K-anonymity : The devil's advocate

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Introduction

With increasing amount of *public data*, increases the need for *data privacy*!

Anonymization

K-Anonymization: general idea

- **Direct identifier** attributes
- **Quasi–identifier** attributes

- **Generalization**
  - Generalization hierarchies
- **Suppression**

Trade-off

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Anonymization is primarily a **privacy** concept → it **always** generates information loss.

- How much anonymization is too much?
- How does the anonymization affect the performance of the ML algorithms?
- Can we optimize datasets for model performance while keeping privacy?

Objective

Analyze the impact of anonymization in performance of ML tasks.

- ## Problem

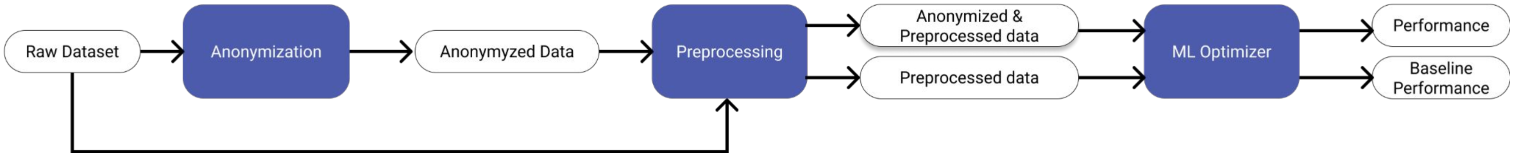
  Previous studies are **limited** in data science aspects:

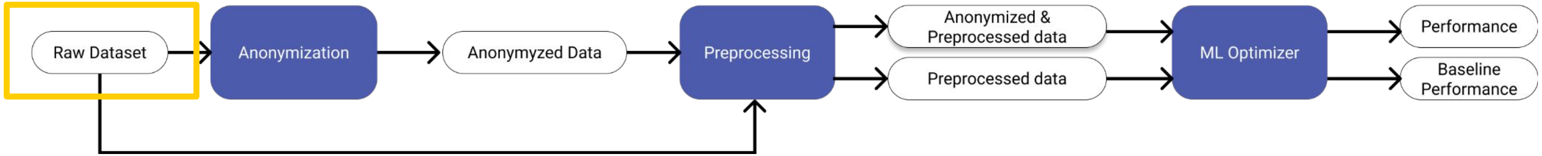
  - Evaluate one dataset, model trained with default hyperparameters!
  - Evaluation conditions are not fair!

Objective

Analyze the impact of anonymization in performance of ML tasks.

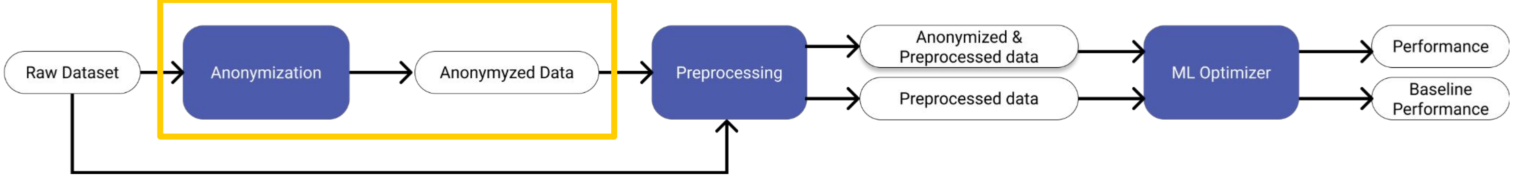
- ## Solution
  - **Three datasets** with diversity of domain and tasks
  - **Two ML** algorithms
  - Search for the **best hyperparams** for each ***K***, using Bayesian optimization
  - **Lots** of models!





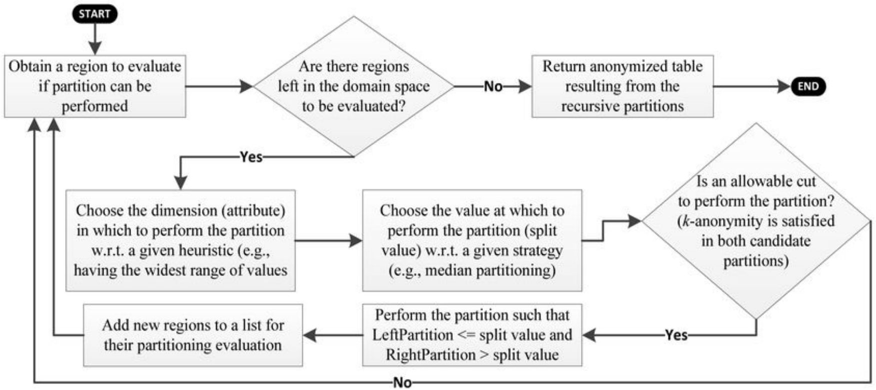
Datasets

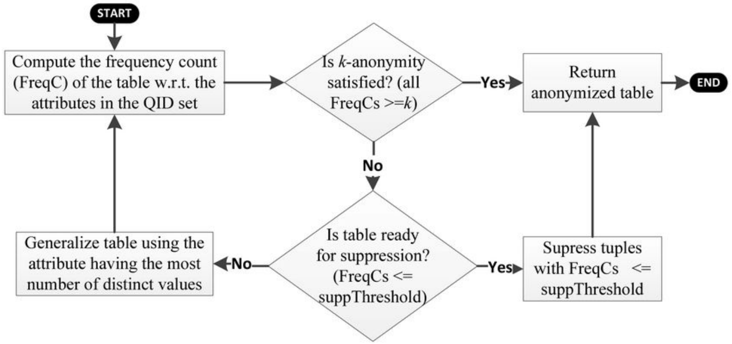
- **ADULT**
  - target variable: income (1= “<= 50K”, 2=” 50K”)
  - QIDs: “age”, “education”, “marital status”, “native country”, “occupation”, “race”, “sex”, and “work class”
  - Size: 45K
- **California Housing**
  - target variable: median house value (continues values)
  - QIDs: “latitude”, “longitude”, “housing median age”, “median income”
  - Size: 20K
- **Contraceptive Methods Choice**
  - target variable: choice of contraceptive method (1=None, 2=Short-term, 3=Long-term)
  - QIDs: “education”, “age” and the “number of children ever born”
  - Size: 1473

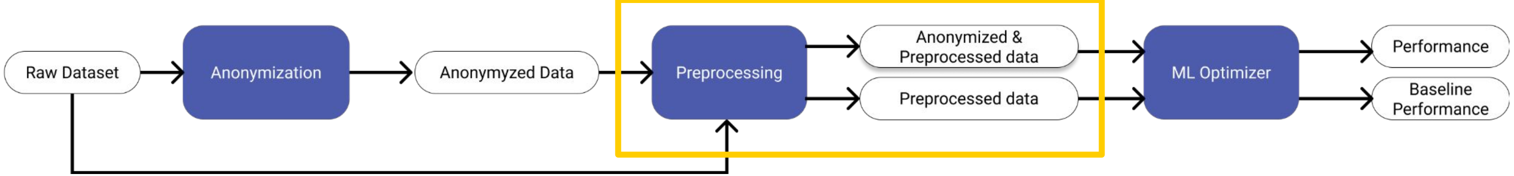


K-Anonymization: methods

- Classic & Basic Mondrian
- Datafly







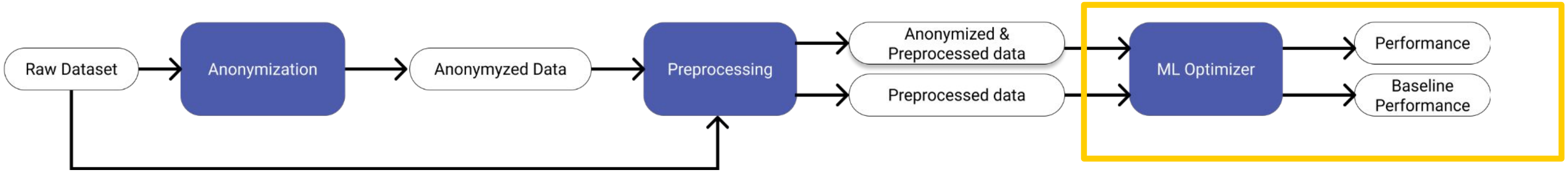
Preprocessing

- Initial:
  - *Removal of the irrelevant variables*
  - *Encoding of the categorical variables*

- After anonymization:
  - *Complete suppression*
  - *Overlapping categories*
    - Numerical values – solved with mean imputation
    - Categorical values – tricky problem

ID	Age	Imputed
1	20~36	28
2	31	31
3	20~30	25

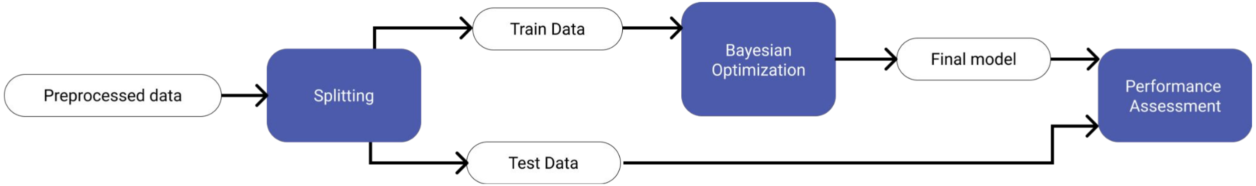
ID	Occupation	Imputed
1	Programmer	?
2	Tech-sector	?
3	Private-sector	?



ML tasks

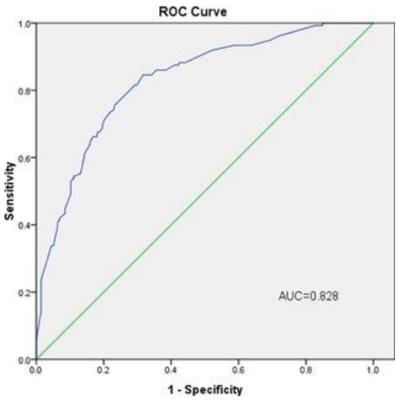
- Algorithms
  - Random Forest
  - XGBoost

- Bayesian Optimization implemented with *Hyperopt*
  - 20 search rounds
  - 4-fold CV in the training set for each round



Metrics

- Classification
- Regression
- Multiclass

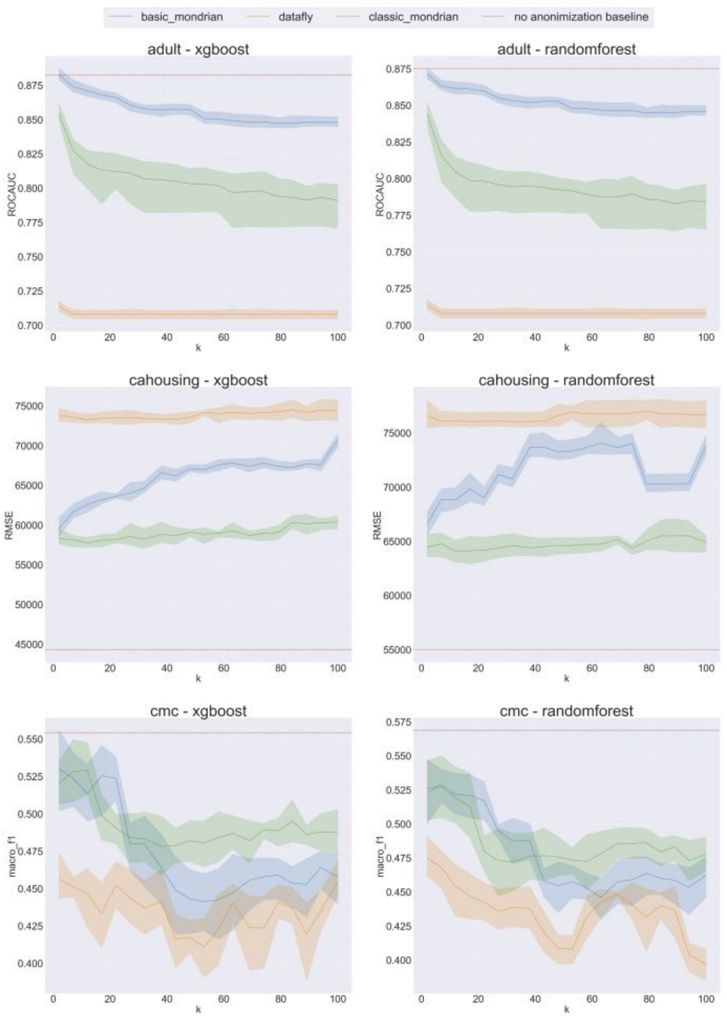


$$RMSE = \frac{1}{n}\sqrt{\sum_{i=1}^{N}(y-\hat{y})^2}$$

$$F1_{macro} = \frac{1}{M}\sum_{i=1}^{M} F1_i$$

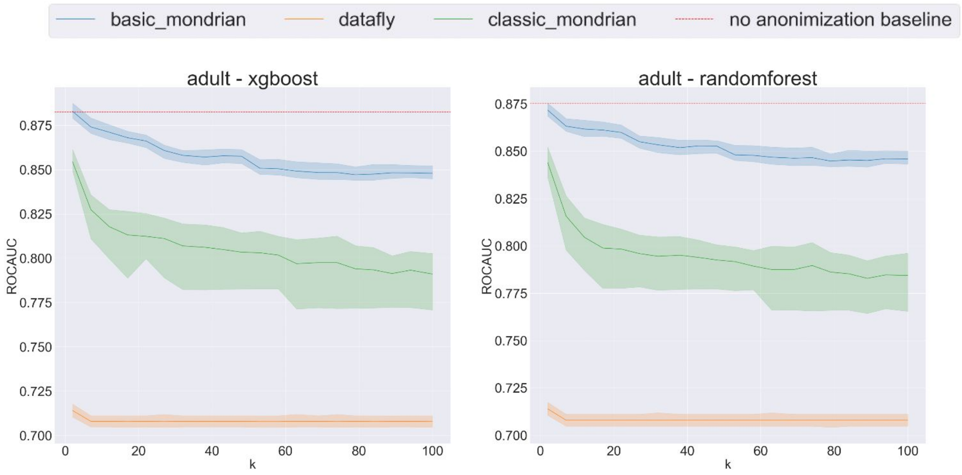
Results

Components	Count
ML Algorithms	2
Datasets	3
Ks	21
Bayesian opt. iterations	20
Cross-validation	4
Pipeline runs	4
Total models	40320



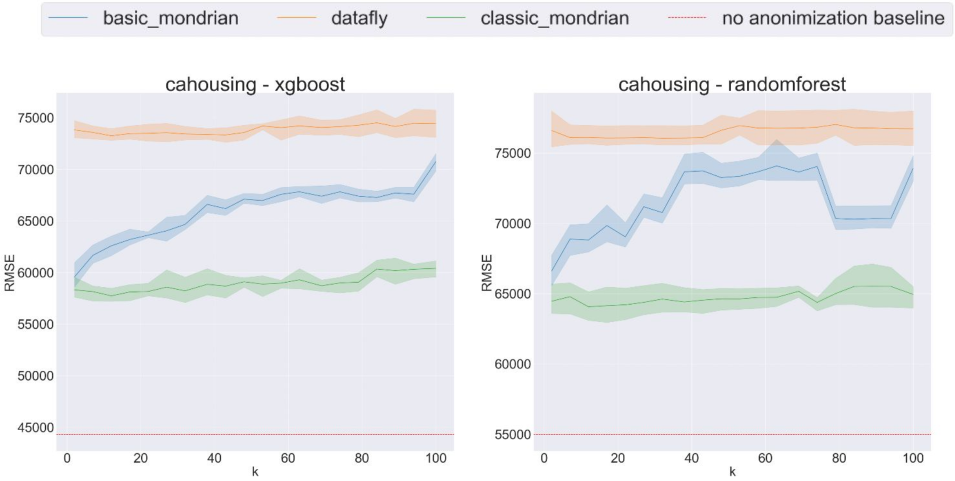
Discussion - ADULT

- **Datafly**
  - Performance drop
  - Overgeneralization
- **Basic Mondrian**
  - Best performance
  - Well-suited for categorical QIDs
- **Classic Mondrian**
  - Worse than Basic Mondrian
  - Ill-suited for categorical QIDs



Discussion - CA Housing

- **Performance gap w.r.t. Baseline**
  - High cardinality of attribute values
- **Datafly**
  - Overgeneralization
- **Classic Mondrian**
  - Best performance
  - Well-suited for numerical QIDs
- **Basic Mondrian**
  - Worse than Classic Mondrian
  - Generalization hierarchies not granular enough

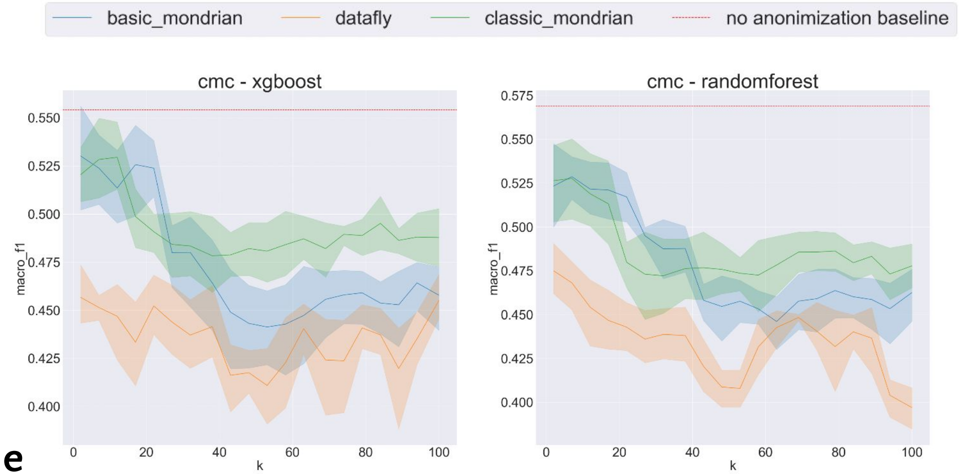


Discussion - CMC

- **Dataset size**
  - Not satisfactory baseline performance
  - High variation
- **High impact of *K***

Dataset	Maximum K	% of the dataset
ADULT	100	0.307
CAH	100	0.484
CMC	100	6.789

- **Smaller performance gap w.r.t. baseline**
  - Low cardinality numerical attributes
  - Granular enough generalization hierarchy



Conclusions

- Important factors **we knew** :
    - Increase K → Information loss → Performance decrease
    - Datafly problem: overgeneralization tendency
- Important factors **we found**:
    - Hierarchy granularity
        - High cardinality attributes, i.e. numerical
    - Type of QID
        - Numerical → Ordering based
        - Categorical → Generalization hierarchy based

Conclusions

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References

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