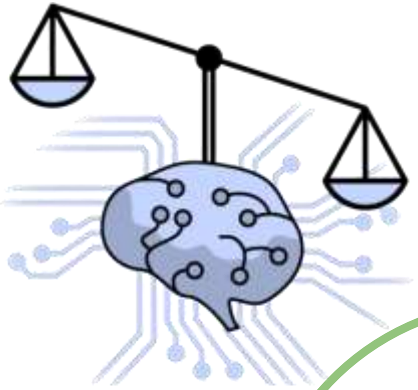
Software Engineering for Artificial Intelligence Course - A.A. 2023/2024
University of Salerno

IMPACT OF DATA SMELLS ON FAIRNESS IN ML SOLUTIONS



Annamaria Basile – 0522501844
Mario Cicalese – 0522501799
Paolo Carmine Valletta – 0522501828

sesa lab
SOFTWARE ENGINEERING SALERNO

OUR TEAM

ANNAMARIA BASILE

Software Engineering
&
IT Management

MARIO CICALESE

Data Science
&
Machine Learning

PAOLO CARMINE VALLETTA

Software Engineering
&
IT Management

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PROJECT CONTEXT

DATA **SMELLS**

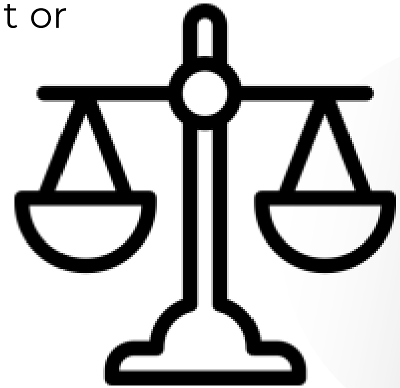
Data smells are indicators ***suggesting the presence of issues*** *within a dataset. Data smells are not explicit errors or bugs but rather* ***characteristics of the data*** *that* ***may indicate potential problems*****.**

EXAMPLES

- MISSING VALUES
- OUTLIER VALUES
- DUPLICATED VALUES
- SUSPECT VALUES

FAIRNESS

In the context of decision-making, **Fairness** is the presence of impartiality and equal treatment toward individuals or groups, without any prejudice or favoritism based on their inherent or acquired characteristics.



FAIRNESS METRICS

We analyzed three fairness metrics:

- **SPD (Statistical Parity Difference):**
  calculates the disparity in favorable rates between the privileged and unprivileged groups.

- **AOD (Average Odds Difference):**
  captures the average discrepancy in false-positive rates and true-positive rates between the privileged and unprivileged groups.

- **EOD (Equal Opportunity Difference):**
  assesses the disparity in true-positive rates between the privileged and unprivileged groups

BIAS MITIGATION ALGORITHMS

Bias mitigation algorithms are employed in literature **to address** ethical bias issues (Fairness) within machine-learning solutions.
They are divided into **three** types:

- **Pre-processing:** work on the **training data**
- **In-processing:** work on the **model**
- **Post-processing:** works on the **model's output**

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PROJECT GOALS

MAIN OBJECTIVE

Analyze:	The relationship between data smell with fairness and bias mitigation algorithms
For the purpose of:	understanding whether data smells influence the level of fairness of bias mitigation algorithms
From the point of view:	of data engineering aiming to address fairness issues while ensuring quality
In the context of:	ML-enabled System

RESEARCH QUESTIONS

RQ_1 : *"Does the presence of data smells impact the fairness of machine learning models?"*

RQ_2 : *"Does the presence of data smells impact on the performances of bias mitigation algorithms?"*

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METHODOLOGICAL STEPS

STEPS TO ADDRESS RQ1

1. DATASETS SELECTION
2. TRAINING SHALLOW-ML MODELS
3. COMPUTE FAIRNESS METRICS
4. DETECTION OF DATA SMELLS
5. REFACTORING OF DATA SMELLS
6. ITERATE THE PROCESS
7. RESULT ANALYSIS

STEPS TO ADDRESS RQ2

1. DATASETS SELECTION AND TRAINING SHALLOW ML MODELS
2. PERFORM BIAS MITIGATION ON RAW DATASET
3. COMPUTE FAIRNESS METRICS
4. DETECTION AND REFACTORING OF DATA SMELLS
5. PERFORM BIAS MITIGATION ON TIDY DATASET
6. ITERATE THE PROCESS
7. RESULT ANALYSIS

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METHODS AND RESULTS FOR RQ1

RQ_1 : *"Does the presence of data smells impact the fairness of machine learning models?"*

DATASETS SELECTION

COMPAS

- SEX
- RACE

ADULT

- SEX
- RACE

GERMAN CREDIT

- SEX
- AGE

DATASETS SELECTION

COMPAS

- SEX
- RACE

~~GERMAN CREDIT~~

- ~~SEX~~
- ~~AGE~~

ADULT

- SEX
- RACE

BANK MARKETING

- AGE

MODELS TRAINING

Support Vector Machine (SVM)

Decision Tree

Random Forest

In this phase, we split the dataset into training and validation sets (80/20) and used the **three most common** classification models to analyze and compare their performance.

COMPUTE FAIRNESS METRICS

UNPRIVILEGED GROUP

ADULT

SEX: FEMALE

RACE: NOT WHITE

COMPAS

SEX: MALE

RACE: NOT CAUCASIAN

BANK MARKETING

AGE: AGE >= 25

AGE < 60

DETECTION OF DATA SMELLS

DSD* TOOL FOUND 7 TYPES OF DATA SMELL:

- DUPLICATED VALUE DATA SMELLS
- CASING SMELL
- MISSING VALUE SMELL
- EXTREME VALUE SMELL
- INTEGER AS FLOATING POINT NUMBER SMELL
- SUSPECT SIGNAL SMELL
- INTEGER AS STRING SMELL

Data Smells: Categories, Causes and Consequences, and Detection of Suspicious Data in AI-based Systems, Harald Foidl et al. (2022)

REFACTORING OF DATA SMELLS

DUPLICATED VALUE DATA SMELLS	ONE HOT ENCODING
CASING SMELL	MAPPED VALUES
MISSING VALUE SMELL	DATA IMPUTATION \ DROP
EXTREME VALUE SMELL	MIN MAX NORMALIZATION

RESULT ANALYSIS

COMPAS

SEX → 7/9 improved (-31%)

RACE → 9/9 improved (-58%)

ADULT

SEX → 9/9 improved (-30%)

RACE → 5/9 improved (-25%)

BANK MARKETING

AGE → 9/9 aggravated (+129%)

ADDRESS OF RQ1

Answer RQ$_1$: *"To summarize the results, after we addressed the data smells from the datasets, **all the Fairness metrics outputs changed**. Thus, The presence of data smells **has influenced** each Fairness metric calculated, either positively or negatively."*

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METHODS AND RESULTS FOR RQ2

RQ_2: *“Does the presence of data smells impact on the performances of bias mitigation algorithms?”*

BIAS MITIGATION ALGORITHMS

We have used **three** Bias Mitigation Algorithms available on AI FAIRNESS 360 (AIF-360):

- **Reweighing (Pre-processing):**
  Adjusts weights of instances in the dataset, creating a balanced dataset that promotes fairness in model training.
- **Exponentiated Gradient Reduction (In-processing):**
  Optimizes a model to reduce bias during training by adjusting weights through an exponentiated gradient approach, balancing fairness and accuracy.
- **Equalized Odds (post-processing):**
  Adjusts the output predictions to ensure equal true positive and false positive rates across different demographic groups, promoting fairness in the final model outcomes.

RESULT ANALYSIS

Raw Model	SPD	AOD	EOD
Decision Tree	-0.088	-0.09	-0.042
SVM	-0.127	-0.127	-0.075
Random Forest	-0.164	-0.169	-0.093

→

Raw Model	SPD	AOD	EOD
Decision Tree	-0.02	-0.011	0.0
SVM	-0.031	0.001	-0.026
Random Forest	-0.028	0.003	-0.019

Tidy Model	SPD	AOD	EOD
Decision Tree	-0.062	-0.06	-0.041
SVM	-0.004	-0.004	-0.001
Random Forest	-0.072	-0.079	-0.043

→

Tidy Model	SPD	AOD	EOD
Decision Tree	0.031	0.06	0.012
SVM	-0.044	-0.024	-0.034
Random Forest	-0.038	-0.015	-0.036

RESULT ANALYSIS

Raw Model	SPD	AOD	EOD
Decision Tree	-0.088	-0.09	-0.042
SVM	-0.127	-0.127	-0.075
Random Forest	-0.164	-0.169	-0.093

Raw Model	SPD	AOD	EOD
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Tidy Model
Decision T
SVM
Random F

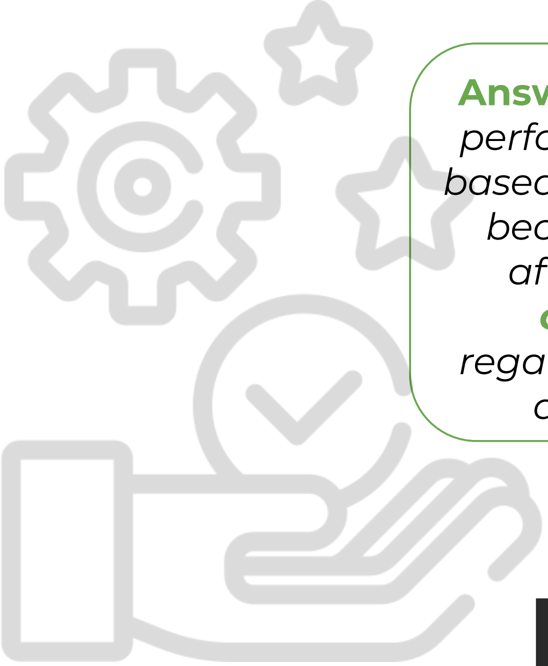
D	EOD
6	0.012
024	-0.034
015	-0.036

Dataset: Compas

Bias mitigation algorithm: Exponentiated GR

Protected attribute: Race

ADDRESS OF RQ2



Answer RQ_2: *there is* ***no evidence*** *that the performance of these algorithms changed based on the presence of data smells. This is because the fairness metrics calculated after applying the algorithms* ***always changed in the same proportion****, regardless of whether the algorithms were applied to the raw or tidy datasets.*

BUT WHY?

BUT WHY?

- **Removal of Relevant Data**
  The cleaning process may have removed useful information that bias mitigation algorithms rely on. Data smells can sometimes contain signals that help identify and correct biases.

- **Altered Data Distribution:**
  Pre-processing may have unpredictably altered data distribution, making bias mitigation algorithms less effective. These algorithms often rely on certain data distribution assumptions, and significant changes can reduce their effectiveness.

- **Models Adapted to Smells**:
  Bias mitigation algorithms may use patterns in data smells to identify disparities. Removing these patterns can reduce the effectiveness of bias mitigation.

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CONCLUSIONS

CONCLUSIONS

The aim of our study was to explore:

Whether datasmells had an impact on the fairness of AI decision making

The presence of data smells impacts the fairness of ML models

How these data smells impact the performance of bias mitigation algorithms.

The performance of bias mitigation algorithms are not influenced by data smells

THANKS!

Do you have any questions?

a.basile40@studenti.unisa.it

m.cicalese21@studenti.unisa.it

p.valletta2@studenti.unisa.it