ALGORITHMIC INSURANCE

AGNI ORFANOUDAKI

Joint work with Prof. Dimitris Bertsimas
Sloan School of Management, MIT
Saïd Business School, University of Oxford

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THE RISK OF AI

Rishi Sunak races to tighten rules for AI amid fears of existential risk

PM pushes allies to draw up agreement that could lead to global regulator, as industry warns new white paper is already out of date

Is No 10 waking up to dangers of AI?

AI poses existential threat and risk to health of millions, experts warn

BMJ Global Health article calls for halt to 'development of self-improving artificial general intelligence' until regulation in place

25 November 2022

Majority of world's population feel self-driving cars are unsafe

Global research by safety charity Lloyd's Register Foundation has uncovered that only a quarter (27%) of the world's population would feel safe in self-driving cars.

HUMAN RIGHTS CHANNEL
LA CHAÎNE DES DROITS HUMAINS

es > How to protect ourselves from the dangers of artificial intelligence

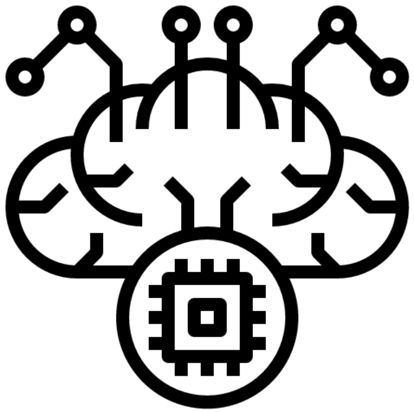
How to protect ourselves from the dangers of artificial intelligence

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.

ALGORITHMIC AVERSION

Vs



Who bears the responsibility for algorithmic mistakes?

THE CAR INSURANCE ANALOGY

THE IDEA OF ALGORITHMIC INSURANCE

BENEFITS OF ALGORITHMIC INSURANCE

WHAT IS THE GOAL OF THIS WORK?

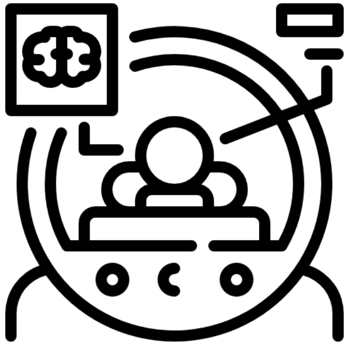
Goal

Provide a quantitative framework for insurance companies and ML modelers in order to estimate the risk of these products.

Examples

Self-driving cars

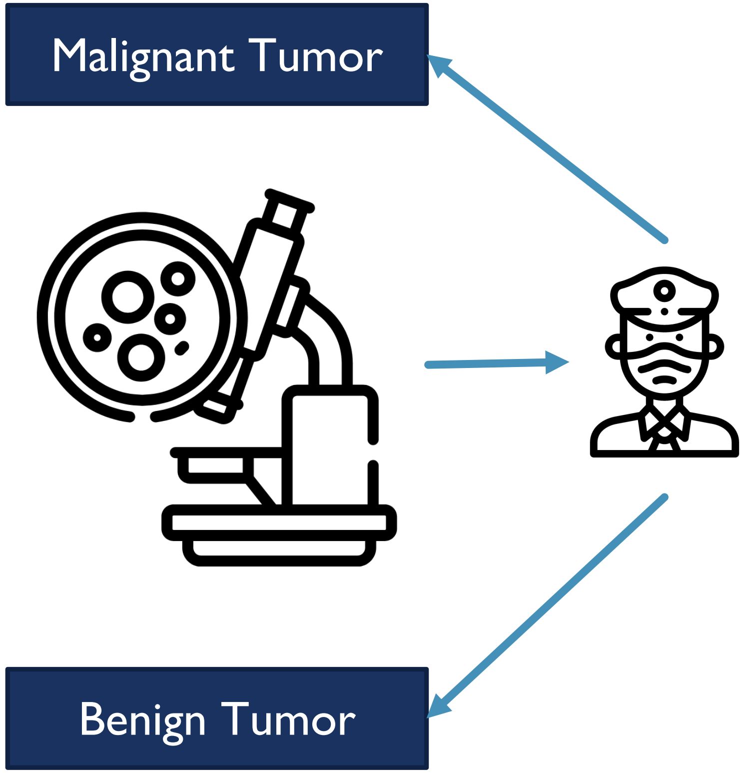
Car Insurance



MRI machines

Medical Liability

THE CLINICIAN DECISION MAKER



What are the scenarios for medical liability?

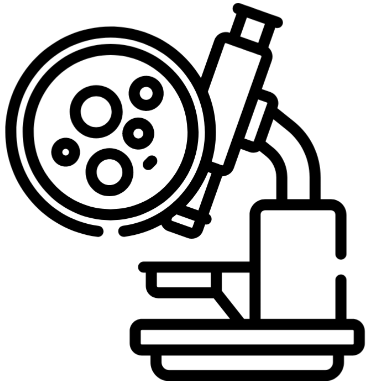
Patient True Outcome	Doctor diagnoses cancer	Doctor does not diagnose cancer
Patient has cancer	\$0.0	$T \sim (M, \sigma_T)$ **False negative**
Patient does not have cancer	$S \sim (\mu, \sigma_S)$ **False positive**	\$0.0

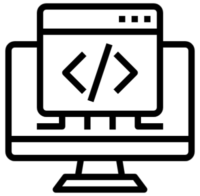
THE ML DECISION MAKER

Malignant Tumor

$p > \tau$

The pathology department has specified a ***classification threshold τ*** *for the probability of being positive at the test.*





Output: p – the probability that the patient has breast cancer

$p \leq \tau$

Benign Tumor

↓ τ → ↑ sensitivity → ↓ false negative rate & ↑ false positive rate

↑ τ → ↓ sensitivity → ↑ false negative rate & ↓ false positive rate

WHAT IS THE COST FOR A SINGLE CLAIM?

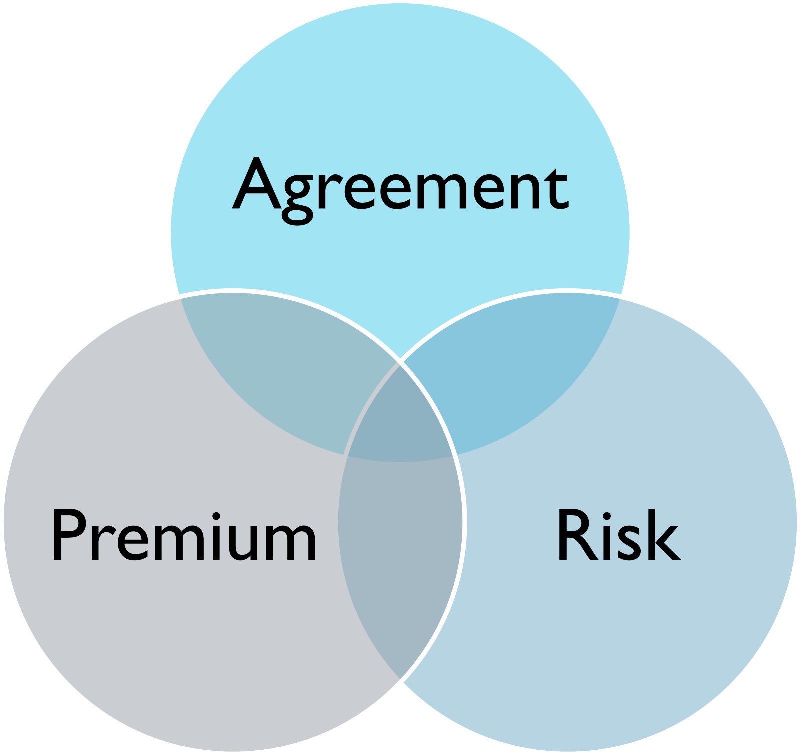
- The expected claim cost of a new patient that is tested by the ML model is:

$$c_{ml} = (1 - \underbrace{\kappa_\tau}_{p(\text{false positive})})\mu + (1 - \overbrace{\lambda_\tau}^{p(\text{false negative})})M$$

- If we assume that N patients arrive at the hospital, the total expected loss of the insurance company is: $C = Nc_{ml}$

QUANTIFYING THE RISK EXPOSURE

THE BUILDING BLOCKS OF A CONTRACT

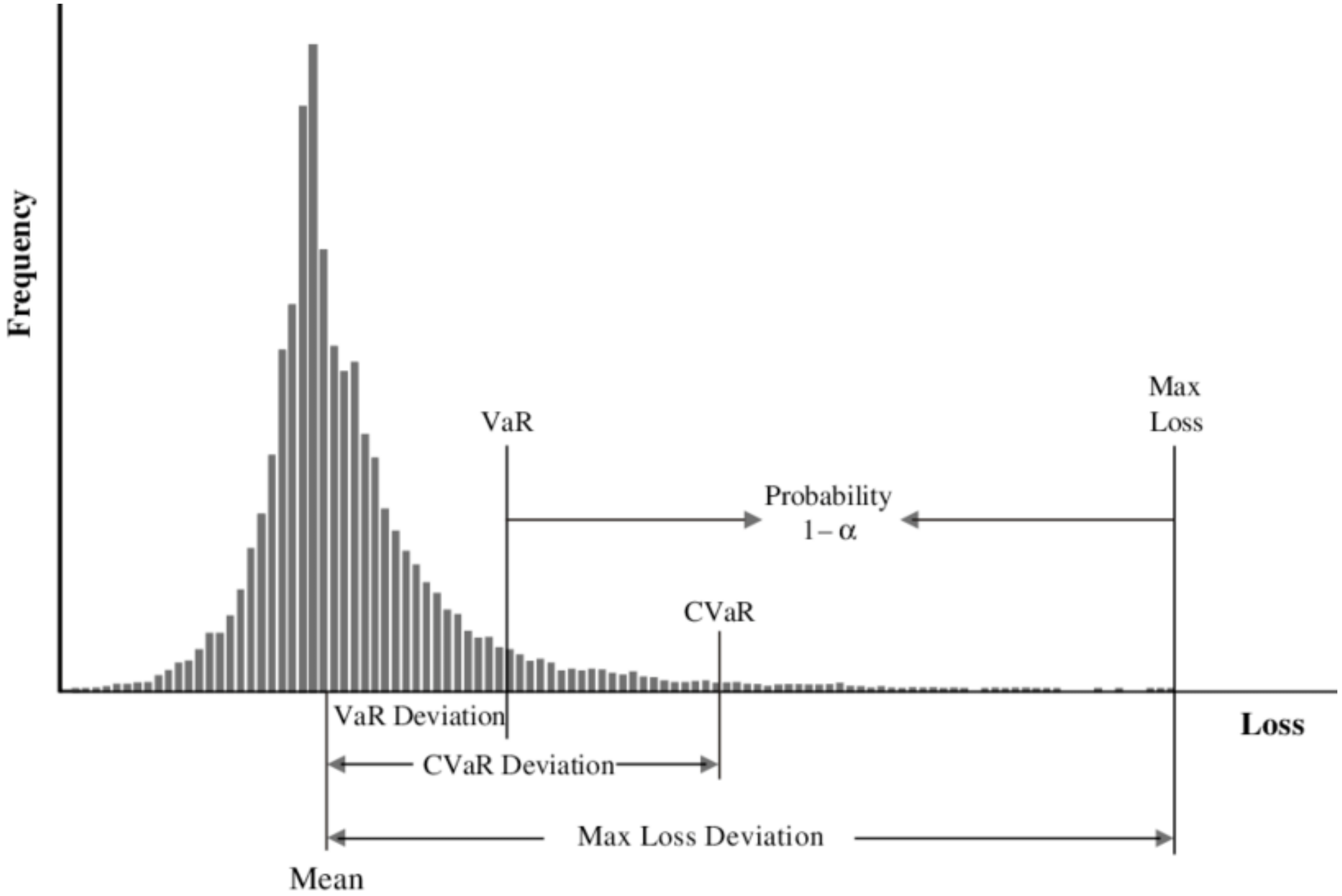


PRICE DETERMINATION AND RISK

- The determination of **price** depends on how much **risk** the company is willing to take.

- We result to the finance industry and well established performance measures of risk:
  - **Value-at-Risk (VaR)**
  - **Conditional-Value-at-Risk (CVaR)**

VAR AND CVAR



- Value-at-Risk (VaR): what is the maximum loss with a specified confidence level.

- Conditional-Value-at-Risk (CVaR): average of the losses that fall beyond the VaR cut-off.

AN LP FORMULATION TO MINIMIZE CVAR

Extending the formulation proposed by Uryasev in 2000, we present an approach for the simultaneous calculation of VaR and CVaR using linear programming techniques.

$$\min \alpha + \frac{1}{(1-\beta)J} \sum_{j=1}^{J} z_j$$

$$\text{s.t. } z_j \geq f\left(\vec{x}, \overrightarrow{y_j}\right) - \alpha, \quad j = 1, \dots, J$$

$$z_j \geq 0, \qquad j = 1, \dots, J$$

$$\vec{x} \in \boldsymbol{X}$$

Past scenarios of loss

Uryasev, S., 2000, March. Conditional value-at-risk: Optimization algorithms and applications. In *Proceedings of the IEEE/IAFE/INFORMS 2000 Conference on Computational Intelligence for Financial Engineering (CIFEr)(Cat. No. 00TH8520)* (pp. 49-57). IEEE.

BASELINE FORMULATION FOR RISK ESTIMATION

We can use this formulation to estimate for a given confidence level (β) and a vector of historic claims (y_j):

- The prices ($\vec{x}$) for each product class (i.e., age groups, vehicle types).
- The Value at Risk (α)
- The Conditional Value at Risk ($\min \alpha + \frac{1}{(1-\beta)J} \sum_{j=1}^{J} z_j$)

Efficient **Data-driven** **Flexible**

CONCLUSIONS

- We have illustrated a quantitative framework for the appreciation of algorithmic risk
- Our formulation has been extended to account for noise in the scenarios y_j using robust optimization
- We incorporate properties of the model, such as its generalizability and interpretability
- Expand the framework to other areas such as self-driving cars.

Thank you!

Questions?

Paper Reference:

Bertsimas, D. and Orfanoudaki, A., 2021. Pricing Algorithmic Insurance. *arXiv preprint arXiv:2106.00839*.

agni.orfanoudaki@sbs.ox.ac.uk

@AgniOrfanoudaki