

MERVE ALANYALI, PHD

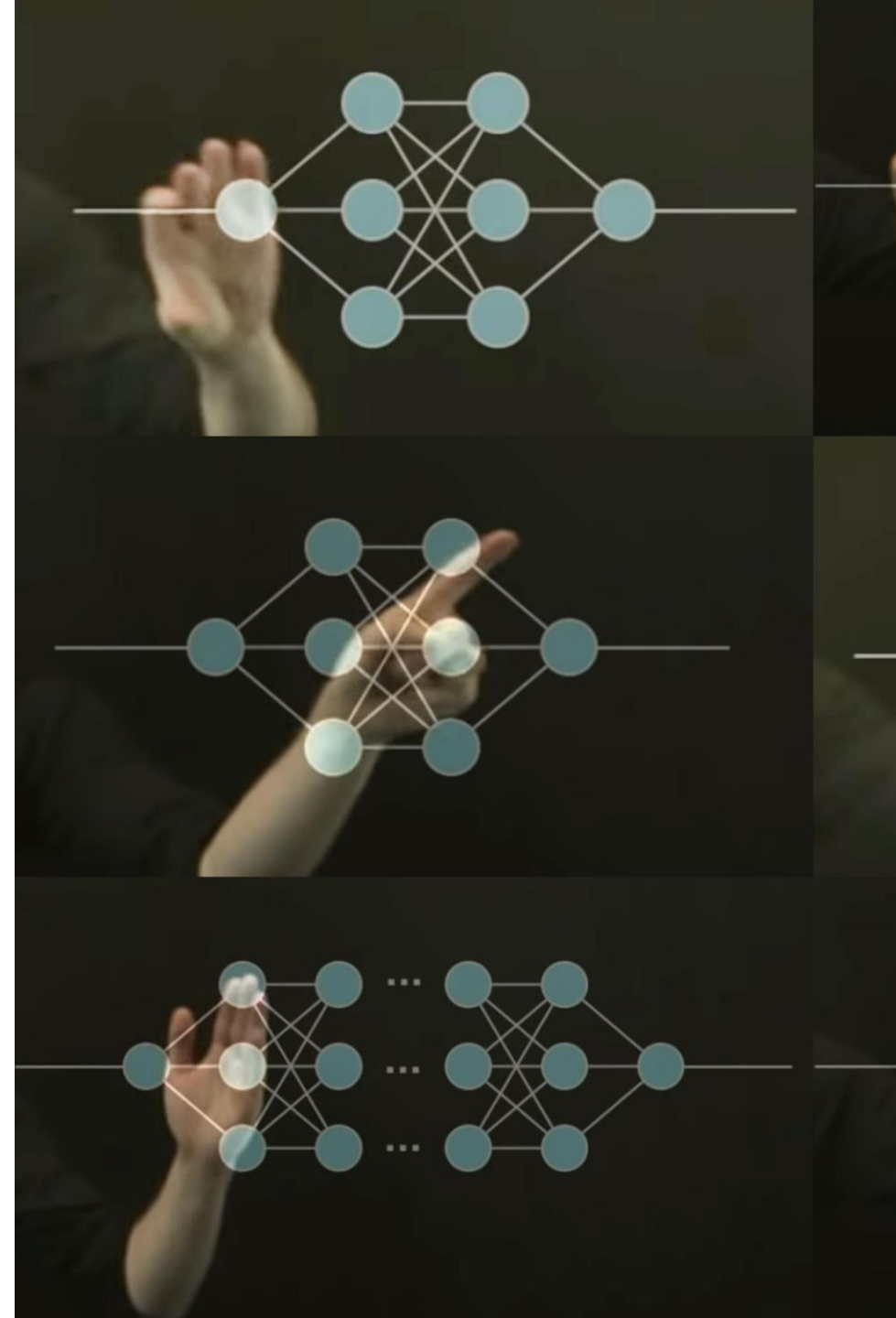
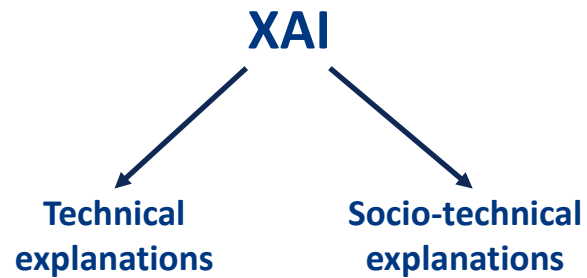
[Head Of Data Science Research
Allianz Personal]



Beyond Interpretability: An Interdisciplinary Approach to Communicate Machine Learning Outcomes

How to explain ML outcomes?

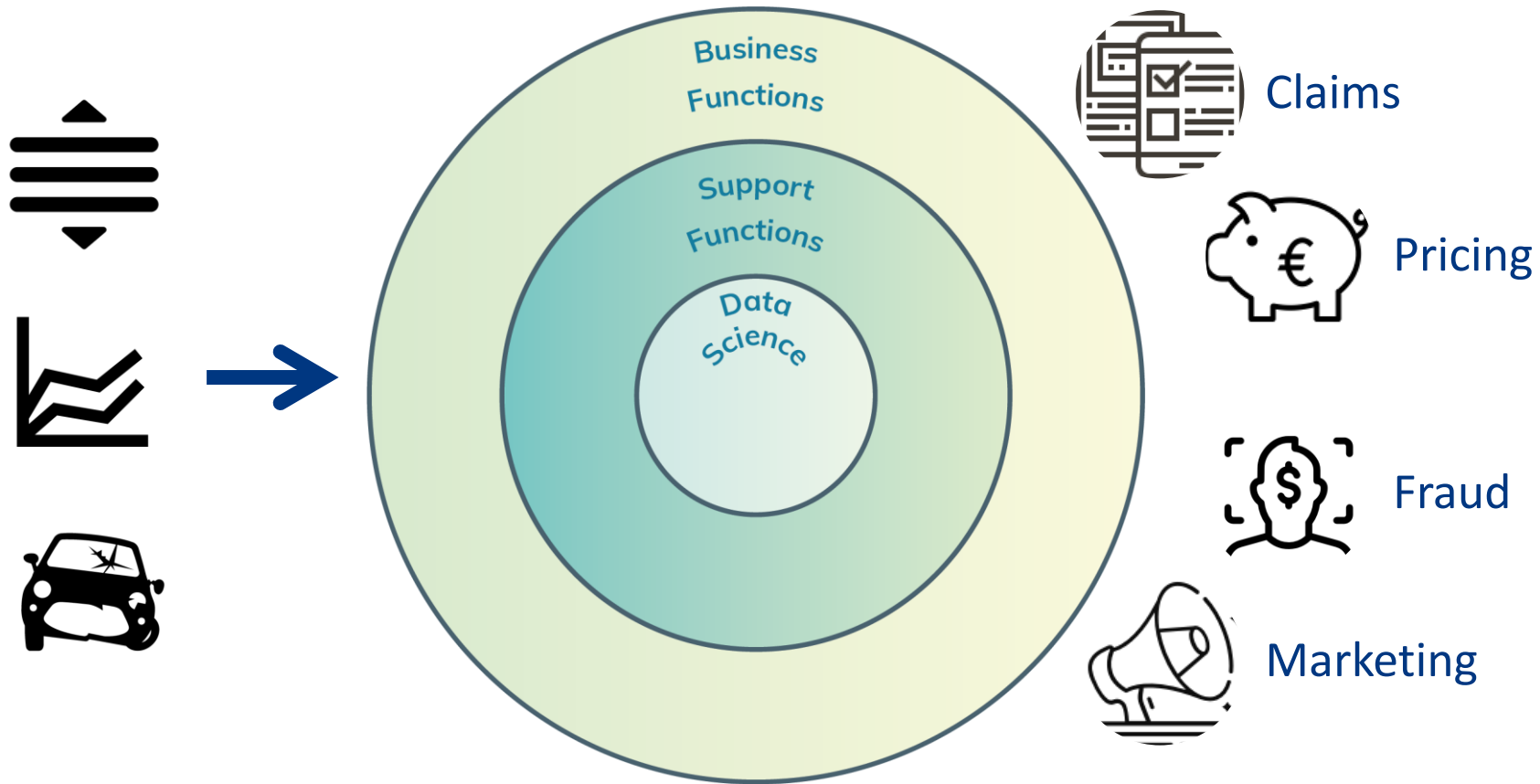
XAI often referred to as **a solution to social, ethical and regulatory considerations** of using ML models



Data Science at Allianz Personal



Putting machine learning into practice



7+ years

since
team inception

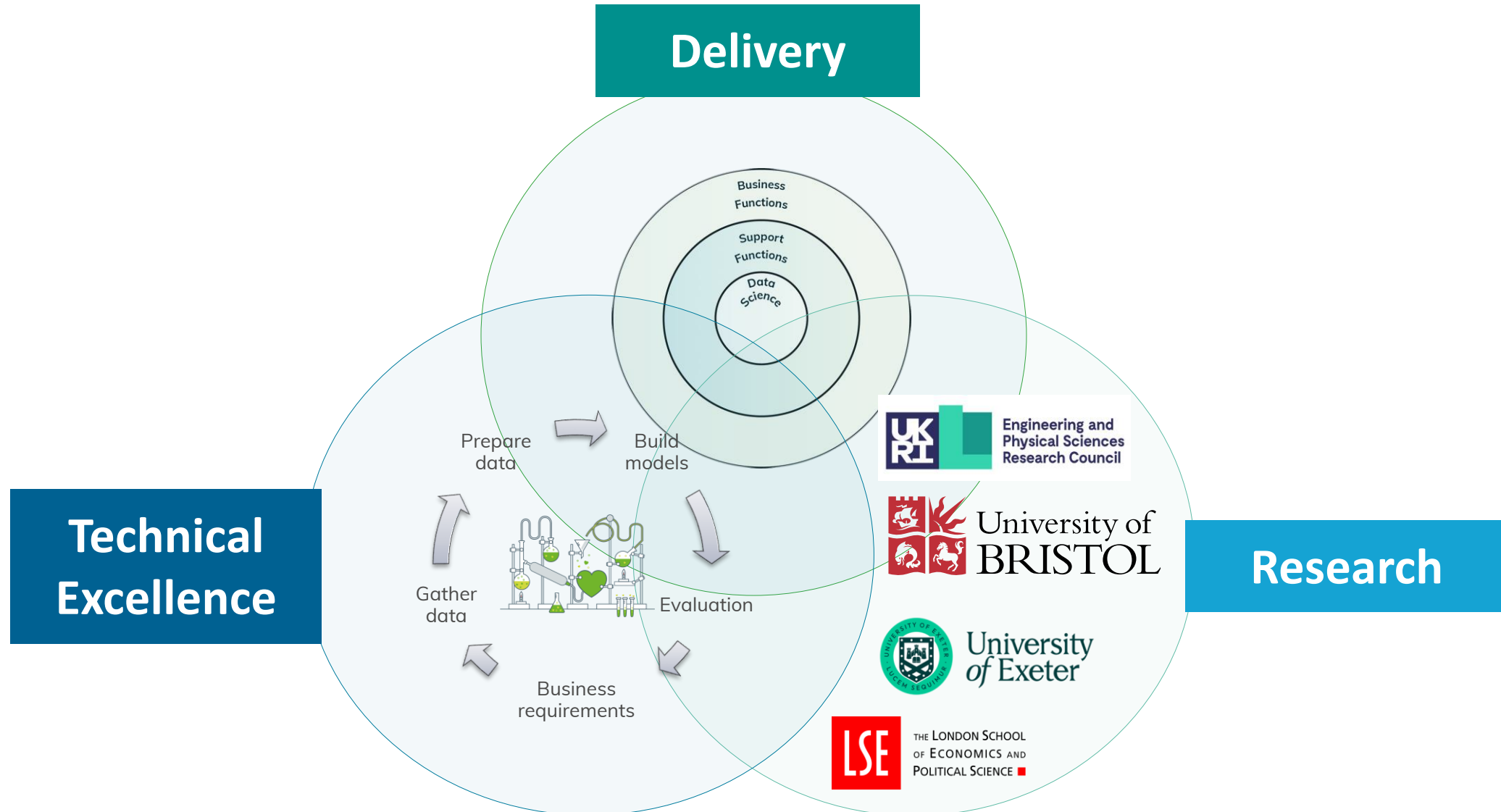
50+

decisions influenced
by mid 2023

55+

team members

Where do we focus our effort?



Interpretability vs Explainability

Interpretability

“... to understand exactly why and how the model is generating predictions,... observe the inner mechanics of the model.”

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$$

Ex: Keeping everything else same, one unit increase in x_1 will make β_1 change on y .

Explainability

“... take an ML model and explain the behaviour in human terms.”

Ex: Why does this model predict that I would find this film boring? (see the next slide for the model details😊)

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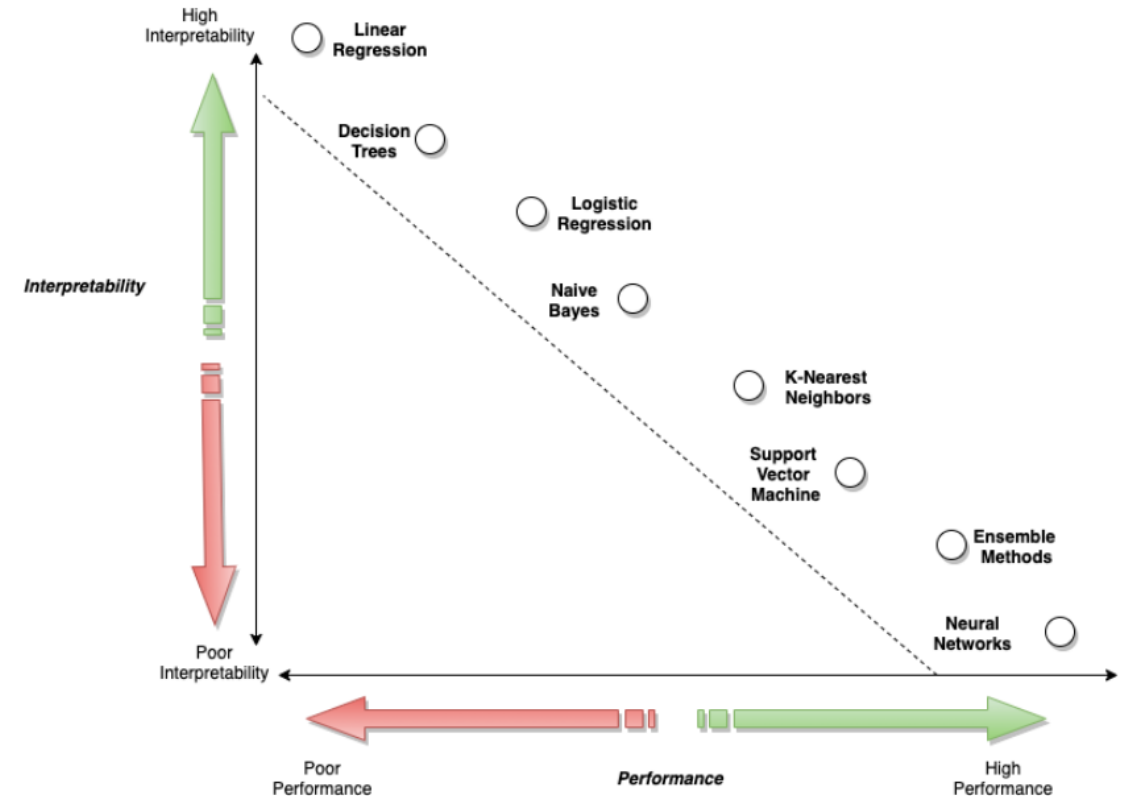
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Glass-box vs Black-box models

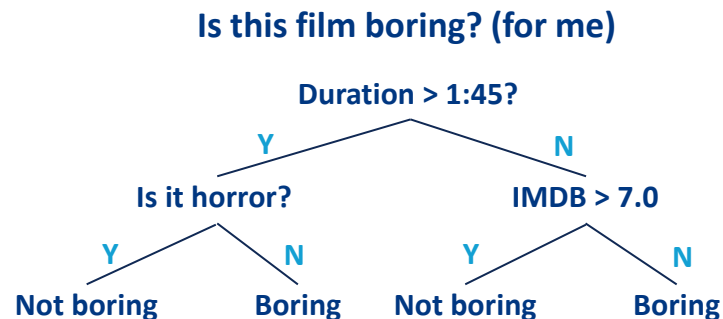
Glass-box (white-box) models

Models that are built directly for interpretability.

Examples include:

- Linear models (linear and logistic regression)
- Decision trees
- Explainable boosting machines ([paper](#), [code](#))
- Automatic piecewise linear regression ([paper](#), [code](#))

Great for interpretability however usually fall behind in performance comparison.



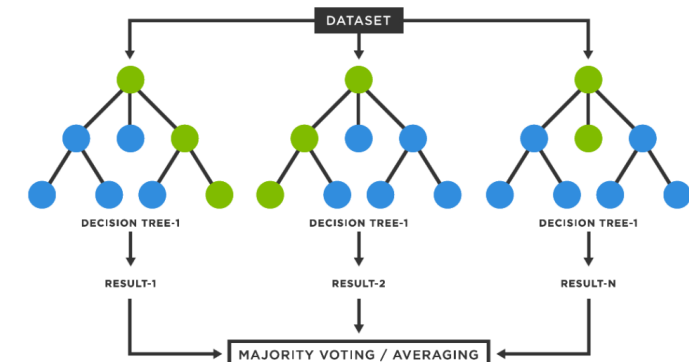
Black-box models

Models that we cannot directly extract how the model components and inner mechanics of the model impact its outcome.

Examples include:

- Ensemble methods (ex: Random forest, xgboost...)
- Deep learning models

Quite often performs better than glass-box models, however they are not easy to interpret. We need to use additional tools to provide “post-hoc” explanations.



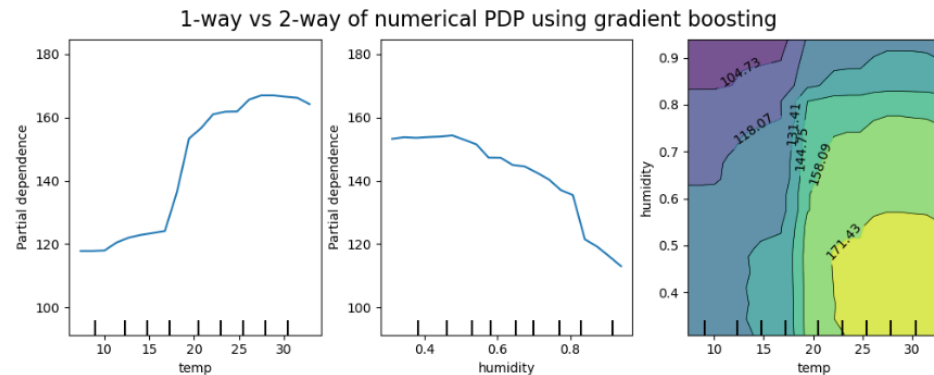
Model-agnostic methods

Global model agnostic methods

Great at creating a summary of an ML model. Useful to provide high-level explanations when communicating with stakeholders

Methods include:

- Partial dependence plots (PDPs)
- Feature importance and interaction
- Global surrogate methods

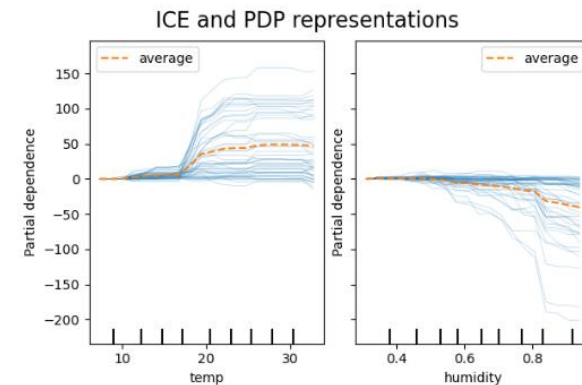


Local model agnostic methods

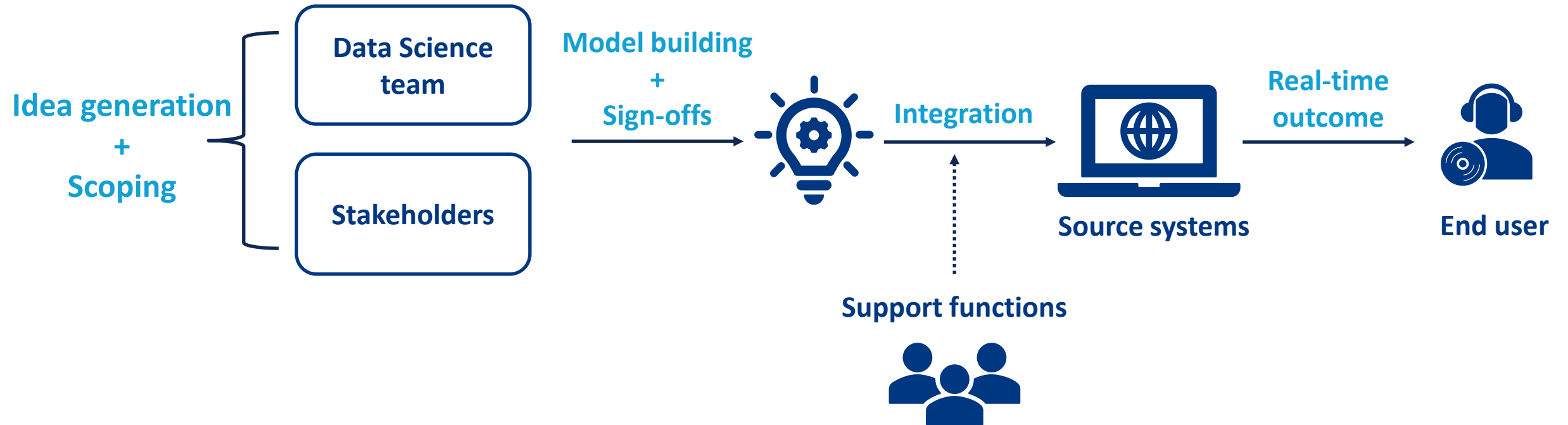
Provide explanations for individual data points. Useful for live-models to provide explanations

Methods include:

- Individual conditional expectation (ICE)
- Local interpretable model-agnostic explanations (LIME)
- Shapley additive explanations (SHAP)



End-to-end process



Bristol Digital Futures Institute collaboration



/BDFI

Bristol Digital Futures Institute (BDFI), is one of the University of Bristol's five research institutes.

The institute is working to fundamentally **transform digital innovation**, and create more inclusive, sustainable and prosperous futures for all.

- Understand the implications of innovative technologies powered by ML
- Create new knowledge and understanding of sociotechnical innovation
- Shape new ways of working across disciplines and sectors through inclusive conversations

- **Explainable AI decision making; Dr Marisela Gutierrez, Prof Susan Halford**
- Machine learning “design” and “use”; Kate Byron, Prof Susan Halford

What makes AI explainable?

Reimagining “Explainable AI”: de-centring ML models from explanations

Explaining **ML models** → Explaining “**ML practices**”

Research methodology:

- Organisational ethnography at AZP
- Co-produced with BDFI community partners



What makes AI explainable?

Reimagining “Explainable AI”: de-centring ML models from explanations

Organisational ethnography – being a “fly on the wall”

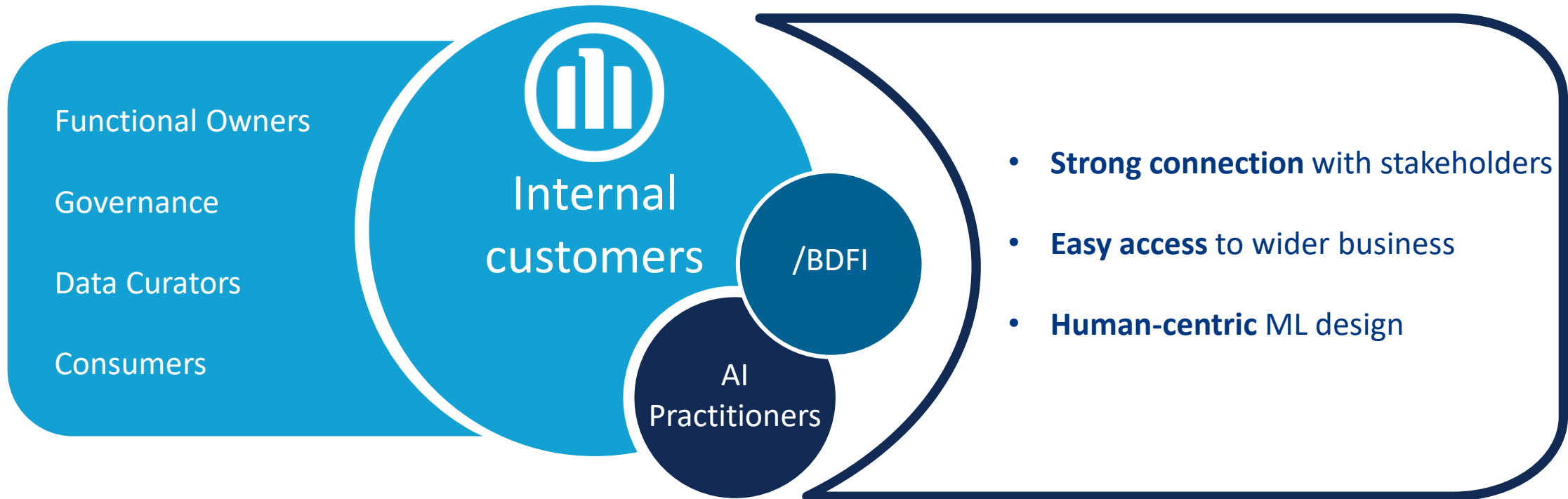
- **Shadowing** different teams and employees and **observing** various meetings
- **Interviews** to gather qualitative data
- **Review of internal documents**, communications, and public information

Research methods

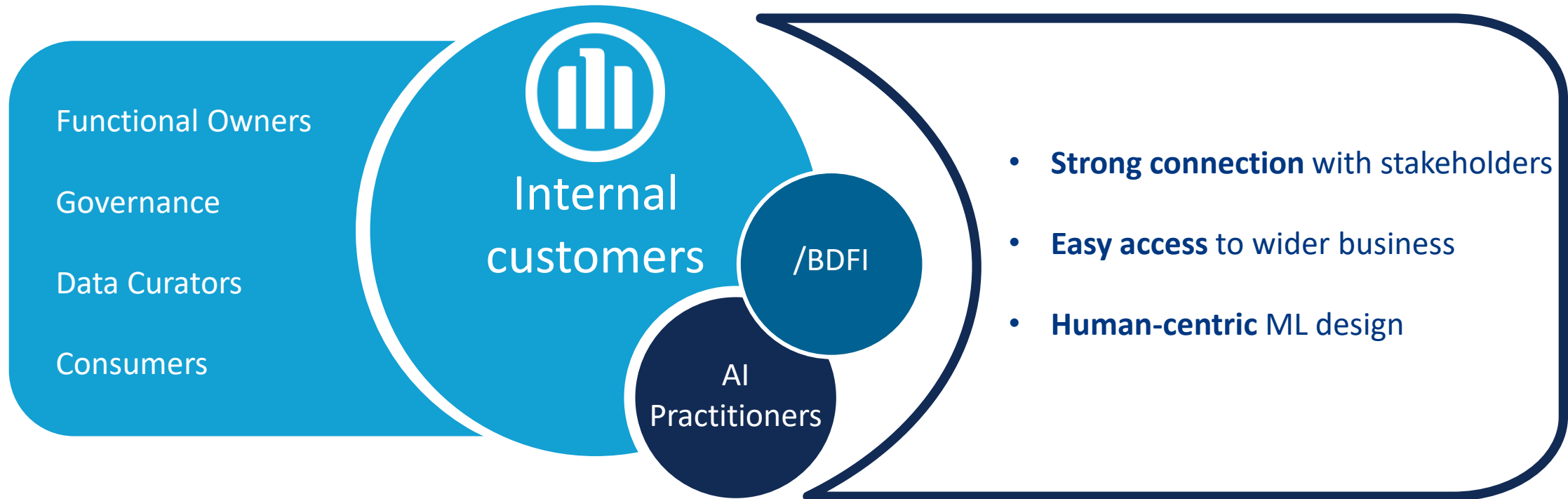
- Organisation
- Co-produce



The missing link



The missing link



Our academic partners **bridge the gap** between
our AI Practitioners and the AI Public

Co-designed = better designed



Impact from qual work

Internal workshops and launched an open-source explainability package.



Closer collaboration

End-users are co-designers, and open communication creates efficient feedback loops.



Raised awareness

Enhanced and meaningful knowledge sharing between DS team and internal customers.

Why explain ML models?

Reasons beyond regulation include (but not limited to):



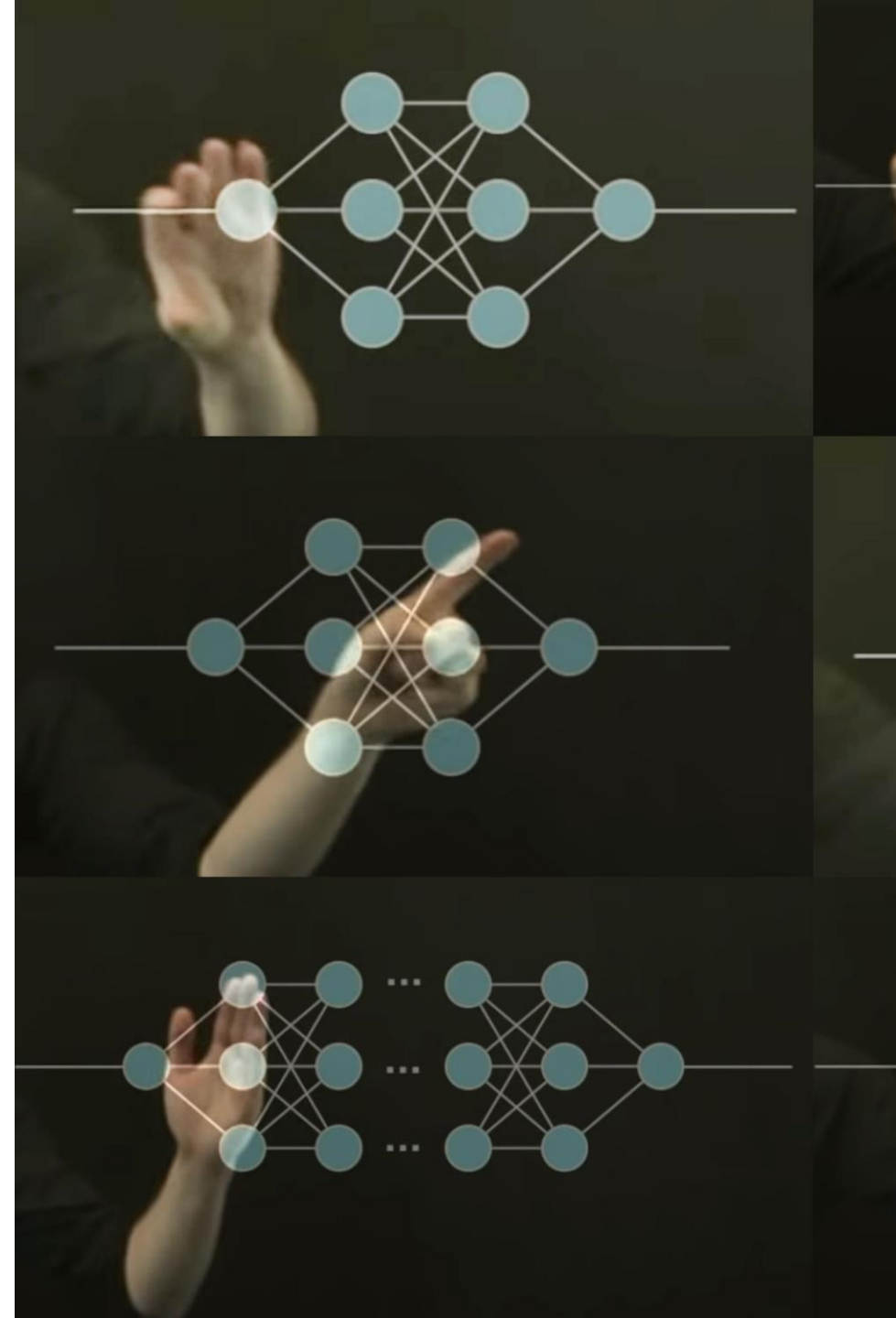
Sanity check



Identifying bias



Social acceptance



Resources and further reading

- AZP model explainer Python package ([GitHub repo](#))
- BDFI Seminar Series Dr Marisela Gutierrez Lopez and LV= General Insurance ([video](#))
- Interpretable Machine Learning ([book](#))
- InterpretML package ([documentation](#))
- Miller, T., 2019. Explanation in artificial intelligence: Insights from the social sciences. *Artificial intelligence*, 267, pp.1-38 ([paper](#))

Special thanks to Marisela and Kieran!



Dr Marisela Gutierrez

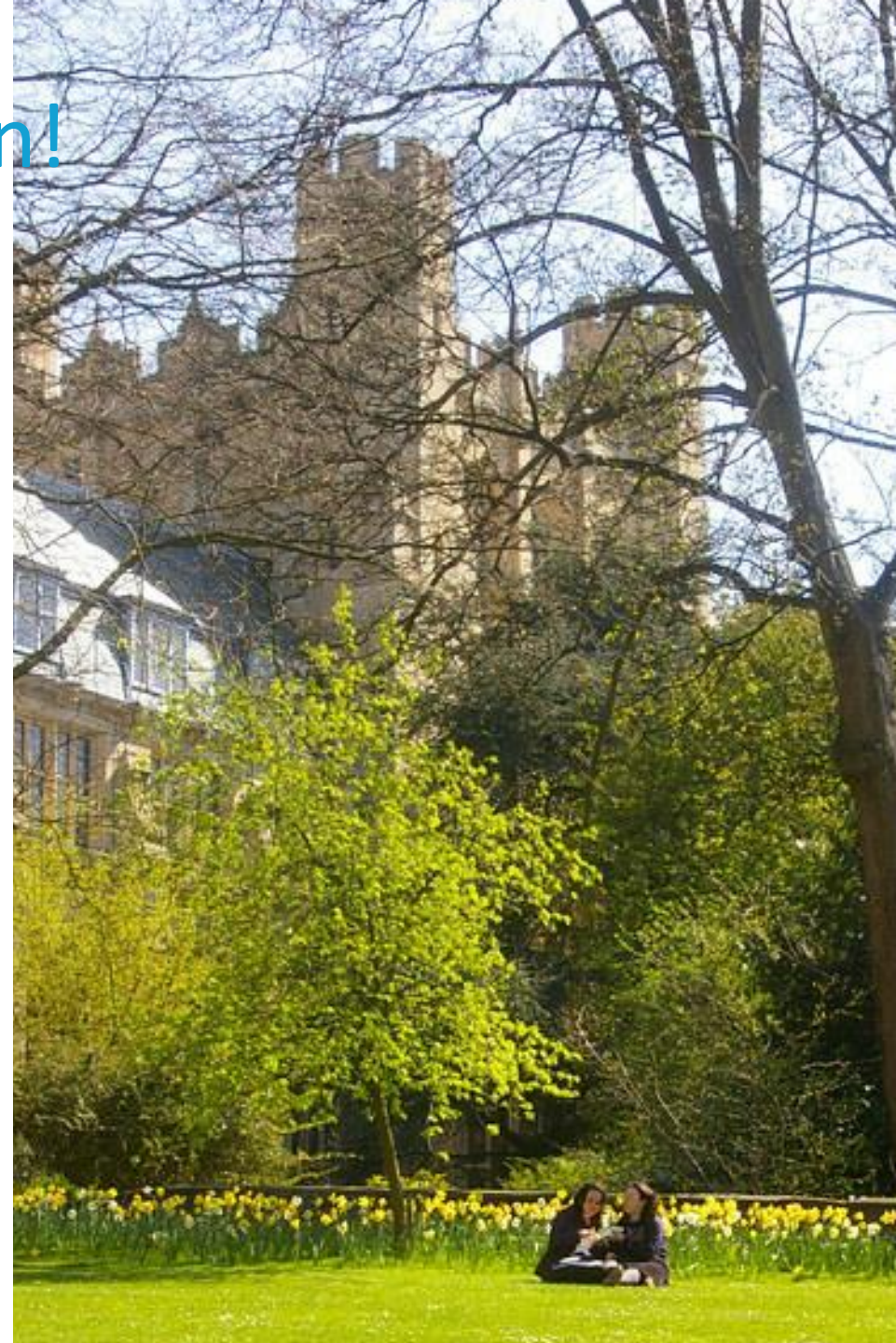
Senior Research Associate
University of Bristol



Kieran Billingham

Senior Data Scientist
Allianz Personal

Our talk: [BDFI Seminar Series Dr Marisela Gutierrez Lopez and LV=General Insurance](#)



Thanks for listening!



Merve Alanyali, PhD

Data Science Leader | Head of Data
Science Research and Academic Part...

