## Human-in-the-loop approaches to XAI

#### **AIRA seminar 20.10.2022**

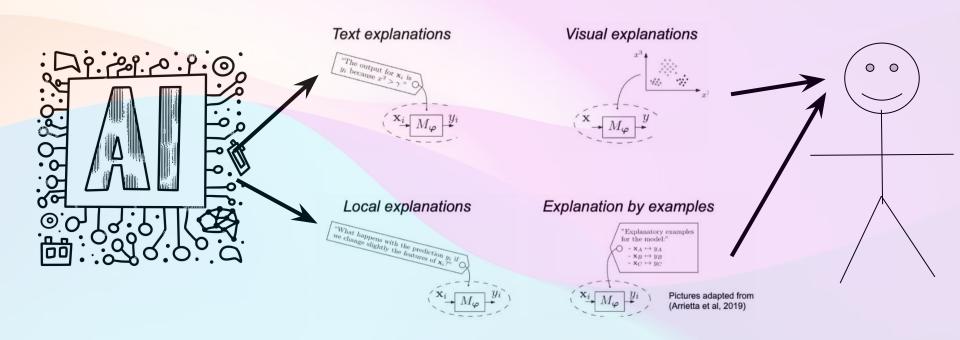


JAGIELLONIAN University In Kraków

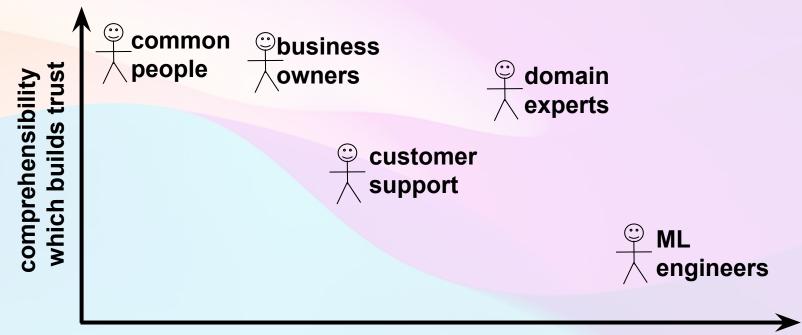


- 1. Explainable Artificial Intelligence
- 2. Human-in-the-Loop approach
  - a. Objective data & metadata
  - **b.** Interactive clustering
- 3. Intelligible eXplainable AI framework
  - a. Metrics for explainers
  - **b.** Time Series extension

#### **EXPLAINABLE AI**



#### XAI approach tailored for specific audience

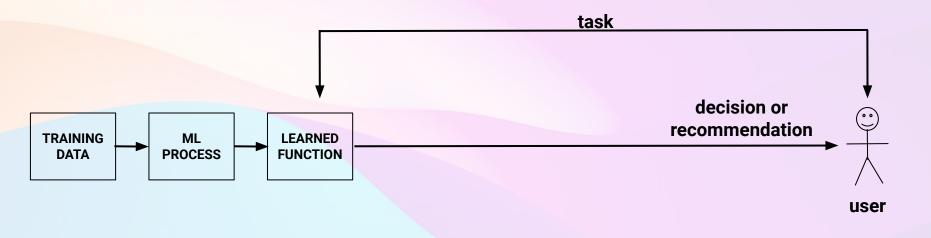


control over the ML algorithm

## How to build trust in EXPLAINABLE AI?

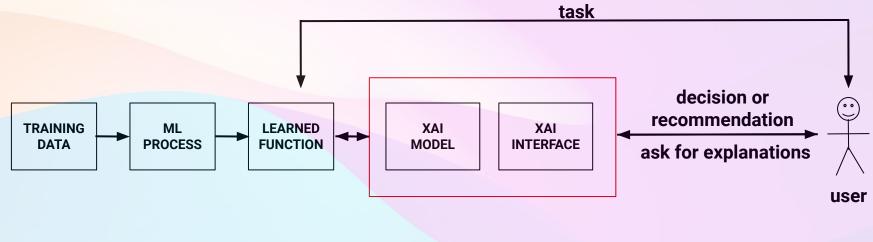
## Human-in-the-Loop approach

#### How to build trust?



Du, M., Liu, N., & Hu, X. (2019). Techniques for interpretable ML. Communications of the ACM, <u>63(1), 68–77</u>.

#### Human-in-the-Loop



Understand why & why not

Know when to trust Al

Is model fair?

Du, M., Liu, N., & Hu, X. (2019). Techniques for interpretable ML. Communications of the ACM, <u>63(1), 68–77</u>.

## eCommerce example

#### eCommerce example



#### metadata

David Beckham Signature Men Deos 2010

Fila Men's Round Neck Navy Blue T-shirt Autumn 2012

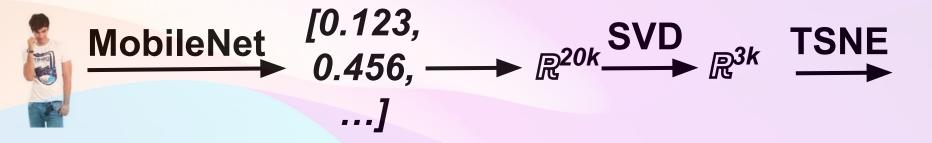
CASIO EDIFICE Men Black Dial Chronograph Watch ED60

#### objective data

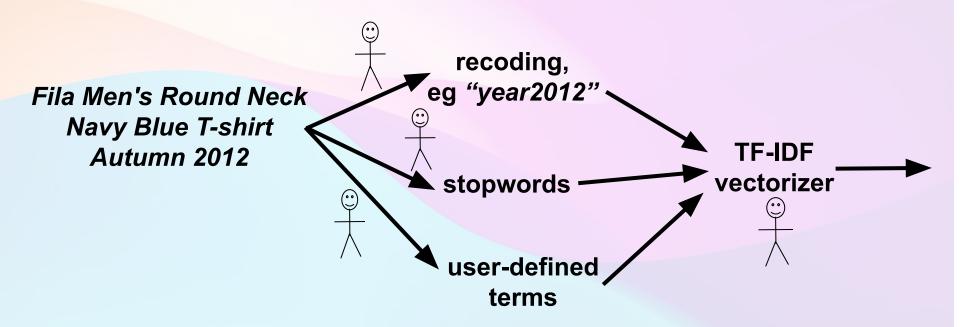
Description data derived directly from measurements "data about data", descriptions, labels (empiricists' approach) Specification closer to the process under study, it is more prone to errors and interpretation, less subject to interpretation, needs laborious to create them, textual, allows explanation for the formulation of an explanation Usage as independent variables in ML models: as explanations of ML models, target classification, regression, clustering, ... variables in ML models, sometimes independent variables **Examples** description of objects under study, how industrial sensors data, images of classes (eq. products, animals), video, the measurement was carried out / data medical data (eg. EEG, CT) collected

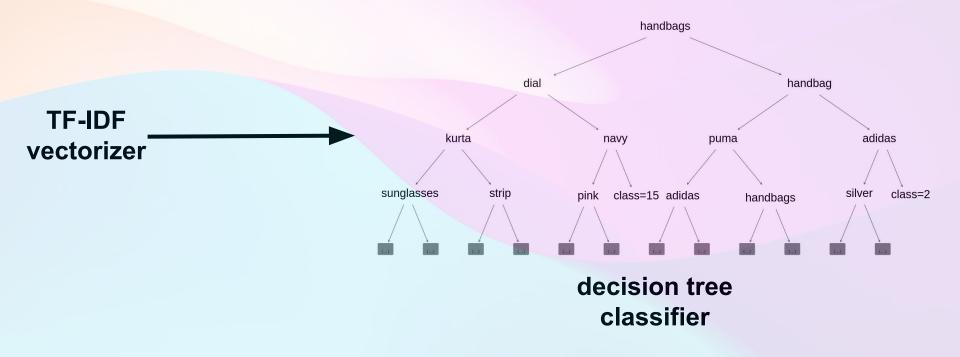
metadata

#### **Objective data** Interactive clustering: select # of clusters









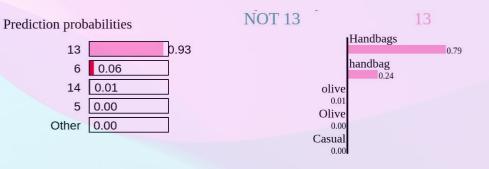
TF-IDF vectorizer



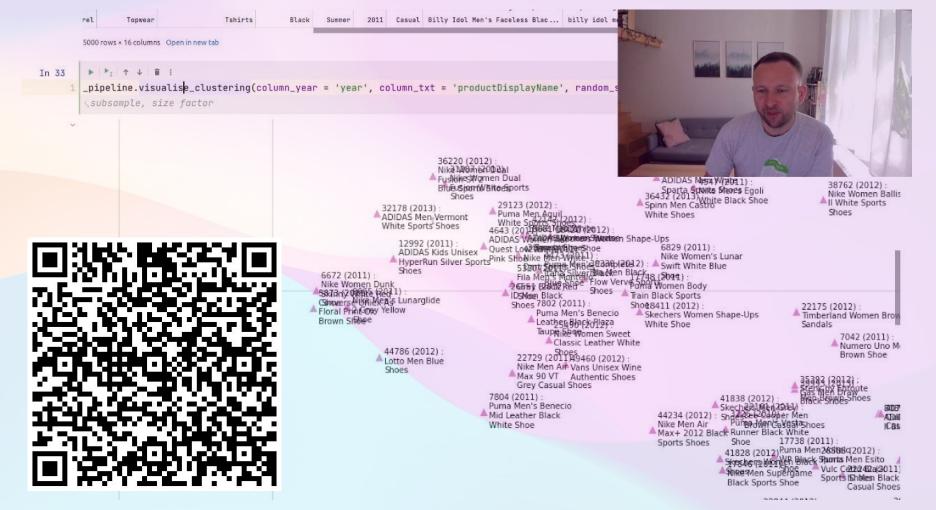
Text with highlighted words

Women Accessories Bags Handbags Olive Fall Year2012 Casual baggit woman olive handbag

TF-IDF vectorizer



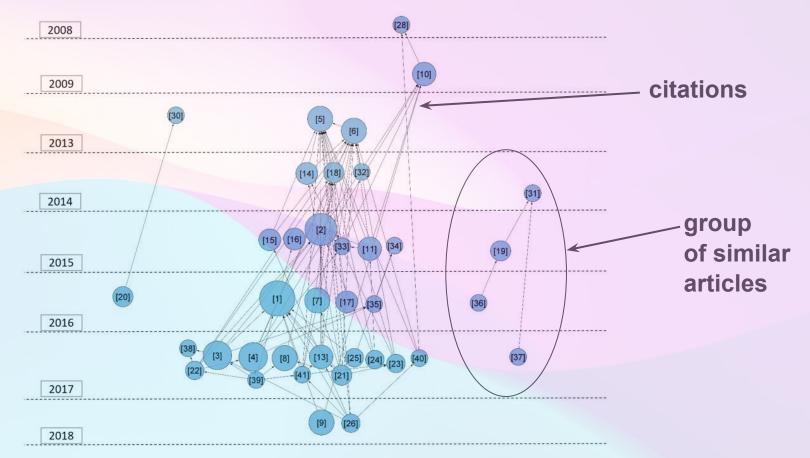
**LIME** explanation



IJCAI-ECAI 2022 Workshop on semantic techniques for narrative-based understanding

## **XAI Survey example**

#### **Field's Evolution Graph**



#### XAI Survey - 2 types of data

# objective data

	article1	article2	article3	
article1	-			
article2	1	-	1	
article3		1	-	



metadata

## **HITL Summary**

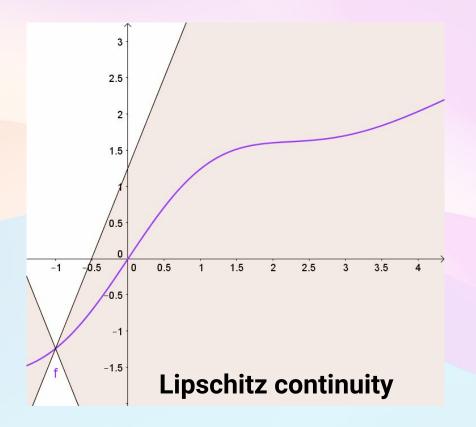
XAI is an intermediary layer between the ML algorithm and the human. It should be tailored for specific audience.

In the Human-in-the-Loop approach ML solution to a task at hand is built in iterative process. Thus this process human can gain trust in the method.

Objective data vs metadata is a distinction which I proposed and it seems well suited for HITL. The pipeline which I presented is suited for ML engineers.

## Intelligible eXplainable Al framework

#### **InXAI: Stability**

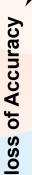


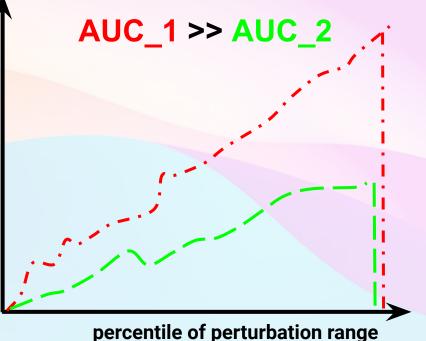
For **given explainer**, are explanations similar for similar input, measured with local Lipschitz continuity in the fixed neighborhood of any datapoint

## Can one trust this explainer?

Bobek S., Mozolewski M., Nalepa G.J. (2021) Explanation-Driven Model Stacking. In: Paszynski M., Kranzlmüller D., Krzhizhanovskaya V.V., Dongarra J. J., Sloot P.M.A. (eds) Computational Science – ICCS 2021. ICCS 2021. Lecture Notes in Computer Science, vol 12747. Springer, Cham.

#### **InXAI: Perturbational Accuracy Loss**



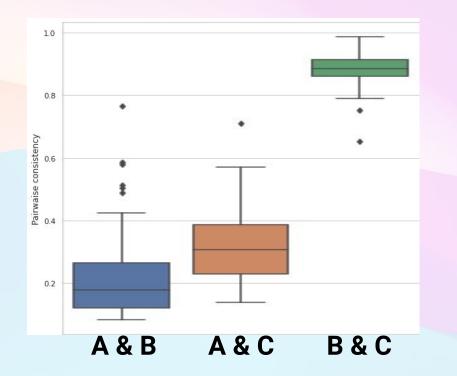


For **given explainer**, how accuracy deteriorates as the data get progressively perturbed, according to their inverse importance in explanation

Which explainer is the most accurate (in line with the ML model)?

Bobek S., Mozolewski M., Nalepa G.J. (2021) Explanation-Driven Model Stacking. In: Paszynski M., Kranzlmüller D., Krzhizhanovskaya V.V., Dongarra J. J., Sloot P.M.A. (eds) Computational Science – ICCS 2021. ICCS 2021. Lecture Notes in Computer Science, vol 12747. Springer, Cham.

#### InXAI: Consistency (pairwise)



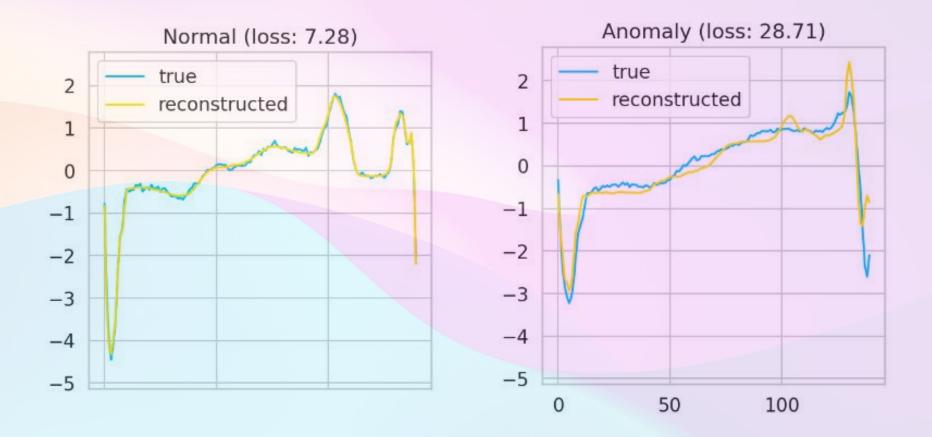
To what extent **different explainers** for predictions of ML model(s) are similar to each other (do agree)

Can I exchange one explainer with another one?

Bobek S., Mozolewski M., Nalepa G.J. (2021) Explanation-Driven Model Stacking. In: Paszynski M., Kranzlmüller D., Krzhizhanovskaya V.V., Dongarra J. J., Sloot P.M.A. (eds) Computational Science – ICCS 2021. ICCS 2021. Lecture Notes in Computer Science, vol 12747. Springer, Cham.

## **WIP: Time Series**

#### **TS-data & anomaly detection with Autoencoders**



## **InXAI Summary**

Another way to build trust in XAI is to provide metrics that allow you to evaluate your explanations.

**Metrics should answer questions such as:** 

- 1. Will I be able to trust the explanation in all circumstances? -> STABILITY
- 2. Which of the explanations is most consistent with the model being explained? -> AUC FOR PAC
- 3. To what extent do the different explanations agree with each other? Can I combine the explanations to make it even better? -> CONSISTENCY

## Bibliography

- Bobek S., Mozolewski M., Nalepa G.J. (2021) Explanation-Driven Model Stacking. In: Paszynski M., Kranzlmüller D., Krzhizhanovskaya V.V., Dongarra J. J., Sloot P.M.A. (eds) Computational Science – ICCS 2021. ICCS 2021. Lecture Notes in Computer Science, vol 12747. Springer, Cham. <u>Download</u>.
- 2. Mozolewski M., Jamshidi S., Bobek S., Nalepa G.J. (2022) Explain your clusters with words. The role of metadata in interactive clustering. CEUR Workshop Proceedings. <u>Download</u>.

## Summary

comprehensibility

XAI tailored for specific audience (agents/principals)

#### Trust in XAI:

- via engagement of the user
  HITL approach
- via metrics

ust	business owners	
which builds trust		domain experts
W	customer	support
		ML engineers
		full control over

full control over the ML algorithm