

AI in Finance: **QUO VADIS?**

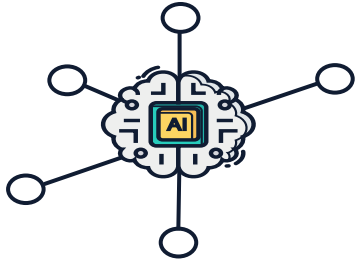
@Swiss Risk Association
16th November 2021

hey.

Dr. Branka Hadji Misheva
Senior Researcher @ZHAW

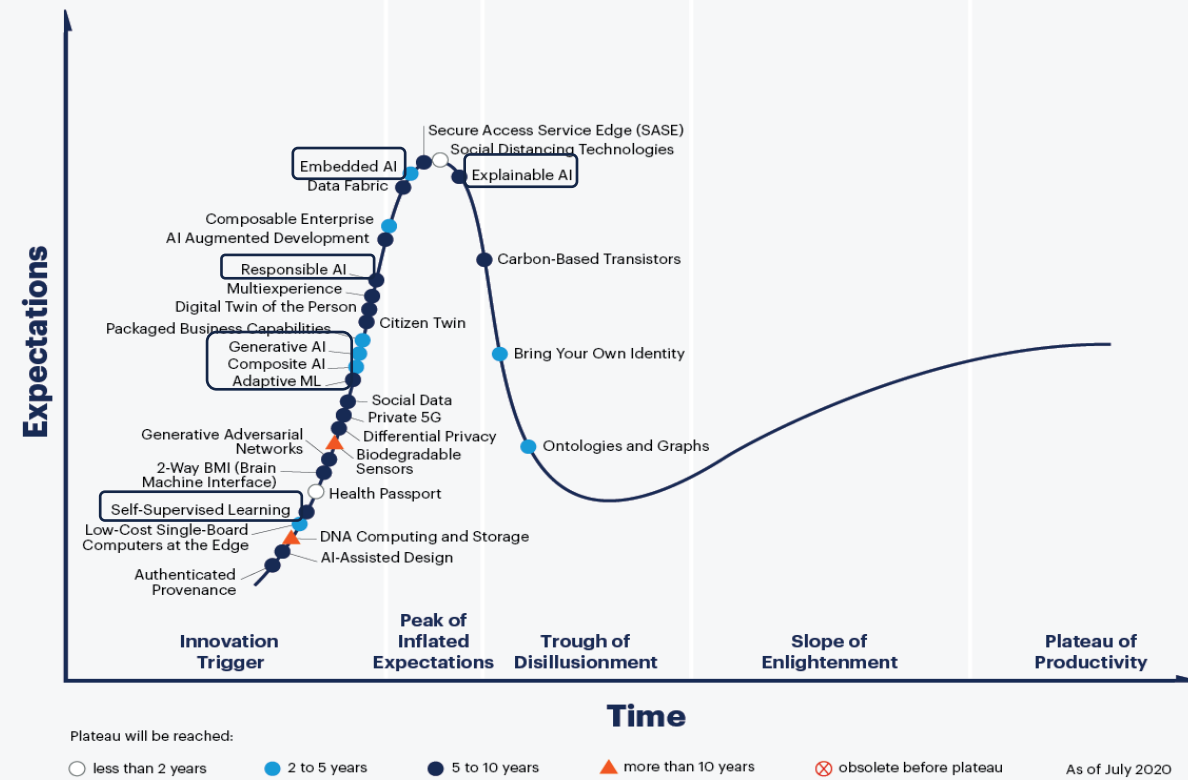


Hype vs Real?



AI in finance?

Hype Cycle for Emerging Technologies, 2020

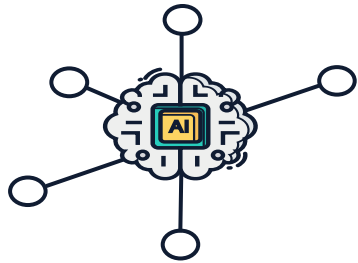


gartner.com/SmarterWithGartner

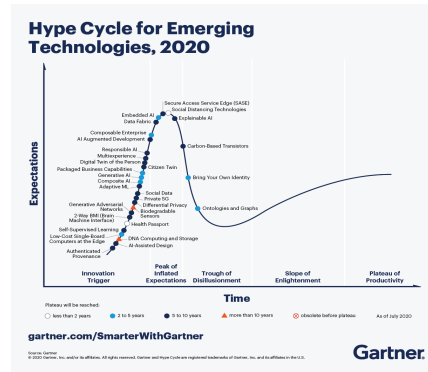
Source: Gartner
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Gartner

Hype vs Real?



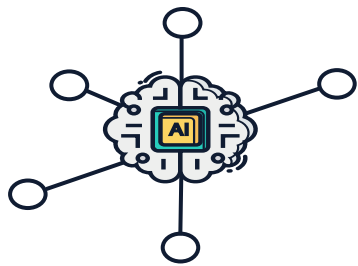
AI in finance?



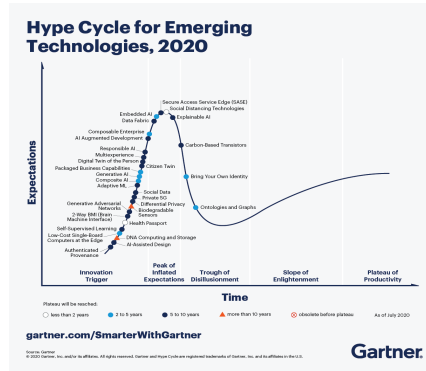


QUANTITATIVE PROBLEMS

Hype vs Real?



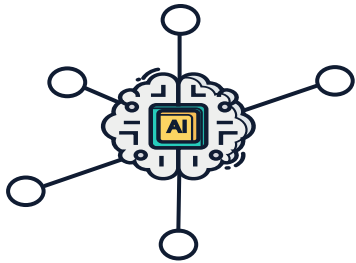
AI in finance?



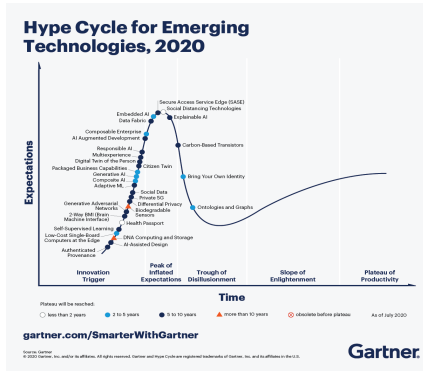
Where is the progress?



Hype vs Real?



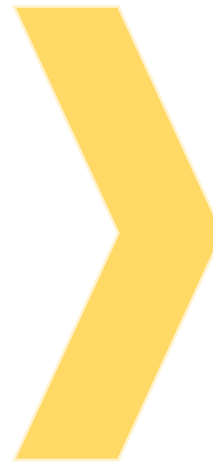
AI in finance?



VOLUMES OF
DATA



QUANTITATIVE
PROBLEMS



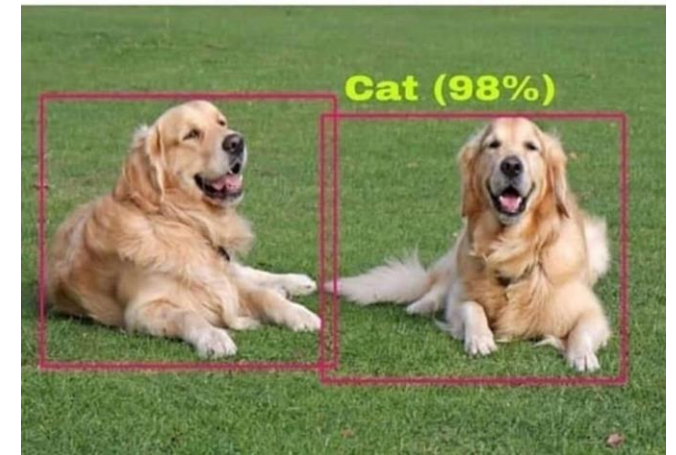
Where is the
progress?



Well ...

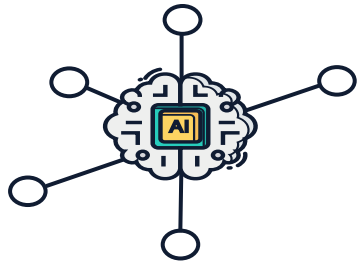
People: *fearing* AI takeover

AI:

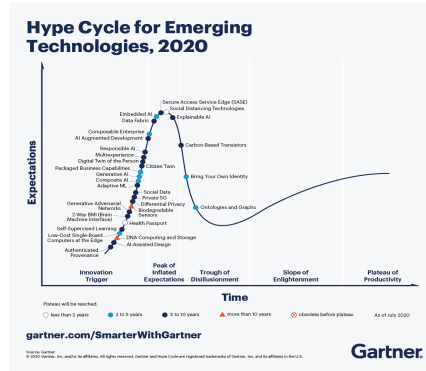


AI in practice is
difficult

Hype vs Real?



AI in finance?



VOLUMES OF
DATA



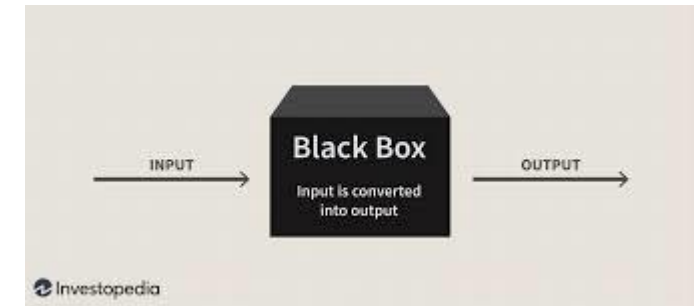
QUANTITATIVE
PROBLEMS



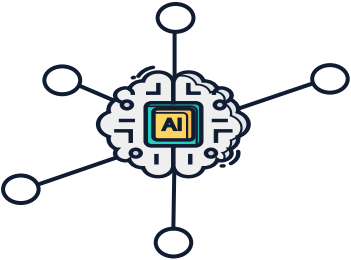
Where is the
progress?



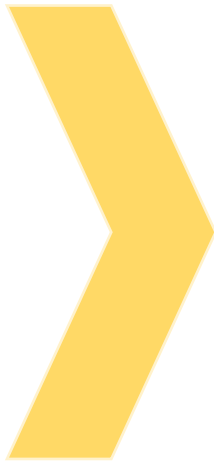
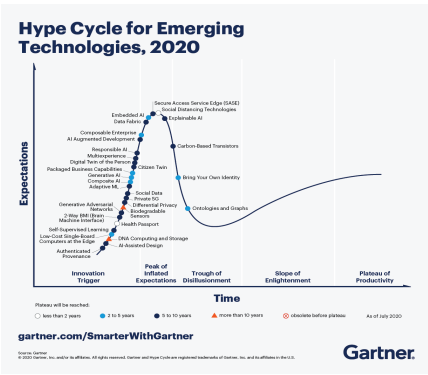
Well ...



Hype vs Real?



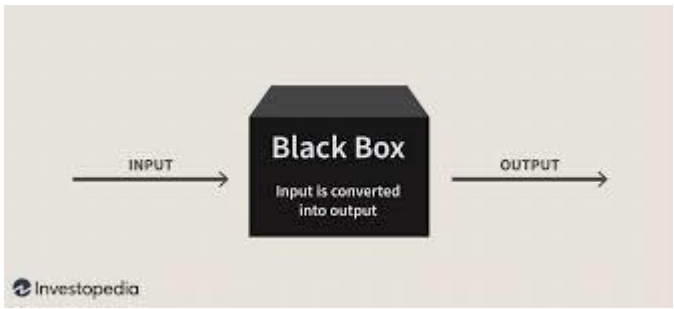
AI in finance?



Where is the progress?



Well ...



Hype Cycle for Emerging Technologies, 2020



Hype vs Real?



AI in finance?

Explainability is the name of the game!

Well ...



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DATA

PROBLEMS

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KEEP CALM
AND
COMPLY WITH
GDPR

The Need for **eXplainable AI**



It is not clear how variables are being combined to make predictions!



Why do we **NEED** this?

- Trust in models is **key**!

One
Mistake!

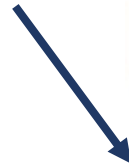
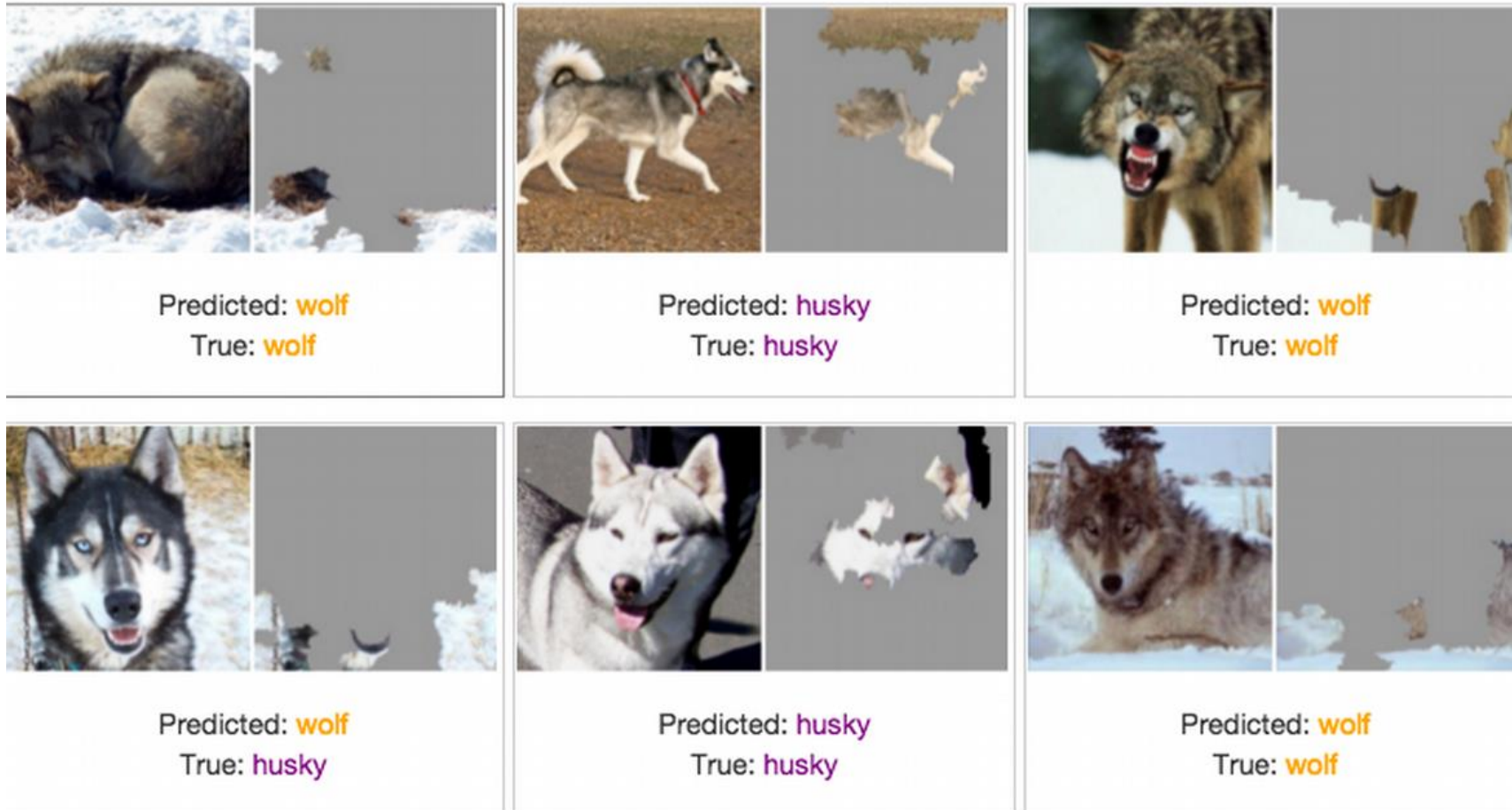


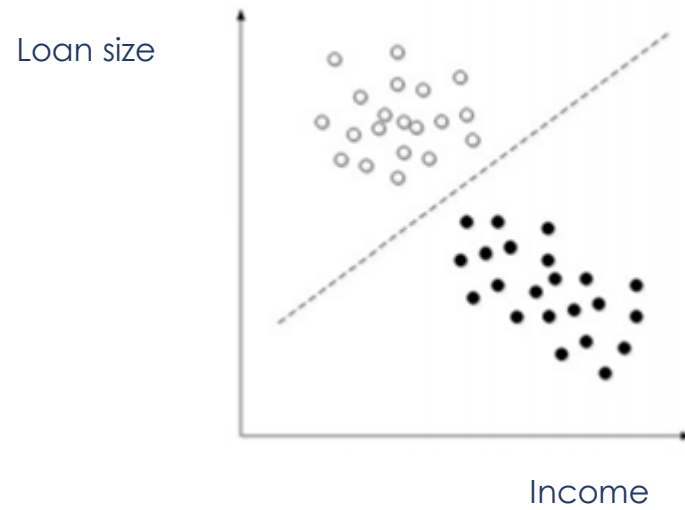
Image source: medium.com

Why do we **NEED** this?

It has found some snow!

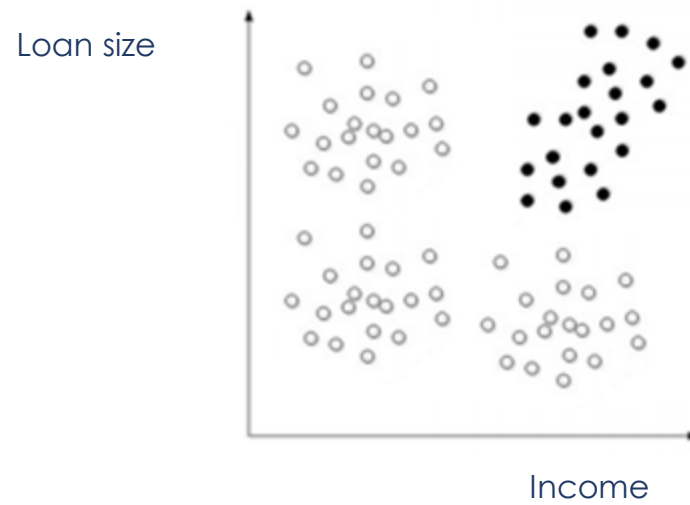


CREDIT RISK Management



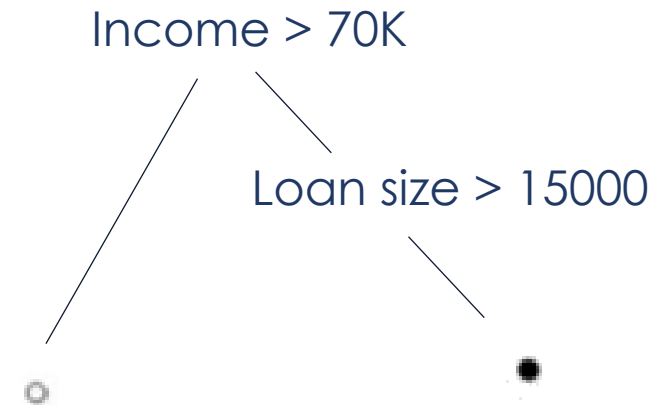
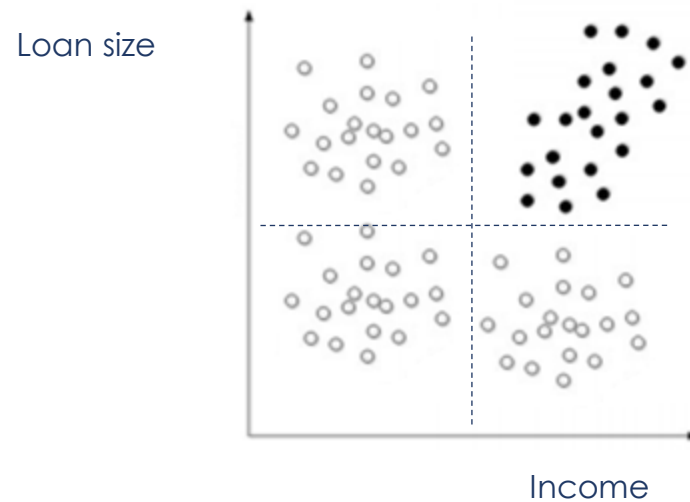
CREDIT RISK Management

What about **non-linear relationships**?



CREDIT RISK Management

What about **non-linear relationships**?
Still interpretable!



N-dimensions and **HIGH COMPLEXITY**

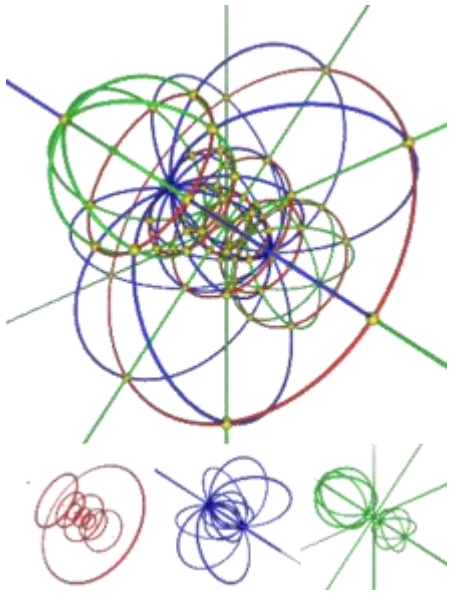


Image source: [wikipedia](https://en.wikipedia.org/wiki/High_dimensional_data)

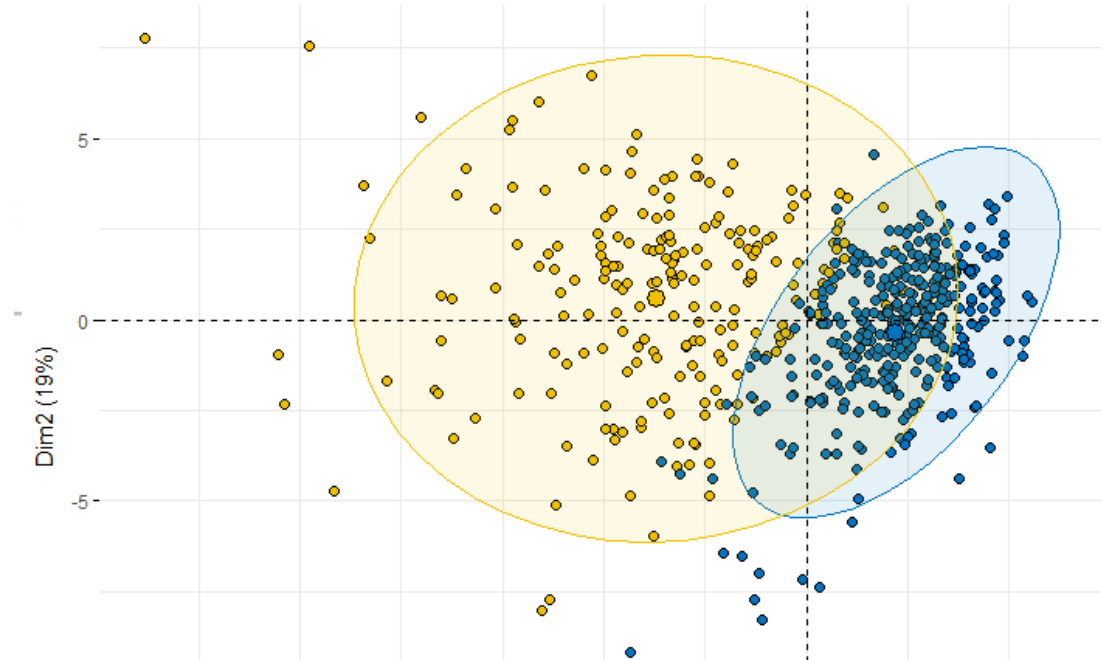


Image source: towardsdatascience.com

FEATURE IMPORTANCE

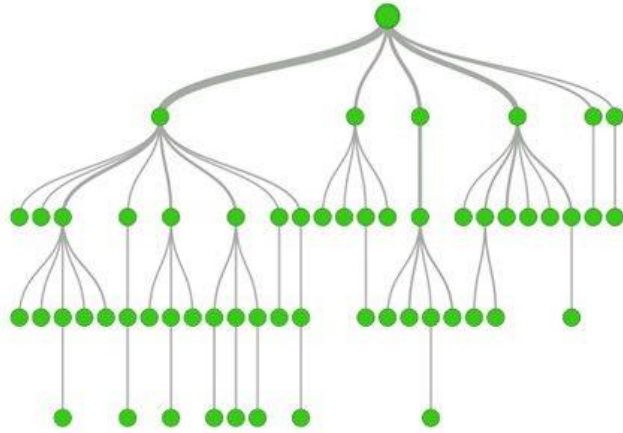


Image source: opendatascience.com

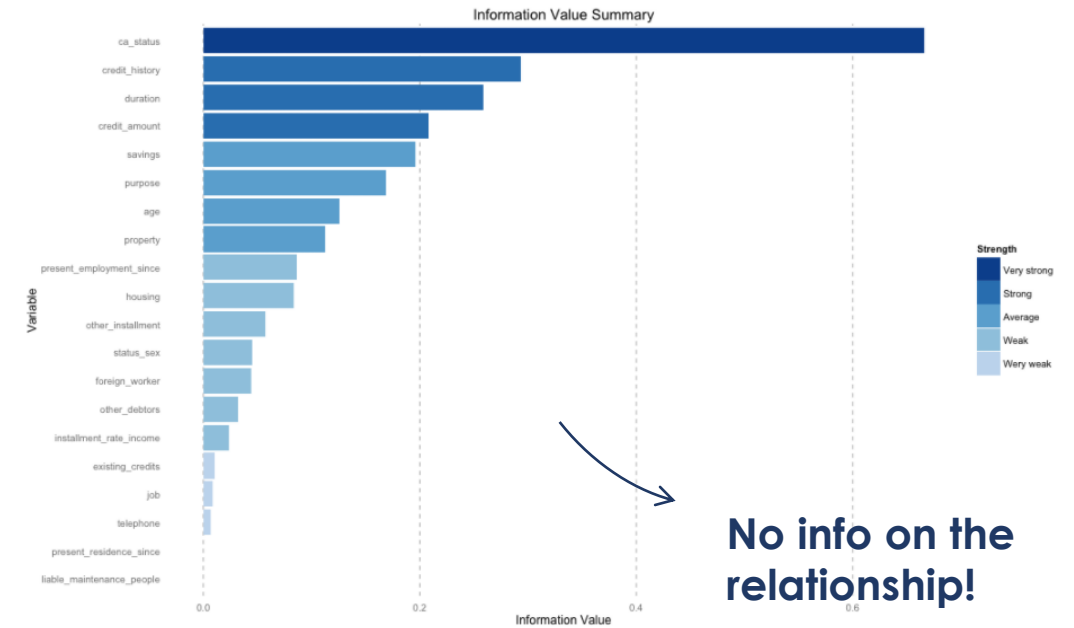


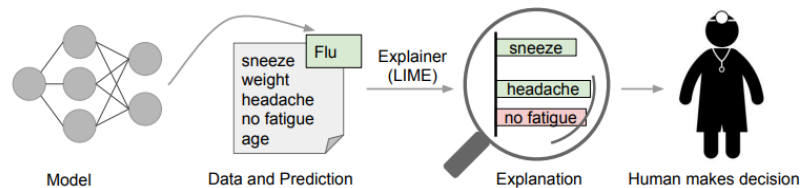
Image source: stackoverflow.com

State-of-Art XAI METHODS: LIME

LIME - Local Interpretable Model-agnostic Explanations



- explains the prediction of **any machine learning classifier** by learning an interpretable model **locally** around the prediction.



x



Highly accurate at local level!

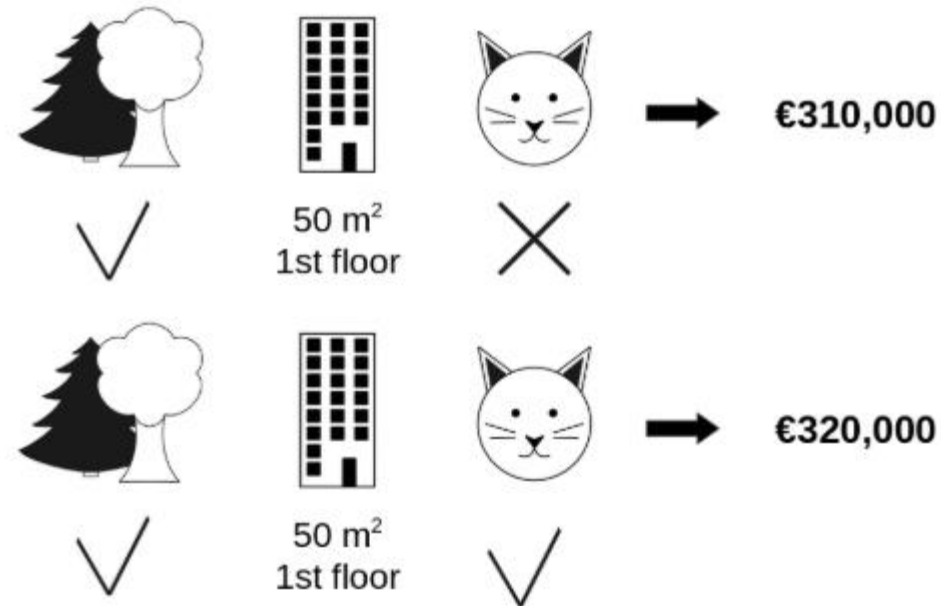


So local that one can apply a linear model to understand the relationship!

State-of-Art **XAI METHODS: SHAPLEY** Values

- The Shapley value is the average marginal contribution of a feature value across all possible coalitions.

The contribution of the cat-banned is -10K!



This greatly depends on our random pick!

We repeat the sampling step and average the contribution!

Image source: [christophm.github.io](https://github.com/christophm)



Figure 1. Arora et al. (2019) proposed taxonomy based on questions about what is explained, how it is explained and at what level



Figure 2. Loeckens et al. (2021) taxonomy mind-map of machine learning interpretability techniques

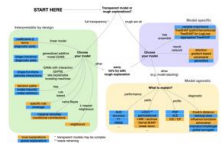


Figure 3. Molnar et al. (2021) model-oriented taxonomy for XAI methods



XAI Research

Match explainability
needs of stakeholders
with the XAI methods



Figure 1: A complex hierarchical diagram showing various XAI methods categorized by their level of explanation (local, global, model-agnostic, model-specific) and their type (post-hoc, integrated).



Figure 2: A diagram showing the taxonomy of XAI methods, categorized into model-agnostic, model-specific, and model-agnostic methods.

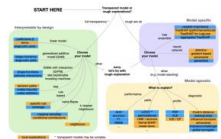
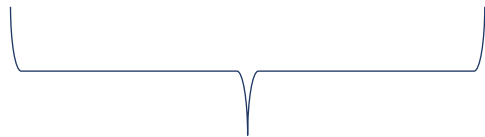
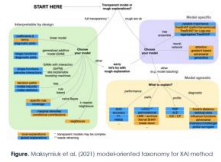
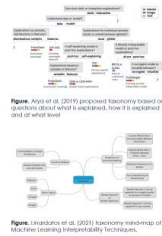


Figure 3: A diagram showing the taxonomy of XAI methods, categorized into model-agnostic, model-specific, and model-agnostic methods.



XAI Research



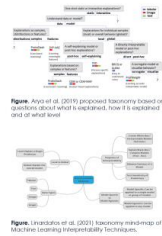
Match explainability
needs of stakeholders
with the XAI methods

Performance of XAI
methods in view of
the unique features of
financial data



XAI Research

XAI research in **FINANCE**



Match explainability needs of stakeholders with the XAI methods

Performance of XAI methods in view of the unique features of financial data

What is the best way to bring those explanations to different stakeholders in the financial world?

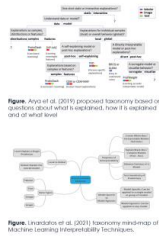


Wider adoption of AI-based use cases in finance

What is the best way to bring those explanations to different stakeholders in the financial world?

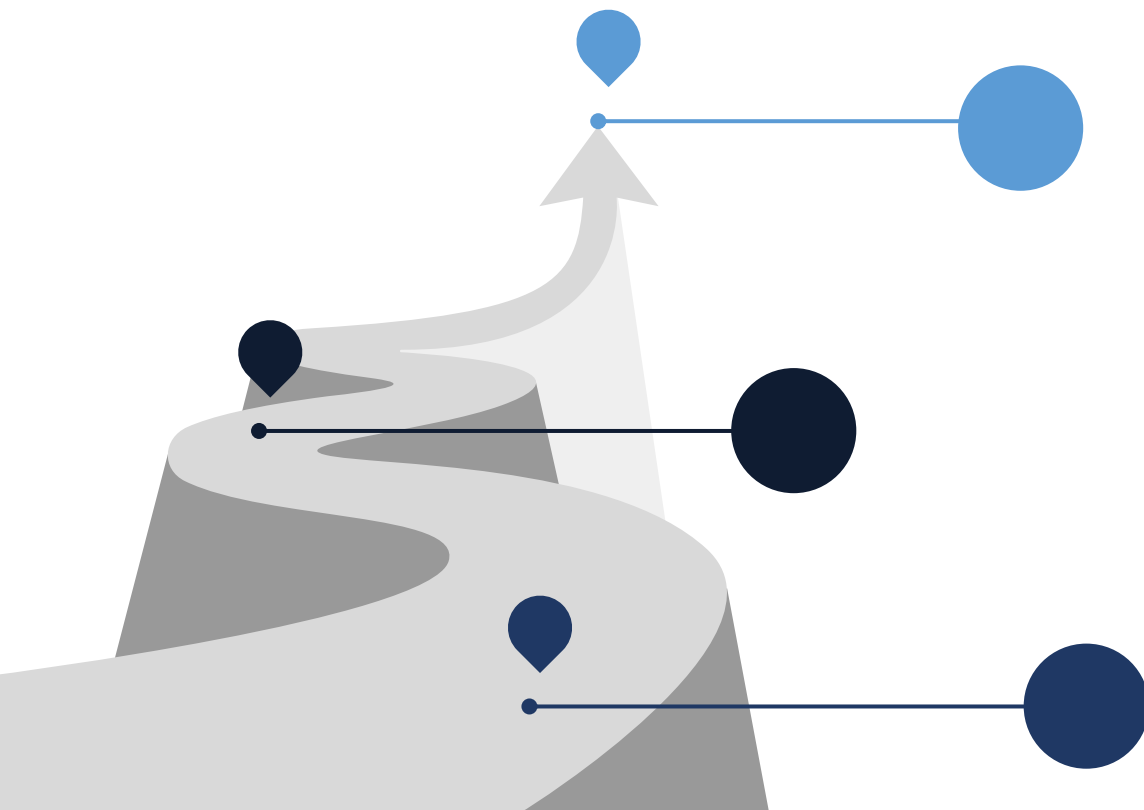
Performance of XAI methods in view of the unique features of financial data

Match explainability needs of stakeholders with the XAI methods



RESEARCH Projects

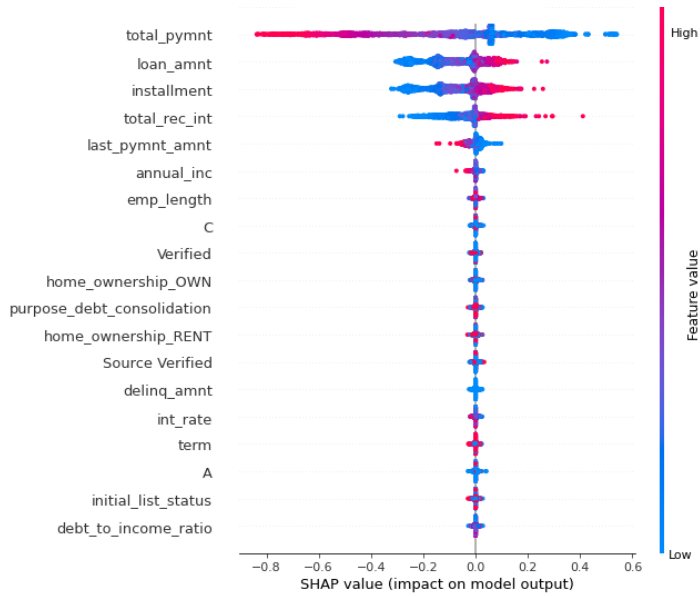
Context: Credit Risk Management



To explore the **utility of state-of-art XAI frameworks in the context of credit risk management**

Stability and robustness of explanations

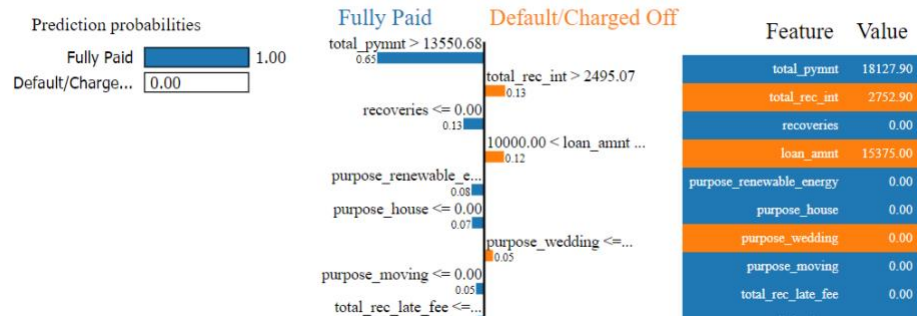
Human-centric and mathematical issues



SHAP

HUMAN-CENTRIC Issues

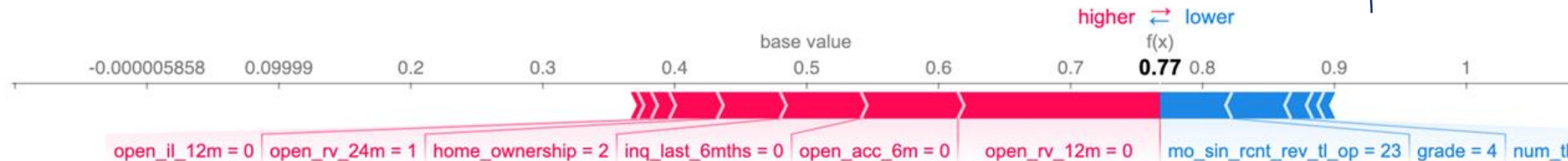
- Explanations for **model developers**
- Could provide value for end users as well – however, **counterfactual explanations preferred**
- Visualization **only suited for model developers**



LIME

SHAP

Ground Truth: Paid



TECHNICAL Issues

- Issue with the **different estimation procedures**
 - the exact computation of the Shapley value is computationally intensive
 - Feature selection can be crucial
 - The choice of features that count as players can affect the resulting explanations
- Not applicable to time series data
- Only few attempts to address such issues (with no solutions proposed for time series data)

Wider adoption of AI-based use cases in finance

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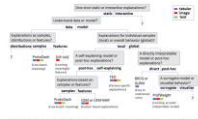


Figure. Anya et al. (2019) proposed taxonomy based on questions about what is explained, how it is explained and of what level.

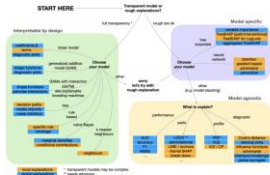
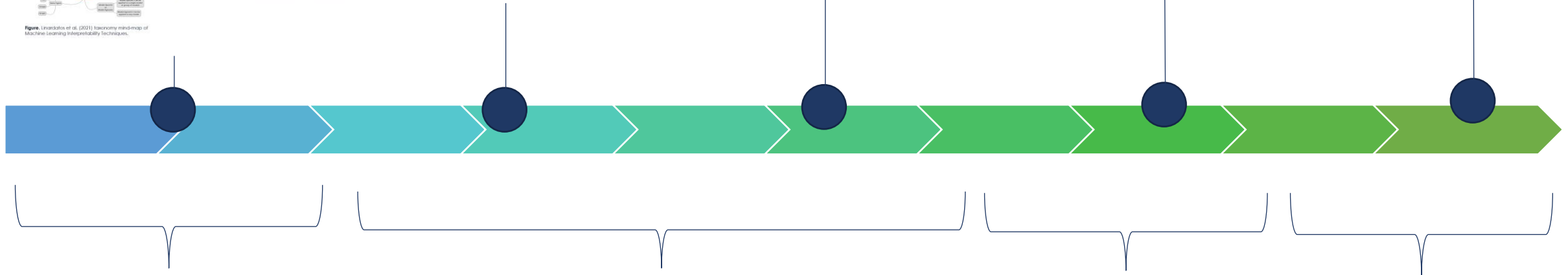


Figure. Matyskiw et al. (2021) model-oriented taxonomy for XAI method.

Figure. Uricchio et al. (2021) taxonomy mindmap of machine learning interpretability techniques.



XAI Research

XAI research in **FINANCE**

Deployment

Productivity

Wider adoption of AI-based use cases in finance

What is the best way to bring those explanations to different stakeholders in the financial world?

Performance of XAI methods in view of the unique features of financial data

Match explainability needs of stakeholders with the XAI methods

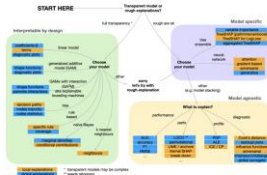
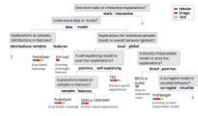


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XAI Research

XAI research in **FINANCE**

Deployment

Productivity