Challenges for Explainable Machine Learning in Production

OpML ‘20

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INTRODUCTION

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Machine learning is increasingly used in practice

- Automation of administrative tasks
- Credit scoring
- Recommender systems
- Automated vehicles
- Chatbot

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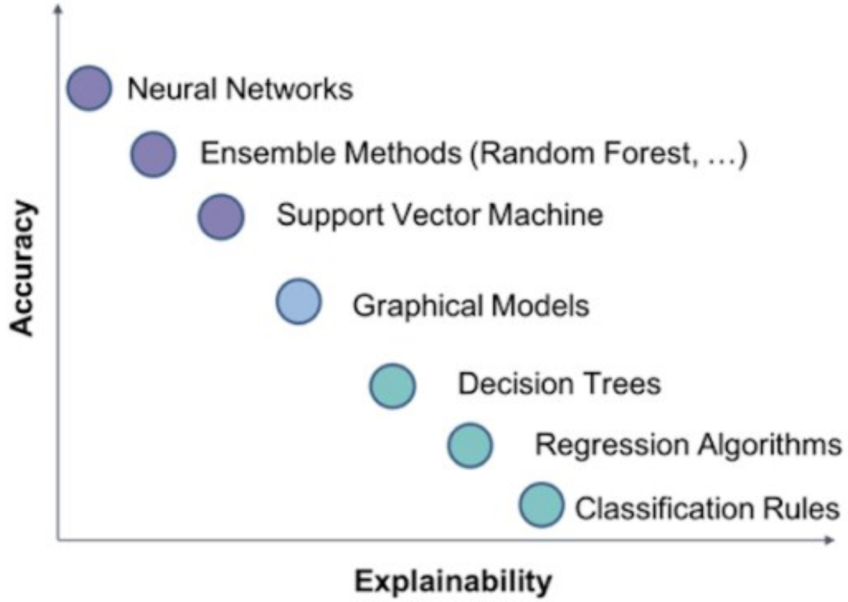
BLACK BOXES

Nevertheless, those algorithms are black box

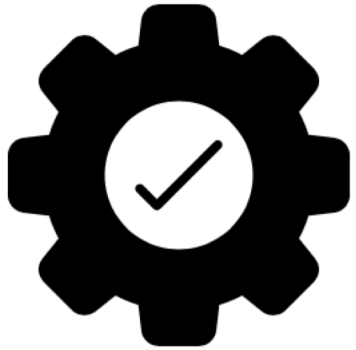
- The inner workings of how the model made a decision given the inputs is not readily interpretable
- Trade-off between accuracy and interpretability



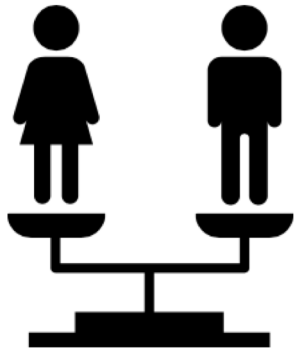
(DARPA, 2017)

MOTIVATIONS

Legal



Practical



Ethical

Prudential

MOTIVATIONS

*[GDPR] will also effectively create a "**right to explanation**," whereby a user can **ask for an explanation** of an algorithmic decision that was made about them.*

*Indeed, articles 13 and 14 state that, when profiling takes place, a data subject has the right to "**meaningful information about the logic involved**."*

- *Goodman and Flexman (2016)*

MOTIVATIONS

In complex tasks, industrials will favour transparent and interpretable models even if they have lower accuracy in performance. However, interpretability frameworks can solve this issue.

- Ross et al. (2017)

INDUSTRIAL PARTNER

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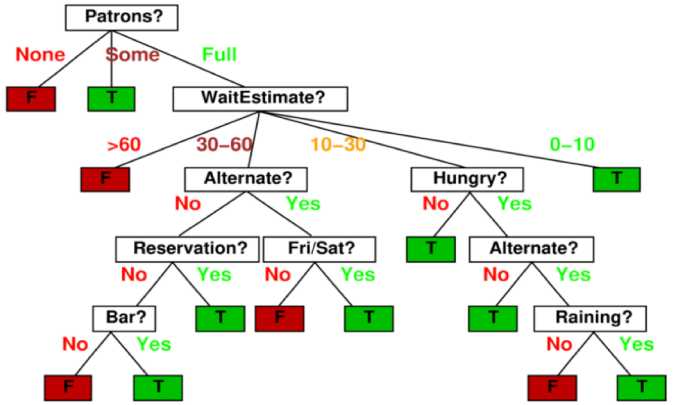
The context of our industrial partner:

- **FinTech** sector interested in explanations of automated decision-making systems
- Operating in a highly **regulated environment**, governed mostly by GDPR in Europe
- **Different audiences** to address (clients, financial analysts, regulators, managers)
- Explainability to be added to **pre-existing models** (Random Forest [RF])
  - RF is based on decision trees, but it increases exponentially and become non-interpretable
- High need for **security and privacy** to be assured



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EXPLAINABILITY

EXPLAINABILITY - DEFINITION

- There exists several, sometimes **conflicting**, definitions of explanability.
- Here we refer to *explainability* as:

> *Explainability is used interchangeably with interpretability. It aims to respond to the opacity of the inner workings ofthe model while maintaining the learning performance. It gives machine learning models the ability to explain or to present their behaviours in understandable terms to humans.*

TYPES OF EXPLANATION

There are two main parameters which define the **different types of explainability**:

- The difference between global and local will define the **granularity of the explanations**
- Inherent model incorporate interpretability in the **structure** of the initial model
- Post-hoc requires **another framework** to generate explanations

	Inherent	Post-hoc
Local	The ML model is already readily interpretable at the instance level. No need of an additional framework generating explanations	An explainability framework or method is applied to the initial ML model to produce explanations at the instance level.
Global	The ML model is already readily interpretable from an overall perspective. No need of an additional framework generating explanations.	An explainability framework or method is applied to the initial ML model. This produces explanations for the overall model.

TYPES OF EXPLANATION

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Those different types come with an **accuracy trade-off**

- Inherently explainable models offers accurate explanations but lower performance
- Post-hoc explainability is limited in their explanation but keep the initial performance intact
- Global explanations increase the model transparency: increase **trust in the model**
- Uncover the mapping for a specific prediction: increase **trust in a prediction**

	Inherent	Post-hoc
Local	Choice of a readily interpretable model that explains examples (e.g. decision tree)	Choice of a framework or method to deploy on the original model to explain examples (e.g. sensitivity analysis)
Global	Choice of a readily interpretable model that explains the overall model (e.g. linear regression)	Choice of a framework or method to deploy on the original model to explain the overall model (e.g. feature importance)

TYPES OF EXPLANATION

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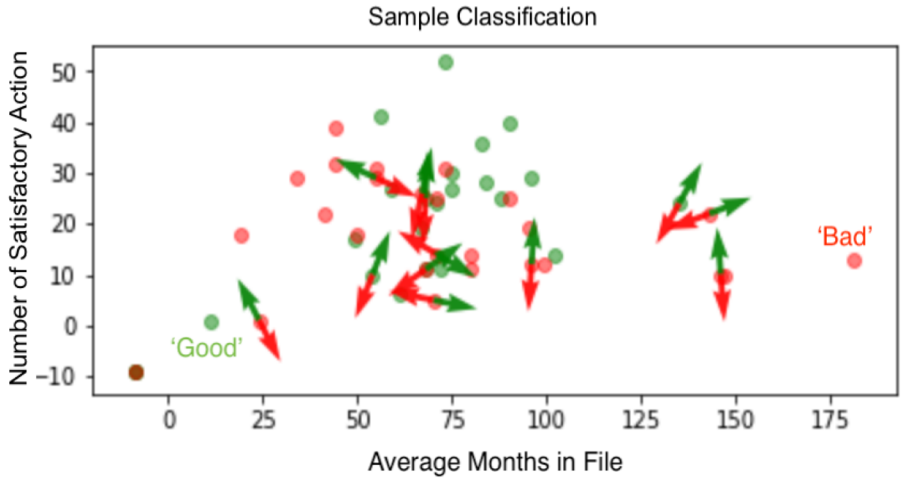
Here is **what to consider in industrial deployment**:

- Post-hoc frameworks will need to adapt to the initial ML model
- Some post-hoc frameworks generate both local and global explanations

FORMATS OF EXPLANATION

Explanations are usually generated through:

- Visualization-based framework (more frequent)
  - Producing graphical representations of the predictions



Experiment using the RRR framework from Ross et al. (2017)

FORMATS OF EXPLANATION

Explanations are usually generated through:

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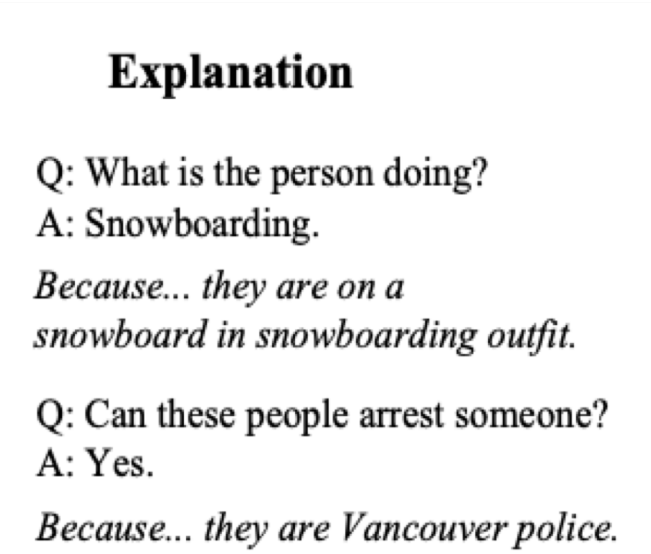
- Text-based framework
  - Textual explanations of a decision



Explanation

Q: What is the person doing?
A: Snowboarding.

Because... they are on a snowboard in snowboarding outfit.

Q: Can these people arrest someone?
A: Yes.

Because... they are Vancouver police.

Explanation from Park et al. (2018)

FORMATS OF EXPLANATION

Explanations are usually generated through:

- Visualization-based framework (more frequent)
  - Producing graphical representations of the predictions

- Text-based framework
  - Textual explanations of a decision

However, visualization-based framework are rarely validated through user study. Applied to other tasks than used in the design process, the visualizations can end to be as non-interpretable as the initial model.

CHALLENGES AND RECOMMENDATION

CHALLENGES FOR INDUSTRIAL APPLICATION

Existing frameworks comes with challenges in industrial application, as seen with our industrial partner:

- Data Quality
- Task and Model Dependency
- Security

DATA QUALITY

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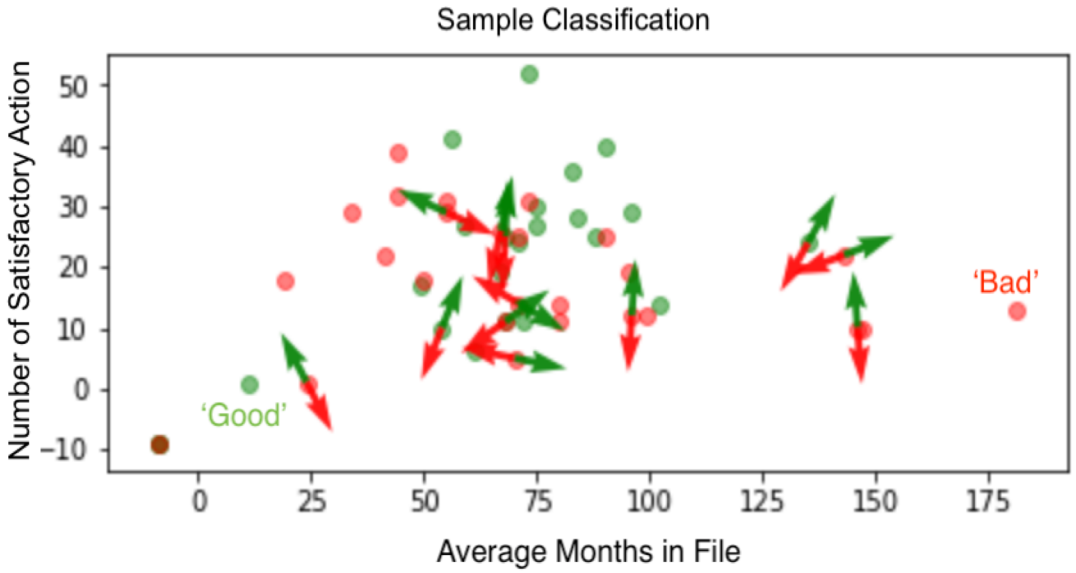
Challenge:

- Explainability framework focus on **Computer Vision and NLP tasks**
- Not addressing **tabular data quality** (missing values, no clear-cut clusters)
- Thus, framework **explainability is reduced**
- If based on tabular data, then rely on **optimal data** for visualization



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DATA QUALITY

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Recommendation:

- **More consideration** to industrial need during framework design
- **Systematic user validation** of interpretability framework on different data formats

MODEL AND TASK DEPENDENCY

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Challenge:

- Model Dependency: some frameworks are **designed for a specific model type**
  - Resolved by **model-agnostic approach** (e.g. LIME)
  - Resolved by **surrogate models** but they don't provide explanations when model and surrogate differ
- Task Dependency:
  - Need of different types of explanations for different audiences
  - Insufficient consideration of different tasks in the different designed framework

Recommendation:

- **Clearly define** needs and explanation needed before undertaking the tasks
- **Systematic review** of relevant interpretability frameworks for comparison

SECURITY

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Challenge:

- Robustness:
  - If access to model reasoning, can implement adversarial behaviour to alter the model
- New research:
  - If provided explanations, part of the initial dataset can be recovered

Recommendation:

- **Simulate adversarial behaviour** and observe alterations in model behaviour
- **Give on to the exercise** of recovering part of the dataset given gradient explanations

CONCLUSION

- Data are crucial for operational decision-making
- Trade-off between explainability and accuracy
- Explainable ML make the model interpretable to users
- Challenges towards explainable ML implementation (data quality, task and model dependency, security)
- Overcoming those challenges can be complex. Still, systematic user review of new interpretable framework and of operational use case can ease those challenges

Thank for listening and to everyone who contributed to the paper !

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