

Cyber incident reports: extrapolating severity using neural networks

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About the speaker

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Hugo is part of the TCP program at Detralytics, and works/has worked on R&D topics, P&C pricing, modelling and more especially on cyber.
- **Kher Justin**– *TAP Consultant, Detralytics*
Justin is part of the TAP program at Detralytics. Justin works on P&C pricing, cost of claims and R&D topics related to cyber risk assessment.

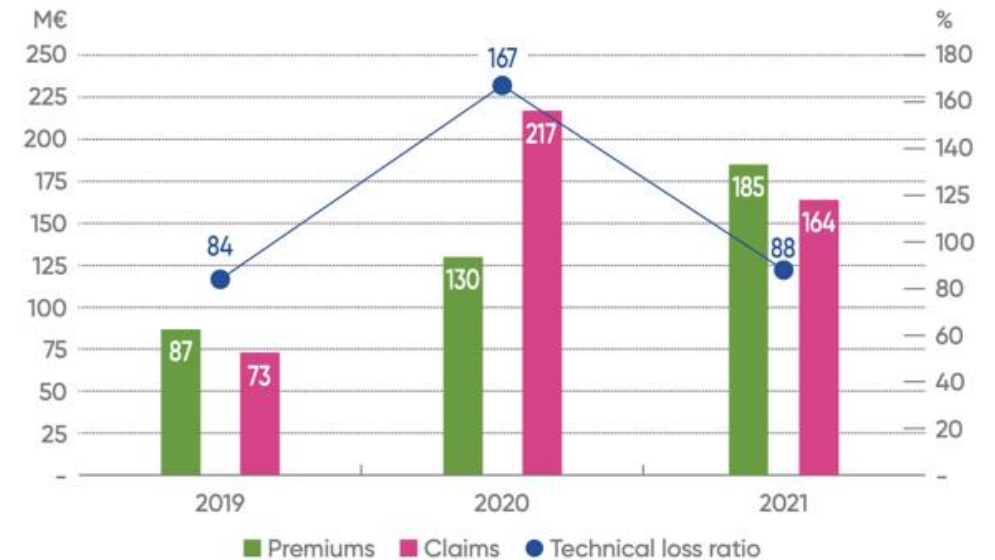


Detralytics is a consulting and training firm focused on Actuarial Science, Data Science and Risk Management. Detralytics was founded to support companies in the advancement of actuarial science and help them to solve their challenges, while offering the perfect stepping stone to the most talented actuarial students. We guarantee to go beyond traditional consulting, by offering a unique combination of academic expertise, deep career and market knowledge.



Introduction

- LUCY Report from the AMRAE :
 - Loss ratios : 84% in 2019, 167% in 2020, 88% in 2021
 - Premiums : +44% collected, for a growth in numbers of 27,5%
- Report from the General Treasury Directorate on the cyber risk, in September 2022:
 - Raises questions on data
 - Points the necessity of innovating methods (e.g. the bayesian)



Source: 2022 AMRAE LUCY Study.

Introduction

- **Question** : Can we use the multiple textual resources at hand (such as the incident/claims descriptions) to get a better understanding of the underlying risk?
- **Objectives** :
 - Data augmentation
 - Transform "literary" insight in quantitative insight, to feed into bayesian models
 - Better anticipate and foresee within the processes of incident management



Summary

1- Embedding techniques

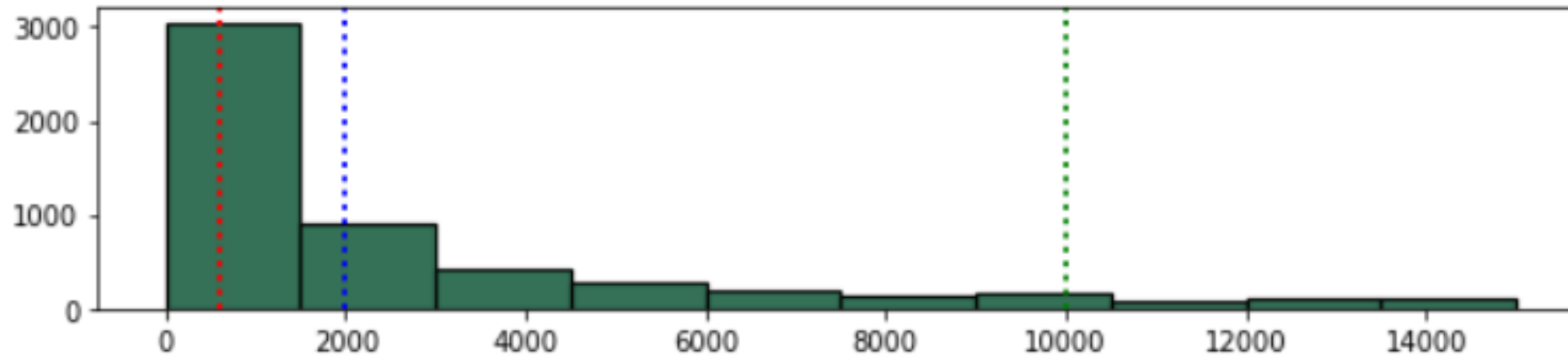
2- Neural Networks

3- Model enrichment

4- Uses and perspectives

Base PRC: Privacy Rights Clearinghouse (US)

- Variable being a marker of severity (the number of records) and the claim description



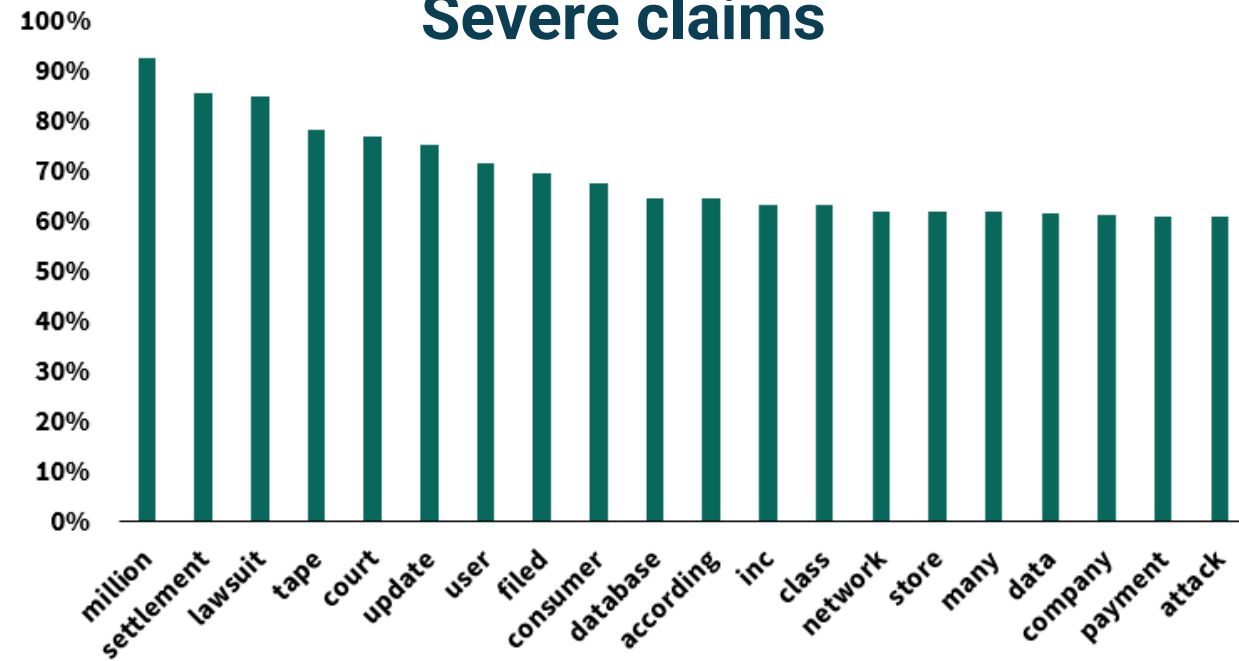
- Splitting of the base and flagging of the most severe claims using the number of records variable.

NB OF RECORDS < 4767 ?	NB OF RECORDS > 4767 ?
Attritionnal claim	Severe claim

Base PRC: Privacy Rights Clearinghouse (US)

- The words used in the claim description also inform on the level of severity

Severe claims



Attritionnal claims

The following words are associated with the description of attritionnal claims :

- Paper
- Document
- Dishonest
- Accidentally
- School

Pre-treating the textual data

Treating the claim description

Claim description	Cleaned description
Union Hospital suffered an inadvertent disclosure on approximately 1/18/16 that resulted in 1 record being exposed, which included social security numbers.	union hospital suffered inadvertent disclosure approximately resulted record exposed included social security number

Interfering information :

- Stopwords
- Dates
- Punctuation
- Numbers



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Corpus dictionary

- Each word within the corpus is called a **token**
- An analysis of the text allows the identification of new tokens, each one having 2 or 3 words to add in the dictionary

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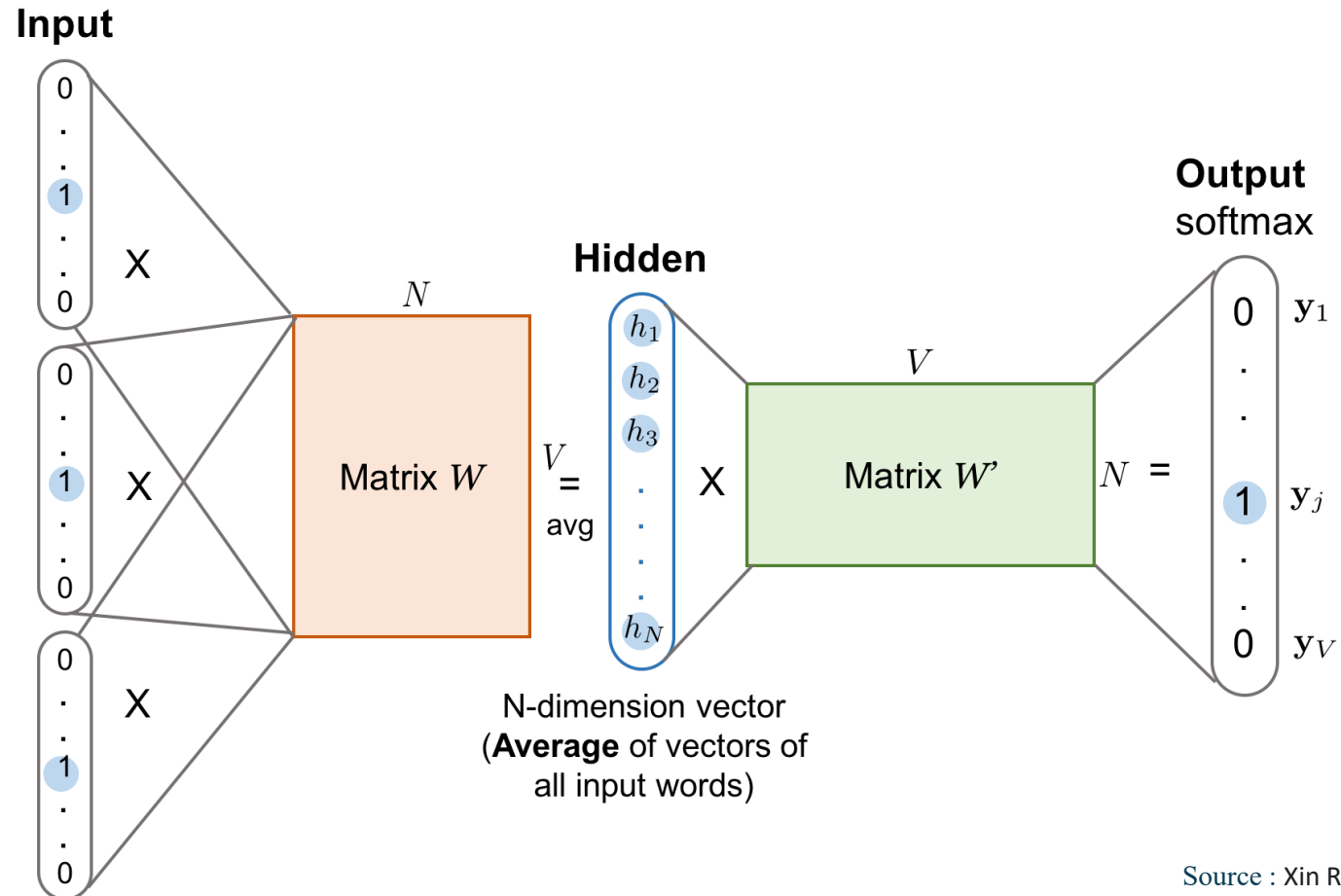
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Relevant string of words

- « social security number »
- « personal information »
- « email adress »

Word embedding – Word2Vec



Source : Xin Rong. [word2vec Parameter Learning Explained](#)

Word embedding – Word2Vec

A word is encoded in an **N-dimensional space**

Words with close **meaning** or **influence** will be close in that space

	Man (5182)	Woman (9742)	King (4815)	Queen (7464)	Apple (421)	Orange (6151)
Gender	-1	1	-0,95	0,97	0,00	0,01
Royal	0,01	0,02	0,93	0,95	-0,01	0,00
Age	0,03	0,02	0,7	0,69	0,03	-0,02
Food	0,04	0,01	0,02	0,01	0,95	0,97
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Word embedding – Word2Vec

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Close words to « insurance »

Life

Insurer

Coverage

Enrollee

Plan

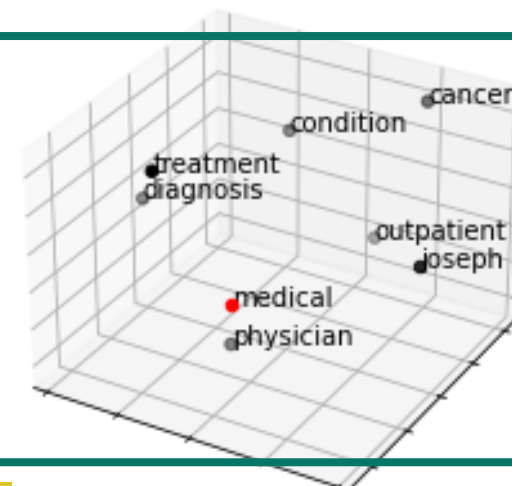
Guarantor

Aflac

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3D Representation

The close words to « **medical** » in our corpus of claim description can be **3D plotted**





Summary

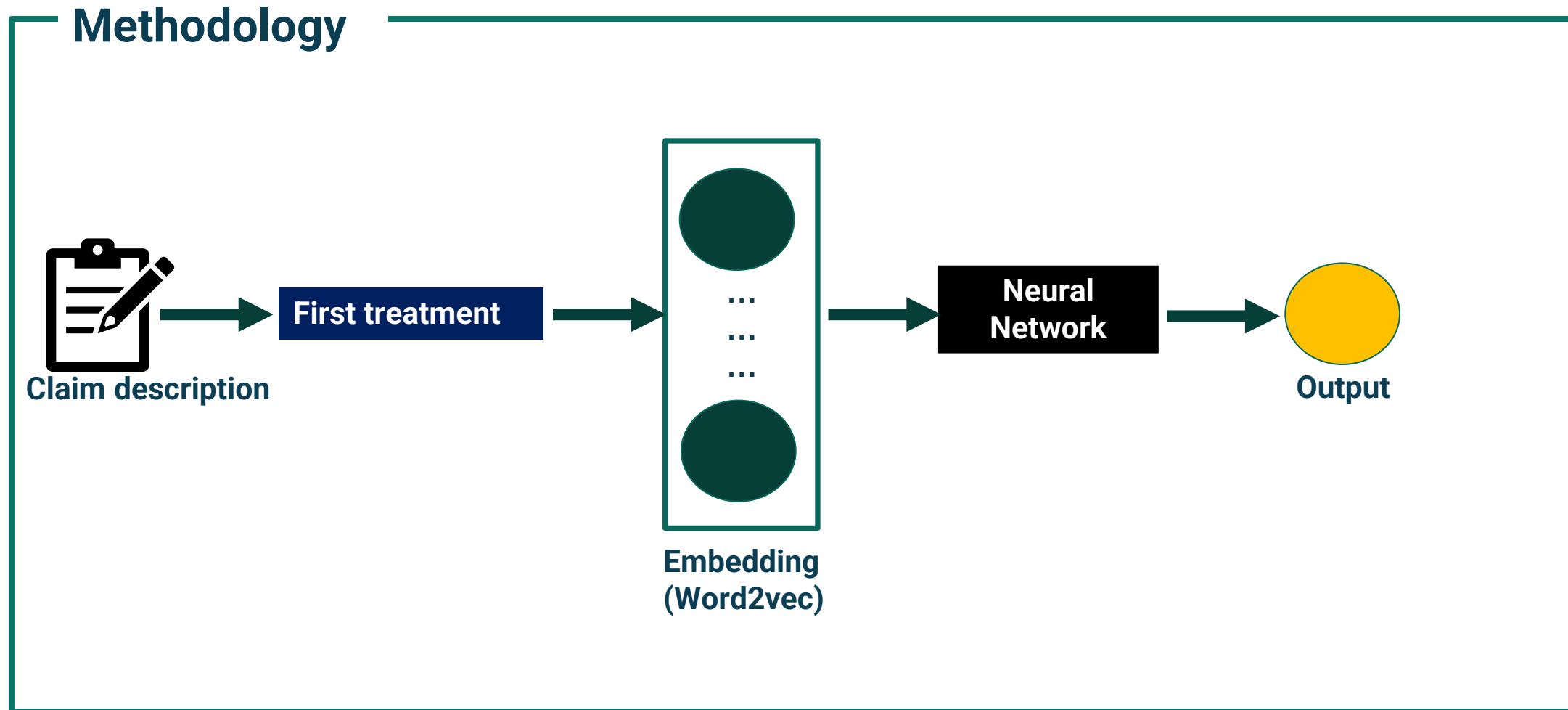
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Summary of the method

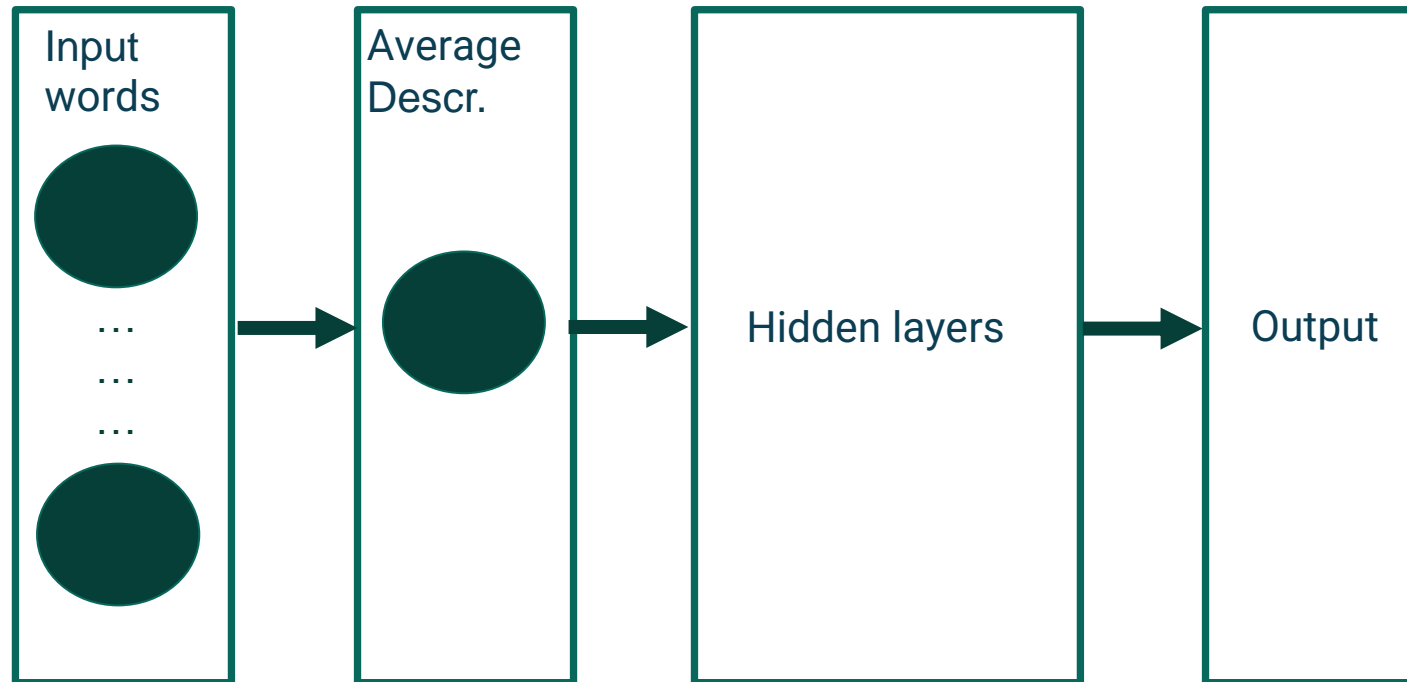


The family of model we chose: Multilayer perceptron

- Zooming on the part

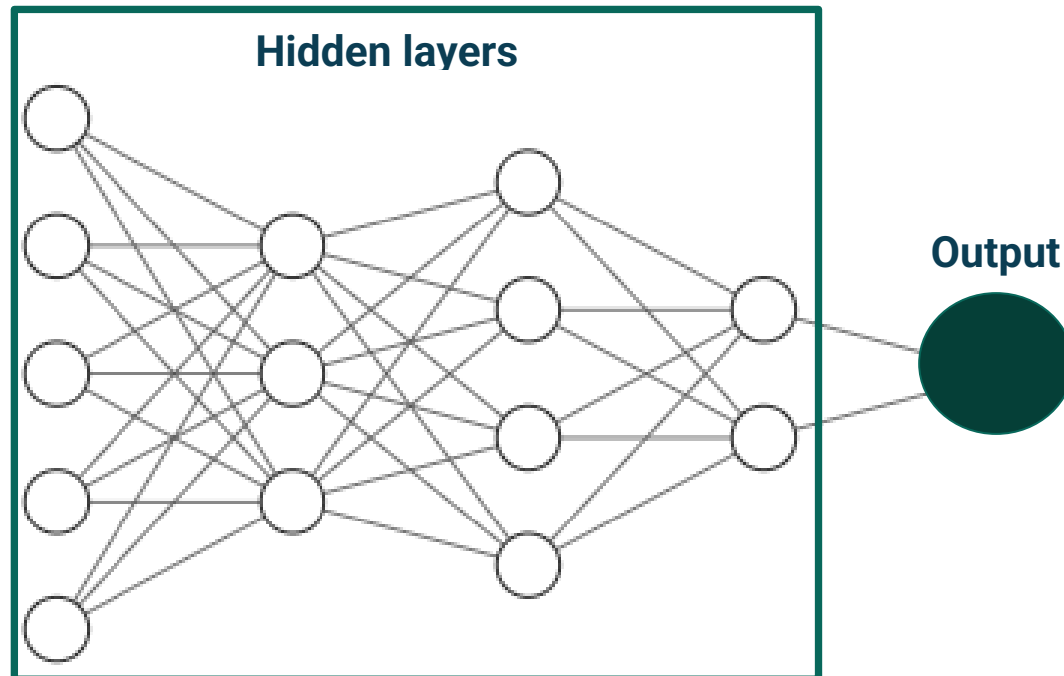
Neural Network

-> Multilayer perceptron



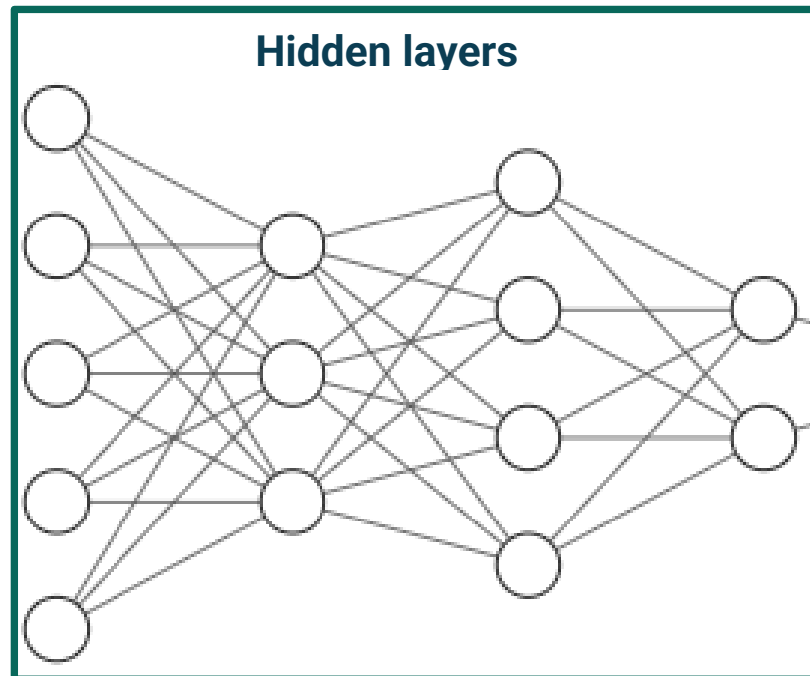
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- Gridsearch on the hidden layers of the neural network (F1 score)



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Output

$$F1\ score = \frac{TP}{TP + MEAN(FP; FN)}$$

TP : True positives

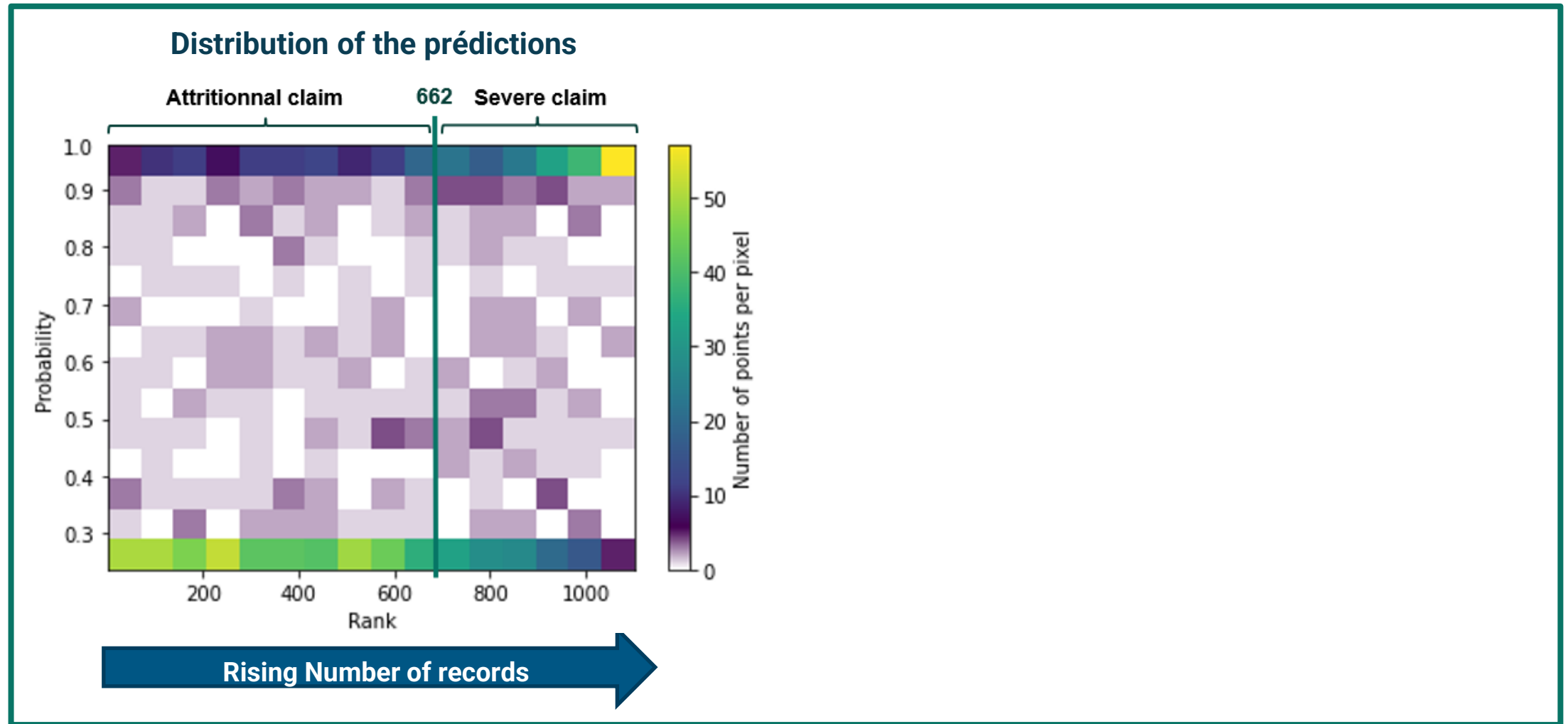
FP : False positives

FN : False negatives

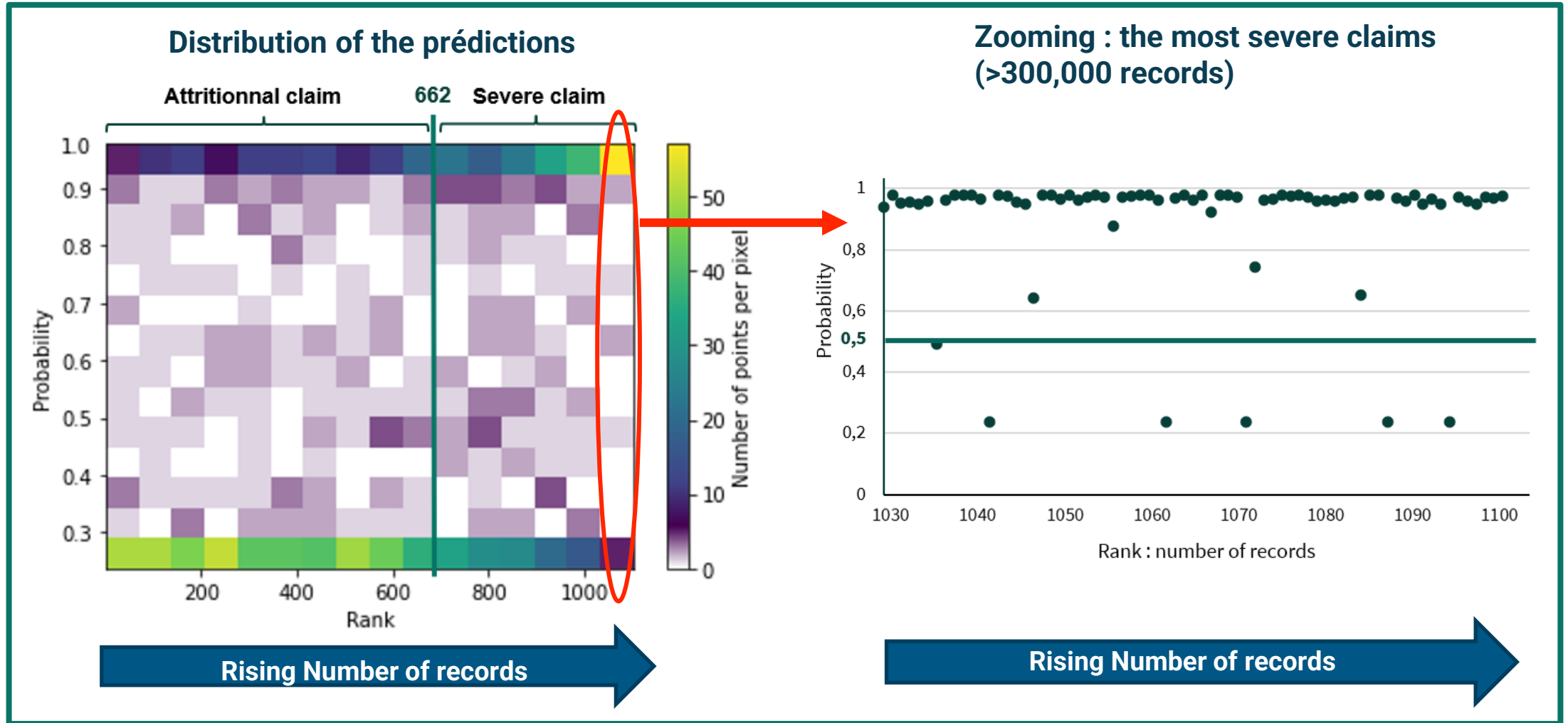
		Severity?	
		0	1
Pred	0	479	176
	1	182	265

F1-Score = 60%

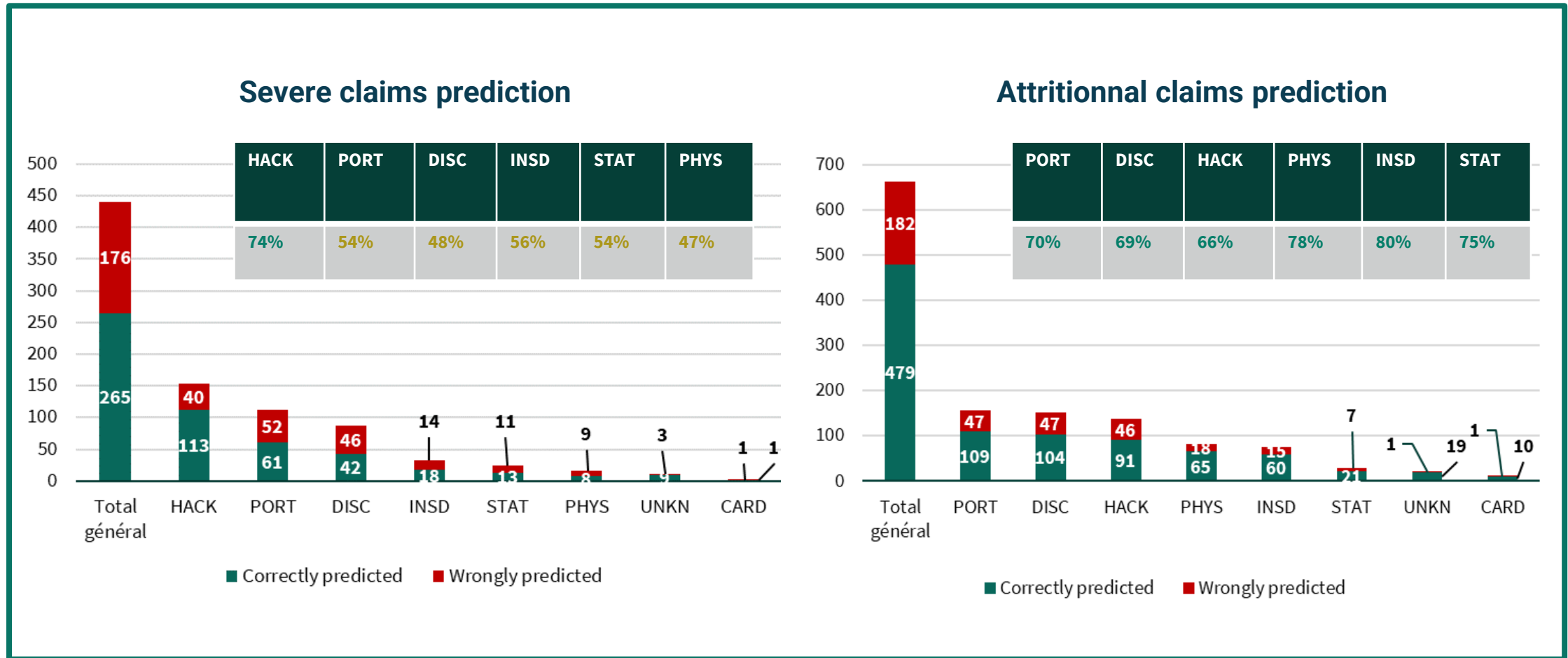
Results : Distribution of the predictions



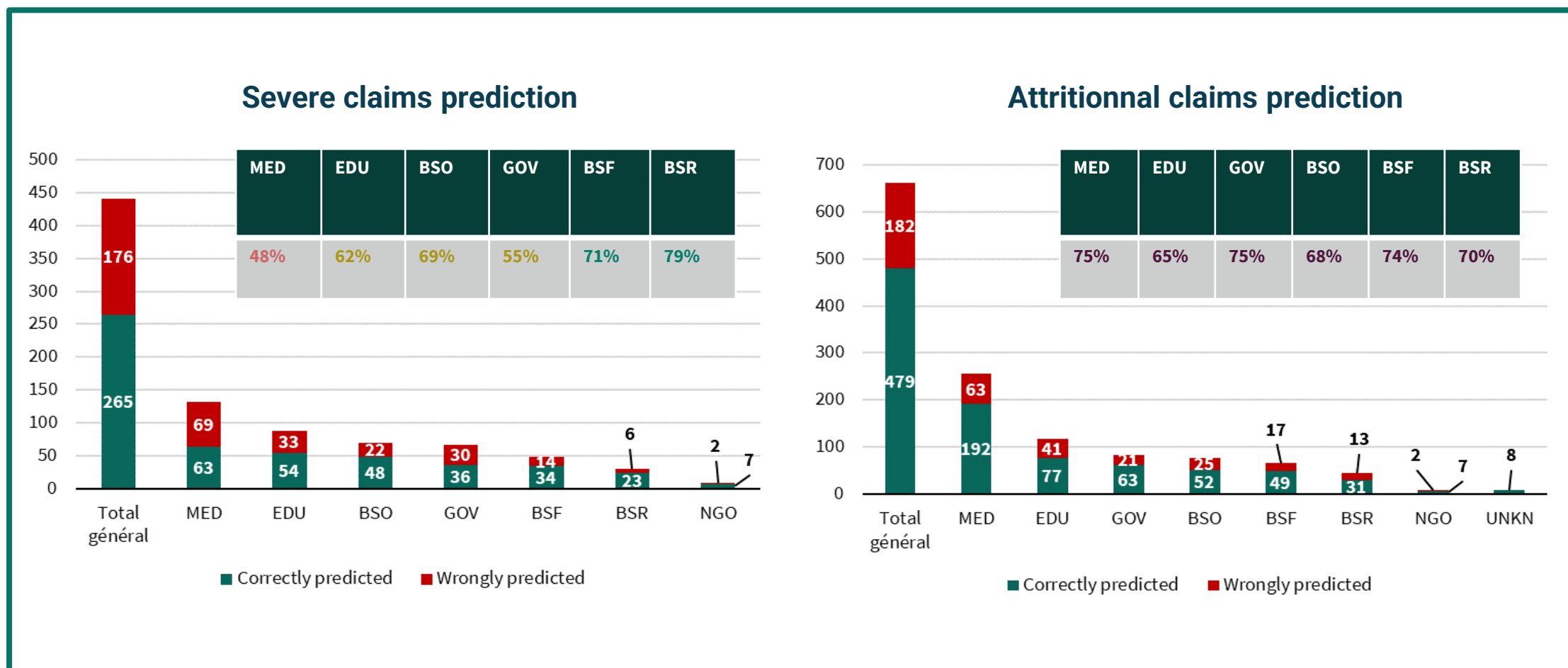
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Prediction quality by type of intrusion



Prediction quality by type of organisation





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Text mining : expressions régulières

A neural network cannot understand nor interpretate the link between numbers and words

12 social security numbers \neq 12 companies
 \neq 12 million

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How to use and interpretate numerical data within claim descriptions ?

- In 50% of the descriptions, we can observe frequent forms such as :

number × words

- **Those informations are directly linked to the value of the *number of records* variable**

=> The numerical data is a direct indicator of the claim severity

Text mining : regular expressions

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Approximation :

*A hacker [...] has potentially revealed the names, Social Security numbers, and, in some cases, the birth dates and bank accounts of **27,000 employees** working at **1,900 companies** nationwide.*

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Regular expressions

Dictionary

Word	nb. Pred false	nb. Pred True	Total	Predictive power ?
patient	16	55	71	77%
people	15	52	67	78%
million	43	5	48	10%
record	2	27	29	93%
student	4	24	28	86%
employee	2	22	24	92%
current	7	14	21	67%
individual	2	19	21	90%
year	12	7	19	37%
customer	3	15	18	83%
...

Word	nb. Pred false	nb. Pred True	Total	Predictive power ?
companies	5	0	5	0%

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Dictionnaire V et paires (N_u, M_u)

$$\sum_{k=0}^n N_u \mathbf{1}_{M_u \in V} < \text{Seuil}$$

Let's come back to our example

A hacker [...] has potentially revealed the names, Social Security numbers, and, in some cases, the birth dates and bank accounts of **27,000 employees** working at **1,900 companies** nationwide.

$$27000 * 1 + 1900 * 0 = 27000 > 4700$$

This is a severe claim for our new estimator !

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This is a severe claim for our new estimator !

Type of organisation	Perceptron	Regular expressions
MED	63	+ 10
EDU	54	+ 11
BSO	48	+ 7
GOV	36	+ 10
BSF	34	+ 1
BSR	23	+ 0
NGO	7	+ 1

Number of severe claims with method used



Summary

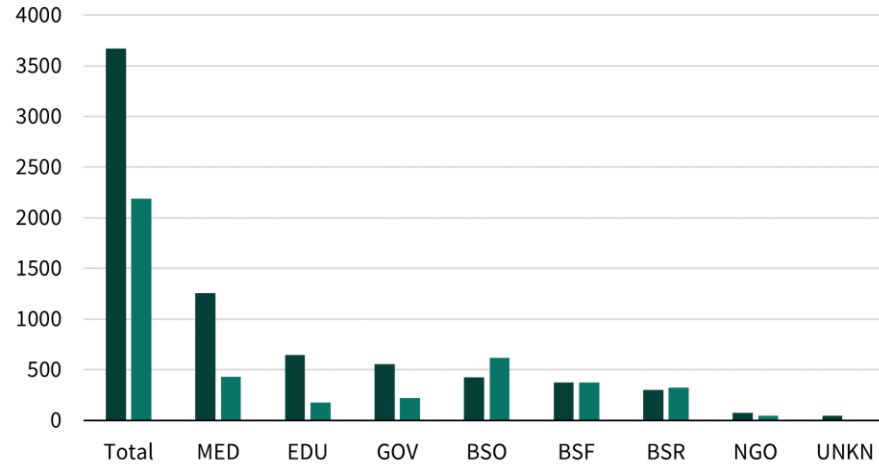
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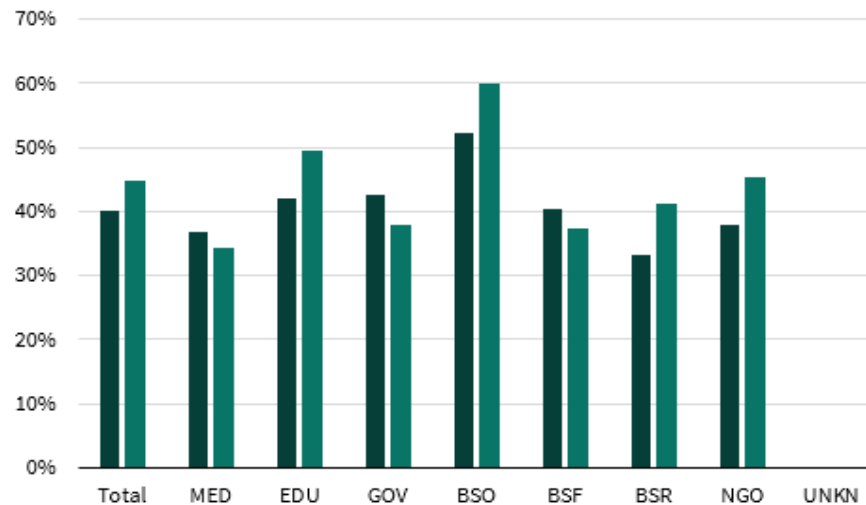
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Database : missing number of records



BSO, BSF, BSR

- The business categories are particularly represented in the sub-database
- The diagnosis (regarding the nb. of records) seems hence less transparent



EDU & business unaffiliated to the financial and banking field (BSO, BSR)

- Higher rate of severe claims

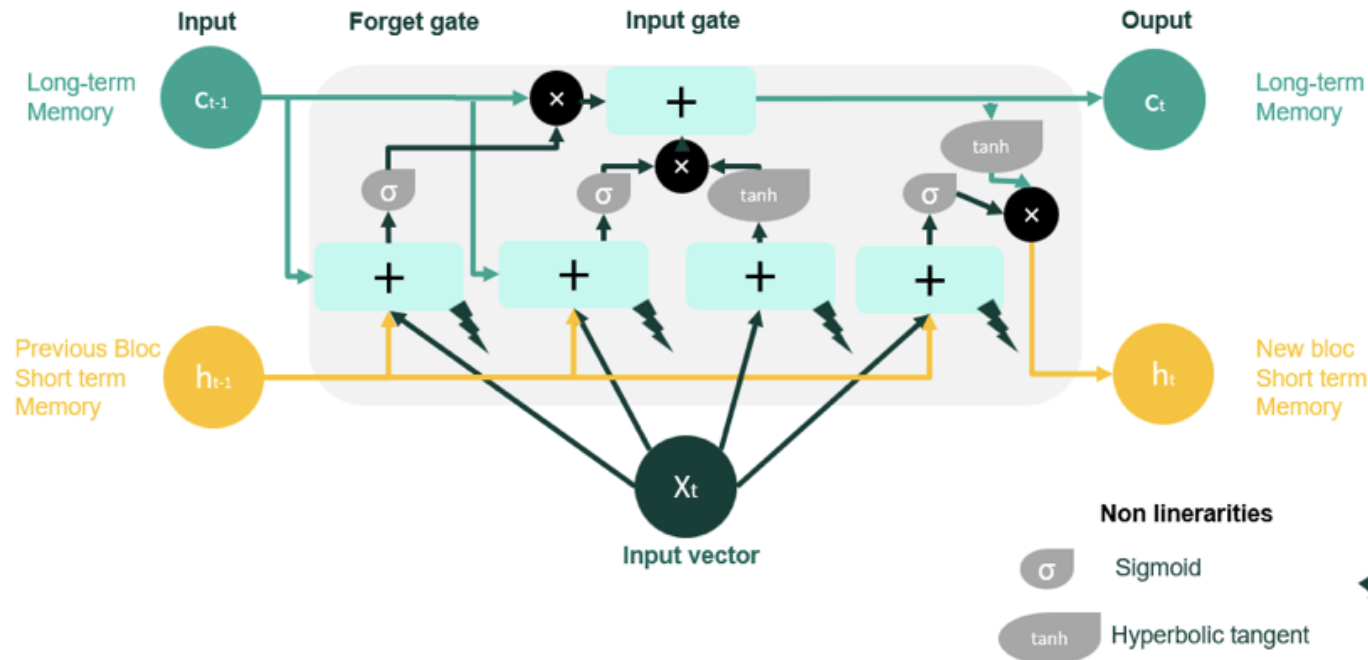
Hypotheses :

- Those type of organisations are "inferior" when it comes to doing a diagnosis
- They do not wish to or do not know how to quantify the loss related to the lost data

The issue of claim management

- Cyber insurance has a component of **victim assistance**
- Despite the assistance business not being new, the insurer lacks expertise in the cyber component
- A use of the presented methods : **Help detecting the claims that need a particular type of answer, to improve the way they are handled** (and to minimize their detrimental consequences)
- **Input** : Claim reports, preliminary expertise
- **Output** : diagnosis and assistance recommendations
- **Extension** : Follow-up of the evolution with time of the claims

Recurrent Neural Network (RNN) for text analysis



- Example of the LSTM
- Other reference on connex issue : Cohen-Sabban,I.,Lopez,O.,Mercuzot,Y. (2021) *Automaric analysis of insurance reports through deep neural networks to identify severe claims*, **Annals of Actuarial Science**.

Perspective of evolution : the bayesian

Differences in the type of vision :

- **Frequentist approach** : we have (X_1, \dots, X_n) of distribution \mathbb{P}_{θ_0} , and we infer/estimate θ_0 using those only informations
- **Bayesian approach** : We suppose θ_0 to be a random variable, of given distribution *a priori* π , and we observe (X_1, \dots, X_n) of distribution, given $\theta_0 = t, \mathbb{P}_t$
- The *a priori* approach implies a preliminary insight/diagnosis
- Question : how can we transform this insight mathematically speaking ?

Thank you!

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