

# Increasing Profitability of Credit Scoring Models with Bias Correction Algorithms

Preprint



Slides



# Presentation Outline

## 1. Background

- What is credit scoring?
- What are the business goals?

## 2. Problem Description

- Sampling bias illustration
- Bias impact on ML models

## 3. Approach

- Improving model evaluation
- Improving model training

## 4. Results

- Offline evaluation
- Business impact

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# What is Credit Scoring?

## Customer perspective:

**Instant loan in 10 minutes**

**Amount**

10 000 ₽

2 000 ₽ 15 000 ₽ 30 000 ₽

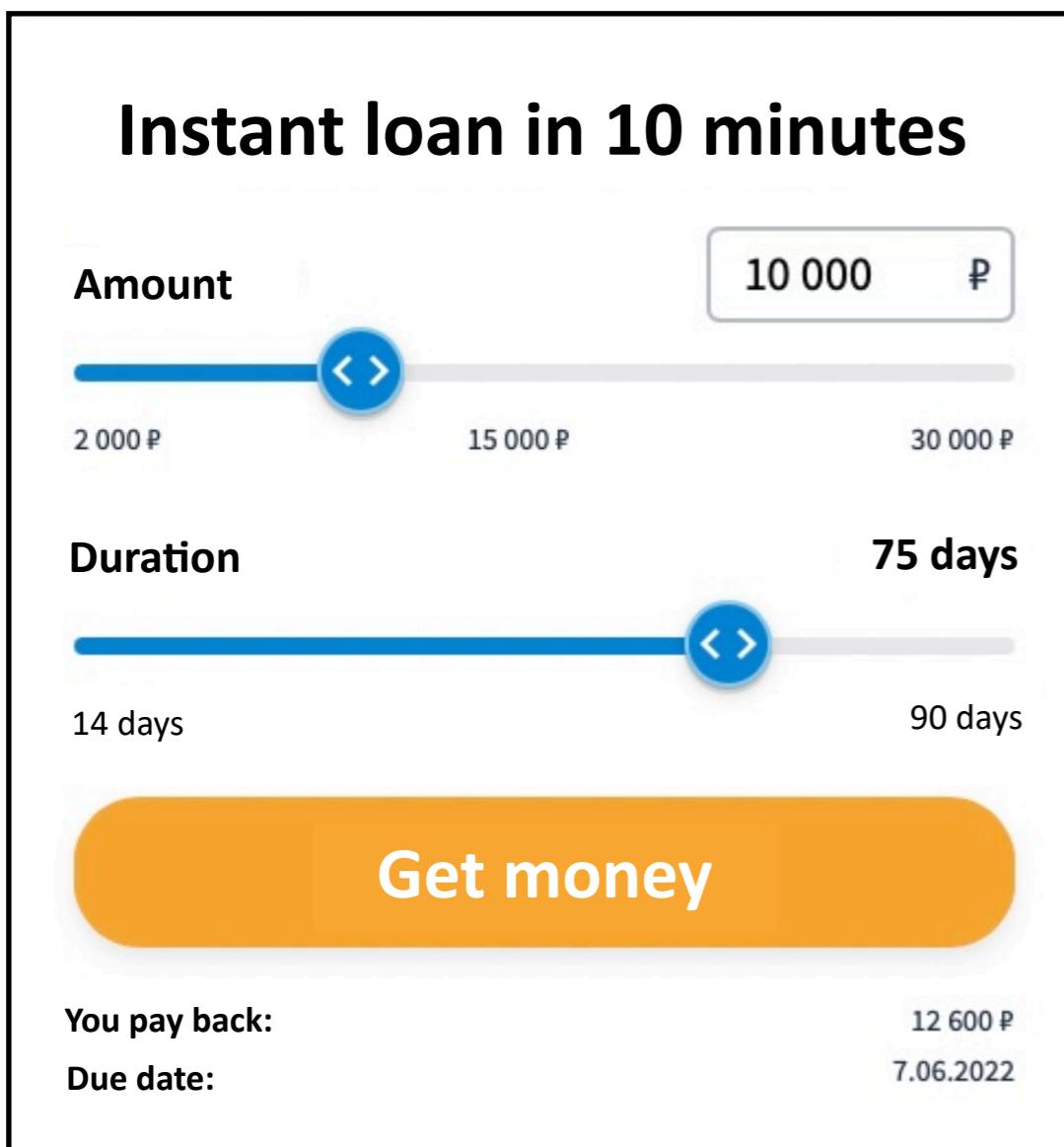
**Duration**

75 days

14 days 90 days

**Get money**

You pay back: 12 600 ₽  
Due date: 7.06.2022



**Name**

First Name

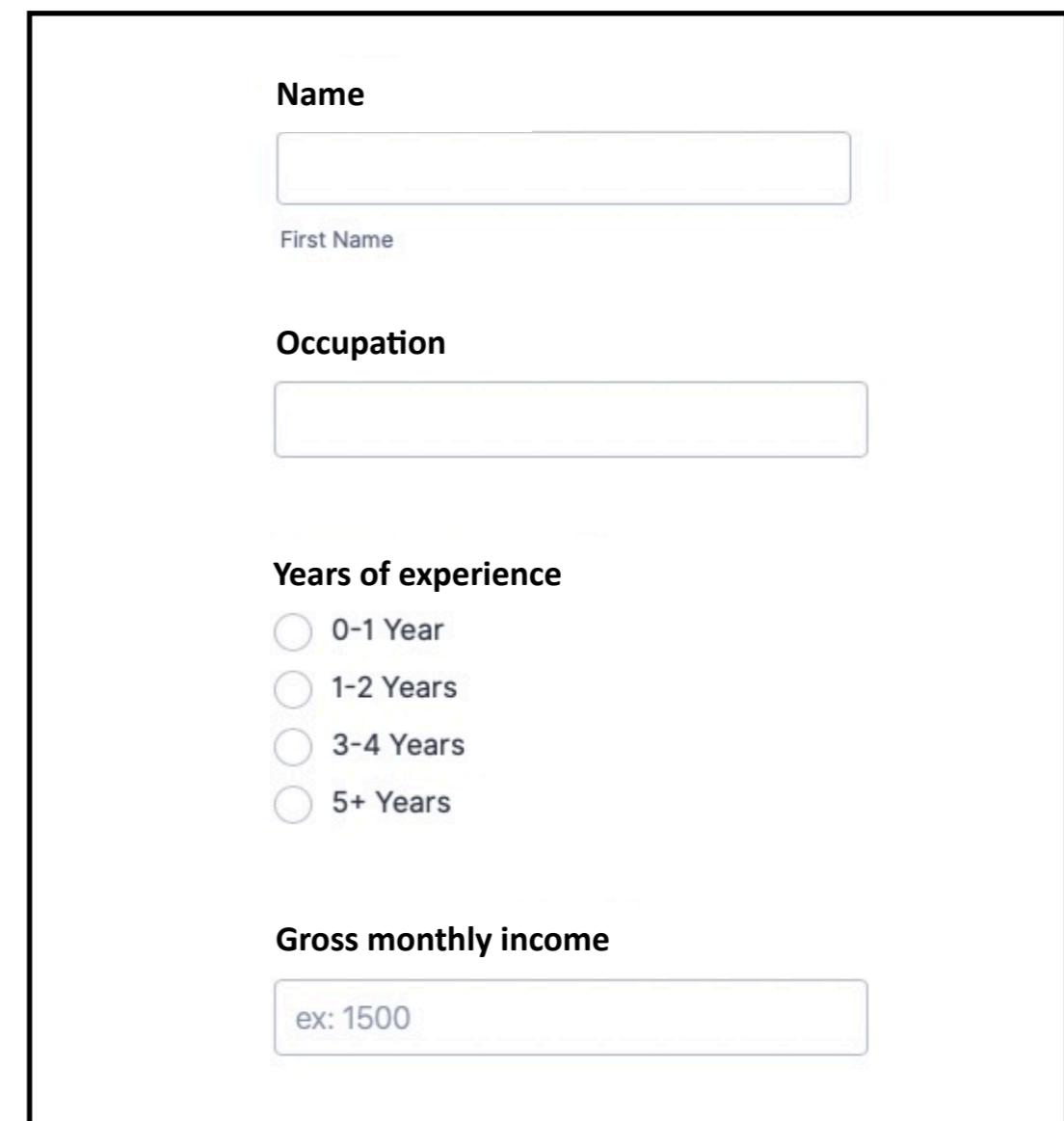
**Occupation**

**Years of experience**

- 0-1 Year
- 1-2 Years
- 3-4 Years
- 5+ Years

**Gross monthly income**

ex: 1500



# What is Credit Scoring?

## Customer perspective:

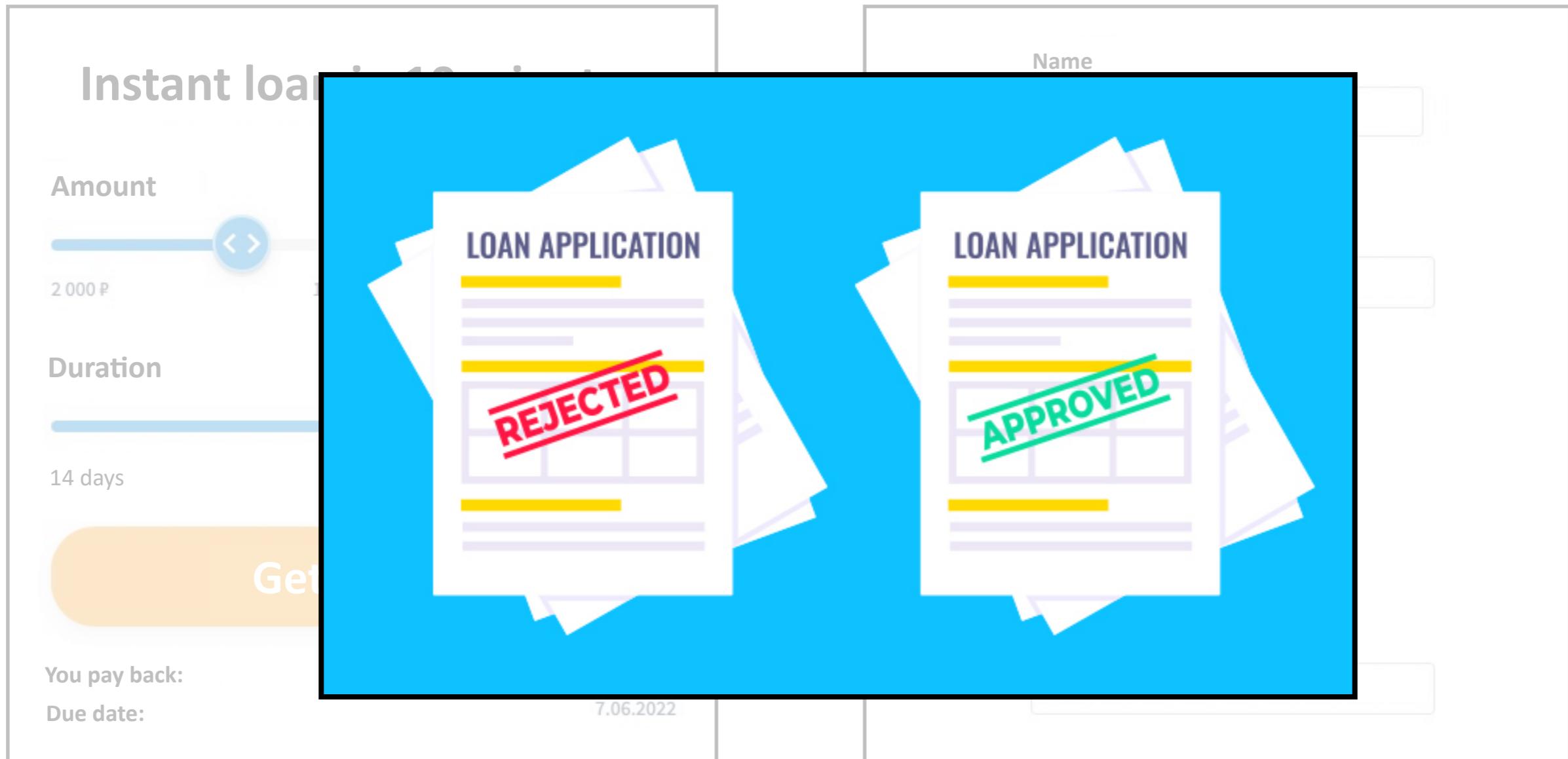
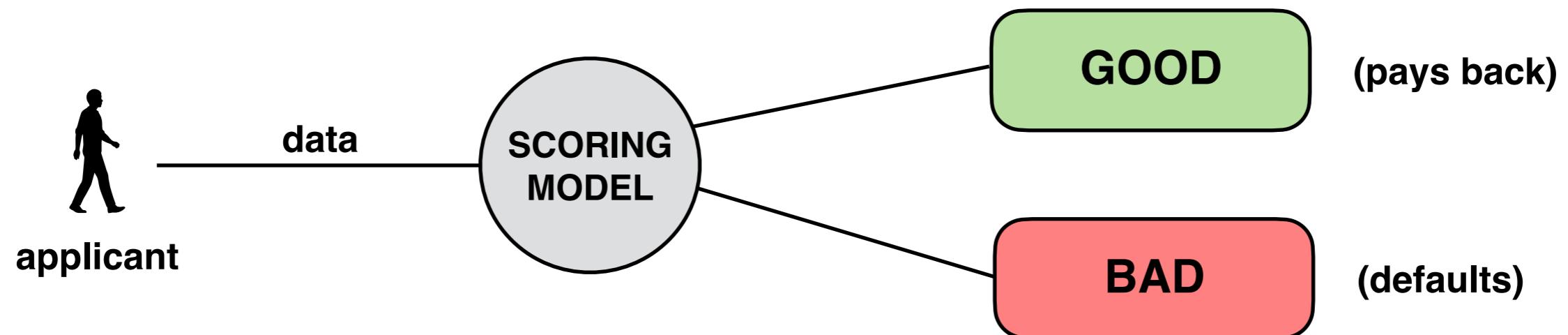


Image source: <https://www.indusind.com/>

# What is Credit Scoring?

## Business perspective:

- classification task of distinguishing **BAD** and **GOOD** loans
- scorecard – model that predicts probability of default
- increasing reliance on Machine Learning (e.g., Wei et al. 2016)
  - consumer credit in the US exceeds \$4,325 billion<sup>1</sup>
  - FinTechs account for 49.4% of consumer loan market<sup>2</sup>



<sup>1</sup> The Federal Reserve: Statistical Release on Consumer Credit (2021)

<sup>2</sup> Experian: FinTech vs. Traditional FI Trends (2019)

# Business Goals

**Goal:** improving accuracy of credit scoring models

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## Costs:

- accepting **BAD** customer results in a **high loss**
  - business: loss = amount that the client does not pay back
  - customer: long-term financial difficulties
- rejecting **GOOD** customer results in a **moderate loss**
  - business: loss = potential interest and fees earned from the client
  - customer: limited access to finance

		<u>Decision</u>	
		Accept	Reject
<u>Outcome</u>	GOOD	+ interest	- interest
	BAD	- amount	0

# Business Goals

Goal: improving accuracy of credit scoring models

## Costs:

- accepting **BAD** customer results in a **high loss**
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- rejecting **GOOD** customer results in a **moderate loss**
  - business: loss = potential interest and fees earned from the client
  - customer: limited access to finance

## Project goal:

- maximize scorecard profitability
  - minimize **BAD** rate among accepts

		<u>Decision</u>	
		Accept	Reject
<u>Outcome</u>	GOOD	+ interest	- interest
	BAD	- amount	0

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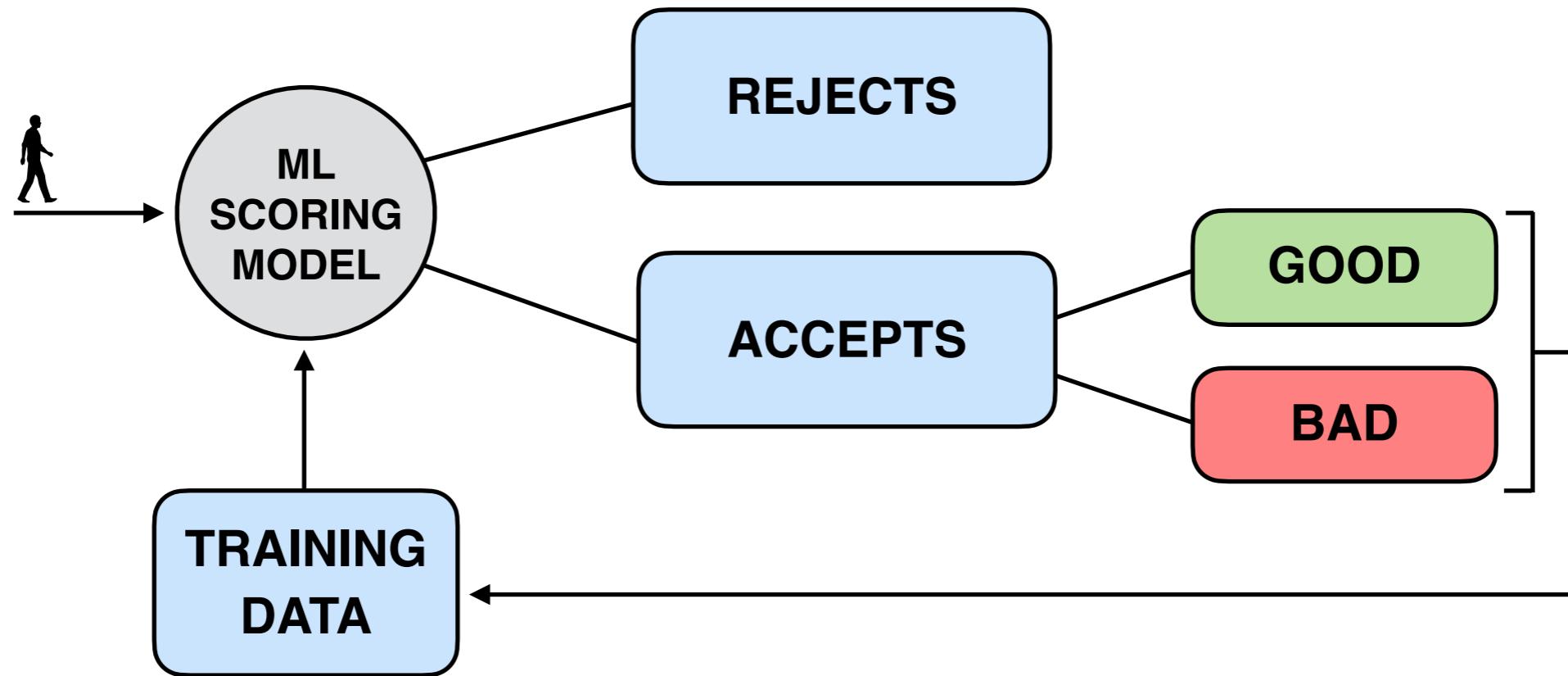
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# Loan Approval Process at Monedo

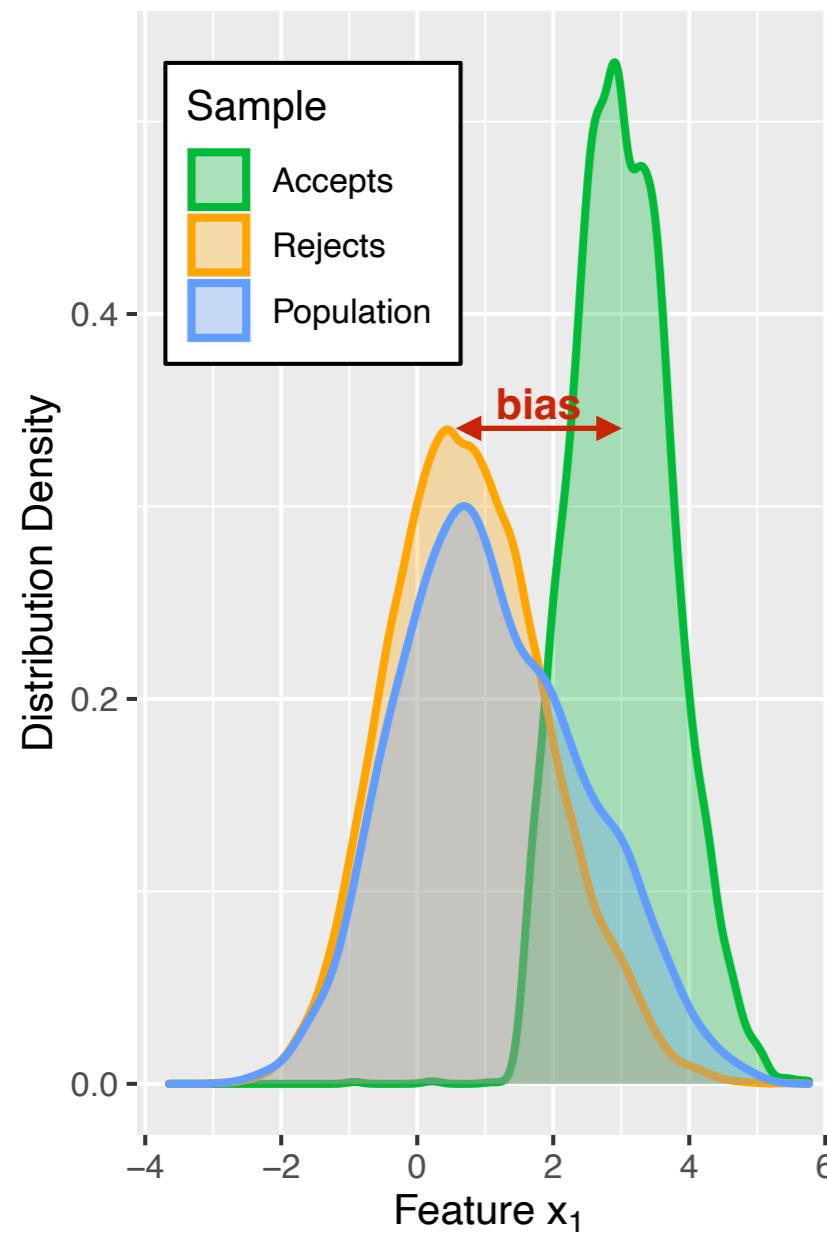


- **scoring model filters incoming loan applications**
  - ML model observes applicants' features and predicts **P(GOOD)**
  - top-ranked applicants are accepted and receive a loan
- **training a model requires data with known outcomes**
  - outcomes are only observed for previously **accepted clients**
  - labels of **rejects** are missing not at random (*Crook et al. 2004*)
  - historical data suffers from sampling bias

# Sampling Bias Illustration

- **sampling bias** originates in the **training data**

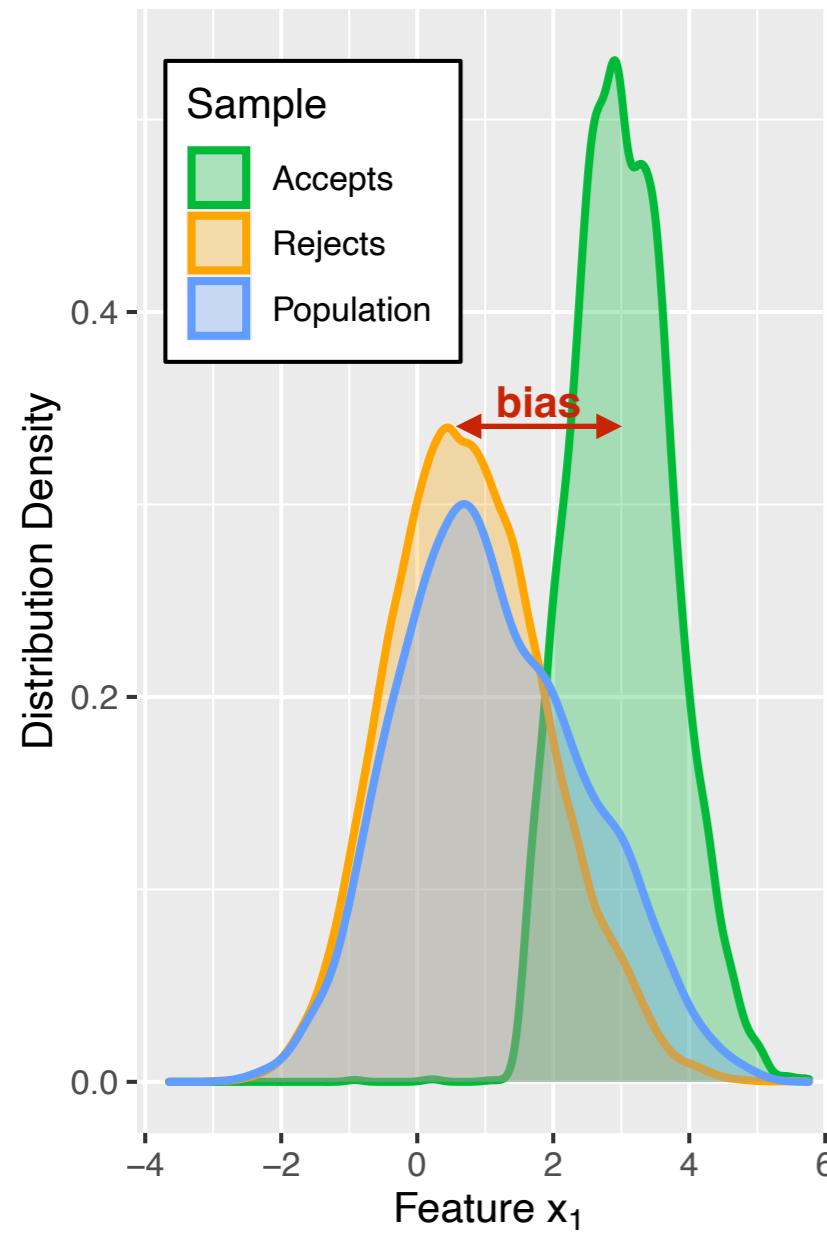
(a) Bias in Data



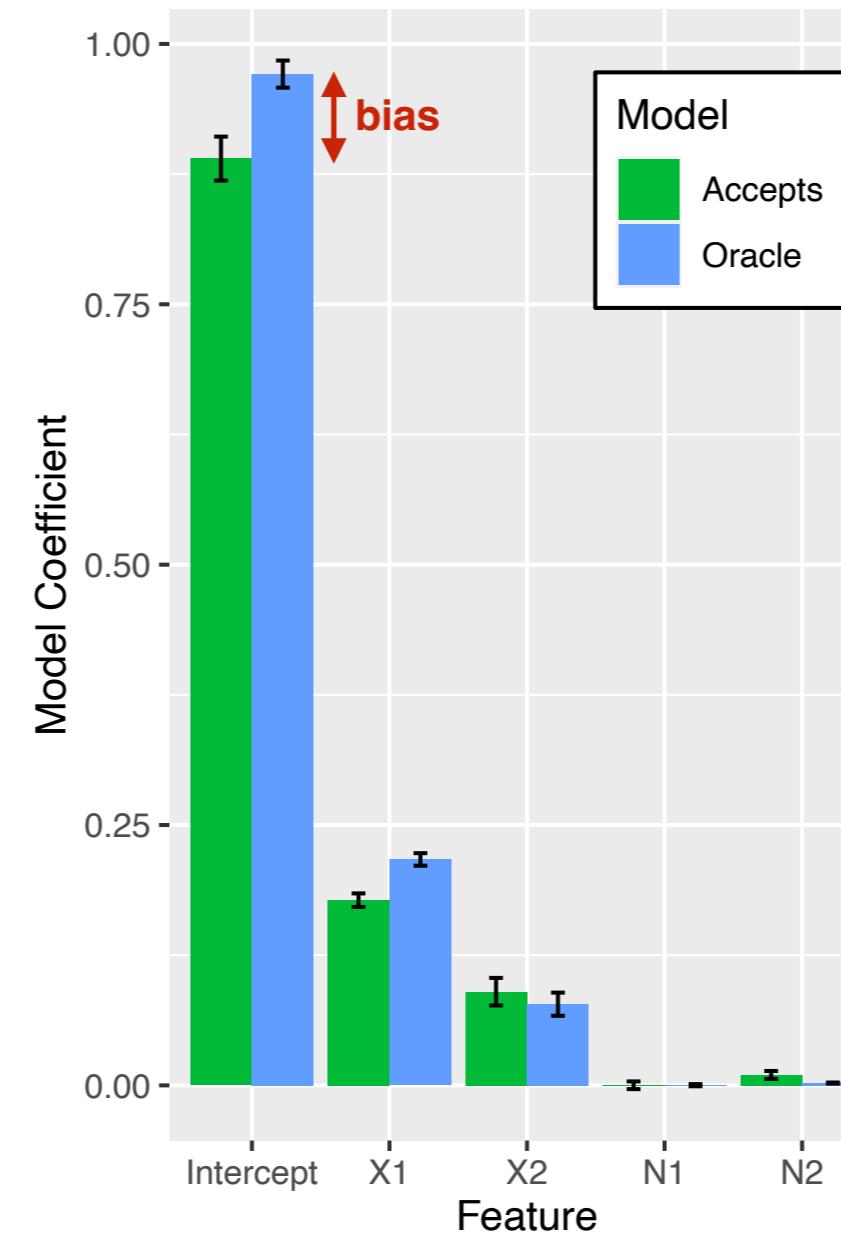
# Sampling Bias Illustration

- **sampling bias** originates in the **training data**
- propagates to the **model parameters**

(a) Bias in Data



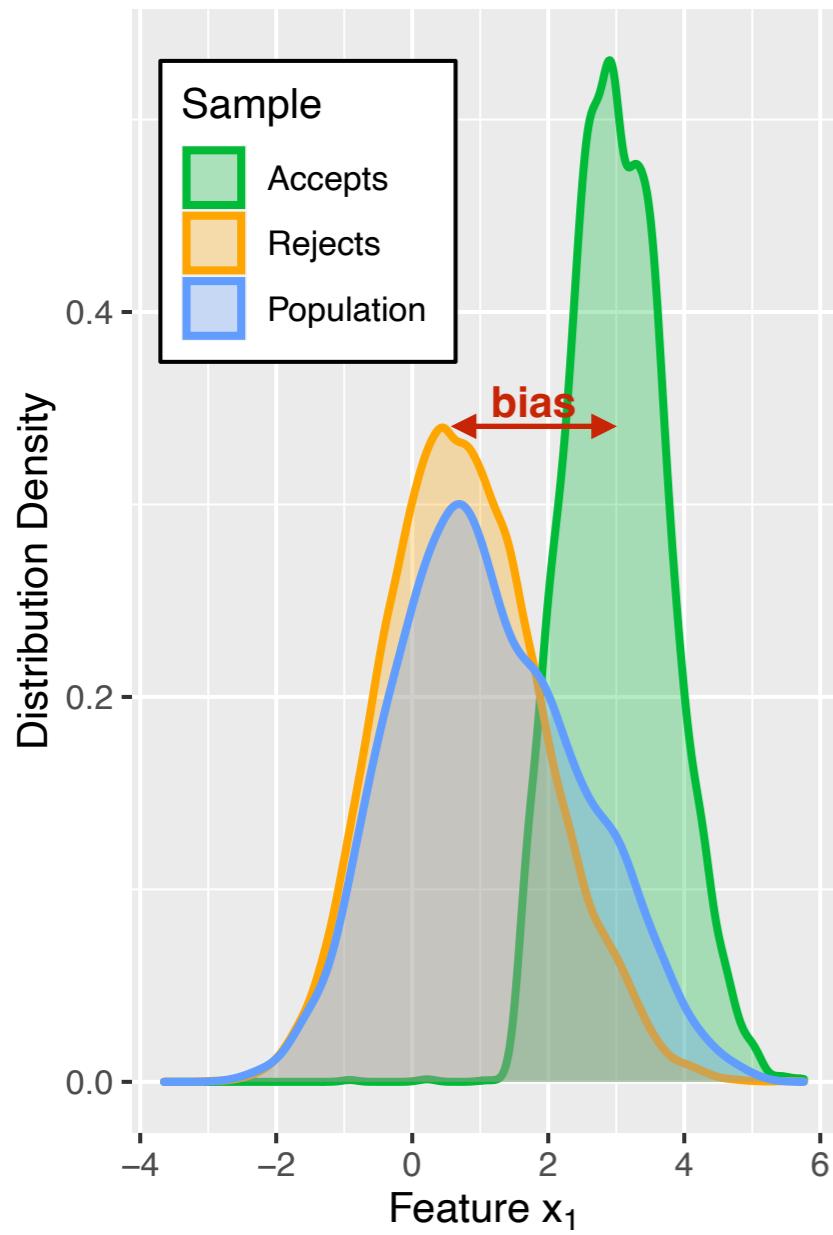
(b) Bias in Model



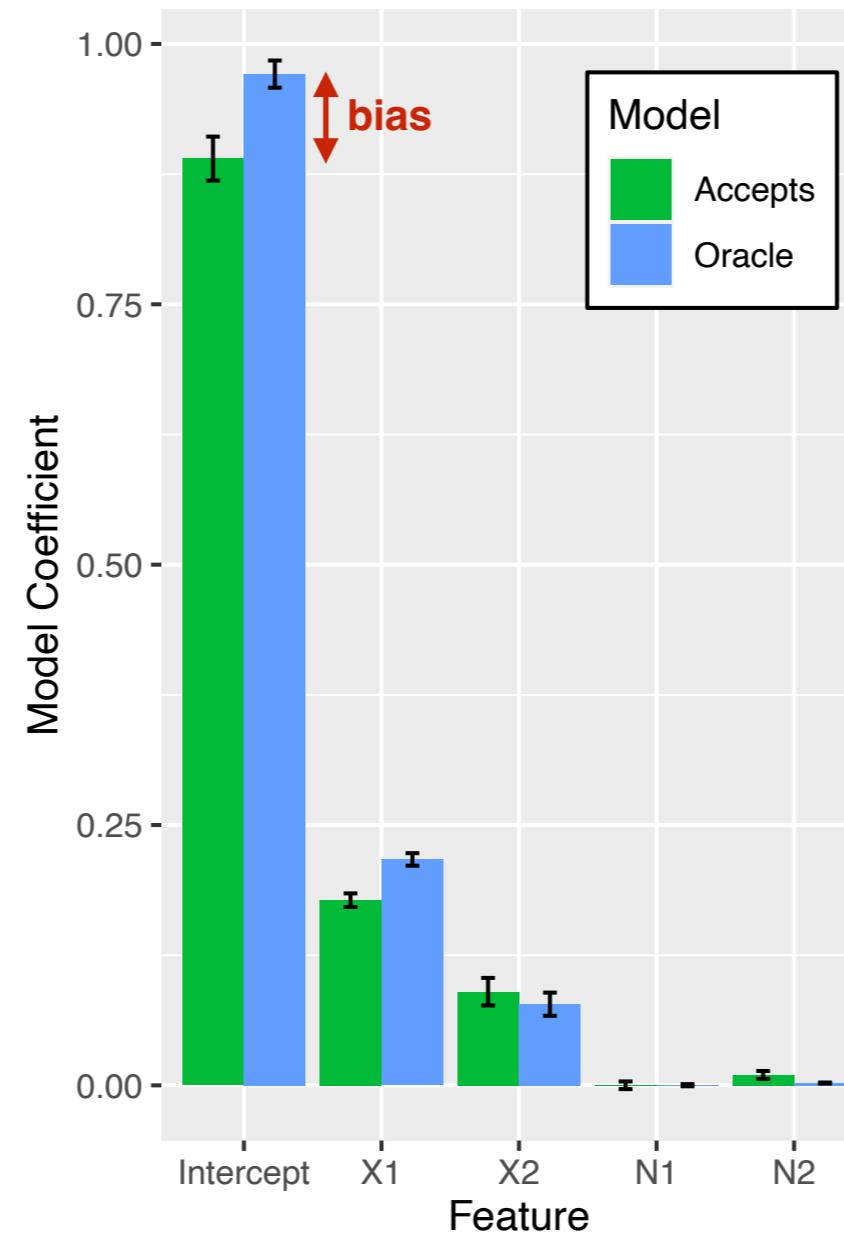
# Sampling Bias Illustration

- **sampling bias** originates in the **training data**
- propagates to the **model parameters**
- and affects **model predictions**

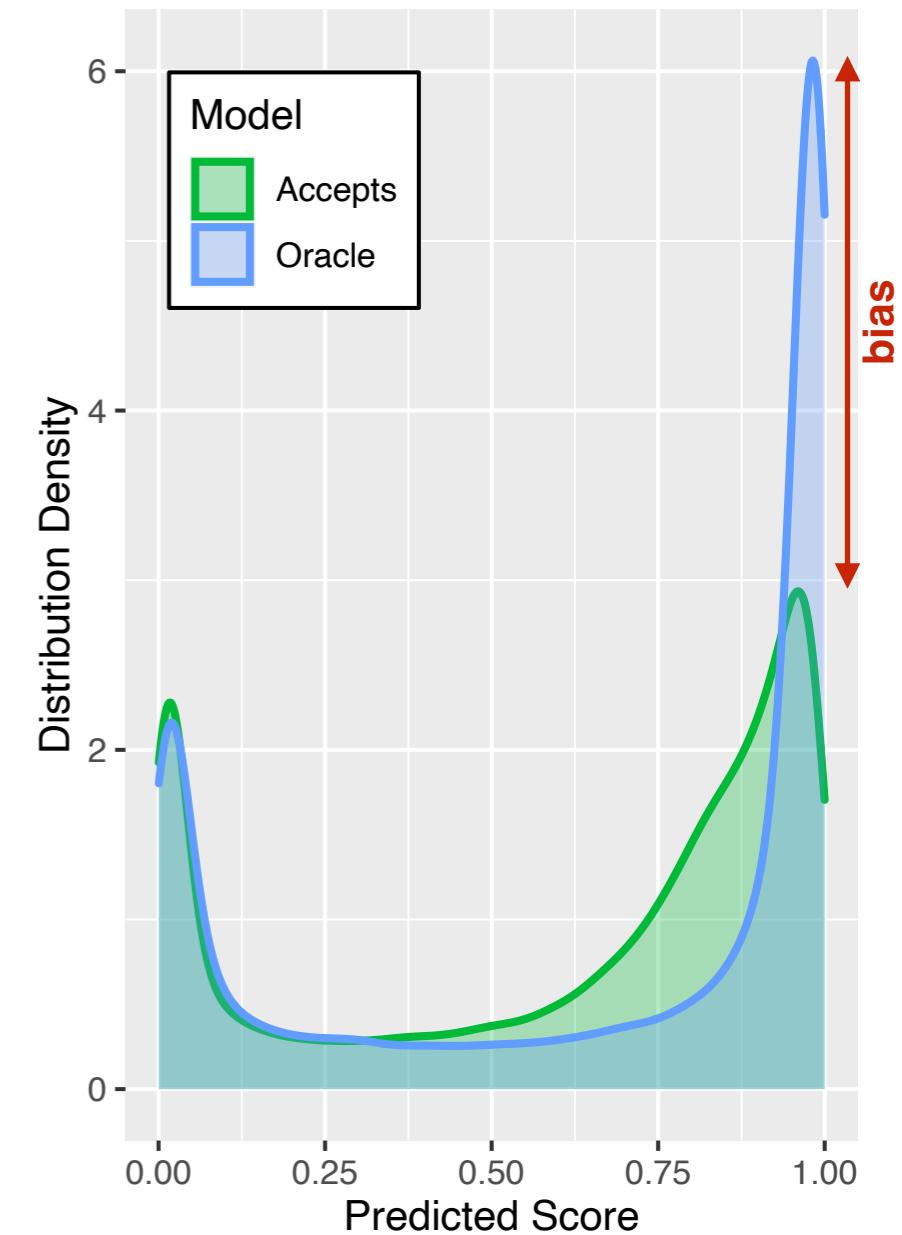
(a) Bias in Data



(b) Bias in Model

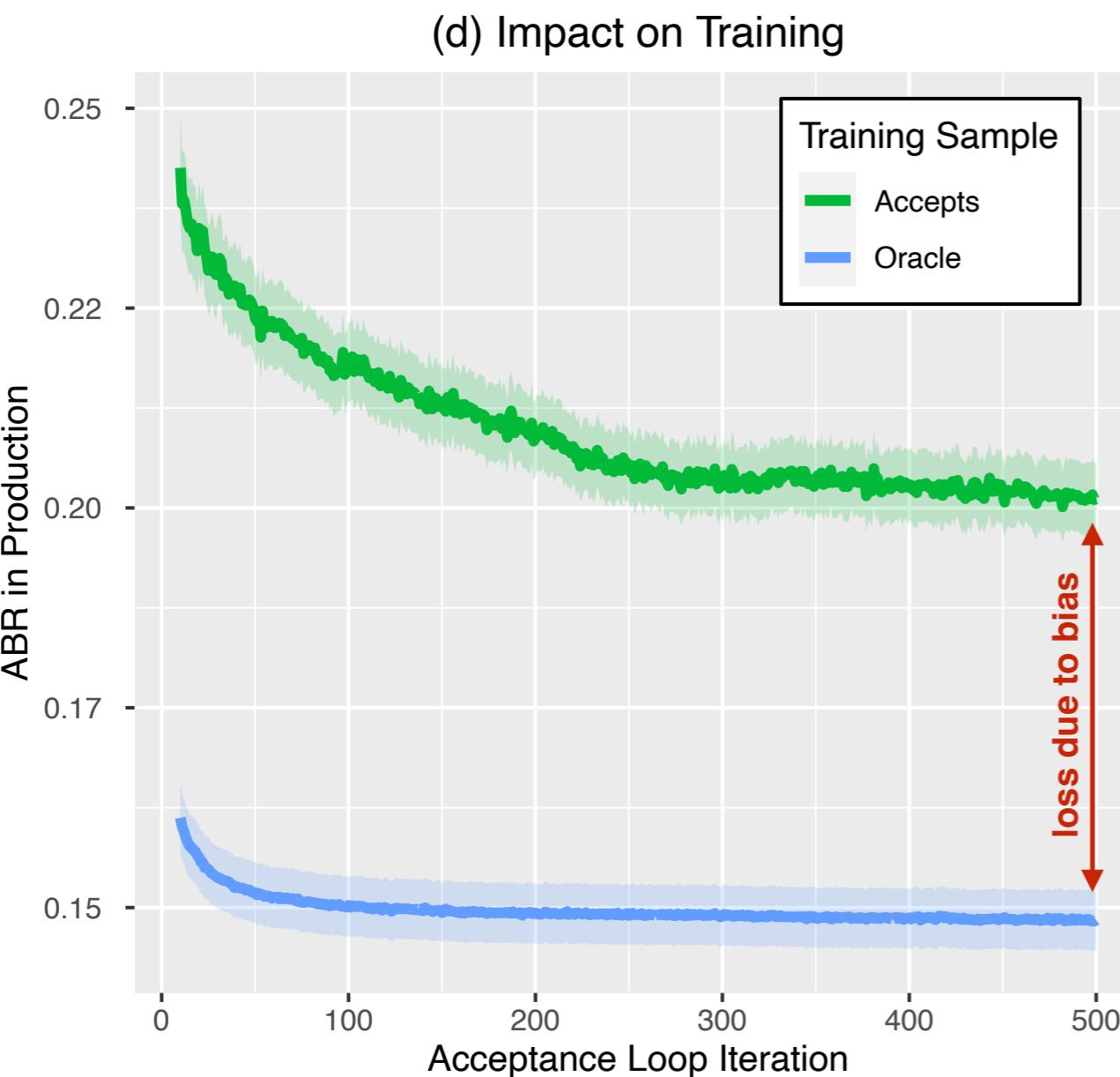


(c) Bias in Predictions



# Sampling Bias Consequences

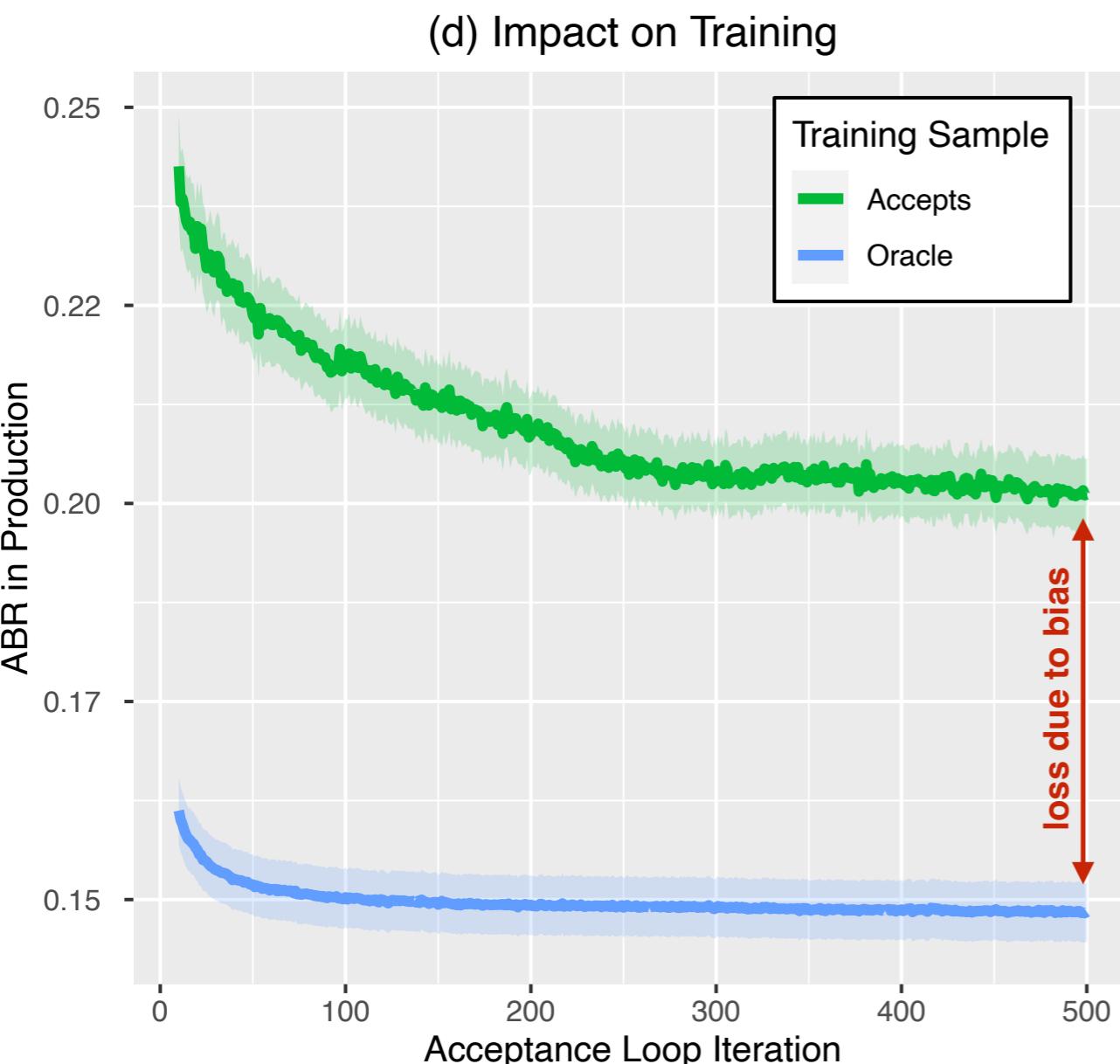
- **training a model on a biased sample decreases its production performance**



**ABR = BAD** rate when accepting top-30% applicants; lower is better

# Sampling Bias Consequences

- training a model on a biased sample **decreases its production performance**

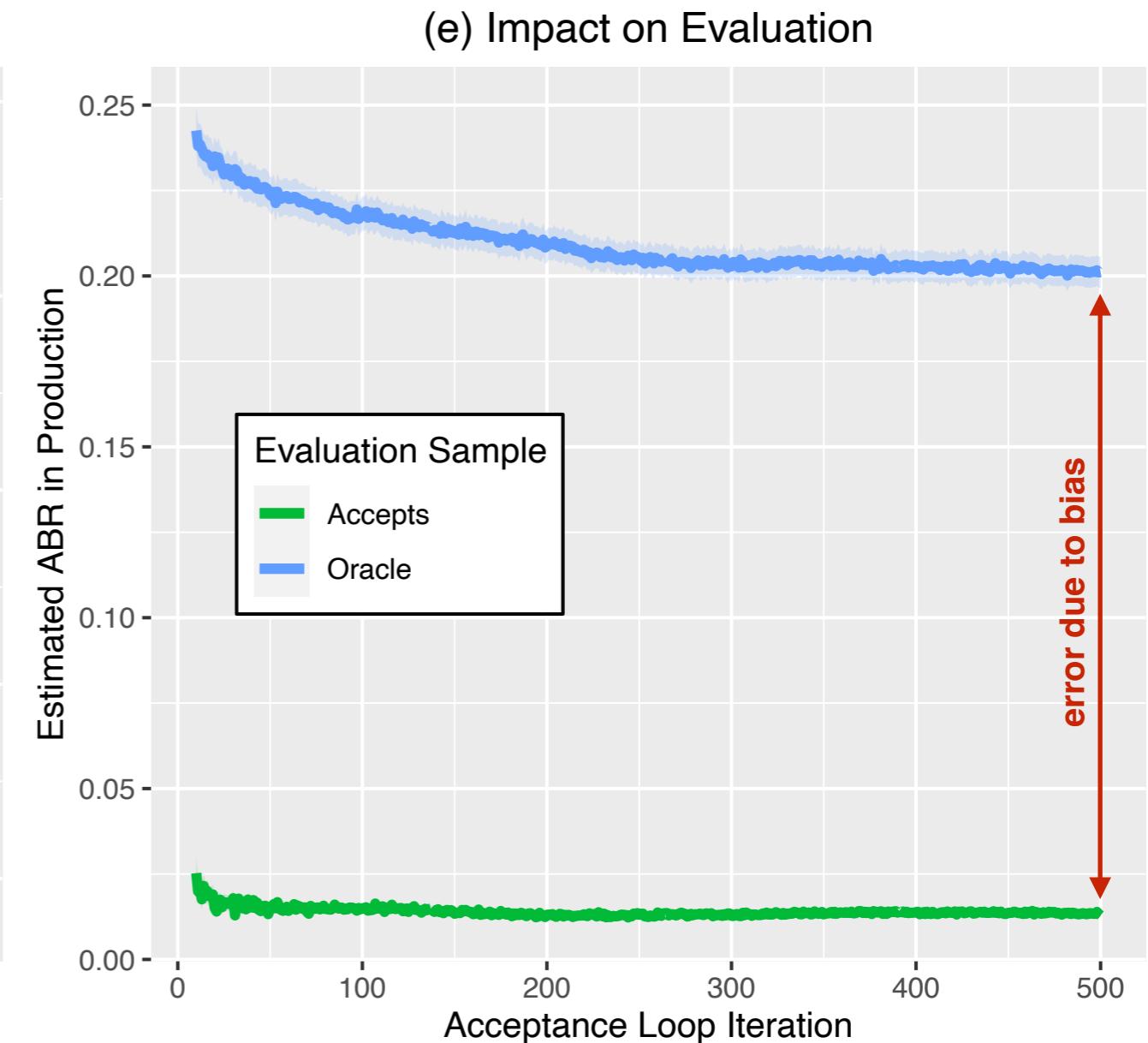
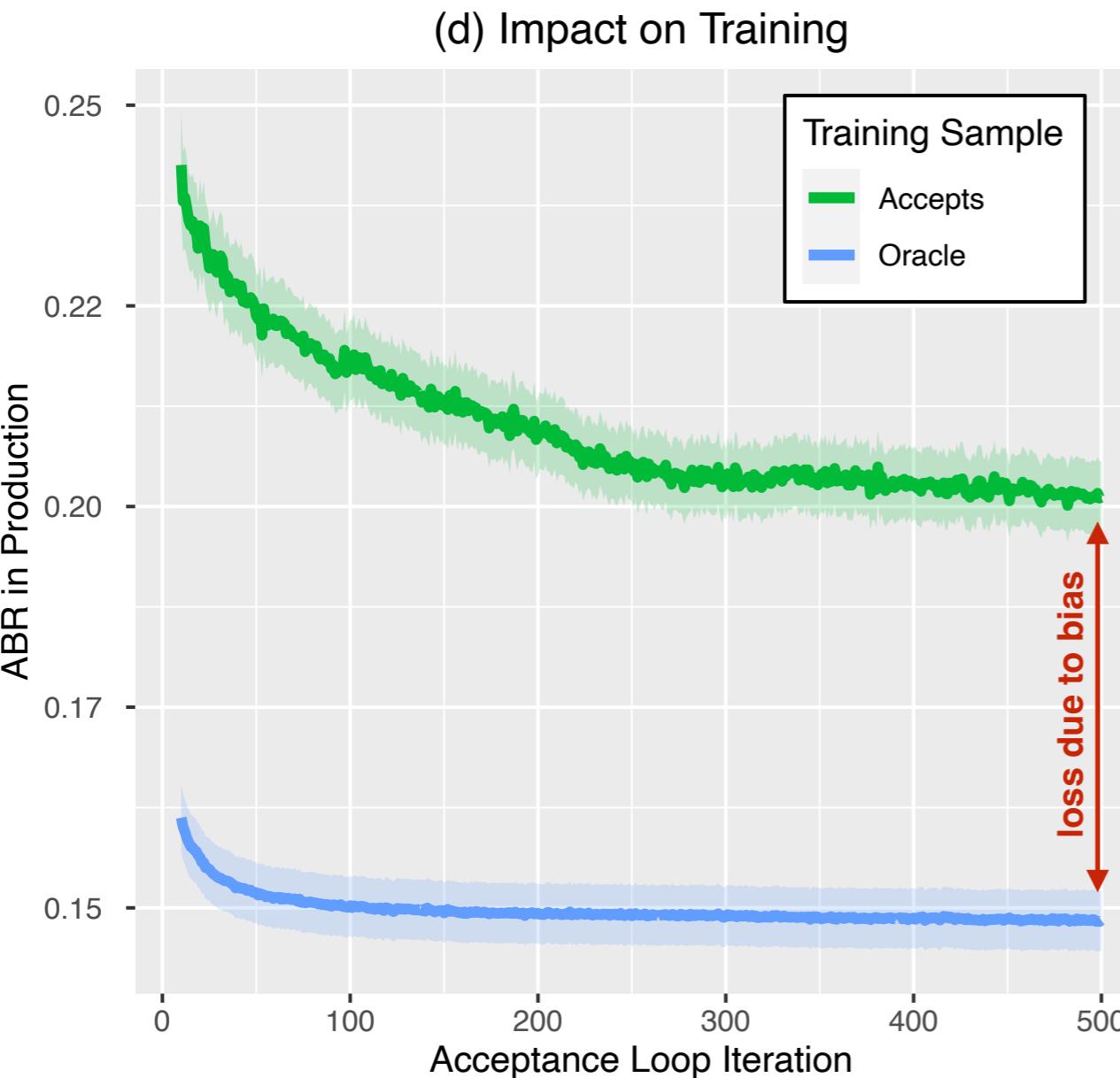


Decision	
Outcome	
GOOD	+ interest
BAD	- amount
	0

ABR = **BAD** rate when accepting top-30% applicants; lower is better

# Sampling Bias Consequences

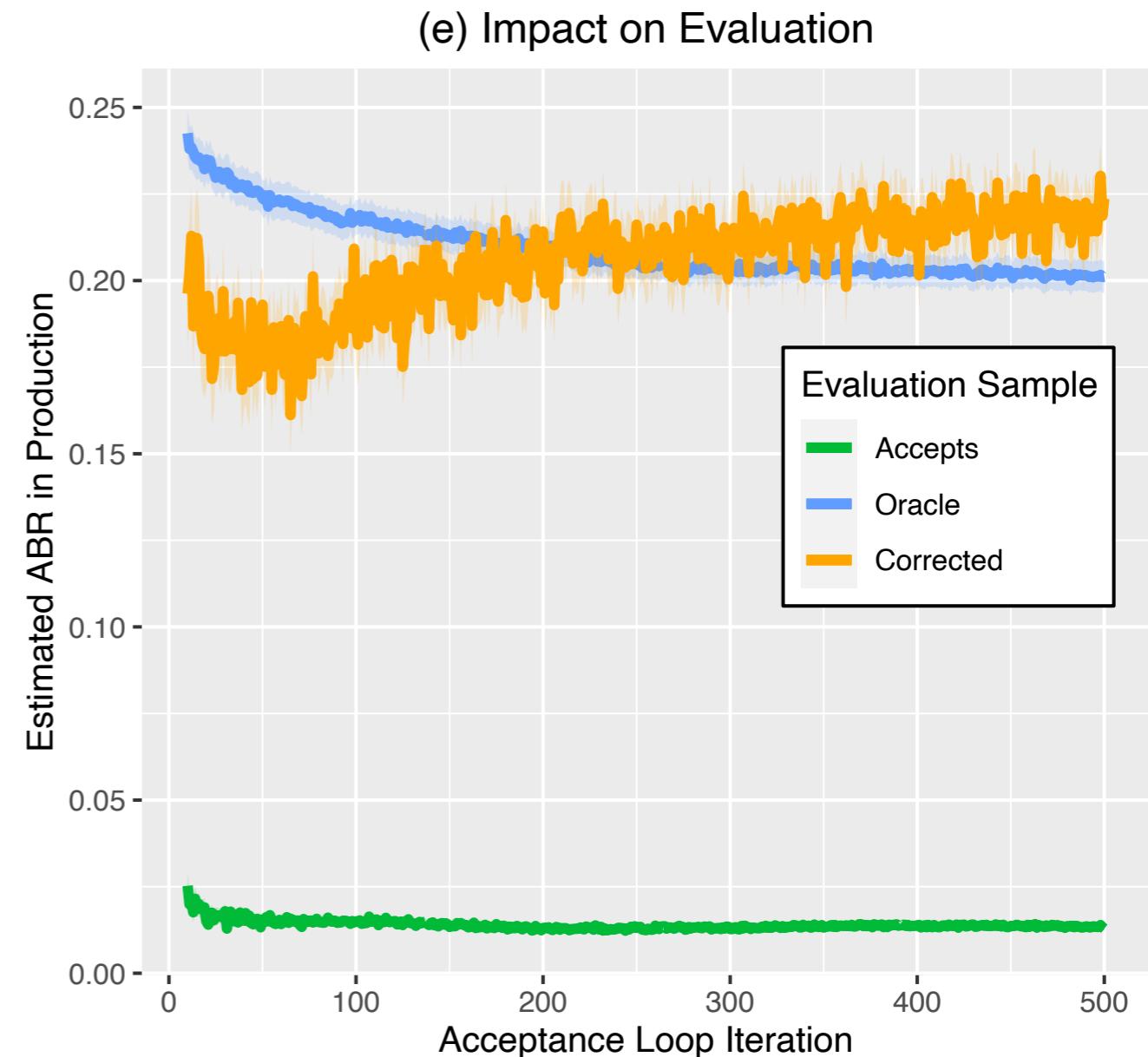
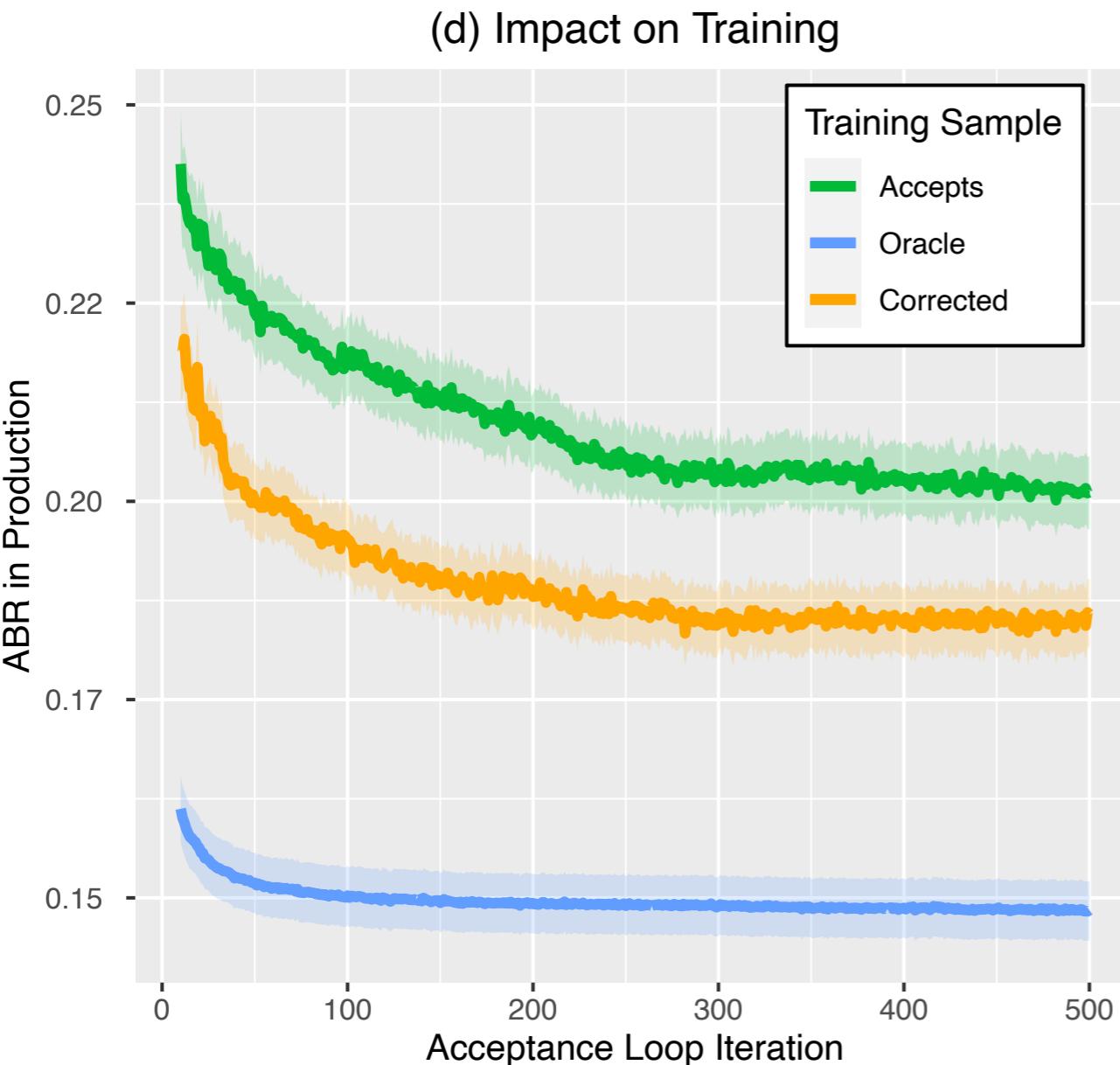
- training a model on a biased sample **decreases its production performance**
- evaluating a model on a biased sample provides a **misleading estimate**



**ABR = BAD** rate when accepting top-30% applicants; lower is better

# Potential Performance Gains

- bias correction can **improve the model performance in production**
- bias correction can provide a **better estimate of production performance**



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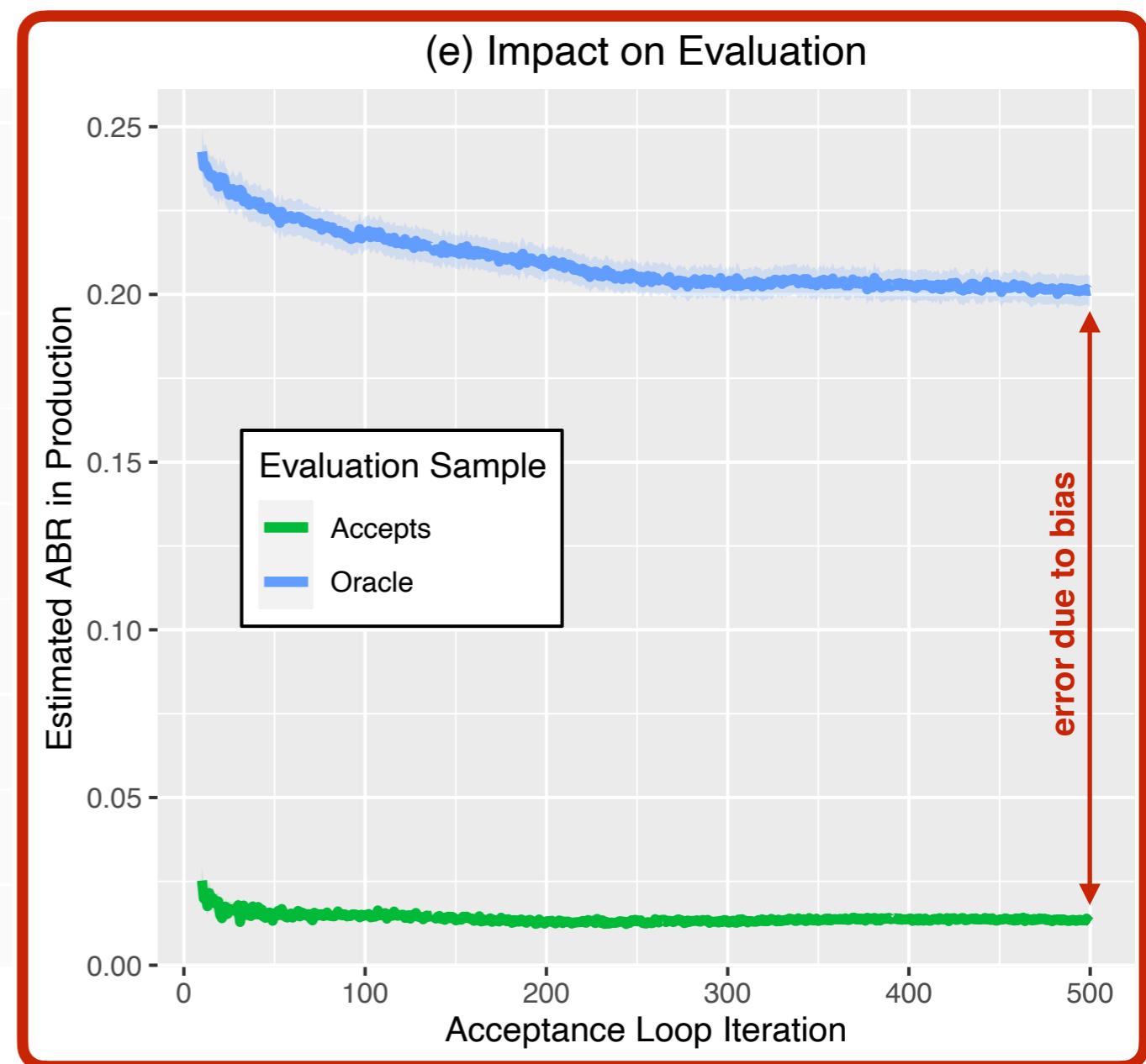
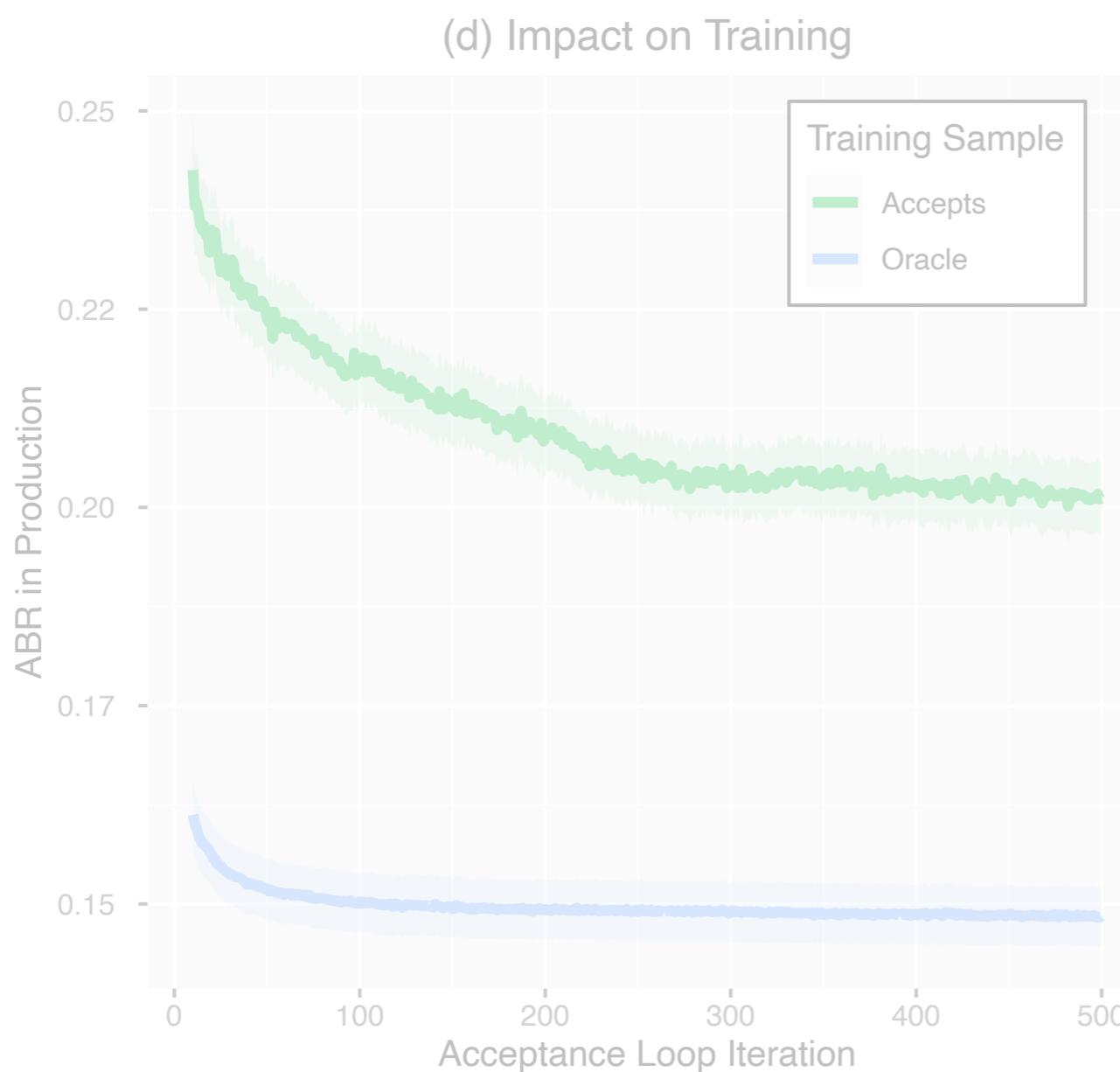
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## 4. Results

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# Bias Impact on Evaluation

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



ABR = **BAD** rate when accepting top-30% applicants; lower is better

# Evaluation under Sampling Bias

## How to improve evaluation?

Collect  
unbiased sample

- completely avoids sampling bias
- requires issuing loans to **random set of applicants** without scoring
- issue: very costly

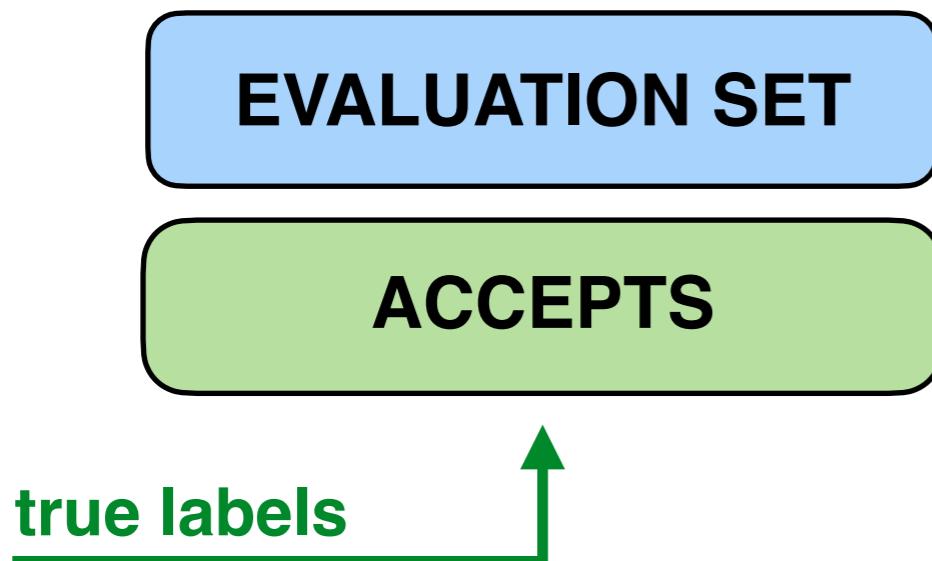
Adjust evaluation  
framework

- use bias correction methods to account for **distribution mismatch**
- issue: labels of **rejects** are unknown

# Standard Practice: Evaluate on Accepts

## Idea:

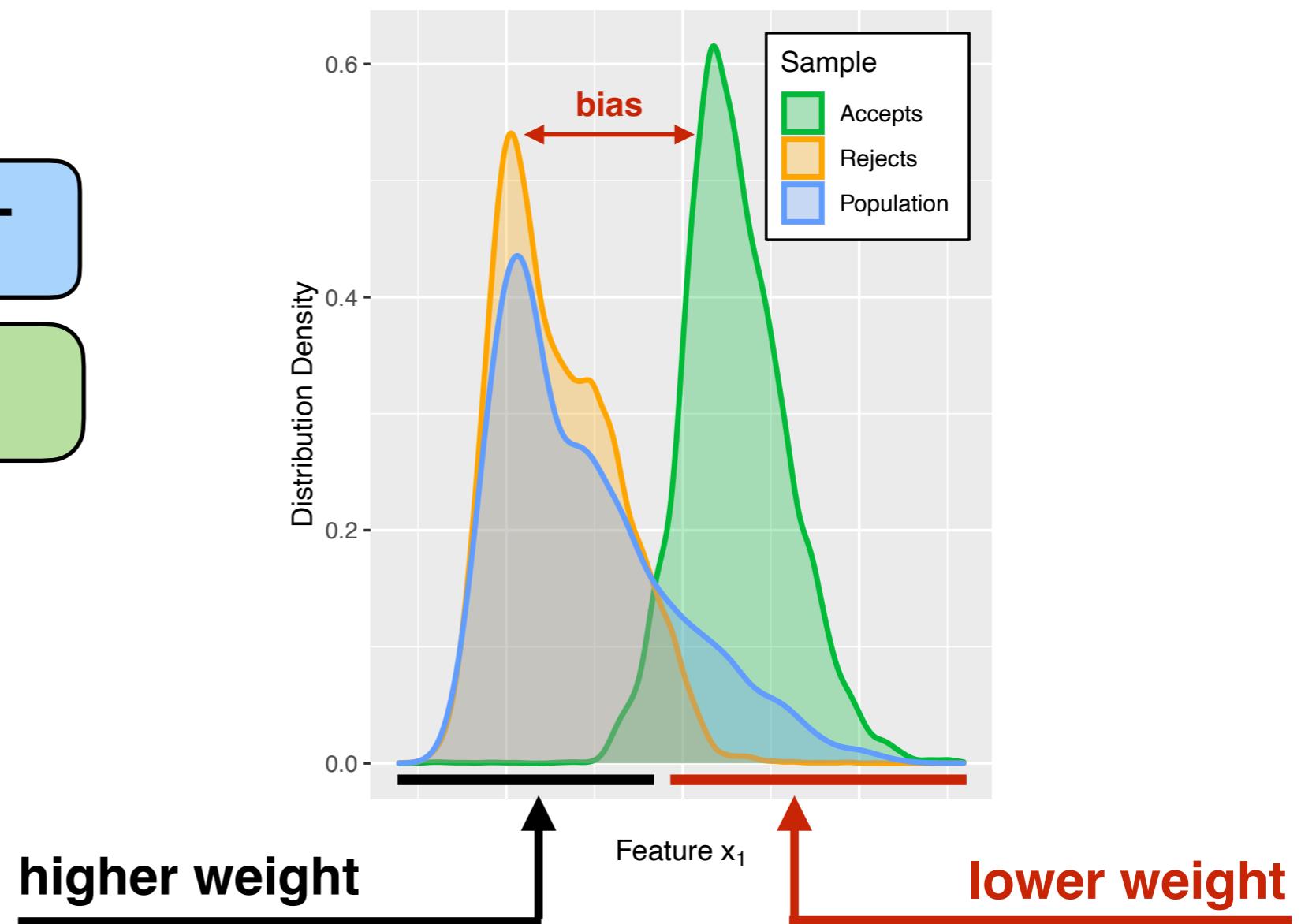
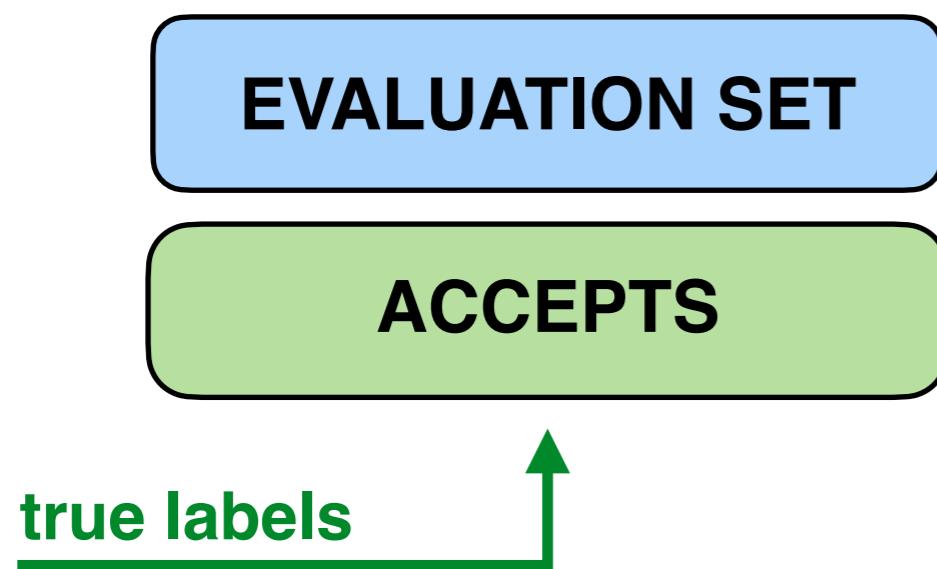
- evaluate metric  $M$  on evaluation set containing labeled **accepts**



# State-of-the-Art: Reweighting

## Idea:

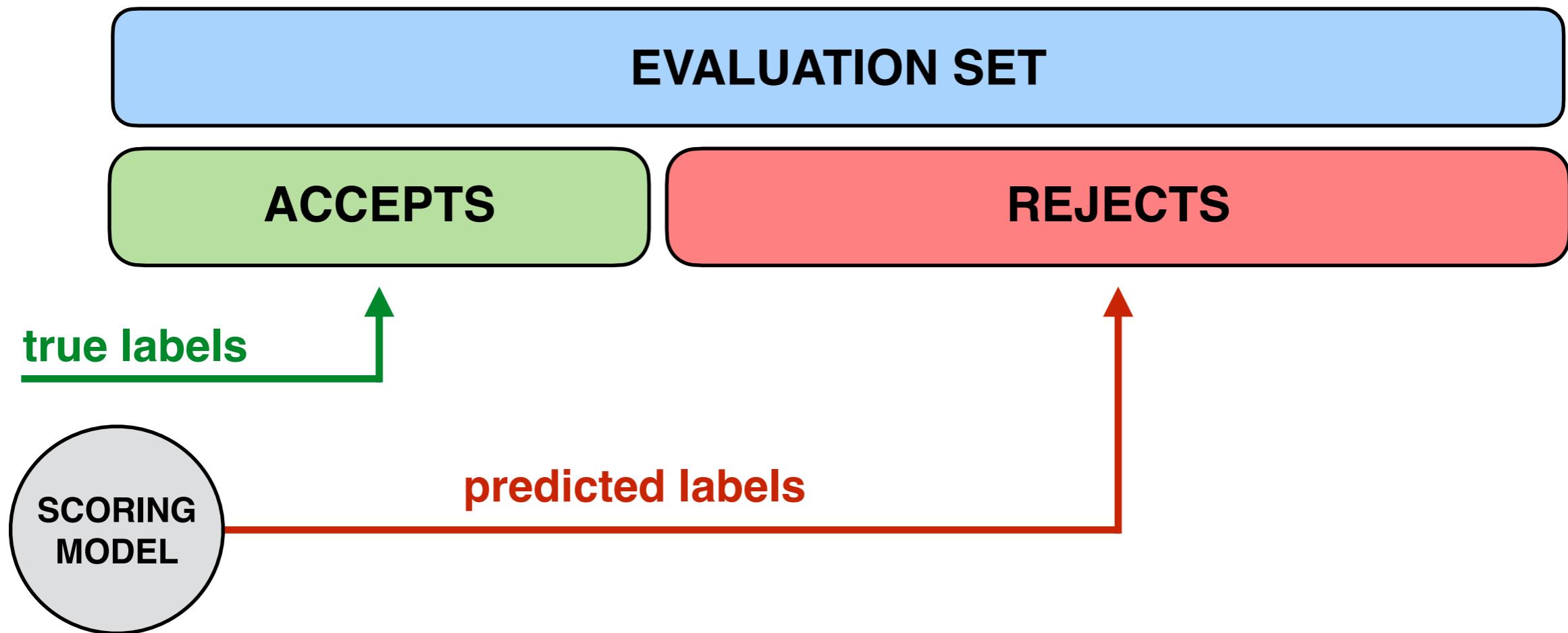
- evaluate metric  $M$  on evaluation set containing labeled **accepts**
- reweigh the metric to focus on **representative cases**



# Bayesian Evaluation (BE)

## Idea:

- evaluate metric  $M$  on evaluation set containing:
  - labeled **accepts**
  - pseudo-labeled **rejects**
- estimate prior **P(BAD)** for **rejects** using the **current scorecard  $f(X)$**



# Bayesian Evaluation (BE)

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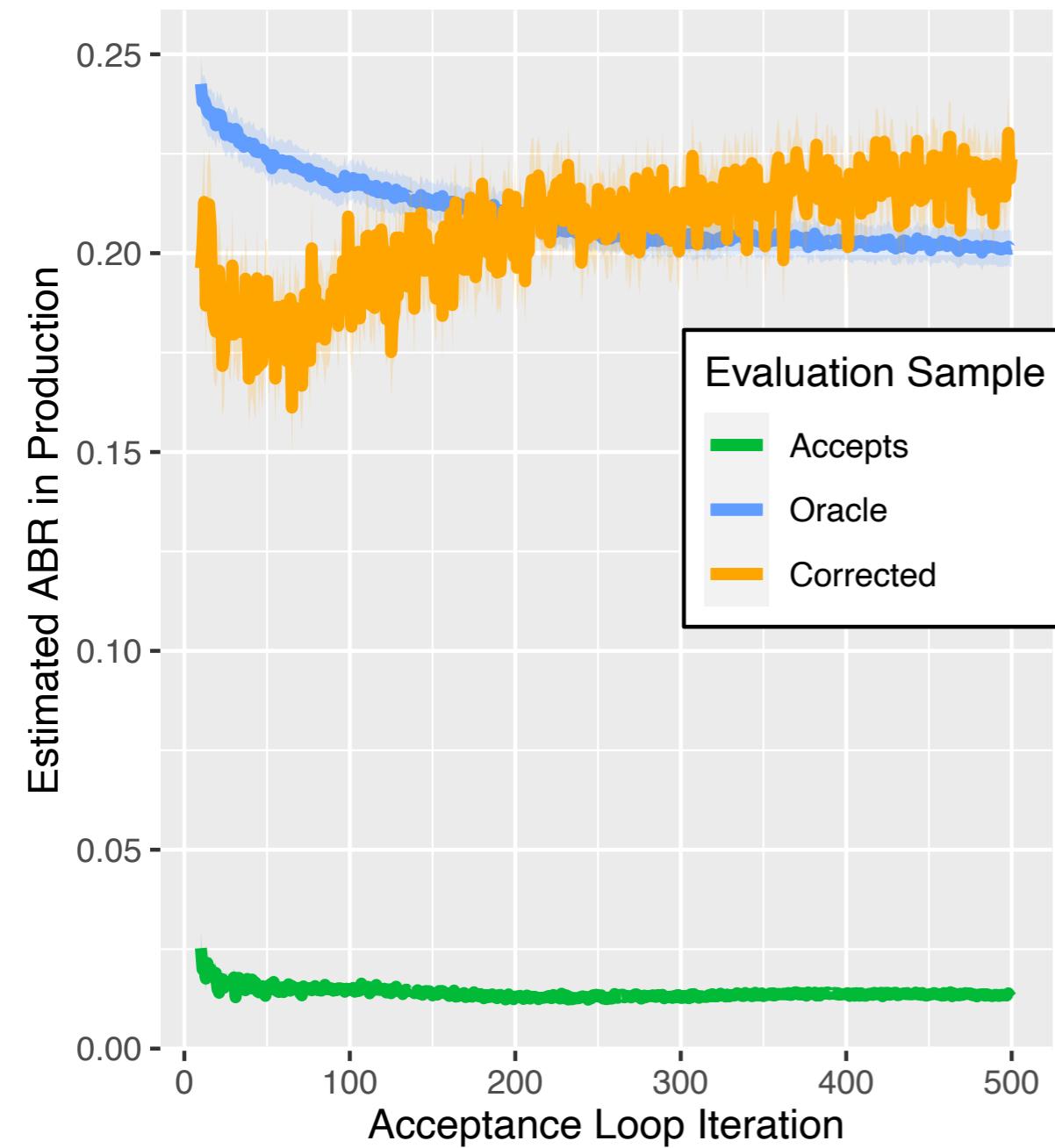
**input :** model  $f(X)$ , evaluation sample  $S$  consisting of labeled accepts  $S^a = \{(\mathbf{X}^a, \mathbf{y}^a)\}$  and unlabeled rejects  $\mathbf{X}^r$ , prior  $\mathbf{P}(\mathbf{y}^r | \mathbf{X}^r)$ , evaluation metric  $M(f, S, \tau)$ , meta-parameters  $j_{max}, \epsilon$

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

```
1  $j = 0; \Delta = \epsilon; E^c = \{\}$  ; // initialization
2 while ( $j \leq j_{max}$ ) and ( $\Delta \geq \epsilon$ ) do
3    $j = j + 1$ 
4    $\mathbf{y}^r = \text{binomial}(1, \mathbf{P}(\mathbf{y}^r | \mathbf{X}^r))$  ; // generate labels of rejects
5    $S_j = \{(\mathbf{X}^a, \mathbf{y}^a)\} \cup \{(\mathbf{X}^r, \mathbf{y}^r)\}$  ; // construct evaluation sample
6    $E_j^c = \sum_{i=1}^j M(f(X), S_i, \tau) / j$  ; // evaluate
7    $\Delta = E_j^c - E_{j-1}^c$  ; // check convergence
8 end
9 return  $BM(f, S, \tau) = E_j^c$ 
```

# BE: Simulation Results

## Performance Dynamics



## Aggregated Results

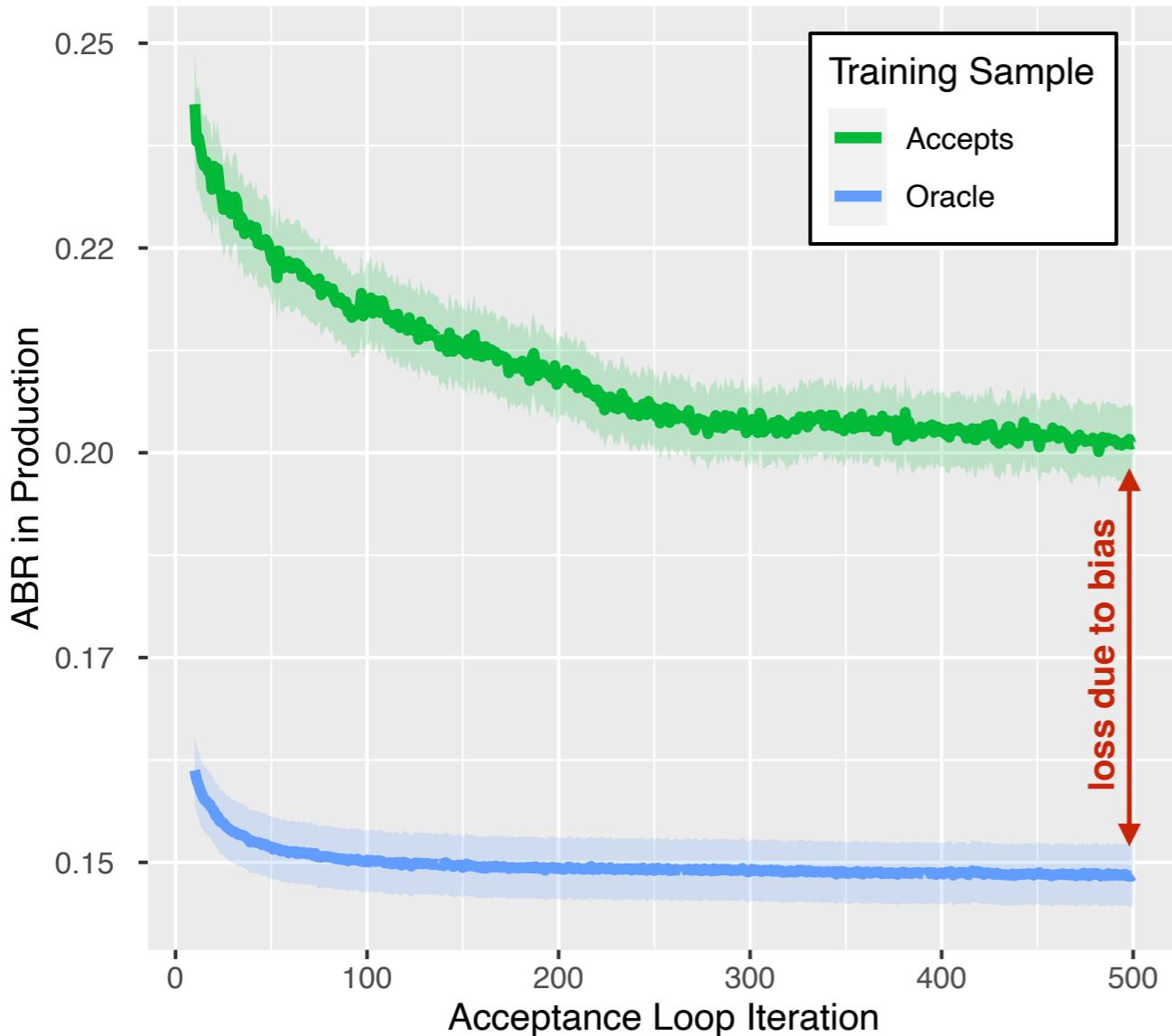
Metric	RMSE due to bias	Gains from BE
ABR	.2058	55.83%
BS	.0829	36.55%
AUC	.2072	67.57%
PAUC	.2699	70.80%

- BE improves **performance estimates**
- gains are **statistically significant at 5%**

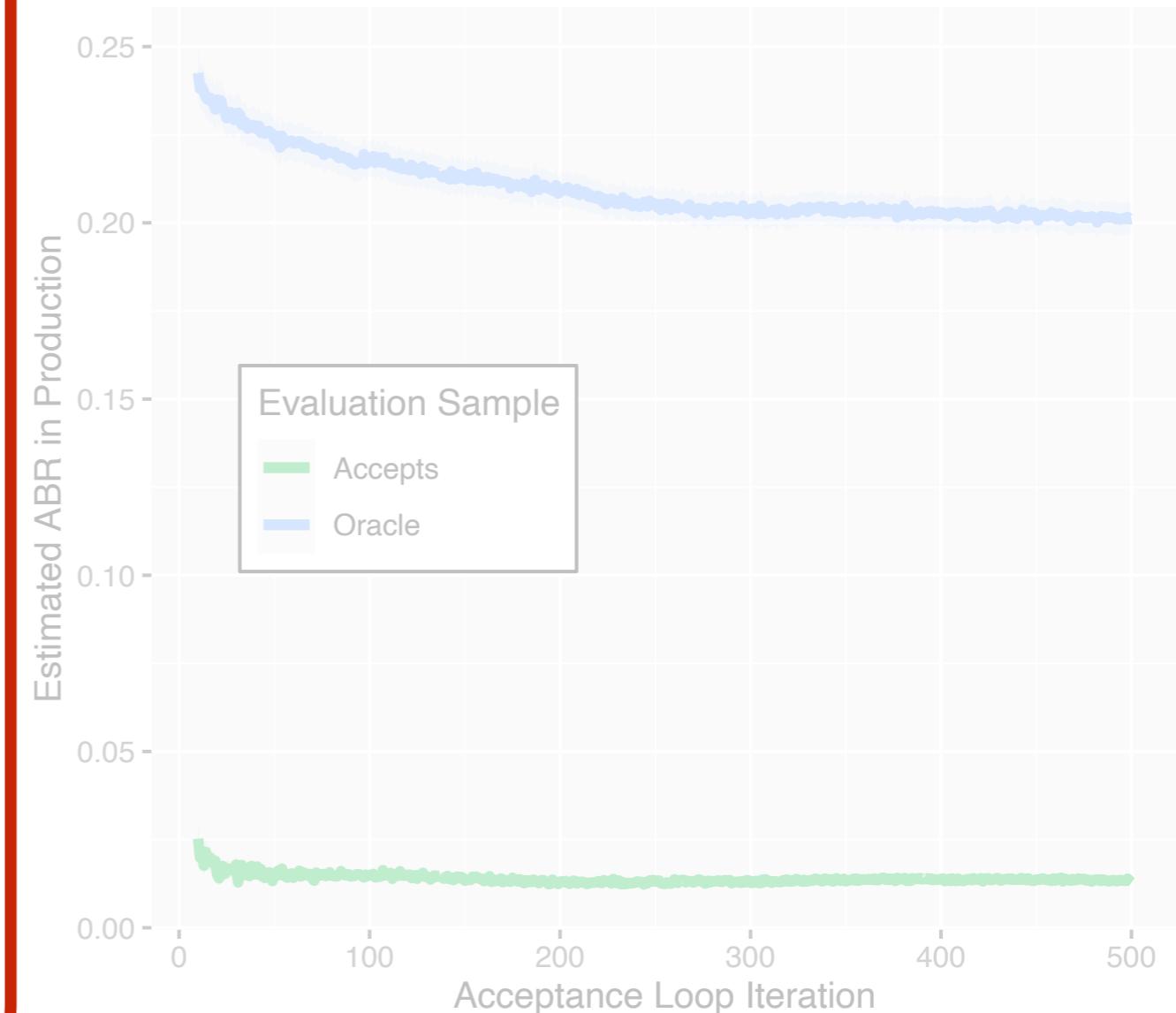
# Bias Impact on Training

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

(d) Impact on Training



(e) Impact on Evaluation



ABR = **BAD** rate when accepting top-30% applicants; lower is better

# Training under Sampling Bias

## How to improve training?

Collect unbiased sample

- completely avoids sampling bias
- issue: very costly

Data augmentation (label rejects)

- predict labels of **rejects**
- use combined data of **accepts** and **rejects** for model training
- issue: high risk of error propagation

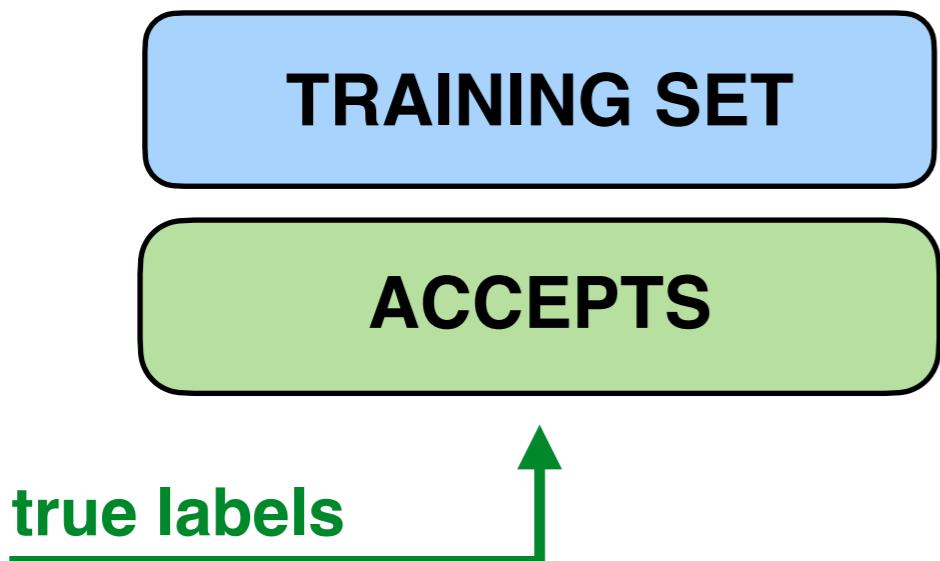
Extract information from rejects

- estimate **distribution mismatch** between **accepts** and **rejects**
- modify training procedure
- issue: hard in high-dimensional data

# Standard Practice: Train on Accepts

## Idea:

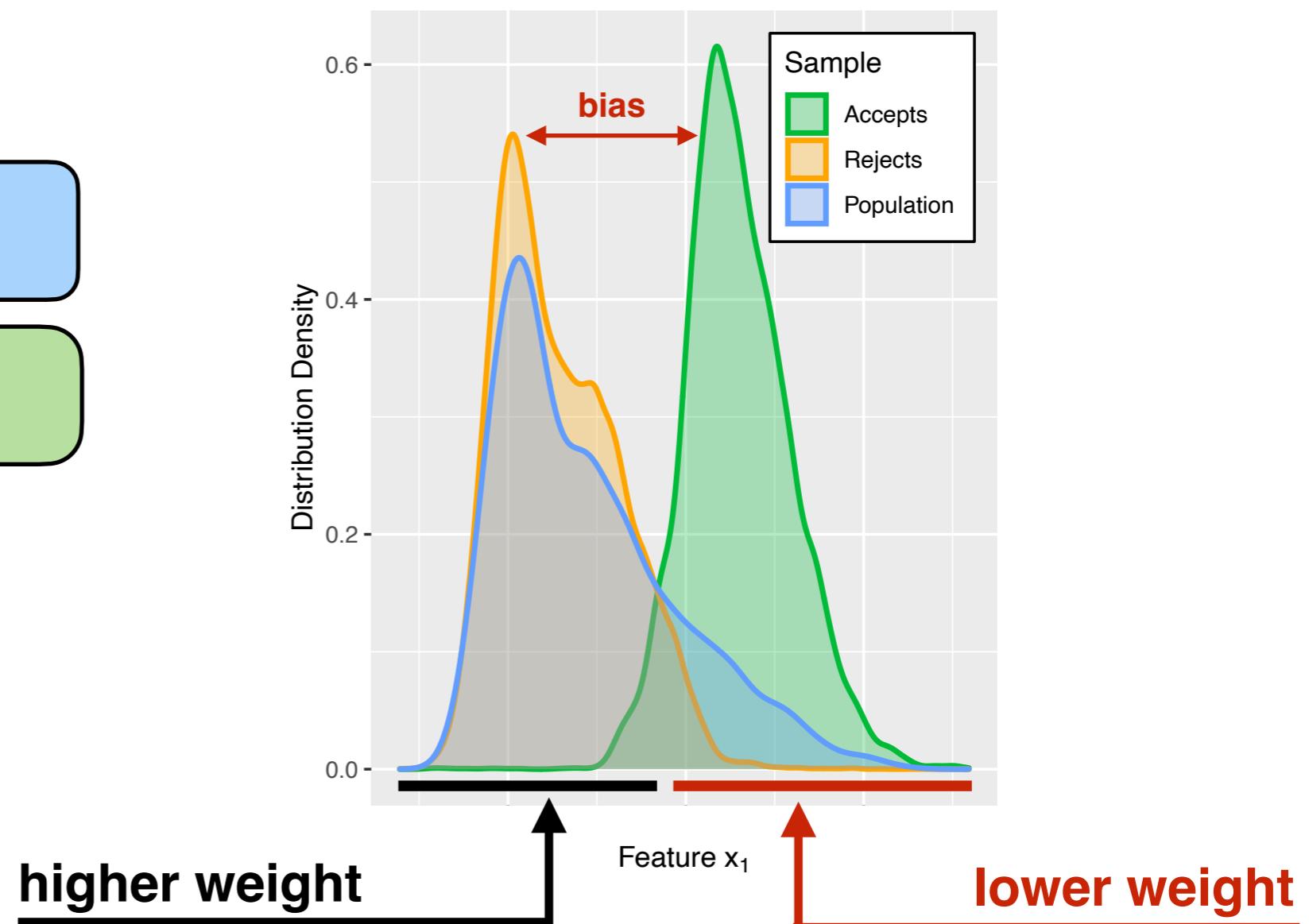
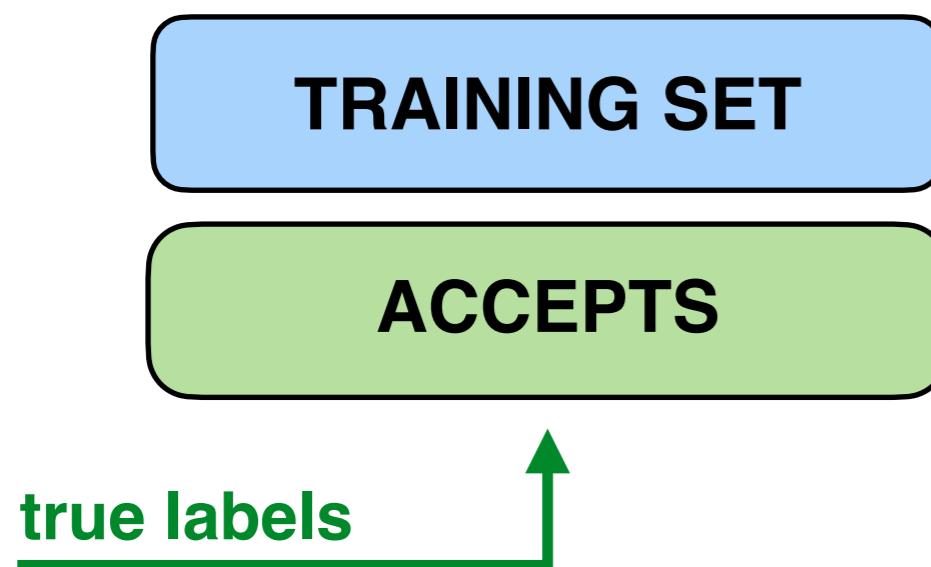
- train model  $f(x)$  on training set containing labeled **accepts**



# State-of-the-Art: Reweighting

## Idea:

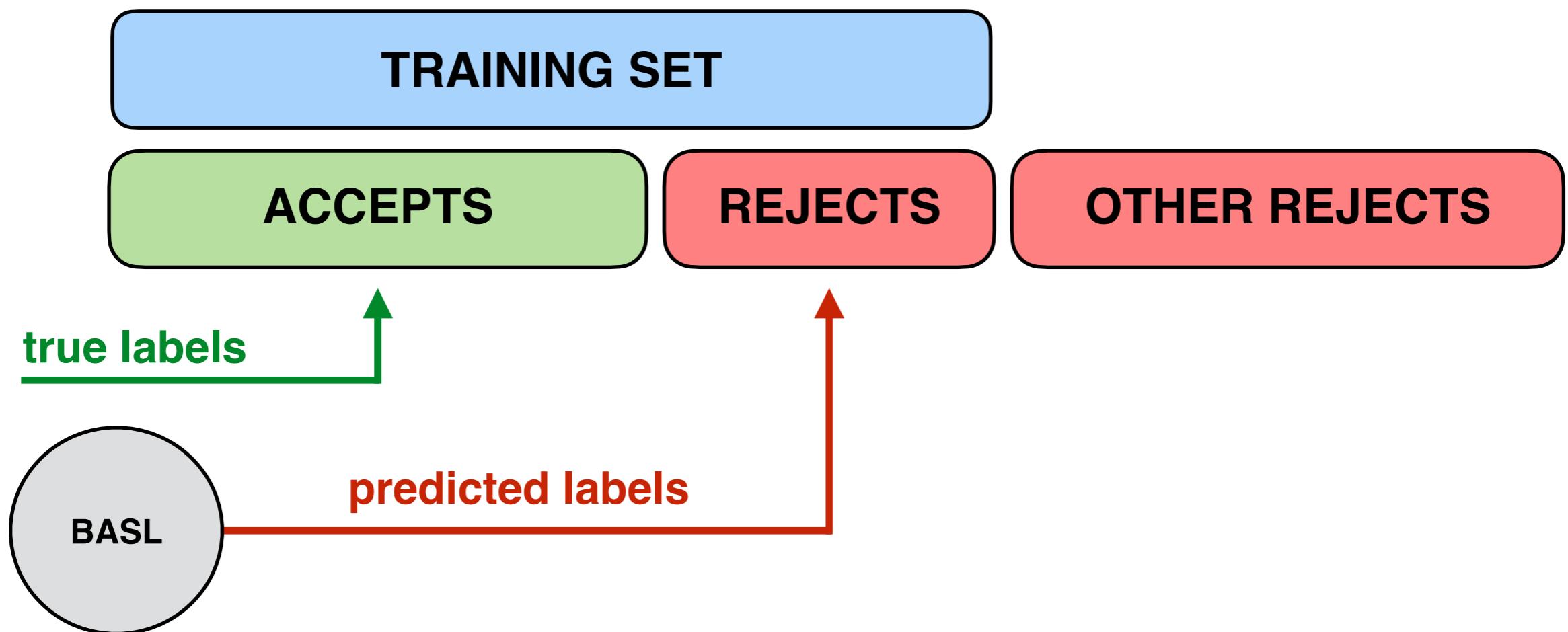
- train model  $f(x)$  on training set containing labeled **accepts**
- reweigh model loss to focus on **representative cases**



# Bias-Aware Self-Learning (BASL)

## Idea:

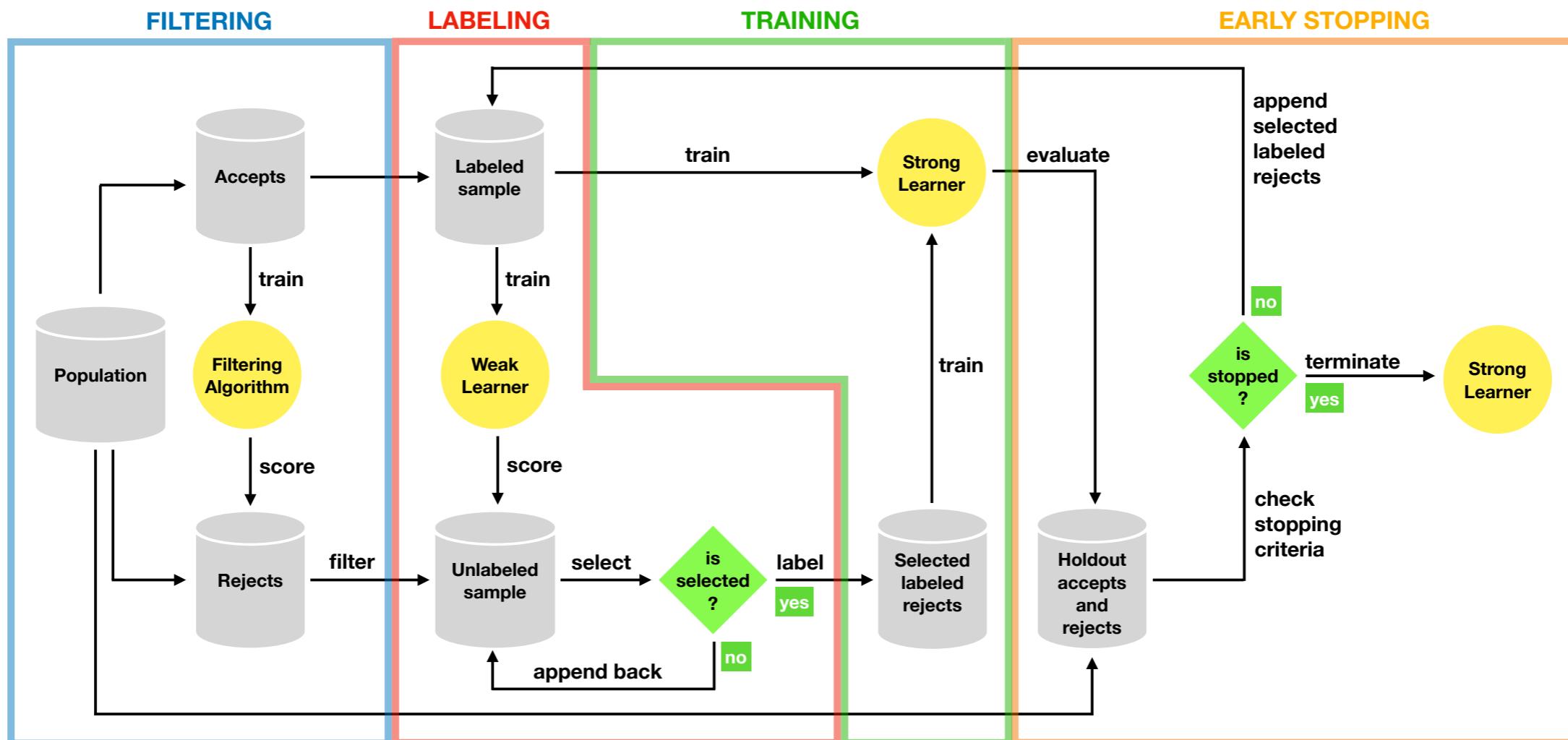
- train model  $f(x)$  on augmented training set containing:
  - labeled **accepts**
  - selected pseudo-labeled **rejects**
- use modified self-learning framework (e.g., Triguero et al. 2013)
  - implement techniques to reduce the risk of error propagation



# Bias-Aware Self-Learning (BASL)

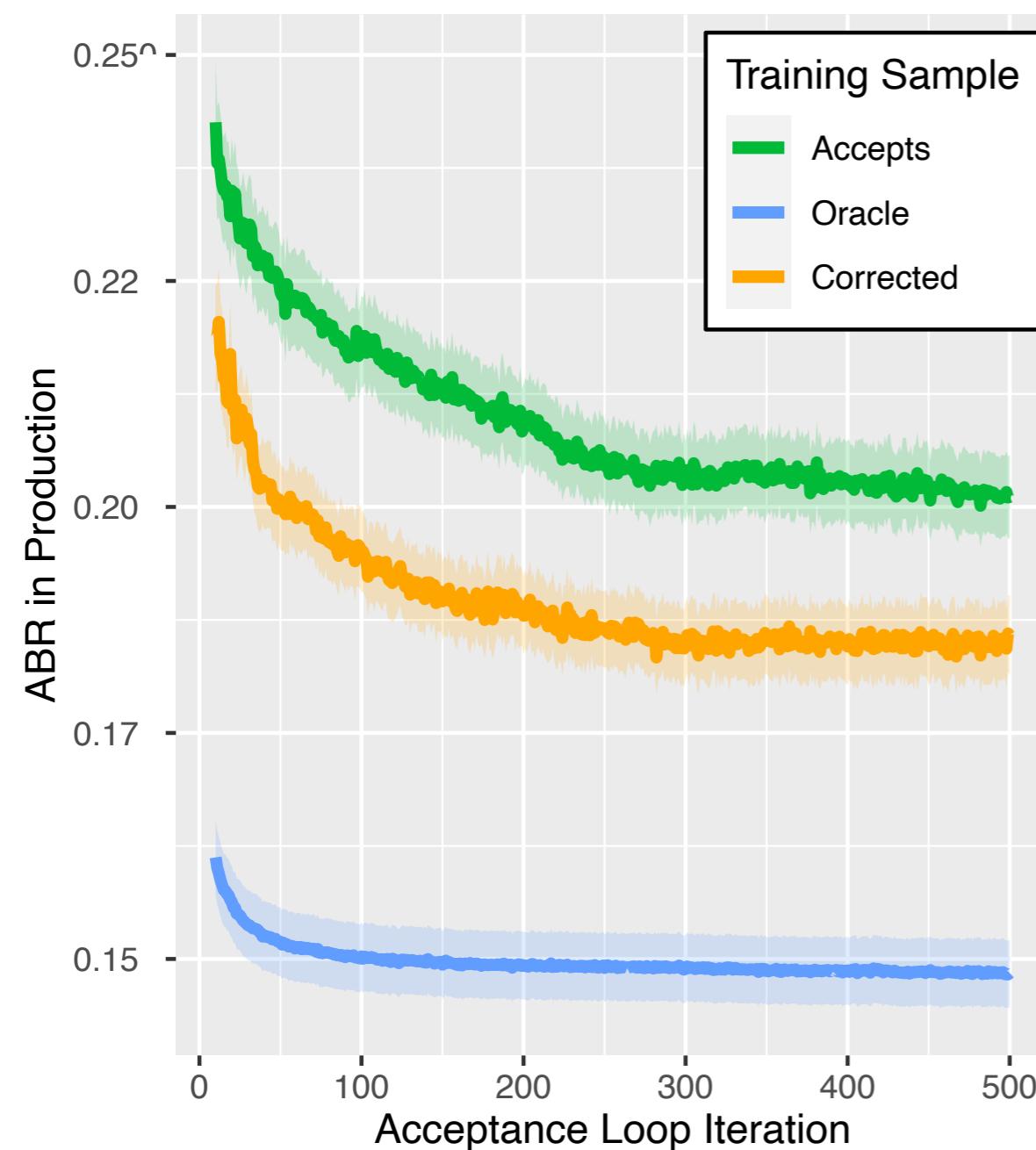
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  - implement techniques to reduce the risk of error propagation



# BASL: Simulation Results

## Performance Dynamics



## Aggregated Results

Metric	Loss due to bias	Gains from BASL
ABR	.0547	36.86%
BS	.0404	45.28%
AUC	.0589	48.84%
PAUC	.0488	33.93%

- BASL improves **model performance**
- gains are **statistically significant** at 5%

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# Offline Evaluation: Experimental Setup

## Data description:

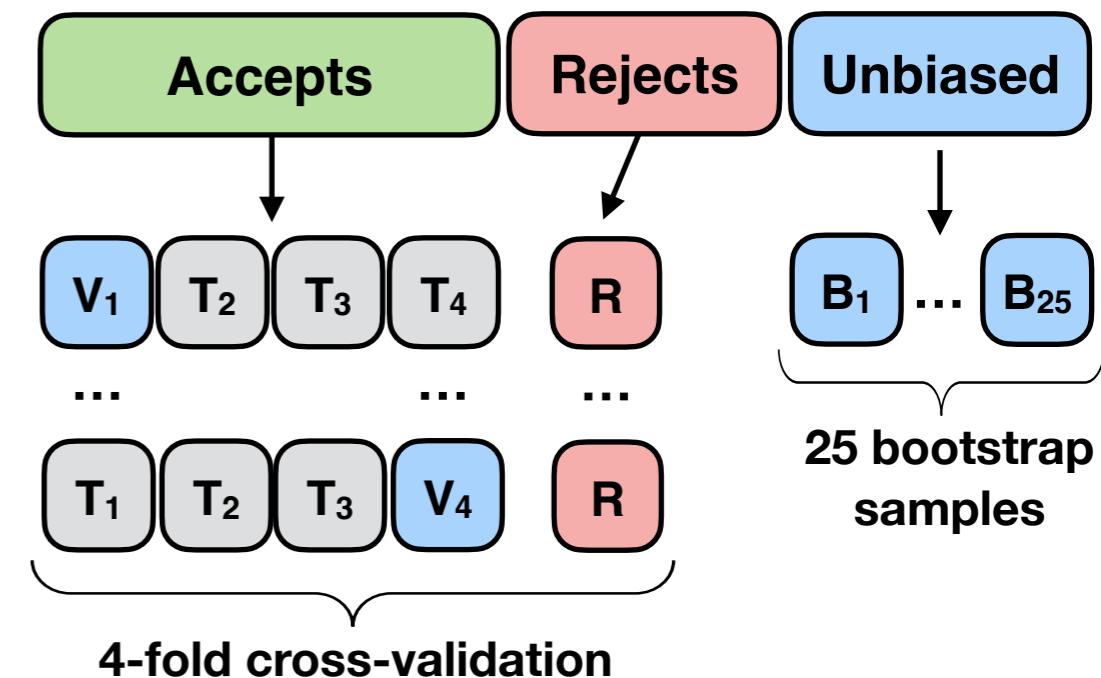
- consumer loans issued by  Monedo in Spain in 2017 - 2019
- contains **labeled accepts** and **unlabeled rejects**
- includes **unbiased sample**: loans from randomized trial

## Data summary:

	Accepts	Rejects	Unbiased
No. clients	39,579	18,047	1,967
No. features	2,410	2,410	2,410
BAD* rate	39 %	-	66 %

\* missed payments for 3 consecutive months

## Data organization:



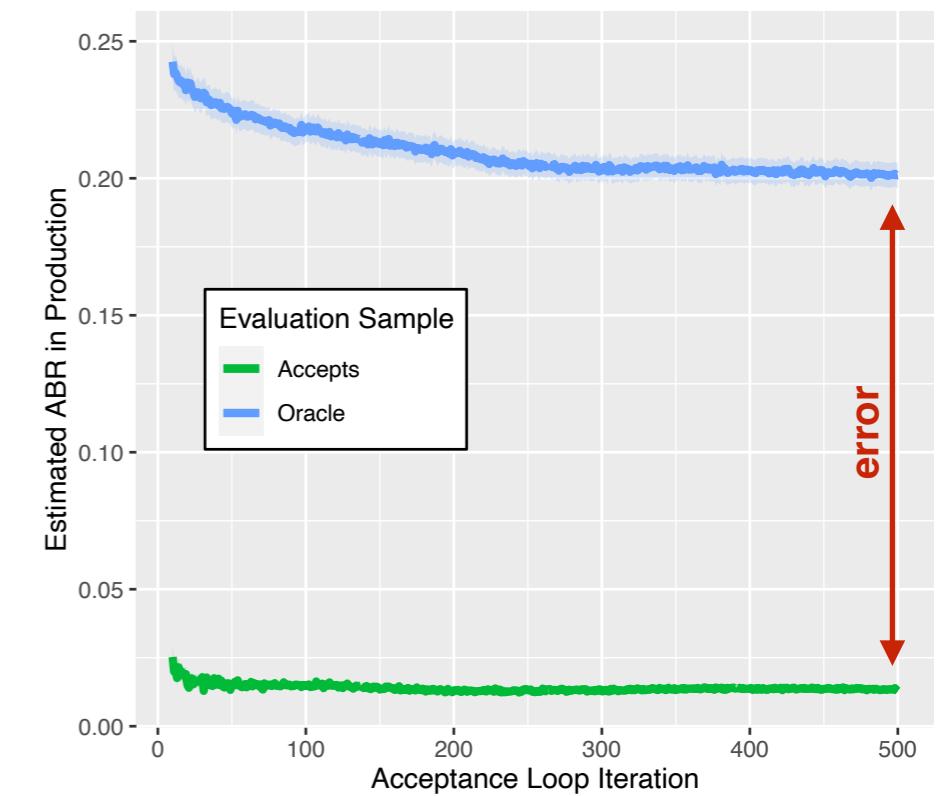
# Experiment I: Improving Evaluation

## Goal:

- compare accuracy of evaluation methods

## Methodology:

- build a scoring model and assess it on **unbiased sample**
  - four evaluation metrics: ABR, BS, AUC, PAUC
- evaluate the same model on historical data
  - Bayesian evaluation
  - benchmarks
- compute RMSE between the two estimates



# Experiment I: Results

Evaluation Method	ABR	BS	AUC	PAUC
Standard practice	.0356	.0983	.1234	.0306

- **ABR** = BAD rate at 30% acceptance
- **BS** = Brier Score
- **AUC** = area under the ROC curve
- **PAUC** = partial AUC at FNR in [0, 0.2]

# Experiment II: Results

Evaluation Method	ABR	BS	AUC	PAUC
Standard practice	.0356	.0983	.1234	.0306
Doubly robust evaluation	.1167	-	-	.0506
Reweighting	.0315	.0826	.1277	.0348
Bayesian evaluation	.0130	.0351	.0111	.0073

- ABR = BAD rate at 30% acceptance
- BS = Brier Score
- AUC = area under the ROC curve
- PAUC = partial AUC at FNR in [0, 0.2]

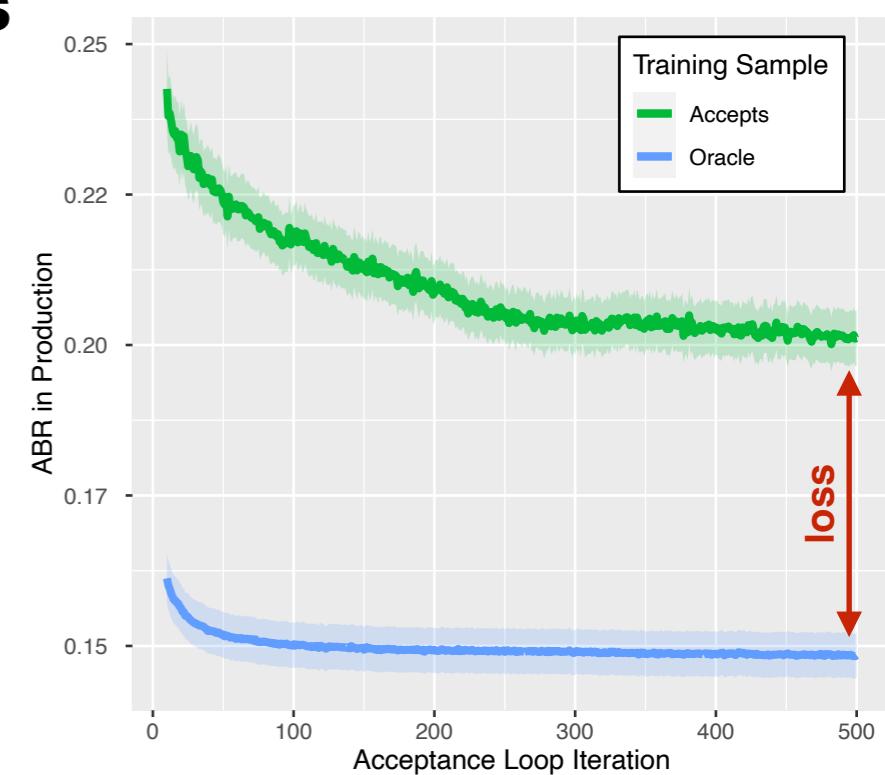
# Experiment II: Improving Training

## Goal:

- compare performance of bias correction methods

## Methodology:

- build a scoring model on **accepts**
- assess performance on **unbiased sample**
  - four evaluation metrics: ABR, BS, AUC, PAUC
- improve the model with bias correction methods
  - BASL
  - benchmarks



# Experiment II: Results

Training Method	ABR	BS	AUC	PAUC
<b>Standard practice</b>	.2388	.1819	.7984	.6919
<b>Label all rejects as BAD</b>	.3141	.2347	.6676	.6384
<b>Bias-removing autoencoder</b>	.3061	.2161	.7304	.6373
<b>Heckman model</b>	.3018	.2124	.7444	.6397
<b>Bureau score based labels</b>	.2514	.1860	.7978	.6783
<b>Hard cutoff augmentation</b>	.2458	.1830	.8033	.6790
<b>Parceling</b>	.2396	.1804	.8038	.6885
<b>Reweighting</b>	.2346	.1840	.8040	.6961
<b>Bias-Aware Self-Learning</b>	.2211	.1761	.8166	.7075

- ABR = BAD rate at 30% acceptance
- BS = Brier Score
- AUC = area under the ROC curve
- PAUC = partial AUC at FNR in [0, 0.2]

# Business Impact: Setup

## Parameters:

- acceptance rate
- loan principal
- interest rate

	Micro loans	Installment loans
Acceptance rate $\alpha$	[20%, 40%]	[10%, 20%]
Loan principal $A$	\$375 (SD = \$100)	\$17,100 (SD = \$1,000)
Total interest $i$	17.33% (SD = 1%)	10.36% (SD = 1%)

## Two markets:

- micro-loans
- installment loans

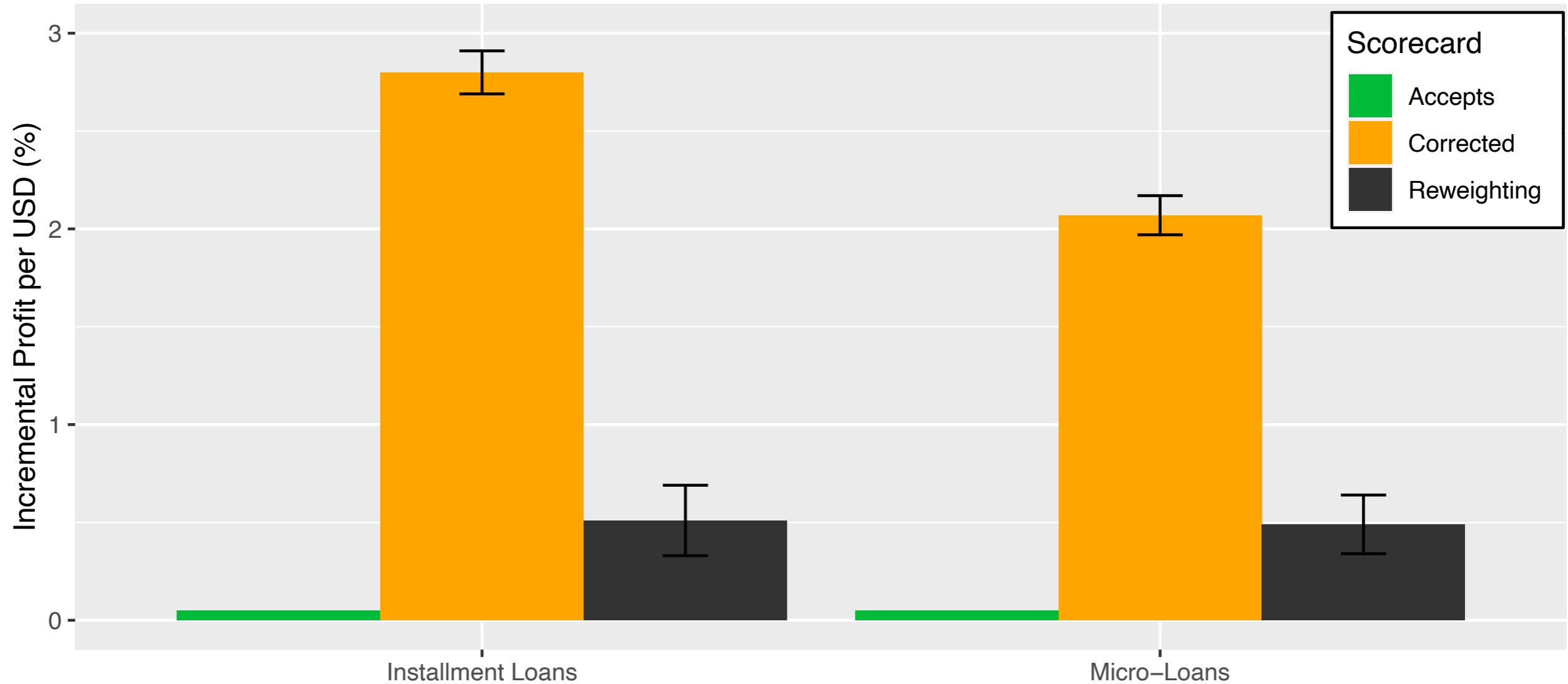
## Calculations:

- average profit per loan for each algorithm:

$$\pi = \frac{1}{100} \sum_{j=1}^{100} \left[ \underbrace{(1 - ABR_j) \times A \times (1 + i)}_{\text{GOOD clients}} - \underbrace{ABR_j \times A \times (1 + i) - A}_{\text{BAD clients}} \right]$$

- averaging over 100 values (4-fold CV x 25 bootstrap samples)

# Business Impact: Results

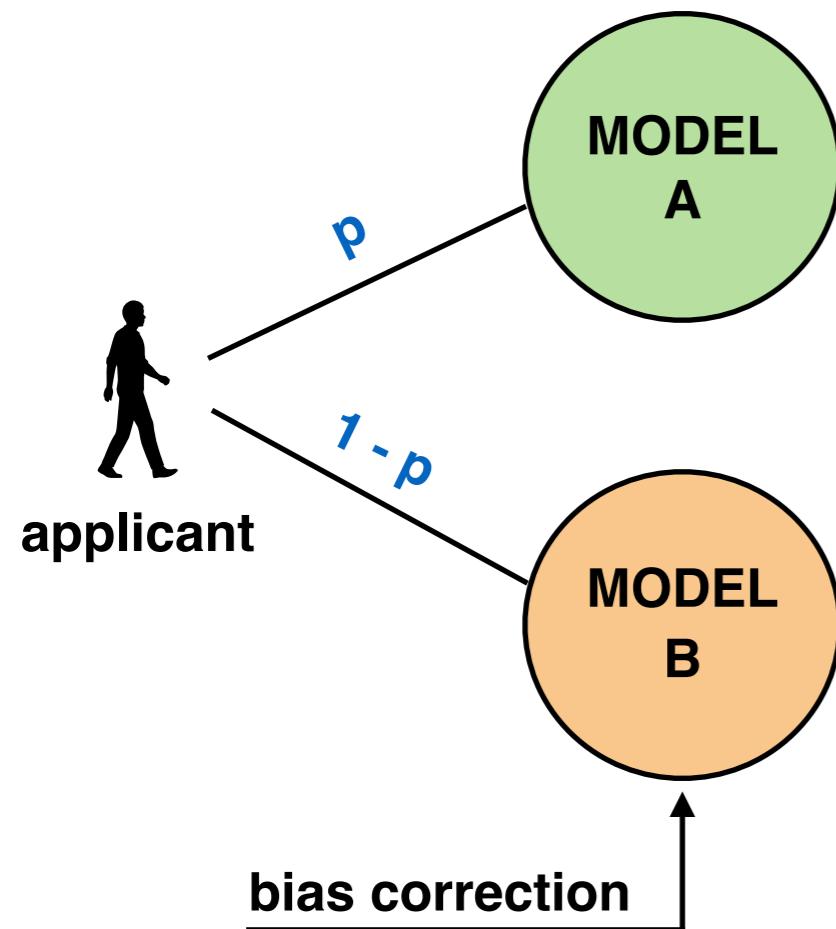


## Incremental gains:

- installment loans: up to **\$461.70** per loan
- micro-loans: up to **\$7.78** per loan

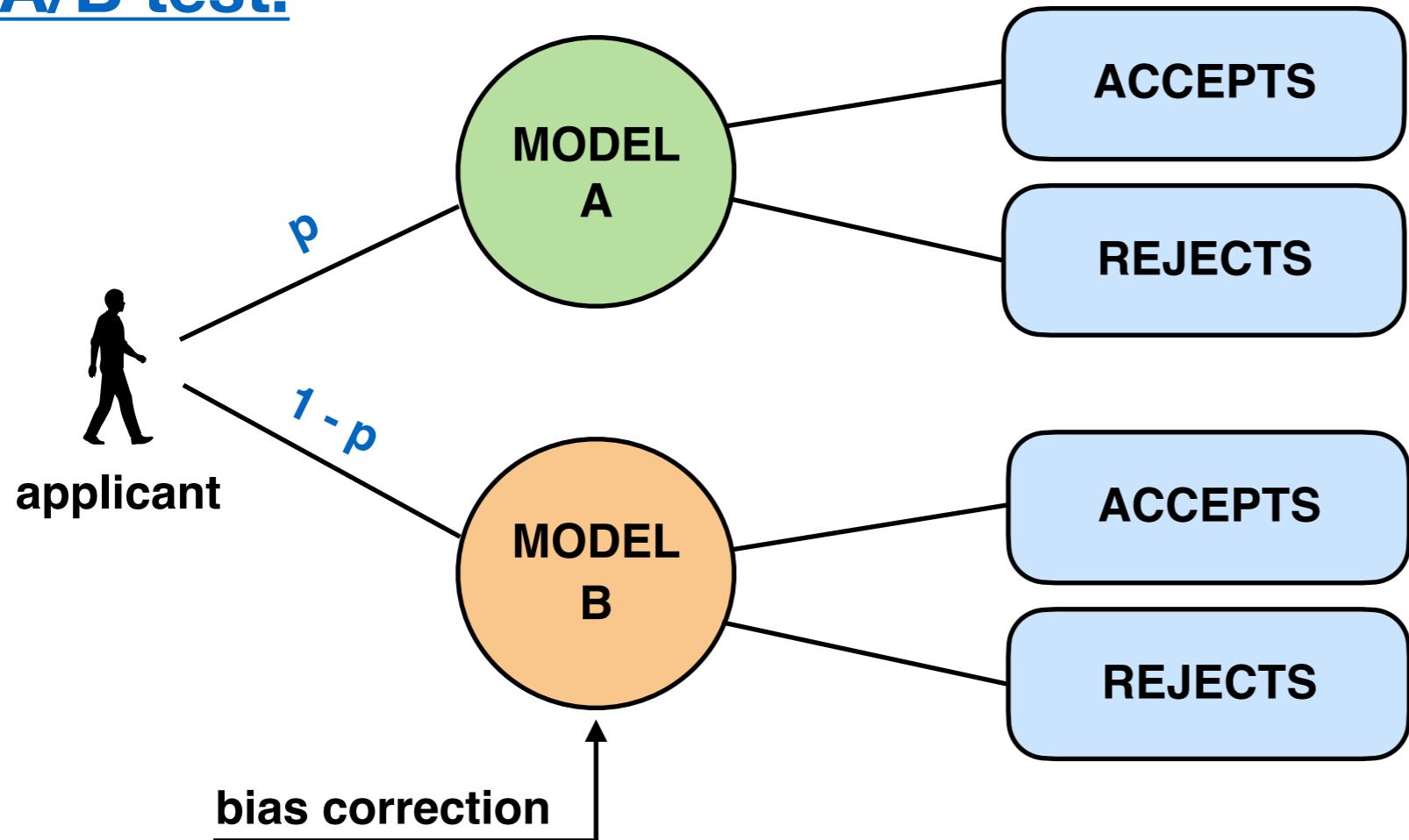
# From Offline to Online

## A/B test:



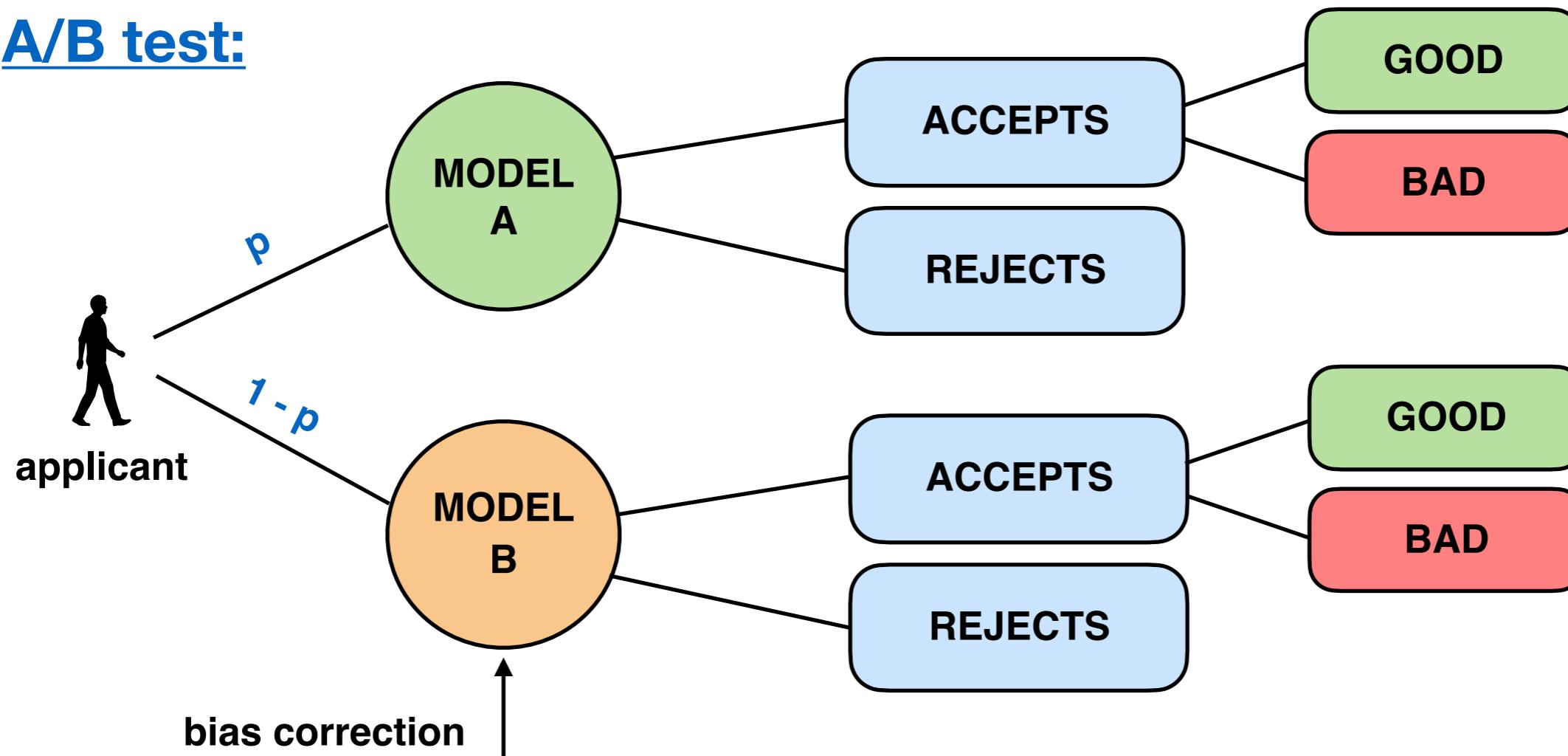
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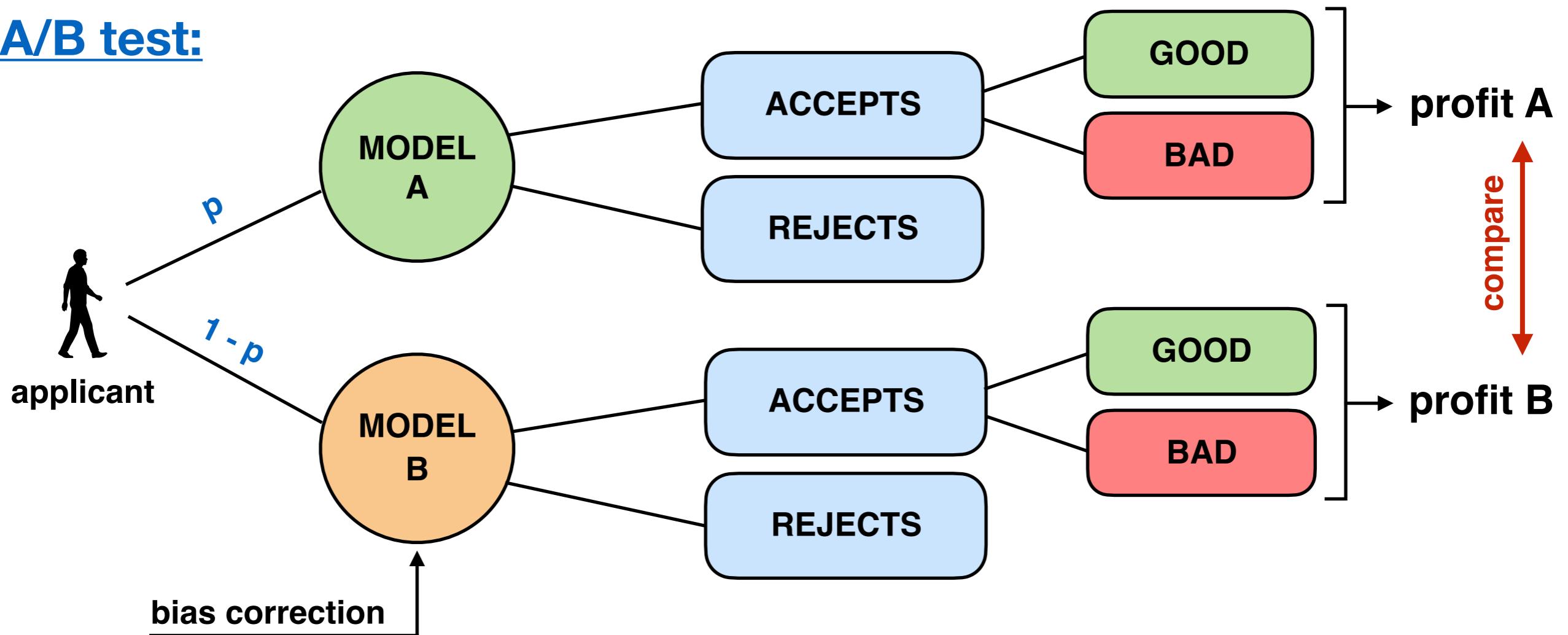
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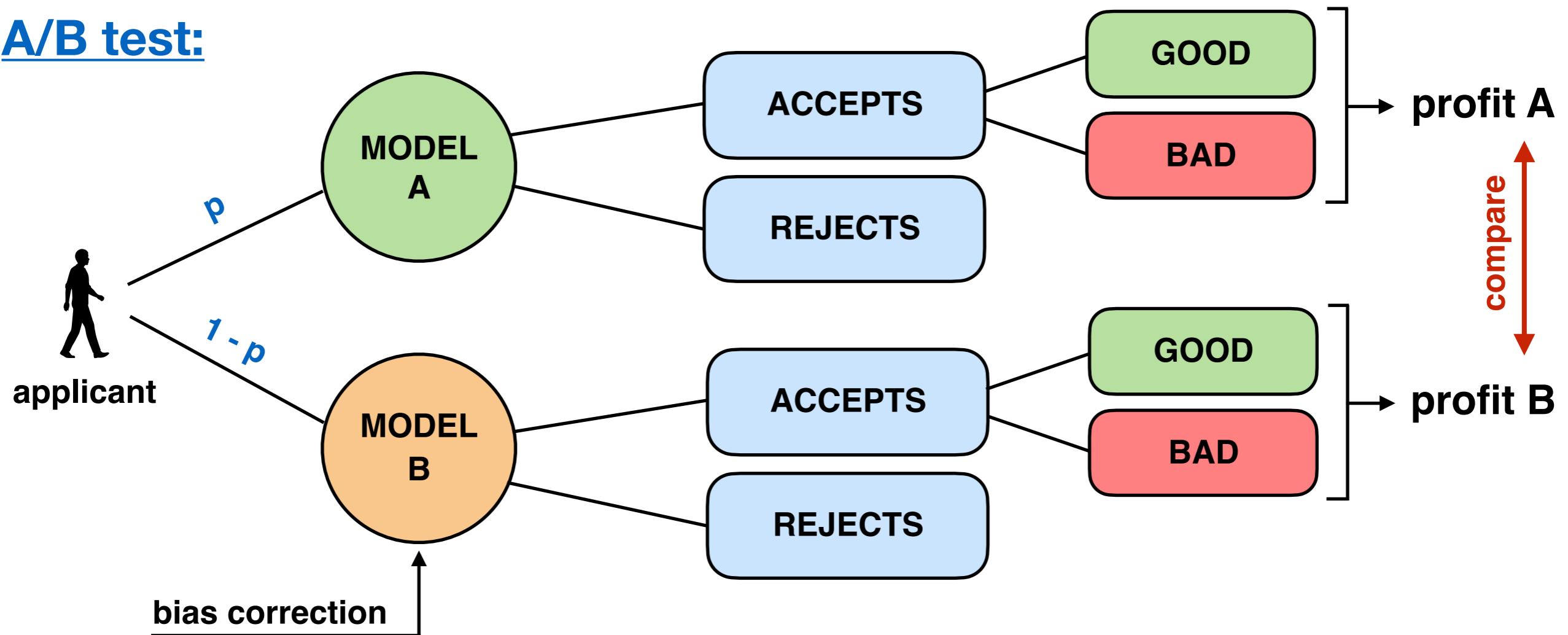
# From Offline to Online

A/B test:



# From Offline to Online

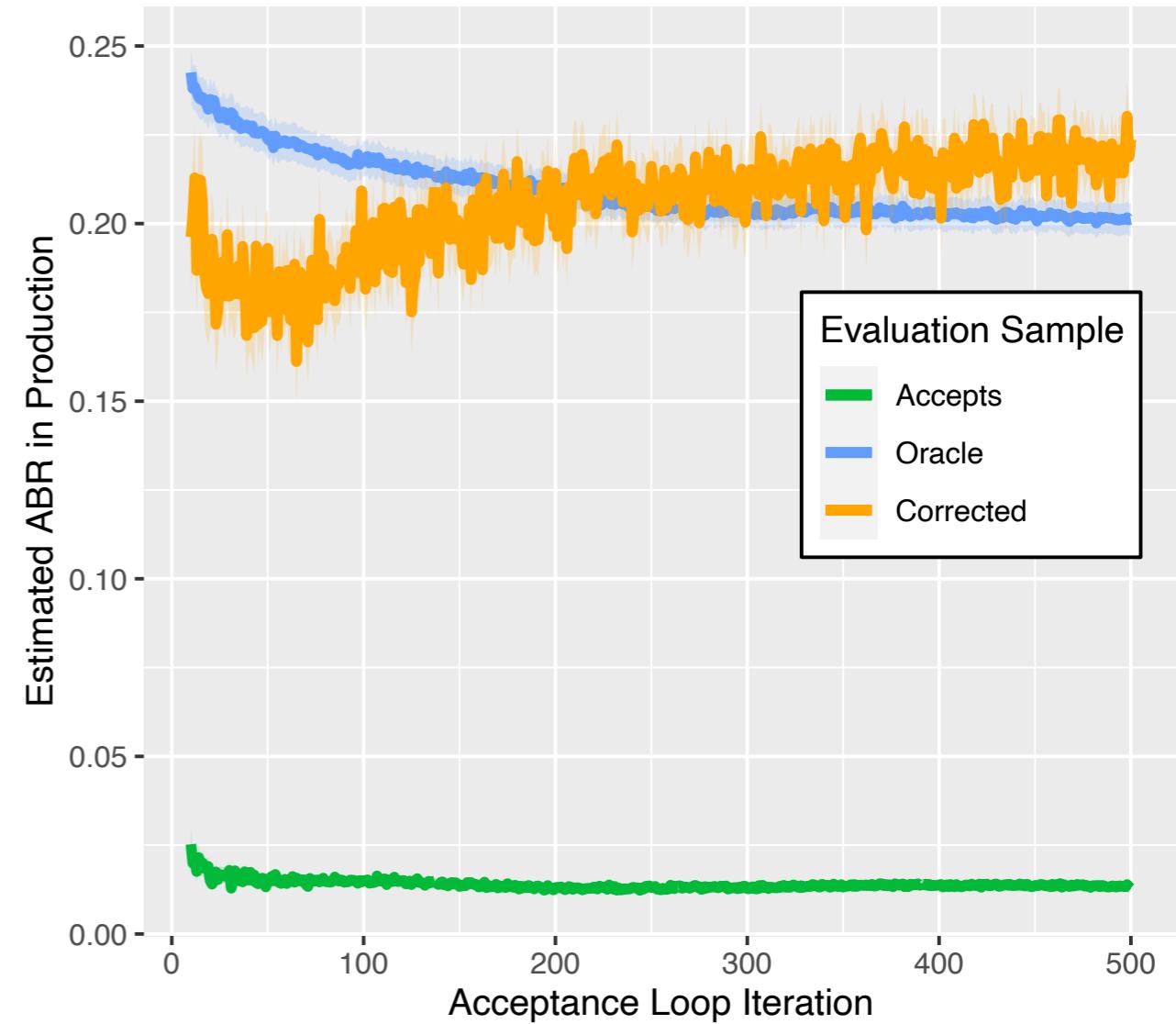
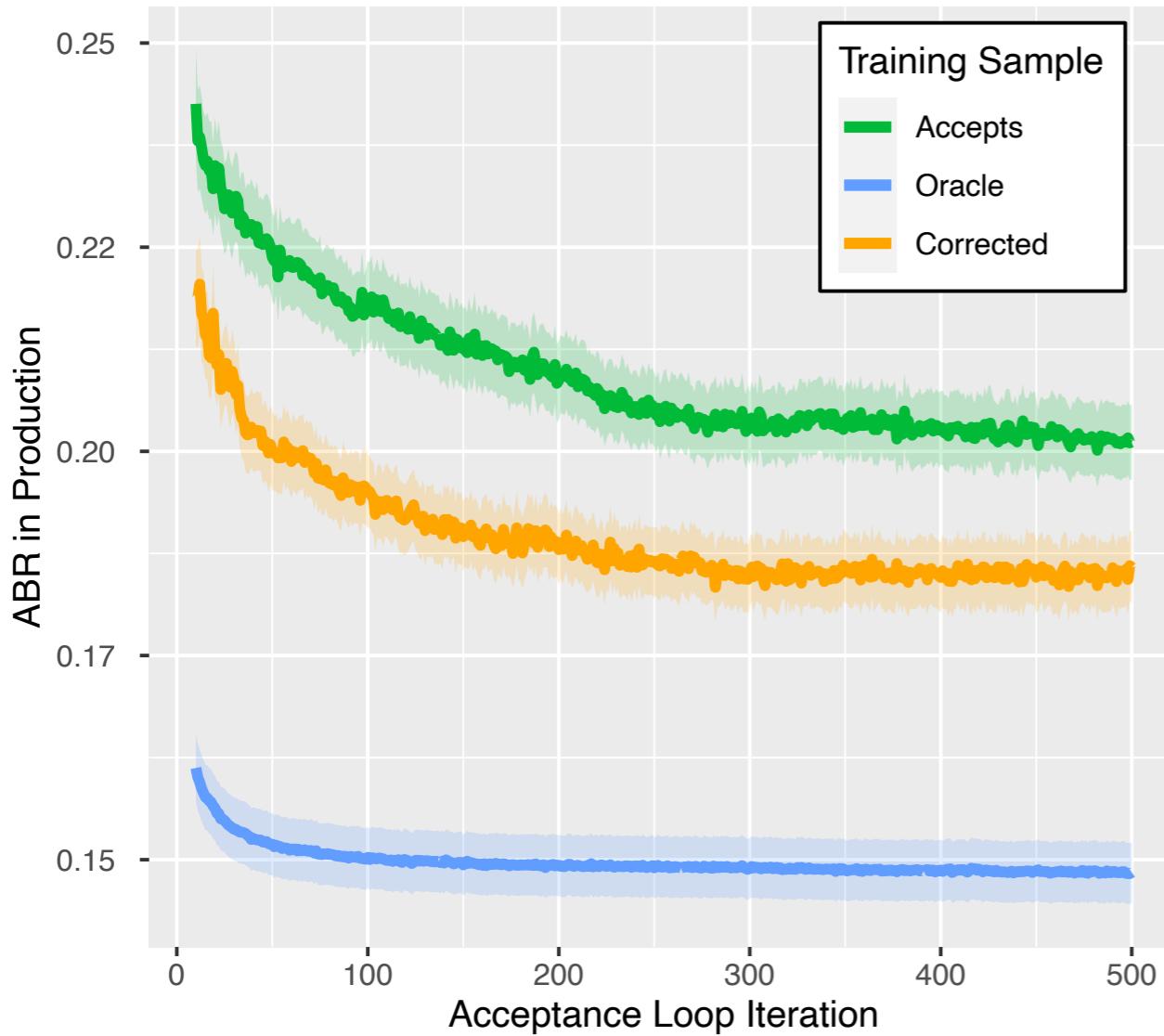
## A/B test:



## Challenges:

- long delay before observing the metrics
- regulations regarding data on rejected clients

# Thank You for Your Attention!



Preprint:



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- micro-loans: up to **\$7.78** per loan

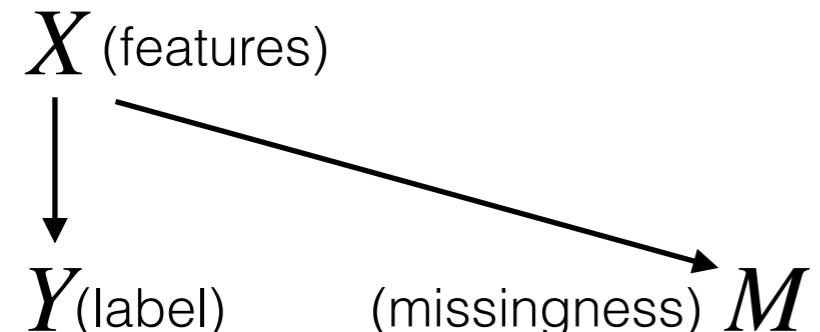
Slides:



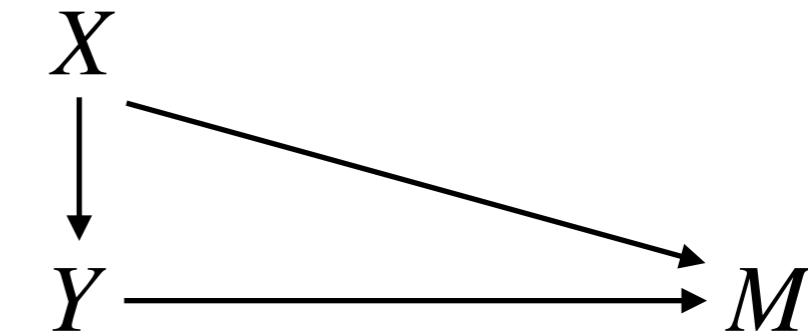
# A1. RELATED WORK

# Sampling Bias as Missing Data Problem

## Missing at random (MAR)



## Missing not at random (MNAR)



- **missingness depends on  $X$  but not on  $Y$** 
  - e.g., fixed scorecard
- **affects training of some ML algorithms**
  - regression-type models (LR, NN) can extrapolate outside of the observed  $X$  space
  - tree-based models (RF, GB) cannot extrapolate (*Malistov & Trushin 2019*)
- **affects model evaluation**
  - performance estimates are misleading

- **missingness depends on both  $X$  and  $Y$** 
  - e.g., manual overwriting, omitted variables
- **affects model training**
- **affects model evaluation**

Missingness types by (*Little & Rubin 2019*)

# Related Work in Different Streams

## Missing data and sample selection

- Assume labels are MNAR
- Sample selection methods (*Langford et al. 2007*)
  - Heckman model (*Heckman 1976, 1979*)
  - Bivariate probit (*Meng & Schmidt 1985*)
- Recent extensions
  - Shadow variables (*Miao et al. 2019*)
  - Doubly robust evaluation (*Bias et al 2020*)

## Train/test distribution discrepancy

- Domain adaptation and covariate shift
  - Representation change (e.g., *Caseiro et al. 2015*)
  - Bias-removing autoencoder (*Atan et al. 2018*)
  - Generative adversarial networks
- Robust performance evaluation measures
  - Modified AIC (*Shimodaira 2000*)
  - Generalization error (*Sugiyama et al. 2006*)
- Transfer learning

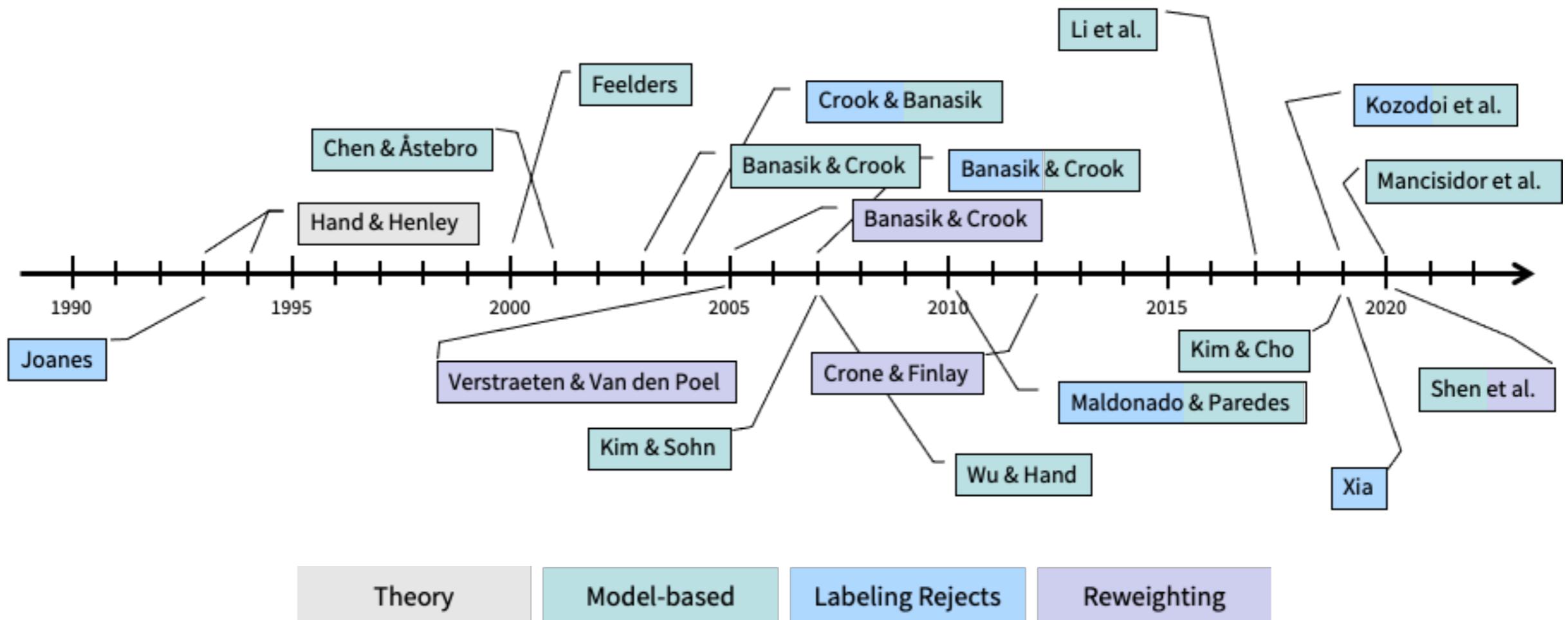
## Policy evaluation and optimization

- Contextual bandit setting (*Langford et al. 2007*)
  - Maximizing reward across a set of actions
  - Rewards depend on the action
  - Rewards are partially observable
- Policy evaluation and optimization
  - Importance reweighing (e.g., *Zadrozny 2004*)
  - Doubly Robust estimator (*Dudik et al 2014*)
- Dynamic treatment regimes in medical studies

## Training data augmentation

- Semi-supervised learning
  - Support vector machines (e.g., *Li et al. 2017*)
  - Self-learning (e.g., *Triguero et al. 2013*)
  - Co-training (e.g., *Chen et al. 2011*)
- Reject inference in credit risk
  - Hard cutoff augmentation (*Banasik et al. 2003*)
  - Parceling (e.g., *Siddiqi 2012*)
- Active learning

# Related Work: Credit Scoring



# Related Work: Credit Scoring

Reference	Implemented technique(s)	Training method(s)	Evaluation method(s)	Representative holdout sample	Profit gains	No. features
Joanes [49]	Reclassification	DA	—			3
Fogarty [33]	Multiple imputation	DA	—			10
Xia [103]	Outlier detection with isolation forest	DA	—			9
Liu et al. [66]	Ensembling classifiers and clusters	MB	—			5, 23
Kang et al. [51]	Label spreading with oversampling	DA	—			22
Boyes et al. [16]	Heckman model variant (HM)	MB	—			42
Feeelders [32]	Mixture modeling	MB	—			2
Chen et al. [21]	HM	MB	—	✓		24
Banasik et al. [9]	HM	MB	—	✓		30
Wu et al. [102]	HM	MB	—			2
Kim et al. [54]	HM	MB	—	✓		16
Chen et al. [22]	Bayesian model	MB	—		✓	40
Li et al. [59]	Semi-supervised SVM (S3VM)	MB	—			7
Marshall et al. [75]	HM	MB	—			18
Tian et al. [96]	Kernel-free fuzzy SVM	MB	—			7, 14
Xia et al. [104]	CPL-E-LightGBM	MB	—			5, 17
Anderson [1]	Bayesian network	MB	—			7, 20
Kim et al. [53]	S3VM with label propagation	MB	—			17
Shen et al. [85]	Unsupervised transfer learning	MB	—			20
Banasik et al. [7]	Banded weights	RW	—	✓		30
Verstraeten et al. [98]	Resampling	RW	—	✓	✓	45
Bücker et al. [19]	Missing data based weights	RW	—			40
Crook et al. [26]	Banded weights, extrapolation	RW, DA	—	✓		30
Banasik et al. [8]	HM with banded weights	MB, RW	—	✓		30
Maldonado et al. [70]	Self-learning, S3VM	MB, DA	—			2, 20, 21
Anderson et al. [2]	HCA, Mixture modeling	DA, MB	—			12
Nguyen [78]	Parceling, HM, Banded weights	DA, MB, RW	—			9
Mancisidor et al. [72]	Bayesian model, self-learning, S3VM	DA, MB	—			7, 58
<b>This paper</b>	<b>BASL, Bayesian evaluation</b>	<b>DA</b>	<b>EF</b>	<b>✓</b>	<b>✓</b>	<b>2,410</b>

Abbreviations: DA = data augmentation, MB = model-based, RW = reweighting, EF = evaluation framework. “Representative holdout sample” indicates whether the study has access to a sample from the borrower’s population for evaluation. “Profit gains” indicates whether gains from bias correction are measured in terms of profit. “Heckman model variant” includes a linear Heckman model and a bivariate probit/logistic model with non-random sample selection.

# Related Work: Bias Correction

Reference	Method	Type	Reference	Method	Type
Blitzer et al. [14]	Structural correspondence learning	RC	Heckman [42]	Heckman's model	MB
Daumé III [27]	Supervised feature augmentation	RC	Meng et al. [77]	Heckman-style bivariate probit	MB
Saenko et al. [83]	Supervised feature transformation	RC	Lin et al. [60]	Modified SVM	MB
Gopalan et al. [38]	Sampling geodesic flow	RC	Daumé III et al. [28]	Maximum entropy genre adaptation	MB
Gong et al. [37]	Geodesic kernel flow	RC	Yang et al. [105]	Adapt-SVM	MB
Caseiro et al. [20]	Unsupervised feature transformation	RC	Marlin et al. [73]	Multinomial mixture model	MB
Saptal et al. [84]	Penalized feature selection	RC	Bickel et al. [13]	Kernel logistic regression	MB
Pan et al. [80]	Transfer component analysis	RC	Chen et al. [23]	Co-training for domain adaptation	MB, RC
Long et al. [68]	Transfer joint matching	RC	Duan et al. [30]	Domain adaptation machine	MB
Sun et al. [95]	Correlation alignment	RC	Long et al. [67]	Regularized least squares	MB
Wang et al. [100]	Extreme dimension reduction	RC	Liu et al. [64]	Robust bias-aware classifier	MB
Atan et al. [3]	Bias-removing autoencoder	RC	Joachims et al. [48]	Modified ranking SVM	MB
Heckman [42]	Heckman's model	MB	Chen et al. [24]	Robust bias-aware regression	MB
Meng et al. [77]	Heckman-style bivariate probit	MB	Liu et al. [63]	Modified bias-aware classifier	MB
Lin et al. [60]	Modified SVM	MB	Kügelgen et al. [56]	Semi-generative model	MB
Daumé III et al. [28]	Maximum entropy genre adaptation	MB	Rosenbaum et al. [81]	Model-based probabilities	RW
Yang et al. [105]	Adapt-SVM	MB	Shimodaira [86]	Distribution density ratios	RW
Marlin et al. [73]	Multinomial mixture model	MB	Zadrozny [106]	Selection probabilities are known	RW
Bickel et al. [13]	Kernel logistic regression	MB	Huang et al. [45]	Kernel mean matching	RW
Chen et al. [23]	Co-training for domain adaptation	MB, RC	Cortes et al. [25]	Cluster-based frequencies	RW
Duan et al. [30]	Domain adaptation machine	MB	Sugiyama et al. [93]	Kullback-Leibler weights	RW
Long et al. [67]	Regularized least squares	MB	Kanamori et al. [50]	Least-squares importance fitting	RW
Liu et al. [64]	Robust bias-aware classifier	MB	Loog [69]	Nearest-neighbor based weights	RW
Joachims et al. [48]	Modified ranking SVM	MB	Gong et al. [36]	Focusing on cases similar to test data	RW
Chen et al. [24]	Robust bias-aware regression	MB	Shimodaira [86]	Modified AIC	EM
Liu et al. [63]	Modified bias-aware classifier	MB	Sugiyama et al. [94]	Subspace information criterion	EM
Kügelgen et al. [56]	Semi-generative model	MB	Sugiyama et al. [92]	Generalization error	EM
			Sugiyama et al. [91]	Importance-weighted validation	EF
			Bruzzone et al. [18]	Circular evaluation strategy	EF

# How to Use Rejects?

## Assigning labels:

- **Traditional:** hard cutoff augmentation, parcelling
- **Semi-supervised:** self-training, SVMs
- **Label noise:** CV-based
- **Evolutionary algorithms:** GA with labels as genes

## Filtering rejects:

- **Instance selection:** genetic algorithms
- **Novelty detection:** isolation forest
- **Active learning:** error minimization, uncertainty sampling

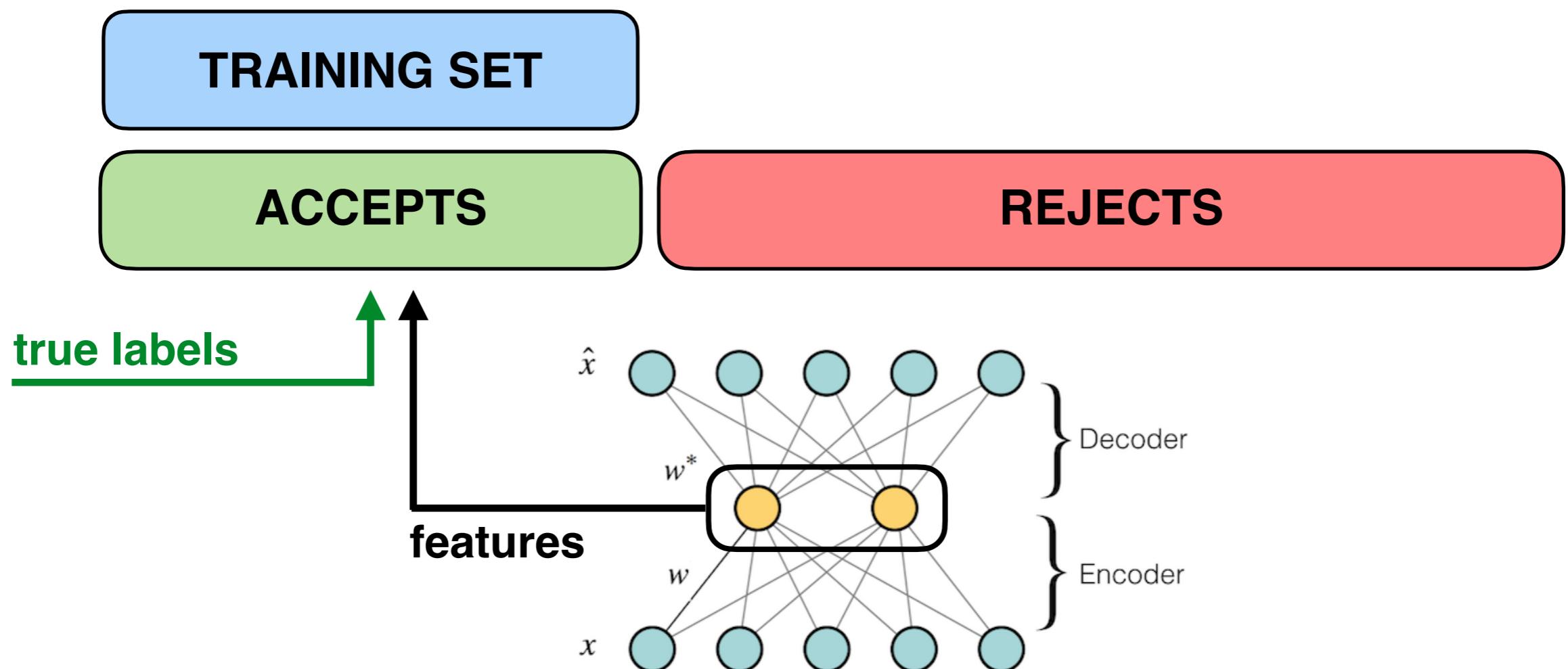
## Extracting information:

- **Autoencoders**

# Bias-Removing Autoencoder

## Idea:

- train Autoencoder on **accepts** + **rejects**
  - add distribution mismatch penalty to the loss function
- extract features from the bottleneck layer
- append new features to **accepts** and train a new model



# Reject Inference Techniques

## Label as BAD:

- Label all rejects as **BAD** risks
- Augment the known data with the labeled rejects
- Retrain the scoring model on the full data

## Bureau score based inference:

- Use bureau scores to assign labels to **rejects**
- e.g., label “A” examples as **GOOD**, “B” and below - as **BAD**
- Augment the known data with the labeled rejects
- Retrain the scoring model on the full data
- Can use other informative attributes (e.g., previous loan delinquency)

# Reject Inference Techniques

## Hard cutoff augmentation:

- Train a scoring model based on **accepts**
- Predict default probabilities for **rejects** using this model
- Assign labels based on a certain threshold
- Augment the known data with the labeled rejects
- Retrain the scoring model on the full data

## Parceling:

- Split **rejects** into groups based on the model score
- Assign labels within groups proportionally to the expected bad rate
- **BAD** ratio for rejects is usually assumed to be higher

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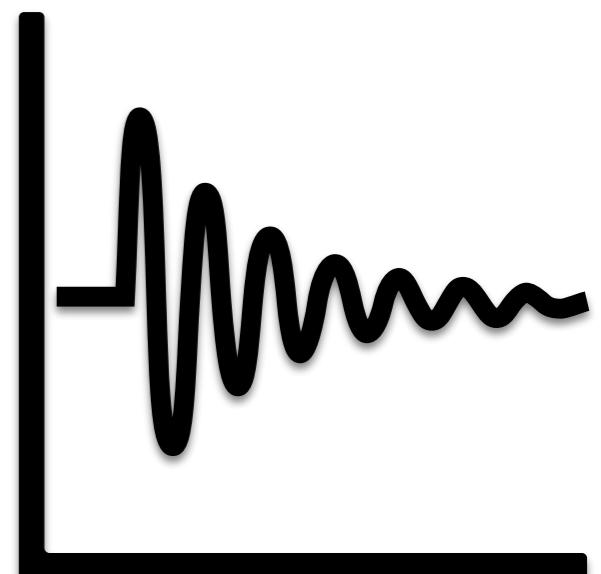
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## A2. CHALLENGES

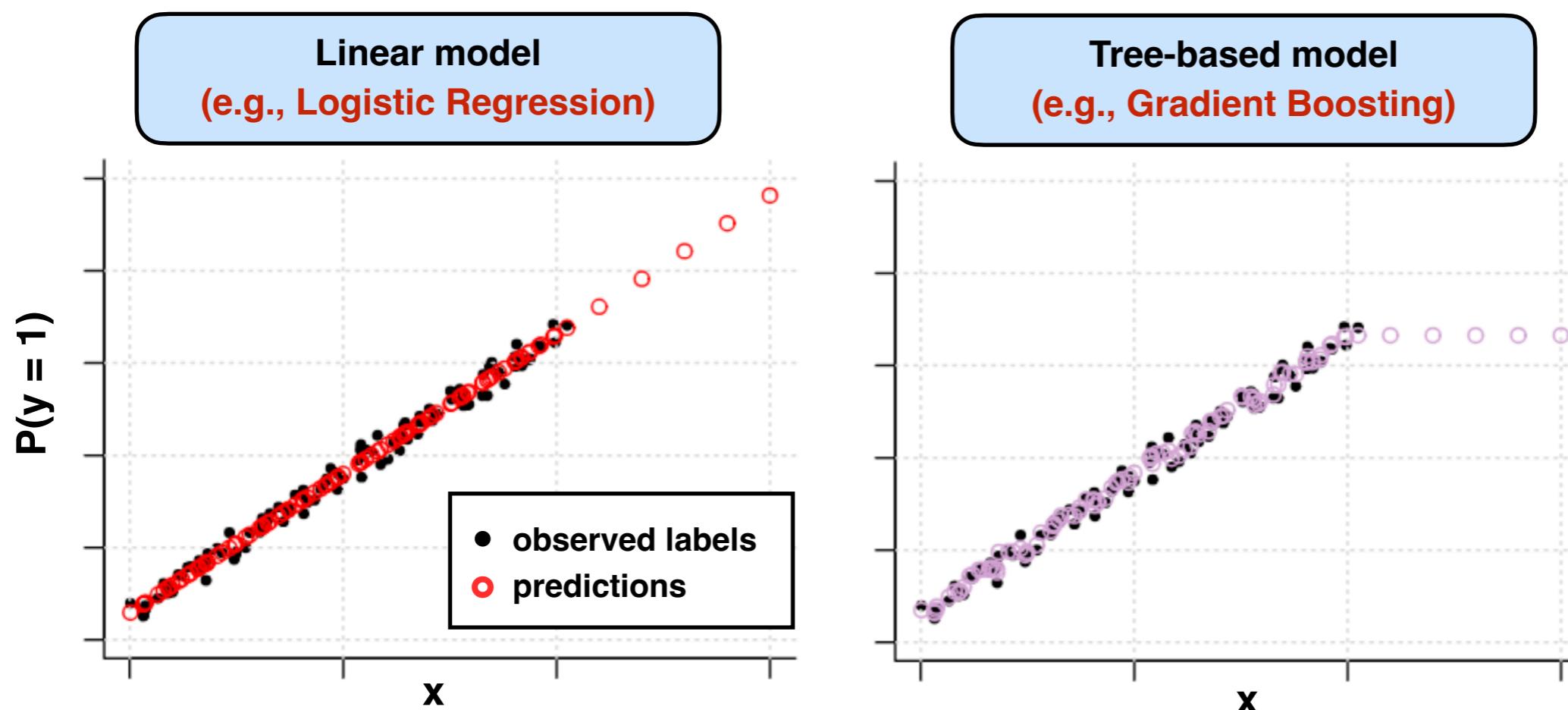
# Dataset Shift and Sampling Bias

- **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
- e.g., 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 ability and bias sensitivity



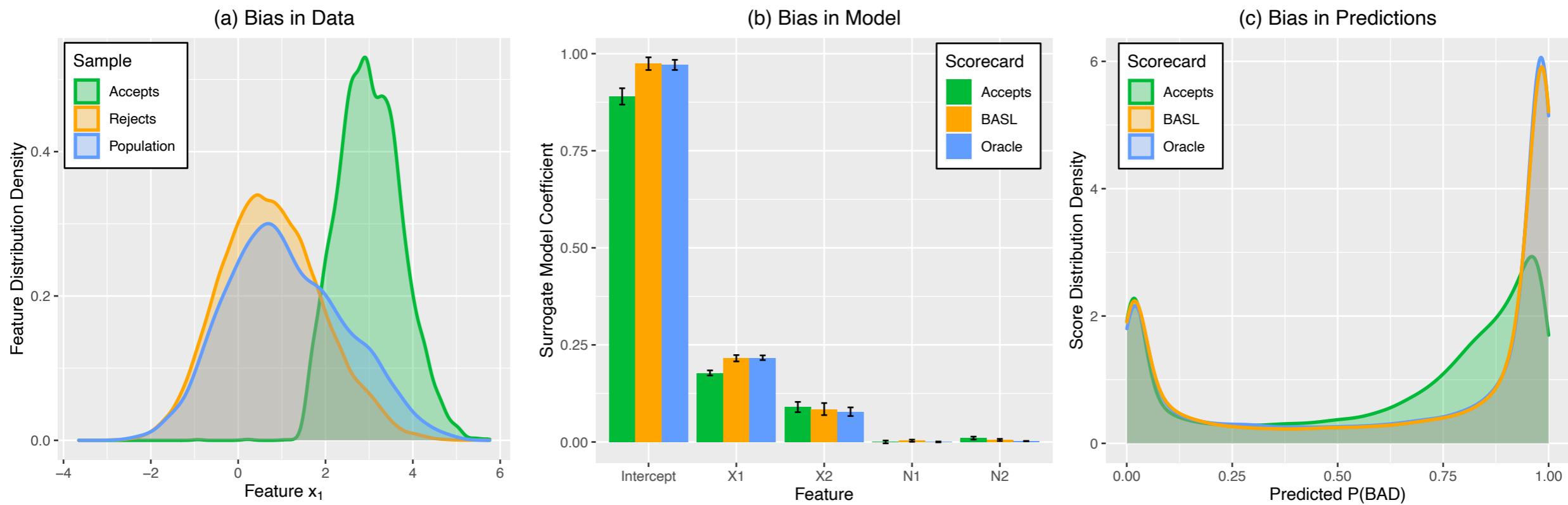
# Some Further Challenges

- **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**

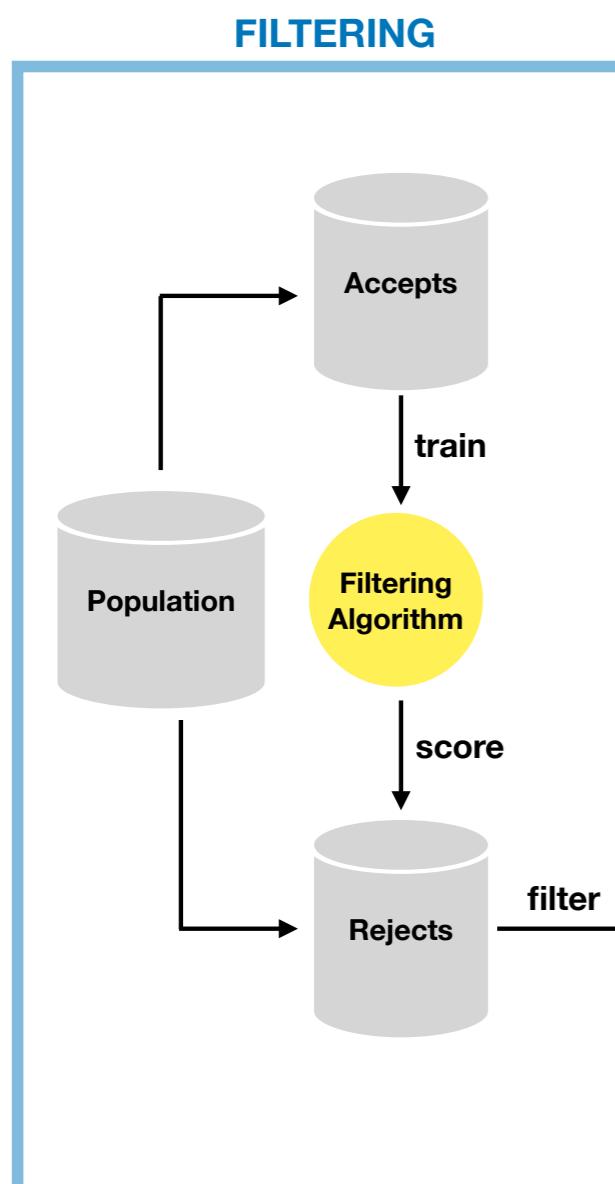
- detecting bias in non-parametric models is **not straightforward**
- need to illustrate bias through the lens of performance / model predictions



# A3. TRAINING

# BASL: Framework Stages [1/4]

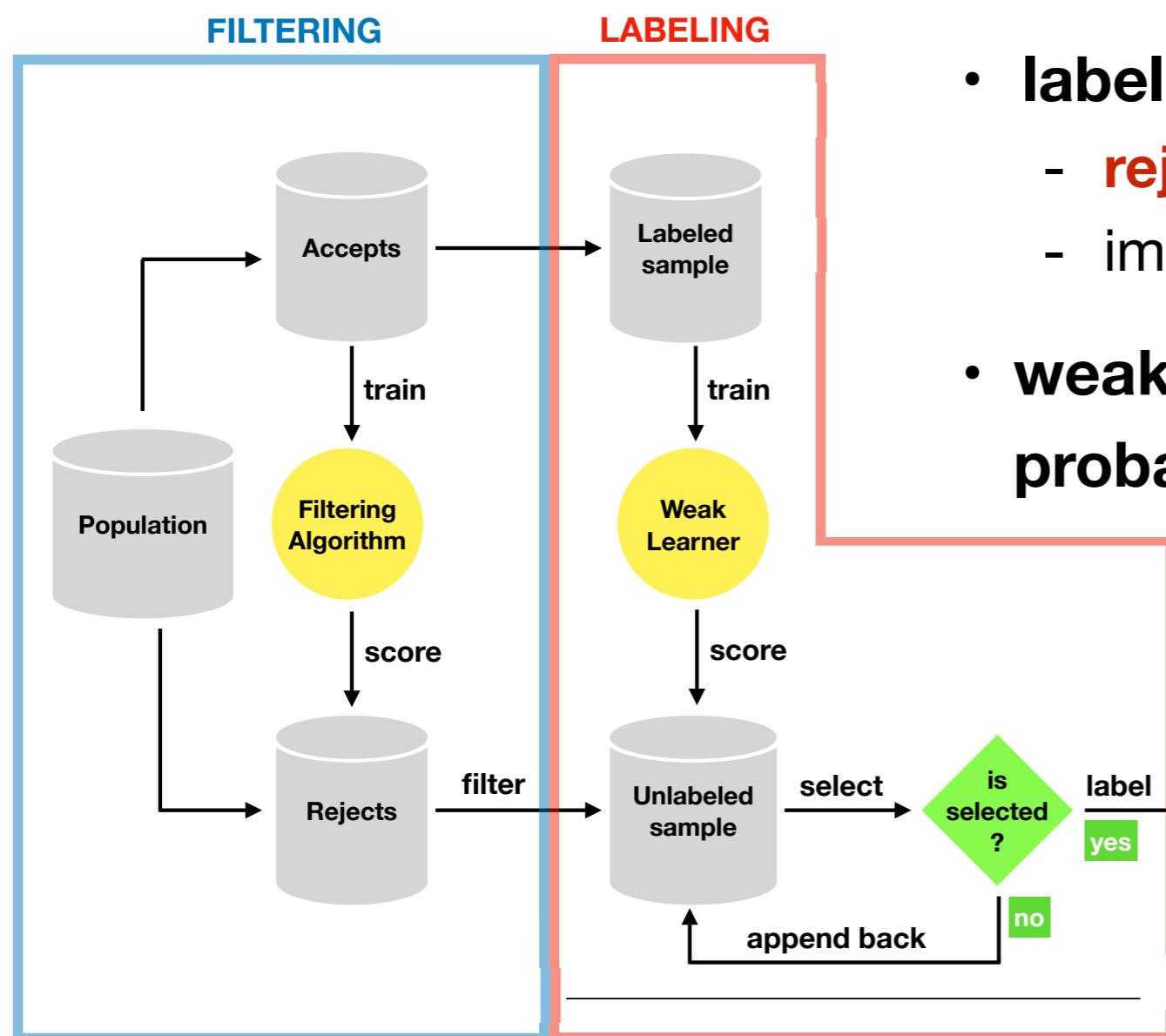
- augmenting training data with **selected rejects** to reduce bias
  - inspired by self-learning framework (e.g., Triguero et al. 2013)
  - model-agnostic nature
- implement multiple techniques to reduce the risk of error propagation



- removing **rejects** whose distribution is most different from the observed **accepts**
  - predictions for such cases may not be reliable
  - reduces risks of error propagation
- estimating similarity using isolation forest
  - novelty detection algorithm (Liu et al. 2008)
  - fitted on **accepts**

# BASL: Framework Stages [2/4]

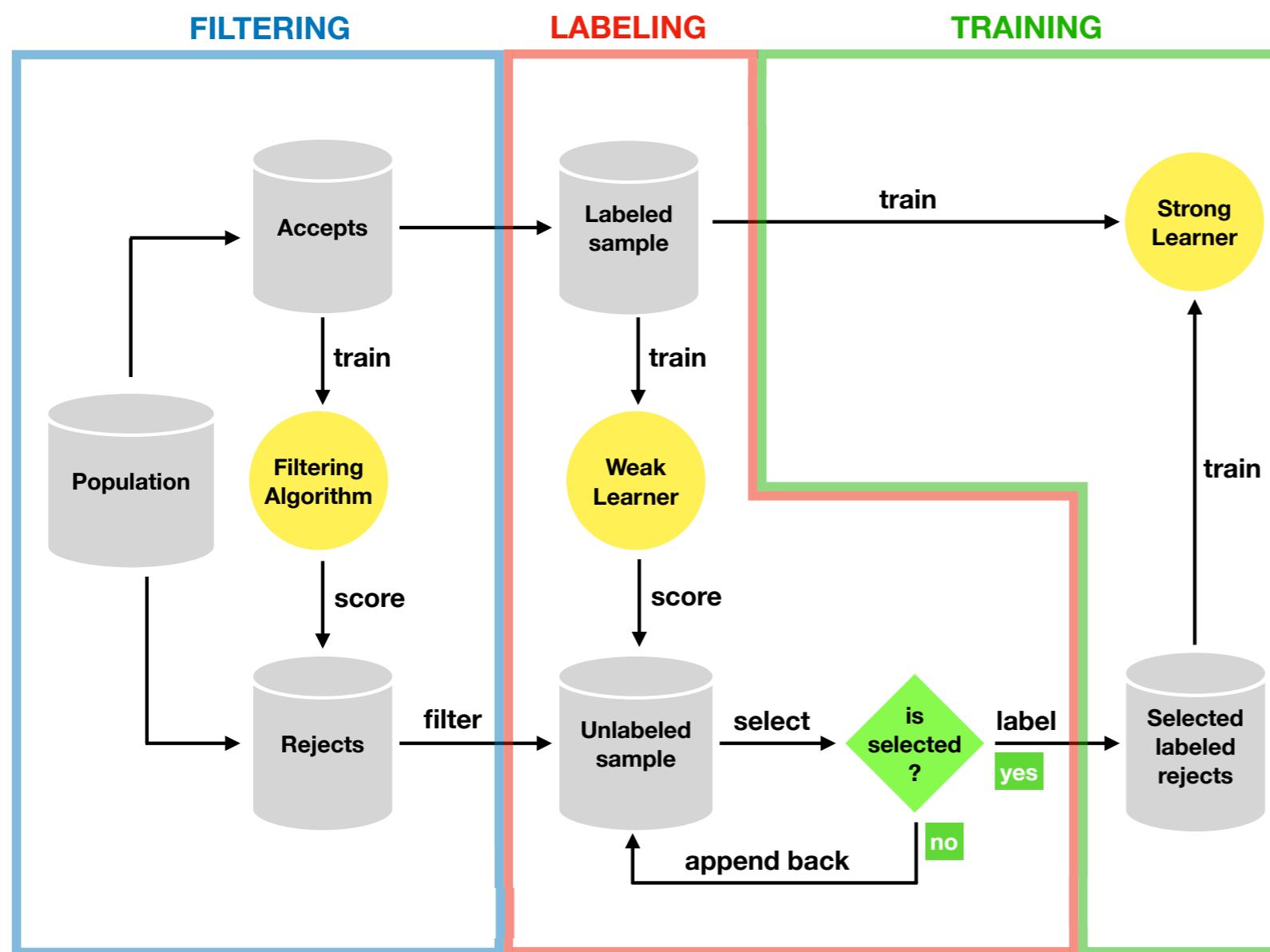
- augmenting training data with **selected rejects** to reduce bias
  - inspired by self-learning framework (e.g., Triguero et al. 2013)
  - model-agnostic nature
- implement multiple techniques to reduce the risk of error propagation



- labeling and appending selected **rejects**
  - **rejects** classified with high confidence
  - imbalance multiplier to add more **BAD** loans
- weak learner produces well-calibrated probabilities (*Niculescu-Mizil et al., 2005*)
  - L1-regularized logistic regression
  - trained on **accepts**
- extrapolating outside observed  $X$

# BASL: Framework Stages [3/4]

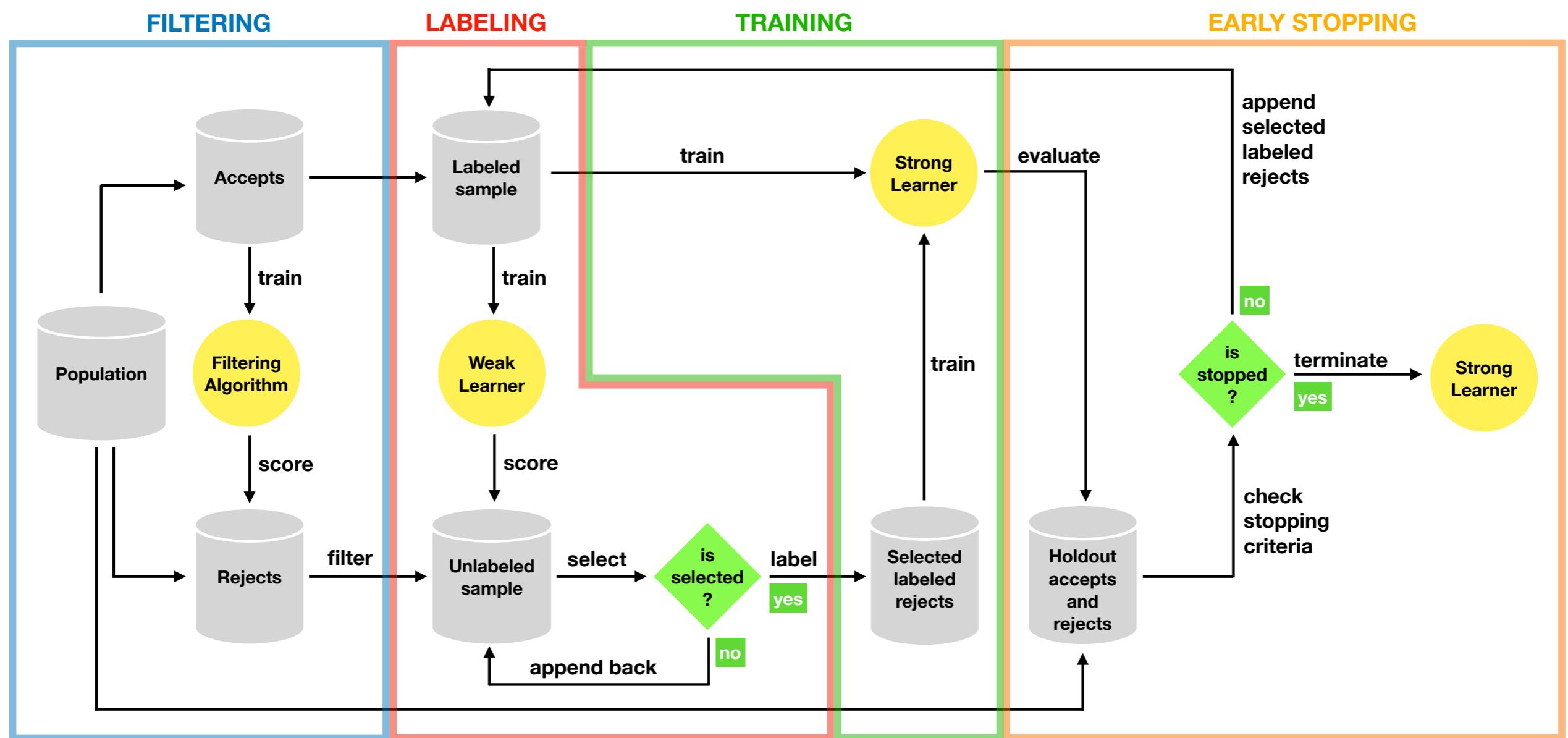
- augmenting training data with **selected rejects** to reduce bias
  - inspired by self-learning framework (e.g., Triguero et al. 2013)
  - model-agnostic nature
- implement multiple techniques to reduce the risk of error propagation



- train on augmented data
  - **accepts**
  - **labeled rejects**
- use strong learner
  - e.g., gradient boosting  
(Chen et al., 2015)

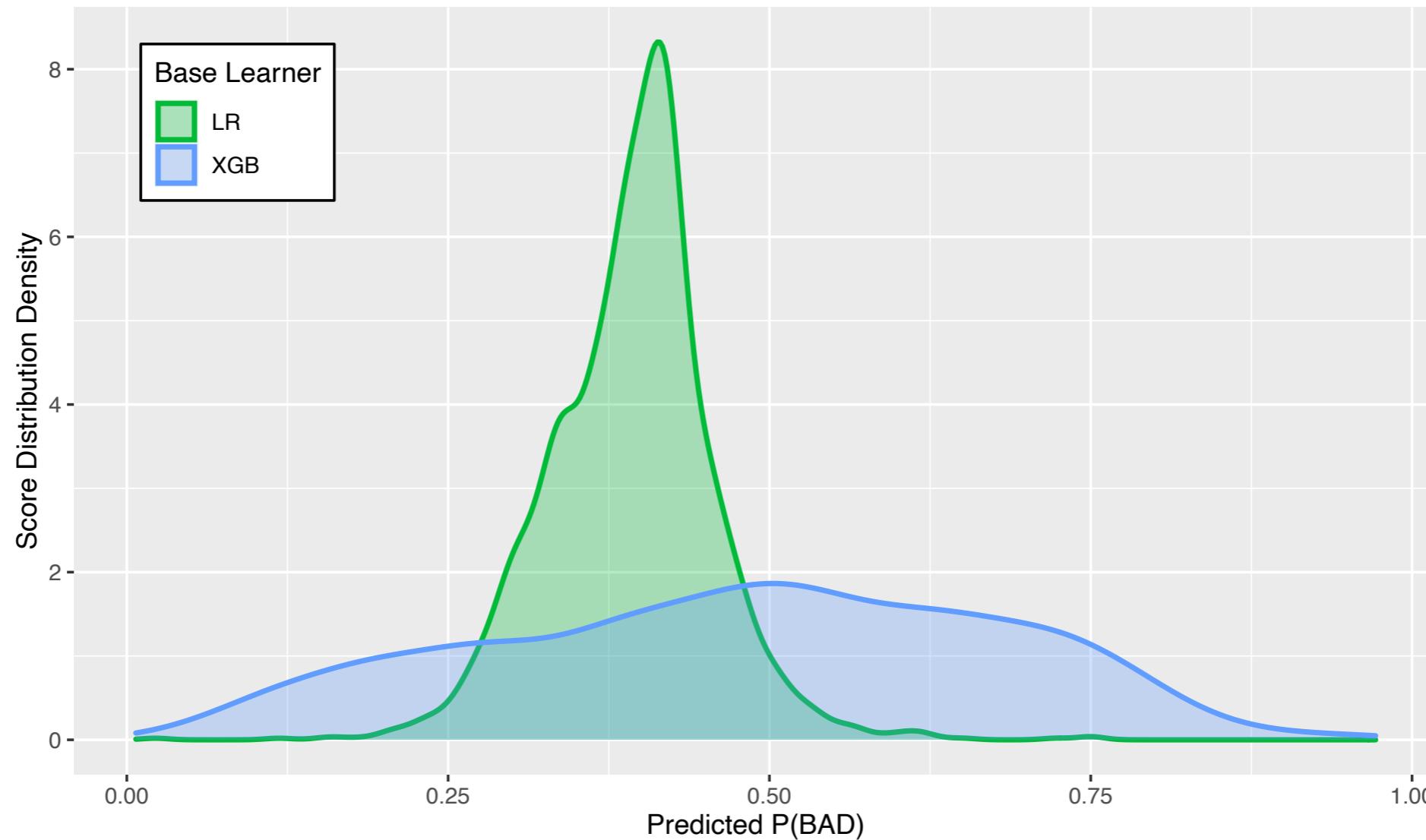
# BASL: Framework Stages [4/4]

- augmenting training data with **selected rejects** to reduce bias
  - inspired by self-learning framework (e.g., Triguero et al. 2013)
  - model-agnostic nature
- implement multiple techniques to reduce the risk of error propagation



# Comparing Prediction Density

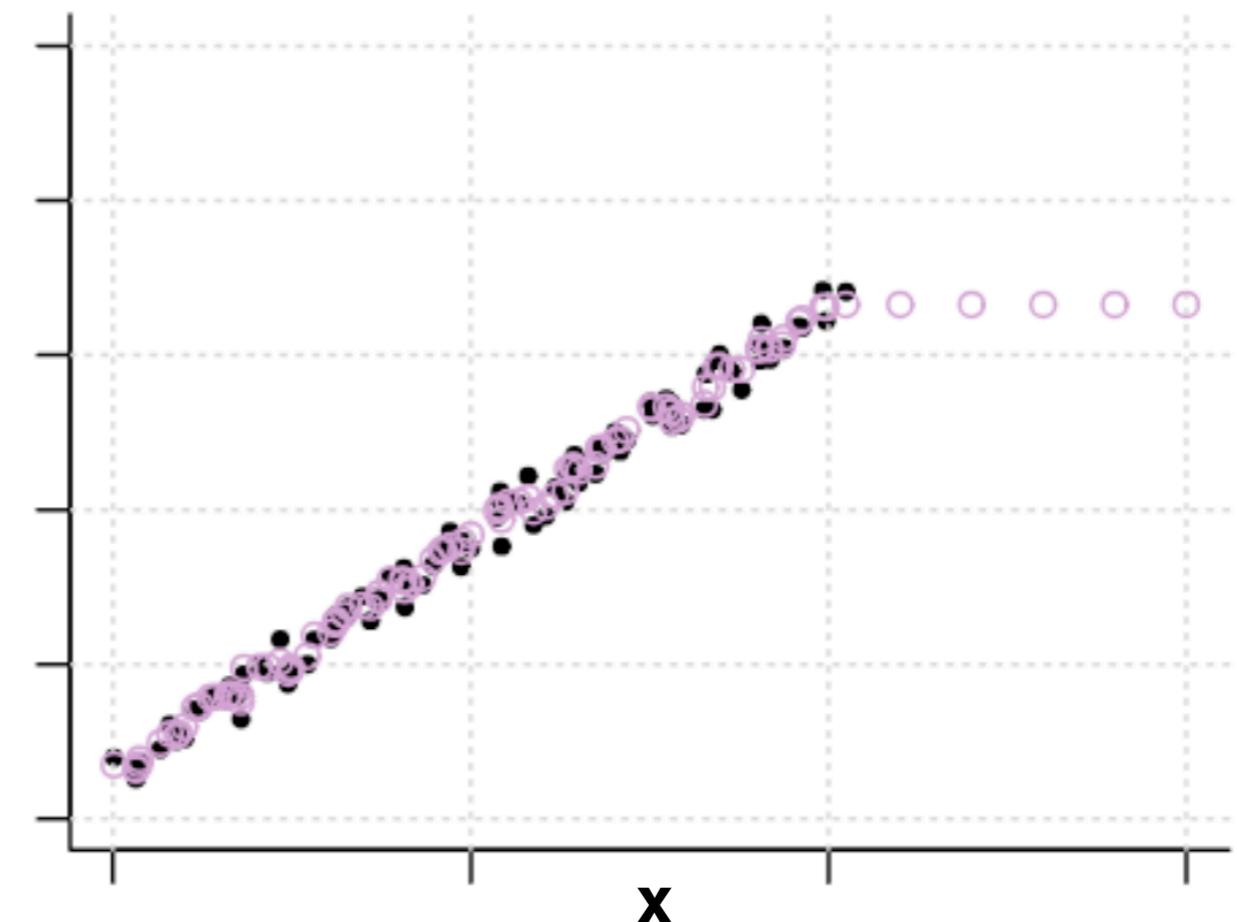
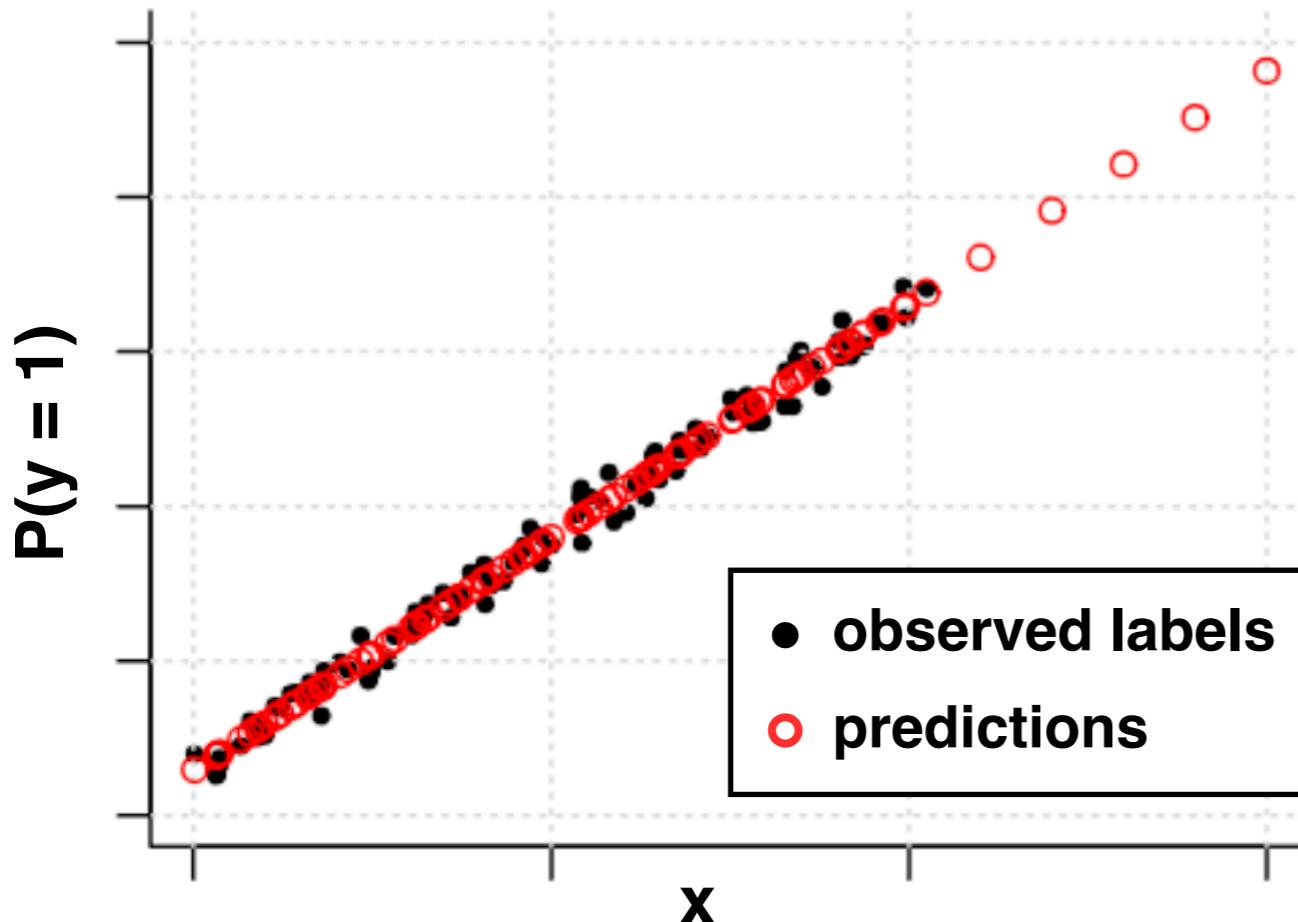
- **strong learners (e.g. XG) tend to produce overconfident scores on the extremes of the score distribution (Niculescu-Mizil et al., 2005)**
- **weak learners (e.g., LR) output well-calibrated probabilistic predictions**



# Extrapolation: Regression vs Tree Methods

Regression-type model  
(e.g., Logistic Regression)

Tree-based model  
(e.g., Gradient Boosting)



- **logistic regression** can extrapolate outside of the observed feature space
- **tree-based methods** can not extrapolate and produce constant predictions

Source: Hengl, T. et al (2018). Random forest as a generic framework for predictive modeling of spatial and spatio-temporal variables. *PeerJ*, 6, e5518.

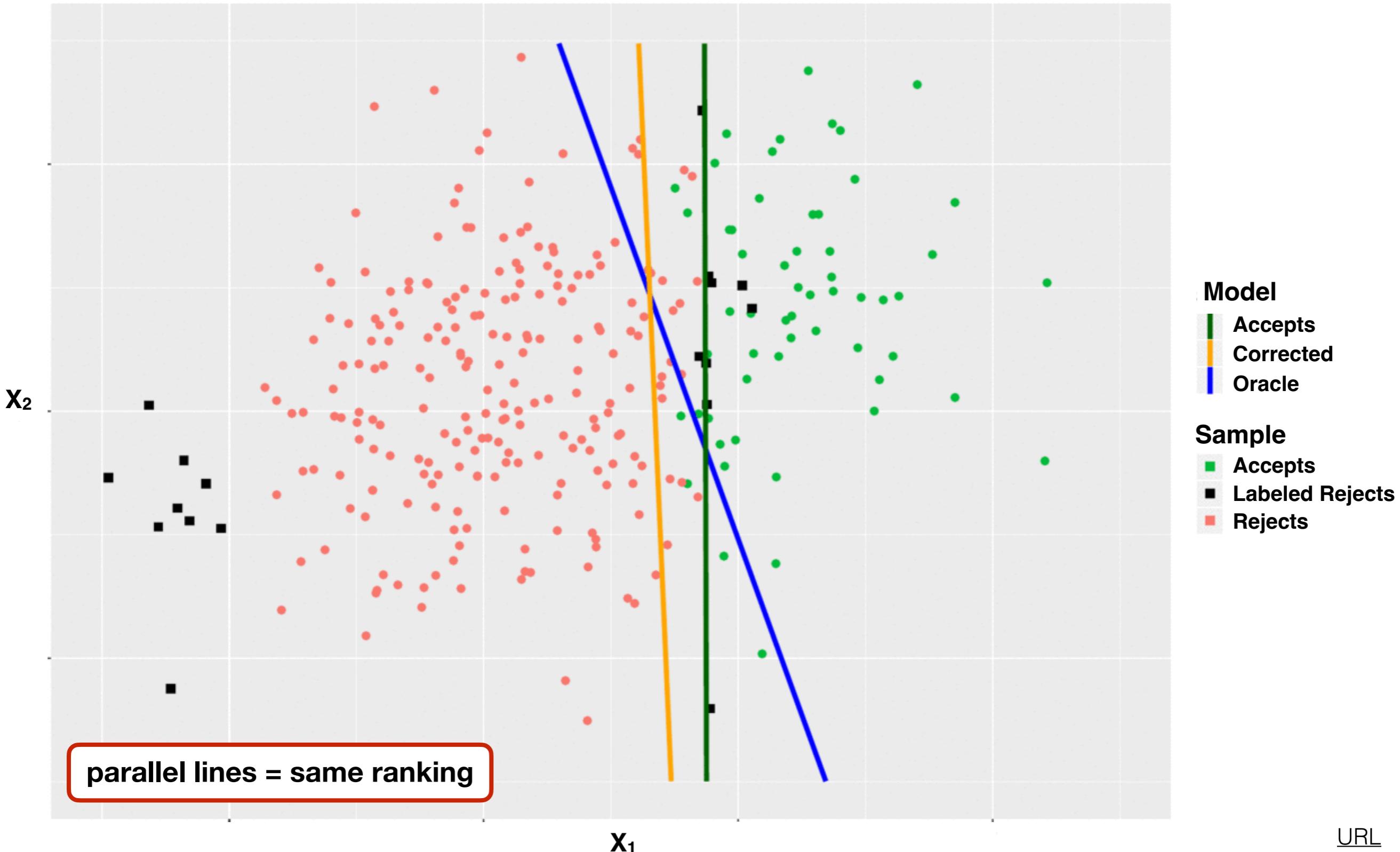
# BASL: Ablation Study

Framework extension	AUC	BS	PAUC	ABR	Rank
Traditional self-learning	.8059 (.0010)	.1804 (.0004)	.6868 (.0011)	.2387 (.0020)	4.80
Filter rejects using isolation forest	.8054 (.0011)	.1790 (.0004)	.6981 (.0013)	.2312 (.0022)	3.93
Label rejects with a weak learner	.8134 (.0006)	.1774 (.0002)	.6992 (.0009)	.2294 (.0011)	3.60
Introduce the imbalance multiplier	.8133 (.0006)	.1796 (.0002)	.7026 (.0010)	.2238 (.0012)	3.48
Sampling rejects at each iteration	.8157 (.0006)	.1765 (.0002)	.7035 (.0010)	.2254 (.0013)	2.85
Performance-based early stopping	<b>.8166</b> (.0007)	<b>.1761</b> (.0003)	<b>.7075</b> (.0011)	<b>.2211</b> (.0012)	<b>2.34</b>

- **original self-learning algorithm as reference**
- **incrementally activate proposed extensions**
- **measure marginal performance of each extension**

# BASL: Illustrative Example

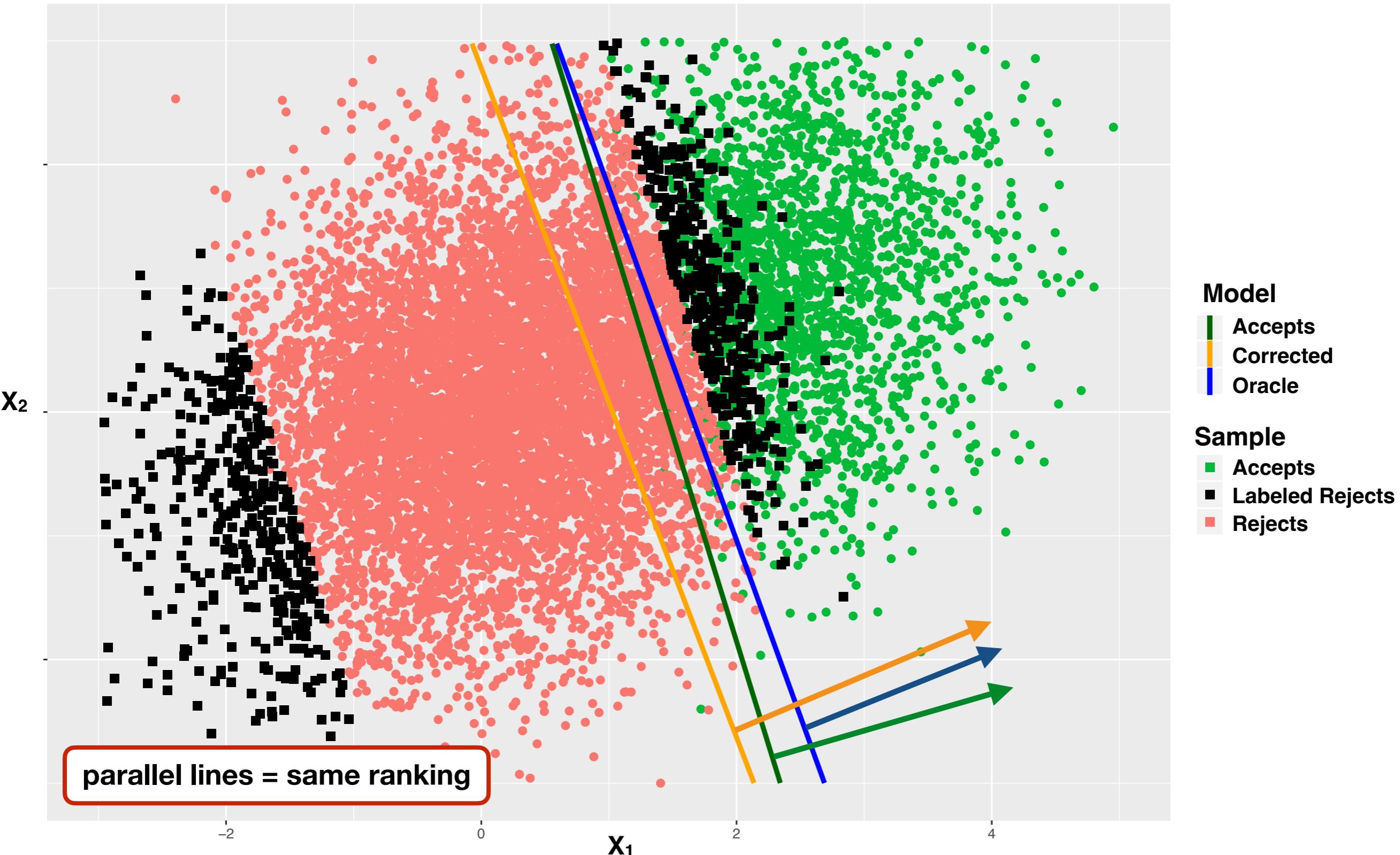
Acceptance Cycle 5/300



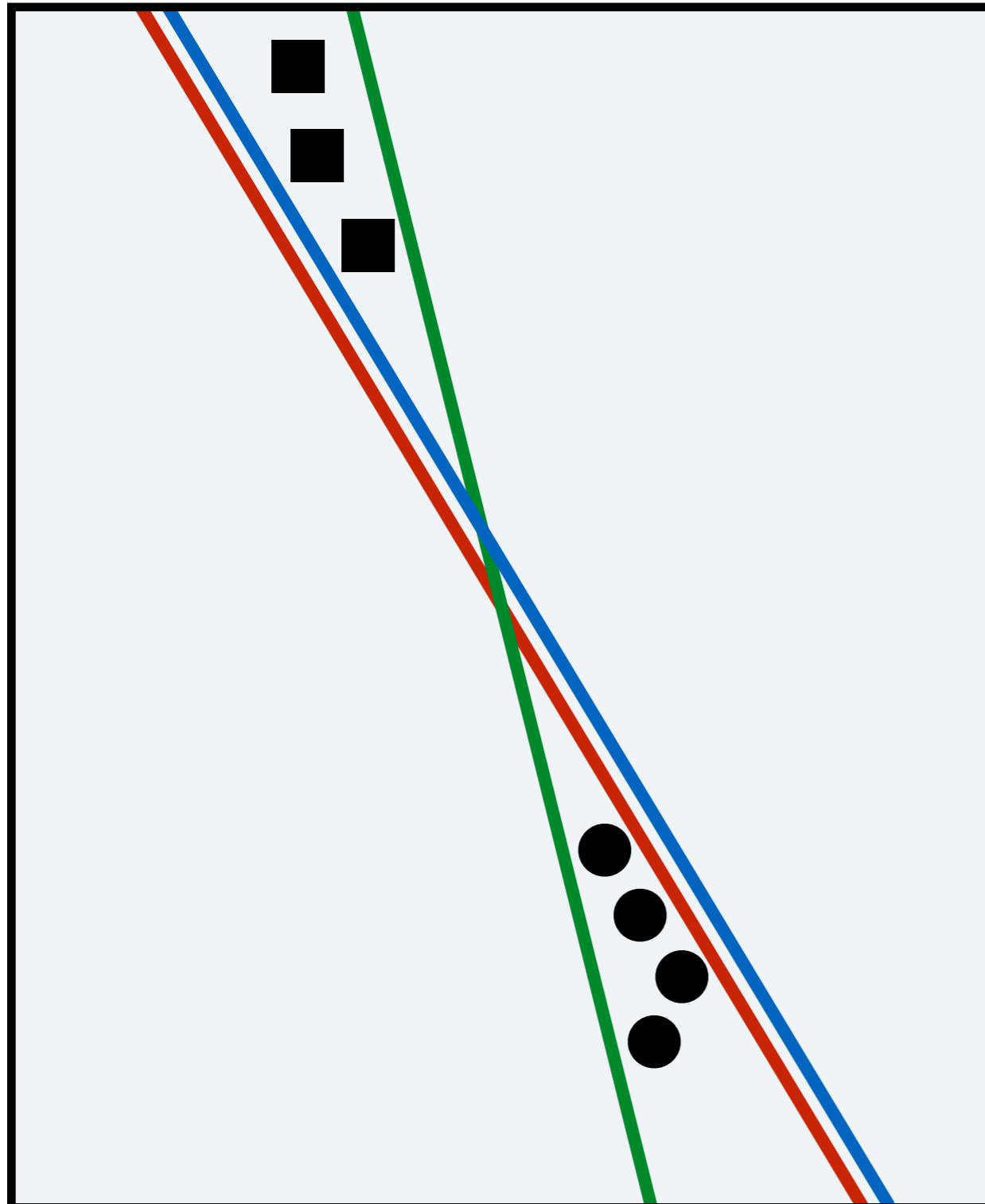
URL

# BASL: Illustrative Example

Acceptance Cycle 300/300



# Results on Synthetic Data: Example



- **Red model** ranks ■ higher than ●
- **Blue model** ranks ■ higher than ●
- **Green model** ranks ● higher than ■

# BASL: Simulation Results

**Missing at random  
(MAR)**

	Loss due to bias	Gain from BASL	Gain from Heckman
AUC	.0597	<b>39.83%</b>	11.54%
PAUC	.0528	<b>24.98%</b>	-39.81%
BRS	.0482	<b>40.47%</b>	-116.30%
ABR	.0589	<b>27.71%</b>	-40.48%
MMD	.5737	<b>7.93%</b>	-

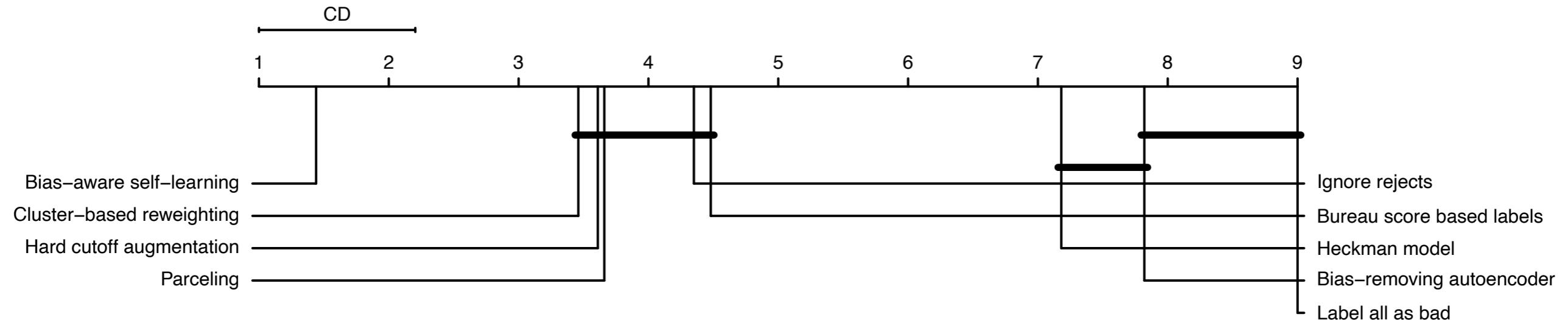
**Missing not at random  
(MNAR)**

	Loss due to bias	Gain from BASL	Gain from Heckman
AUC	.0589	<b>48.84%</b>	27.36%
PAUC	.0488	<b>33.93%</b>	-21.93%
BRS	.0404	<b>45.28%</b>	-129.17%
ABR	.0547	<b>36.86%</b>	-18.08%
MMD	.5746	<b>7.97%</b>	-

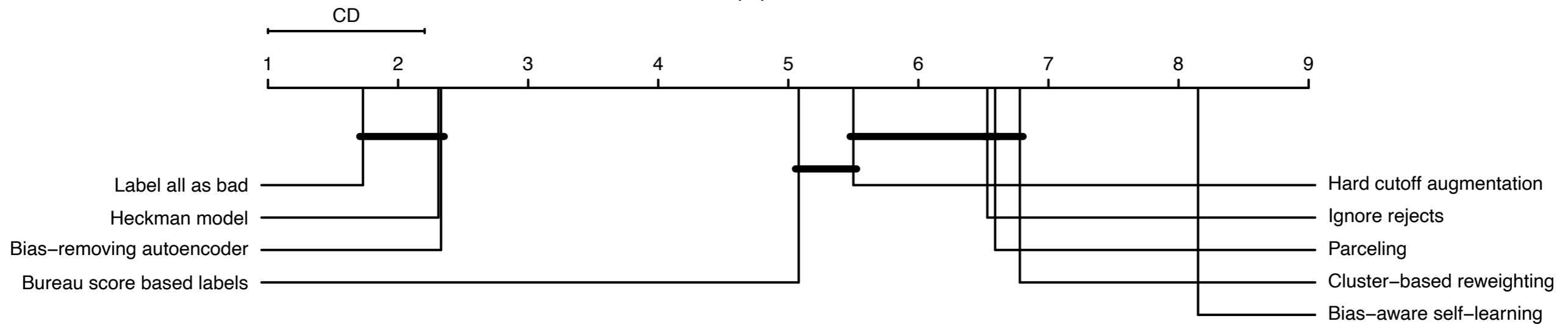
- BASL helps to improve **scorecard performance** in both settings
- data augmented with BASL demonstrates **lower sampling bias**
- all differences are **statistically significant** at 5% (Nemenyi rank test)

# Significance Tests: Nemenyi Plots

(a) AUC



(d) ABR



# A4. EVALUATION

# Bayesian Evaluation Framework

## ■ Notation

$X \in \mathbb{R}^k$	denotes a loan applicant
$\mathbf{X} = (X_1, \dots, X_n)^\top$	matrix of applicants' characteristics
$y \in \{0,1\}$	class label indicating repayment ( $y = 0$ ) or default ( $y = 1$ )
$\mathbf{y}$	random vector of binary labels
$\mathbf{P}_{XY}, \mathbf{P}_X, \mathbf{P}_Y$	joint and marginal distributions of $\mathbf{X}$ and $\mathbf{y}$

## ■ Modeling task

- Given a set of IID credit applications  $D = \{(\mathbf{X}, \mathbf{y})\}$  with  $(\mathbf{X}, \mathbf{y}) \sim \mathbf{P}_{XY}$
- Lender's approval policy partitions  $D$  into  $D^a = (\mathbf{X}^a, \mathbf{y}^a)$  and  $D^r = (\mathbf{X}^r)$
- Infer function  $f(X)$  approximating  $\mathbf{P}(y = 1|X)$ 
  - Due to filtering,  $D^a$  has different empirical joint and marginal distributions compared to  $\mathbf{P}_{XY}, \mathbf{P}_X, \mathbf{P}_Y$
  - Assuming MNAR,  $\mathbf{P}(y = 1|X) \neq \mathbf{P}(y = 1|X^a)$  holds independent of the scoring model

**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  $\mathbf{P}(\mathbf{y}^r|\mathbf{X}^r)$ , evaluation metric  $M(f, S, \tau)$ , meta-parameters  $j_{max}, \epsilon$

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

```
1  $j = 0; \Delta = \epsilon; E^c = \{\}$  ; // initialization
2 while ( $j \leq j_{max}$ ) and ( $\Delta \geq \epsilon$ ) do
3    $j = j + 1$ 
4    $\mathbf{y}^r = \text{binomial}(1, \mathbf{P}(\mathbf{y}^r|\mathbf{X}^r))$  ; // generate labels of rejects
5    $S_j = \{(\mathbf{X}^a, \mathbf{y}^a)\} \cup \{(\mathbf{X}^r, \mathbf{y}^r)\}$  ; // construct evaluation sample
6    $E_j^c = \sum_{i=1}^j M(f(X), S_i, \tau)/j$  ; // evaluate
7    $\Delta = E_j^c - E_{j-1}^c$  ; // check convergence
8 end
9 return  $BM(f, S, \tau) = E_j^c$ 
```

# Bayesian Evaluation: Simulation Results

## Missing at random (MAR)

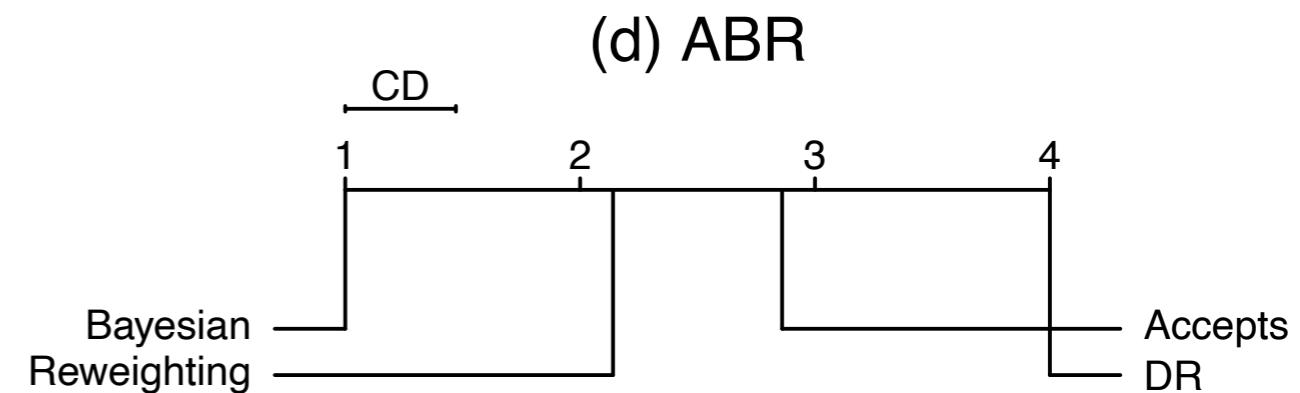
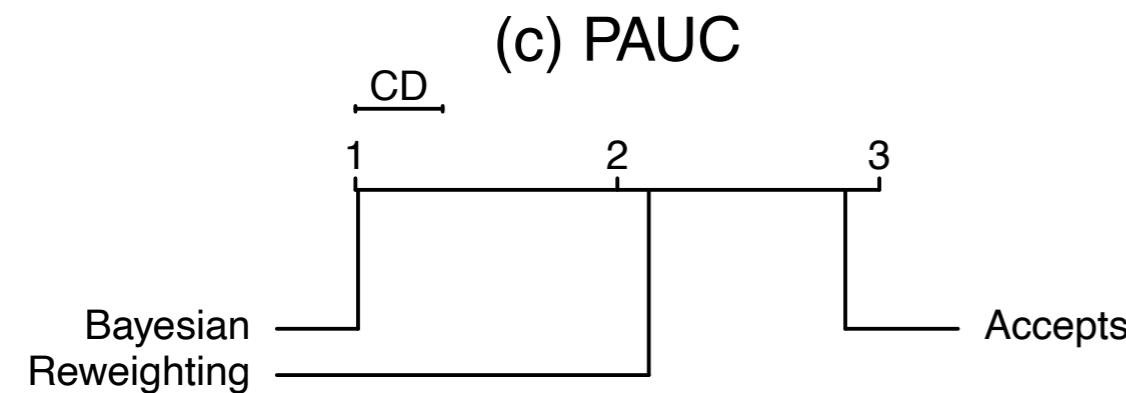
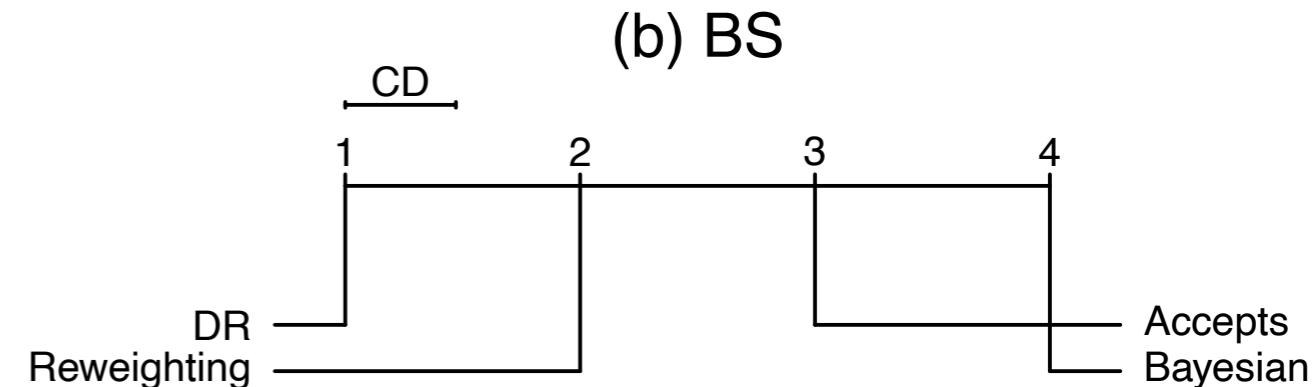
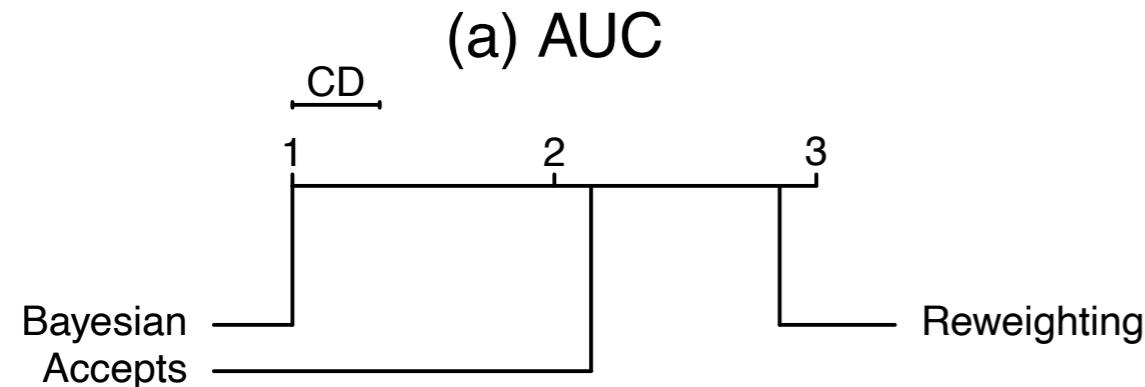
	Method	Bias	Variance	RMSE
AUC	Accepts	.2018	.0423	.2290
	IPW	.0762	<b>.0049</b>	.1113
	<b>Bayesian</b>	<b>.0093</b>	.0053	<b>.0740</b>
PAUC	Accepts	.2720	.0338	.2831
	IPW	.3120	.0222	.3525
	<b>Bayesian</b>	<b>.0113</b>	<b>.0076</b>	<b>.0835</b>
BRS	Accepts	.0797	<b>.0006</b>	.0907
	IPW	.0283	.0115	.0644
	<b>Bayesian</b>	<b>.0139</b>	.0026	<b>.0545</b>
ABR	Accepts	.1946	<b>.00003</b>	.1998
	IPW	.1915	.0003	.1973
	<b>Bayesian</b>	<b>.0166</b>	.0053	<b>.0956</b>

## Missing not at random (MNAR)

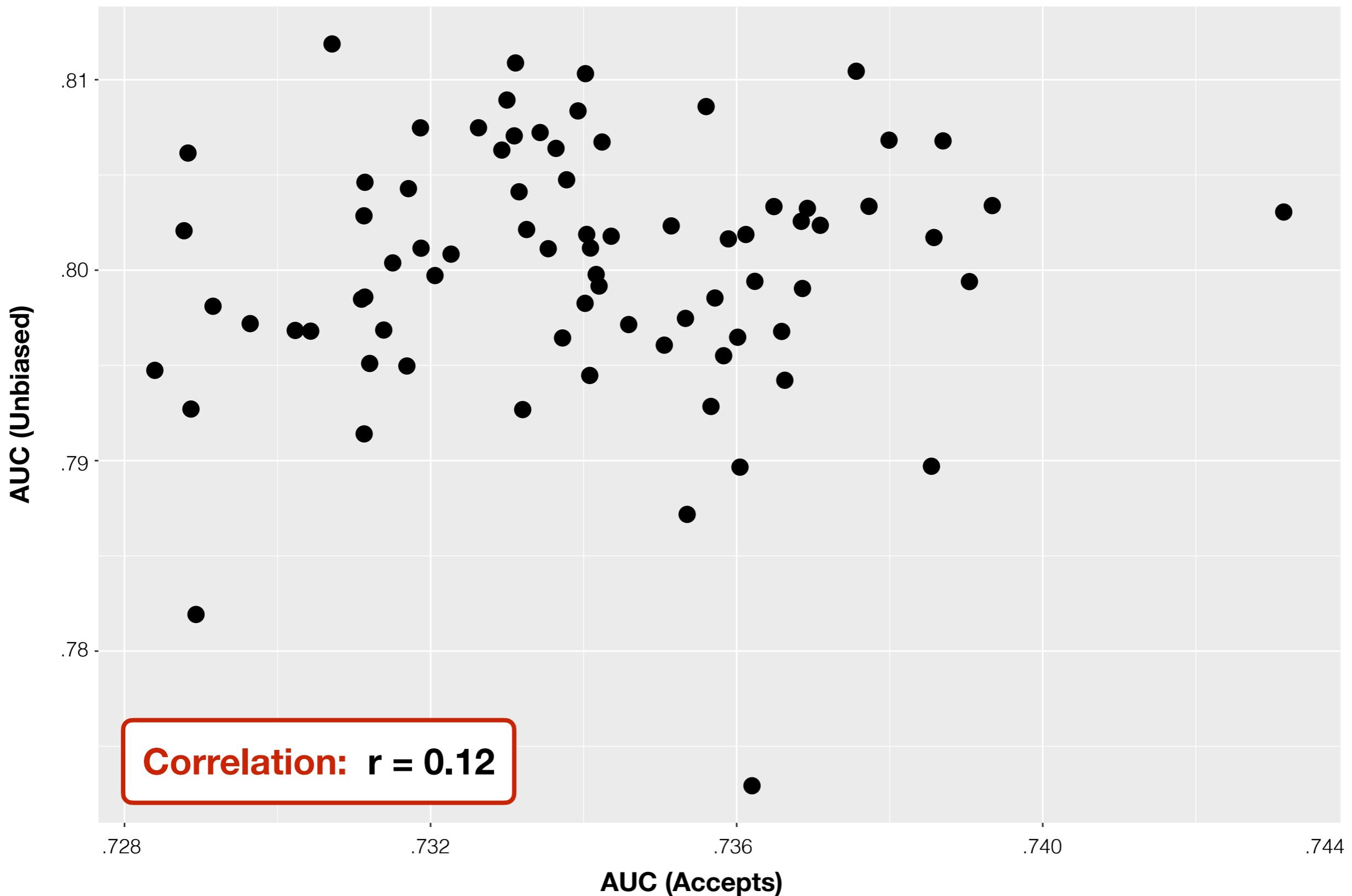
	Method	Bias	Variance	RMSE
AUC	Accepts	.1843	.0253	.2072
	IPW	.0707	.0047	.0988
	<b>Bayesian</b>	<b>.0068</b>	<b>.0048</b>	<b>.0672</b>
PAUC	Accepts	.2579	.0258	.2699
	IPW	.2969	.0145	.3346
	<b>Bayesian</b>	<b>.0117</b>	<b>.0063</b>	<b>.0788</b>
BRS	Accepts	.0754	<b>.0003</b>	.0829
	IPW	.0210	.0086	.0552
	<b>Bayesian</b>	<b>.0171</b>	.0026	<b>.0526</b>
ABR	Accepts	.2017	<b>.0001</b>	.2058
	IPW	.1988	.0003	.2034
	<b>Bayesian</b>	<b>.0065</b>	.0079	<b>.0909</b>

- Bayesian framework provides estimates with lower **bias** and **RMSE**
- all RMSE differences are **significant** at 5%

# Significance Tests: Nemenyi Plots



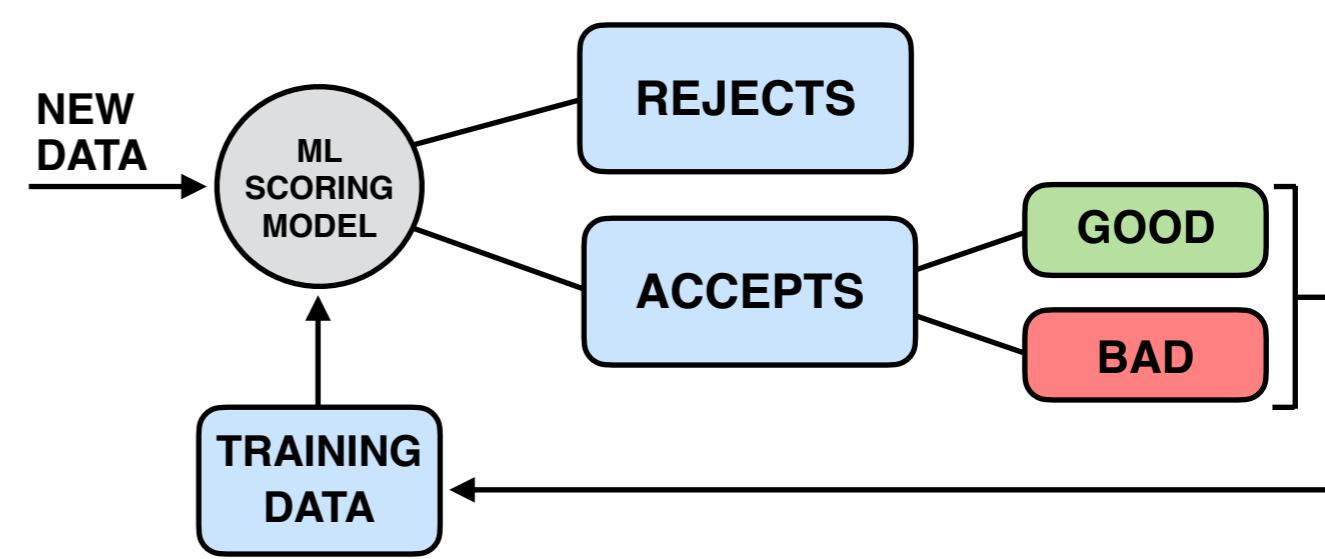
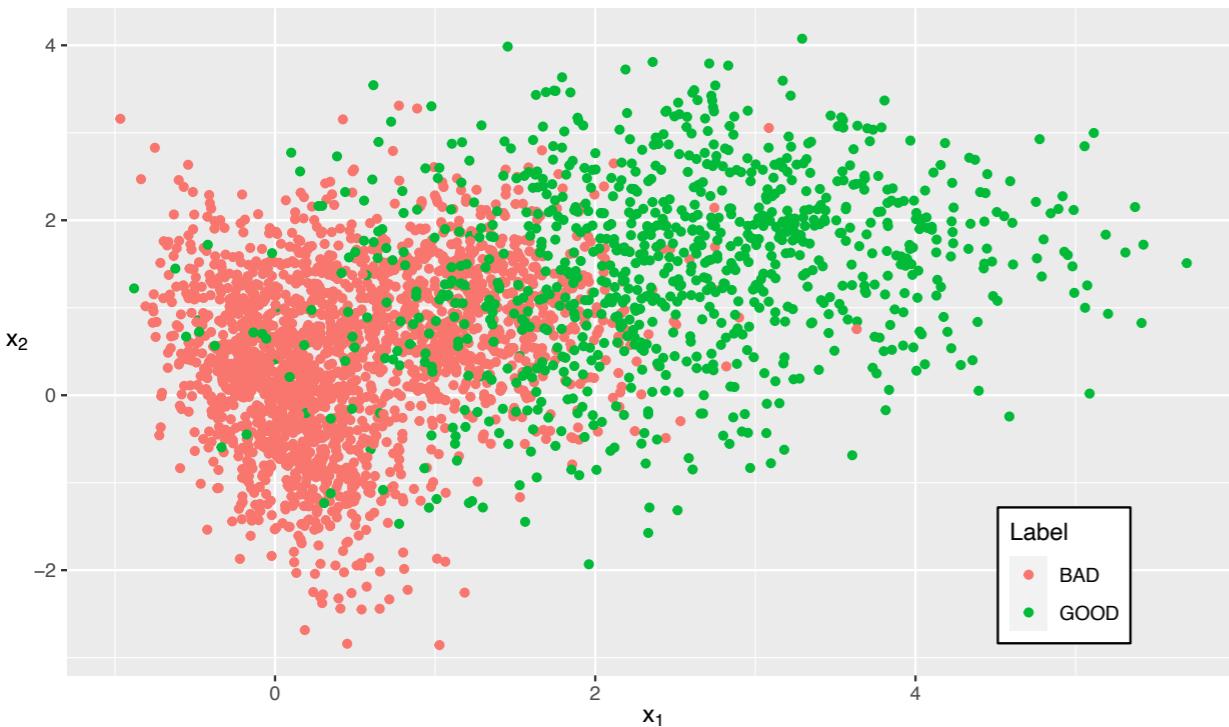
# Evaluation Problem: Illustration



# A5. SIMULATION

# Simulation for Bias Illustration

- sampling **GOOD** and **BAD** risks from Gaussian mixtures
  - difference in class means and covariance
  - varying dimensionality, class imbalance, noise, etc.
- simulating real-world acceptance loop
  - generate a batch of new loan applications
  - use a scoring model to **accept** and **reject** applications
  - update the model after observing labels of **accepts**
  - repeat for 500 iterations and track performance on an unbiased sample



# Data Generation & Acceptance Cycle

## 1. Initial population

- Create a small (unbiased) sample of applicants from multivariate Gaussians
- Use a simple rule to accept  $a\%$  applicants (e.g. bureau score  $> b$ )
- Partition data into  $\mathbf{A}$  (accepts) and  $\mathbf{R}$  (rejects)

## 2. Updating scorecard

- Train a scoring model  $f(\mathbf{x})$  on  $\mathbf{A}$

## 3. New applicants

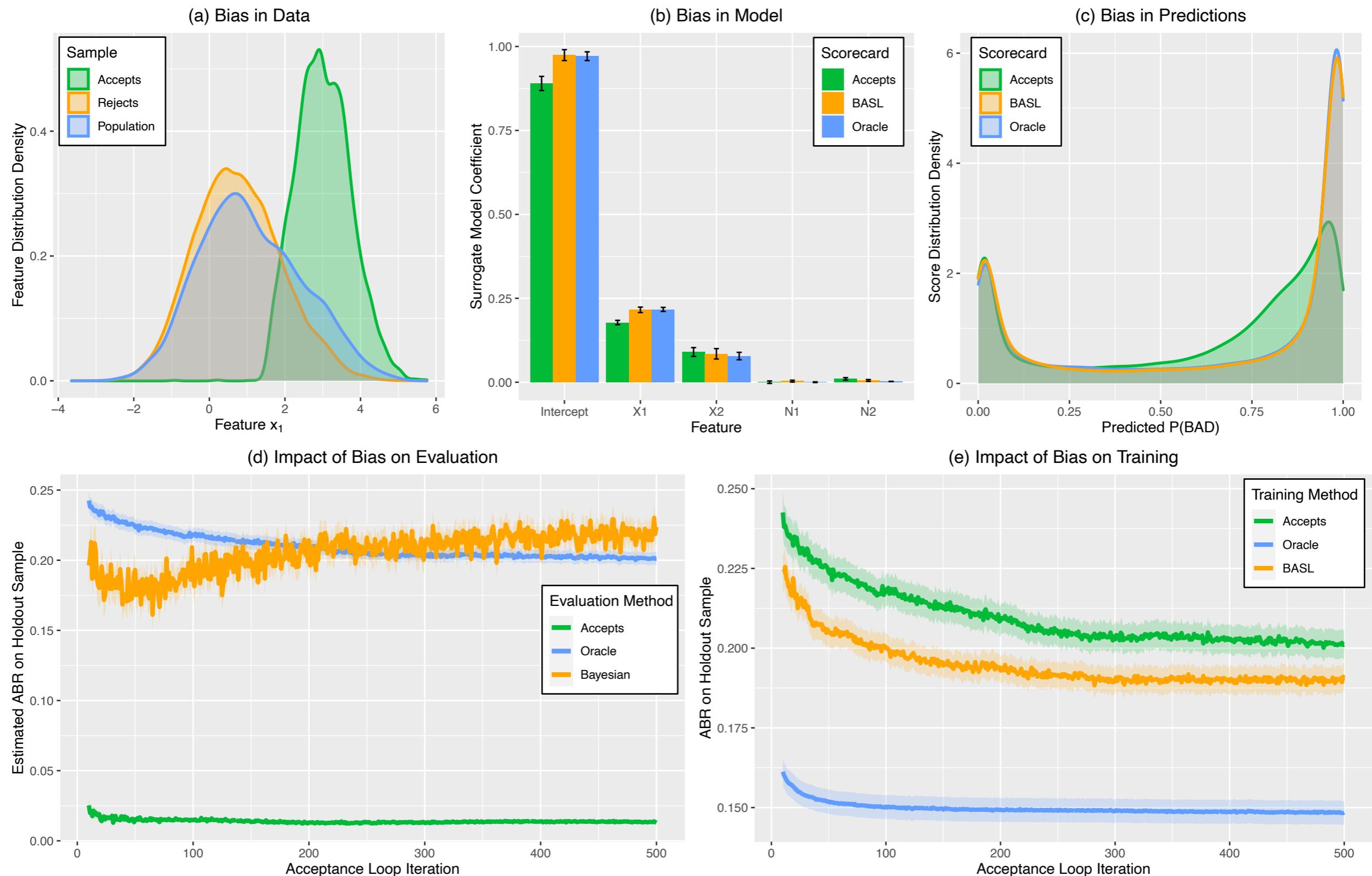
- Generate a new (unbiased) sample of applicants  $\mathbf{N}$
- Score applicants in  $\mathbf{N}$  using a scoring model  $f(\mathbf{x})$
- Use model scores to accept  $a\%$  applicants from  $\mathbf{N}$
- Partition  $\mathbf{N}$  into  $\mathbf{A}_N$  (new accepts) and  $\mathbf{R}_N$  (new rejects)

## 4. Merging data

- append  $\mathbf{A}_N$  (with labels) to  $\mathbf{A}$ ; append  $\mathbf{R}_N$  (no labels) to  $\mathbf{R}$

repeat for  $g$  iterations

# Simulation Study Results



# Simulation Study Summary

## Bayesian evaluation

- useful under both **MAR** and **MNAR**
  - consistent and statistically significant gains
- more helpful at **low acceptance**
  - error is present at any acceptance < 100%
  - highest gains at low acceptance
- performance depends on **two factors:**
  - **validation set distribution**
    - important to match population distribution
    - feasible when storing data on past **rejects**
  - **prior quality**
    - both accuracy and calibration of **P(BAD)** affect the performance
    - recommend using calibrated scores from the current scorecard

## Bias-aware self-learning

- useful under both **MAR** and **MNAR**
  - consistent and statistically significant gains
- more helpful at **low acceptance**
  - loss is present if acceptance < 30%
  - highest gains at lower acceptance
- more helpful in **simpler tasks**
  - loss due to bias is consistently present irrespective of the complexity
  - easier to label rejects
- more helpful at **moderate imbalance**
  - highest gains at [2%, 5%] ratio of **BAD** applicants among **accepts**

# Simulation Study: Missingness [1/2]

## Missingness mechanism:

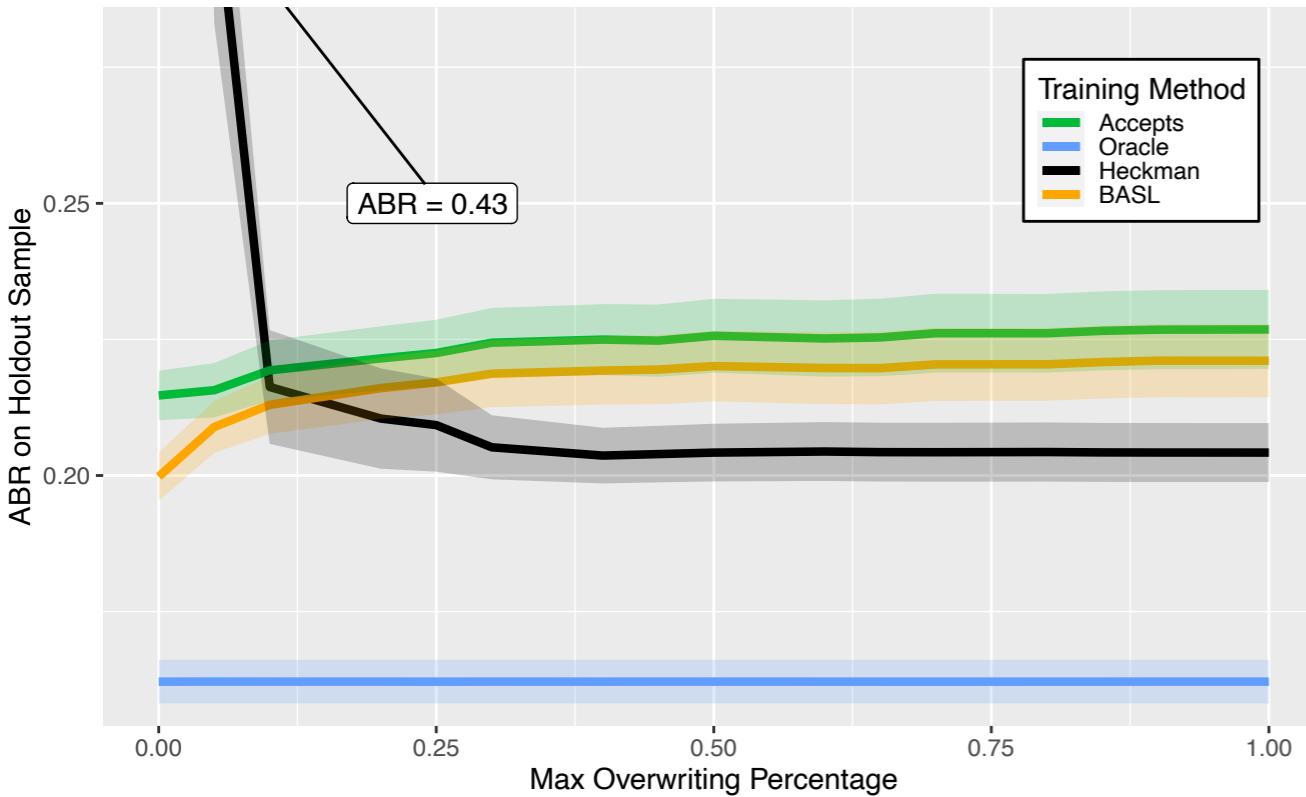
- **missing at random (MAR)**
  - generate data with two explanatory features
  - include both features in the scoring model
- **missing not at random (MNAR)**
  - generate data with three explanatory features
  - exclude one of the features from the scoring model
  - **omitted variable bias** leads to MNAR
    - variable that correlates with P(**BAD**) and P(**accepted**)
    - not included in both outcome and selection equations

## Evaluation:

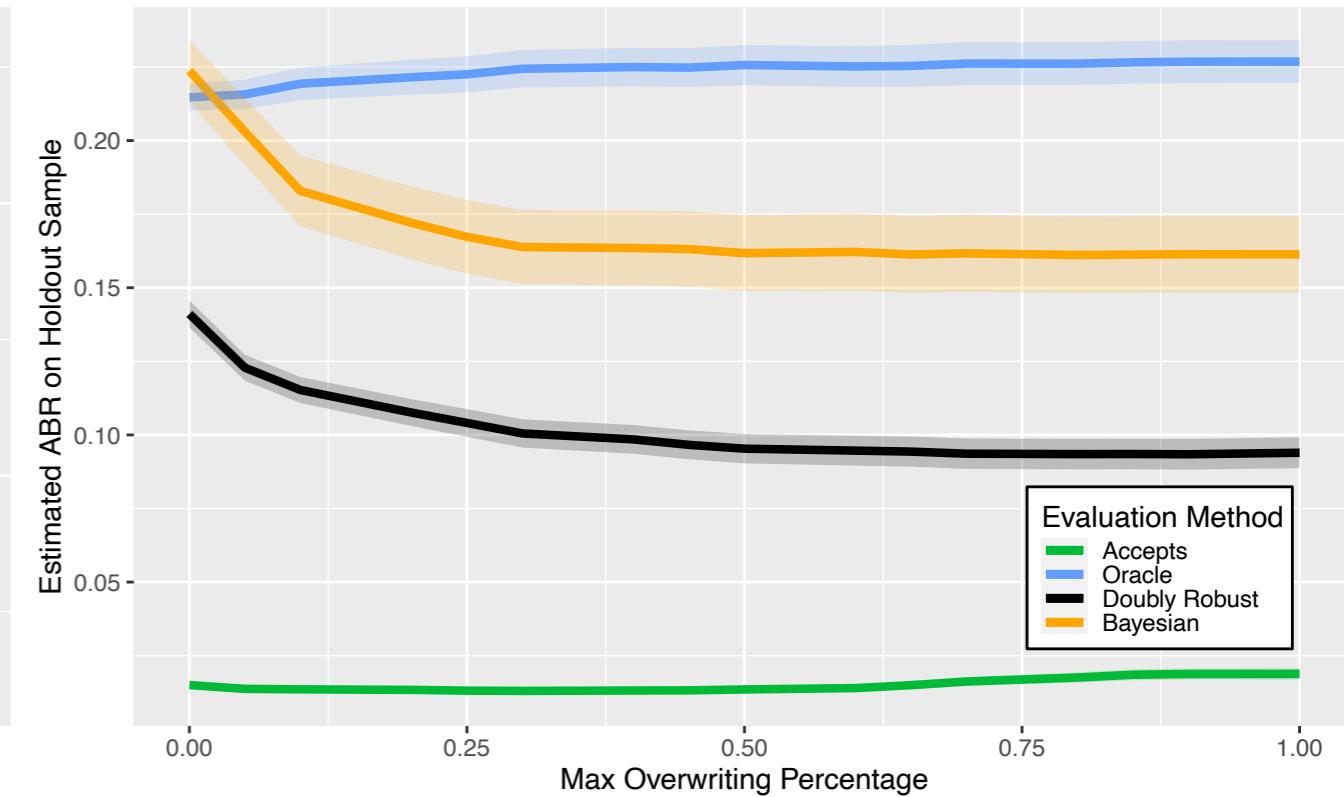
- **generating a holdout sample from population**
  - contains a representative sample of loan applications
  - allows to evaluate scoring model performance in real conditions

# Simulation Study: Missingness [2/2]

(a) Missingness: Impact on Training



(b) Missingness: Impact on Evaluation



- manual overwriting gears the data from **MAR** towards **MNAR**
  - introduces external feature in the selection equation
- **Bayesian evaluation** outperforms the best competitor in **both setups**
- **BASL** performs well when overwriting is **below 20%**
  - in credit scoring, such high values of overwriting are unlikely

# BASL: Sensitivity Analysis

## Goal:

analyzing how gains from **BASL** change under **different conditions**

## Parameters:

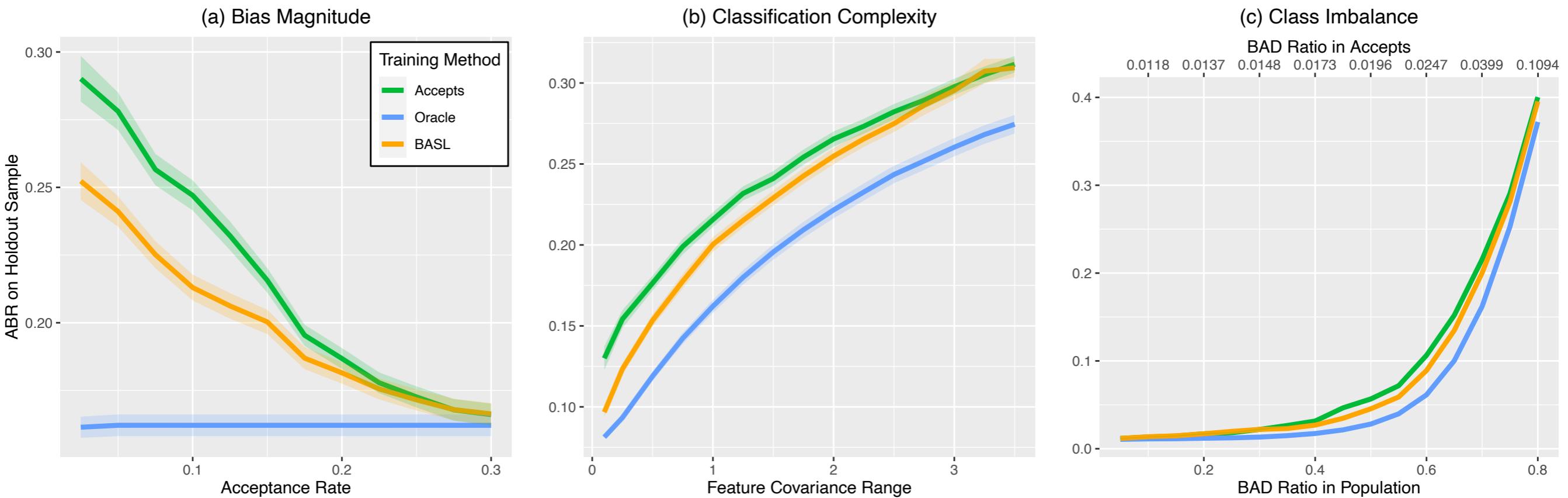
- **past acceptance rate**
  - past acceptance policy determines the **magnitude of sampling bias**
  - sampling bias affects scorecard performance on unseen applicants
- **class imbalance**
  - class imbalance affects exposure to both client types in the **training data**
  - imbalance affects the magnitude of the loss due to sampling bias
- **class separation**
  - class separation affects the scorecard ability to distinguish **GOOD** and **BAD** risks
  - loss due to bias may depend on the classification task complexity

# BASL: Sensitivity Analysis

## Goal:

analyzing how gains from **BASL** change under **different conditions**

## Results:



# BASL Sensitivity: Acceptance [1/2]

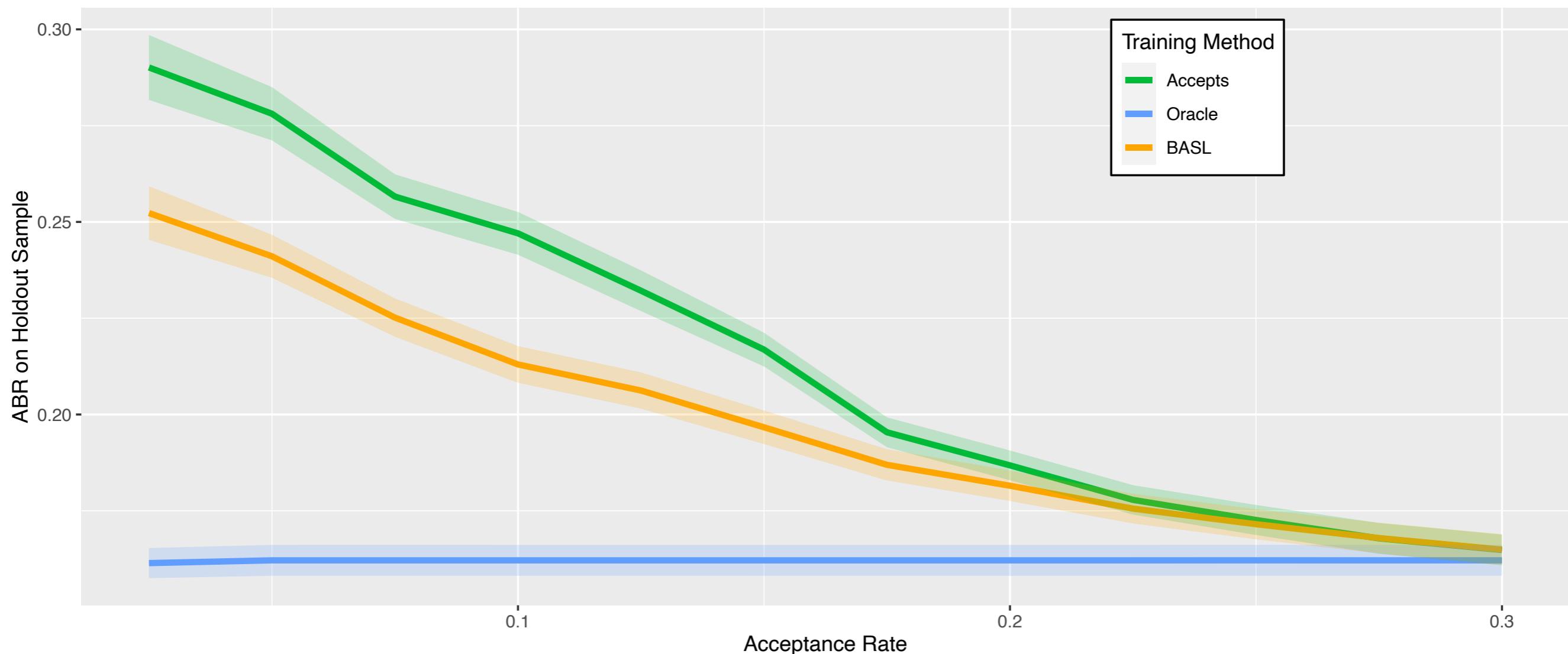
## Setup:

- running acceptance loop with a grid of different **acceptance rates**
  - varying acceptance in **[1%, 2.5%, 5%, ..., 30%]**
  - 100 simulation trials per each acceptance
- other acceptance loop parameters **are fixed**
  - same data generating process, acceptance policy, scorecard meta-parameters
  - only the split into **accepts/rejects** changes depending on acceptance
- evaluating performance of **BASL**
  - comparing to **accepts-based** scorecard and **oracle** scorecard
  - averaging performance over **100 trials**

## Intuition:

- lower acceptance leads to a stronger sampling bias
- **BASL** should be more useful at lower acceptance

# BASL Sensitivity: Acceptance [2/2]



## Results:

- **lower acceptance** increases loss due to bias
  - correction is not required at acceptance above 25%
- **BASL** is more useful at lower acceptance
  - performance gains are highest at **very low acceptance**
  - more typical for prime market segments

# BASL Sensitivity: Imbalance [1/2]

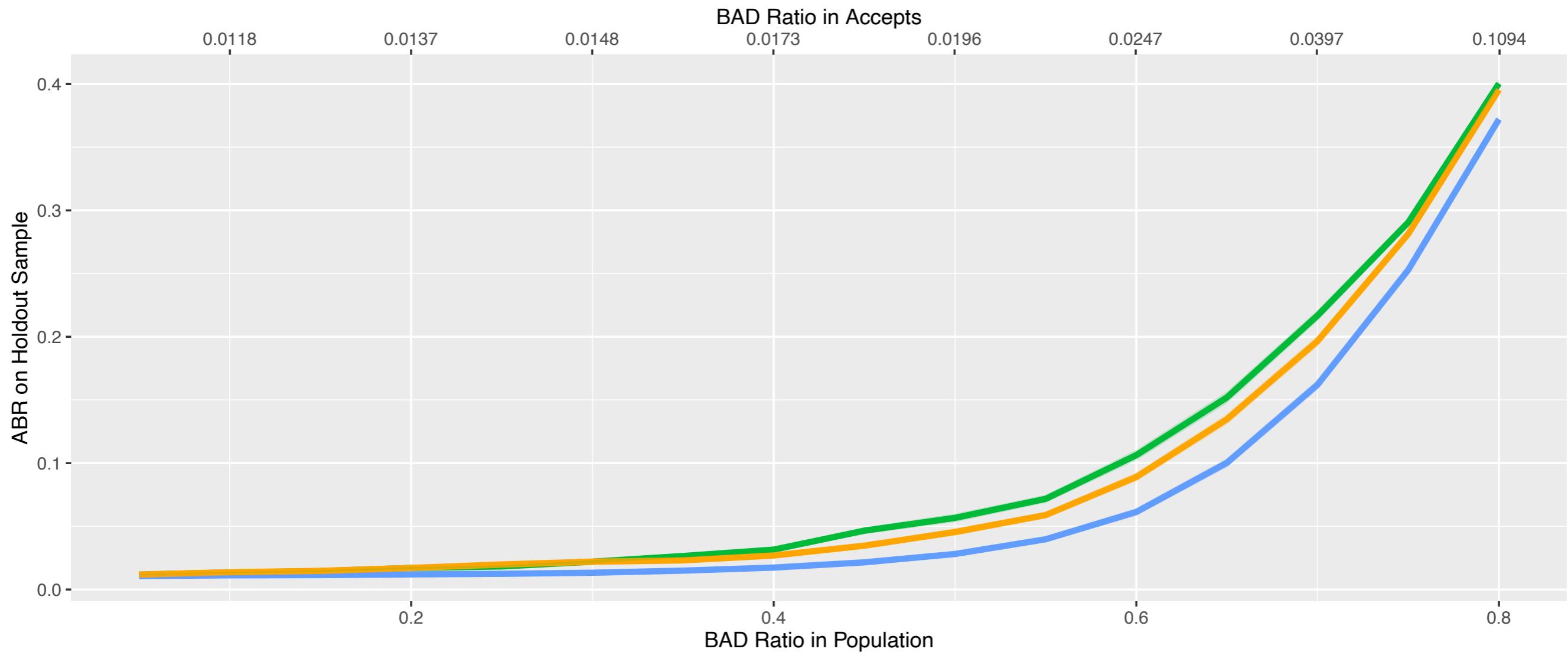
## Setup:

- running acceptance loop with a grid of different **class imbalance ratios**
  - varying **BAD** rate in population in **[5%, 10%, 15%, ..., 80%]**
  - 100 simulation trials per each **BAD** rate
- **imbalance in population** translates into **imbalance in accepts**
  - the latter depends on imbalance in population and the acceptance rate
  - manipulating **imbalance in population** as environment property
  - fixed **acceptance rate** to isolate the population class imbalance effect
- other acceptance loop parameters **are fixed**
- evaluating performance of **BASL**
  - comparing to **accepts-based** scorecard and **oracle** scorecard
  - averaging performance over **100 trials**

## Intuition:

- severe imbalance limits the number of **BAD** cases in training data

# BASL Sensitivity: Imbalance [2/2]



## Results:

- even high **BAD** rate in population **creates imbalance in accepts**
- loss due to bias **shrinks** when class imbalance is **too severe**
  - specific to the ABR metric since it is based on the top least risky cases
- **BASL** is most helpful at **moderate imbalance in accepts** in [2%, 5%]

# BASL Sensitivity: Separation [1/2]

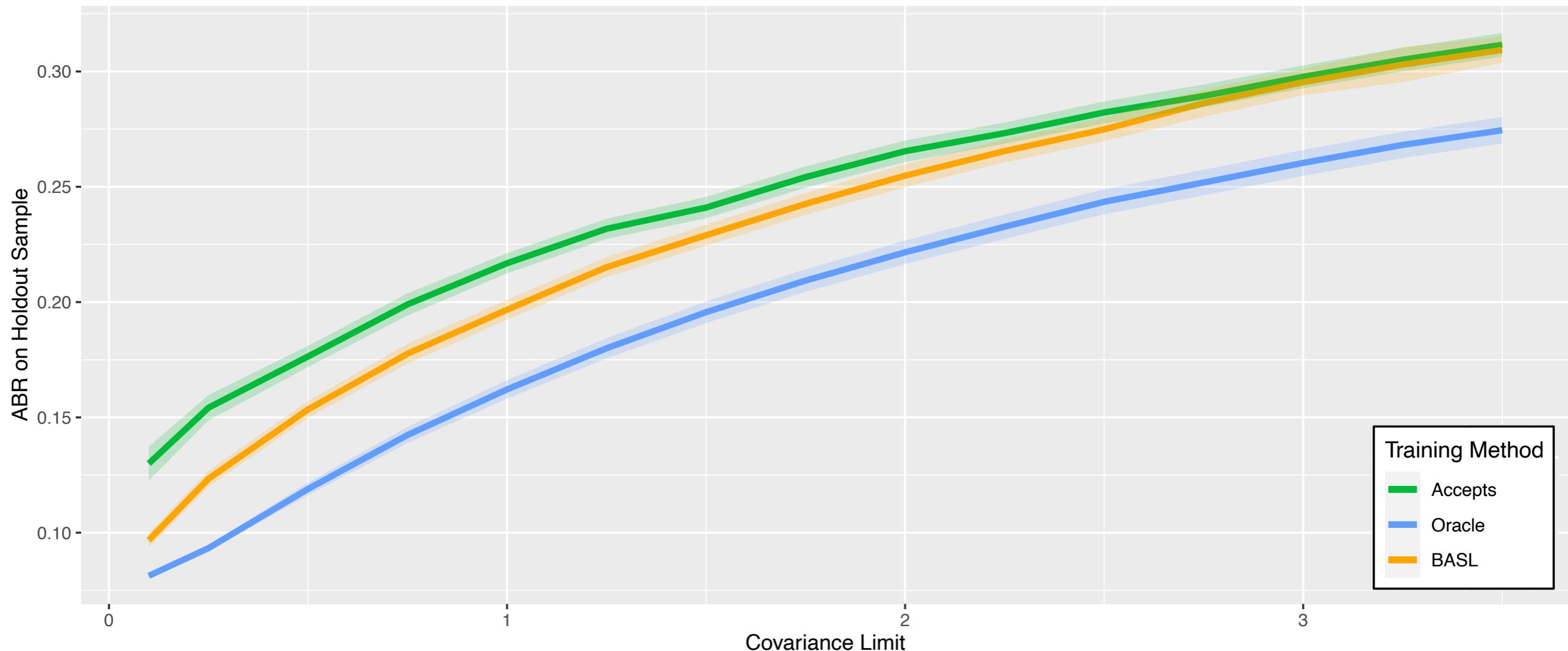
## Setup:

- running acceptance loop with a grid of different **S**
  - **S** = **upper bound** on the randomly generated feature covariance values
  - varying **S** in **[0.25, 0.50, 0.75, ..., 3.50]** to affect distribution
  - 100 simulation trials per each **S** value
- other acceptance loop parameters **are fixed**
- evaluating performance of **BASL**
  - comparing to **accepts-based** scorecard and **oracle** scorecard
  - averaging performance over **100 trials**

## Intuition:

- higher sigma complicates the classification task
  - more intersection between the **GOOD** and **BAD** clusters
  - classes become more difficult to distinguish
- labeling rejects may be more difficult in complex tasks

# BASL Sensitivity: Separation [2/2]



## Results:

- loss due to bias is **consistently present**
  - magnitude does not depend on the classification task complexity
- **BASL** is more helpful for **simpler tasks**
  - easier to correctly label rejects by extrapolating patterns

# Bayesian Evaluation: Sensitivity Analysis

## Goals:

- analyze gains from **Bayesian framework** in **different conditions**
- **explain** the performance of **Bayesian framework**

## Parameters:

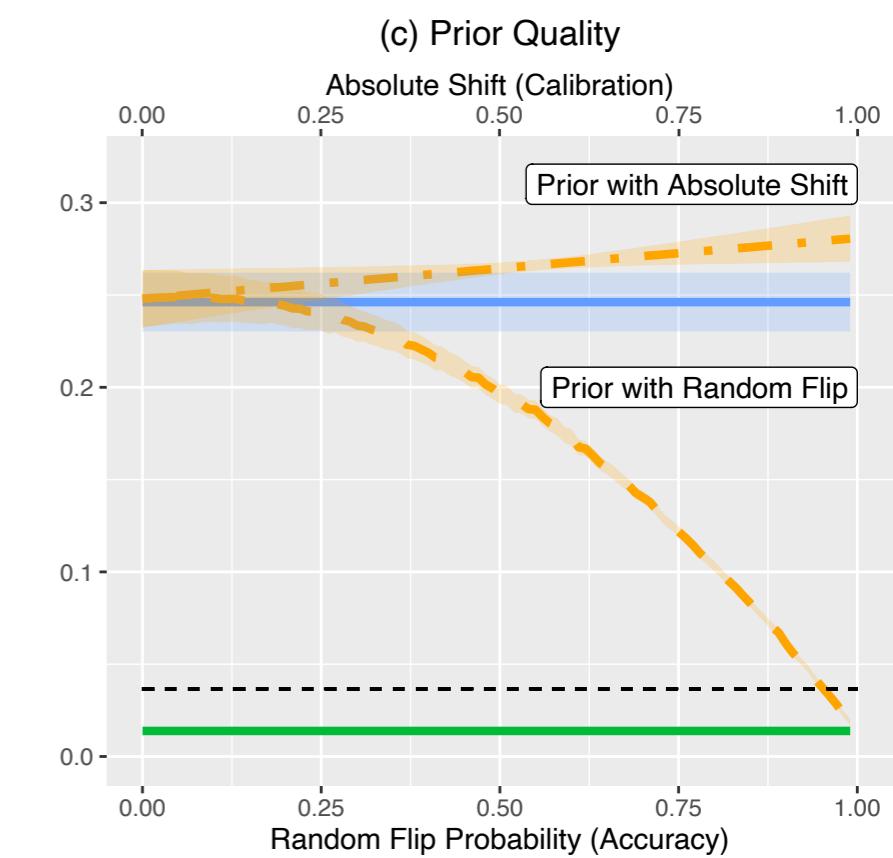
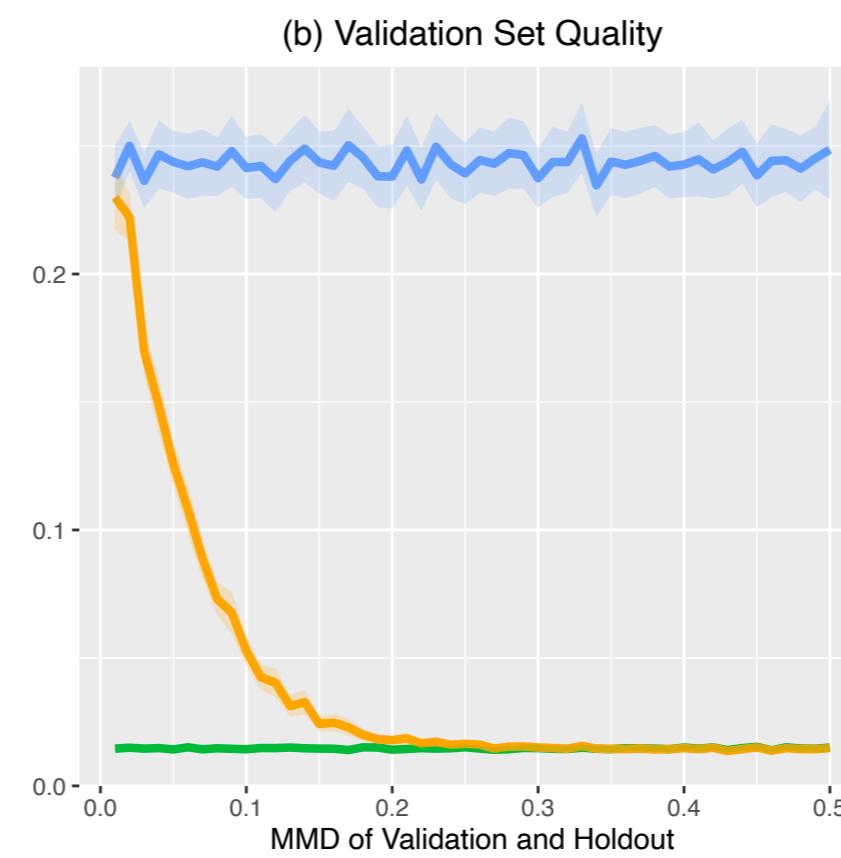
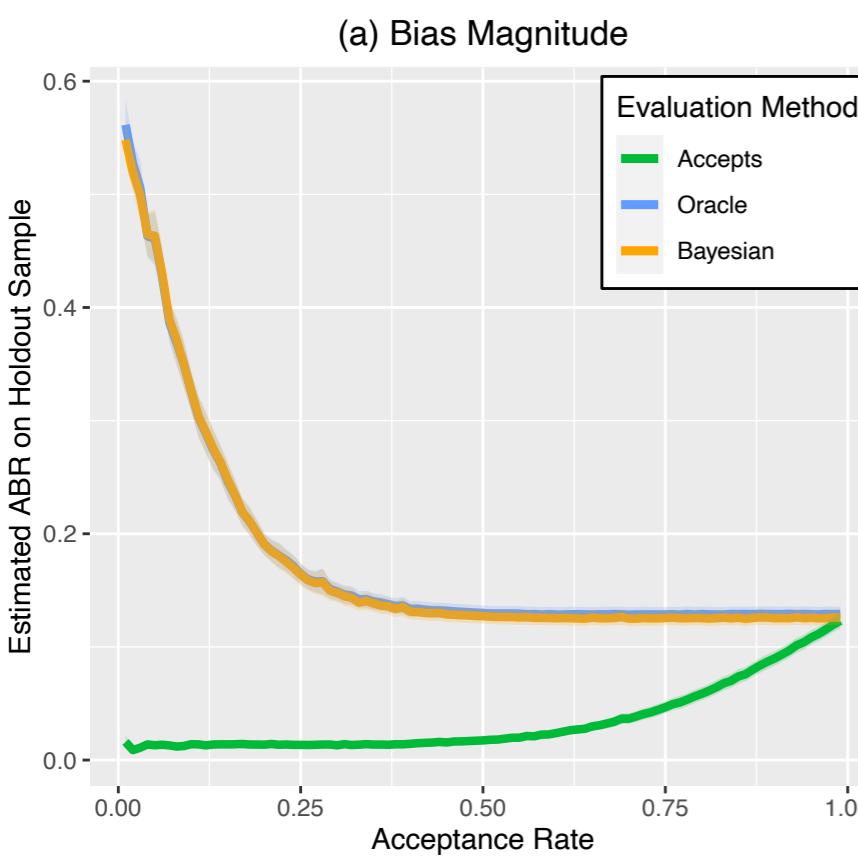
- **past acceptance**
  - acceptance policy determines the **magnitude of sampling bias**
  - sampling bias affects **evaluation error**
- **validation set quality**
  - Bayesian evaluation on validation set with **accepts** and **rejects**
  - **feature distribution** in validation set affects performance
- **prior  $P(BAD)$  quality**
  - **rejects** are pseudo-labeled using a prior  **$P(BAD)$**
  - **accuracy** and **calibration** of prior affects performance

# Bayesian Evaluation: Sensitivity Analysis

## Goals:

- analyze gains from **Bayesian framework** in **different conditions**
- **explain** the performance of **Bayesian framework**

## Results:



# Bayesian Sensitivity: Acceptance [1/2]

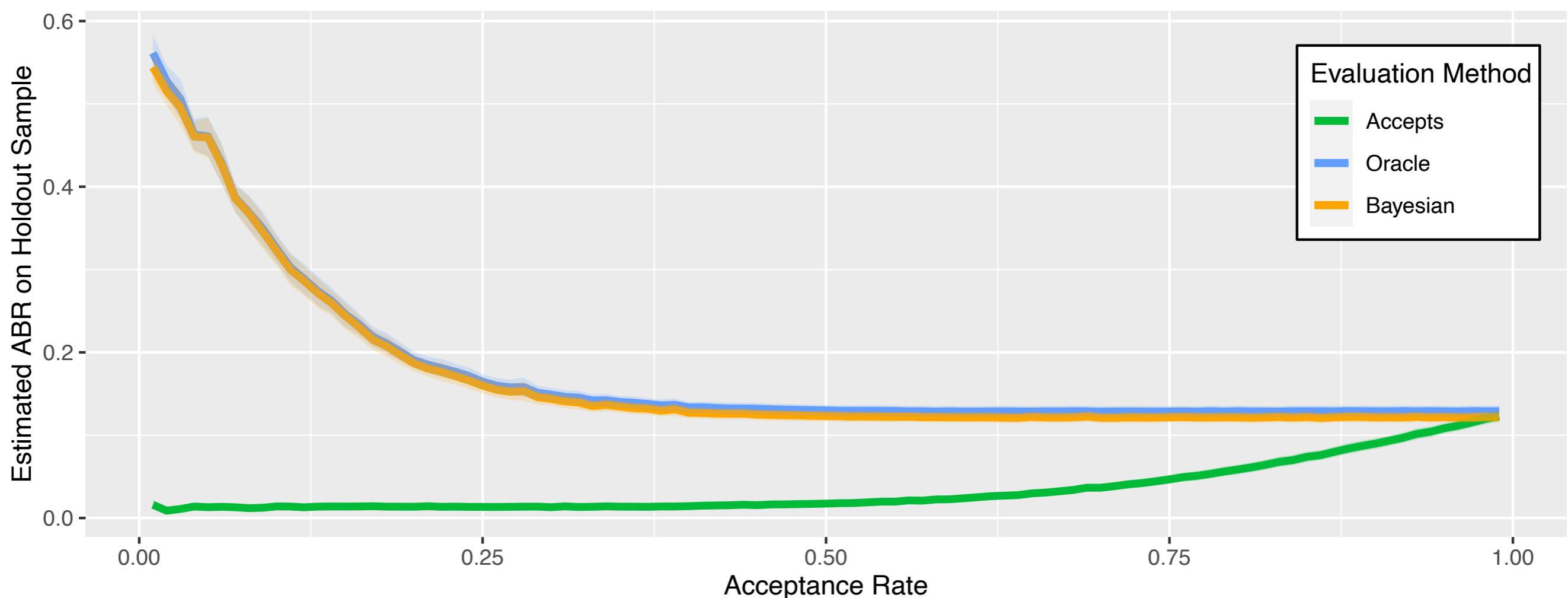
## Setup:

- running acceptance loop with a grid of different **acceptance rates**
  - varying acceptance in **[1%, 2%, 3%, ..., 100%]**
  - 100 simulation trials per each acceptance rate
- other acceptance loop parameters **are fixed**
- evaluating the **accepts-based** scorecard with different methods
  - **accepts-based** evaluation on a biased validation set
  - **oracle** evaluation on a sample from population
  - **Bayesian evaluation** on **accepts** and **rejects**
  - averaging performance over **100 trials**
- assuming **perfect prior** on **P(BAD)** for **rejects**
  - helps to isolate the acceptance effect
  - shows highest potential gains from the **Bayesian evaluation**

## Intuition:

- lower acceptance leads to a stronger error due to sampling bias

# Bayesian Sensitivity: Acceptance [2/2]



## Results:

- evaluating on **accepts** is overoptimistic
  - ABR is consistently **underestimated**
  - evaluation error is present even at **high acceptance**
  - lower acceptance **increases evaluation error** due to sampling bias
- **Bayesian framework** helps at any acceptance
  - evaluation gains are higher at **low acceptance**

# Bayesian Sensitivity: Validation Set [1/2]

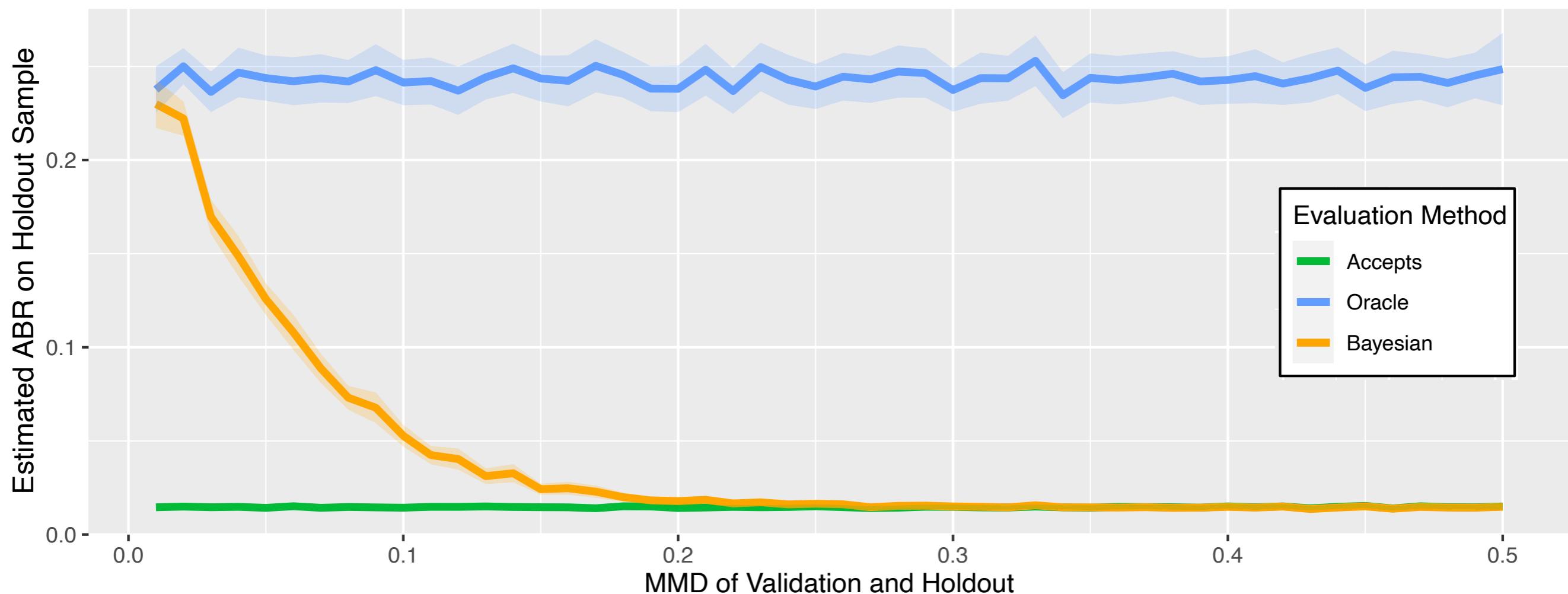
## Setup:

- varying **accept/reject** ratio in validation set
  - the ration affects the feature distribution in the validation set
  - using **MMD** to measure **discrepancy** between validation and holdout
- other acceptance loop parameters **are fixed**
- evaluating the **accepts-based** scorecard with different methods
  - **accepts-based** evaluation on a biased validation set
  - **oracle** evaluation on a sample from population
  - **Bayesian evaluation** on **accepts** and **rejects**
  - averaging performance over **100 trials**
- assuming **perfect prior** on **P(BAD)** for **rejects**
  - helps to isolate the validation set quality effect

## Intuition:

- better validation set should improve **Bayesian evaluation** performance

# Bayesian Sensitivity: Validation Set [2/2]



## Results:

- **matching population distribution** during evaluation is important
  - higher discrepancies lead to larger errors
- **Bayesian framework** shows good performance over **accepts** even under high distribution mismatch

# Bayesian Sensitivity: Prior [1/2]

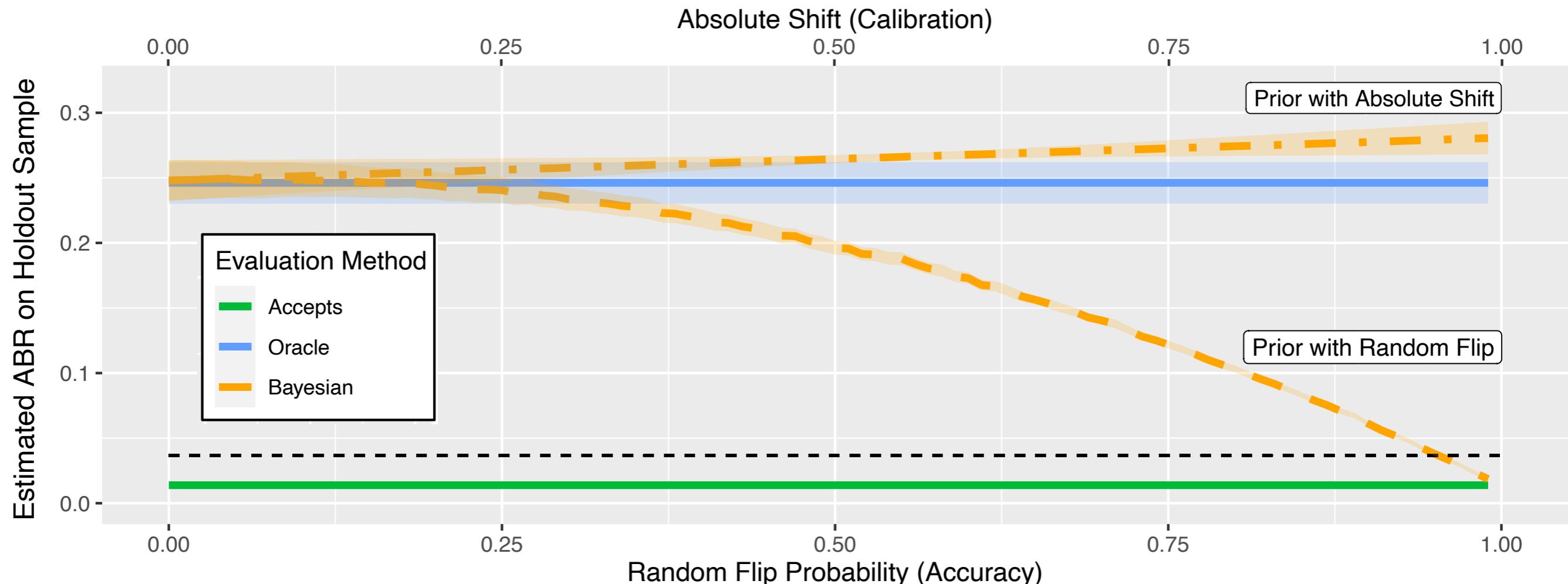
## Setup:

- manipulating prior **P(BAD)** for **rejects** used by **Bayesian evaluation**
  - starting from the **perfect prior**
  - randomly flipping labels to affect **accuracy**
  - shifting labels to affect **calibration**
- other acceptance loop parameters **are fixed**
- evaluating the **accepts-based** scorecard with different methods
  - **accepts-based** evaluation on a biased validation set
  - **oracle** evaluation on a sample from population
  - **Bayesian evaluation** on **accepts** and **rejects**
  - averaging performance over **100 trials**

## Intuition:

- better prior should improve **Bayesian evaluation** performance

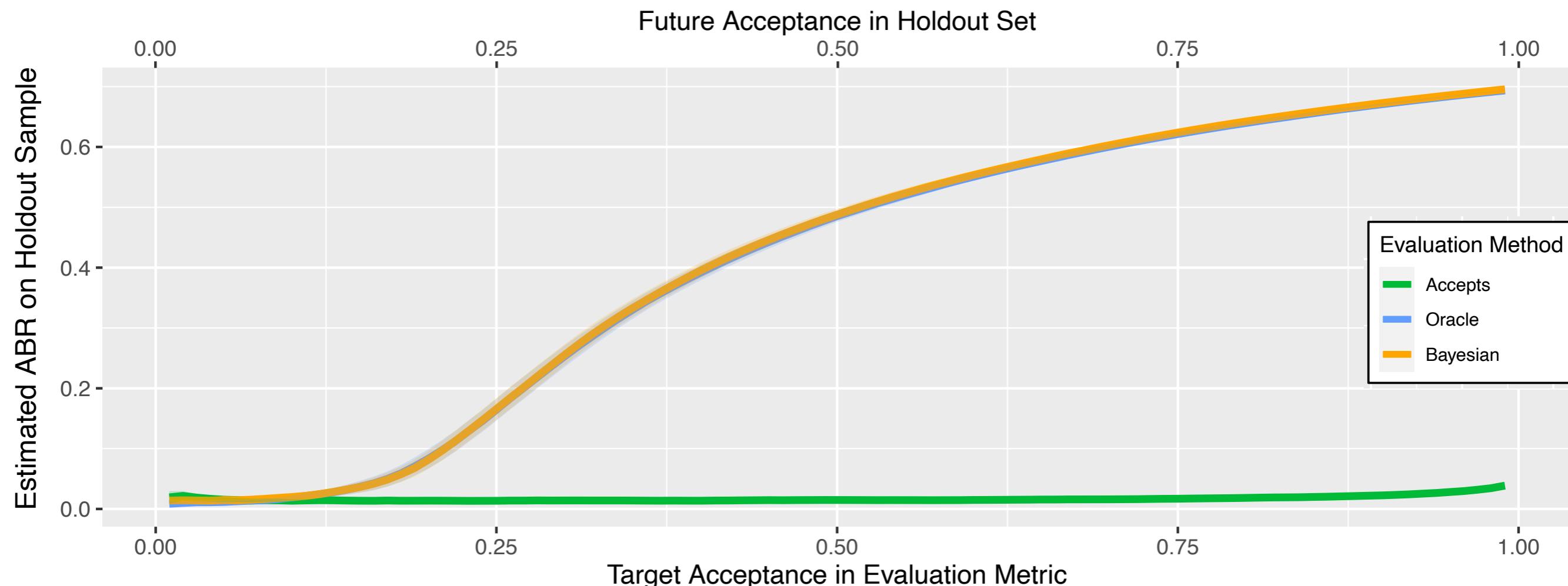
# Bayesian Sensitivity: Prior [2/2]



## Results:

- **prior quality** affects performance
  - both **accuracy** and **calibration**
  - **accuracy** is more important (for the ABR metric)
- **Bayesian framework** outperforms **accepts** even with a **poor prior**

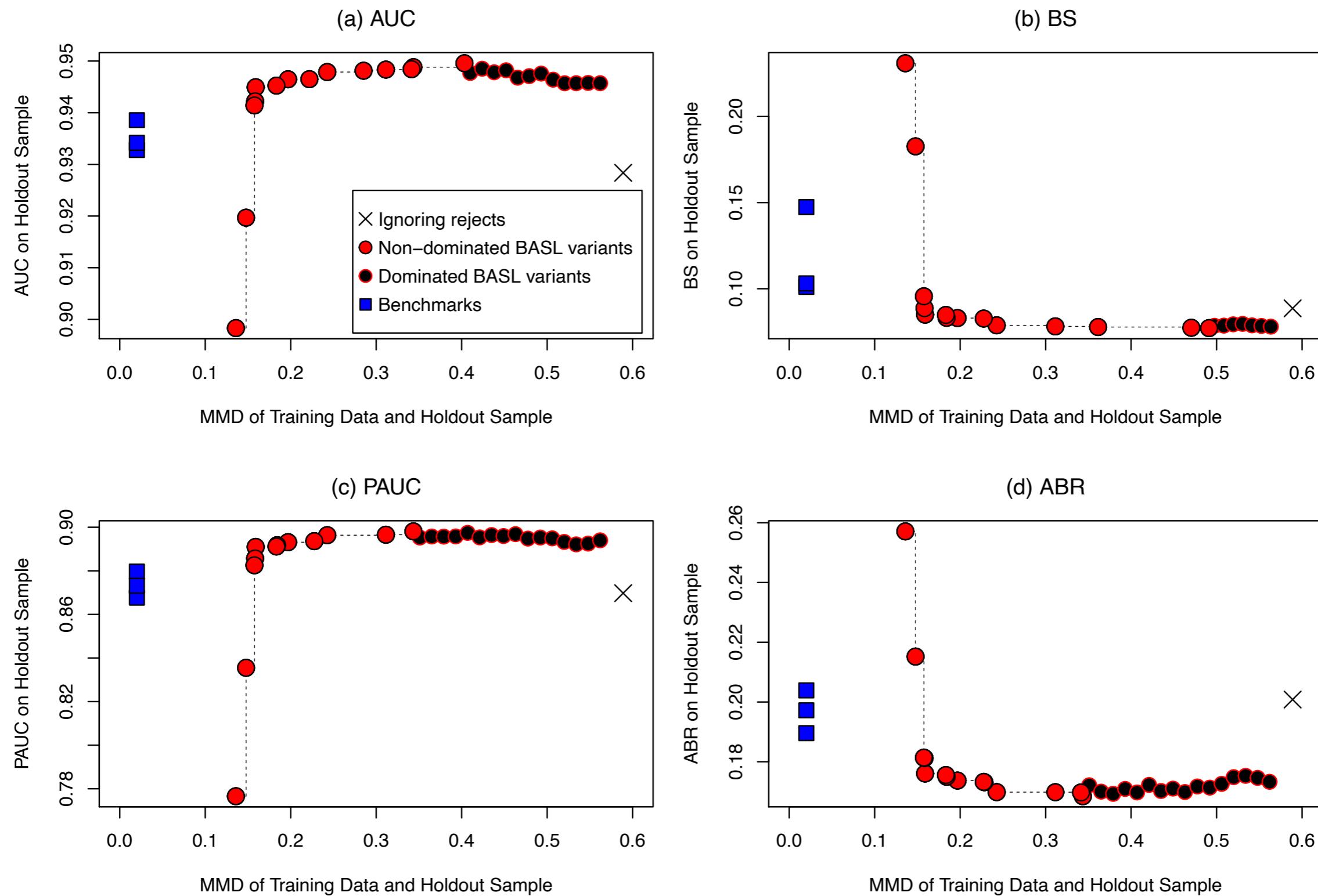
# Bayesian Evaluation: Forward-Looking Tool



- varying **future acceptance** in [1%, 100%]
  - acceptance rate as a parameter of the ABR metric during evaluation
  - simulates **future changes** in the acceptance policy
- **Bayesian framework** provides good ABR predictions
  - evaluating on **accepts** is **misleading** at high target acceptance
  - **forward-looking tool** to predict future performance as a function of **acceptance**

# A6. FURTHER RESULTS

# Data Augmentation: Pareto Frontiers



# Heckman Model

## Heckman model:

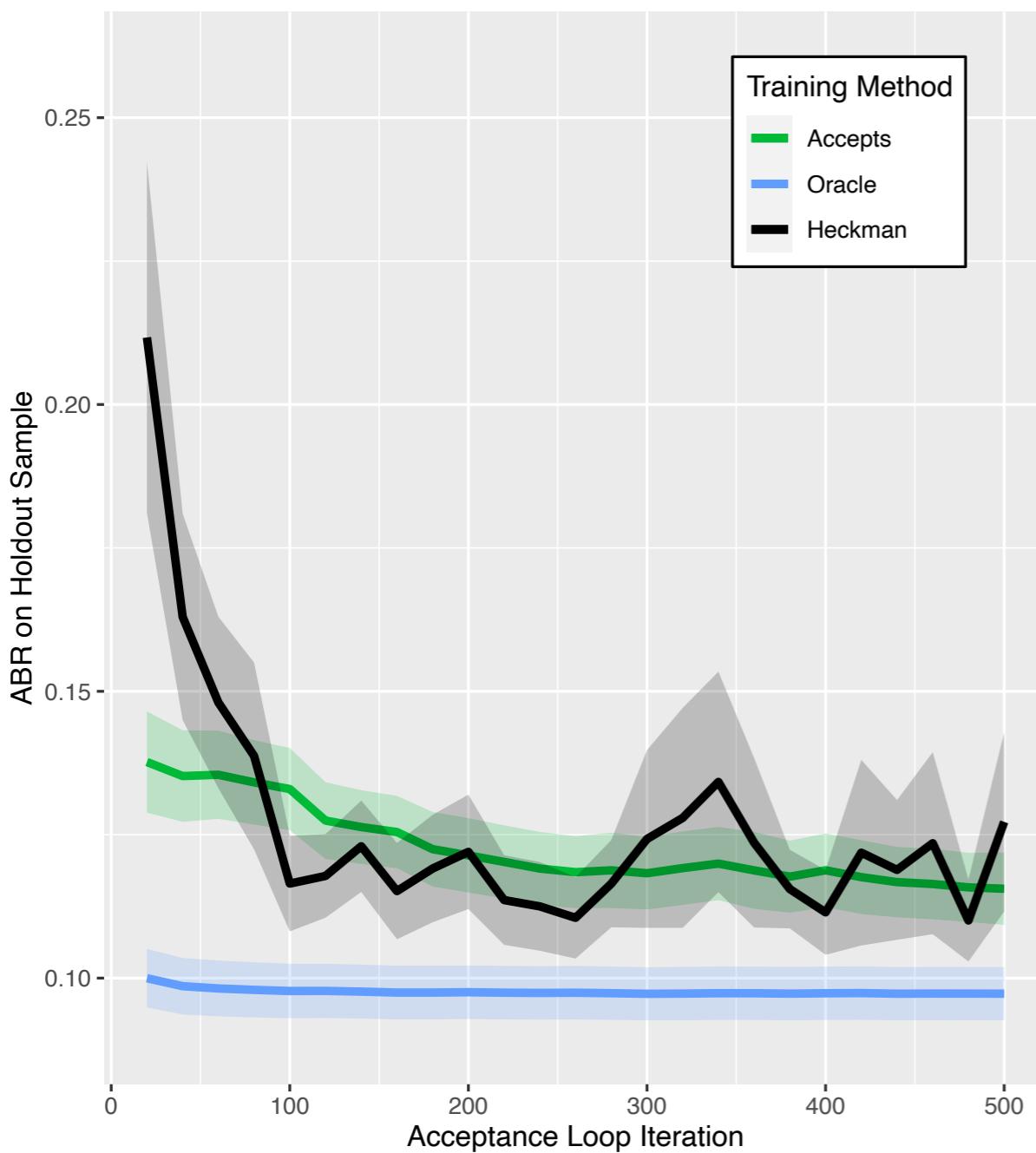
- **bivariate binary model with Heckman-type sample selection**
  - developed by (Meng & Shmidt, 1985)
  - applied to credit scoring (e.g, Banasik & Crook, 2007)
- **simultaneously estimates two equations:**
  - outcome equation:  $P(BAD) = X\beta + \varepsilon_1$ 
    - estimated on **accepts** only
  - selection equation:  $P(\text{accepted}) = X\gamma + \varepsilon_2$ 
    - estimated on both **accepts** and **rejects**
    - highly correlated with the outcome equation
    - uses the same set of applicant features
- **yields consistent estimates when**  $\rho(\varepsilon_1, \varepsilon_2) \neq 0$

## Model variants:

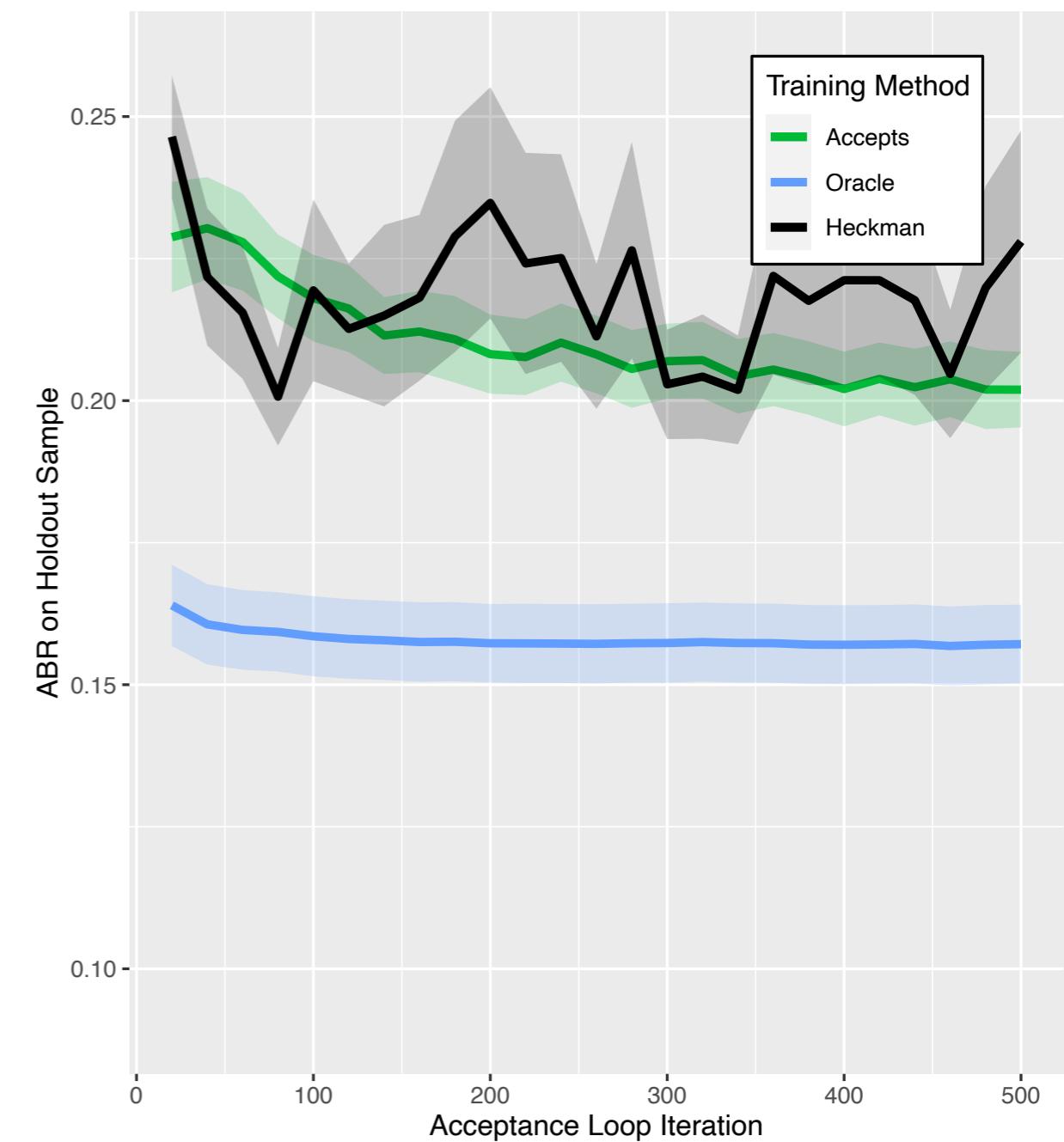
- **outcome & selection equation:** probit, logistic or linear (outcome only)
- **estimation:** maximum likelihood, two-stage method
- **nonlinearity:** with / without regression splines

# Heckman on Synthetic Data

Data with  
single Gaussians

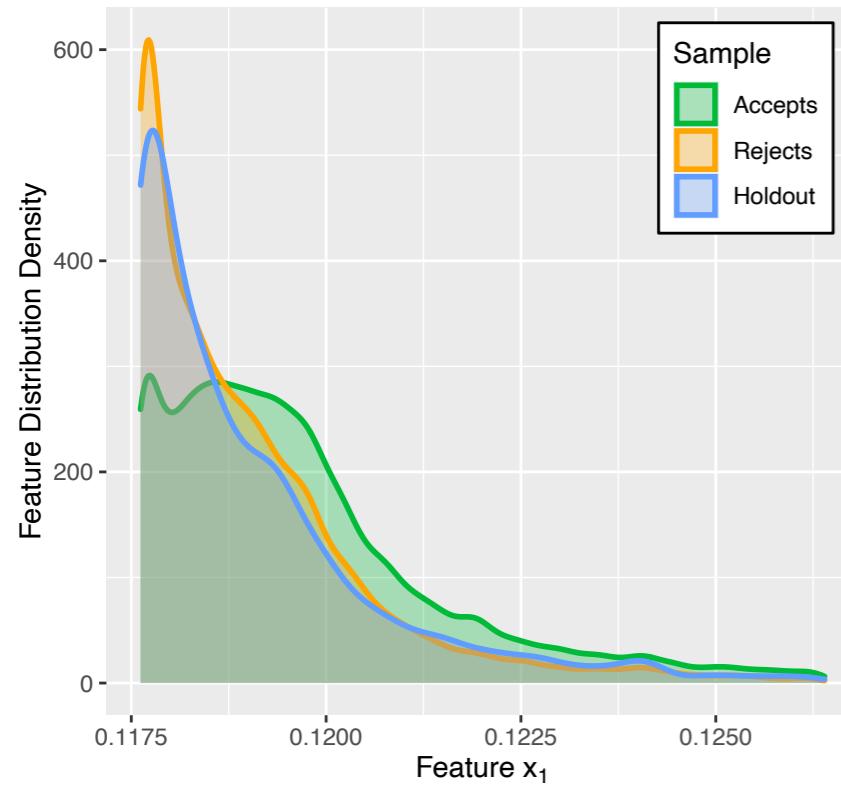


Data with  
Gaussian mixtures

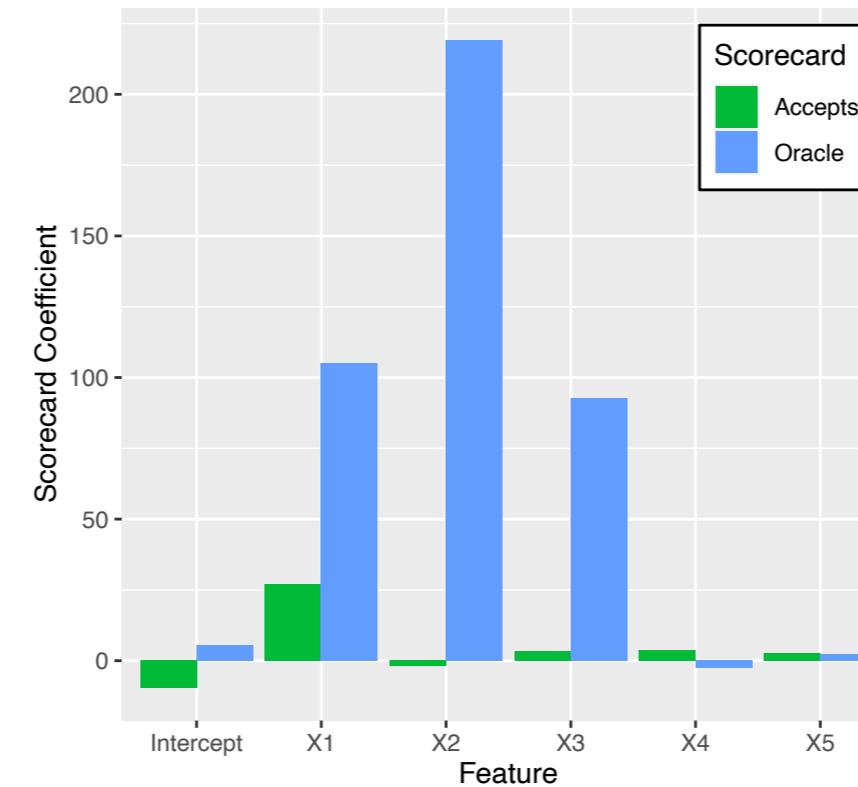


# Sampling Bias on Real Data

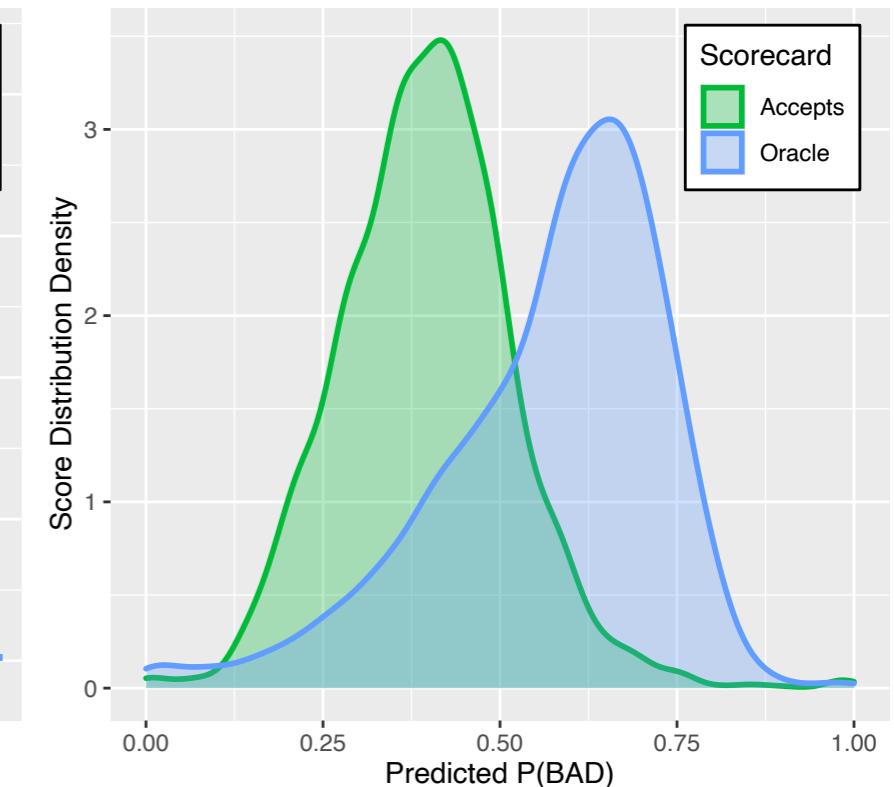
(a) Bias in Data



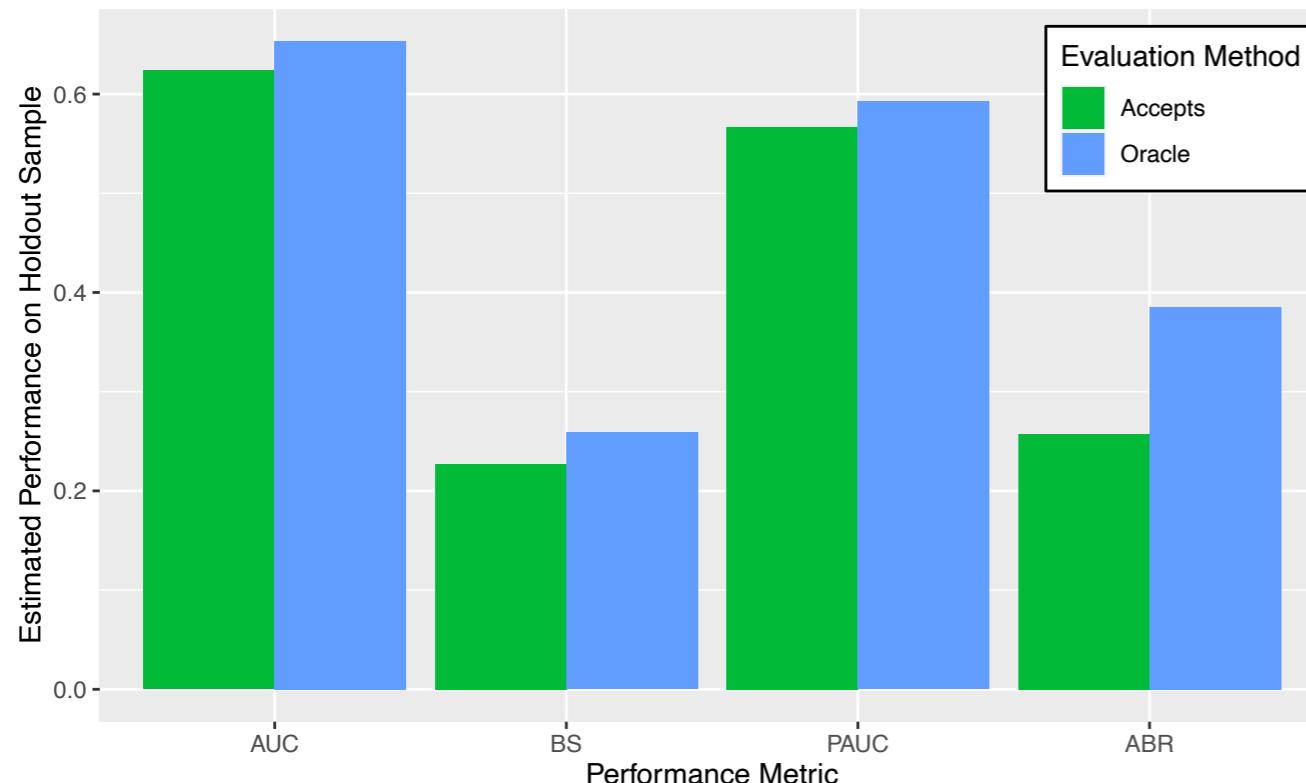
(b) Bias in Model



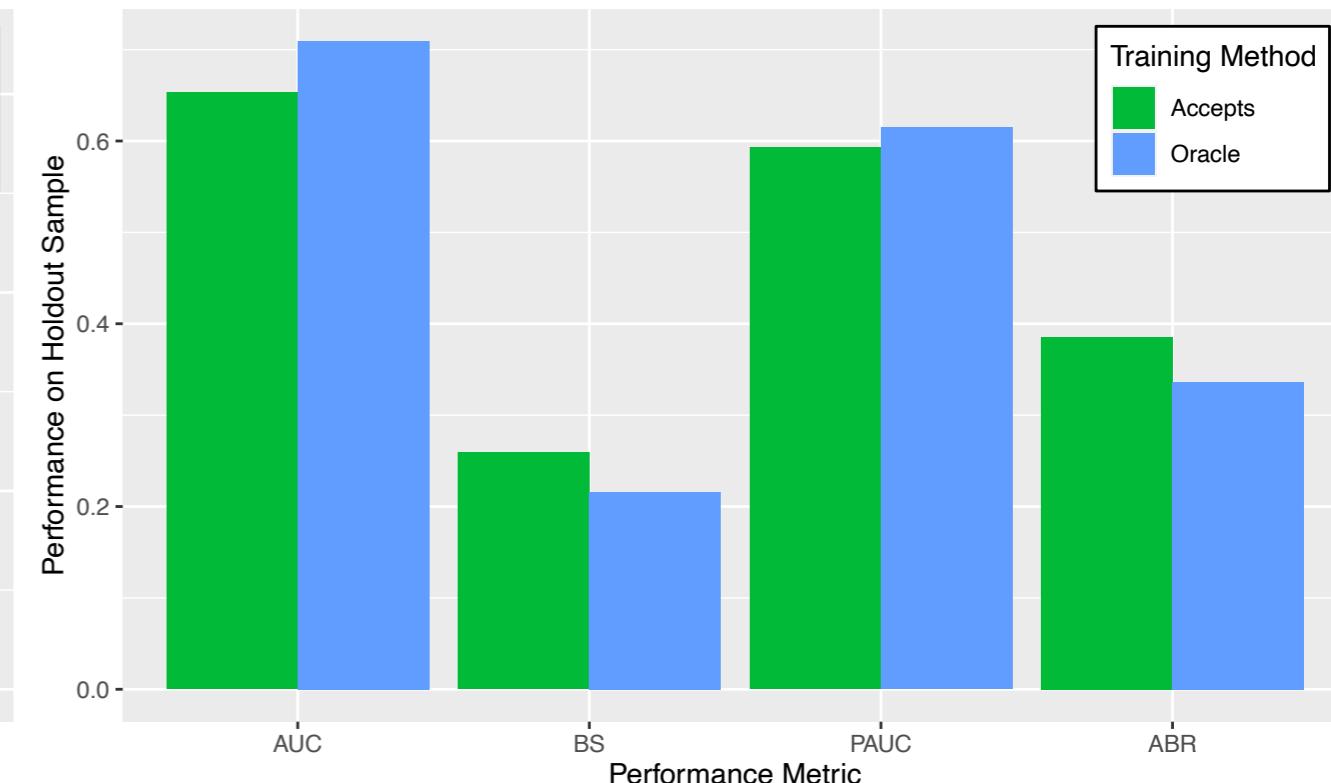
(c) Bias in Predictions



(d) Impact of Bias on Evaluation



(e) Impact of Bias on Training



# Business Impact with Variable LGD

## Parameters:

- **acceptance rate:** varied over reasonable range
- **principal and interest:** fixed for two markets
- **loss given default:** varied from 0 to 100%

	Micro-loans	Installment loans
Acceptance rate $\alpha$	[20%, 40%]	[10%, 20%]
Loan principal $A$	\$375 (SD = \$100)	\$17,100 (SD = \$1,000)
Total interest $i$	.1733 (SD = .01)	.1036 (SD = .01)
Loss given default $L$	[0, 1%, ..., 100%]	

## Two markets:

- **micro-loans**
- **installment loans**

## Calculations:

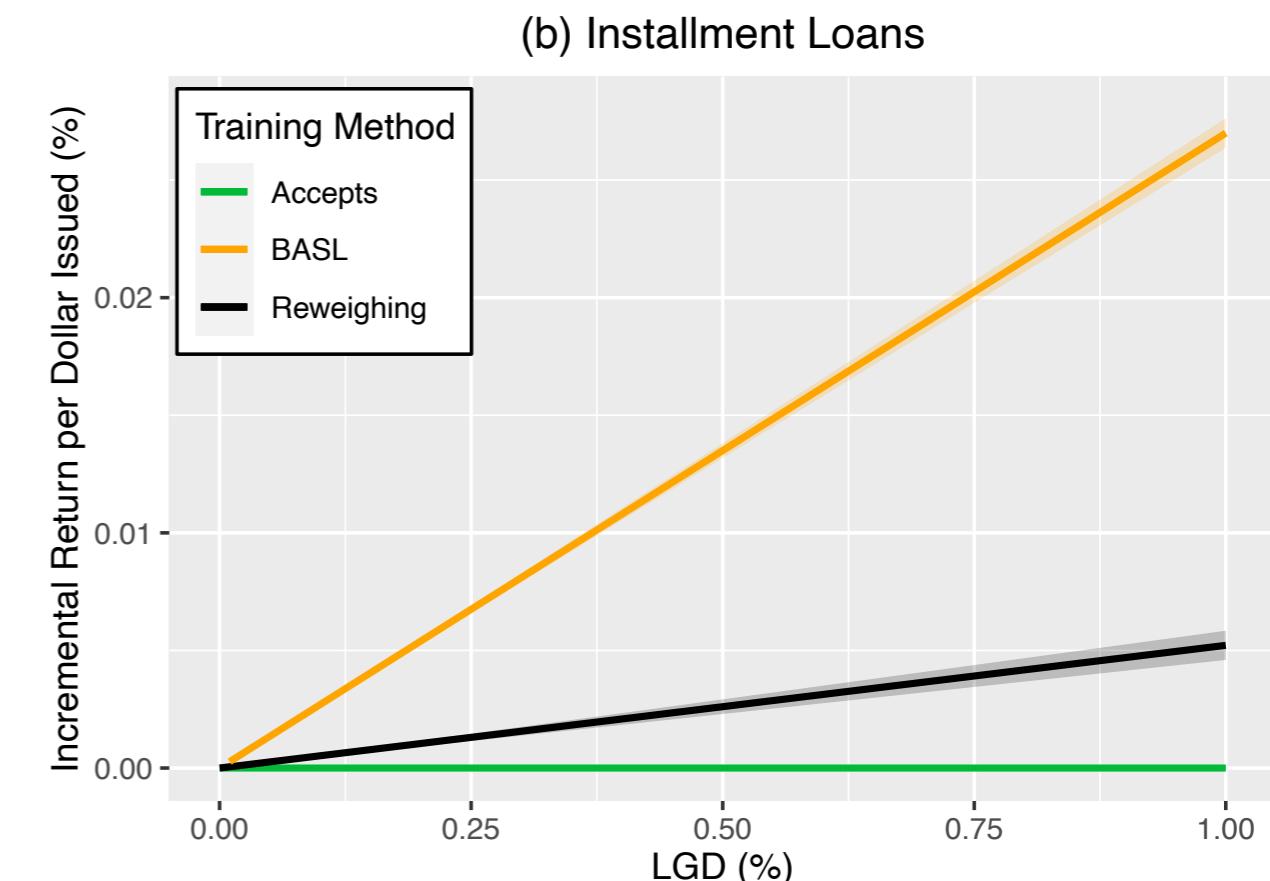
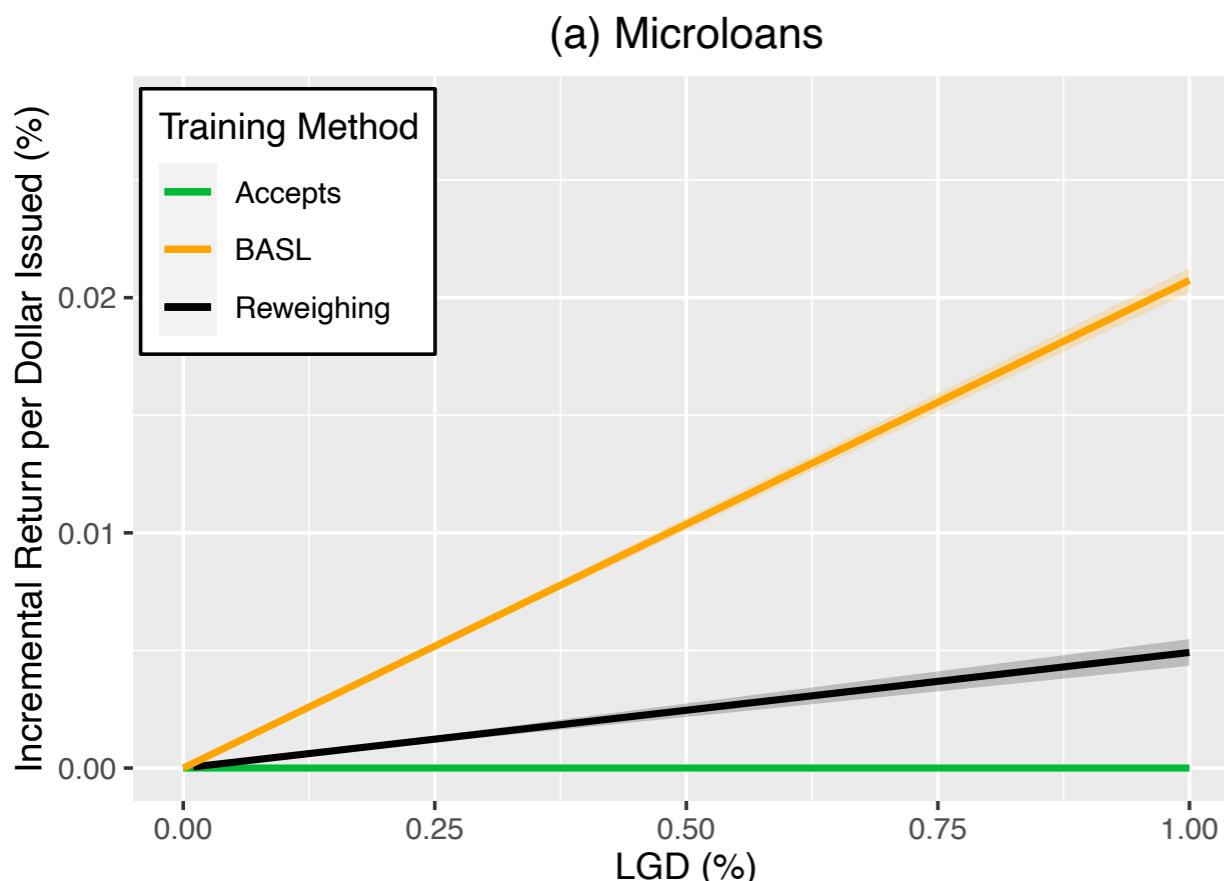
- **average profit per loan for each algorithm:**

$$\pi = \frac{1}{100} \sum_{j=1}^{100} \frac{\text{ABR}_j \times A \times (1 + i) \times (1 - L) + (1 - \text{ABR}_j) \times A \times (1 + i) - A}{\text{BAD clients}} \quad \text{GOOD clients}$$

- **averaging over 100 ABR values** (4-fold CV x 25 bootstrap samples)

# Business Impact with Variable LGD

- comparing our framework and its strongest competitor
- measuring incremental profit per loan over ignoring rejects

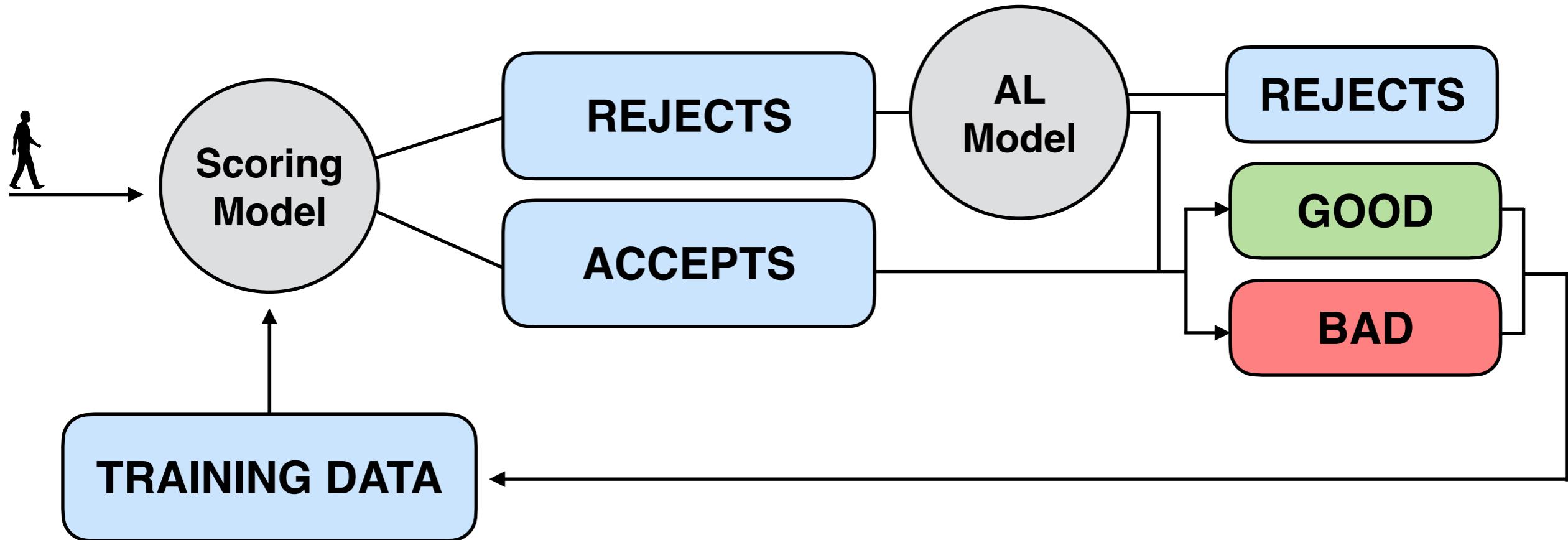


## Incremental monetary gains:

- micro-loans: up to **\$7.78** per loan
- installment loans: up to **\$461.70** per loan

# A7. ACTIVE LEARNING

# Acceptance Loop with AL



- **scoring model filters incoming loan applications**
  - **ML model** observes features of incoming applicants
  - predicts whether an applicant will repay the loan
- **active learning selects additional cases rejected by a scorecard**
  - **AL model** observes features of rejects and scorecard predictions
  - predicts whether an applicant will be «useful»

# Selected AL Techniques

## Uncertainty sampling:

- selects observations that the ML model is **least confident about**
- e.g., cases with predicted **P(BAD)** close to 0.5

## Query-by-committee (QBC):

- trains a set (committee) of ML models (e.g., on different training folds)
- selects observations where the committee **disagrees the most**
- e.g., cases with the highest Kullback-Leibler divergence over predictions

## Optimized probabilistic active learning (OPAL):

- measures «**spatial usefulness**» of an unlabeled observation
- selects observations that maximize the expected reduction in (asymmetric) misclassification cost
- e.g., cases from high-density areas with potentially higher error costs

# Experimental Setup

## Acceptance loop:

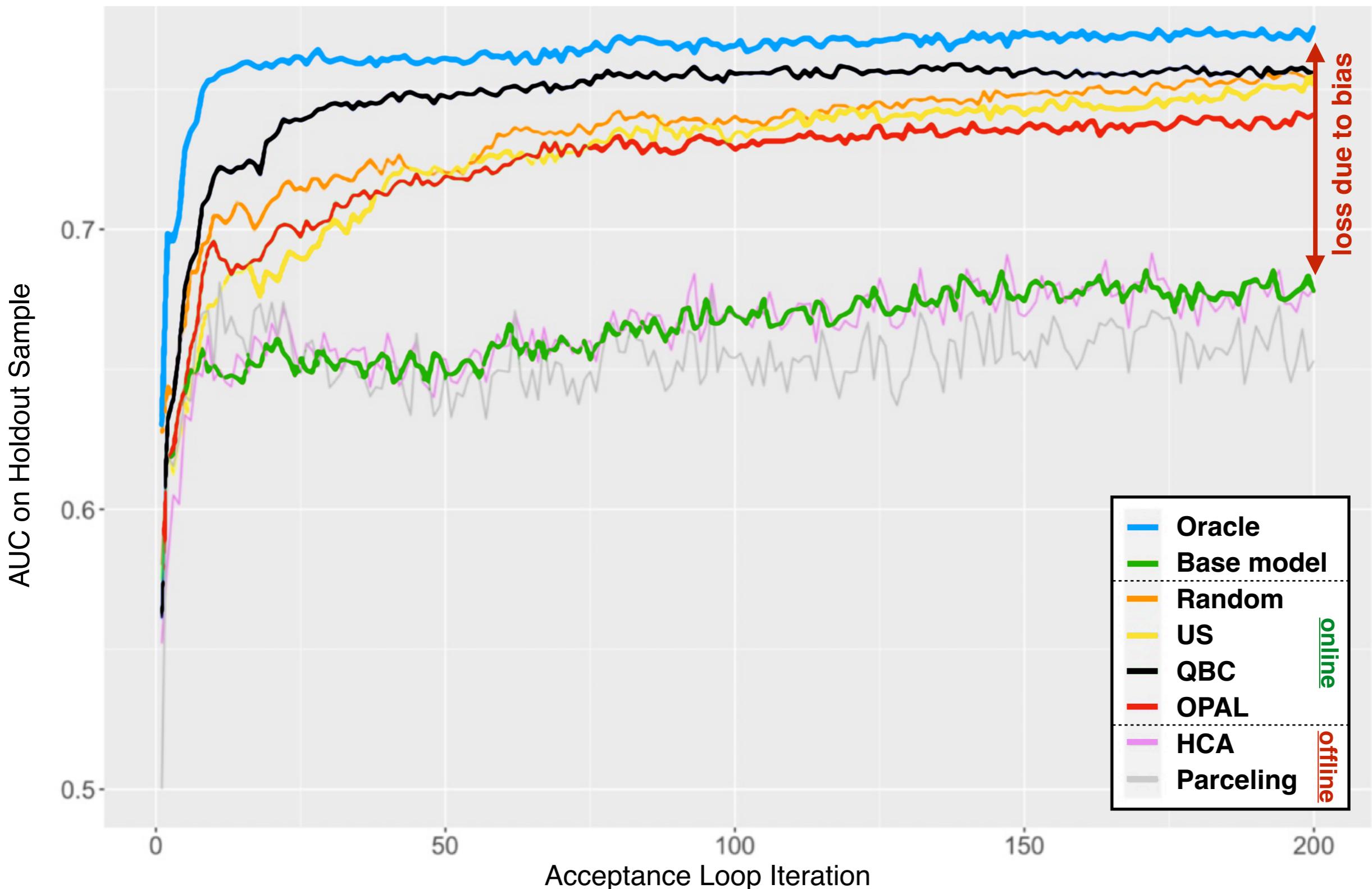
- draw / generate a batch of **new applications**
- **accept a subset** of loan applications
  - select 20% low-risk cases with **ML model**
  - select 10% «useful» cases with **AL model**
- **augment training data** with labeled accepts
- **retrain the scoring model** on new data
- **evaluate** performance on a holdout sample

repeat for 200 iterations

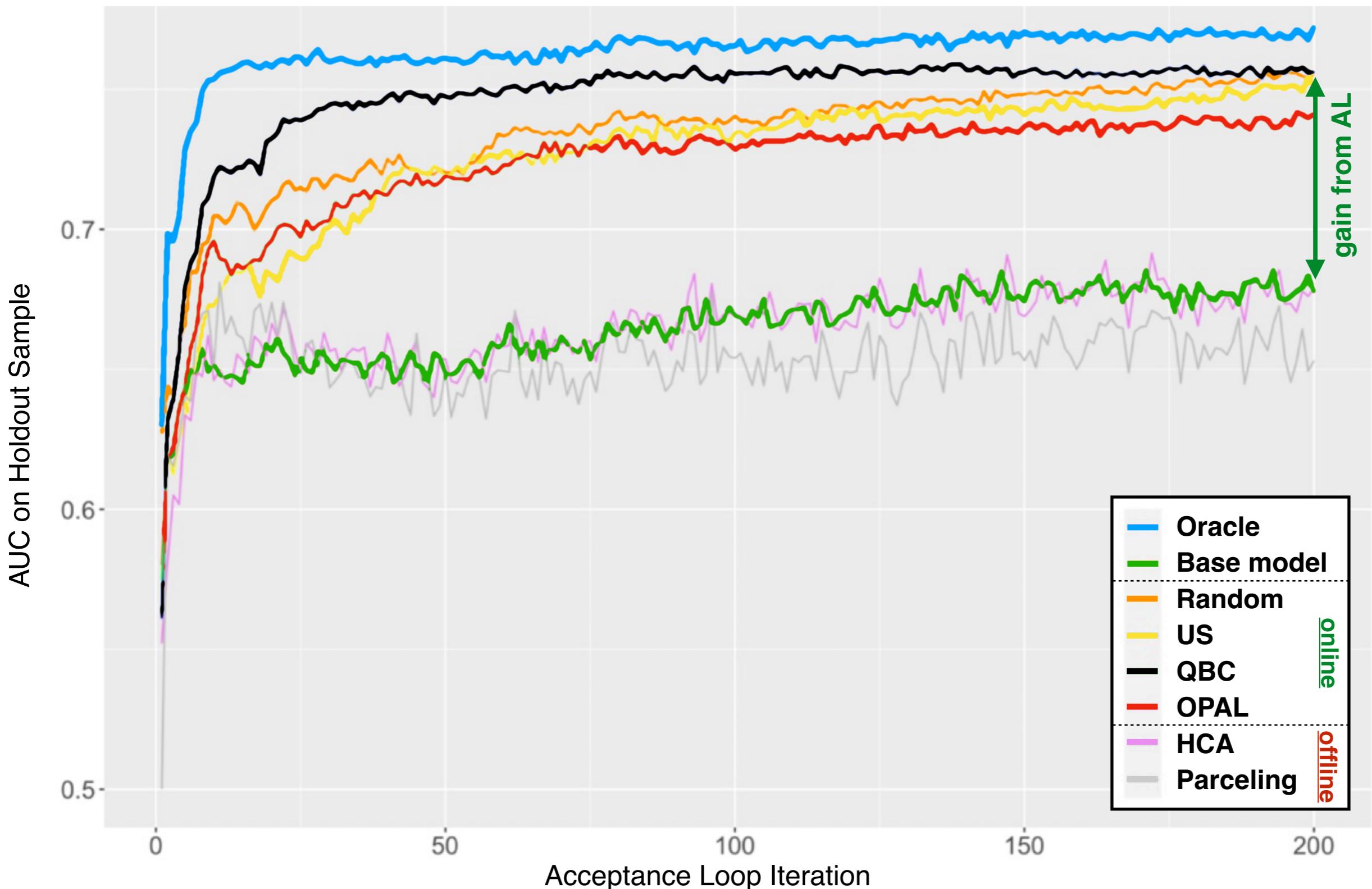
## Performance evaluation:

- **two cost / benefit components compared to base model:**
  - **model performance:** improved accuracy of the retrained **ML model**
  - **data augmentation:** accepting extra applicants with the **AL model**

# Results: LendingClub [2/3]



# Results: LendingClub [3/3]



# Results: Overall Profit [2/2]

**LendingClub  
Dataset**

Method	Data profit	Model profit	Total profit
Random	.124	.000	.125
US	.132	.001	.133
QBC	.154	.001	.155
OPAL	.095	.000	.096
Oracle	1.271	.002	1.272

**Synthetic  
Dataset**

Method	Data profit	Model profit	Total profit
Random	-.098	.002	-.095
US	-.115	.003	-.112
QBC	-.040	.003	-.036
OPAL	-.167	.003	-.163
Oracle	-1.068	.005	-1.062

- **data profit** = profit from assigning loans to applicants selected with AL
- **model profit** = profit from model improvement after data augmentation
- values represent average profit per EUR issued

# Summary

- **AL improves performance and profitability of credit scorecards**
  - positive gains in different performance metrics
  - query-by-committee demonstrates most potential
- **trade-off between labeling cost and model improvement**
  - labeling cost can outweigh the model improvement
  - percentage of labeled cases is an important meta-parameter
  - when to stop labeling?
- **further experiments needed to clarify the potential of AL**
  - strong impact of the data characteristics on costs & benefits
  - in which environments AL is useful?