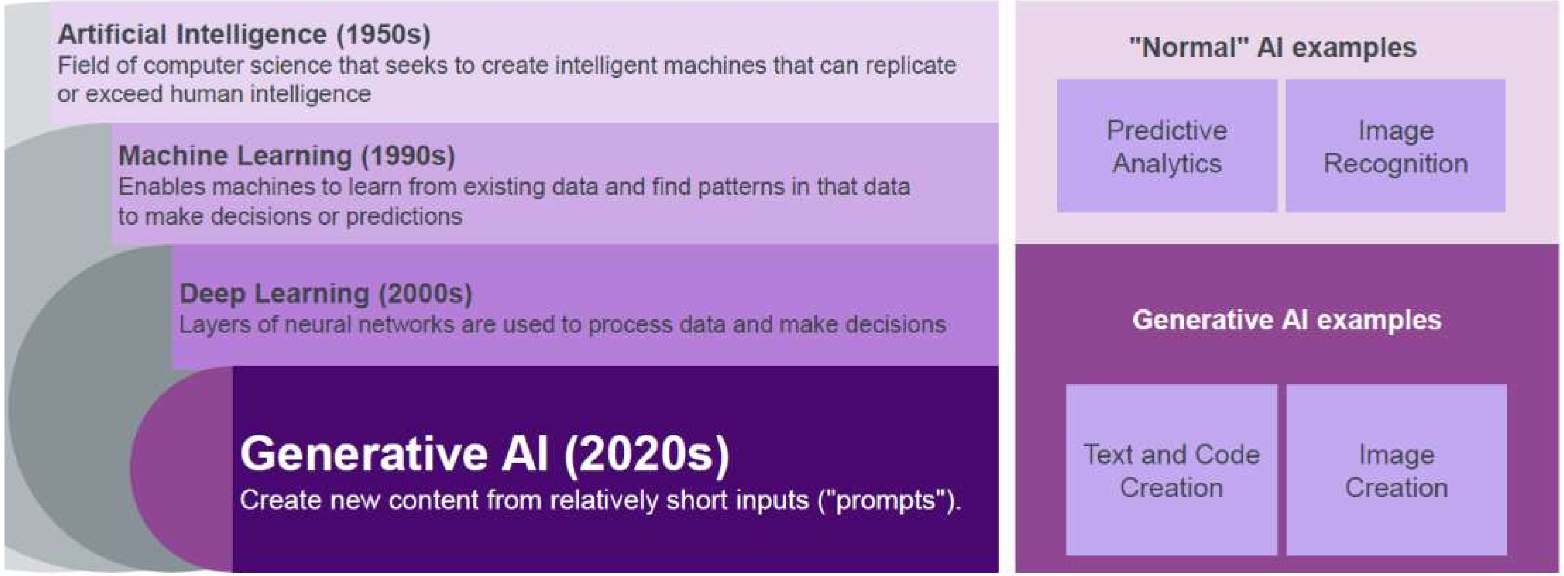
According to Data Science working group of the SAA:

- 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



Definitions and Diagram from Data Science working group of the Swiss Association of Actuaries (SAA)

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' paramete
- e.g. *output = 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")

Institute

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)

Human input

Feature engineering

Model Specification

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
- 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
  - Uncertainity 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 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. (2013).

https://cran.r-project.org/web/packages/DCL/DCL.pdf

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).
- About Italian Researchers, it is worth mentioning Giovanna Ferrara (2003), Gigante et al. (2004) and Cavastracci e Tripodi (2018)

- **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**

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 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.

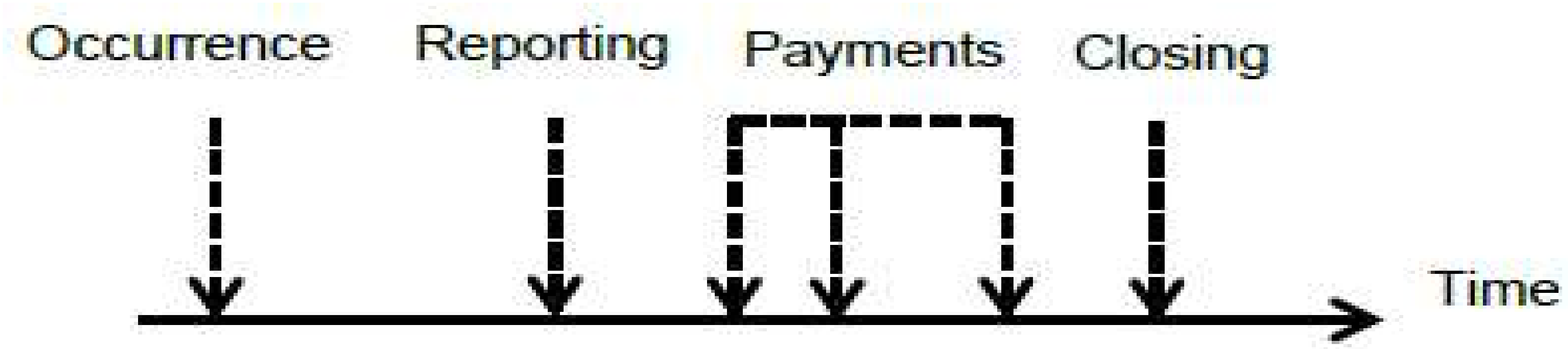
Remarks - 1

- 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**
  - 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**

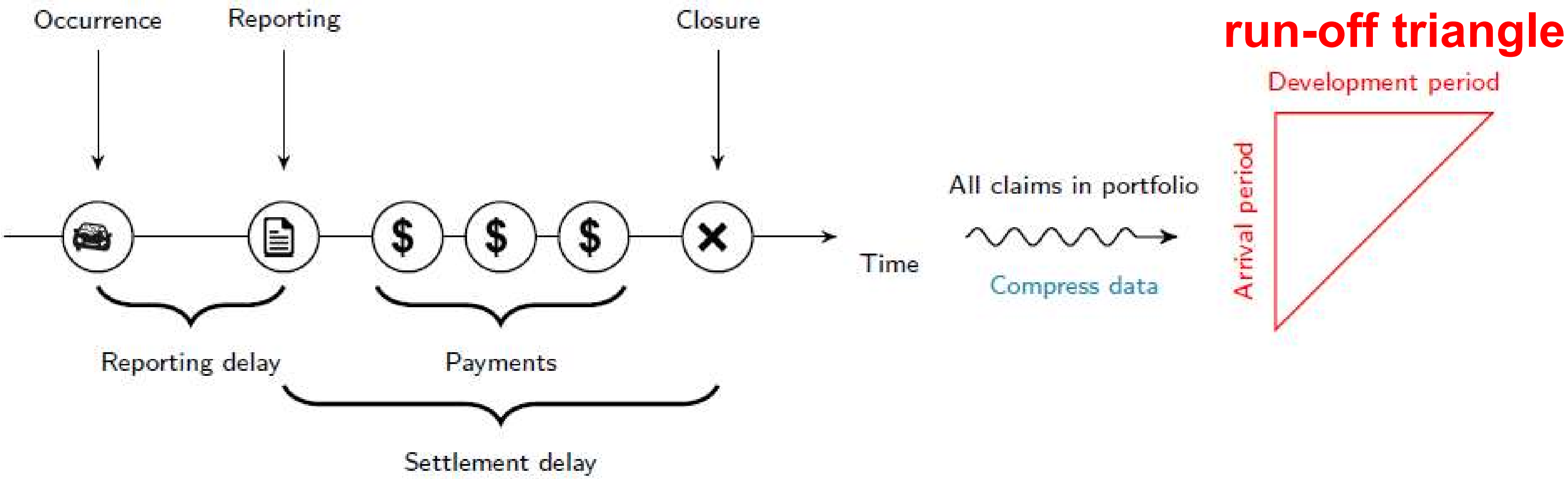
- **A proper use of the information embedded in individual claims data combined with appropriate individual claims development models represent a promising future.**

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)



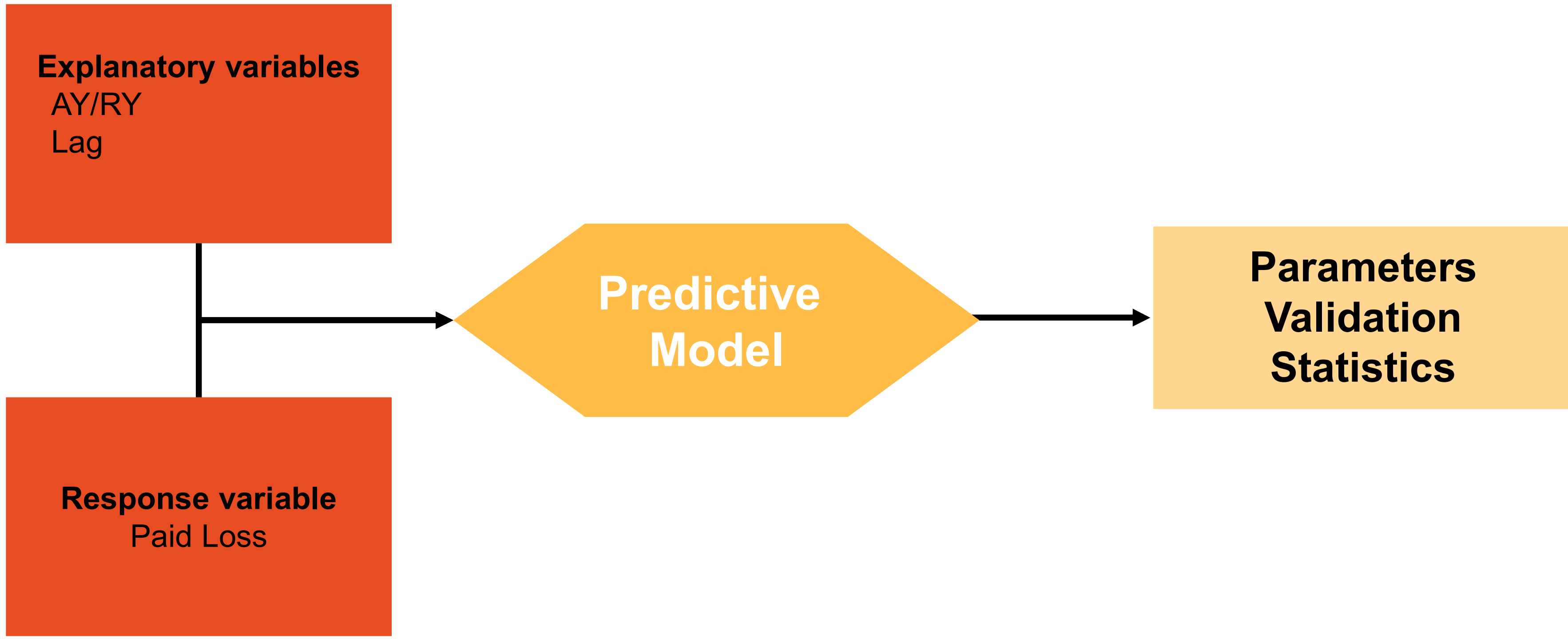
Remarks – 3



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

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

Response Variable **=** **Systematic Component** **+** **Random Component**

y = h (Linear Combination of Rating Factors) + Error

$g = h^{-1}$ is called the LINK function and is chosen to measure the signal most accurately

Explanatory variables

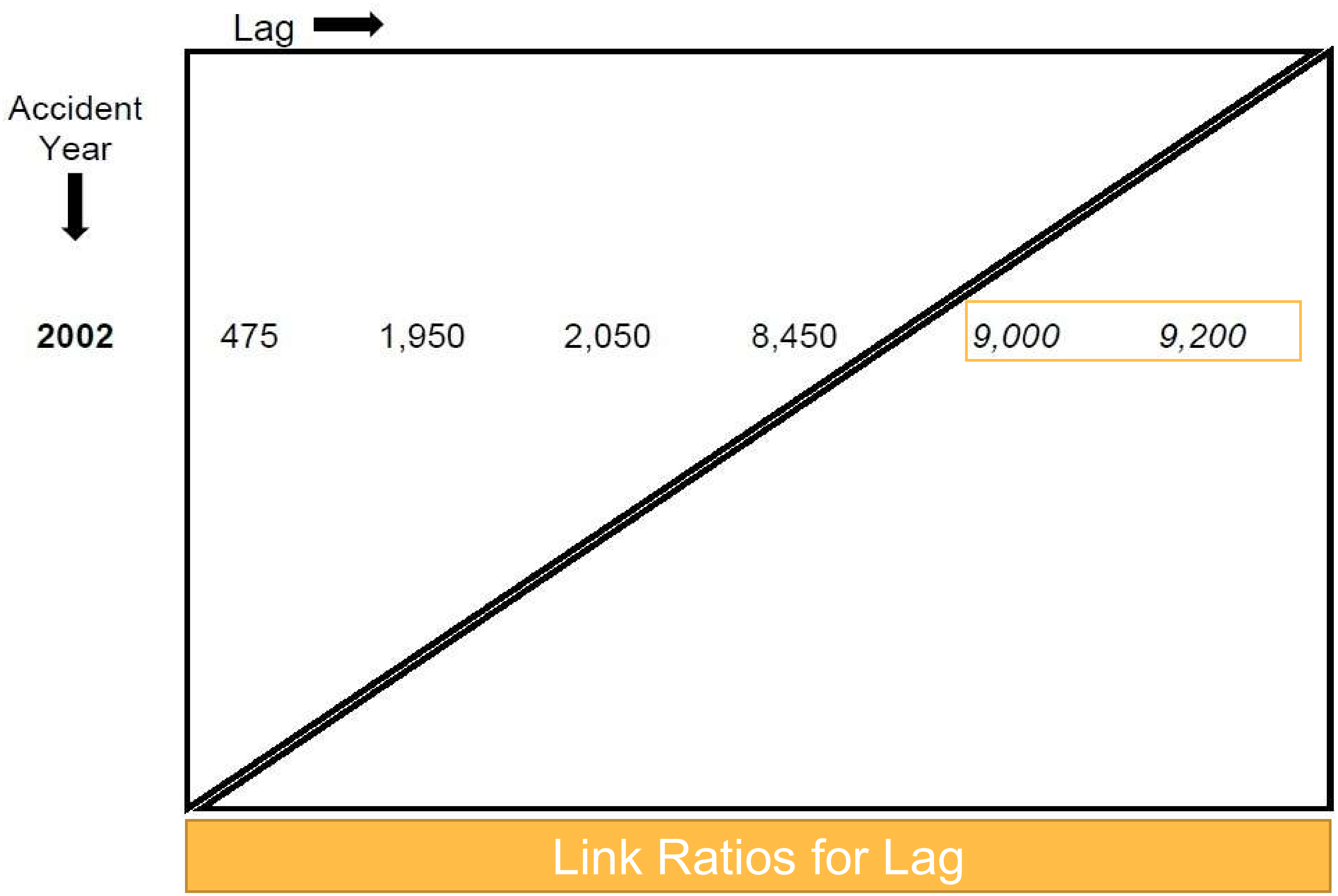
Error should reflect underlying process and comes from the exponential family

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

https://cran.r-project.org/web/packages/ChainLadder/vignettes/ChainLadder.html#generalised-linear-model-methods

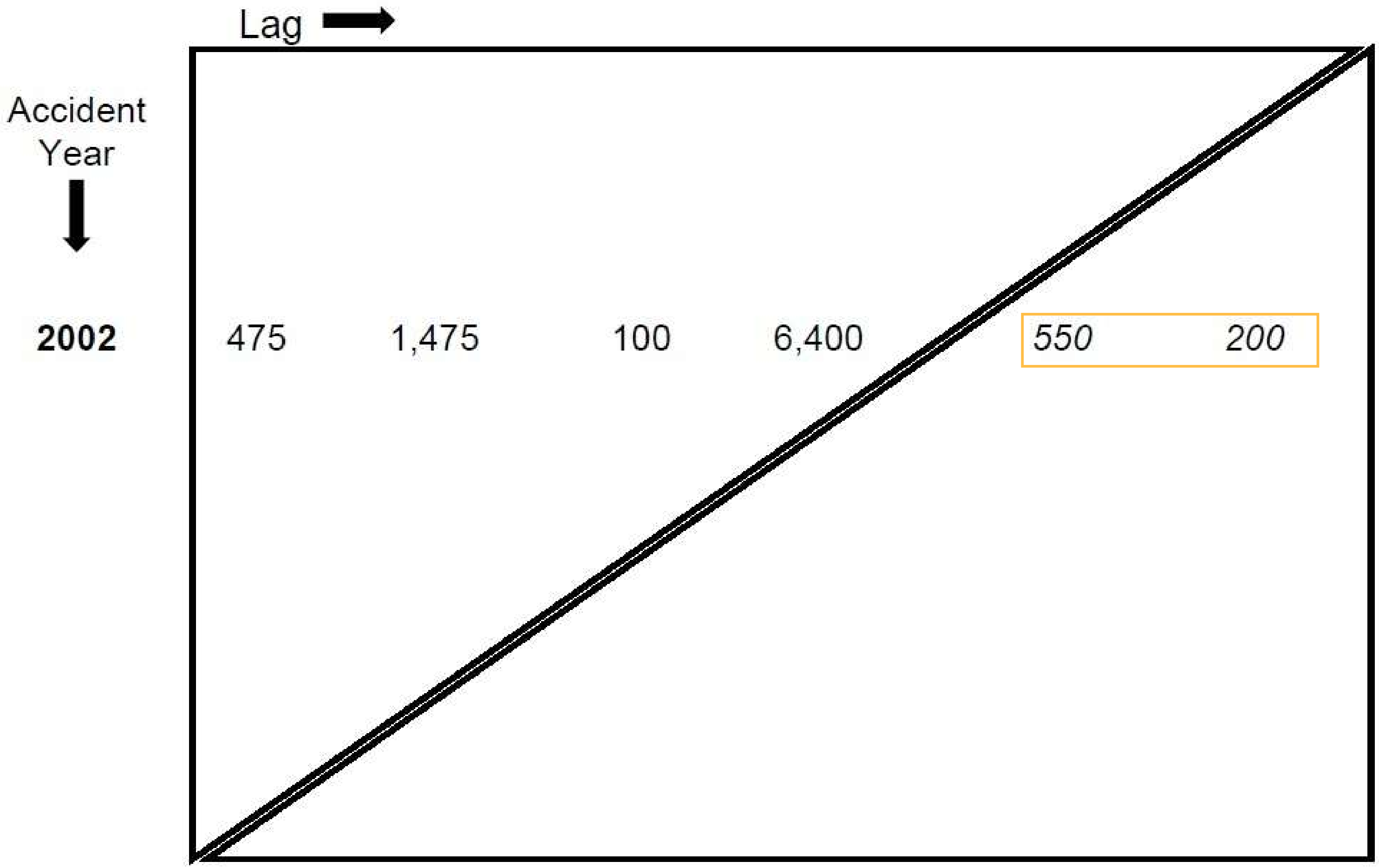
From the traditional to the ICR – Loss Development Method

- 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

Response Variable = Systematic Component + Random Component

y = h (Linear Combination of Rating Factors) + Error

Incremental Paid Loss = Log Link Function (Accident Year + Lag) + Poisson Error

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)

https://www.ivass.it/pubblicazioni-e-statistiche/pubblicazioni/quaderni/2017/iv9/ivassq0022.pdf

From the traditional to the ICR– the ICR

GLM triangle is set to an incremental basis

Lag →

Accident Year	Claim				
2002	000001	0	1,000	0	4,000
2002	000021	50	0	0	0
2002	000060	0	0	0	250
2002	000124	300	200	0	250
2002	000328	125	275	0	0
2002	000443	0	0	100	1,900

Results can still replicate a traditional aggregate development method

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

Response Variable = **Systematic Component** + **Random Component**

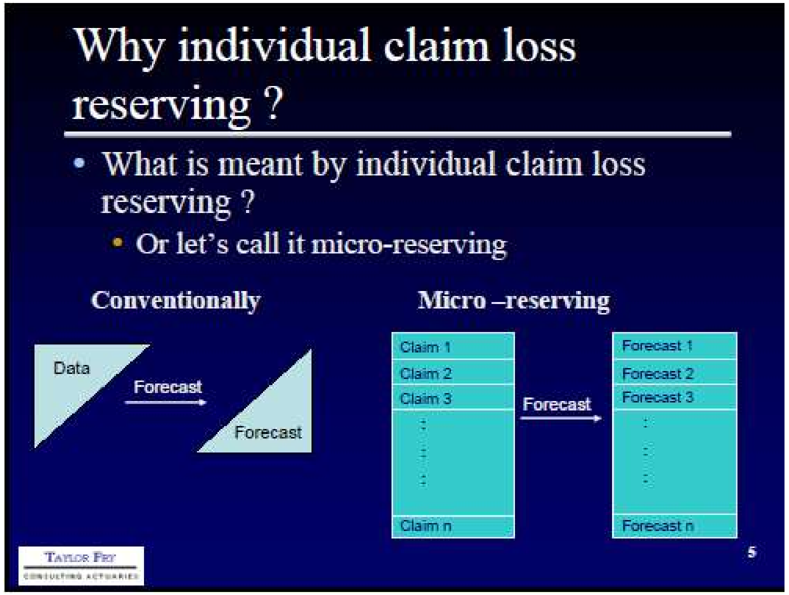
y = h (Linear Combination of Rating Factors) + Error

Incremental Paid Loss = **Log Link Function** **(Accident Year + Lag + Risk Factor Info + Claims Info)** + **Poisson Error**

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

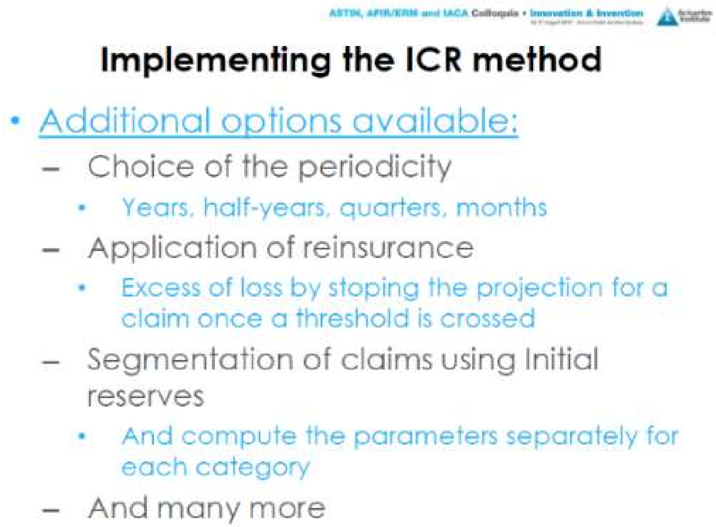
ICR → Outstanding claims reserve (“OCR”) are estimated “claim by claim“



- 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

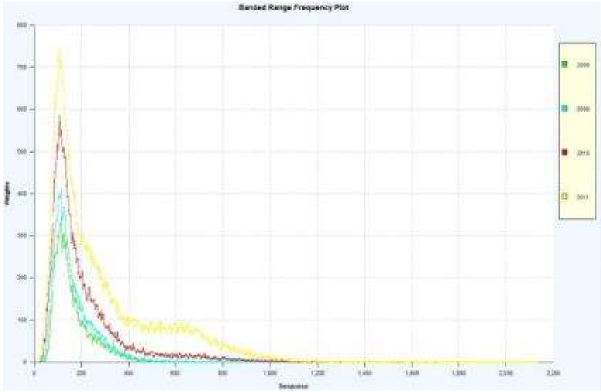


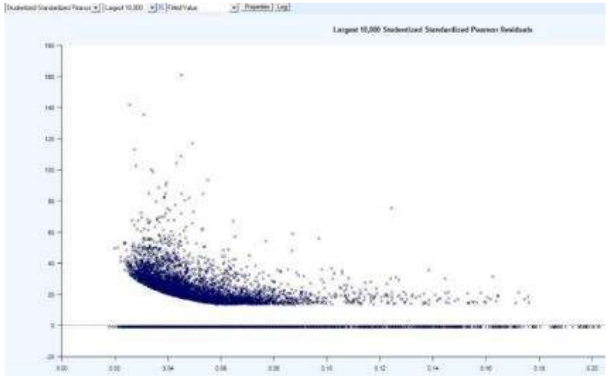
Why we use the ICR for Reserving

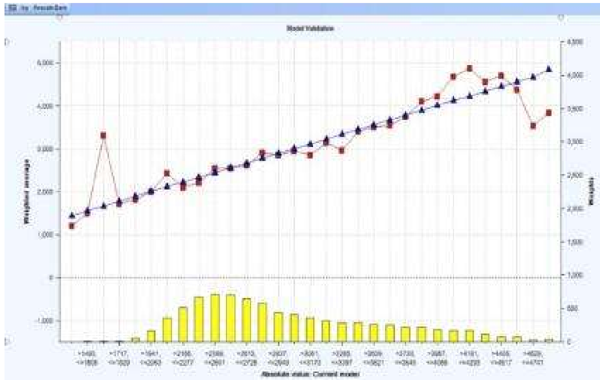
- ICR method could adjust the cost of claim for the IBNeR at single claim level

- 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 statistc, 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

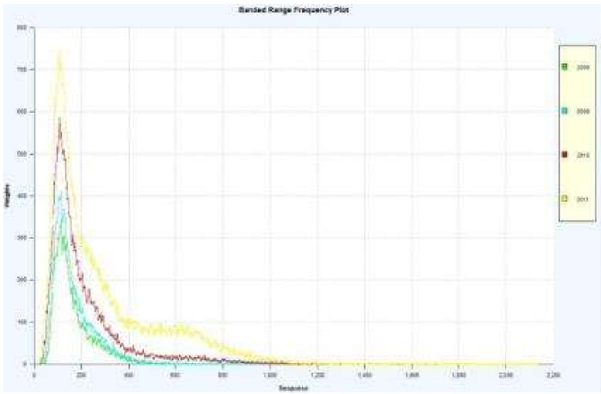
- In Boumezoued et al. 2011 paper ("One-year reserve risk including a tail factor: closed formula and bootstrap approaches") two adaptations of GLM, generating samples of the CDR in a one-year view, have been developed:
  - **First approach**: this approach has been proposed by Lacoume (2008) and Boisseau (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.

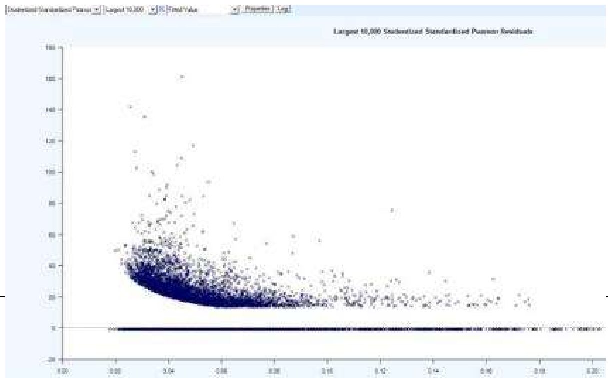
Solvency II – ICR and one-year view of reserve risk

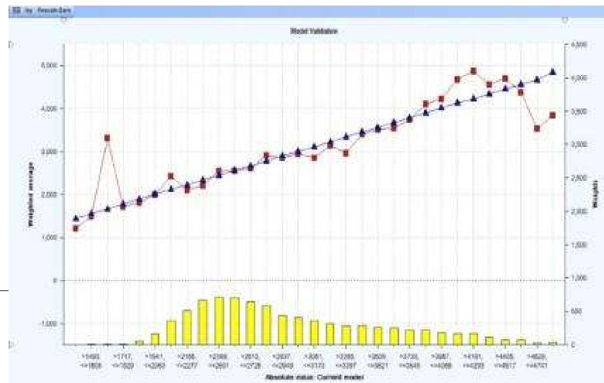
- A GLM with an Over-Dispersed Poisson distribution➔ pdf of claim provision (e.g. package Chain ladder of R by Carrato et al.).

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

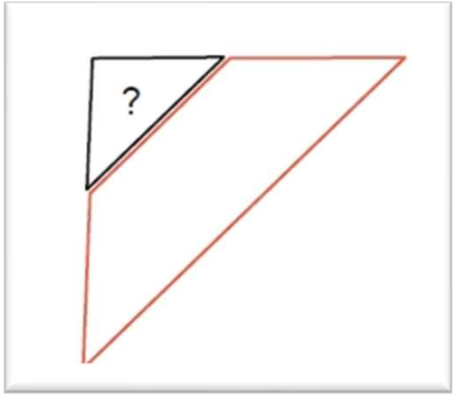






Some remarks

- 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?

- Further discussions about IBNyR in next slides

B) Individual Claim Reserving (ICR) and Machine Learning

- TheActuary 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 we can analyze reserves on individual claims, we can capture changing portfolio mixes and we can 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 *(reported but not settled*) 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**;
    - **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.

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.

ICR-ML and Clustering

OUR ALGORITHM: TWO STEPS APPROACH

Aggregating homogeneous claims

- We make use of clustering techniques to **identify claims which are similar**, considering their **paid and incurred histories** (and other factors, eg. AY)
- Ideally, by clustering you can obtain different triangles for which the traditional methods' **assumptions of homogeneity hold true**

+

Projection of the ultimate cost

1. Chain-ladder can be seen as a **constrained linear regression**; we proved(*) that this holds true also **on an individual claim basis**
2. The idea is that **one can gradually extend the model**, by removing constraints or adding more features, to improve **prediction power**

The algorithm automatically selects the best combination of clusters and parameters to predict the ultimate cost claim by claim

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 $c_j = f(\mathbf{x}_{j-1}) + \varepsilon_{j-1}$, where f is found via **gradient boosting** or **neural networks**

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ML techniques and ICR

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 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.***

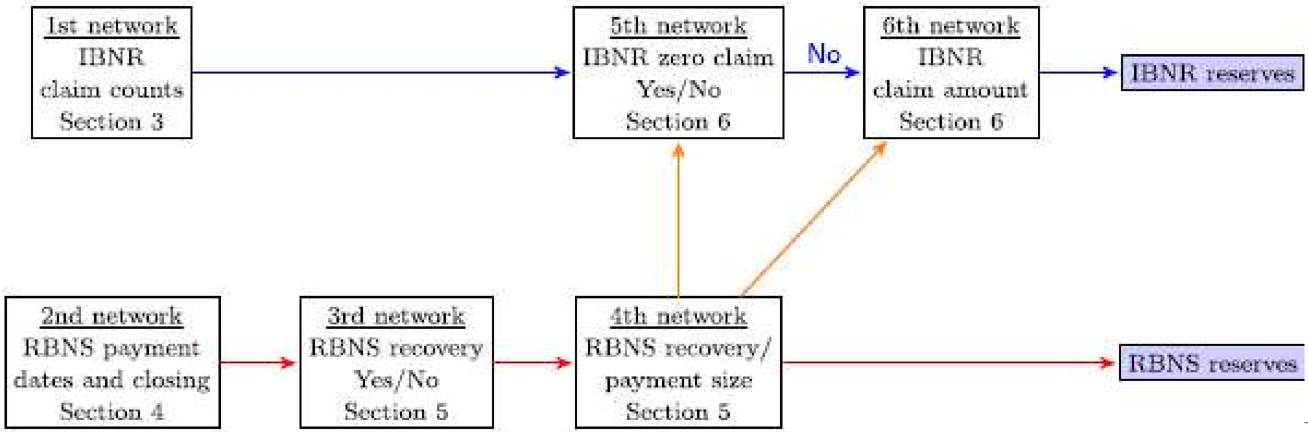


Figure 1. Claims reserving architecture used consisting of six networks.

ML techniques and ICR

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 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)
Crevecoeur J, Antonio K (2019)	Carrato (2023)
Hiabu M, Margraf C, Martínez-Miranda MD, Nielsen JP (2016)	De Felice M, Moriconi F (2019)
Jessen AH, Mikosch T, Samorodnitsky G (2011)	Delong L, Lindholm M, Wüthrich MV (2020)
Larsen CR (2007)	Delong L, Wüthrich MV (2020)
Martínez-Miranda MD, Nielsen JP, Verrall RJ, Wüthrich MV (2015)	Duval F, Pigeon M (2019)
Pigeon M, Antonio K, Denuit M (2013)	Kuo K (2020)
Taylor G, McGuire G, Sullivan J (2008)	Lopez O, Milhaud X, Thérond P-E (2019)
Zhao XB, Zhou X, Wang JL (2009)	Wüthrich MV (2018)

(Some) Actuarial Applications of Deep Learning

	Pricing	Reserving	Telematics	Mortality Forecasting	Quantitative Risk Management
Feed-forward Nets	• Ferrario, Noll and Wüthrich (2018) • Noll, Salzmann and Wüthrich (2018) • Wüthrich and Buser (2018)	• Castellani, Fiore, Marino et al. (2018) • Doyle and Groendyke (2018) • Gabrielli and Wüthrich (2018) • Hejazi and Jackson (2016, 2017) • Wüthrich (2018) • Zarkadoulas (2017)	• Gao and Wüthrich (2017) • Gao, Meng and Wüthrich (2018) • Gao, Wüthrich and Yang (2018)		• Castellani, Fiore, Marino et al. (2018) • Hejazi and Jackson (2016, 2017)
Convolutional Neural Nets			• Gao and Wüthrich (2019)		
Recurrent Neural Nets		• Kuo (2018a, 2018b)		• Nigri, Levantesi, Marino et al. (2019)	
Embedding Layers	• Richman (2018) • Schelldorfer and Wüthrich (2019) • Wüthrich and Merz (2019)	• Gabrielli, Richman and Wüthrich (2018) • Gabrielli (2019)		• Richman and Wüthrich (2018)	
Autoencoders			• Richman (2018)	• 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)

Multi LoB IBNR reserving (2)

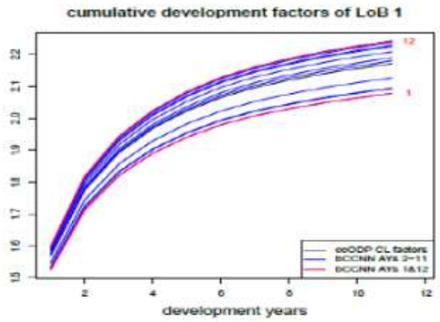
- **Recent work embedding the ODP CL model into a deep neural network (multi-LoB solution)**

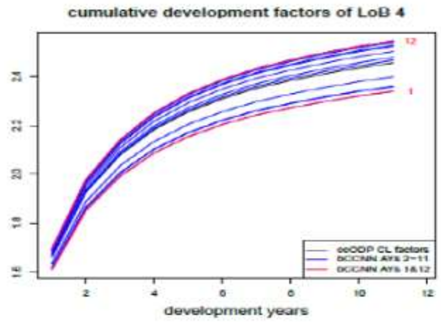
- **6 Paid triangles generated using the simulation machine of Gabrielli and Wüthrich (2018)**
  - Know true reserves
  - Relatively small data (12*12*6=478 data points)

- **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





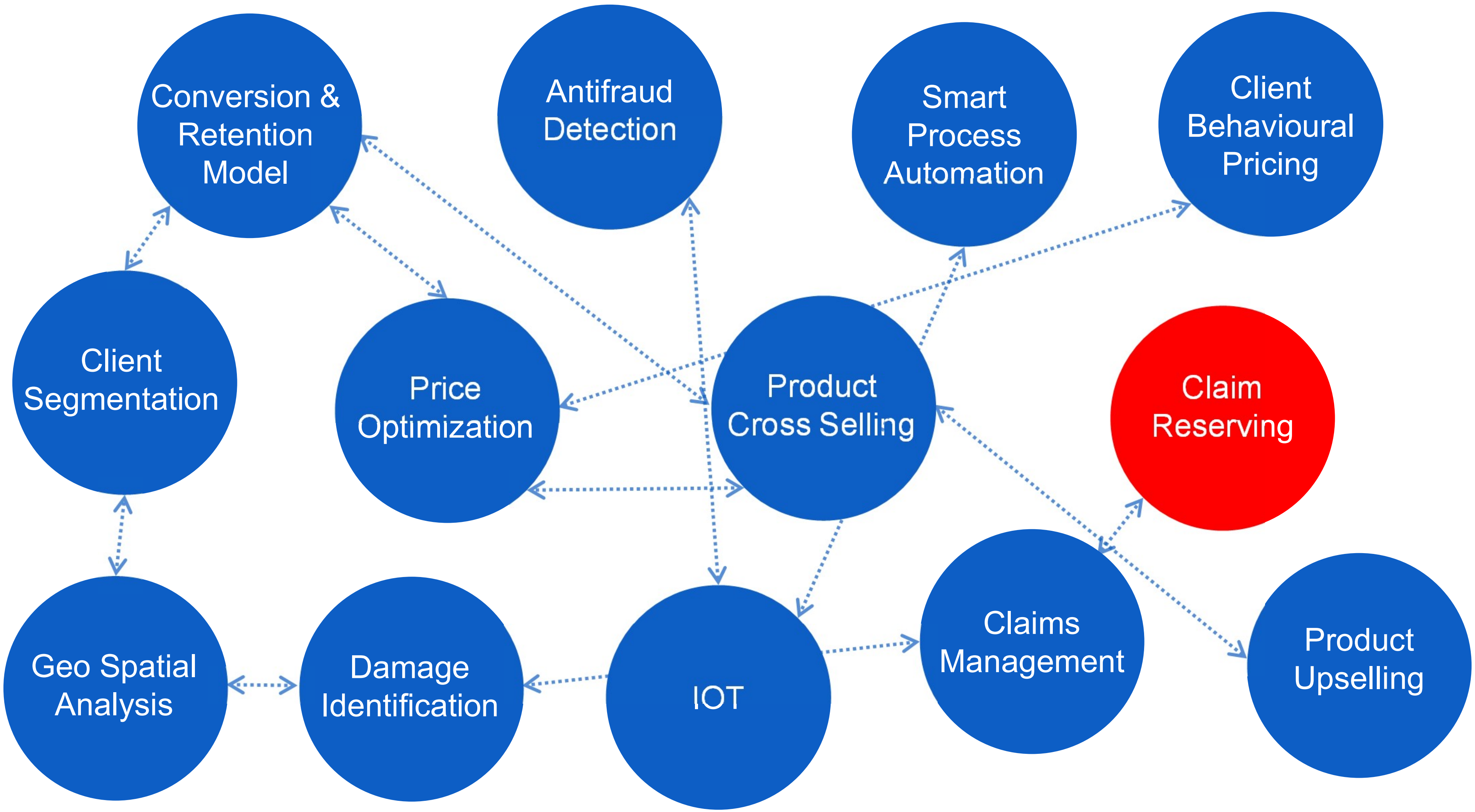
		LoB 1	LoB 2	LoB 3	LoB 4	LoB 5	LoB 6
(i)	true claims reserves R_m^{true}	39'689	37'037	16'878	71'630	72'548	31'117
(ii)	CL reserves R_m^{CL}	38'569	35'460	15'692	67'574	70'166	29'409
(iii)	single NNDODP reserves R_m^{ind}	39'407	36'283	16'123	70'547	71'873	31'092
(iv)	multiple NNDODP reserves R_m^{joint}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

Agenda

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

State of the Art – Best Practice

Applications of machine learning in the insurance sector



EXPLORING DIGITAL REGULATION
ANIA 2023

ANIA's commitment to explore the evolution of digital regulation and the relevant impacts on the insurance market continues in 2023 (see the "ANIA Exploring Digital Regulation" newsletter).

This year's focus will be the analysis of the recently introduced Regulation (EU) no. 2022/2554 ofthe European Parliament and of the Council of December 14, 2022 on digital operational resilience for the financial sector, so-called "DORA" ("**Digital Operational Resilience Ac**t").

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**.

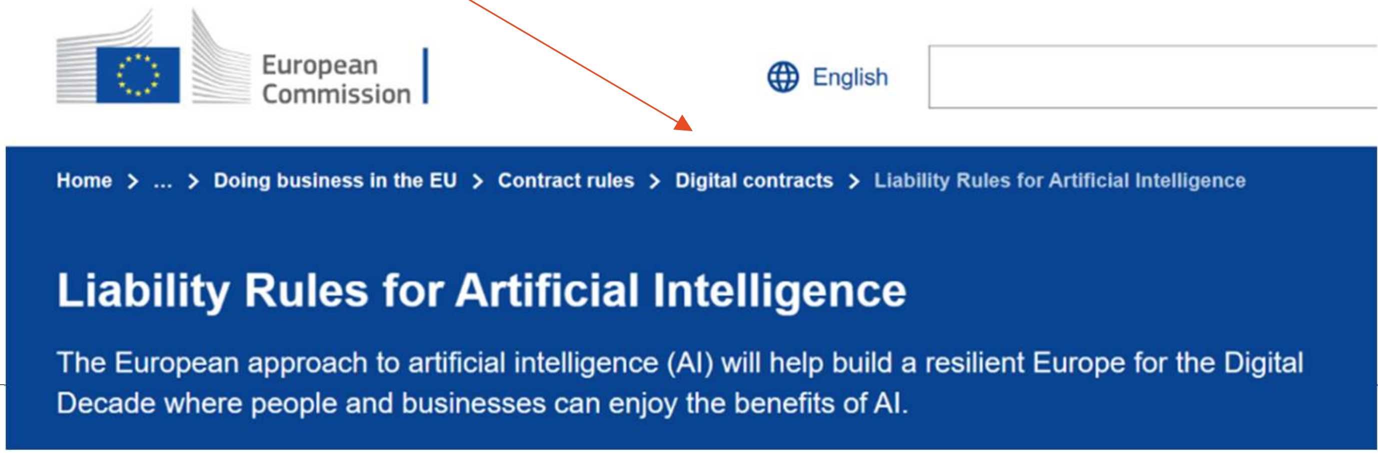
LINK: ANIA Exploring Digital Regulation - ANIA Exploring Digital Regulation - ANIA - Welcome

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**).



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.

https://commission.europa.eu/business-economy-euro/doing-business-eu/contract-rules/digital-contracts/liability-rules-artificial-intelligence_en

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

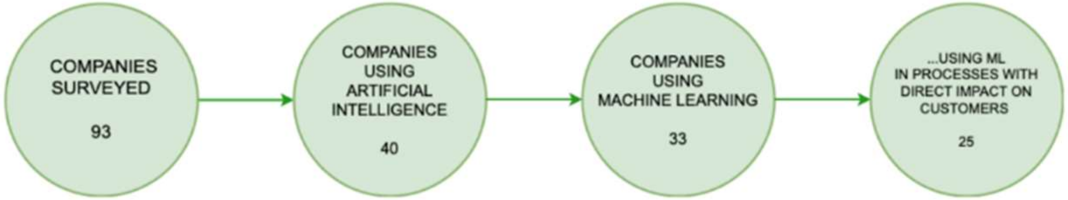
The use of new technologies is accelerating change in the insurance industry, leading to the development of products and services to intercept the demand from increasingly digital consumers and implement new ways of dealing with customers. Among the various technologies investigated by IVASS, an in-depth 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 :

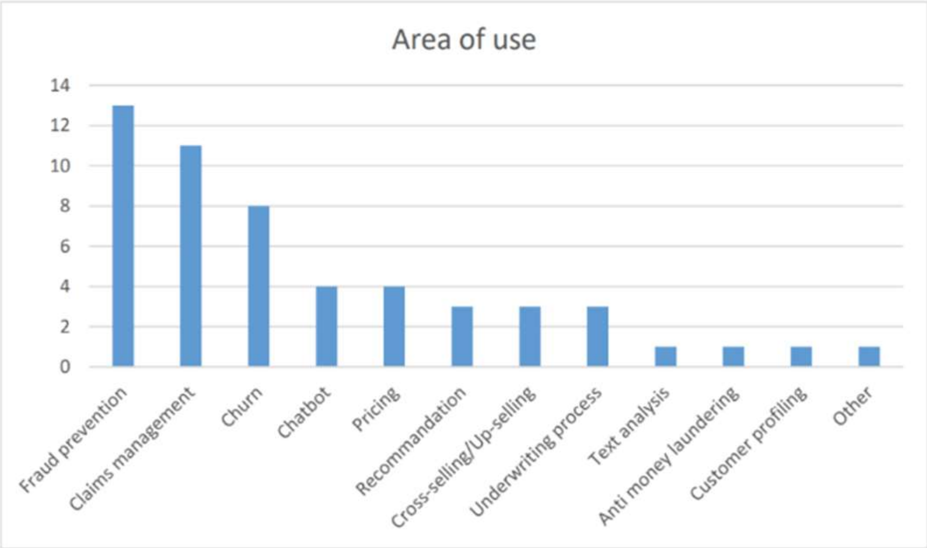
- Governance
- Security
- Explainability
- Fairness
- Outsourcing
- Main ML algorithms used by undertakings

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:

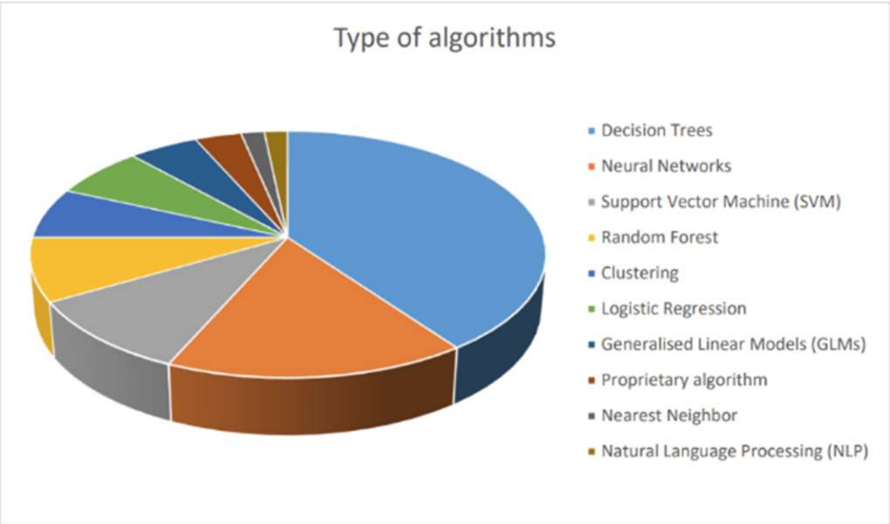
- among other technologies used by undertakings in conjunction with AI models,

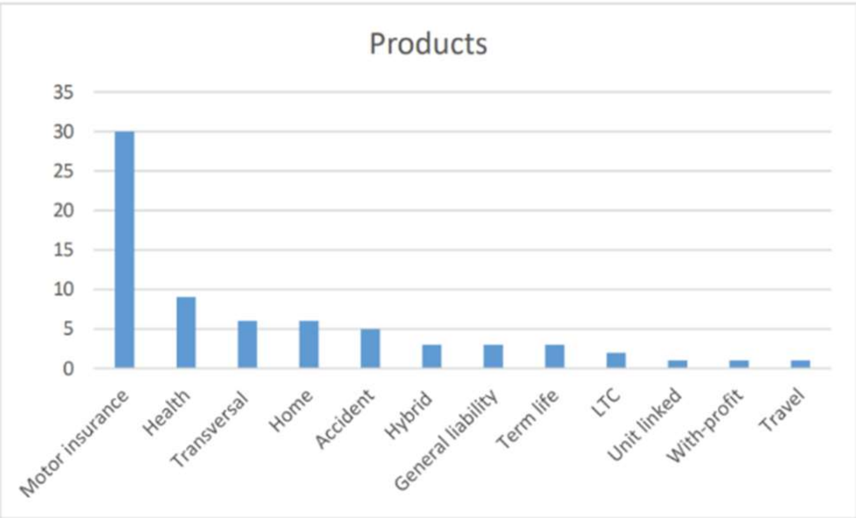
- 1% of undertakings indicate that they employ blockchain-related technologies,
- 37% use cloud computing,
- 16% adopt IoT - Internet of Things, and
- 27% exploit information from big data;

- **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**;

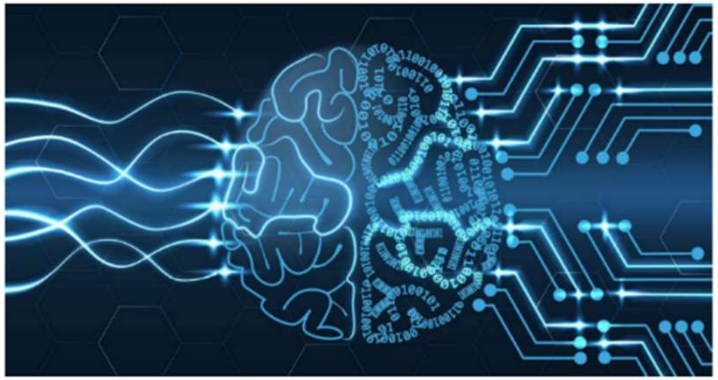
- among the companies using ML, **70% of those pursuing business in the non-life sector and 22% in the life sector say they use specific KPIs/KRIs** (key performance indicator/key risk indicator) in relation to the algorithms, to evaluate the performance of the models; the indicators are not yet applied 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.

IVASS
ISTITUTO PER LA VIGILANZA SULLE ASSICURAZIONI

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

IFoA WP – ML in Non-Life Reserving

Blog

Machine Learning in Non-Life Reserving

AUTHOR
Machine Learning in Reserving Working Party

PUBLISHED
October 28, 2023

Preface

The General Insurance Machine Learning in Reserving working party (MLRWP) is a group of over 70 volunteers, bringing together a range of data scientists, actuaries and academics from around the globe.

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.

In this book, we have gathered together much of the material from our blog.

Over the last four 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

https://mlrwp.github.io/mlrwp-book/ (BLOG)

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)

- Machine Learning in Non-Life Reserving - 3 Introduction to R (mlrwp.github.io)
- Python For Beginners | Python.org

IFoA WP – ML in Non-Life Reserving

Posts

Order By

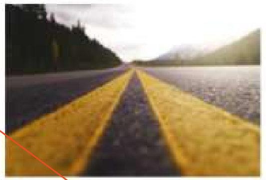
Filter

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



Categories

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

AUTHOR
Adam Stanley

PUBLISHED
October 31, 2023

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

https://institute-and-faculty-of-actuaries.github.io/mlr-blog/posts.html (Posts)

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

https://institute-and-faculty-of-actuaries.github.io/mlr-blog/faq.html

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

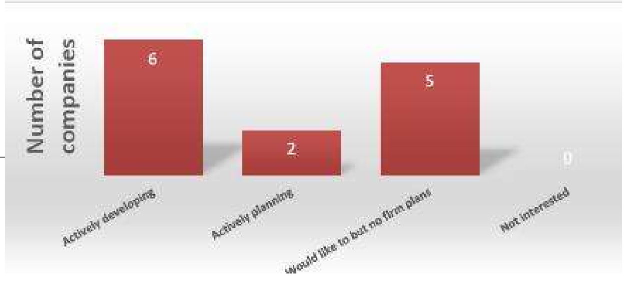
Enthusiasm from reserving actuaries but stakeholder engagement low

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,

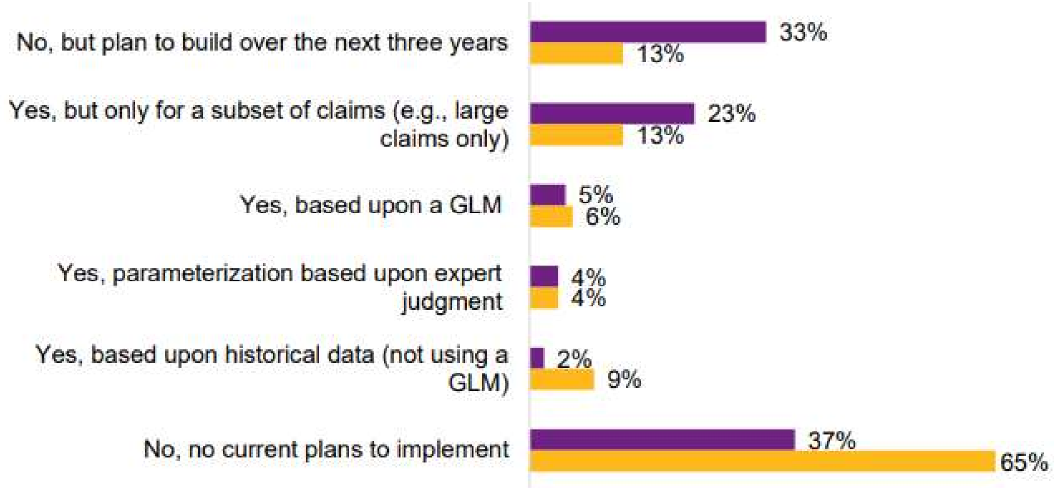
- with four insurers currently using ML in the reserving process.
- For three of these insurers, ML was used for additional insights, **but, significantly, the final insurer used ML to book reserves.**

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 barrier 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) Rocco Roberto Cerchiara 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%

Agenda

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

Final Remarks

Model	Advantages	Drawbacks
Aggregate	• 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	• 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	• 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 MLM in that it automates model selection, and also provides a powerful guard against over-parameterisation.

Final Remarks

<table>
<tr><th>Model</th><th>Advantages</th><th>Drawbacks</th></tr>
<tr><td>GM (and GLM)</td><td>• 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</td><td>• 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.</td></tr>
</table>

Final Remarks

Model	Advantages	Drawbacks
GM (and GLM)	• This approach may extract valuable information about the claim process that would otherwise be unavailable	• 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	• 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	• **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)	• **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.	• **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.

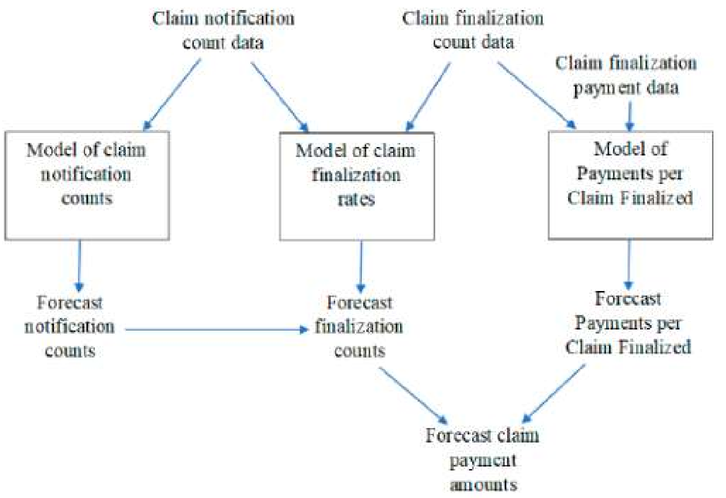


Figure 4. The Payments per Claim Finalized model and its sub-models.

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 o**ver-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 1. 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 MSEP 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

- 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.**

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

LLMs excel at generating text that closely resembles text written by humans

These models are competent at solving novel unseen problems

LLMs make use of additional context to inform their responses

LLMs can be fine-tuned for specific tasks and behaviors

LLMs can be biased based on the data it has been trained on

LLMs can very confidently generate incorrect answers

LLMs can struggle with arithmetic and computational tasks

Strengths and limitations of generative AI (2)

Incredibly powerful at writing code (and adjacent areas)

Incredibly powerful at reading and 'digesting' large volumes of text

Can be biased

Can be incorrect

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

Source: Edwards et al. (2023)

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.

Source Deloitte US (2023) "Implications of generative AI for insurance"

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APPENDIX

Additional survey – IFRS17

ASTIN
Non-Life Insurance

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.

Additional survey – IFRS17

ASTIN
Non-Life Insurance

TERMS OF REFERENCE

ASTIN WORKING PARTY ON
IFRS 17 ACTUARIAL BEST PRACTICES

Timeline / Milestones

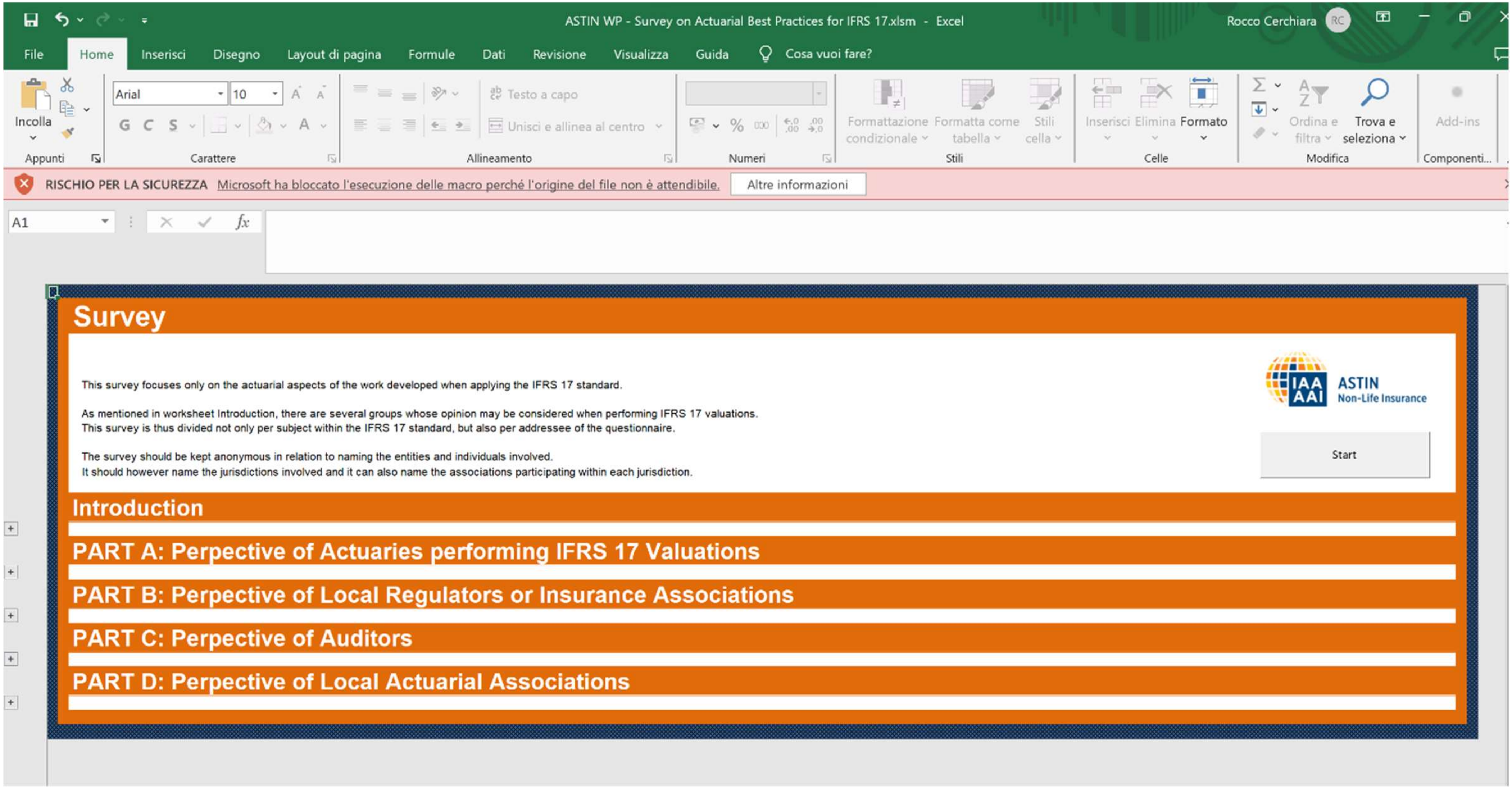
1. Q4 2023
   Recruit volunteer ASTIN working party members to gather data and perform the research. The candidates are kindly requested to send an email with a short resume to the following address: iaasections@actuaries.org.

2. Q1 2024:
   a. Design the survey.
   b. Send the survey.

3. Q3 2024
   a. Analyze the results of the survey.
   b. Write the report.

4. Q4 2024:
   Disseminate findings by:
   a. presenting the results at the ASTIN Colloquium in Brussels (2024), if possible. Otherwise, the following one.
   b. sending the results to all participating entities.
   c. promoting an ASTIN webinar.

Additional survey – IFRS17



Grazie

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