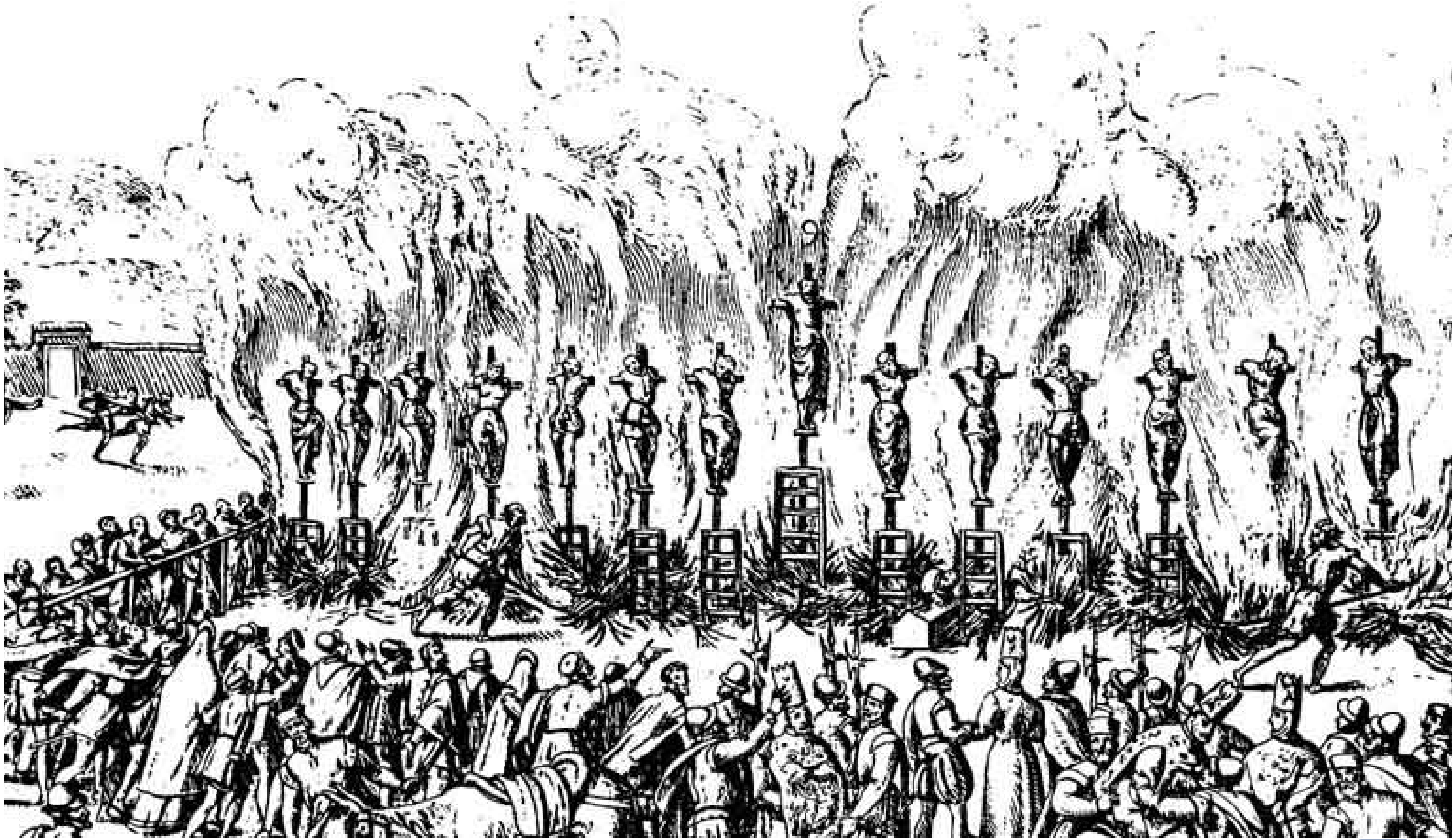
Artificial Intelligence and its Utilization in Insurance Operations

Frank Cuypers

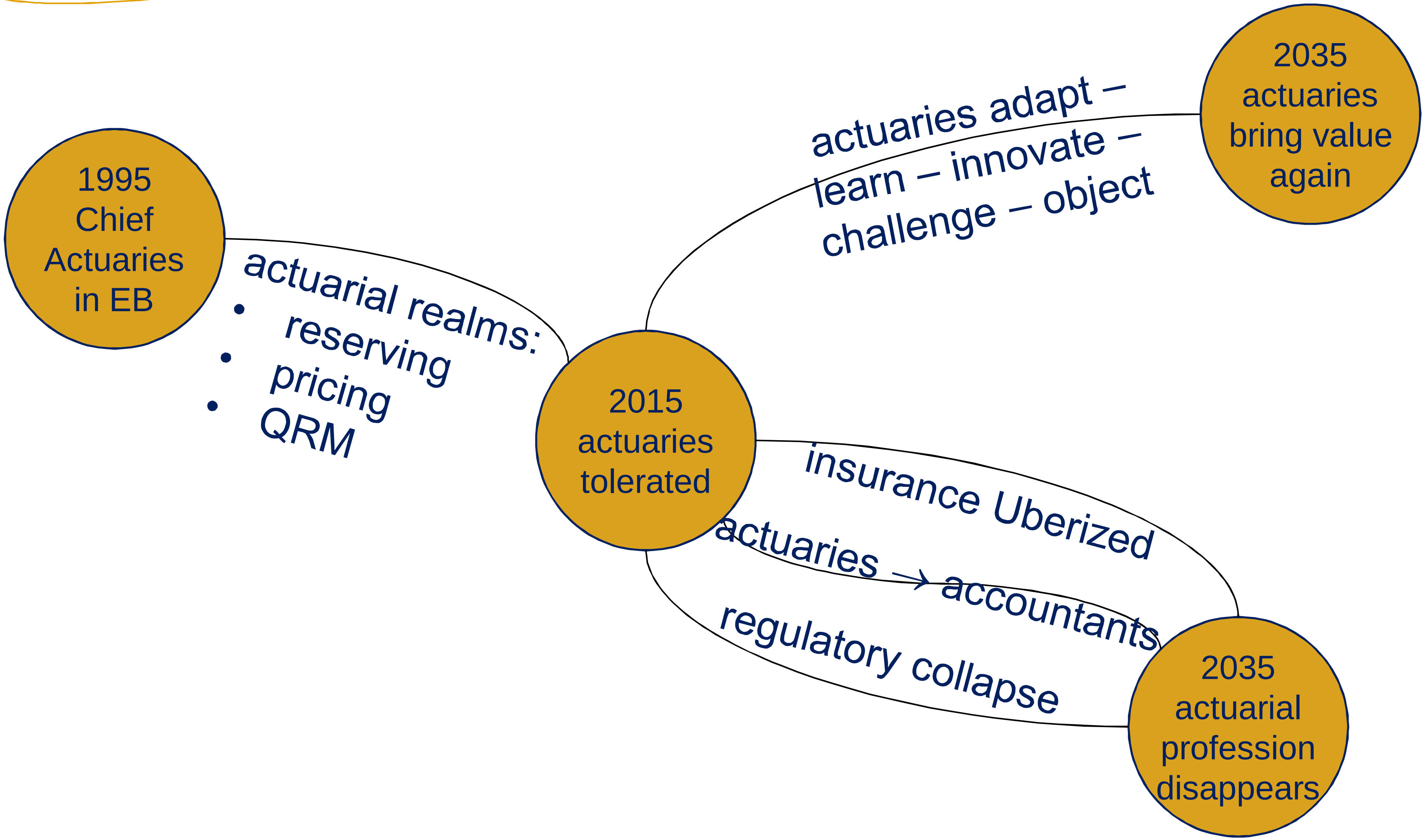
Scenario

- 2016
  - Solvency II initiates
- 2020
  - New players flood the market with ñdigitalòalternatives to insurance
- 2025
  - Insurance industry flood the market with ñFickle Superannuationsòwith little Solvency II capital requirements
- 2030
  - 30% of the insurance players file for bankruptcy
  - The weaknesses of the Solvency II standard formula become obvious
  - Who should have known? Who should have warned?
- 2035
  - The actuarial profession is discredited
  - The last Presidents of the SAA, DAV and IFO are burnt at the stake

Scenario



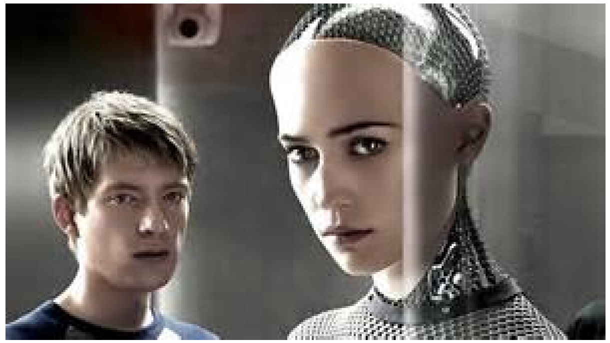
Scenarios



1995 Chief Actuaries in EB
actuarial realms:
• reserving
• pricing
• QRM
2015 actuaries tolerated
actuaries adapt – learn – innovate – challenge – object
2035 actuaries bring value again
insurance Uberized
actuaries → accountants
regulatory collapse
2035 actuarial profession disappears

Whom Shall we Still Need in 2035?

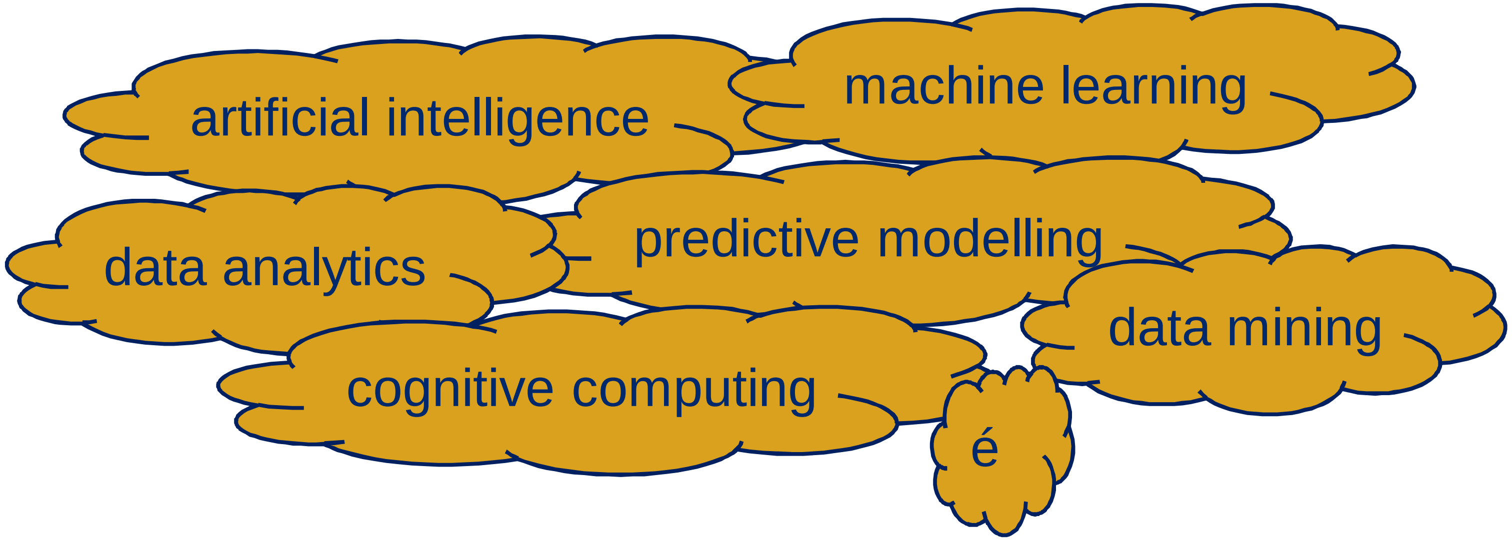
- Drivers?
- Nurses?
- é
- Translators?
- Lawyers?
- Physicians?
- Psychiatrists?
- Actuaries?
- é
- Programmers?
- é



How Shall we Live in 2035?

- Will our children still learn how to read & write?
- Shall we be terminated?
- Shall we become bionically enhanced?
- Will eventually joint human & machine crowd intelligence supersede artificial intelligence?

What’s Artificial Intelligence?

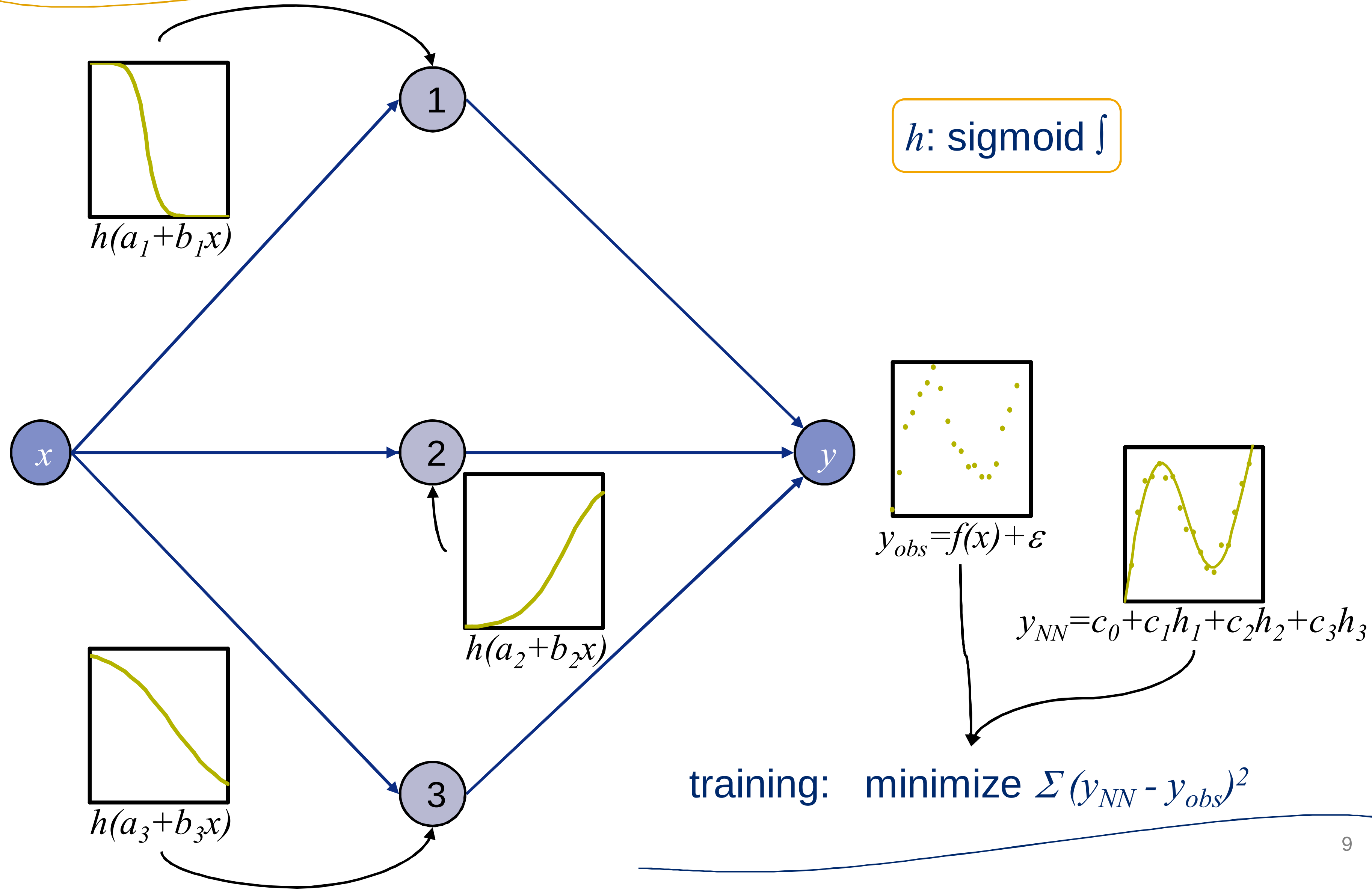


- Neural networks
- Decision trees
- k-nearest neighbours
- Support vector machines
- Bayesian networks
- Genetic algorithms
- é

Ubiquitous Neural Networks

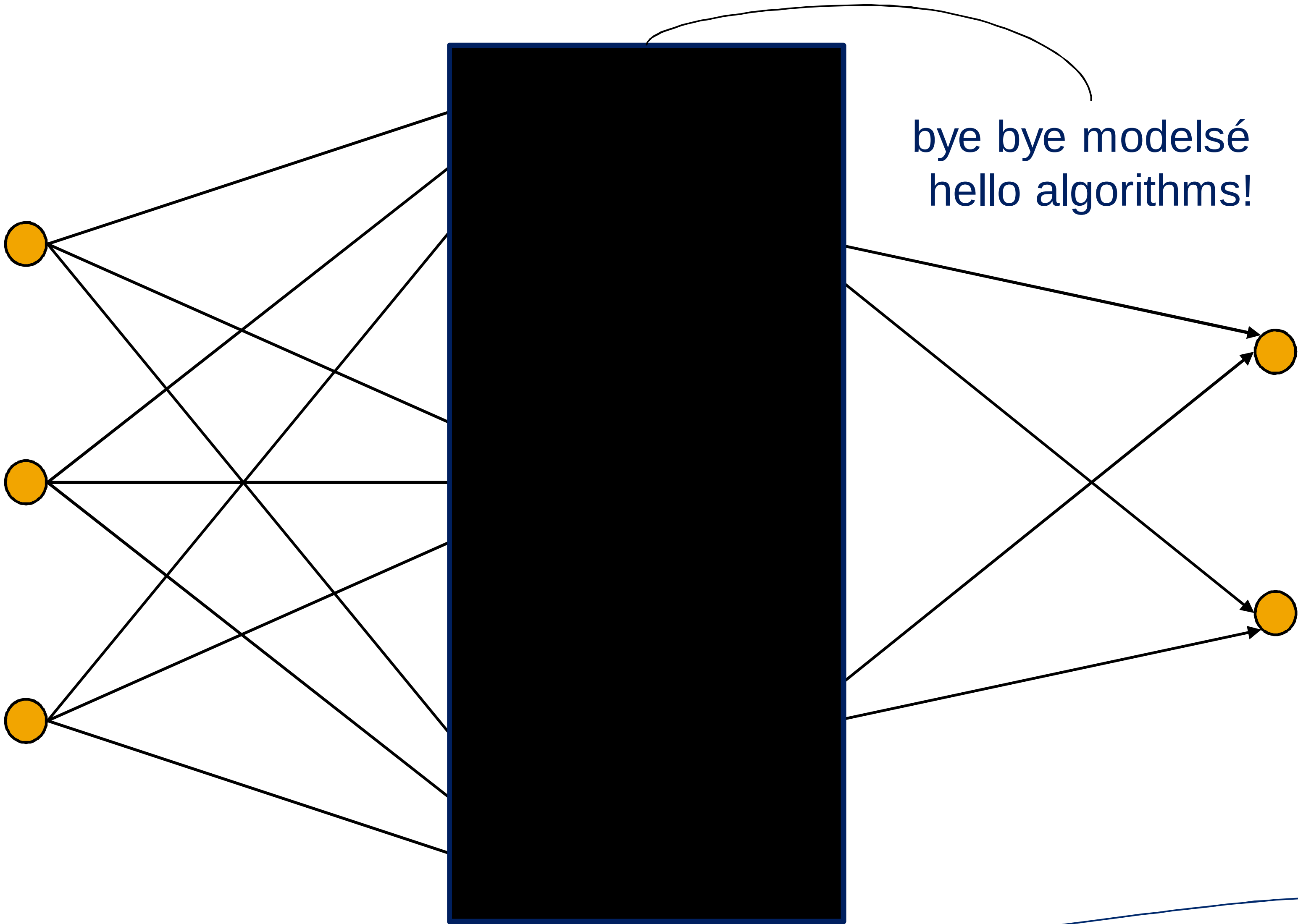
- OCR
- Higgs search
- Spam filters
- Image compression
- Travelling salesman problems
- Medical diagnosis
- Voice recognition & generation
- Translation translate.google.com
- Natural languages processing infocodex.com
- Gaming
- Face recognition how-dude.me how-old.net
- é
- Insurance?

Neural Networks (in a nutshell)

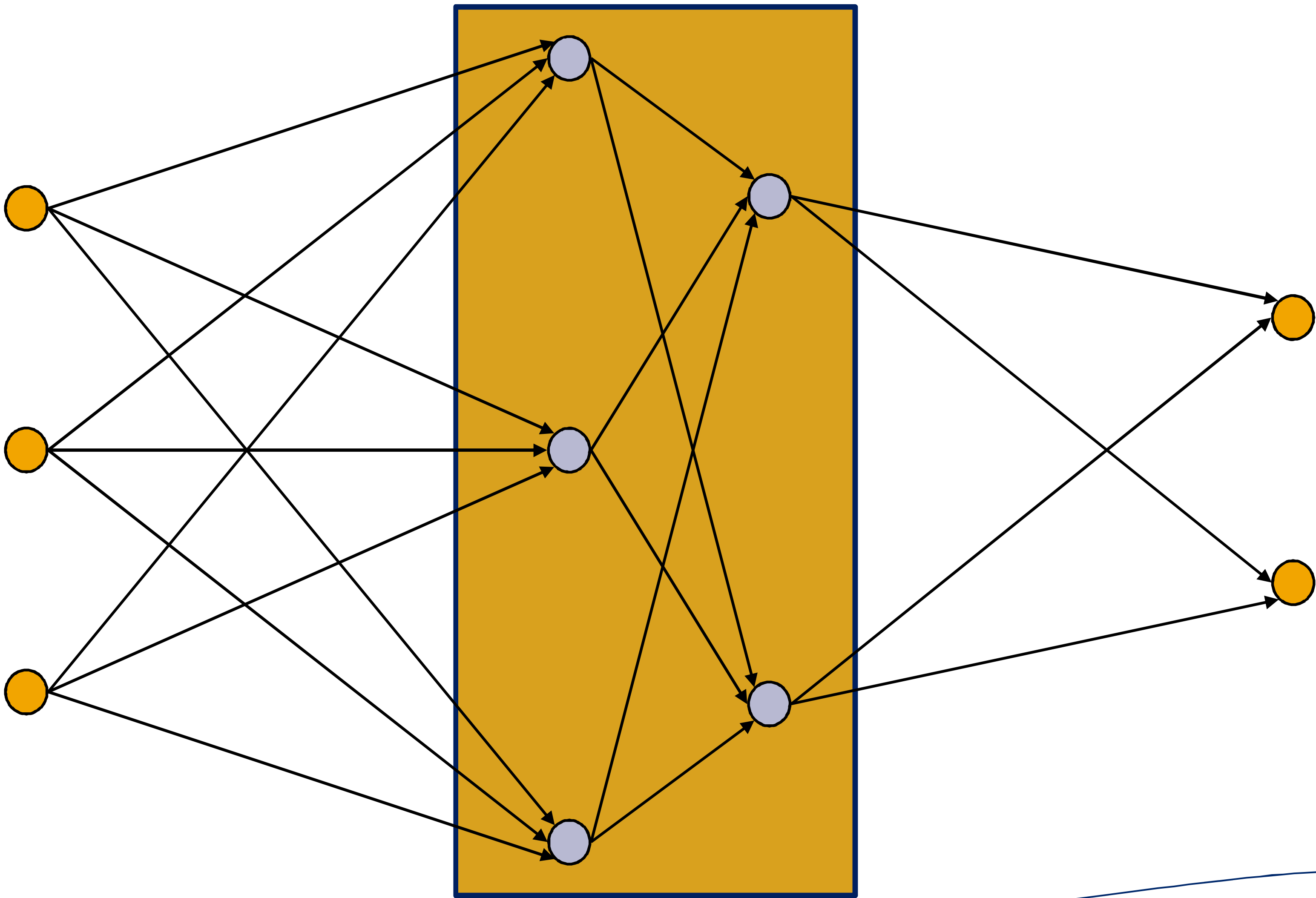


training: minimize $\Sigma (y_{NN} - y_{obs})^2$

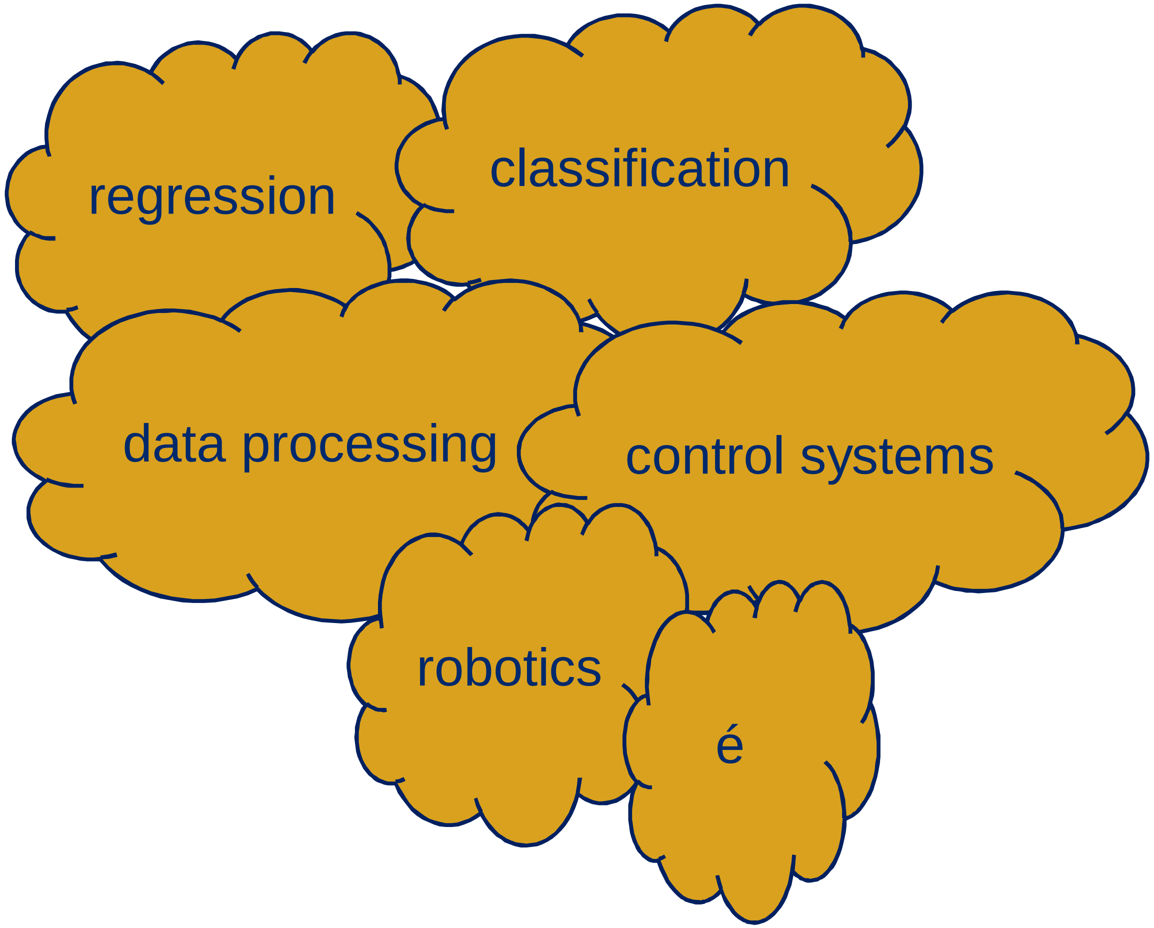
Neural Networks



Neural Networks (2 hidden layers)



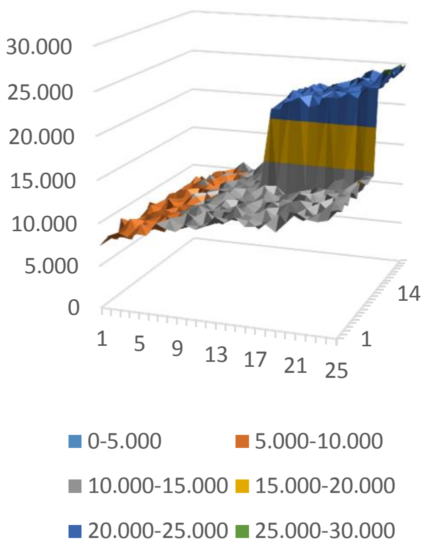
Applications

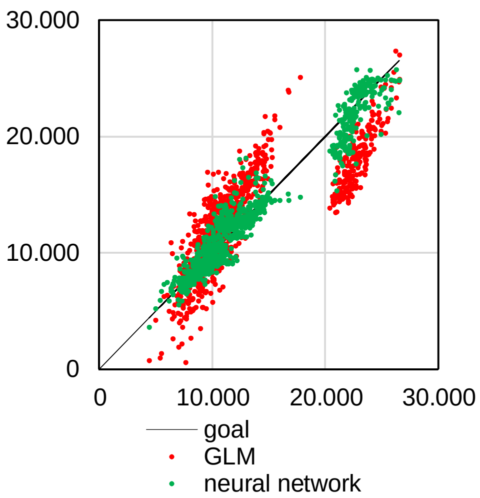


Applications – Supervised Learning

Regression

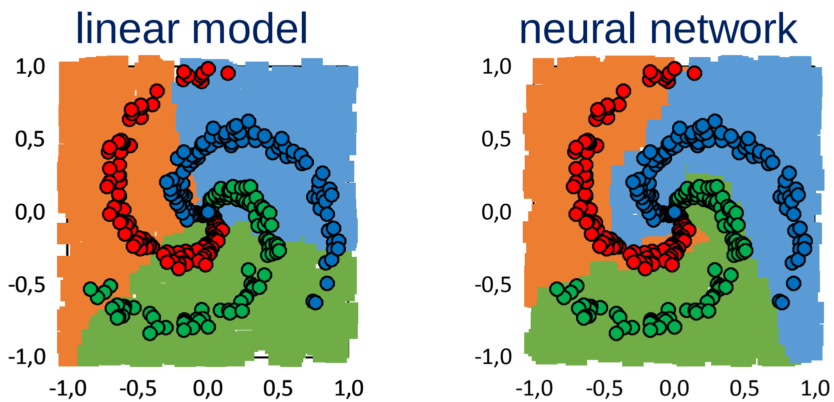
- Output = e.g. size of claim
- Each output neuron
  gives a number,
  which can take any value

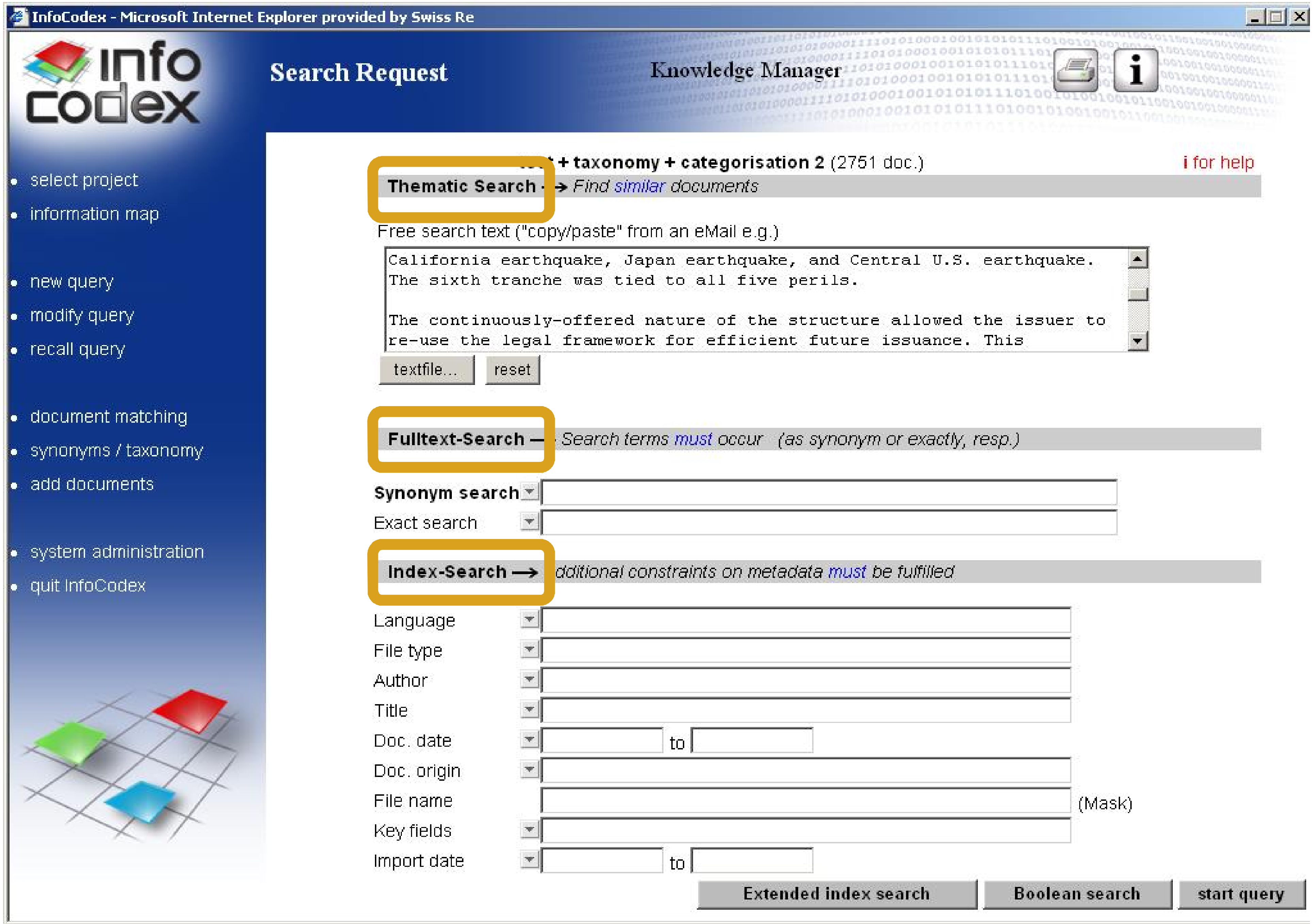




Classification

- Output = e.g. type of claim
- Each output neuron
  gives a probability ,
  which all add up to 100%




InfoCodex - Microsoft Internet Explorer provided by Swiss Re
info codex
Search Request
Knowledge Manager
select project
information map
new query
modify query
recall query
document matching
synonyms / taxonomy
add documents
system administration
quit InfoCodex
+ taxonomy + categorisation 2 (2751 doc.)
i for help
Thematic Search
Find similar documents
Free search text ("copy/paste" from an eMail e.g.)
California earthquake, Japan earthquake, and Central U.S. earthquake.
The sixth tranche was tied to all five perils.
The continuously-offered nature of the structure allowed the issuer to
re-use the legal framework for efficient future issuance. This
textfile...
reset
Fulltext-Search
Search terms must occur (as synonym or exactly, resp.)
Synonym search
Exact search
Index-Search
dditional constraints on metadata must be fulfilled
Language
File type
Author
Title
Doc. date
to
Doc. origin
File name
(Mask)
Key fields
Import date
to
Extended index search
Boolean search
start query

Single Choice (Reduce list in the field 'All with') - Microsoft Internet Explorer p

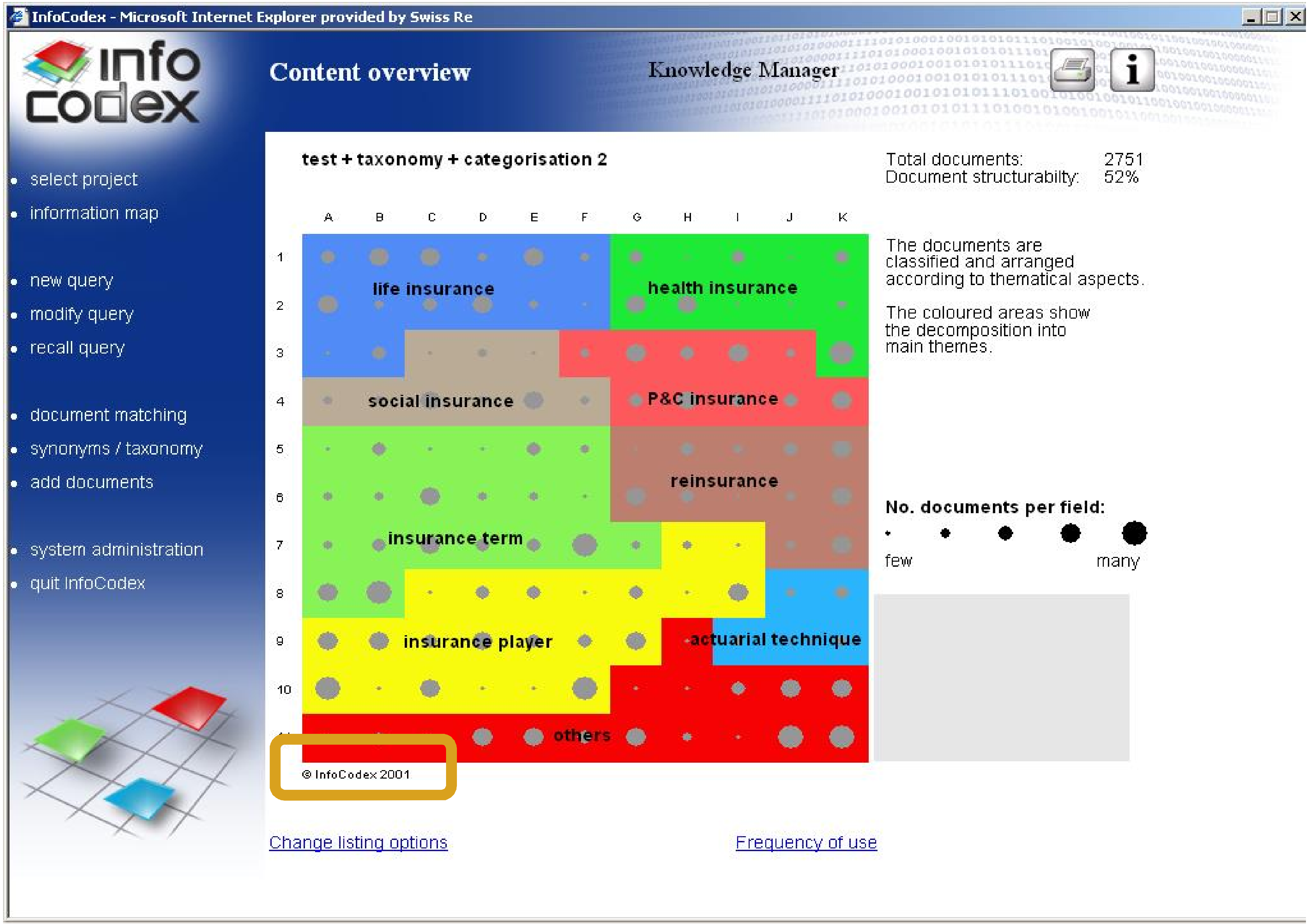
Search OK

All with OK

Help

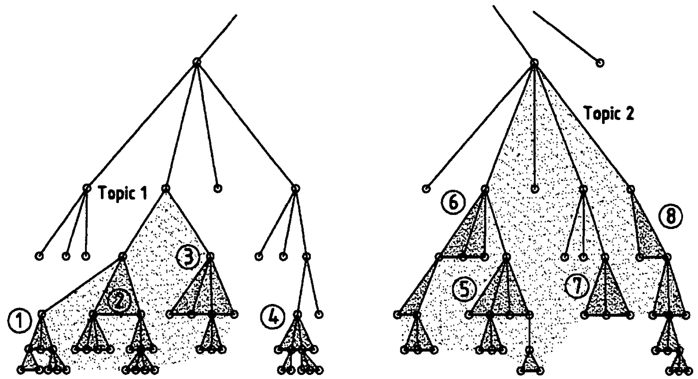
Result of thematic search: 561 documents (by relevance) **Click on no. => direct view**

	Documentname/Date/Priority date	*Wrd/Ra%*	*Document title/Descriptors/Assignees*
1	/usr/l..nts/US5842148.xml	2641	**Method Of Evaluating And Classifying Living Structures For Estimating Poten**
	3.04.05 / 7.10.96 0 hits	*87 %*	earthquake, windstorm, actuarial / **Ass:** Jcp Geologists, Inc.
2	/usr/l../JP23345991A2.xml	160	**Earthquake Derivative System And Its Method**
	3.04.05 / 23.05.02 0 hits	*86 %*	earthquake, electromagnetic, earthquake insurance / **Ass:** Nec Engineering Ltd
3	/usr/l../JP11175623A2.xml	114	**Earthquake Damage Evaluation System And Recording Medium**
	3.04.05 / 11.12.97 0 hits	*85 %*	earthquake, active fault, topographical / **Ass:** Tokio Marine &Amp; Fire Insurance Co l
4	/usr/l../JP11295453A2.xml	93	**Watch With Identity-Storing Function**
	3.04.05 / 9.04.98 0 hits	*85 %*	earthquake, display panel, blood group / **Ass:** Shimamura Hideko
5	/usr/l..s/EP1347399A1.xml	3844	**Travel Insurance Reception Apparatus And Method**
	3.04.05 / 19.03.02 0 hits	*84 %*	travel insurance, itinerary, output program / **Ass:** Kabushikikaisha Equos Research,Ai
6	/usr/l..S2003182165A1.xml	4204	**Travel Insurance Reception Apparatus And Method**
	3.04.05 / 19.03.02 0 hits	*84 %*	travel insurance, itinerary, expressway / **Ass:** Kato Atsushi,Kawamoto Kiyoshi,Kimura l
7	/usr/l../JP22092513A2.xml	167	**Lease Management System**
	3.04.05 / 1.09.00 0 hits	*84 %*	fire insurance, building loan, rental / **Ass:** Zuerich Insurance Co,Jiyatsukusu:kk,Sokei:
8	/usr/l..S2004128170A1.xml	1696	**Method For Intergrating Insurance Quotation, Payment And Issuance To Mort**
	3.04.05 / 19.12.02 0 hits	*84 %*	flood, escrow company, flood insurance / **Ass:** Mackethan Edwin Robeson,Ellsworth J:
9	/usr/l..s/JP6195358A2.xml	156	**Device For Issuing Fire Insurance Form By Utilizing Computer**
	3.04.05 / 25.12.92 0 hits	*84 %*	fire insurance, information storage, memory area / **Ass:** Toraberu Data:kk
10	/usr/l..s/JP6168256A2.xml	181	**Travel Insurance Contract Issuing Device Utilizing Computer**
	3.04.05 / 30.11.92 0 hits	*84 %*	control command, travel insurance, reservation / **Ass:** Toraberu Data:kk
11	/usr/l../JP23108768A2.xml	138	**Insurance Contract Processor, Insurance Contract Processing Method And P**
	3.04.05 / 26.09.01 0 hits	*84 %*	travel insurance, processing method, insurance contract / **Ass:** Mitsui Sumitomo Insur
12	/usr/l..s/JP5012048A2.xml	102	**Processing System For Taking Over Inter Multiple Sub-System Processing**
	3.04.05 / 2.07.91 0 hits	*84 %*	atomicity, taking over, first information / **Ass:** Fujitsu Ltd
13	/usr/l../JP22183440A2.xml	179	**Mutual Aid Premium Management Method In Fire Insurance Service**
	3.04.05 / 11.12.00 0 hits	*84 %*	fire insurance, premium, convenience store / **Ass:** Kurata Takeshi
14	/usr/l..S2002147613A1.xml	2800	**Methods Of Marketing Summary Maps Depicting The Location Of Real Proper**

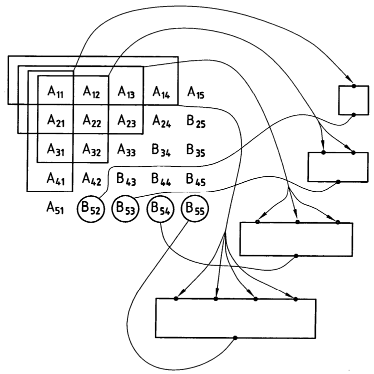

InfoCodex - Microsoft Internet Explorer provided by Swiss Re
info codex
Content overview
Knowledge Manager
select project
information map
new query
modify query
recall query
document matching
synonyms / taxonomy
add documents
system administration
quit InfoCodex
test + taxonomy + categorisation 2
Total documents: 2751
Document structurabilty: 52%
A B C D E F G H I J K
1 2 3 4 5 6 7 8 9 10
life insurance
health insurance
social insurance
P&C insurance
reinsurance
insurance term
insurance player
actuarial technique
others
The documents are classified and arranged according to thematical aspects.
The coloured areas show the decomposition into main themes.
No. documents per field:
few
many
© InfoCodex 2001
Change listing options
Frequency of use

Patents

- [Neural network for classifying speech and textural data based on agglomerates in a taxonomy table]()



- [System and method for automated establishment of experience ratings and/or risk reserves]()



Ubiquitous Neural Networks

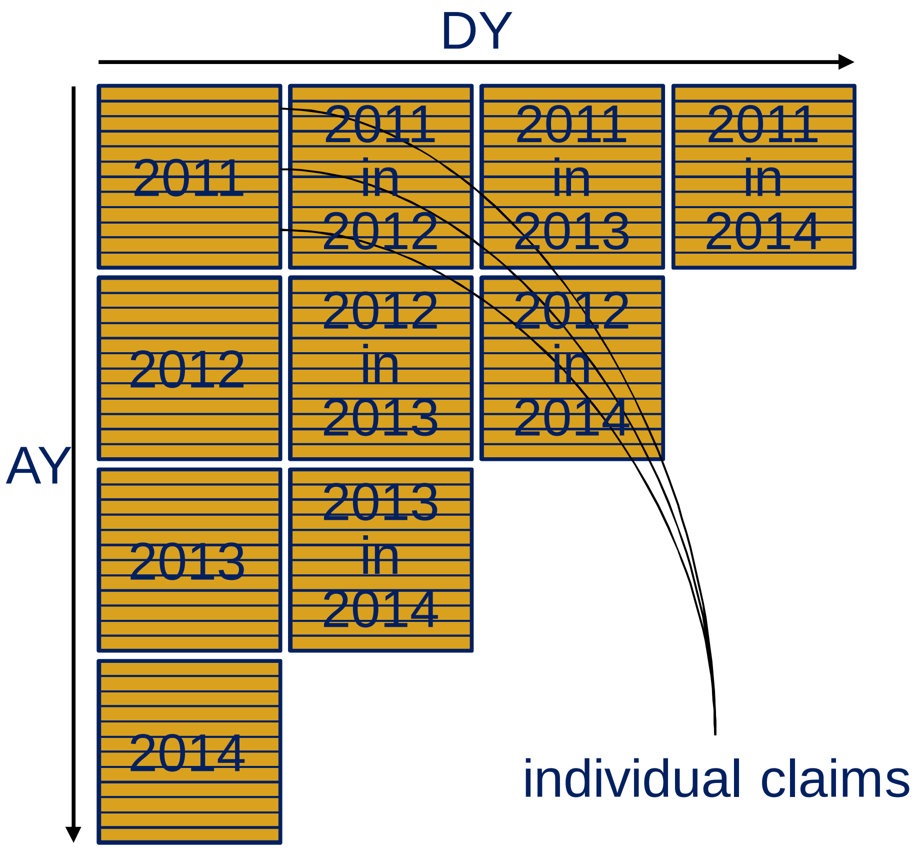
- OCR
- Higgs search
- Spam filters
- Image compression
- Travelling salesman problems
- Medical diagnosis
- Voice recognition & generation
- Translation translate.google.com
- Natural languages processing infocodex.com
- Gaming
- Face recognition how-dude.me how-old.net
- é

- Insurance?

Ubiquitous Neural Networks

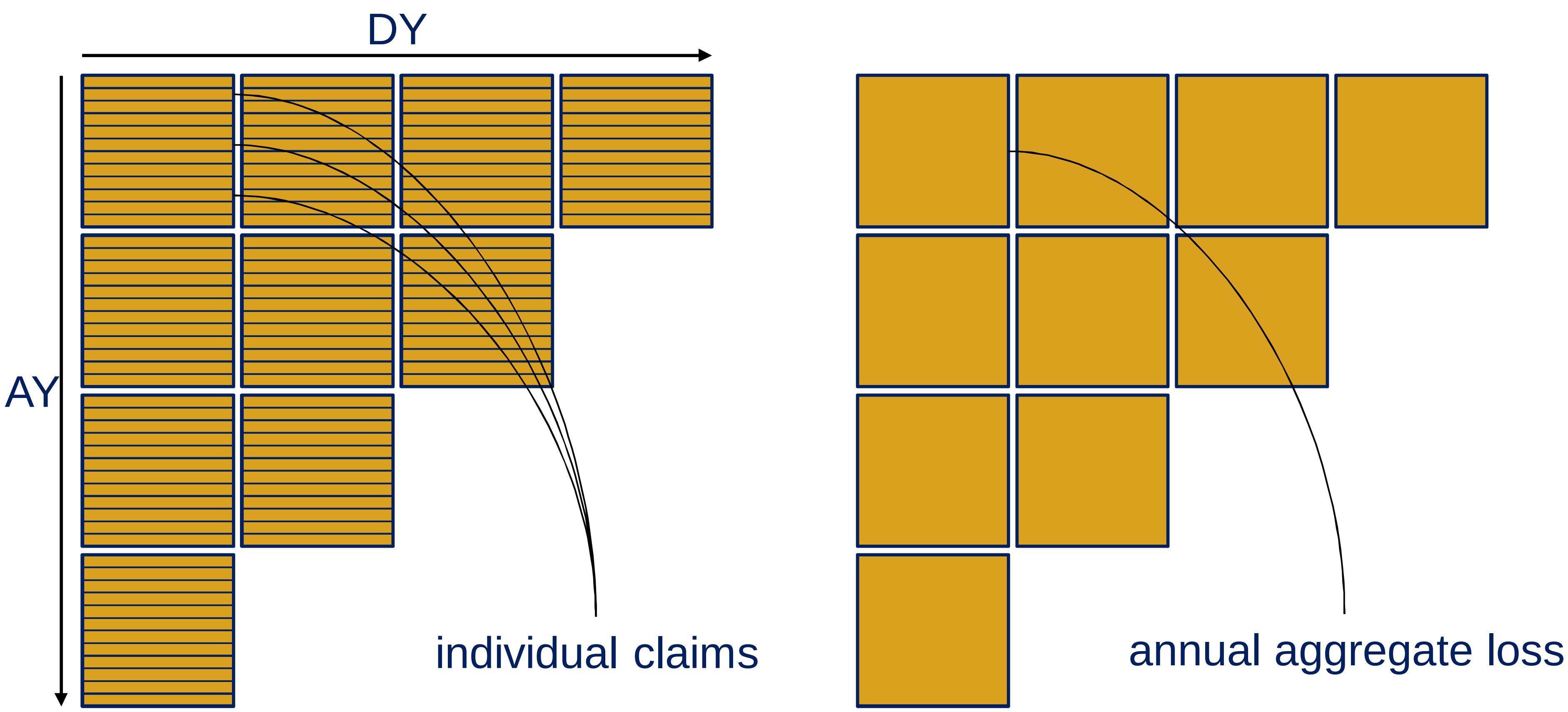
- Insurance?
  - Actuarial engineering
    - Å Individual claims development
    - Å Pricing
    - Å Alternative to replicating portfolios
    - Å é
  - Claims
    - Å Regulation of attritional claims
    - Å Fraud detection
    - Å é
  - Underwriting & customer relations
    - Å Lapse prediction & retention programs
    - Å Medical underwriting
    - Å Behavioural advice (telematics, health,é)
    - Å é
- Alternative insurance
  - ???

Loss Development



Loss Development

- Aggregate all claims of a given AY into a single aggregate loss ☹

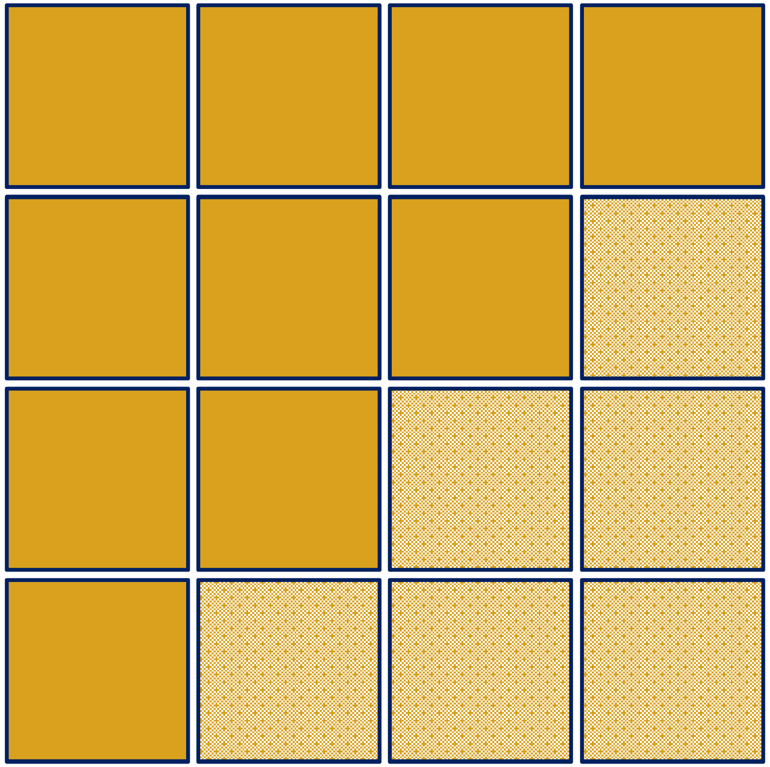


Traditional Loss Development

- Aggregate all claims of a given AY into a single aggregate loss ☹

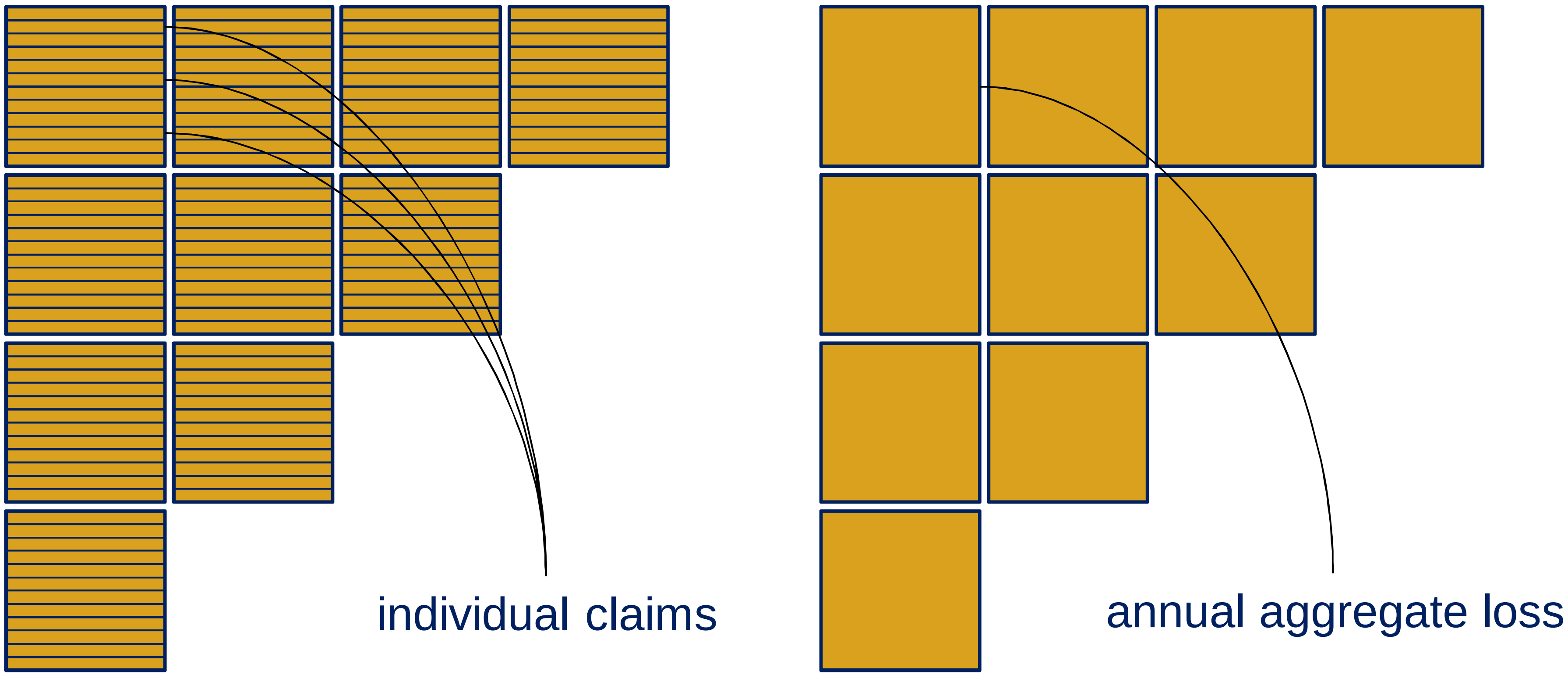
- Develop with
  - Chain Ladder
  - Born-Ferg
  - Cape Cod
  - é

- Assume
  - Homogenous portfolio
  - Independent AY



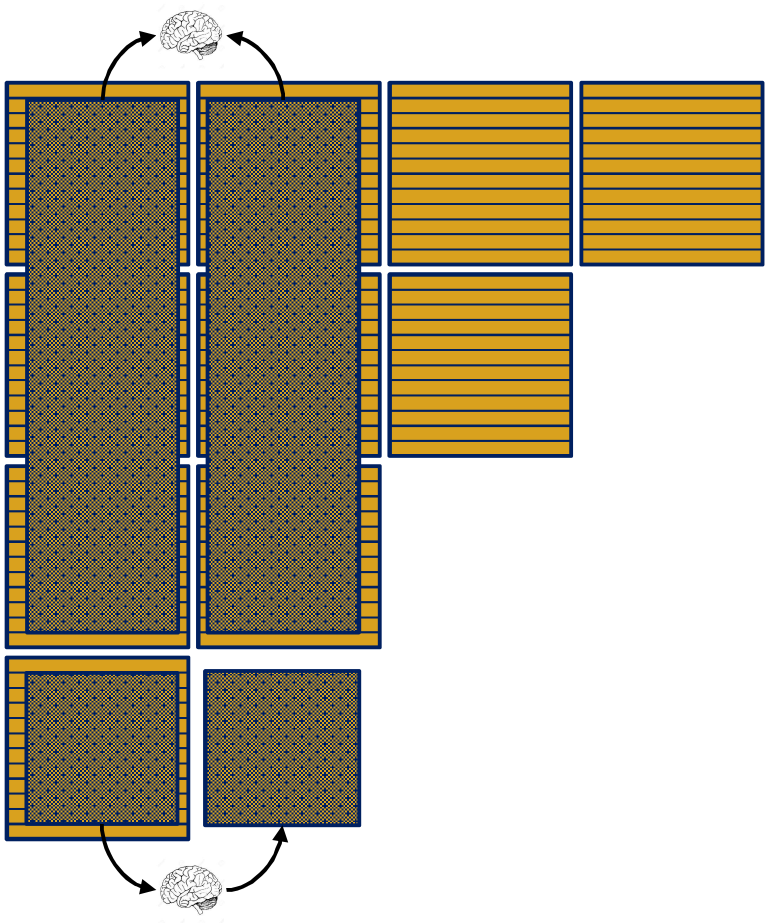
Individual Claims Development

- ~~Aggregate all claims of a given AY into a single aggregate loss ☹~~
- Use individual claims information ☺



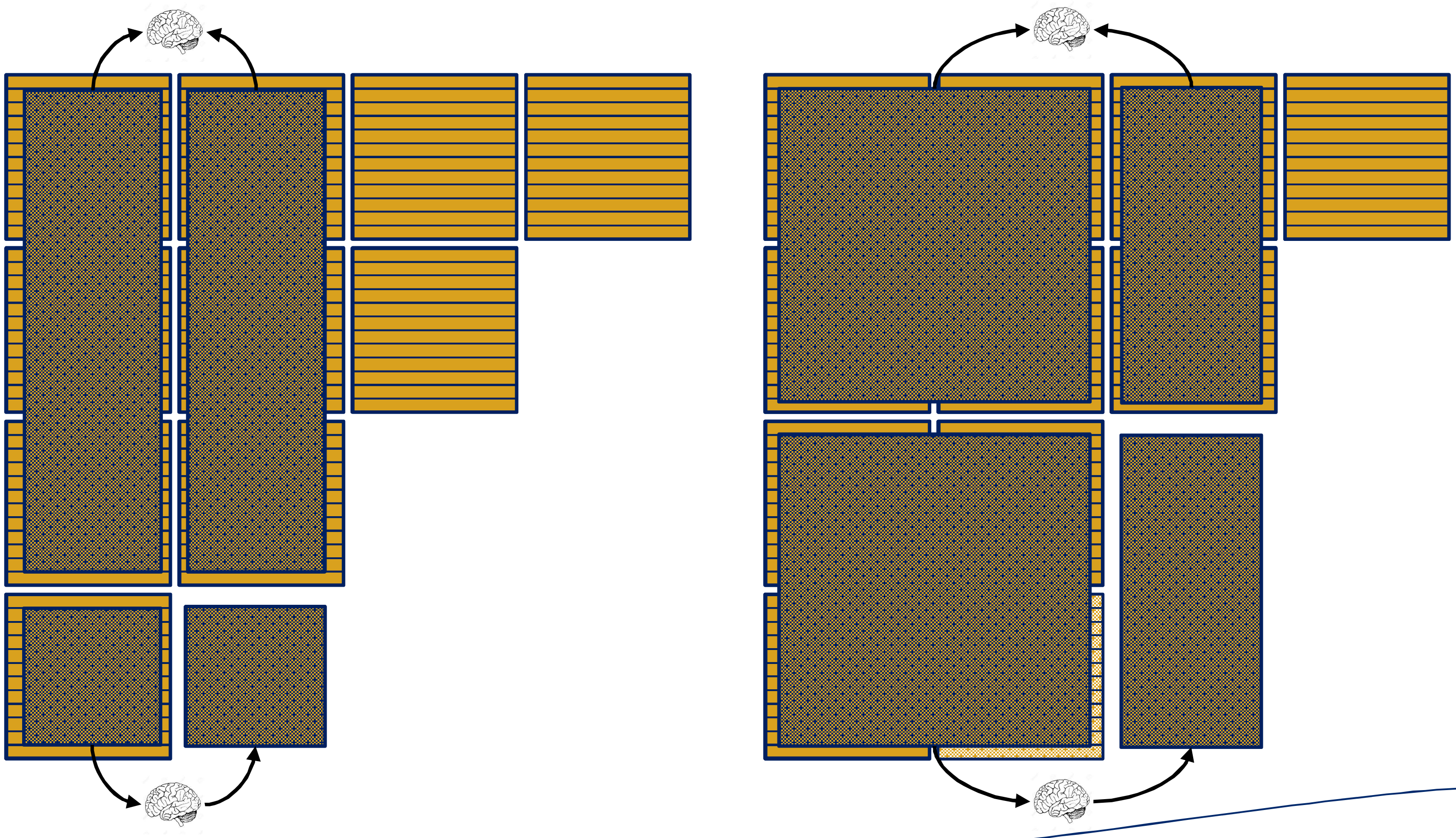
Individual Claims Development

- ~~Aggregate all claims of a given AY into a single aggregate loss~~ ☹
- Use individual claims information ☺ cascading DY neural network



Individual Claims Development

- ~~Aggregate all claims of a given AY into a single aggregate loss~~ ☹
- Use individual claims information ☺ cascading DY neural network



é

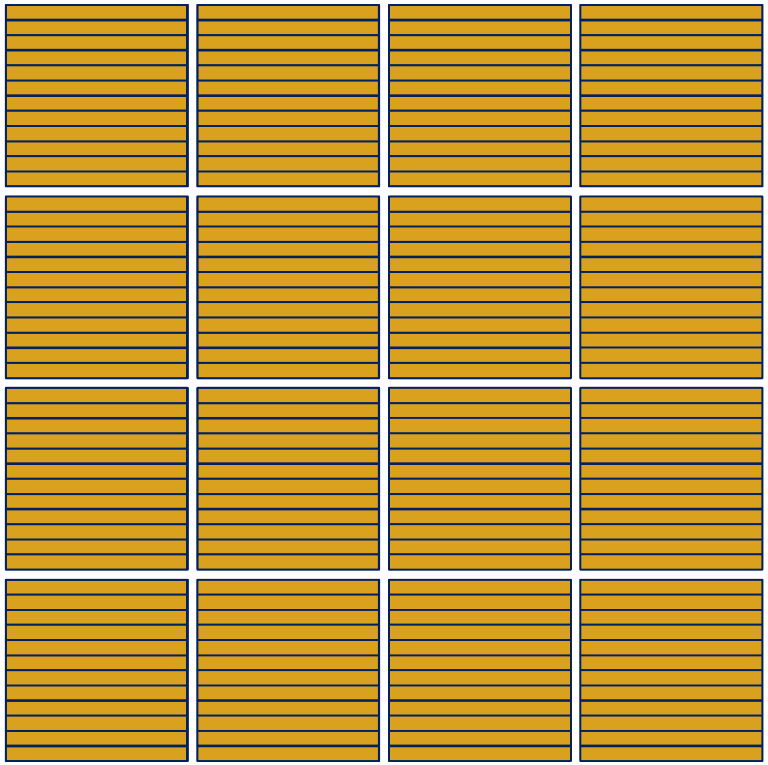
ASTIN Working Party on ICDML

EXPERTS FOR EXPERTS

- Didactic implementation
  - 2 types of synthetic claims
  - Excel
  - Cascading DY
  - 1 hidden layer
  - 8 neurons
  - Paids only

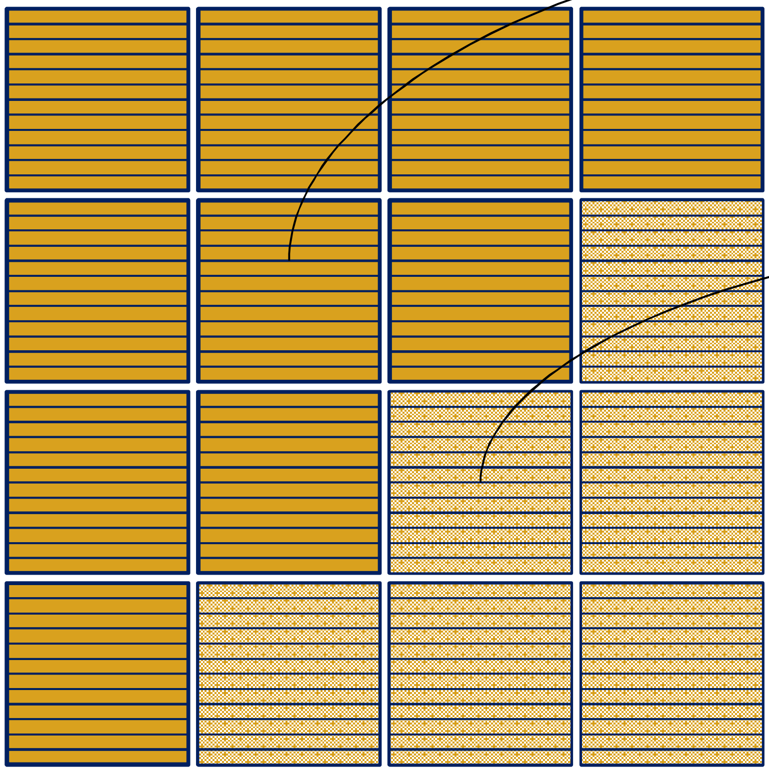
Synthetic Claims

- ☺ Controlled environment



Synthetic Claims

☺ Controlled environment



in-sample
we know ï NN knows
⇒ use for training

out-of-sample
we know ï NN knows not
⇒ use for testing

ASTIN Working Party on ICDML

- Didactic implementation
  - 2 types of synthetic claims
  - Excel
  - Cascading DY
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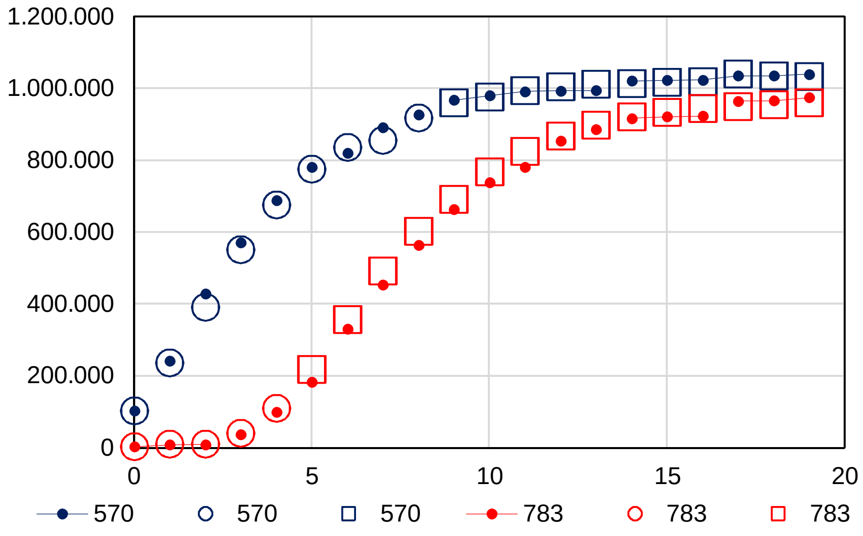
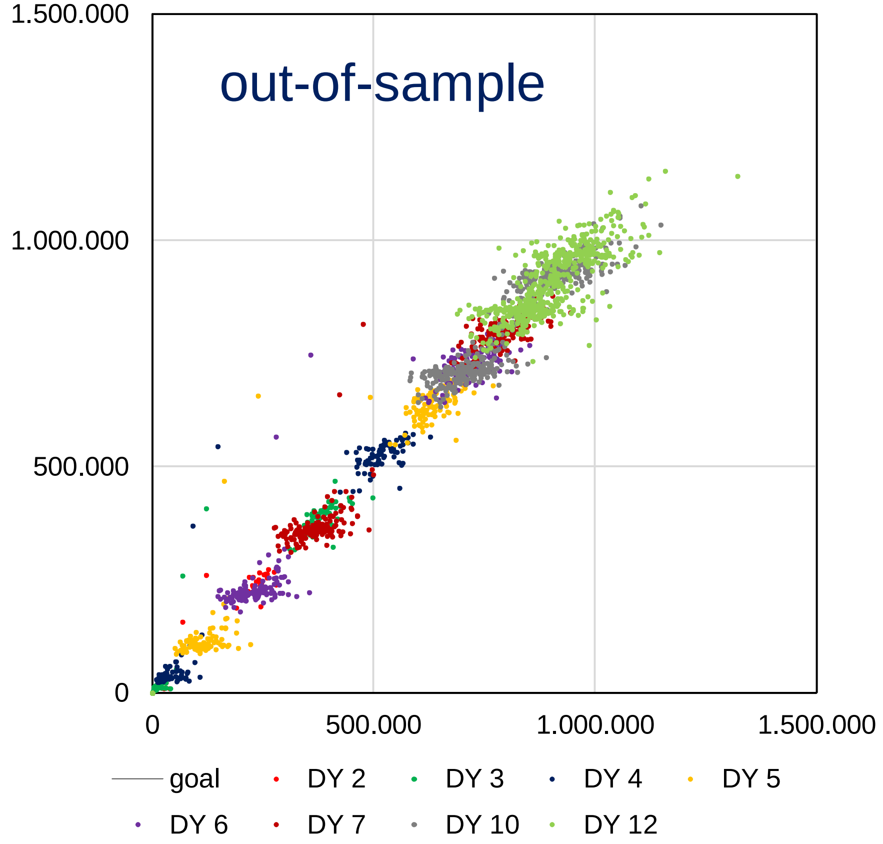
  - 8 neurons
  - Paids only





ASTIN Working Party on ICDML

- Didactic prototype
  - 2 types of synthetic claims
  - Excel
  - Cascading DY
  - 1 hidden layer
  - 8 neurons
  - Paids only

not really a good idea

- Experimental implementation
  - Several types of synthetic claims
  - R, Python,é
  - Cascading DY & AY
  - 1 ï 2 hidden layers
  - 2 ï many neurons
  - Paids & outstandings

- Productive roll-out
  - Real data
  - R or Python or SAS
  - Cascading DY or AY
  - ? hidden layers
  - ? neurons
  - Paids & outstandings
  - Other explanatory variables

work in progress

ICD vs ALD

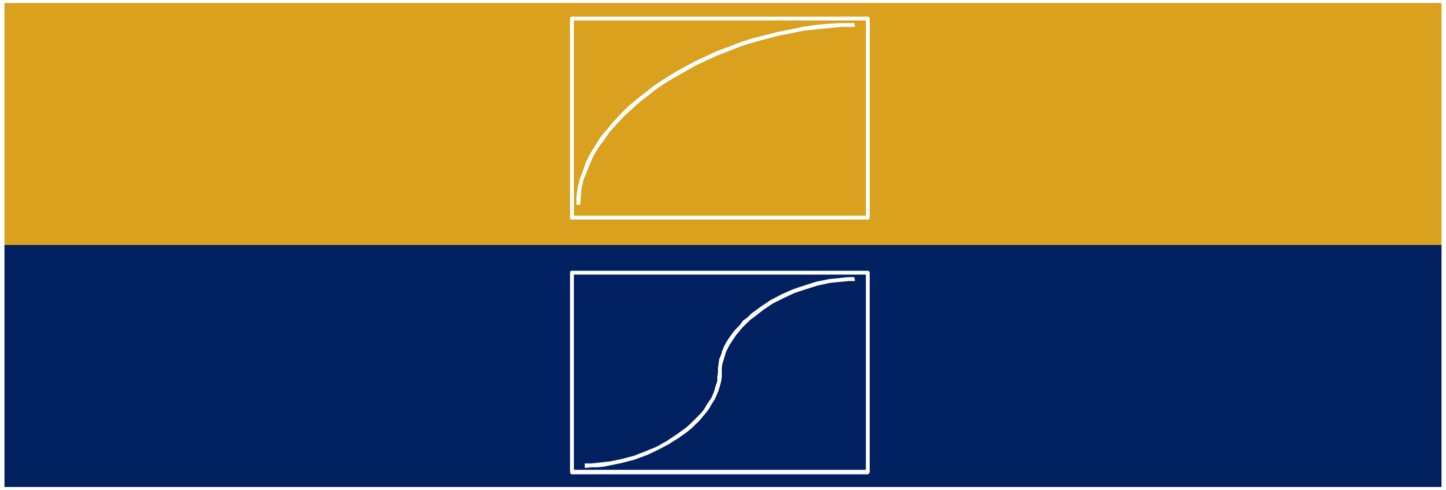
Aggregate Loss Development

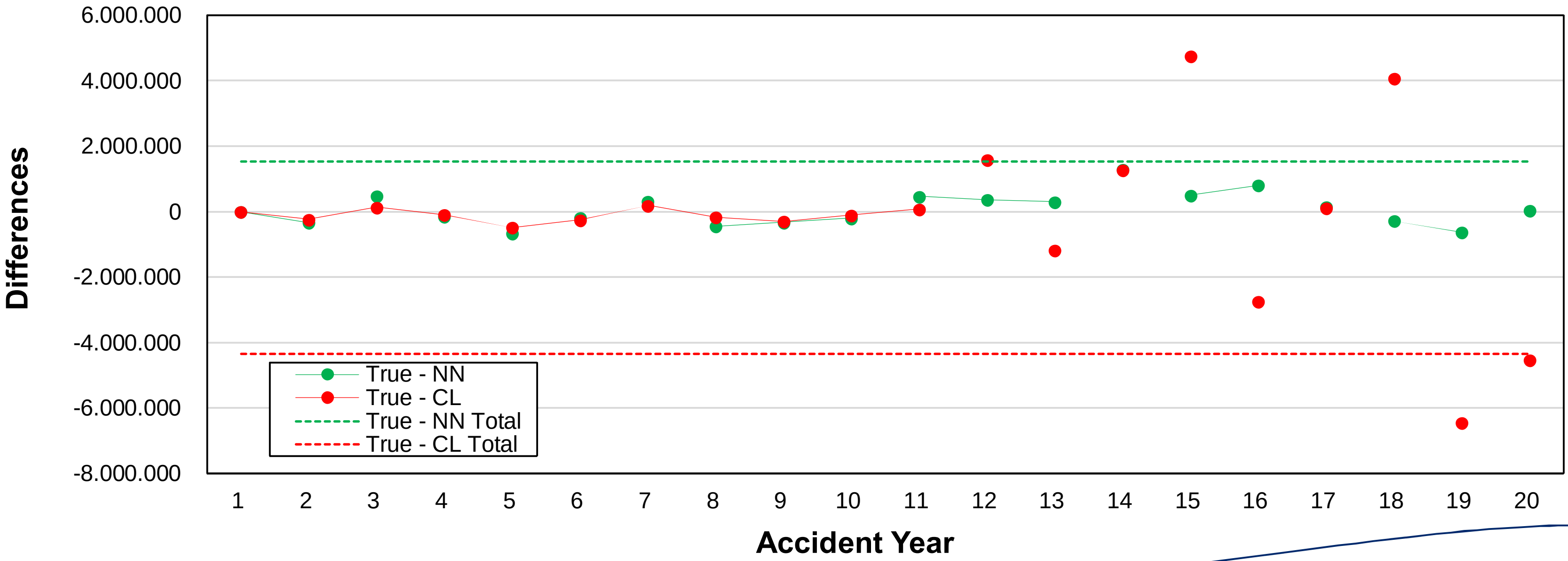
- Develop with
  - Chain Ladder
  - Born-Ferg
  - é
- ☹ Aggregates all claims
  of a given AY
  into a single aggregate loss
- ☹ Works either on paid
  or incurred losses
- 💣 Assumes
  - Homogeneous portfolio
  - Independent AY

Individual Claims Development

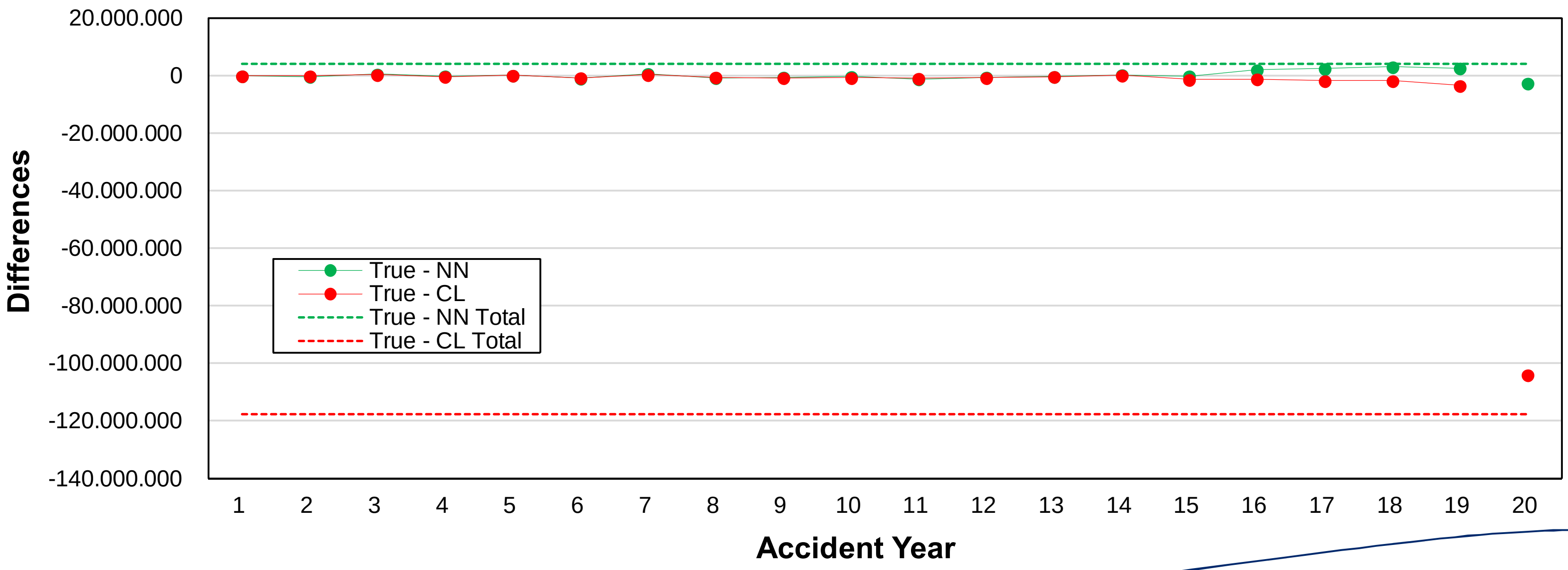
- Develop with
  - DY or AY cascades
  - Convolutional networks
  - é
- ☺ Considers all individual claimsô
  features,
  including non monetary inputs
- ☺ Considers simultaneously
  payments and reserves
- ☺ Works with
  - Heterogeneous portfolios
  - Dependent AY

DY Cascade vs Chain Ladder

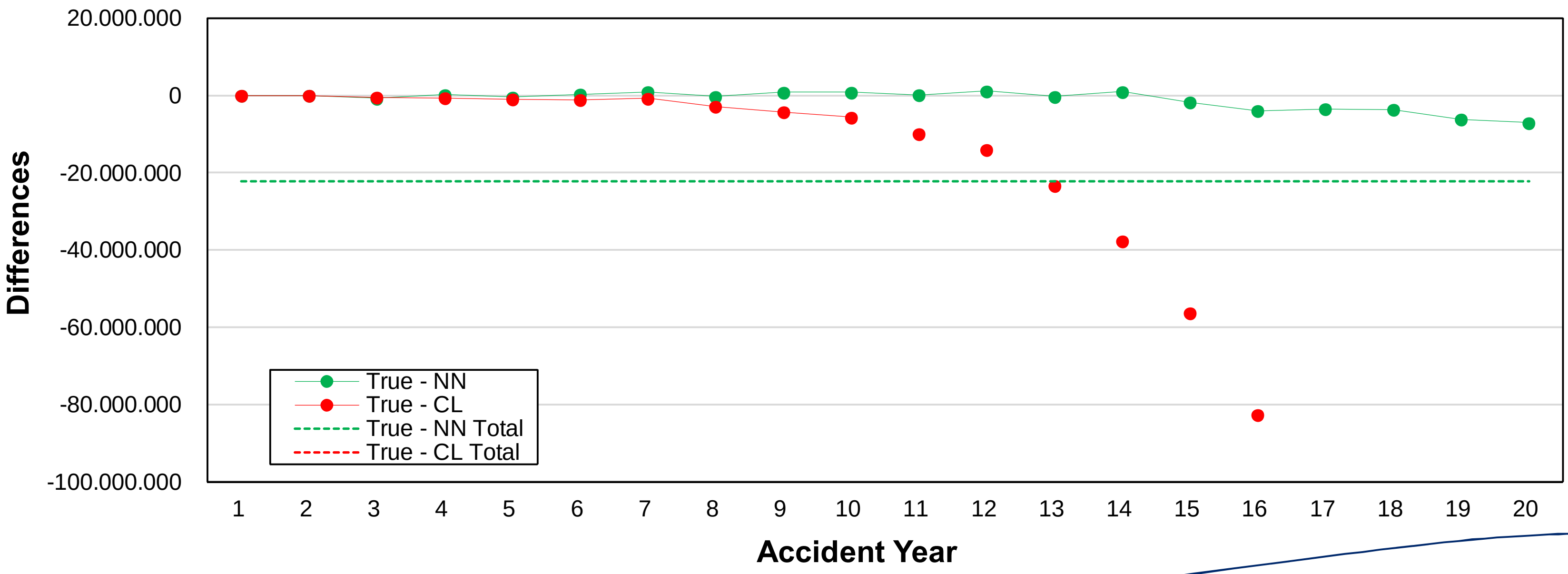




DY Cascade vs Chain Ladder



DY Cascade vs Chain Ladder

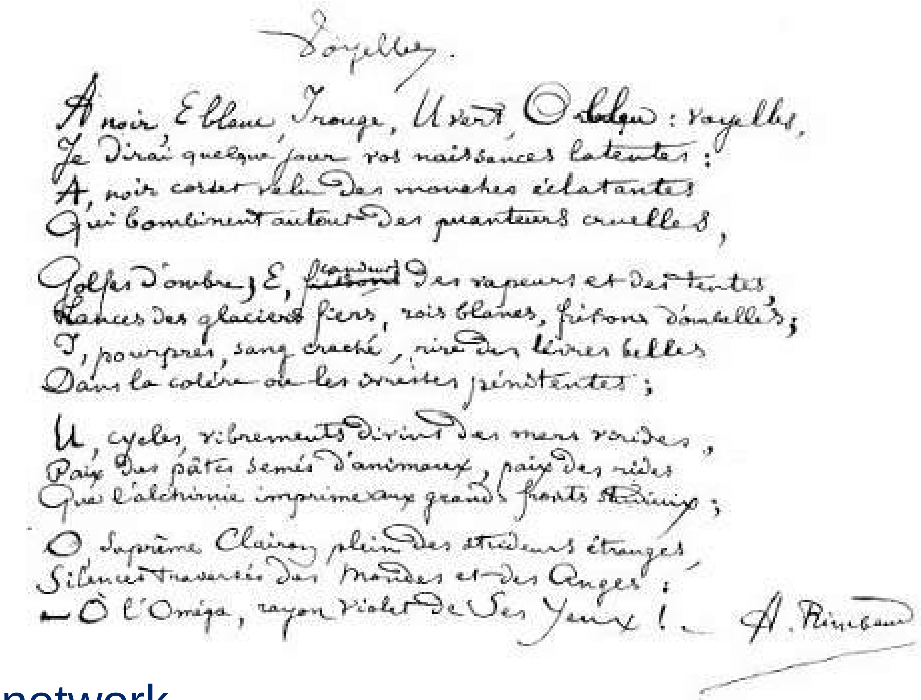


Challenges

- Architecture
- Data pre-processing
- Training
- Communication

Challenges: Architecture

- Monkey & octopus
  - Can solve similar problems
  - Have completely different brains (octopus has 9 brainsé)
- Dyslexic & autistic humans
  - Have same brain architectures
  - Have completely different skills


Voyelles.

A noir, E blanc, I rouge, U vert, O bleu : voyelles,
Je dirai quelque jour vos naissances latentes :
A, noir corset velu des mouches éclatantes
Qui bombinent autour des puanteurs cruelles,

Golfes d'ombre ; E, candeurs des vapeurs et des tentes,
Lances des glaciers fiers, rois blancs, frissons d'ombelles ;
I, pourpres, sang craché, rire des lèvres belles
Dans la colère ou les ivresses pénitentes ;

U, cycles, vibrements divins des mers virides,
Paix des pâtis semés d'animaux, paix des rides
Que l'alchimie imprime aux grands fronts studieux ;

O, suprême Clairon plein des strideurs étranges,
Silences traversés des Mondes et des Anges :
— O l'Oméga, rayon violet de Ses Yeux ! —
A. Rimbaud

- Neural network
  - ? Activation function (sigmoid)
  - ? Penalty function
  - ? Number of layers
  - ? Number of neurons
  - ? Training strategy
  - ? Fully-connected vs convolutional network
  - ? é

Challenges: Data Pre-Processing

- Humans are good at catching flying objects
  - But less if they are myopic
- Humans are good at communicating orally
  - But less if they are hearing-impaired

- Neural network
  - ! Pre-process inputs
  - ! Scale outputs

requires a healthy understanding
of the underlying phenomena

Challenges: Training

- How do you learn
  - A poem
  - A foreign language
  - A programming language
  - A mathematical method
  - é

- Neural network
  - Minimize penalty function over a high dimensional parameter space
  - Backpropagation
    - ☺ Very fast (Python, Matlab)
    - ☹ Steepest gradient ⇒ local minima
  - Simulated annealing?
    - ☺ Global minimum?
    - ☹ Untested?

Challenges: Communication

PRS
EXPERTS FOR EXPERTS

- You ride a car ï do you know **how**
  - your ABS works?
  - your airbag triggers?
  - it will drive on its own?

- You implement Chain Ladder ï do you understand **why**
  - the link factors take these values?
  - you may apply this method?

- Richard Feynman:
  Nobody understands Quantum Mechanics!

- Produce with neural networks ï illustrate with decision trees

Advantages

PRS
EXPERTS FOR EXPERTS

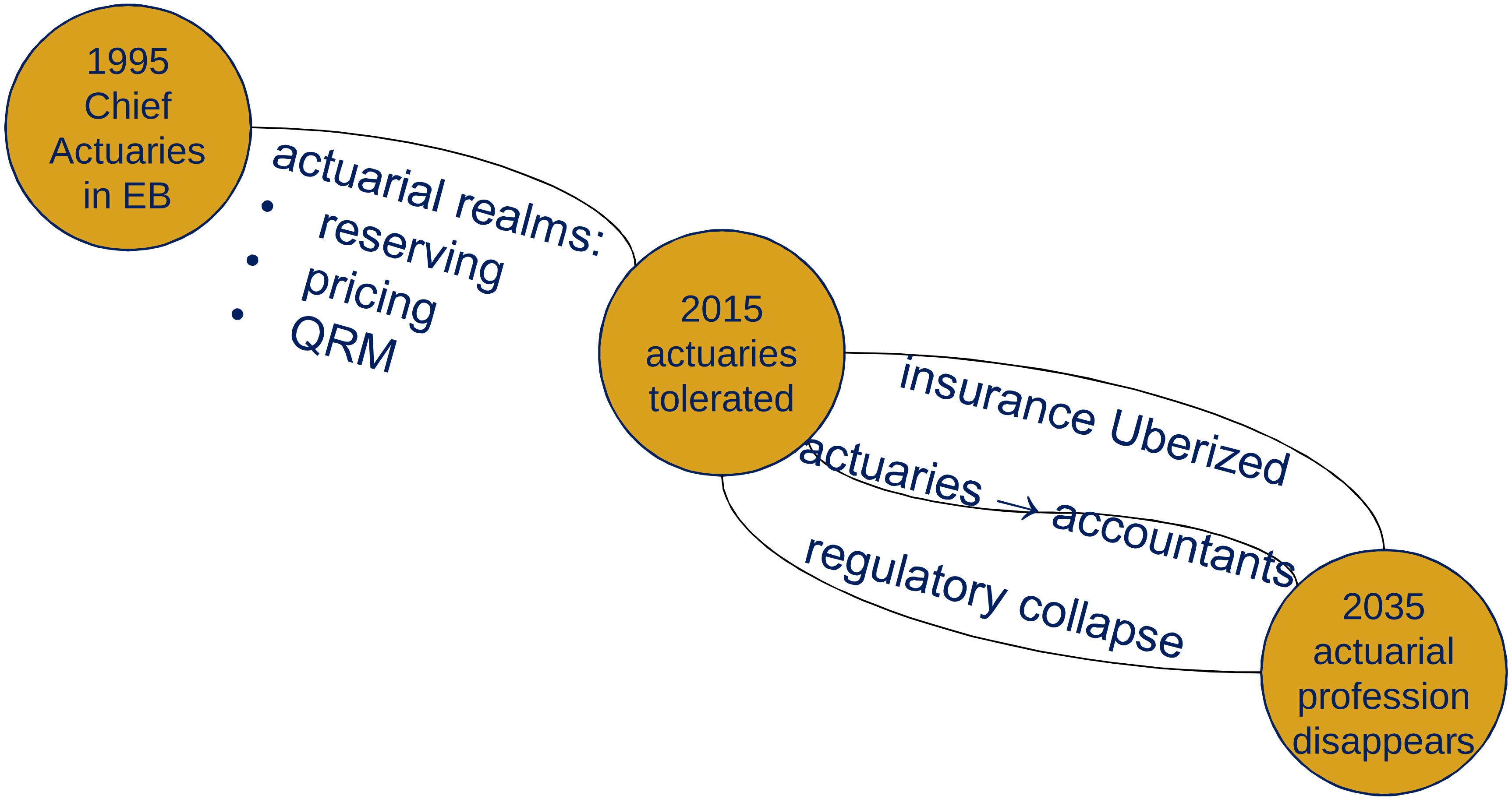
- Respond very fast
  - é but training can take long
- Can generalize
  - é and may get it wrong
- Are robust
  - é most of them
- Are very flexible with regard to inputs
  - é if well pre-processed
- Can update their knowledge continuously

Ubiquitous Neural Networks

PRS
EXPERTS FOR EXPERTS

- Insurance?
  - Actuarial engineering
    - Å Individual claims development
    - Å Pricing
    - Å Alternative to replicating portfolios
    - Å é
  - Claims
    - Å Regulation of attritional claims
    - Å Fraud detection
    - Å é
  - Underwriting & customer relations
    - Å Lapse prediction & retention programs
    - Å Medical underwriting
    - Å Behavioural advice (telematics, health,é)
    - Å é
- Alternative insurance
  - ???

Food for Thoughts



… et Carthago delenda est!

Statutory reserving

Different models depending on

- data availability / quality
- line of business / market
- processes / products
- é
- actuarial judgment

Ÿ 1st moment of a distribution

standard reserving model

Solvency II

Different models depending on

- data availability / quality
- line of business / market
- processes / products
- é
- actuarial judgment

Ÿ nth moment of a distribution

standard solvency formula

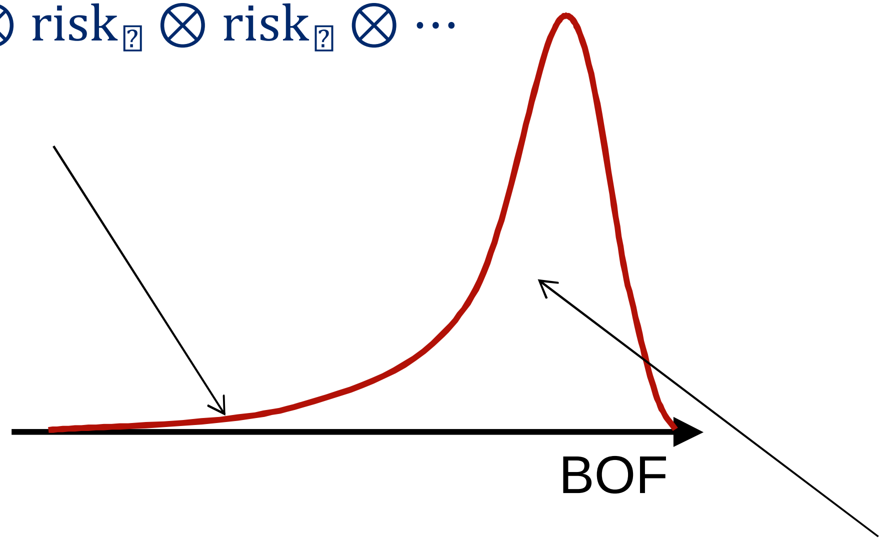
… et Carthago delenda est!

Internal models

- Numerical aggregation of realistic distributions

$$\mathrm{SCR} \leftarrow \mathrm{risk}_1 \otimes \mathrm{risk}_2 \otimes \mathrm{risk}_3 \otimes \cdots$$

- Probe the true tail



Standard Solvency II formula

- Analytic linear approximation

$$\mathrm{SCR} \leftarrow \sigma^2 = \sum \rho_{ij} \sigma_i \sigma_j$$

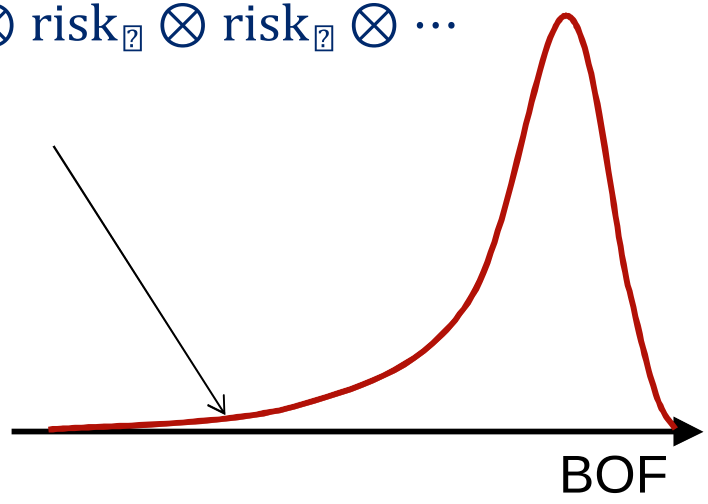
- Probe the tail with 2nd moments

Internal model

- Numerical aggregation of realistic distributions

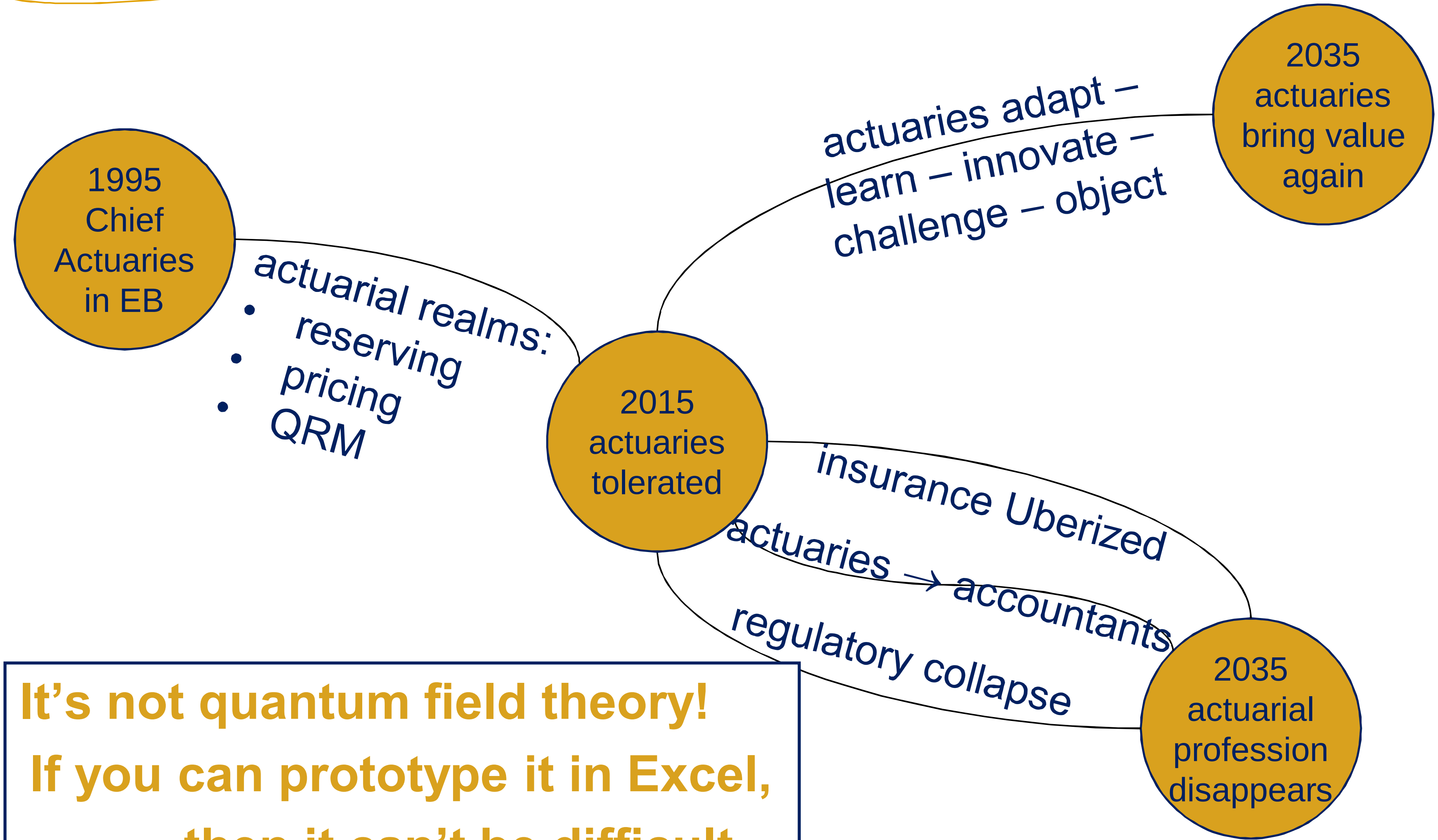
$$\square\square\square \leftarrow \mathrm{risk}_{\square} \otimes \mathrm{risk}_{\square} \otimes \mathrm{risk}_{\square} \otimes \cdots$$

- Probe the true tail



Cut along dotted line

Food for Thoughts



It's not quantum field theory!

If you can prototype it in Excel,

then it can't be difficult…

Lecturer's Coordinates

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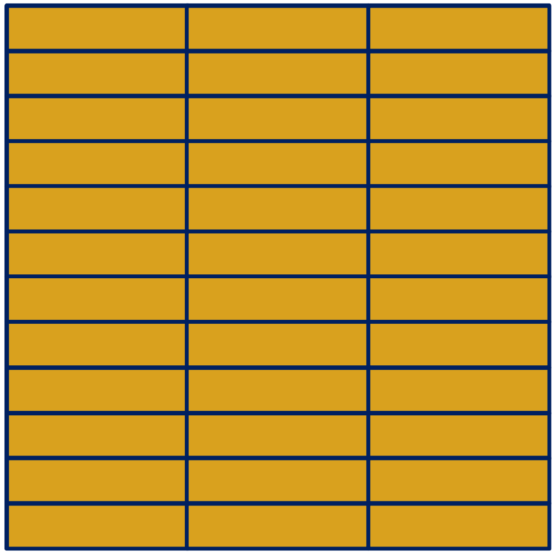
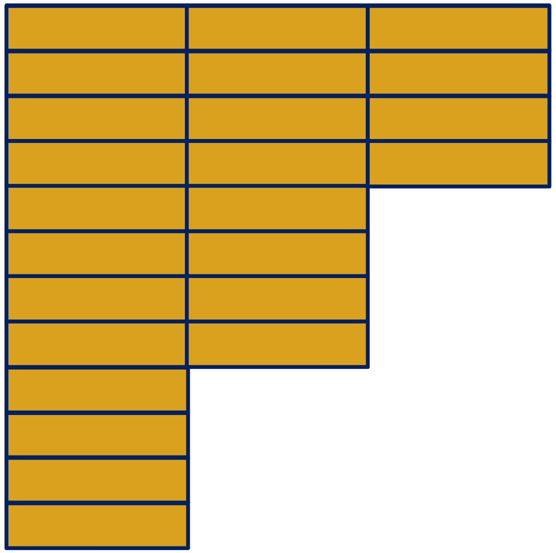
Synthetic vs Real Data

- Synthetic data
  - Training: ignore known DY
  - Validation: use these DY



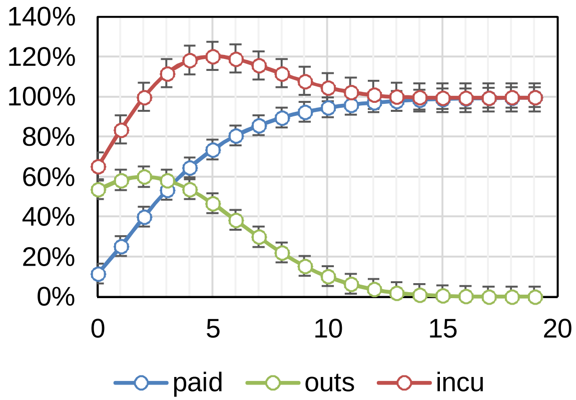
- Real data
  - Training: use all known DY
  - Validation: cross-validate w/in AY



Claims Generator

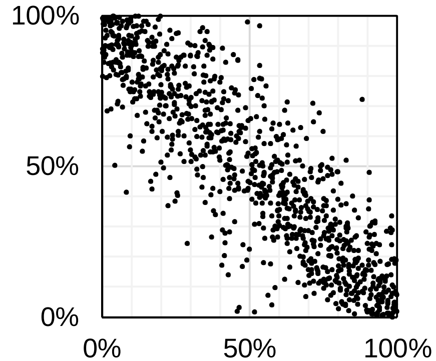
- Generate individual claims with probability distributions of
  - Severity: ultimate $\square \sim \square\square\,(\square, \square)$
  - Development patterns: age-to-ultimate $\square(\square) \sim \square\square\,(\square_{\square}, \square_{\square})$

- Components
  - Paid $\square(\square) = \square \cdot \square_{\square}(\square)$
  - Outstanding $\square(\square) = \square \cdot \square_{\square}(\square)$
  - Incurred $\square(\square) = \square(\square) + \square(\square)$



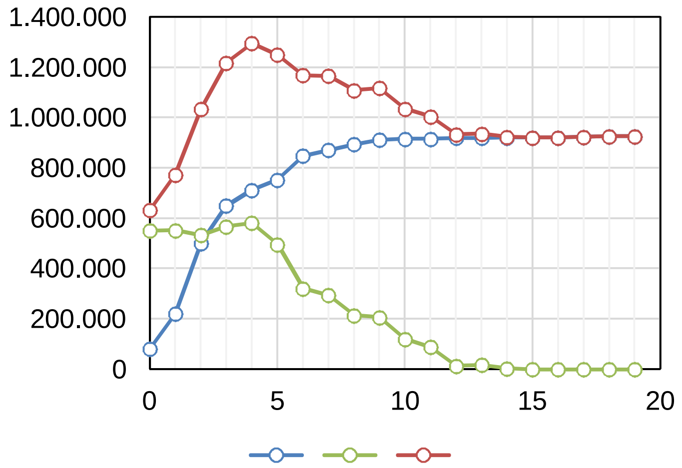
- Patterns
  - $\square_{\square}(\square)$: $\square_{\square} = \left[1 - \square^{\square\frac{\square\square\,\square}{\square}}\right]^{\square}$
  - $\square_{\square}(\square)$: $\square_{\square} = \square\,\square^{\square\left(\frac{\square\square\,\square}{\square}\right)^{\square}}$

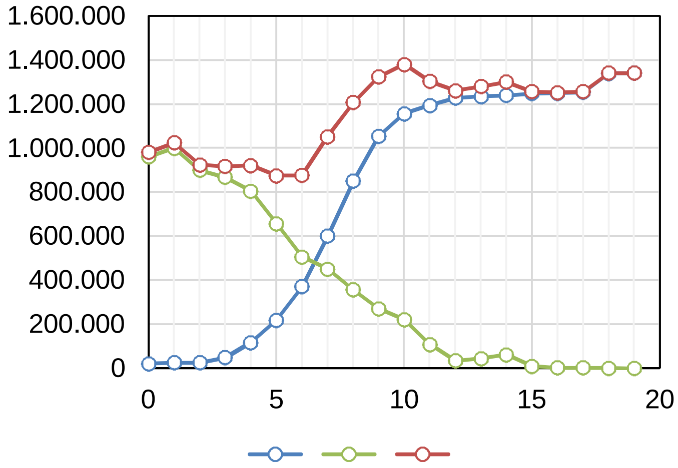
- Dependence
  - Frank Copula $\square_{\square}(\square) \bowtie \square_{\square}(\square)$ for each $\square$



Synthetic Claims

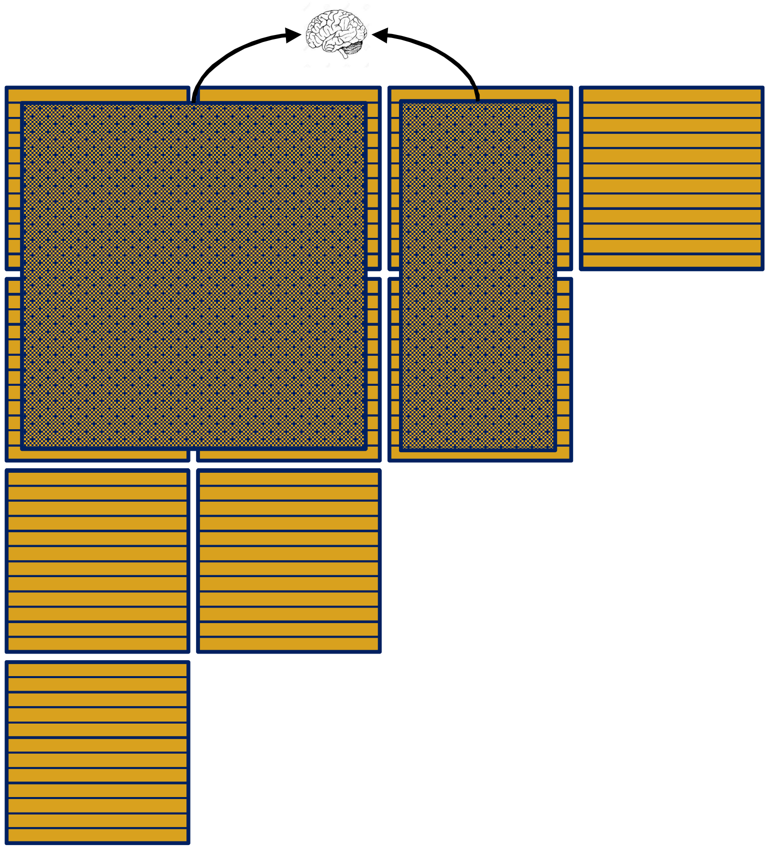
- Generate as many individual claims as needed



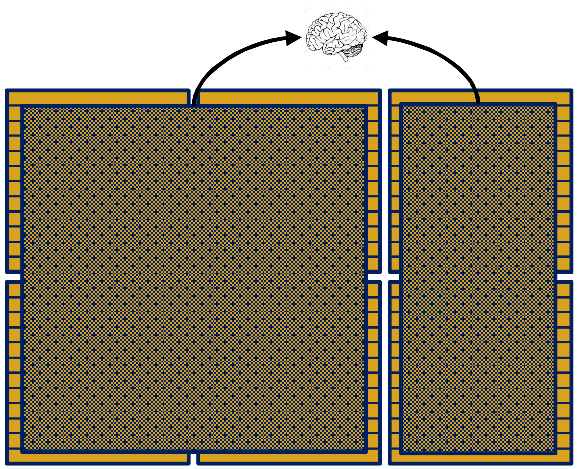


- Mix individuals claims from different models

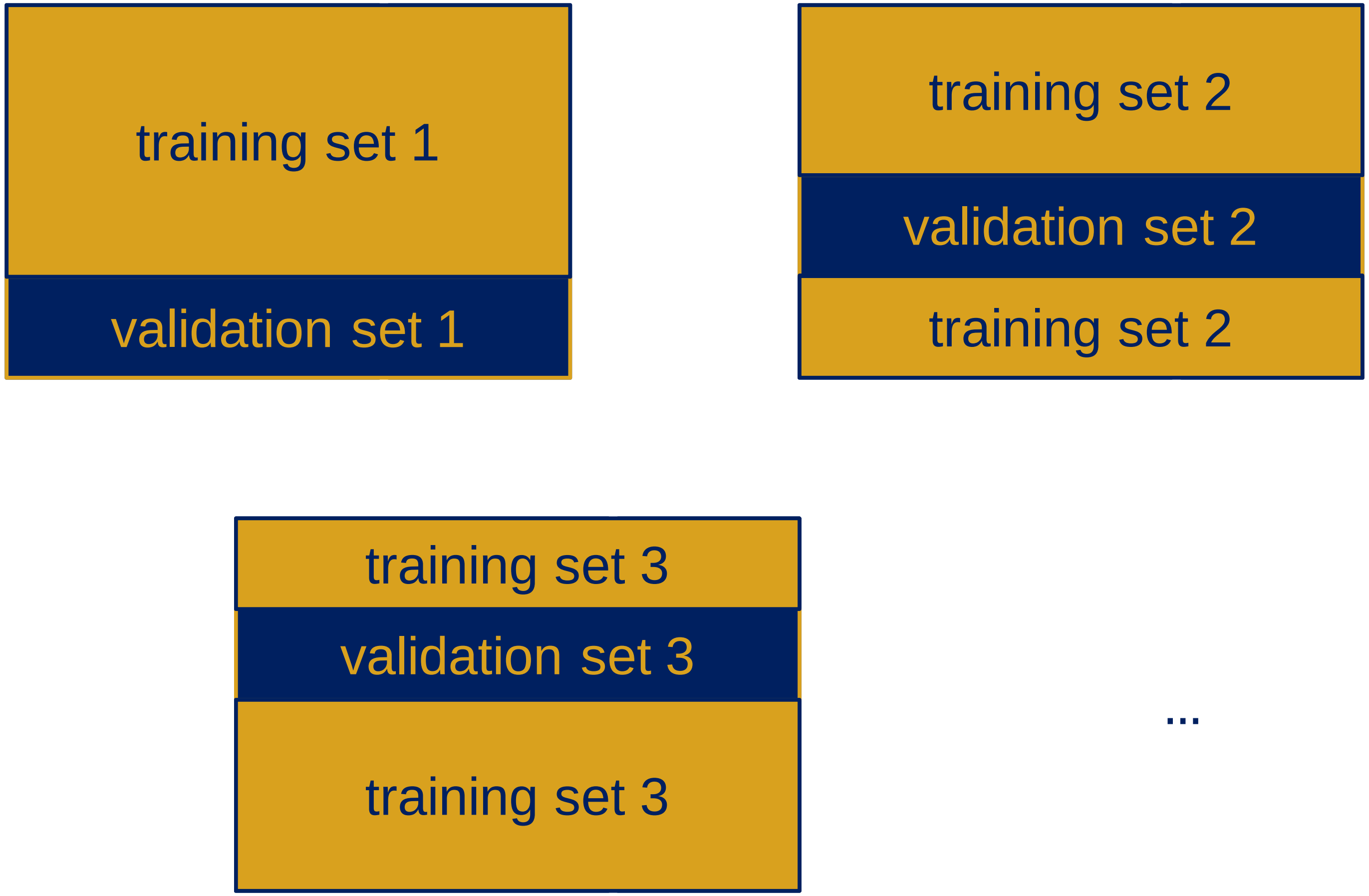
Cross Validation



Cross Validation



Cross Validation

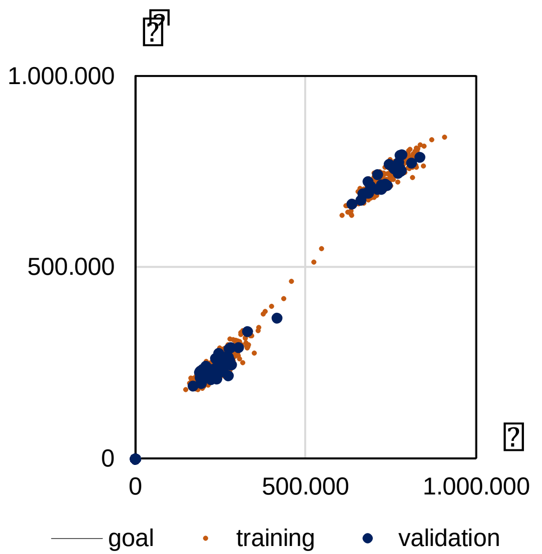


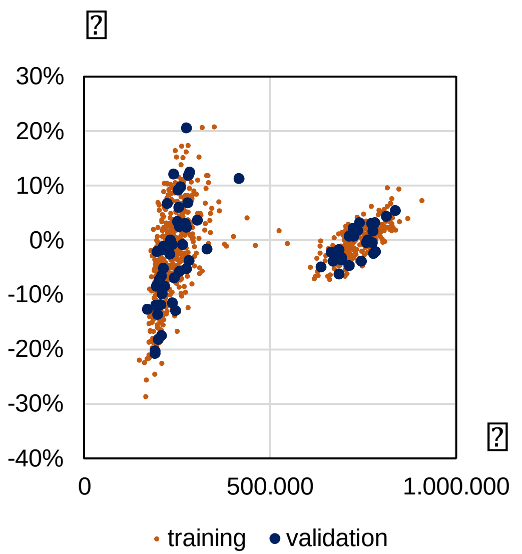
Cross Validation – Residual Analysis

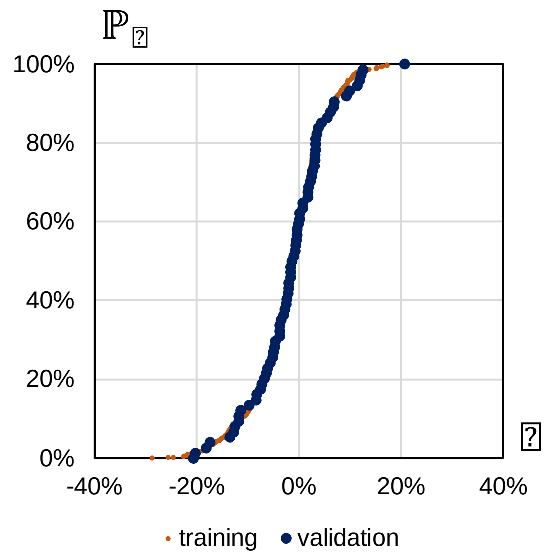
$\square_{\square}$ = true values

$\hat{\square}_{\square}$ = predicted values

$$\square_{\square} = \frac{\square_{\square} - \hat{\square}_{\square}}{\square_{\square}} =$$ residual





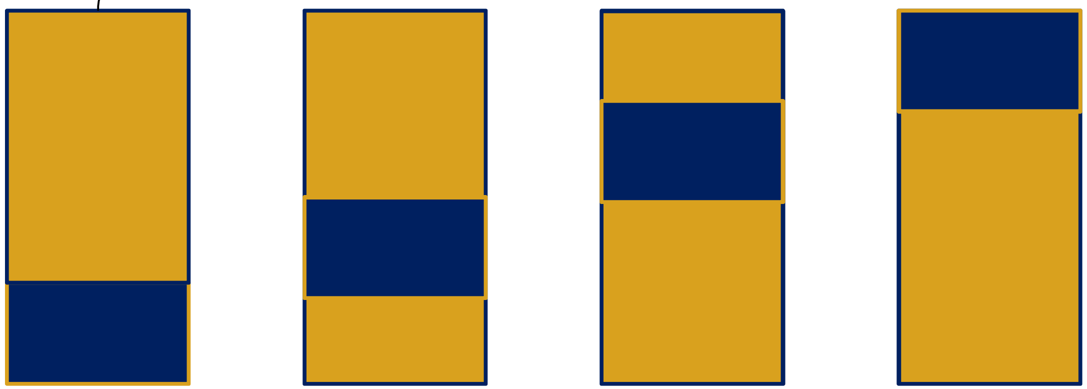


Cross Validation – Measures of Fit

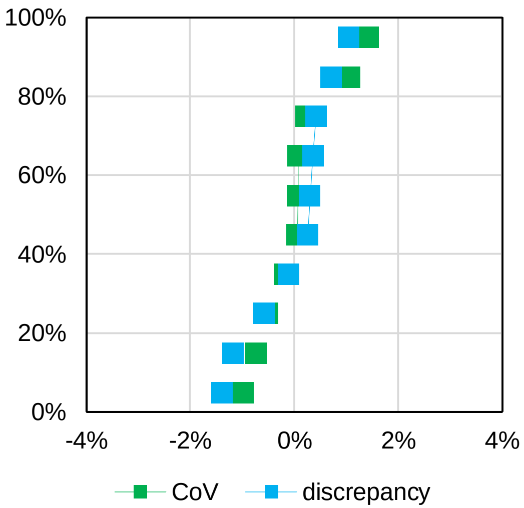
y_i = true values

$\hat{y}_i$ = predicted values

$e_i = \dfrac{y_i - \hat{y}_i}{y_i}$ = residual



validation – training



$$\text{CoV} = \frac{\sqrt{\frac{1}{n}\sum (y_i - \hat{y}_i)^2}}{\frac{1}{n}\sum y_i}$$

$$\text{discrepancy} = \sqrt{\frac{1}{n}\sum e_i^2}$$

...

validation ≫ training ☹

validation ~ training ☺