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Towards Machine Learning: AI as an alternative to GLM's for Ratemaking

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Dubai, UAE

23 October 2018

Agenda

Overview of Machine Learning

- Introduction to Machine Learning
- Types of Algorithms

Generalized Linear Models

- Poisson – Gamma GLM's
- Tweedie Compound-Poisson GLM's

Artificial Neural Networks

- Structure and Architecture
- How ANN's Work and Learn

Applications to Insurance Data

- Fitting models
- Comparison of Poisson-Gamma GLM, Tweedie GLM and Neural Network on data

Building and Training Neural Networks

Key Takeaways and Conclusions

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Machine Learning

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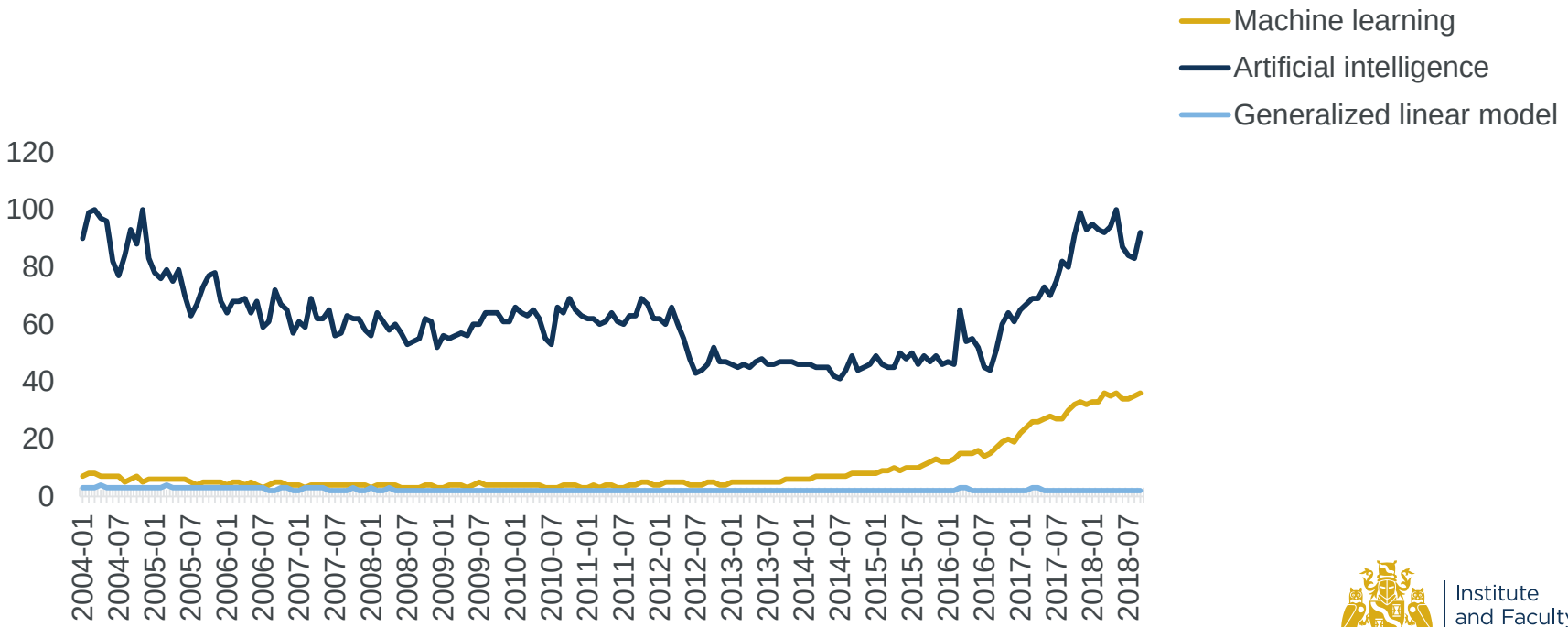
Machine Learning in Perspective



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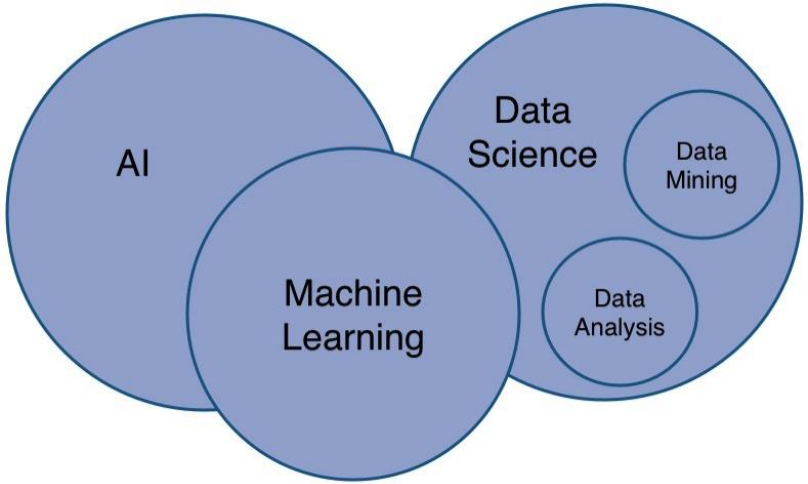
Machine Learning



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Machine Learning

The ”teaching a kid math” analogy

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Machine Learning

All about patterns!!!

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The Roadmap

All about patterns!!!

Computer systems learn from data

We **train** system → System **learns** from that → Then performs operations **on its own**

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The Roadmap

All about patterns!!!

Computer systems learn from data

We **train** system → System **learns** from that → Then performs operations **on its own**

Training phase 1: data is fed into the algorithm, relevant fields and records sorted from data to retrieve **active dataset**

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The Roadmap

All about patterns!!!

Computer systems learn from data

We **train** system → System **learns** from that → Then performs operations **on its own**

Training phase 2: **Model Fitting** – algorithm decodes hidden patterns and relationships in the data

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The Roadmap

All about patterns!!!

Computer systems learn from data

We **train** system → System **learns** from that → Then performs operations **on its own**

Testing phase: new data fed into system, algorithm uses patterns & relationships learnt during the training phase to predict new cases

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Types of Algorithms

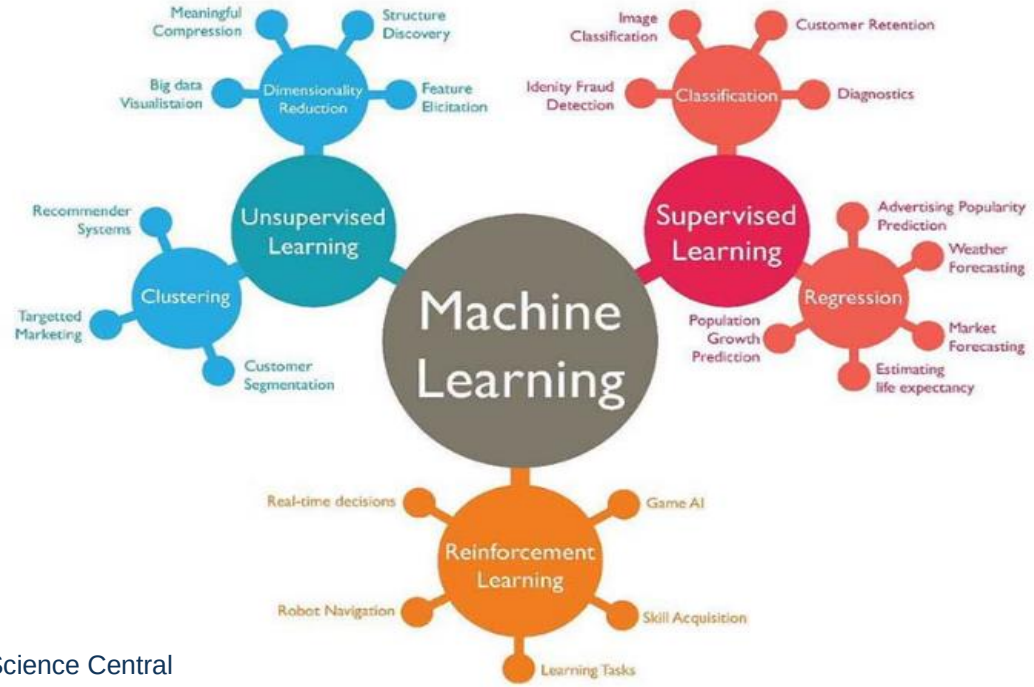

Image Source: Data Science Central

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Generalized Linear Models

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Generalized Linear Models

$$y_i = \sum_{j=1}^{n} \alpha_j x_{ij} + \epsilon_i$$ ← Classical linear model

$$D = \sum(y - \mu)^2$$ ← Error function

Components of this model:

- Random component – Specifies distribution of target variable
- Systematic component – covariates (x's) produce linear predictor (exp.1)
- Systematic component linked to random component

  g(μ) = η → **Link Function**

$$\eta = \sum_{j=1}^{n} \alpha_j x_j$$

Exp. 1

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Poisson-Gamma GLM's

- Claim frequency follows Poisson model with Log link
- Claim severity follows Gamma model with Log link

$$Expected\ Risk\ Premium = Expected\ Claim\ Frequency \times Expected\ Claim\ Severity$$

Poisson model

Gamma model

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Tweedie Compound Poisson GLM's

Standard GLM's – Random Component comes from Exponential Family

Distribution	Variance
Gaussian	ϕ
Binomial	$\frac{\mu_i(1-\mu_i)}{n_i}$
Poisson	μ_i
Gamma	$\phi\mu_i^2$
Inverse Gaussian	$\phi\mu_i^3$

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Tweedie Compound Poisson GLM's

Tweedie models – Variance has a more general relation with expected value

$$V(\mu) = \mu^p$$

p can take any value and is called the *variance power parameter*

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Compound Poisson – p between 1 and 2

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Tweedie Compound Poisson GLM's

Basic idea behind CP models in Ratemaking

- N_i - observed claim count for *i*th category; Z_i - observed claim cost for that category (assuming 1 exposure year)
- N_i ~ Pois(λ_i) & Z_i ~ Gamma(τ_i, α)
- $Z_i | N_i$ ~ Gamma w/mean $N_i \tau_i$
- Tweedie approach assumes: $\mu_i = E(Y_i) = \lambda_i \tau_i$ & $V(Y_i) = \phi \mu_i^p$ where

$$p = \frac{\alpha + 2}{\alpha + 1}$$

- Since $\alpha > 0$, we must have $\mathbf{1 < p < 2}$
- For 0 claims, distribution approximates to Poisson; for non-zero claims, approximates towards Gamma

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The Big Questions

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The Big Questions

- What if claims follow a fit different from Poisson-Gamma?
- What if we didn't have to look for a fit at all?
- What if there was a way to be able to automate pure premium modelling and potentially find a better fit at the same time?

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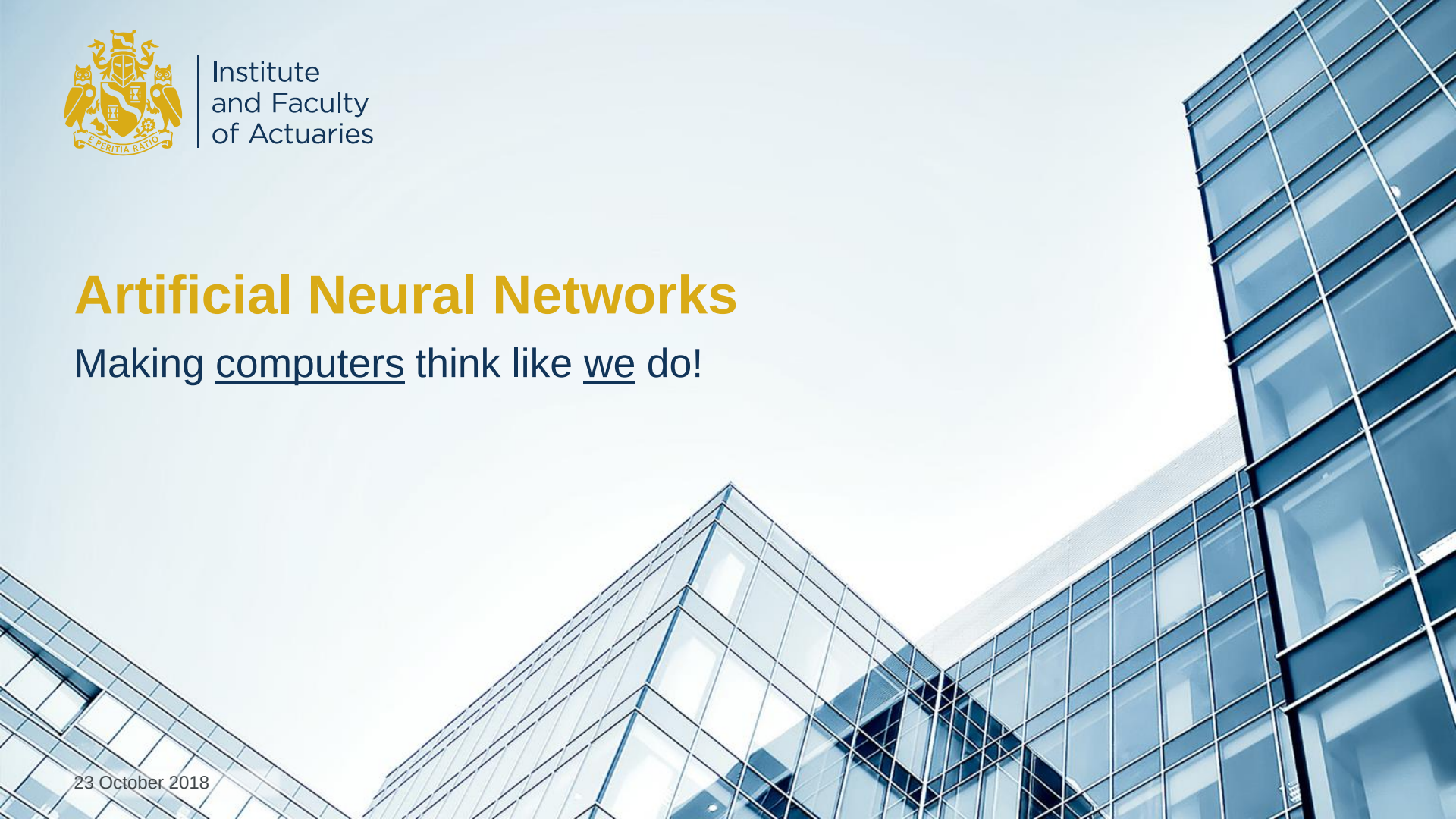

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Artificial Neural Networks

Making computers think like we do!

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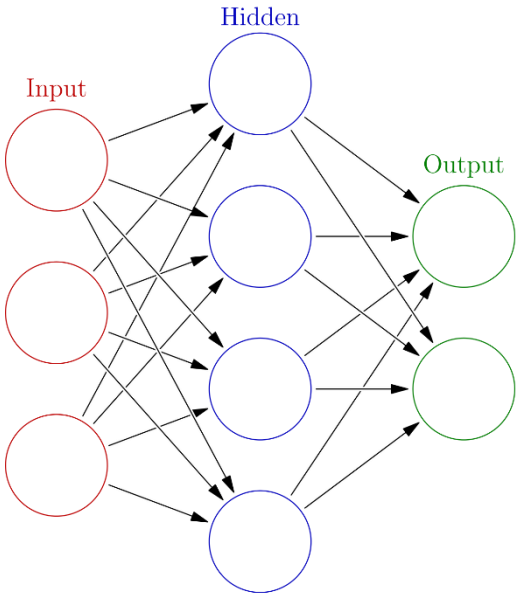
Artificial Neural Networks

Structured Sequential model



Structured: A Neural Network has a defined structure that consists of 3 types of layers

Sequential: Information flows in a sequence from one layer to the next, undergoing operations at each layer – almost like an assembly line

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How ANN's work

How ANN's work

- Data in every neuron is transformed by an activation function:

$$h_k(x) = g(\beta_{0k} + \sum_{i=1}^{n} x_i \beta_{ik})$$

$h_k(x)$ – k^{th} neuron in a hidden layer
β_{ik} - coefficient of the i^{th} previous-layer neuron on above neuron

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- Activation function transforms the linear combination of inputs from one layer and sends it to the next layer.

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- Weights are updated to reduce value of loss function.

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Optimizing Neural Networks

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- Size of this step is the **learning rate.**

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Optimizing Neural Networks

- Suppose for Neuron A and iteration *t*, the weight was found to be W_{At}

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Optimizing Neural Networks

- Suppose for Neuron A and iteration *t*, the weight was found to be $W_{A(t)}$
- Then, for iteration *t* + *1*, weight is optimized to:

$$W_{A(t+1)} = W_{A(t)} - \eta \nabla_{W_{A(t)}} L$$

- $\boldsymbol{\eta}$ – Learning Rate
- $\boldsymbol{\nabla_{W_{A(t)}} L}$ – Gradient of Loss Function w.r.t. weight of Neuron A at iteration *t*

Optimizing Neural Networks

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Optimizing Neural Networks

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  - What if different parameters work differently and require different optimization rates?
- **Stochastic Gradient Descent: Compute gradient for each individual point in the training sample and update weights iteratively for every sample**
  - Too slow – Might cause algorithm to crash or give up for extremely large datasets, thus potentially preventing full convergence

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Optimizing Neural Networks

- In theory, SGD is more accurate

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- Methods such as **Momentum** and the **Nesterov Accelerated Gradient** improve SGD and make it faster by optimizing learning rates internally

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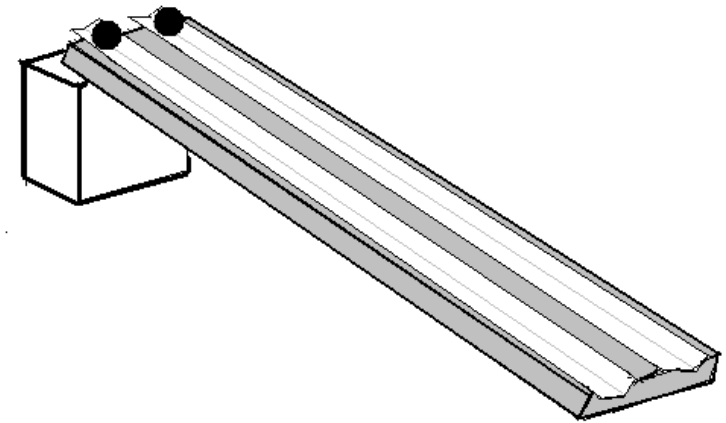

Think of it as a ball rolling down a hill

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So what's going on here?

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The "teaching a kid math" analogy

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With ANN's, no need to…

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With ANN's, no need to…

- …make assumptions about distributions
- …worry about possible correlations between predictors
- …look for interactions between predictors

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Applications to Insurance Data

dataCar from R's insuranceData package

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Data Description

- Policyholder-level information on one-year vehicle insurance policies
- 67,856 records with following rating factors –
  - Vehicle value in $10,000's
  - Vehicle body type (eg. Sedan, convertible, hatchback, bus & other levels)
  - Vehicle age (Levels 1-4 w/1 being the newest & 4 being the oldest)
  - Gender of driver
  - Area
  - Driver age category (Levels 1-6 w/1 being youngest & 6 being oldest)

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Data Description

- Heavily skewed w/no-claim percentage of 93.2%

Distribution of Claims

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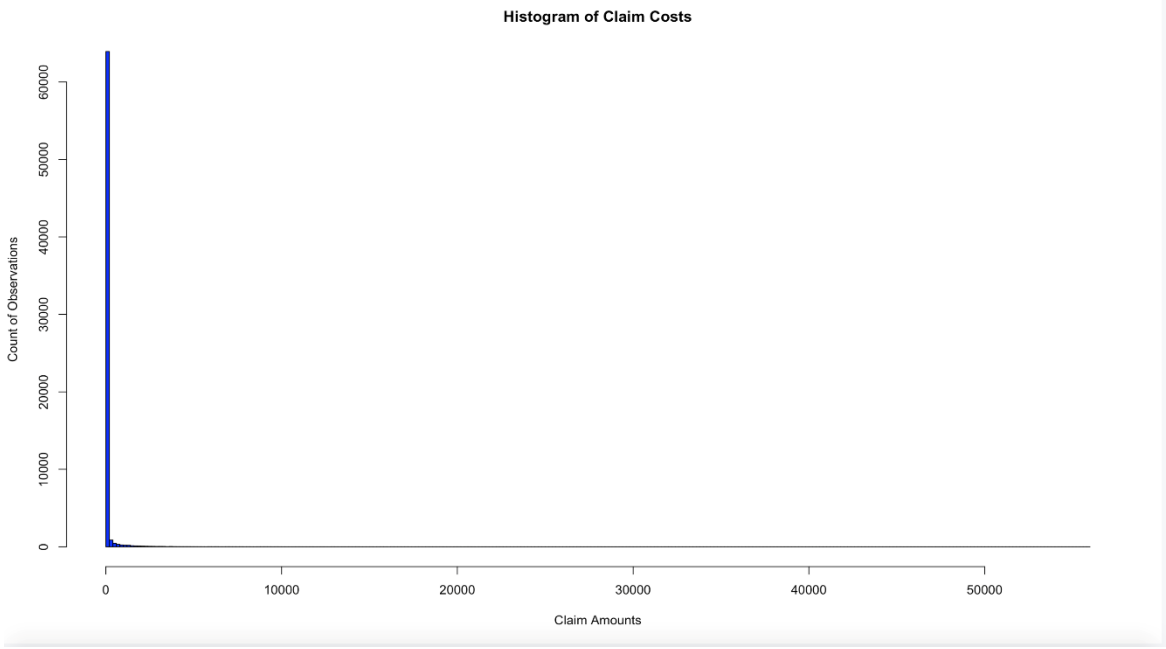

Distribution of raw claims data

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Distribution of Claims

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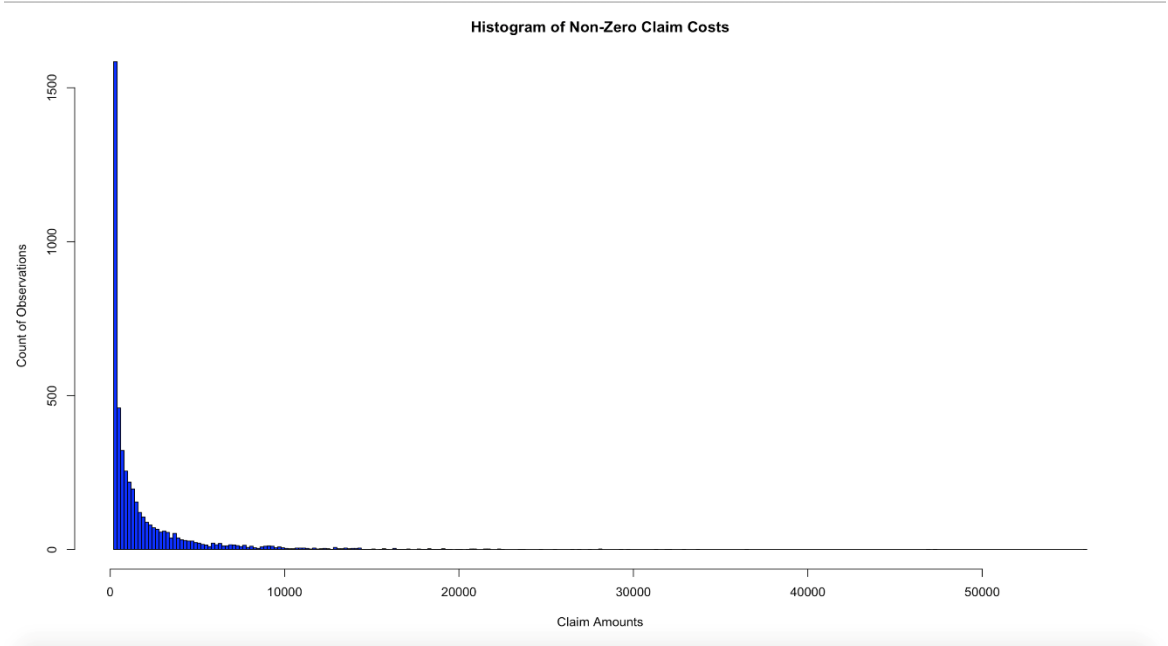

Distribution of
non-zero claims only

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Distribution of Claims

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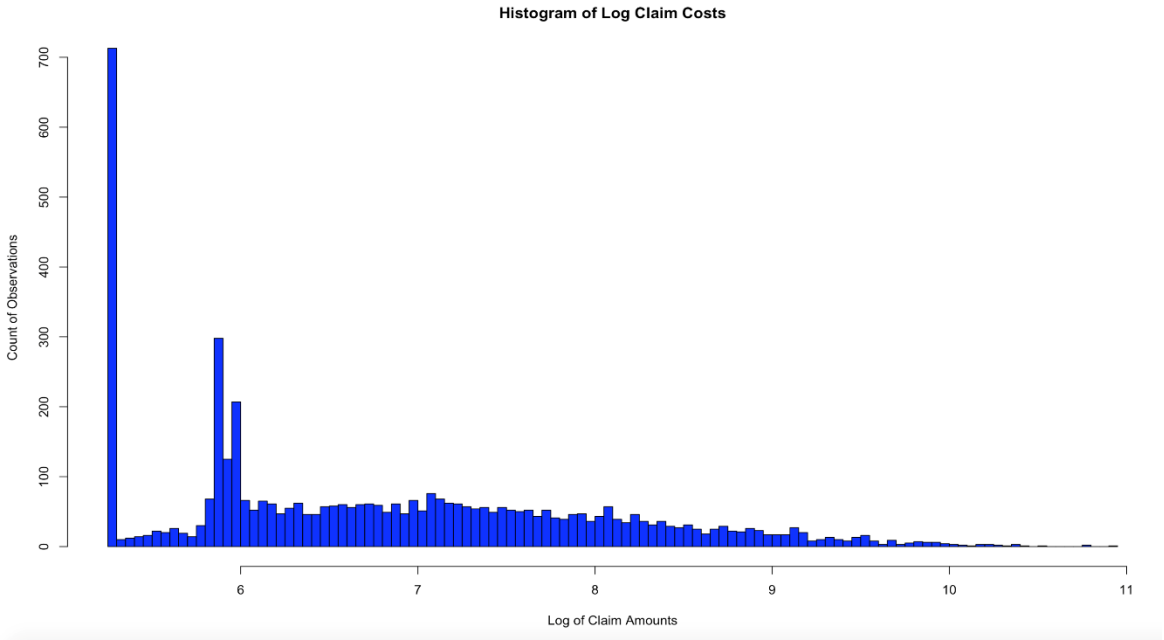

Distribution of the logarithm of claims

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Fitting Tweedie CP GLM

- Optimal variance power parameter tuned by MLE
- Range specified: 1.1 - 1.9 (all values between 1 & 2)
- Optimal value found to be 1.553

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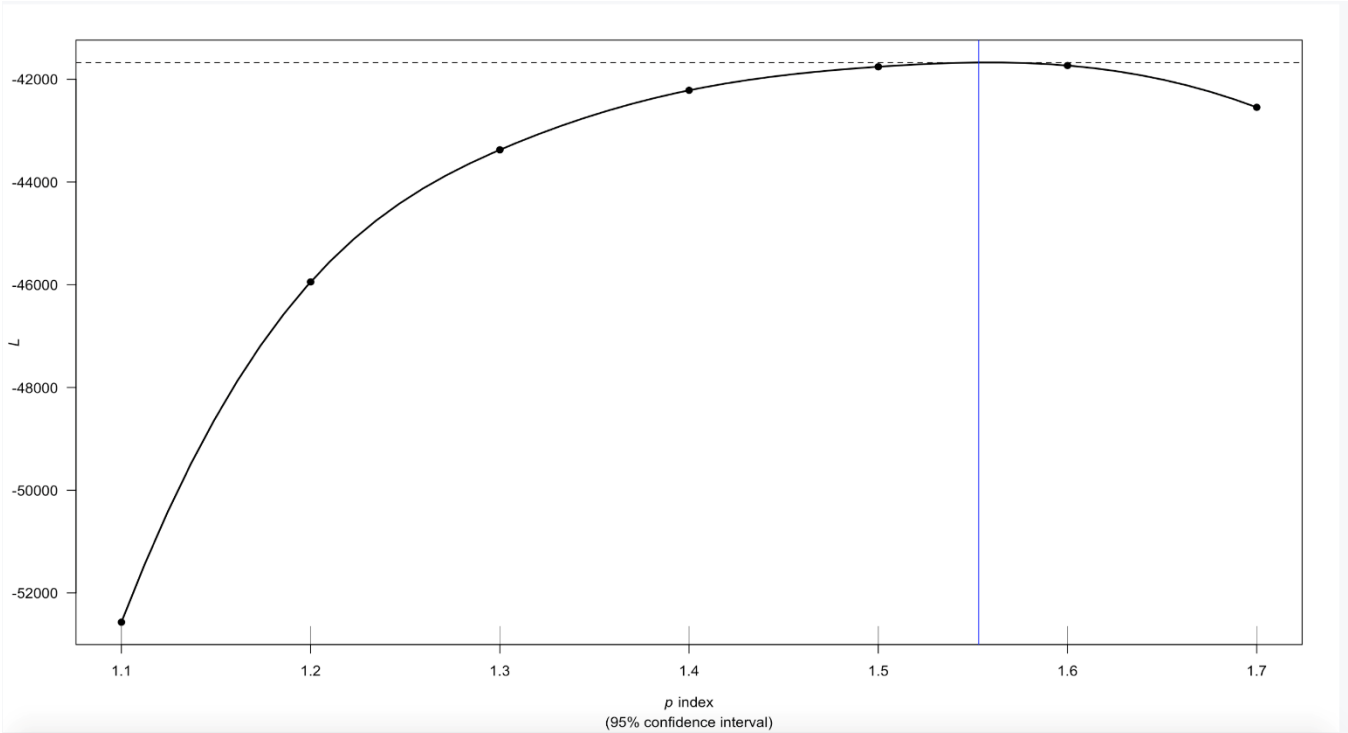
Fitting Tweedie CP GLM



Plot of log-likelihood values against p – values. Vertical blue line shows point of maximum likelihood, justifying choice of parameter

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Fitting Neural Networks– Choice of Network Architecture

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- Fitted by 5-fold cross-validation
- Base network architectures were trained with the same set of hyperparameters chosen at random

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- Architectures chosen: (33-40-1), (33-80-1), (33-100-1), (33-120-1), (33-80-40-1), (33-100-60-1), (33-120-60-1)

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Fitting Neural Networks– Choice of Network Architecture

- Fitted by 5-fold cross-validation
- Base network architectures were trained with the same set of hyperparameters chosen at random
- Architectures chosen: (33-40-1), (33-80-1), (33-100-1), (33-120-1), (33-80-40-1), (33-100-60-1), (33-120-60-1)
- Best network architecture found to be (33-120-60-1) – this was chosen for further tuning
- In general, networks with 2 hidden layers fitted better than networks with 1 hidden layer

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Fitting Neural Networks – Choosing Hyperparameters

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- Learning rate and batch size tuned on architecture chosen from previous step
- Tuning done by 5-fold cross-validation
- Following values were chosen to be tested:
  - Learning rate – 0.001, 0.01, 0.05, 0.1
  - Batch size – 3000, 8000, 10000

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Fitting Neural Networks – Choosing Hyperparameters

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- Tuning done by 5-fold cross-validation
- Following values were chosen to be tested:
  - Learning rate – 0.001, 0.01, 0.05, 0.1
  - Batch size – 3000, 8000, 10000
- Best hyperparameters found to be
  - Learning rate – 0.1
  - Batch size – 3000

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Model Comparison

Model Comparison

- 3 approaches taken
  - Test data predictive accuracy – Test RMSE
  - Resampling Error on Training dataset – 5-fold Cross Validation MSE
  - Goodness-of-fit test – AIC

Test RMSE

Model	Test RMSE ($\times\ 10^3$)
Poisson-Gamma GLM	1.25
Tweedie Compound Poisson GLM	1.25
Artificial Neural Network	1.27

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5-Fold Cross-Validation Error

Model	CV MSE
Poisson-Gamma GLM	1.69×10^6
Tweedie Compound Poisson GLM	1.70×10^6
Artificial Neural Network	19.98

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AIC

AIC

- Stands for Akaike Information Criterion
- Gives a measure of distance between true and predicted trends

AIC

Model	AIC ($\times 10^5$)
Poisson-Gamma GLM	5.72
Tweedie Compound Poisson GLM	5.73
Artificial Neural Network	5.73

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Building and Training Neural Networks

TensorFlow in R

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TensorFlow

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TensorFlow

- Developed by Google Brain
- Released in 2015

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TensorFlow

- Developed by Google Brain
- Released in 2015
- Can be implemented in
  - Python: TF, Keras
  - R: **Keras**, Estimator, TF API

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Building Neural Networks

- Surprisingly easy to build neural networks in R using Keras

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- Models initialized as sequential objects and layers added as nested commands

Building Neural Networks

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- Models initialized as sequential objects and layers added as nested commands
- Once model is constructed, it can be called on a dataset

The Keras Roadmap

The Keras Roadmap

Model Initialization → Layer definition → Compilation & Fitting

An empty neural network is initialized using *keras_model_sequential()*: Layers can then be added sequentially to the model

The Keras Roadmap

Model Initialization → **Layer definition** → Compilation & Fitting

Hidden layers are added and their structure is defined using the command *layer_dense()*: Activation function, # of neurons specified

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The Keras Roadmap

Model Initialization → Layer definition → **Compilation & Fitting**

After model architecture is fixed, hyperparameters, optimizer and loss function are set and using the command *compile()*. Following this, model is trained using the command *fit()*.

Try it out!!!

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Key Takeaways & Conclusions

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AI: The Good and the Not-so-good

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AI: The Good and the Not-so-good

- The Good:
  - Allows for complete automation
  - No need to assume anything about the data, both in terms of rating factors and claim distributions

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- The Good:
  - Allows for complete automation
  - No need to assume anything about the data, both in terms of rating factors and claim distributions
- The Not-so-good:
  - Computationally intensive – requires hardware such as GPU's and fast/powerful processors to run efficiently
  - Interpretability

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Conclusions

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- Machine Learning and AI are powerful tools, can aid actuaries in decision-making
- AI should definitely be explored and experimented with in addition to using GLM's

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- Machine Learning and AI are powerful tools, can aid actuaries in decision-making
- AI should definitely be explored and experimented with in addition to using GLM's
- No one "right" model – best predictions can come from ensemble models
- Further research being done to improve interpretability of AI, applications of Machine Learning in the actuarial realm

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Selected References & Suggested Reading

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Questions

Comments

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