# Fighting Sampling Bias in ML Models in Credit Scoring

N Kozodoi, M Alamgir, Y Gatsoulis, S Lessmann, L Moreira-Matias, K Papakonstantinou

# Presentation Outline

## 1. Sampling Bias Problem

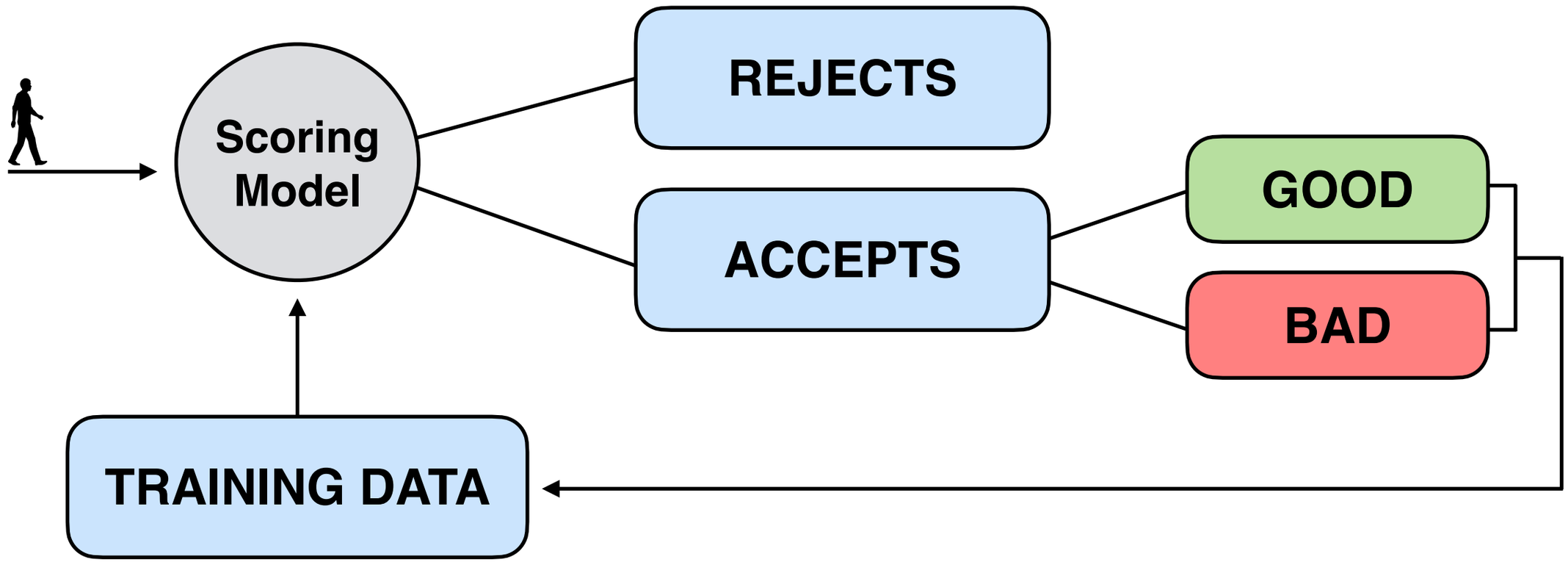
- Problem setup & illustration
- Impact on ML model training and evaluation

## 2. How to Correct Sampling Bias?

- Improving training under sampling bias
- Improving evaluation under sampling bias

## 3. Further Challenges

# Acceptance Loop in Credit Scoring

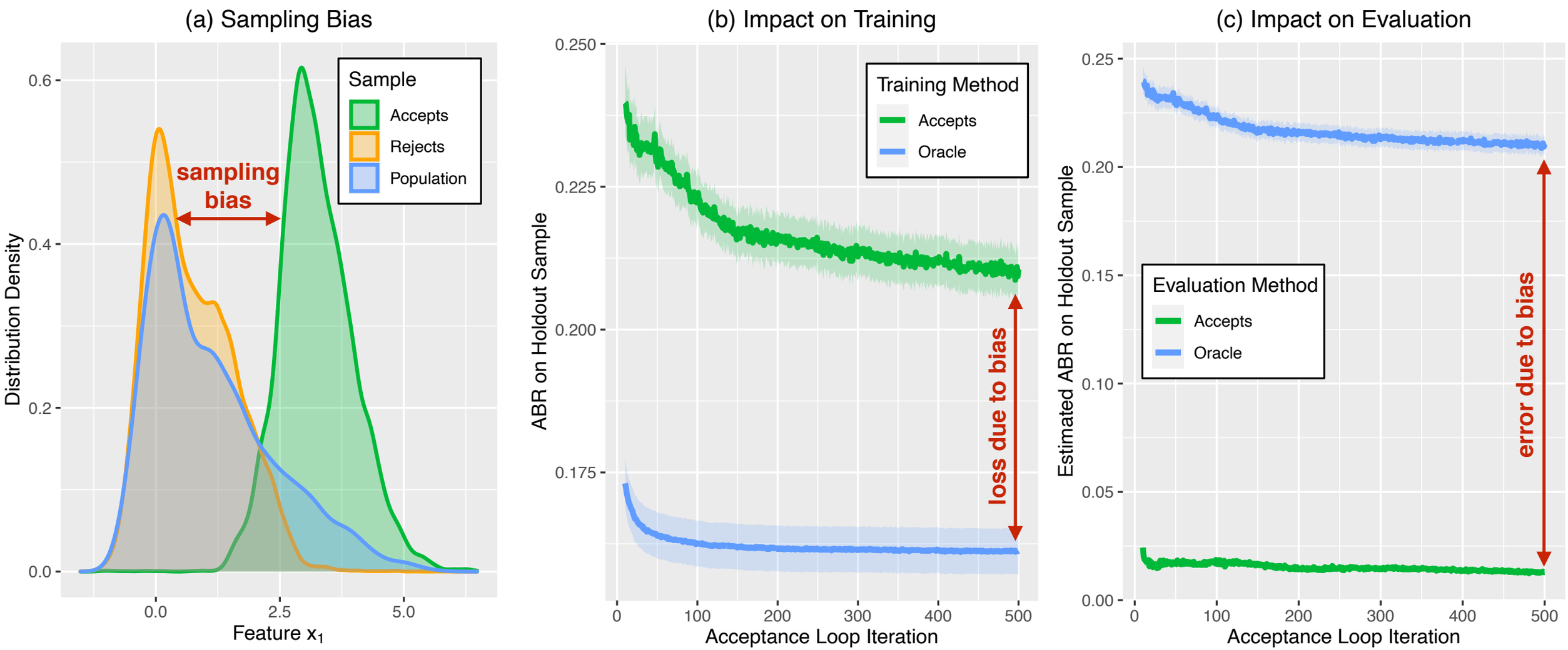



- **scoring model filters incoming loan applications**
  - ML model observes features of incoming applicants
  - predicts whether an applicant will repay the loan
- **training a model requires data with known outcomes**
  - outcomes are only observed for previously **accepted applicants**
  - labels are missing **not completely at random** but depending on the model
- **sampling bias may amplify with acceptance loop iterations**

# Sampling Bias Illustration

**Sampling bias in accepts affects model training and evaluation:**

- training a model on a biased sample **decreases its performance**
- evaluating a model on a biased sample provides a **misleading estimate**




**ABR** = average **BAD** rate among accepts; lower is better

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# Training under Sampling Bias

## How to improve training?

### Data augmentation (label rejects)

- **label rejects** using a certain technique
- **augment training data** of **accepts** with pseudo-labeled **rejects**
- use augmented data for training
- e.g., **label all rejects as BAD**

### Extract information from rejects

- estimate **distribution mismatch** between **accepts** and target population
- account for the mismatch during training without explicitly labeling **rejects**
- e.g., **reweighting the loss**

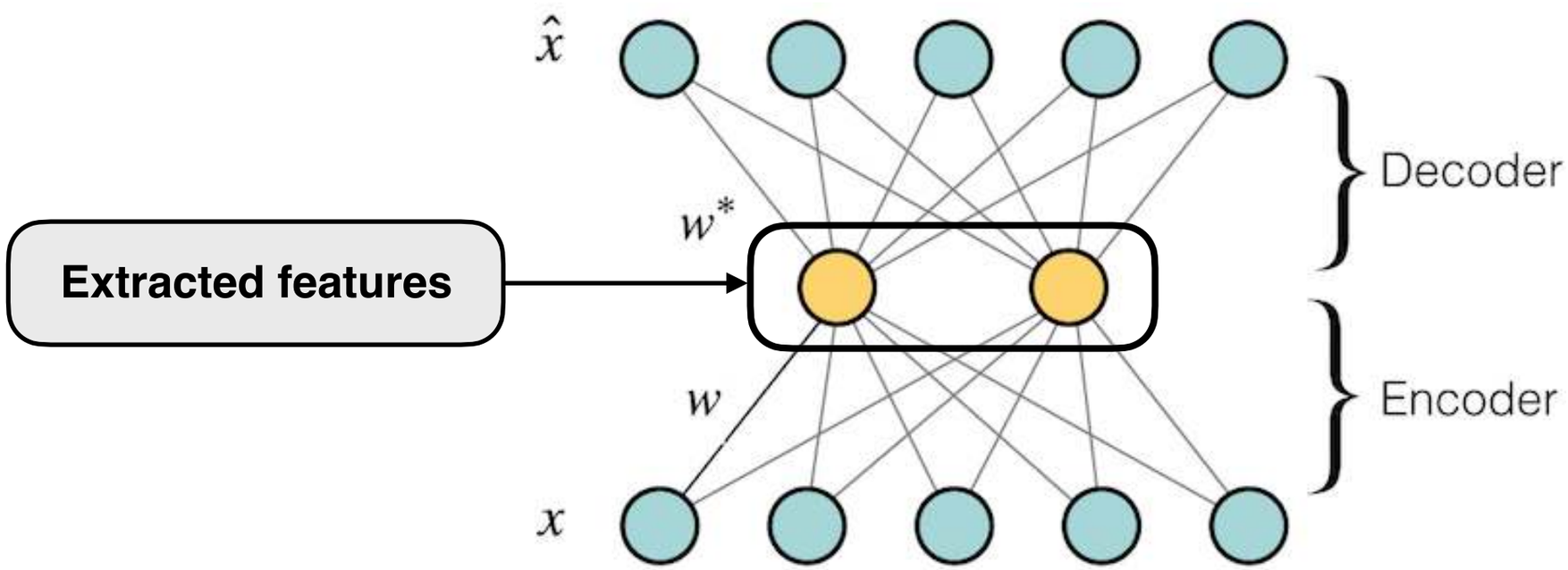
# Extracting Information: Autoencoders

## Idea:

- Use rejects to extract useful features **without labeling them**

## Pipeline:

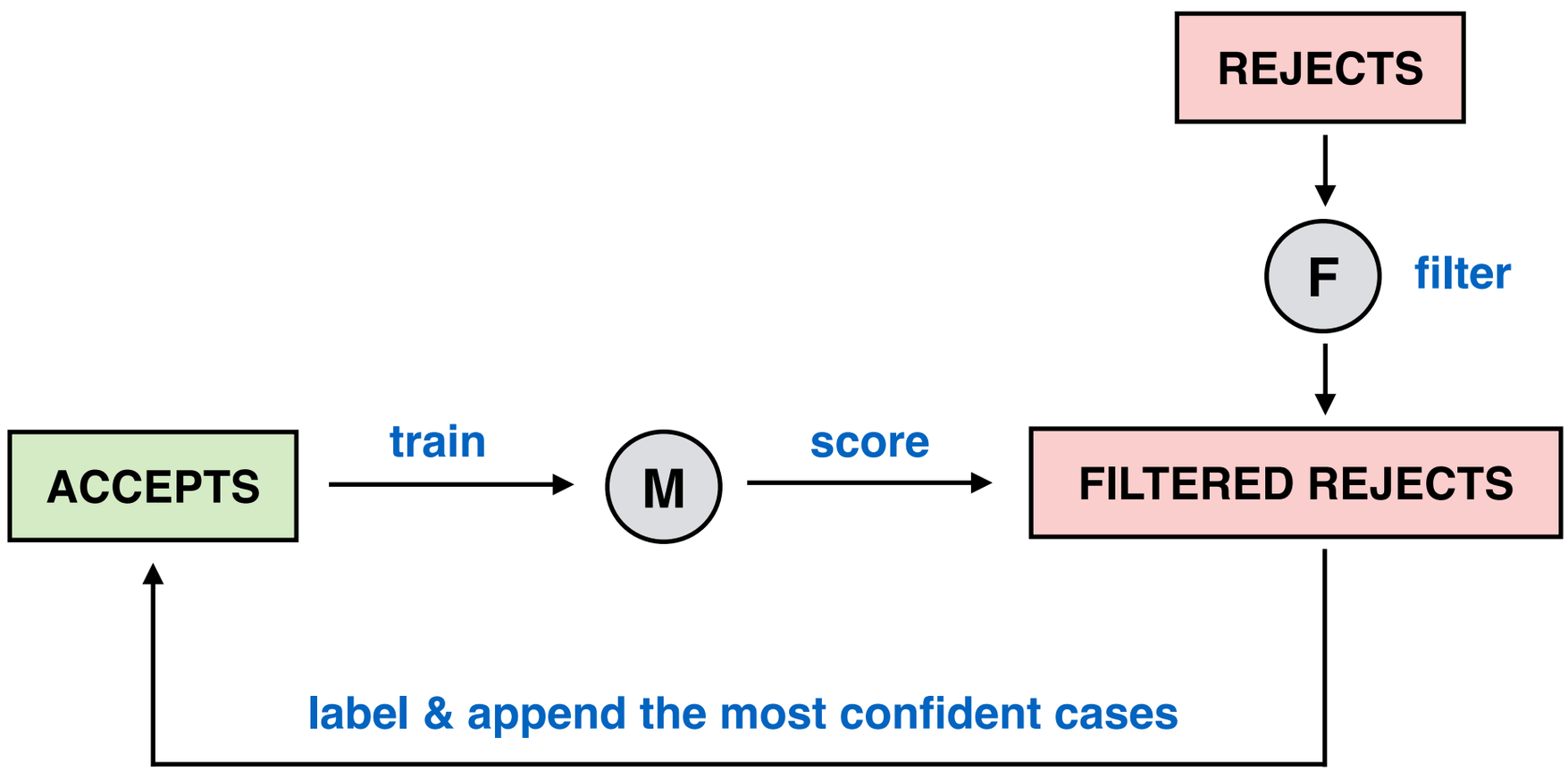
- Train Autoencoder on **accepts** + **rejects**
- Add distribution **mismatch penalty** to the loss function
- Use a bottleneck layer to **extract features**
- Append new features to accepts and train a new model



# Labeling: Bias-Aware Self-Learning

**Pipeline:**

- iteratively label **selected rejects** using predictions from a weak classifier
- implement **multiple techniques** to reduce the risk of error propagation
  - filtering **rejects** coming from the most different distribution region
  - using imbalance multiplier to label & append more **BAD** applicants
  - early stopping labeling iterations to avoid overfitting on **accepts**



# Evaluation under Sampling Bias

## How to improve evaluation?

### Collect unbiased sample

- evaluate on a **representative sample** to avoid sampling bias
- requires issuing loans to **random set of applicants** without scoring
- **issue:** very costly to set up

### Adjust evaluation framework

- use techniques to account for the **distribution mismatch**
- incorporate **rejects** into evaluation
- **issue:** labels of **rejects** are unknown

# Bayesian Evaluation Framework

- estimating evaluation metric ***M*** on a set ***S*** containing:
  - **accepts** with the true labels
  - **rejects** with random pseudo-labels based on the prior P(**BAD**)
- estimate prior P(**BAD**) based on the **current scorecard** $f(X)$

**input** : model $f(X)$, evaluation sample $S$ consisting of labeled accepts $S^a = \{(\mathbf{X}^a, \mathbf{y}^a)\}$ and unlabeled rejects $\mathbf{X}^r$, prior $\mathbf{P}(\mathbf{y}^r|X^r)$, evaluation metric $M(f, S, \tau)$, meta-parameters $j_{max}, \epsilon$

**output:** Bayesian evaluation metric $\mathrm{BM}(f, S, \tau)$

$j = 0$; $\Delta = \epsilon$; $E^c = \{\}$ ; // initialization

**while** $(j \leq j_{max})$ *and* $(\Delta \geq \epsilon)$ **do**

  $j = j + 1$

  $\mathbf{y}^r = \mathrm{binomial}(1, \mathbf{P}(\mathbf{y}^r|\mathbf{X}^r))$ ; // generate labels of rejects

  $S_j = \{(\mathbf{X}^a, \mathbf{y}^a)\} \cup \{(\mathbf{X}^r, \mathbf{y}^r)\}$ ; // construct evaluation sample

  $E^c_j = \sum_{i=1}^{j} M(f(X), S_i, \tau)/j$ ; // evaluate

  $\Delta = E^c_j - E^c_{j-1}$ ; // check convergence

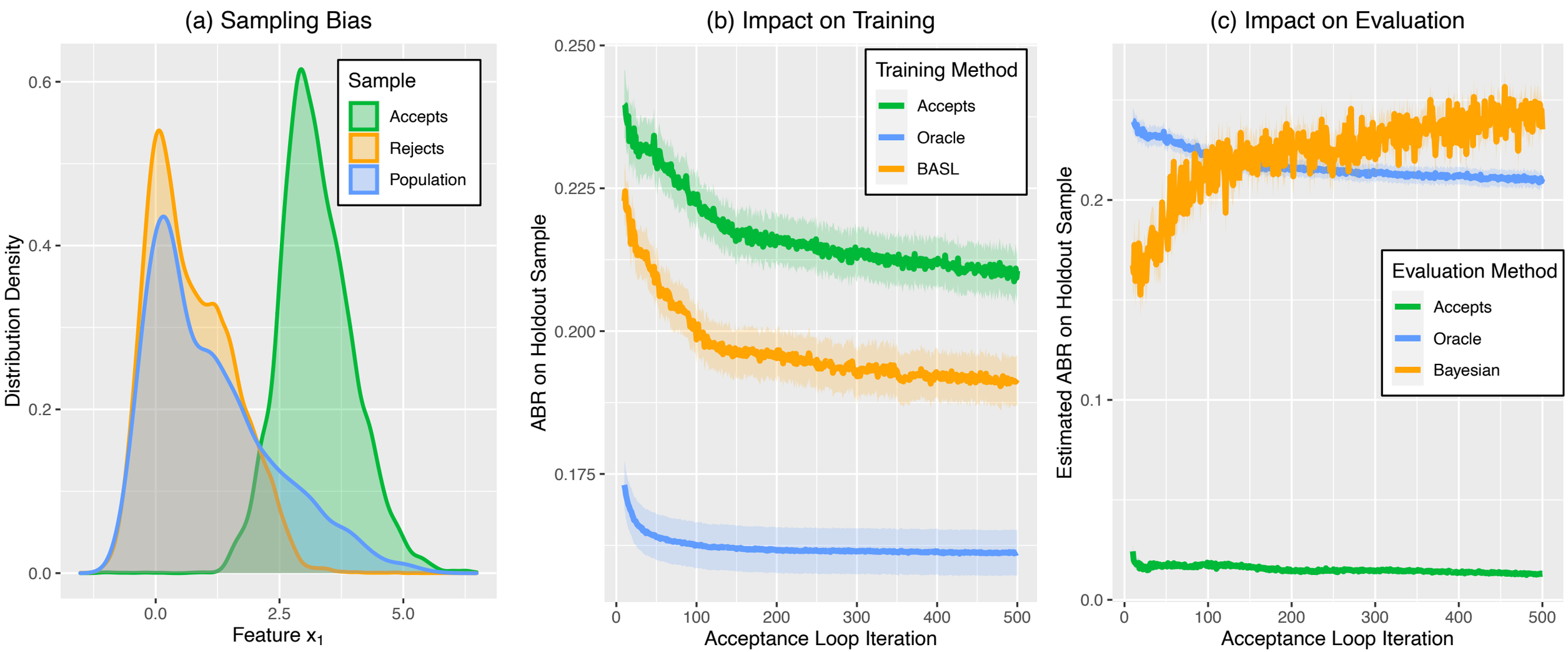
**end**

**return** $BM(f, S, \tau) = E^c_j$

# Potential Performance Gains

**Using bias correction methods allows to partly recover loss due bias**

- **improving performance** of the model on new applications
- **improving performance estimate** of the model on new applications



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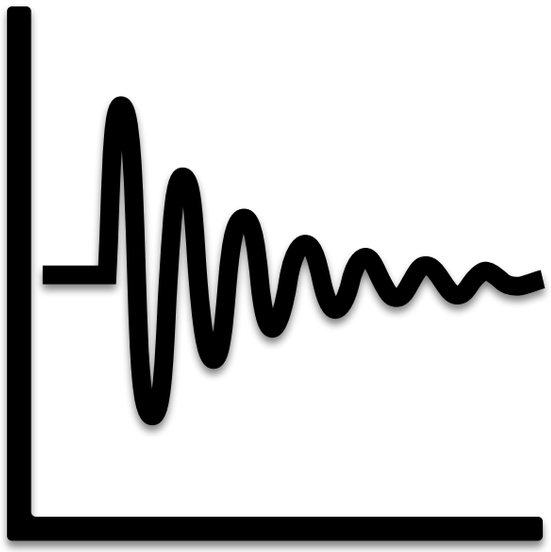
# Dataset Shift and Sampling Bias

- **distribution discrepancy is also affected by dataset shift**
  - complicates the correction of sampling bias between **accepts**/**rejects**
  - long delay between accepting an applicant and learning their label

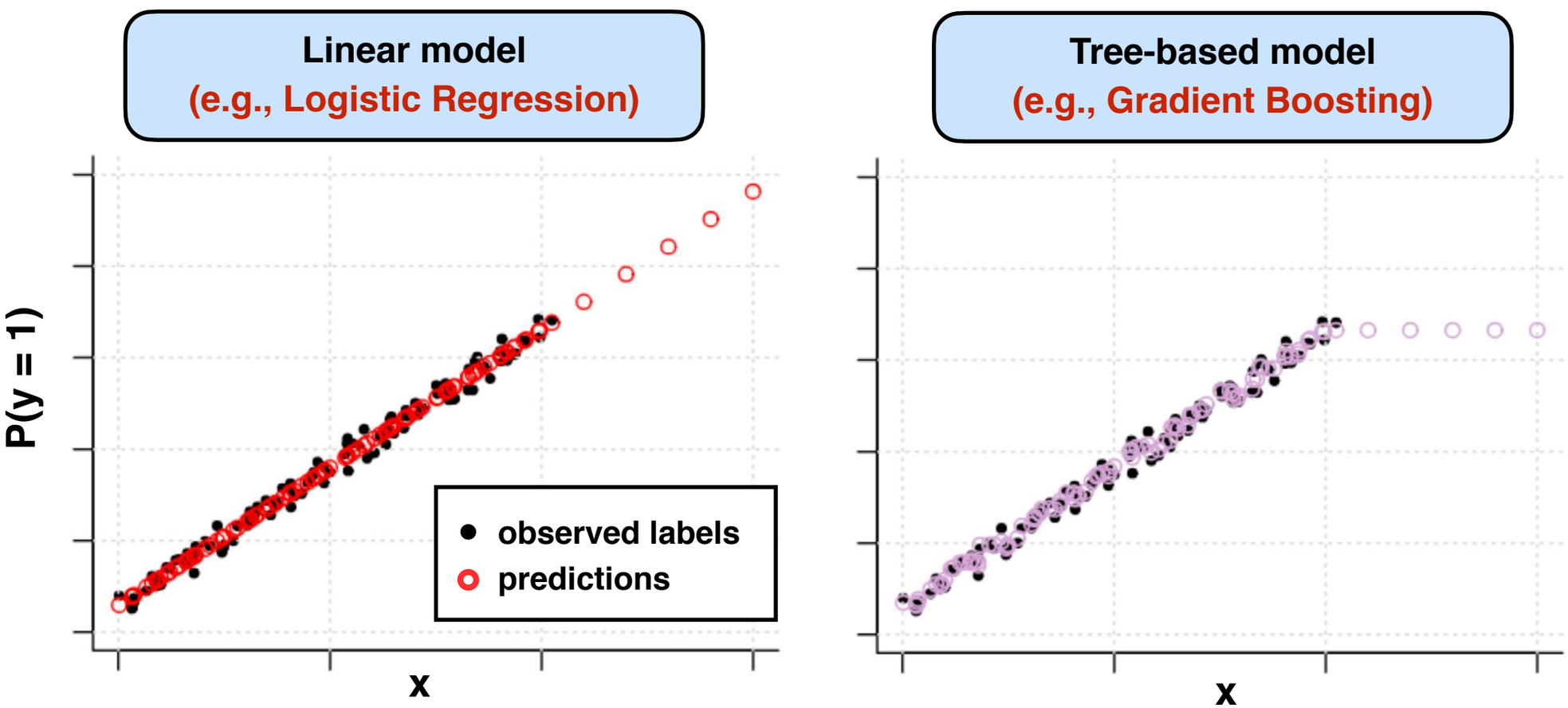
- **covariate shift**
  - change in the feature distribution between train and test data
  - e.g., changes in the acceptance policy or marketing strategy

- **concept shift**
  - change in the functional feature-target relationship
  - e.g., changes in the business cycle



# Sampling Bias in Different Environments

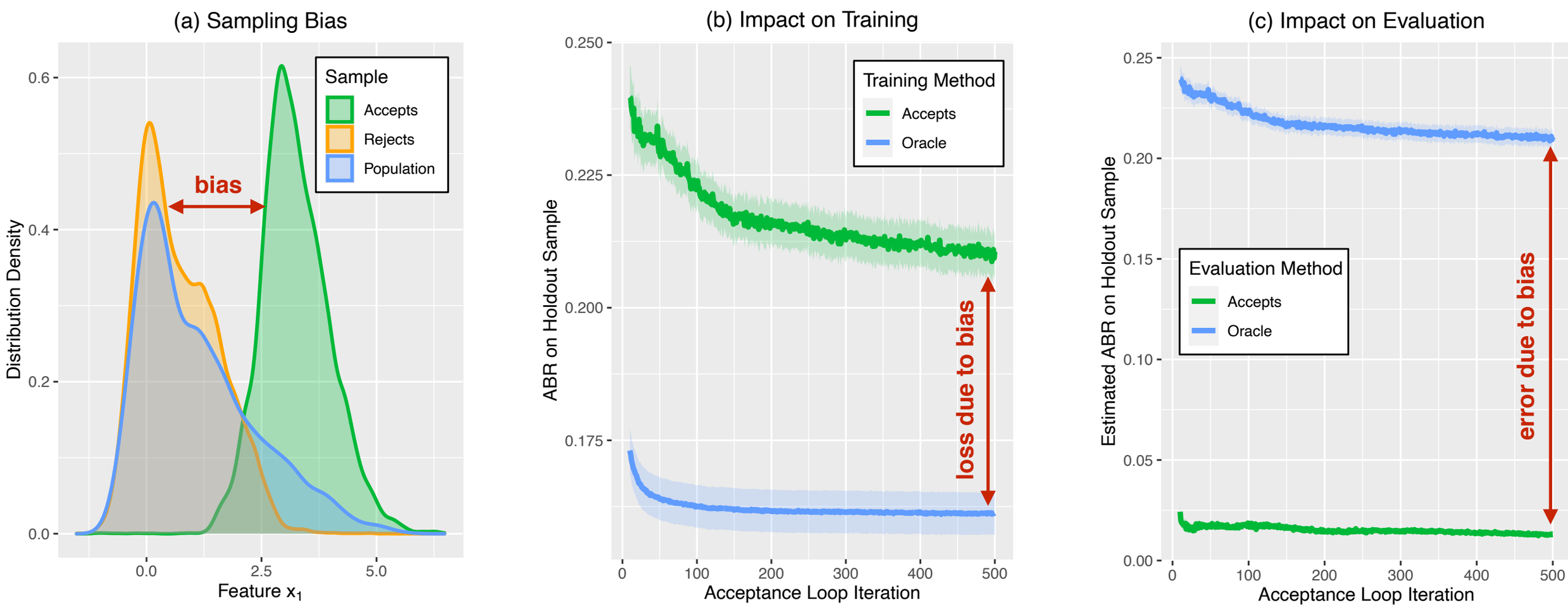
- **magnitude of sampling bias depends on many factors**
- **lower approval rates => stronger bias**
  - low acceptance increases difference between **accepts** and population
  - can make it too difficult for bias correction to work given a sparse sample
- **classifiers have different extrapolation abilities**



# Some Further Challenges

- **regulation-related challenges**
  - keeping data on **rejected applicants** might not be feasible
  - need to create synthetic samples similar to real **rejects**
- **bias illustration in ML models**
  - detecting bias in non-parametric models is not straightforward
  - need to illustrate bias through the lens of performance / model predictions

# Thanks for your Attention!




## Contact:


n.kozodoi@icloud.com

www.linkedin.com/in/kozodoi

www.kozodoi.me


## Slides: