



AI and Ethics in Insurance: A New Solution to Mitigate Proxy Discrimination in Risk Modelling

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The many fairness definitions

Actuary: What is discrimination in insurance?

ChatGPT: Discrimination in insurance occurs when an insurance company treats an individual or group unfairly based on certain characteristics such as race, ethnicity, gender, age, disability, or other protected characteristics. This can manifest in different ways, such as **denying coverage** or **charging higher premiums** to **individuals or groups** based on their characteristics.

For example, if an insurance company charges higher premiums to women than men for the same coverage, it would be considered gender discrimination. Similarly, if an insurance company denies coverage to individuals with pre-existing medical conditions, it could be considered discrimination based on disability.

To prevent discrimination, **many countries have laws and regulations** that prohibit insurance companies from using certain factors in underwriting decisions and require them to provide equal access and pricing to all customers.

ON DISCRIMINATION AND REGULATORS

UK law protects all **consumers** from being discriminated against based on age, gender reassignment, marital status, pregnancy or maternity leave, disability, race including color, nationality, ethnic or national origin, religion or belief, sex or sexual orientation.

Reference: [Discrimination: your rights: Types of discrimination \('protected characteristics'\) - GOV.UK \(www.gov.uk\)](https://www.gov.uk/guidance/discrimination-your-rights-types-of-discrimination-protected-characteristics)

USA, **NCOIL** and **NAIC** advise policymakers on unfair discrimination laws. The Casualty Actuarial Association warned regulators that preventing insurers from differentiating individuals or groups with the usage of protective features such as gender or race would result in less accurate risk knowledge and modelling. Protected variables can just be the result of other non protected individual characteristics.

https://content.naic.org/sites/default/files/call_materials/Unfair%20discrimination%20law%2C%20Nov.%202011%2C%202020.pdf

In June 2021, Colorado State decided to enforce a policy protecting consumers from unfair discrimination.

[SB21-169 - Protecting Consumers from Unfair Discrimination in Insurance Practices | DORA Division of Insurance \(colorado.gov\)](https://www.colorado.gov/pacific/dora/SB21-169-Protecting-Consumers-from-Unfair-Discrimination-in-Insurance-Practices)

ON DISCRIMINATION AND REGULATORS

The European insurance regulator, **EIOPA**, issued a note on the use of artificial intelligence in insurance in June 2021. This note contains some recommendations on fairness and the non-discrimination of models and stresses out the importance of having a fair insurance system for different lines of business.

<https://www.eiopa.europa.eu/system/files/2021-06/eiopa-ai-governance-principles-june-2021.pdf>

*Nota bene: the **AI Act** will also impact the financial industry on the practices in data science: audit, documentation, ... (in progress).*

Type of product	Importance
Motor insurance	Lack of motor insurance can impact negatively the level of mobility required for employability as well as social minimum standard of living e.g. where public transport is inadequate
Health insurance	Inadequate health insurance can prevent access to adequate, basic health care, which will have a negative impact on individuals and societies
Household insurance	Has a very high protective effect against the loss of property, which can be particularly relevant for indebted families. In addition, in some Member States home insurance is a prerequisite to rent or purchase accommodation.
Third party liability insurance	Similar to home insurance, it has a very high protective effect against the loss of patrimony
Life insurance / pension provision	Provides security against poverty after retirement
Workers compensation insurance	Provides wage replacement and medical benefits to persons which are not able to work due to and injury suffered in the course of employment

Source: EIOPA Consultative Expert Group on Digital Ethics in insurance

ON DISCRIMINATION IN STATISTICS



Direct discrimination

Originally, insurers differentiated individuals based on all features to measure risk.

$$E[Y|X, S]$$

Insureds are aware of the use of personal data in risk selection/pricing and want a fairer insurance.

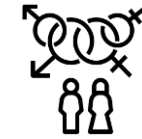


Indirect Discrimination

Insurers don't use protected variables anymore, but variable interactions lead to unfair modelling.

$$E[Y|X]$$

Insureds are discriminated against because of **proxy variables**.



The **protected variables** are defined by the law (depending to jurisdiction and industry).

Current regulation:

- Use of protected variables forbidden
- Use of certain proxy variables advised against

First efforts to define discrimination in insurance in the US with the **Disparate Impact**.

LITERARY REVIEW ON STATISTICAL PARITY

Notations

- S is a protected variable
- Classification
 - Y is the true outcome
 - $\hat{Y}$ is the predicted outcome (estimator of the variable Y)

Group fairness

- **Statistical parity:** $\hat{Y} \perp S$, equivalent to having the same acceptance rates (AR) for all groups
- **Equalized odds:** $\hat{Y} \perp S|Y$, equivalent to having the same TPR and FPR for all groups
- **Equal opportunity:** same TPR for all groups

Individual fairness

Similar individuals are treated similarly: proximity between individuals requires the definition of a distance.

		Predicted outcome	
		Positive	Negative
True outcome	Positive	TP	FN
	Negative	FP	TN

Confusion matrix

$$AR = \frac{TP + FP}{TP + TN + FP + FN}$$

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$



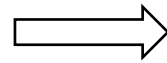
Not all fairness definitions are compatible
No actuarial fairness metric

RISK SELECTION/PRICING AND PARITY

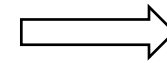
The insurance pipeline

Risk selection

Based on observations,
should I underwrite this
risk?

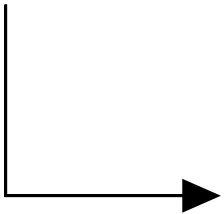


Segmentation by risk level:
homogeneous risk pools

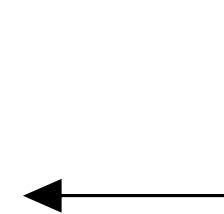


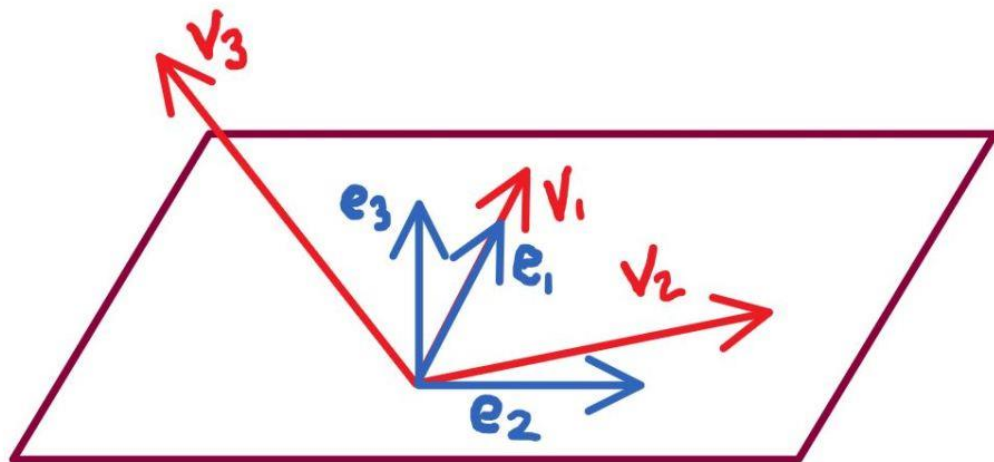
Pricing

Insurance premium based
on pool and individual
characteristics



Some criteria are not socially acceptable
The risk selection and pricing processes
cannot be discriminatory





Proxy
variables
and algebra

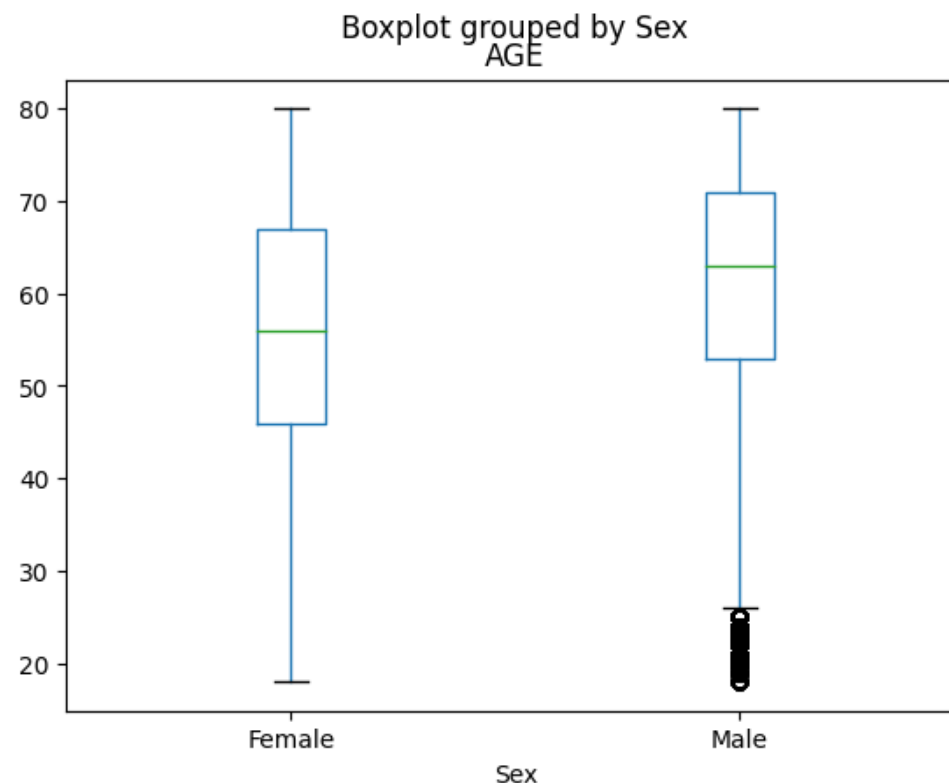
REMOVING THE SENSITIVE VARIABLES DOES NOT LEAD TO A FAIR PRICING MODEL

Observations

- Sensitive variables (gender, origin, marital status ...) are often correlated with other risk factors.
- Under/oversampling to correct the covariate distributions is not enough.
- Traditionally, actuaries and data scientists tackle the issue of fairness by removing sensitive variables from the dataset, which leads to unfair prices.

Necessity of finding a new technique to build a fair pricing model:

- Preprocessing the risk dataset to remove the *proxy variable* effects
- Adding constraints to the fitting algorithm of the model (ie gradient descent to optimize the metric)
- Postprocessing the model predictions to take fairness into account



Age (assumed non sensitive) is a **proxy variable** for Sex (assumed sensitive)

TRANSFORMING THE NON SENSITIVE VARIABLES TO MITIGATE INDIRECT DISCRIMINATION

Reminders

- Variables can be represented as **vectors** of a space.
- Covariance between variables defines a **scalar product** $\langle u, v \rangle = Cov(u, v)$.
- Variance is a proxy for the **distance** $d(u, v) = \langle u - v, u - v \rangle = Var(u - v)$.

Algorithm for decorrelating non sensitive variables from sensitive ones

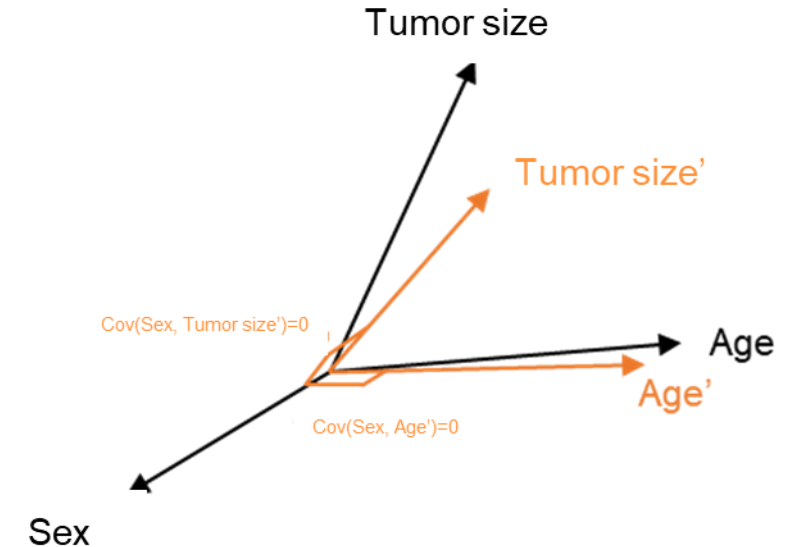
- The sensitive vectors (variables) are $u_1, \dots, u_s$
- The other (non sensitive) vectors are $u_{s+1}, \dots, u_p$
- Algorithm solves the following linear problem:

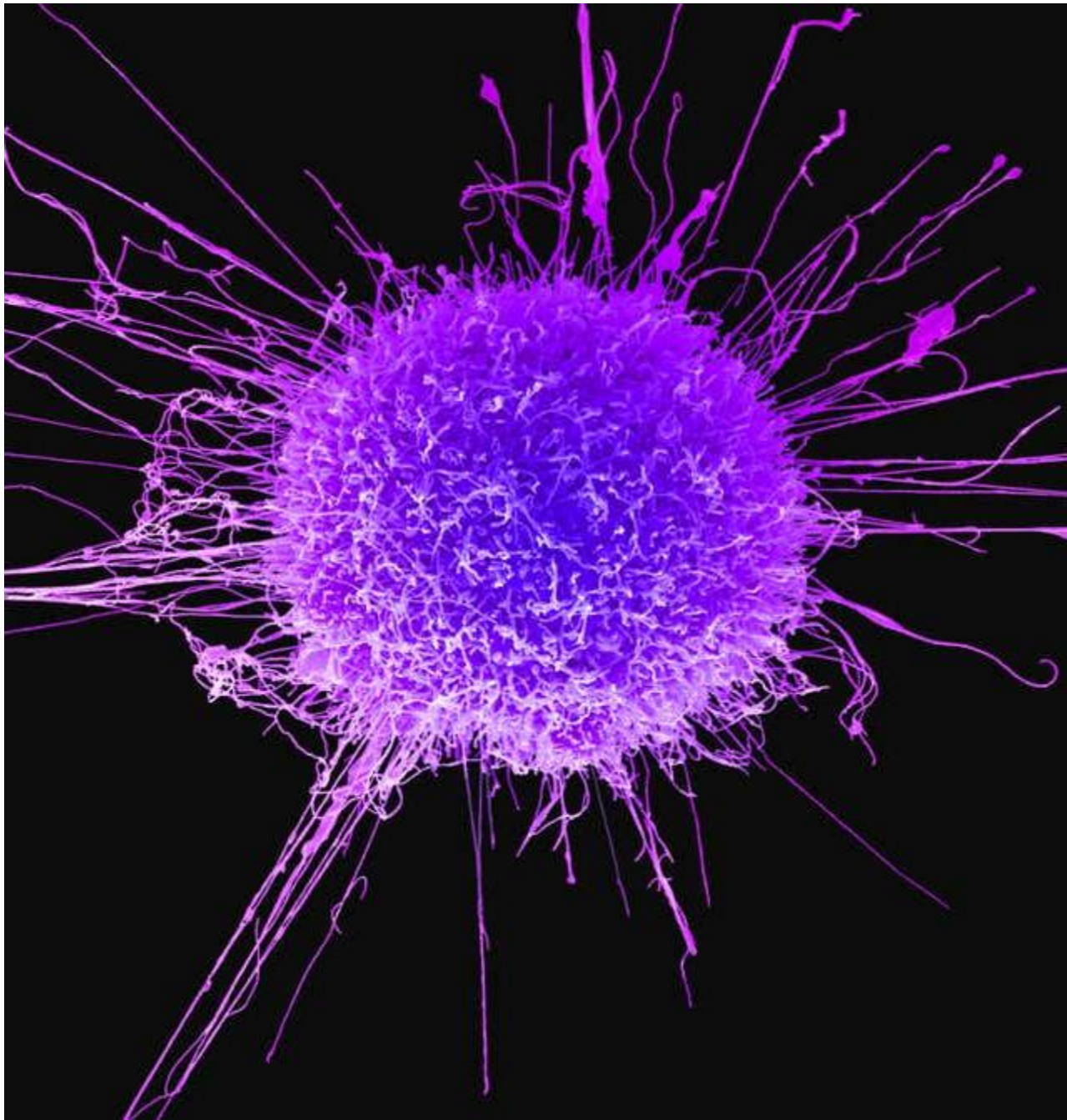
For each non sensitive vector u_k , the algorithm solves the following equation:

$$\min_{\alpha} d(u'_k, u_k) \mid u'_k = \alpha_1 u_1 + \dots + \alpha_s u_s + \alpha_k u_k$$

The **objective function** is the distance between the newly uncorrelated variable and the original variable.

We implemented a solution in Python with Numpy.





Application

A *fairer* risk selection of patients with non-metastatic melanoma of the skin

Business objective

Product class : Critical Illness

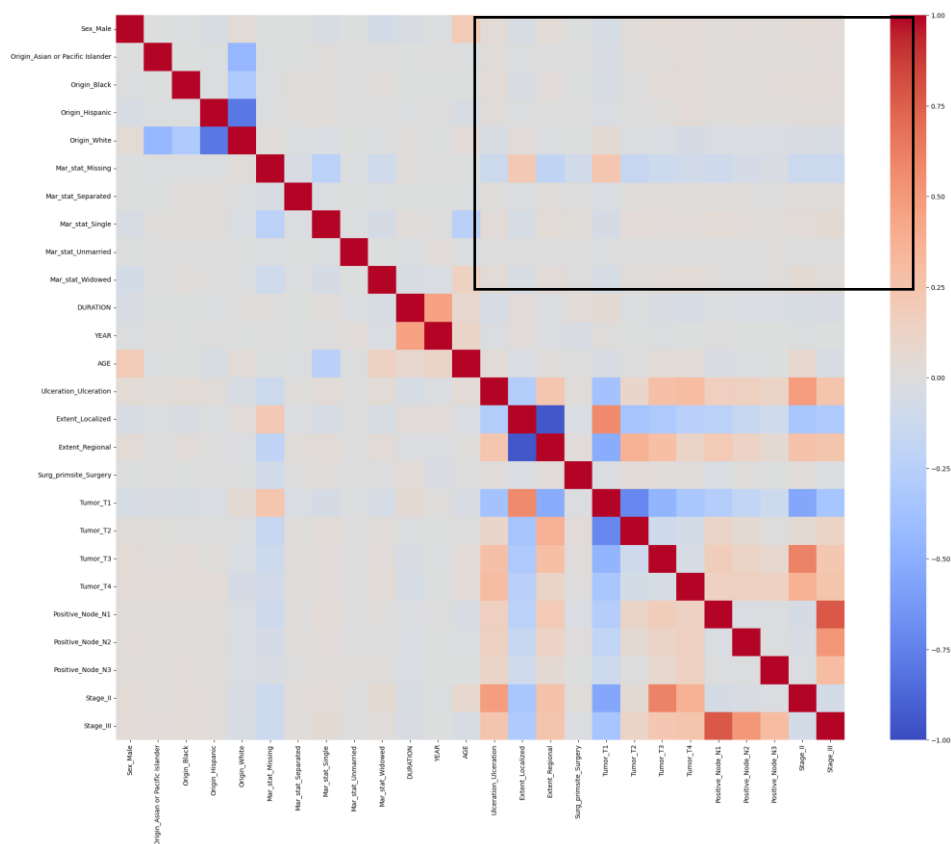
SEER – US database

- ## Model

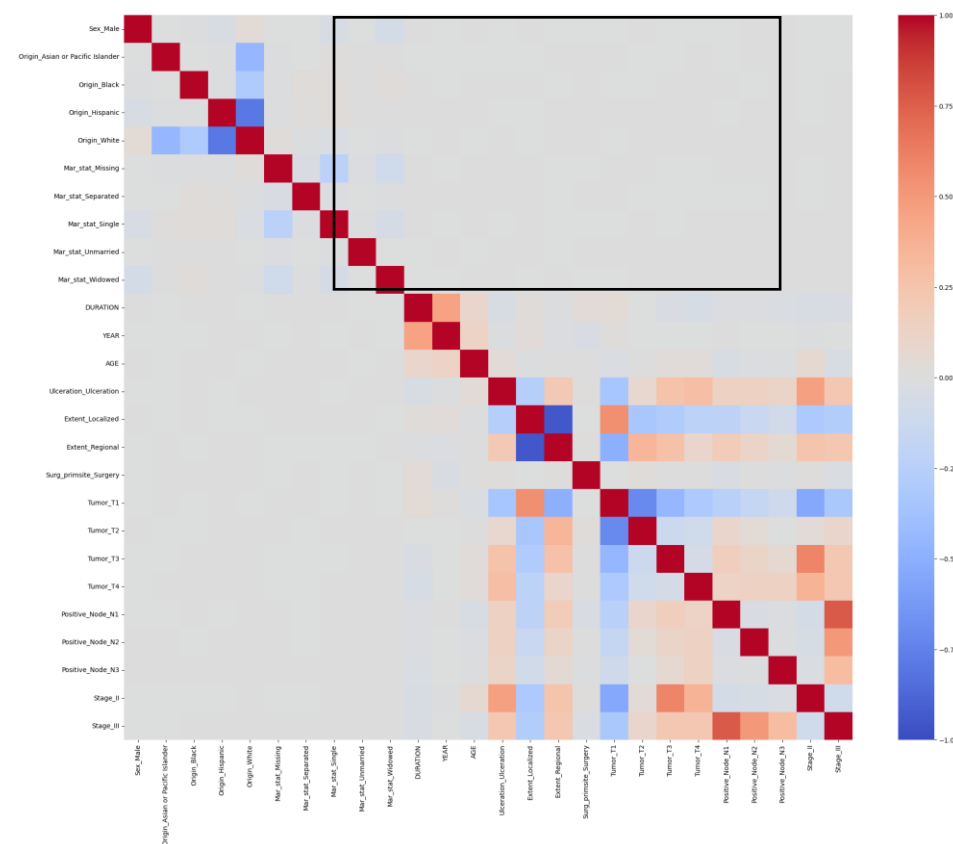
- ## Fairness constraints

- Whatever the origin, gender or marital status, insured pays the same price
- On average, all insureds pay the same original insurance premium

EFFECT OF OUR VARIABLE TRANSFORMATION ON FEATURE CORRELATIONS



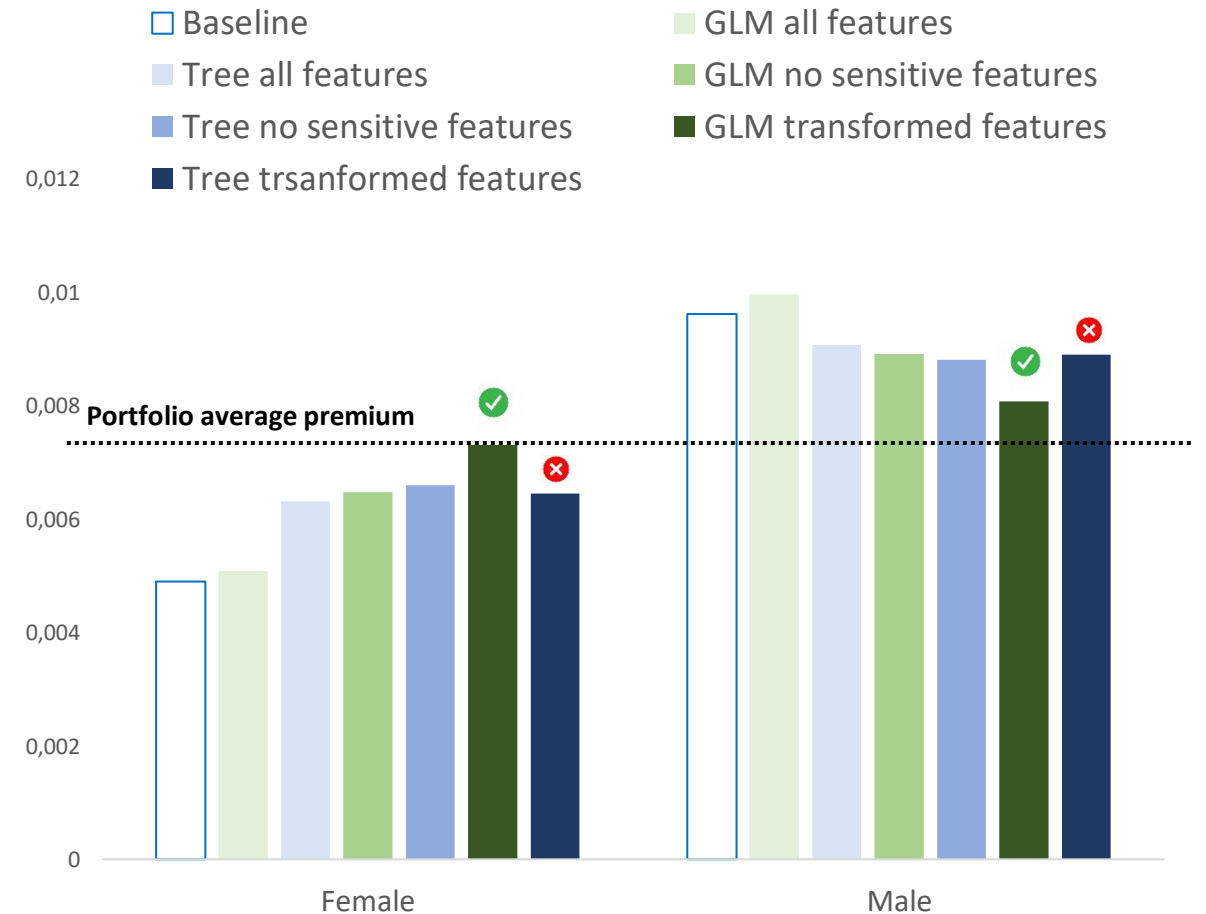
Correlation matrix of the **original** dataset



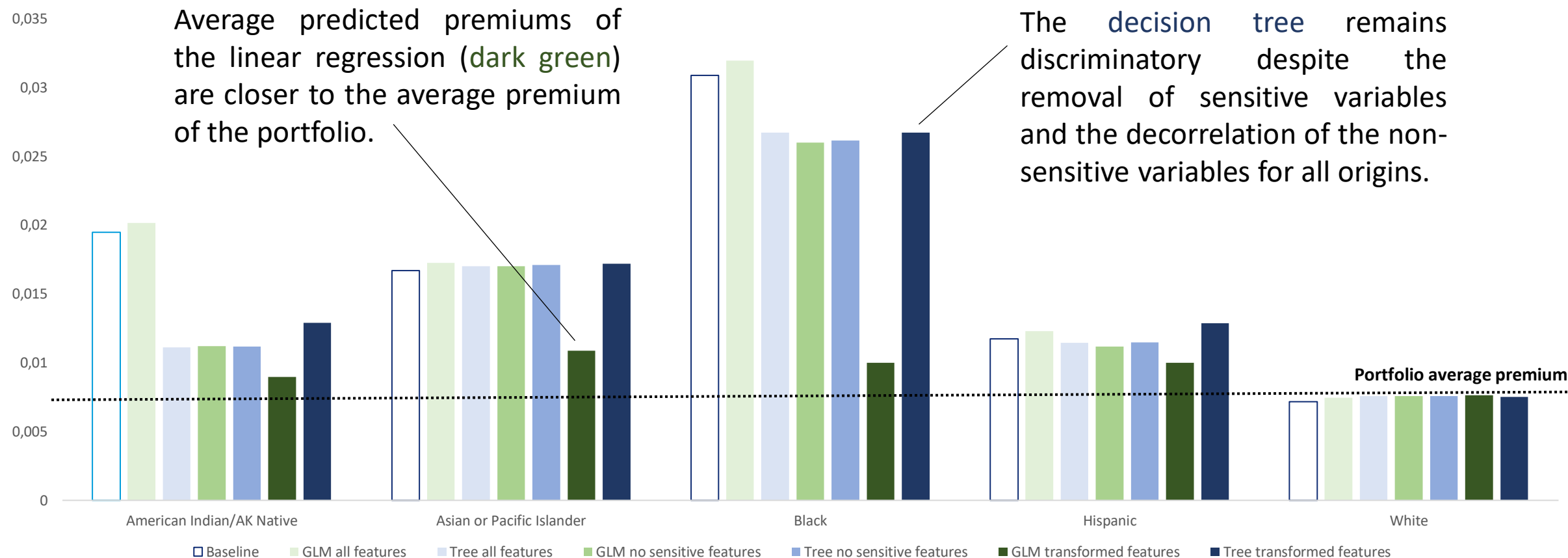
Correlation matrix with the non-sensitive **transformed** variables

EFFECTS OF OUR VARIABLE TRANSFORMATION ON AVERAGE PREMIUMS BY GENDER

- To facilitate the access to insurance coverage, discriminated subpopulations should pay the same price on average.
- The **logistic GLM** calibrated on non-sensitive and transformed variables to adjust the premium for different groups is successful. In this case, male and female pay the same price.
- **The variable transformation has no impact on the average premiums predicted by (highly) non-linear models.** This can be explained by non-linear effects not captured by the transformation applied to the data.



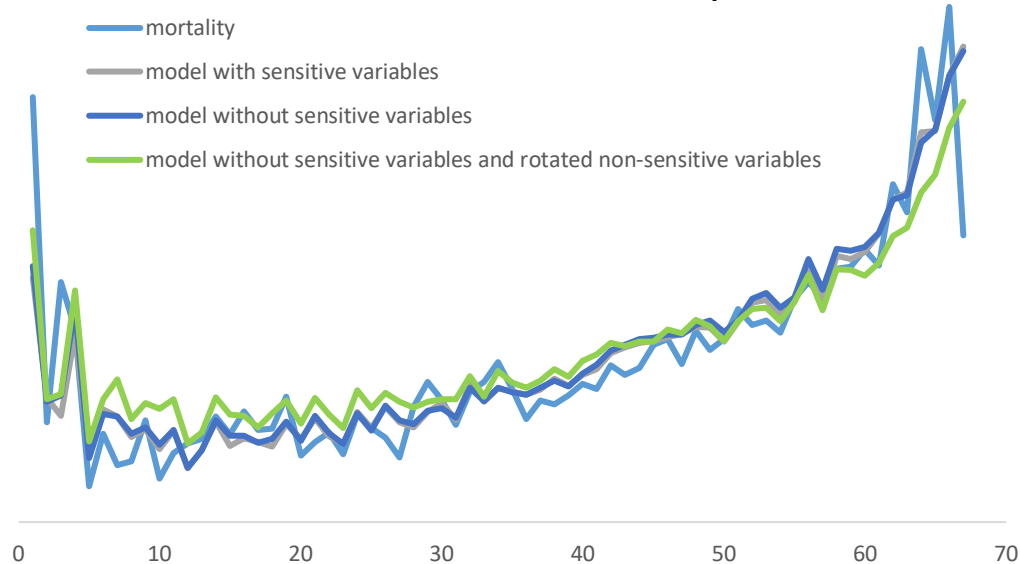
EFFECTS OF OUR VARIABLE TRANSFORMATION ON AVERAGE PREMIUMS BY ORIGIN



PREDICTED AVERAGE PREMIUMS OF THE GLM FOR NON-SENSITIVE VARIABLES

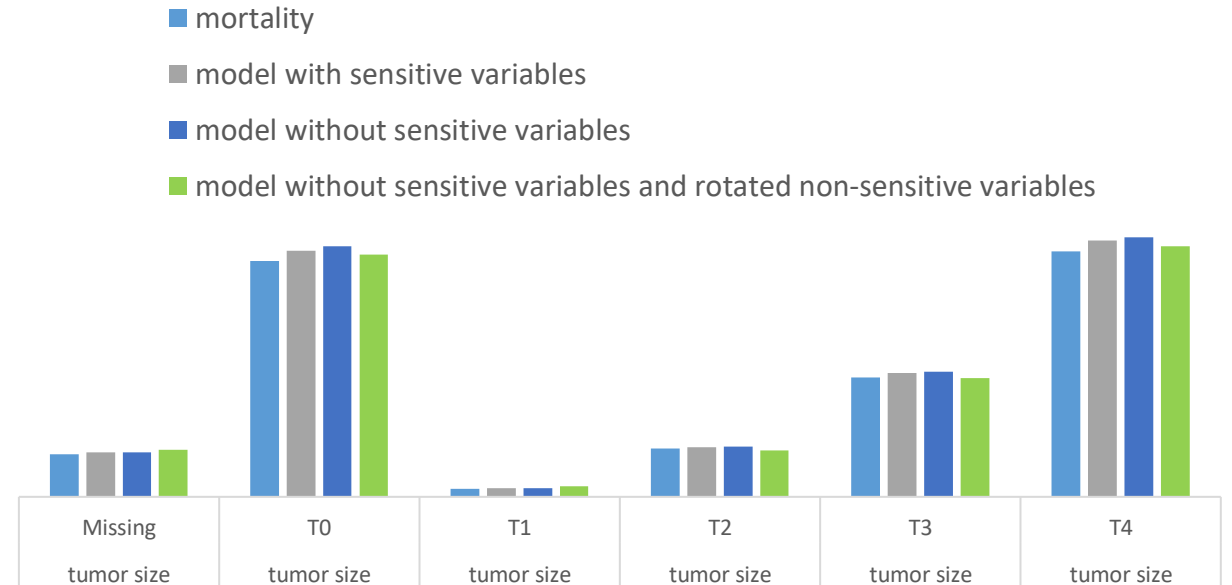
Age

- Premium by age (green line) is not significantly affected by the transformation applied to the variables.
- Slight increase for younger ages compensated by a decrease of the risk for the elderly.



Tumor size

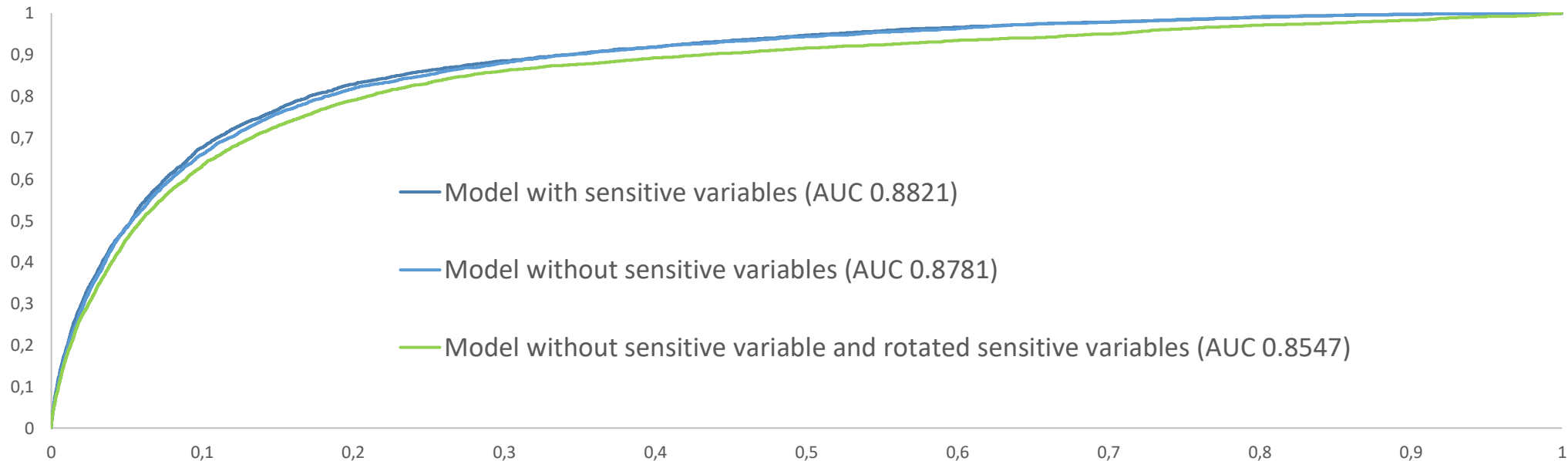
- After transformation, the predicted premiums of the GLM averaged by tumor size match the average expected mortality



PERFORMANCE

Logistic regression

- Model performance is lowered when the sensitive variables are removed. The performance of the model decreases even more with the additional decorrelation of the non-sensitive variables with respect to the sensitive ones.
- In this study, the transformation of non-sensitive variables has a measured impact on the overall performance of the model (cf. AUC score). Performance impact is $\frac{0.8821 - 0.8547}{0.8821 - 0.5} \sim 7\%$.



Regulation on discrimination and fairness of the models

- Worldwide, legal frameworks with different definitions of discrimination (Europe, UK, USA).
- Many definitions of model fairness in Artificial Intelligence.
- Actuarial community must help regulators and law makers to define fairness in insurance.

Data

- Collection of sensitive variables is required to measure the discrimination impact of a model.
- “Simple” linear algebra can help correct correlation effects between the sensitive and non-sensitive variables of a dataset.

Modelling

- The application of the transformation to a mortality dataset as a pricing exercise shows that:
 - The simple linear model predicts fairer average premiums among different subpopulations,
 - More advanced non-linear trees can split the dataset and remain unfair.
- Performance of the linear regression is moderately reduced.

REFERENCES

- *AI and ethics in insurance: a new solution to mitigate proxy discrimination in risk modeling*, Actuarial thesis, M. Saucé, March 2023, soon available at <https://www.institutdesactuaires.com/se-documenter/memoires/memoires-d-actuariat-4651>.
- Publication of an article on Arxiv (on going redaction).

Marguerite SAUCÉ started her career as an actuarial intern at SCOR working on the bias and fairness of insurance models and is now an actuarial analyst at Diot Siaci, working on climate change, cat modelling and parametric insurance.

She is an engineer specialized in statistics and also completed a Specialized Master in Actuarial Science at ENSAE Paristech.

She is a certified French Actuary.

ABOUT ME



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Antoine LY started his career as an R&D consultant for Milliman, world leader in actuarial consulting, for which he led the Paris Data Analytics team from 2018 to 2019.

Antoine graduated from ENSAE Paristech and has a PhD in applied mathematics on the application of machine learning to insurance.

He holds a MSc in Computer Science 'Data, Learning and Knowledge' from Sorbonne University and is a fully qualified French Actuary.

ABOUT ME



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Antoine CHANCEL started his career as a developer for Forsides Actuary in quantitative finance for the generation of market consistent risk neutral scenarios for Solvency 2.

He has a Master of Science in computer science and in financial mathematics. He completed a Specialized Master in Actuarial Science at ENSAE Paristech.

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ABOUT ME



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