Technische Hochschule Brandenburg
University of Applied Sciences

IARIA

INFERRING POLITICAL ORIENTATION FROM CREDIT SCORE-RELEVANT VARIABLES

An Empirical Study on Profiling and Proxy Inference Through Sensitive Attributes

David Schnepp, *Brandenburg University of Applied Science, Germany.*

Olga Levina, *Brandenburg University of Applied Science, Germany.*

Contact mail: schnepp@th-brandenburg.de

DAVID SCHNEPP

Education:

- Research Stay, *Icahn School of Medicine at Mount Sinai, New York City, USA*. Research focuses on how hyperparameter optimization impacts the results of various CCC-tools
- Master of Science, *Brandenburg University of Applied Science, Brandenburg a. d. Havel, Germany*. Business Informatics.
- Bachelor of Arts, *Berlin School of Economics and Law, Berlin, Germany*. Business Administration.

Work history:

- Local area manager, *Lidl, Berlin, Germany*. Managed multiple Lidl stores, with responsibility for staff supervision, operational performance, communication, and compliance with company standards.

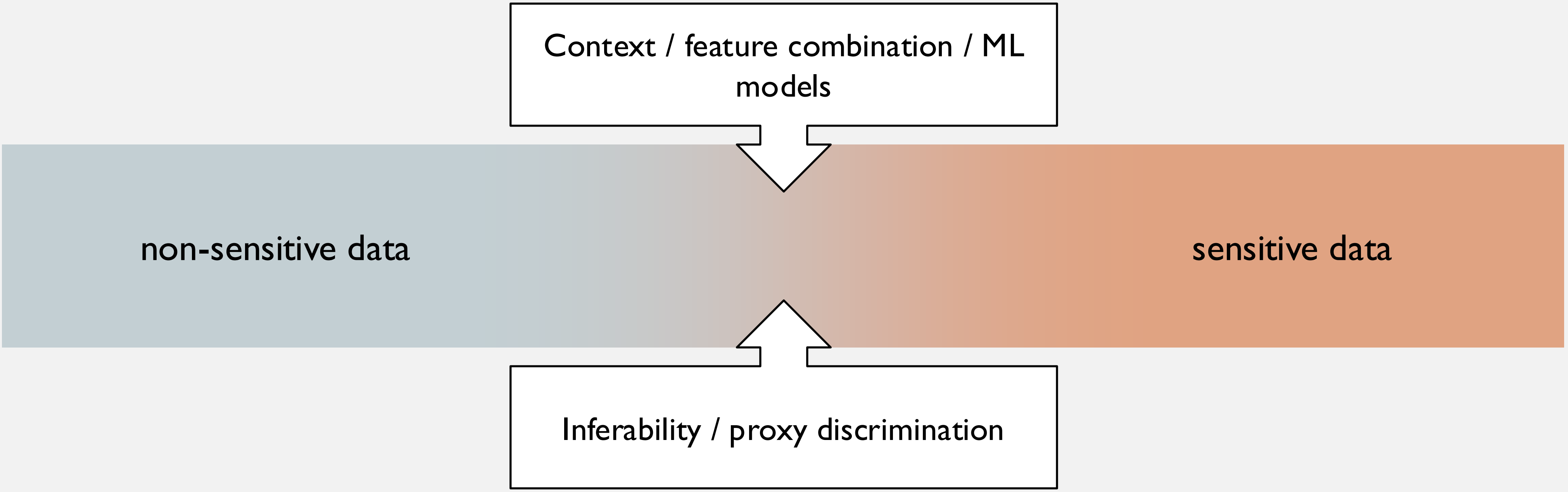
TOPIC & AIM

This paper…

- …discusses the risk that sensitive attributes may be inferred indirectly from seemingly non-sensitive data.
- …examines whether political orientation can be predicted from creditworthiness-related variables using supervised machine learning models in a specific setting.
- …assesses inferability of demographic and socioeconomic data in the context of the 2021 German federal election.
- …outlines implications for proxy-based profiling, data protection, and AI regulation.

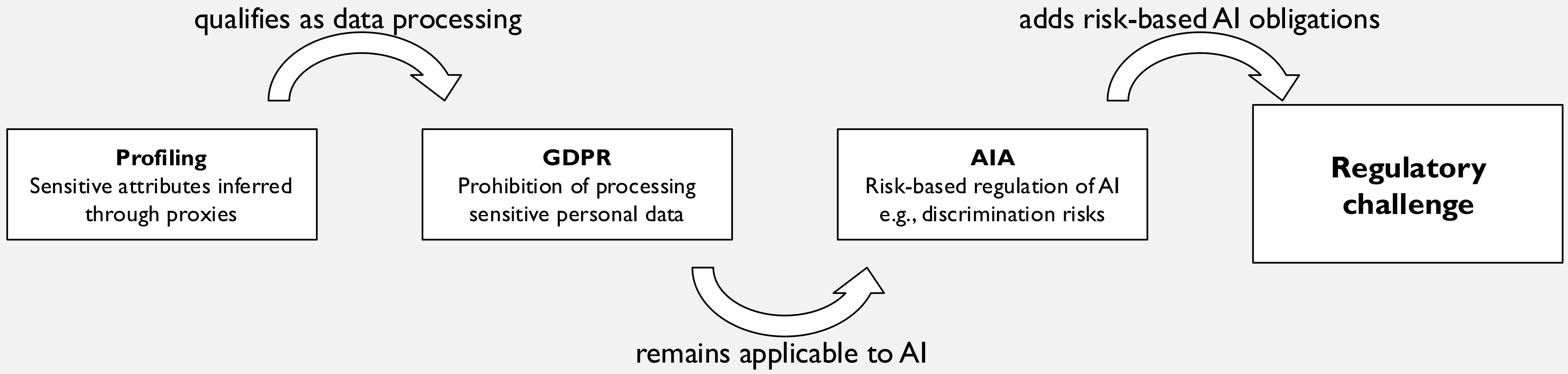
BACKGROUND

- Sensitive attributes do not need to be explicitly collected to become relevant for automated decision-making [1][3[4][5].
- This affects several domains such as finance, public administration, and political processes [1][2].
- The key concern shifts from the type of input data to the information that can be inferred from it [7][8].



BACKGROUND

- Political orientation is a protected sensitive attribute within the meaning of GDPR but may not need to be explicitly collected to become inferable [1][5][10].
- This creates a regulatory challenge where sensitive attributes are inferred rather than directly processed.
- Creditworthiness-related variables often include demographic and socioeconomic information that could potentially act as proxies.



METHODICAL APPROACH

Input [11]

Credit-Scoring related feature [16]	**Data Type** [16]
Gender	Nominal
Age	Metric
Domicile / housing location	Ordinal
Relationship status	Nominal
Household size	Metric
Children living in household	Metric
Contract type	Nominal
General education level	Ordinal
Vocational education level	Ordinal
Household income	Ordinal

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machine learning models

Logistic Regression
Support Vector Machine
K-Nearest Neighbors
Boosting-based Decision Tree

Target [11]

Who did you vote for?
Federal election September 2021, Germany [16]

- ☐ CDU/CSU
- ☐ SPD
- ☐ Die Linke
- ☐ Bündnis 90/Die Grünen
- ☐ FDP
- ☐ AfD

→ Multi-classification problem

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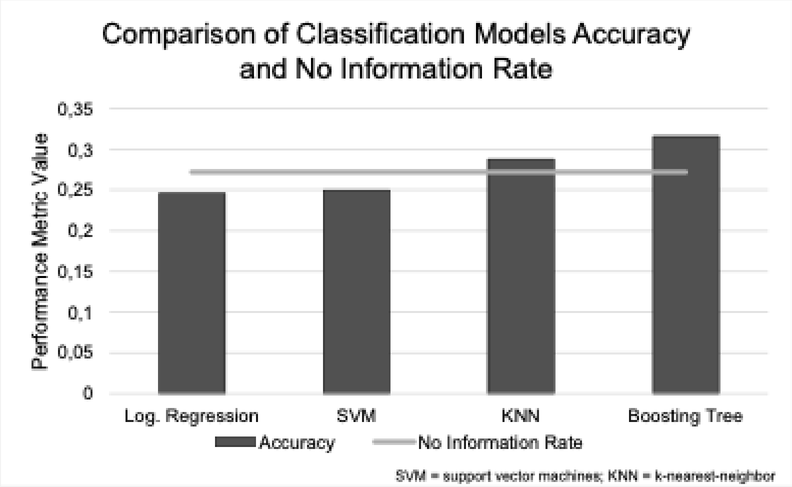
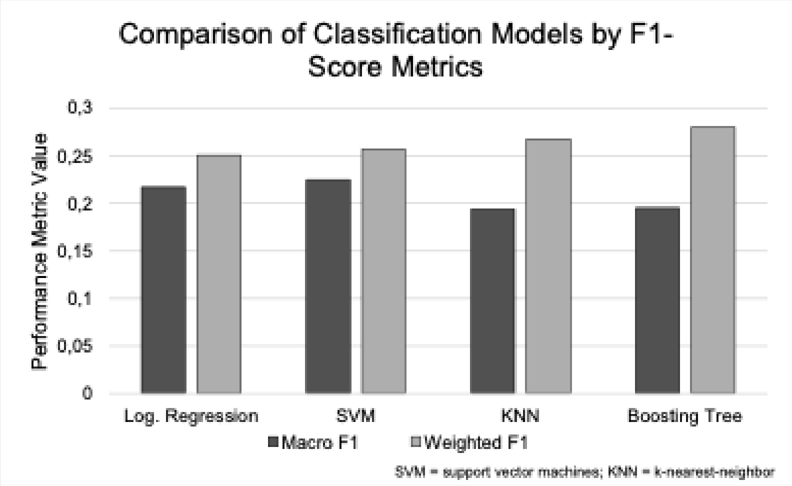
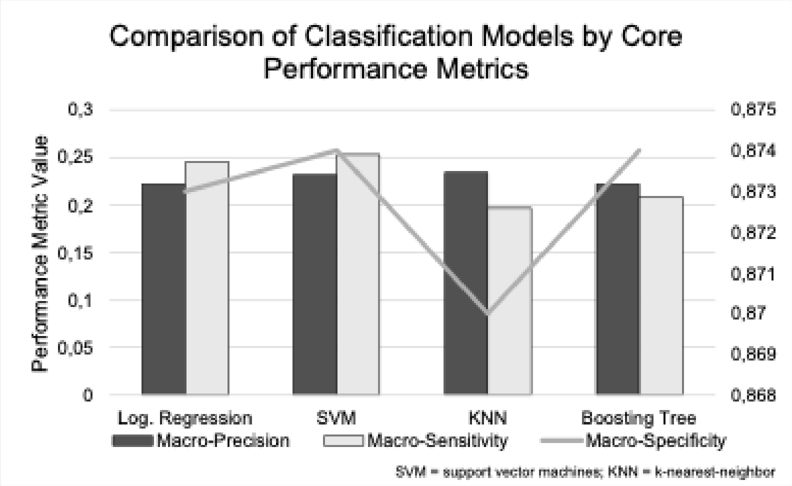
RESULTS

- No reliable prediction of political orientation is possible across all applied model types.
- A permutation-based feature-importance analysis showed that none of the selected creditworthiness-related variables had strong predictive relevance.







DISCUSSION

- **No meaningful inference was observed in this empirical setup.**
  Political orientation could not be reliably predicted from the selected creditworthiness-related variables.
- **The finding is context-specific and not generally transferable.**
  It does not prove that political orientation cannot be inferred from creditworthiness-related data in other datasets, populations, or model settings [12][13][14][15].
- **The reason for the negative result remains open.**
  Poor performance may reflect genuine non-inferability, but also methodological factors such as class imbalance, preprocessing choices, limited feature richness, or model selection.
- **This uncertainty creates a regulatory challenge.**
  Inferability cannot be reliably ruled out ex ante, making proxy-based profiling difficult to assess under GDPR and AI regulation.

OUTLOOK

1) Future research should move from binary risk assessments toward context-sensitive inferability evaluations that systematically examine how data richness, class distribution, model choice, and resampling strategies affect the feasibility of attribute profiling [12][13][14][15].

2) Since inferability appears to be attribute-specific, future work should examine which categories of sensitive information are particularly vulnerable to indirect inference and support this through benchmarks and evaluation protocols.

3) As absence of predictive performance is not evidence of absence, system design and policy should strengthen auditing methods, privacy-enhancing technologies, and data-minimization practices.

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