



# Active Learning for Reject Inference in Credit Scoring

Nikita Kozodoi, Stefan Lessmann

# Presentation Outline



## 1. Sampling Bias in Credit Scoring

- Problem setup & illustration
- Impact on scoring models

## 2. Correcting Sampling Bias

- Offline reject inference
- Active learning for online reject inference

## 3. Empirical Results

- Experimental setup
- Preliminary results

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- Impact on scoring models

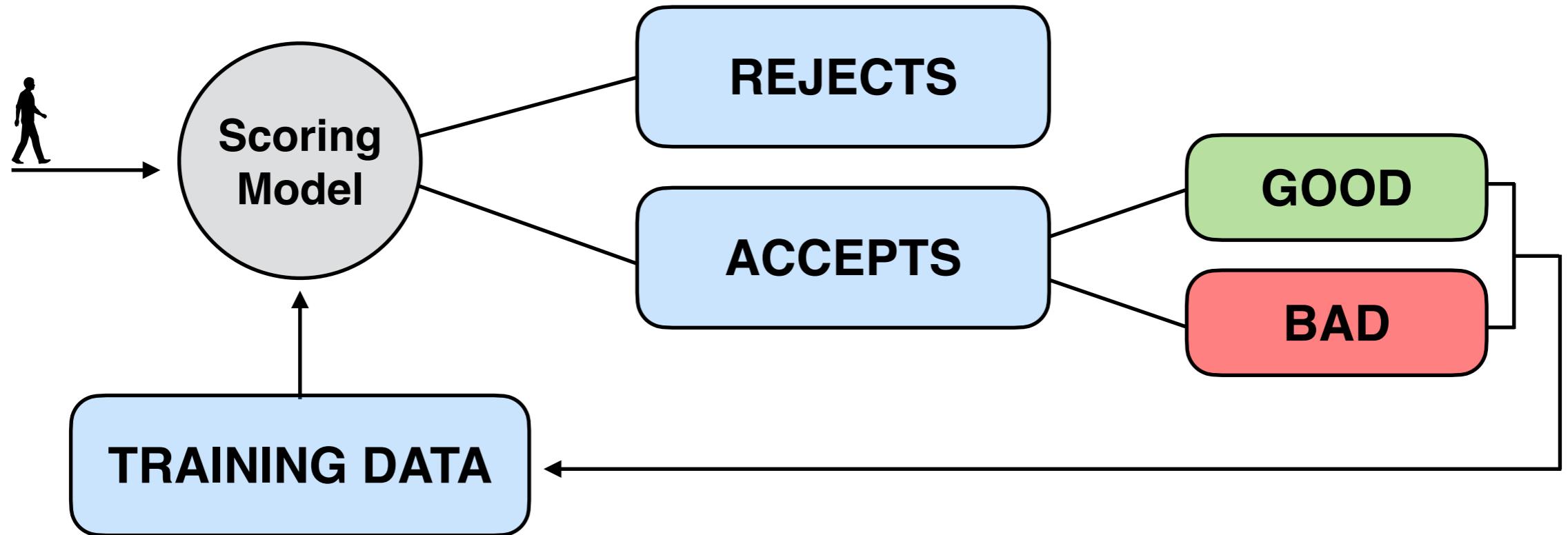
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# Acceptance Loop in Credit Scoring



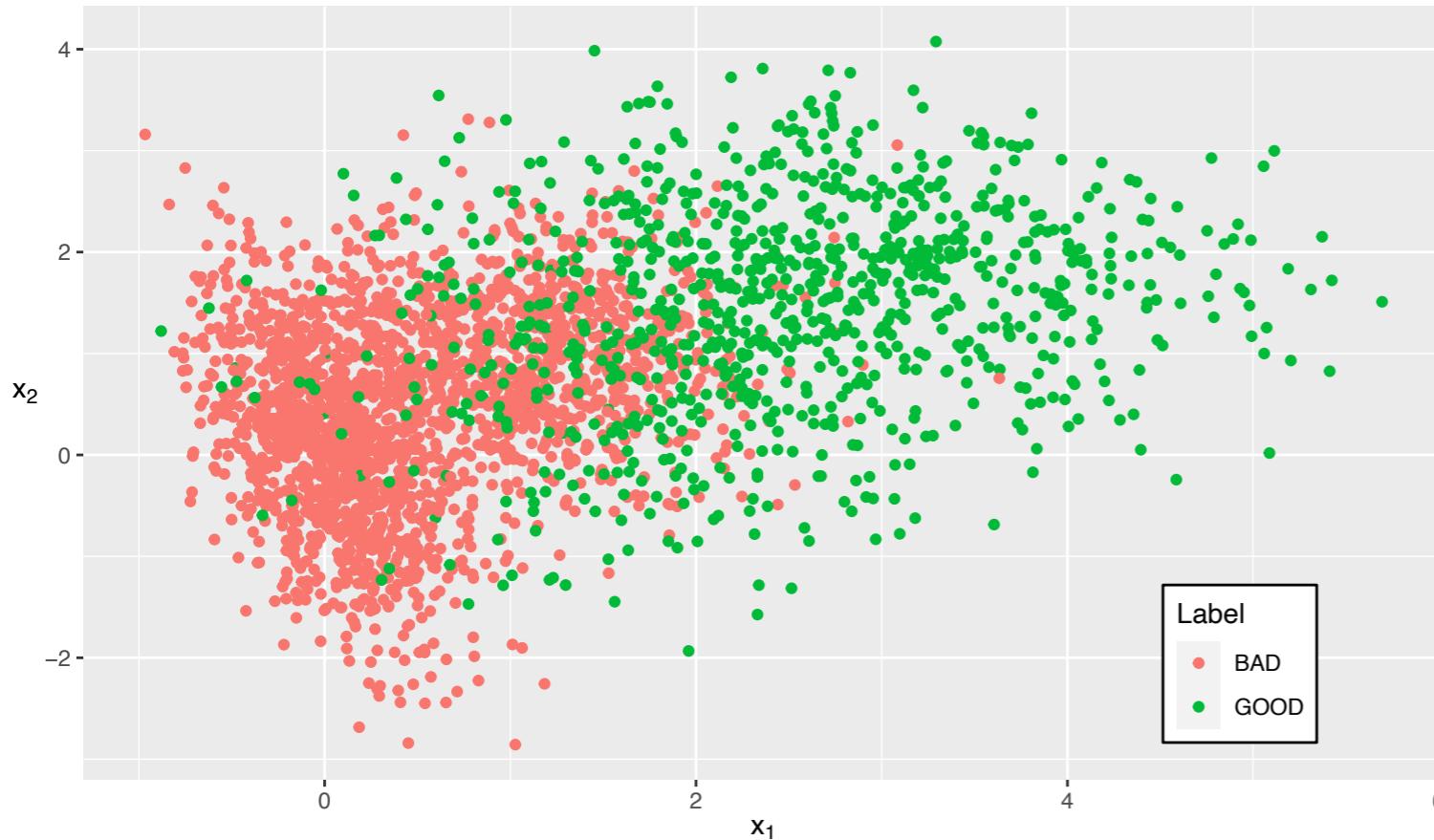
- **scoring model filters incoming loan applications**
  - ML model observes features of incoming applicants
  - predicts whether an applicant will repay the loan
- **training a model requires data with known outcomes**
  - repayment outcome is only observed for **accepted applicants**
  - application labels are missing **not completely at random**
- **acceptance loop creates sampling bias**
  - adverse impact of bias depends on the missingness type

# Sampling Bias Illustration [1/3]



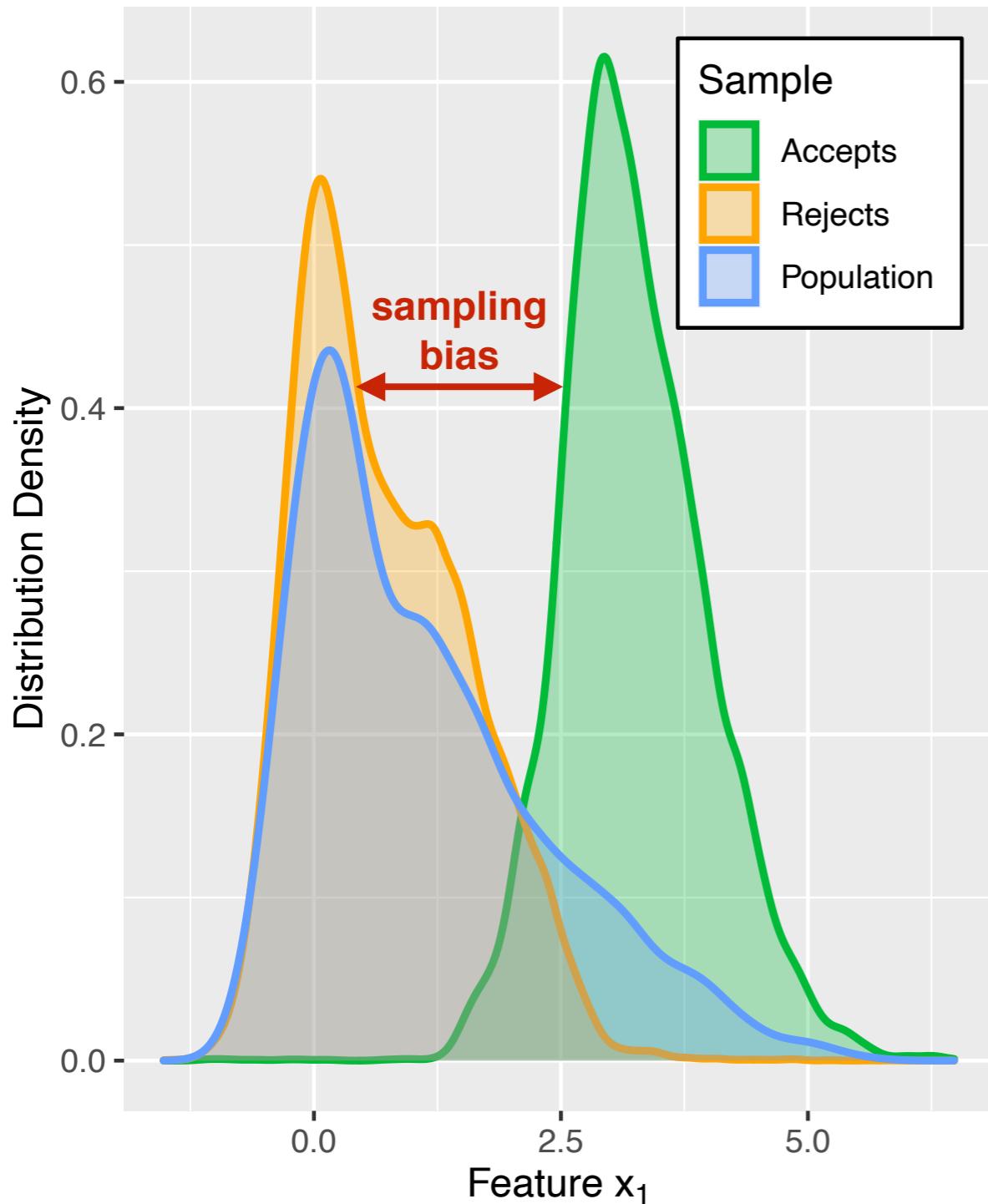
## Synthetic data:

- sampling **GOOD** and **BAD** risks from multivariate Gaussian mixtures
- simulating real-world **acceptance loop**:
  - iteratively generating **batches** of new applications
  - using a scoring model to **accept** and **reject** new applications
  - **updating** the model after learning the labels of **accepts**
- evaluating performance on a **holdout sample** from population



# Sampling Bias Illustration [2/3]

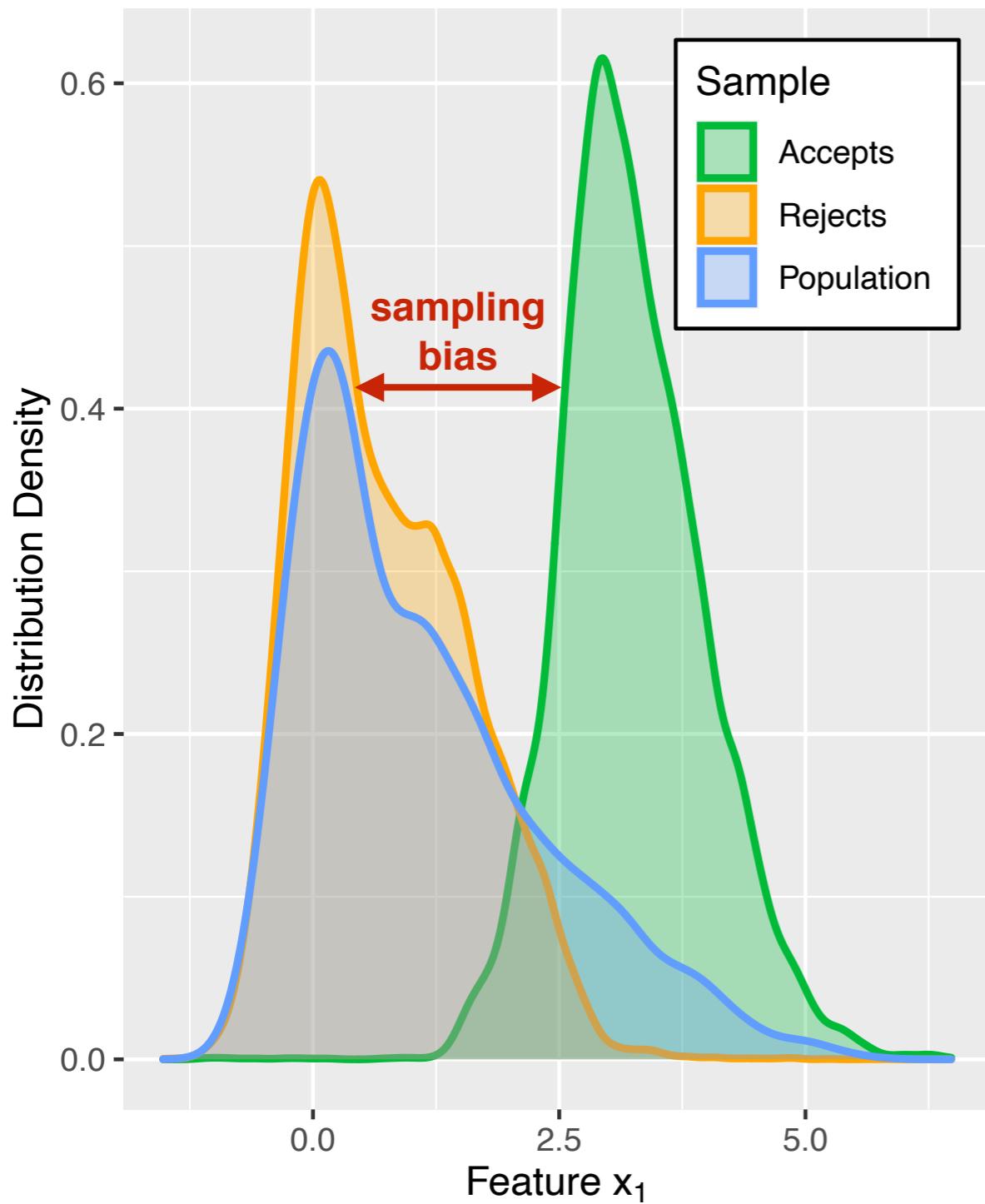
(a) Sampling Bias



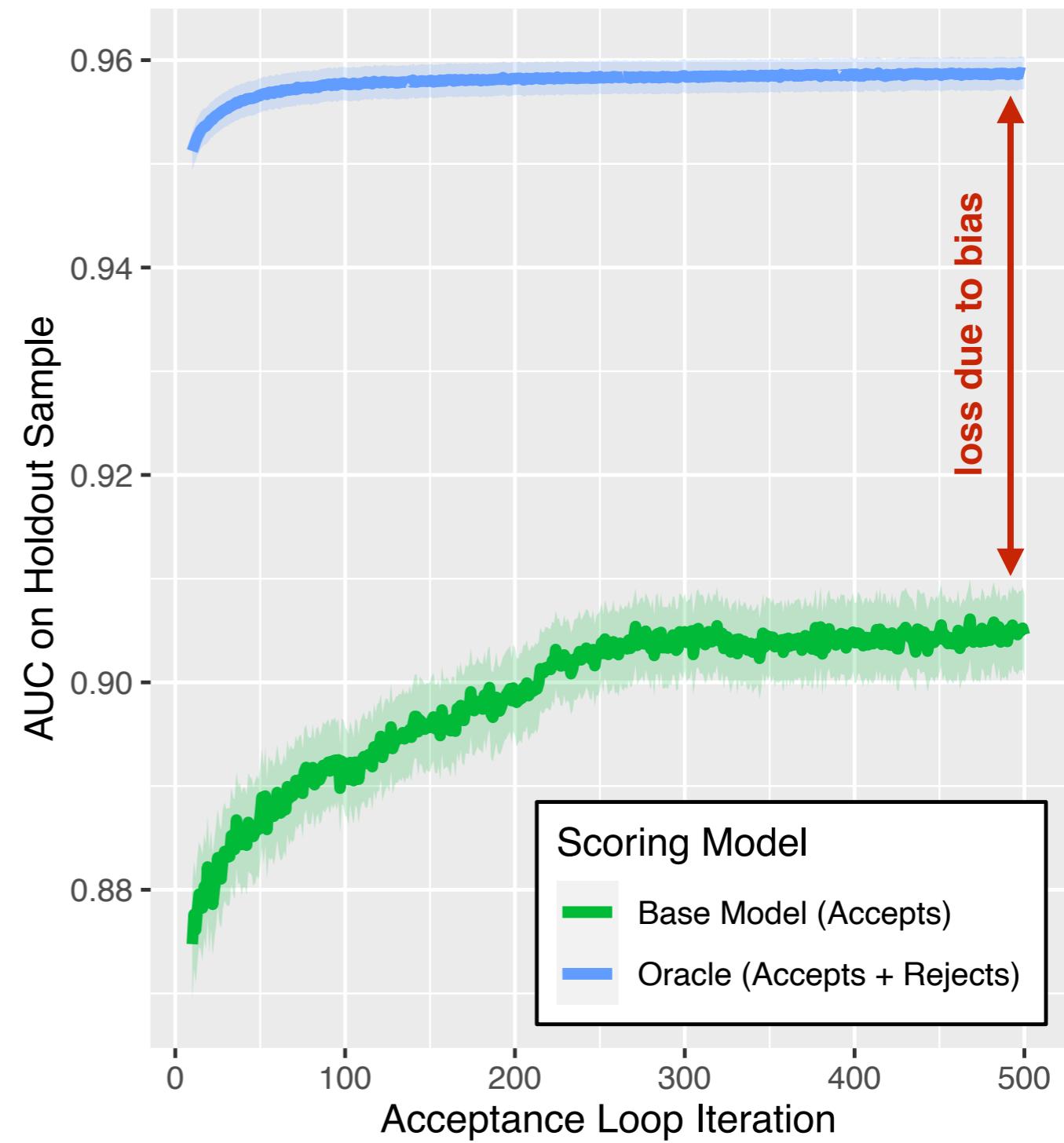
# Sampling Bias Illustration [3/3]



(a) Sampling Bias



(b) Impact on Training



AUC = area under the ROC curve; higher is better

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# Background on Reject Inference [1/2]



**Reject inference mitigates sampling bias by using data on rejects**

- label **rejects** using one of the RI techniques
- train a scoring model on the augmented data
- **examples:** hard cutoff augmentation, parcelling, Heckman model

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- label **rejects** using one of the RI techniques
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- **examples:** hard cutoff augmentation, parcelling, Heckman model

### Hard cutoff augmentation (HCA):

- train a scoring model over **accepts**
- predict  $P(\text{BAD})$  for **rejects** using this model
- assign labels based on a certain threshold

### Parceling:

- split **rejects** into groups based on the model score
- assign labels within groups proportionally to the expected **BAD** rate
- **BAD** rate for **rejects** is usually assumed to be higher than for **accepts**

# Offline vs Online Reject Inference [1/2]

- traditional reject inference methods are offline
  - sampling bias is mitigated by working with past **rejects**
- offline reject inference has limitations
  - actual labels of the **rejects** are never observed
  - rejects become less relevant with dataset shift (e.g., business cycle)
  - regulation may prohibit using data on rejected customers

# Offline vs Online Reject Inference [2/2]

- traditional reject inference methods are offline
  - sampling bias is mitigated by working with past **rejects**
- offline reject inference has limitations
  - actual labels of the **rejects** are never observed
  - rejects become less relevant with dataset shift (e.g., business cycle)
  - regulation may prohibit using data on rejected customers
- we propose online reject inference with active learning (AL)
  - working with applications about to be rejected by a scorecard
  - issuing a loan to selected **rejects** to learn the actual labels
- online reject inference stands on the cost-benefit trade-off
  - cost from issuing loans to risky customers
  - gain from obtaining a more representative training data

# What is Active Learning? [1/4]

**ML framework in which a learning algorithm interactively queries to label currently unlabeled data points**

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**ML framework in which a learning algorithm interactively queries to label currently unlabeled data points**

- consider a classification task with labeled and unlabeled data

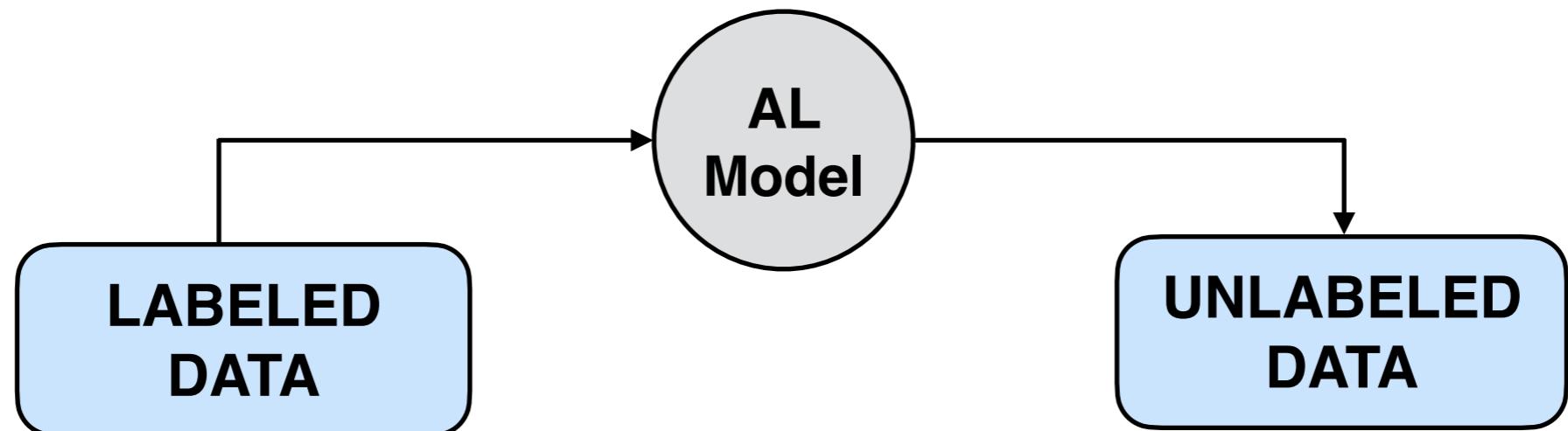
LABELED  
DATA

UNLABELED  
DATA

# What is Active Learning? [3/4]

ML framework in which a learning algorithm interactively queries to label currently unlabeled data points

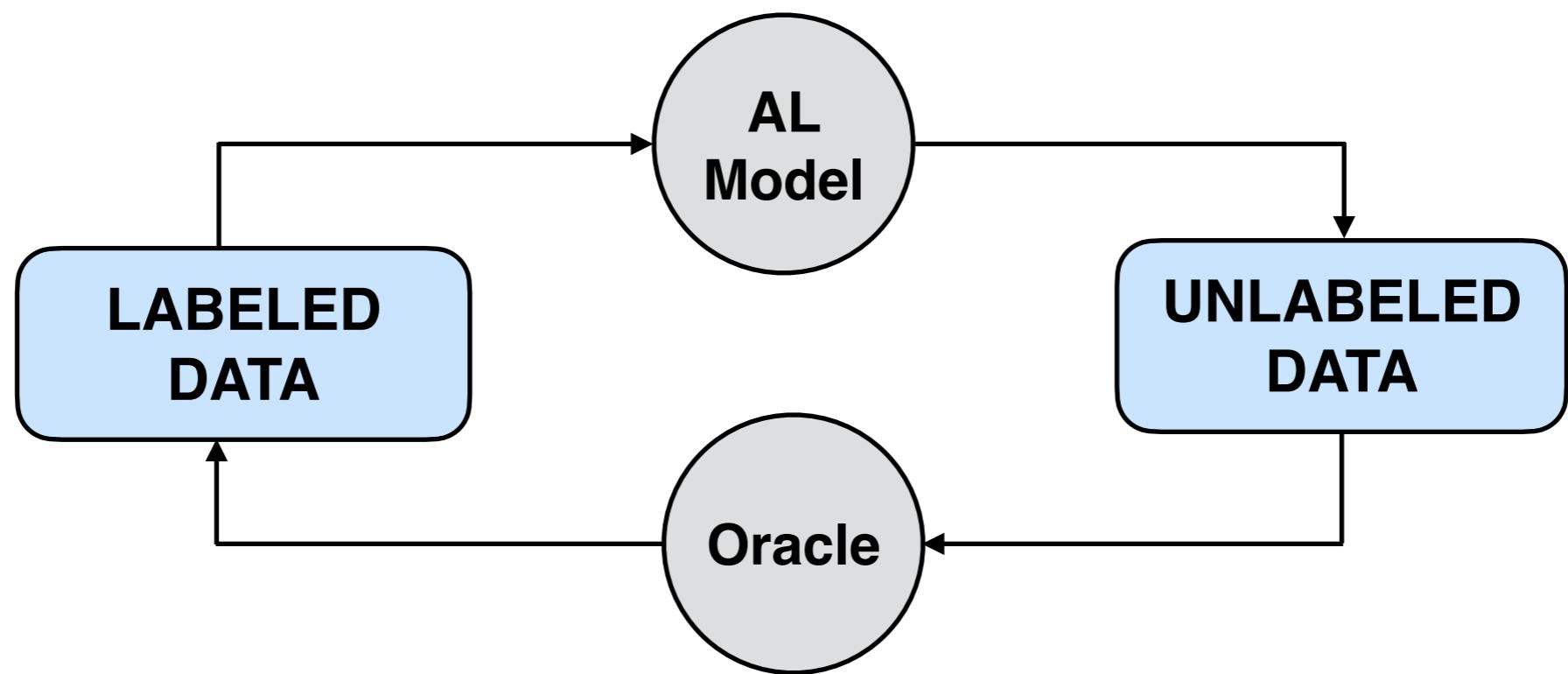
- consider a classification task with labeled and unlabeled data
- AL identifies “**most interesting**” unlabeled data points
  - which observations would improve classifier performance if they had labels?
  - can be measured as **uncertainty, correlation, expected error decrease**, etc.



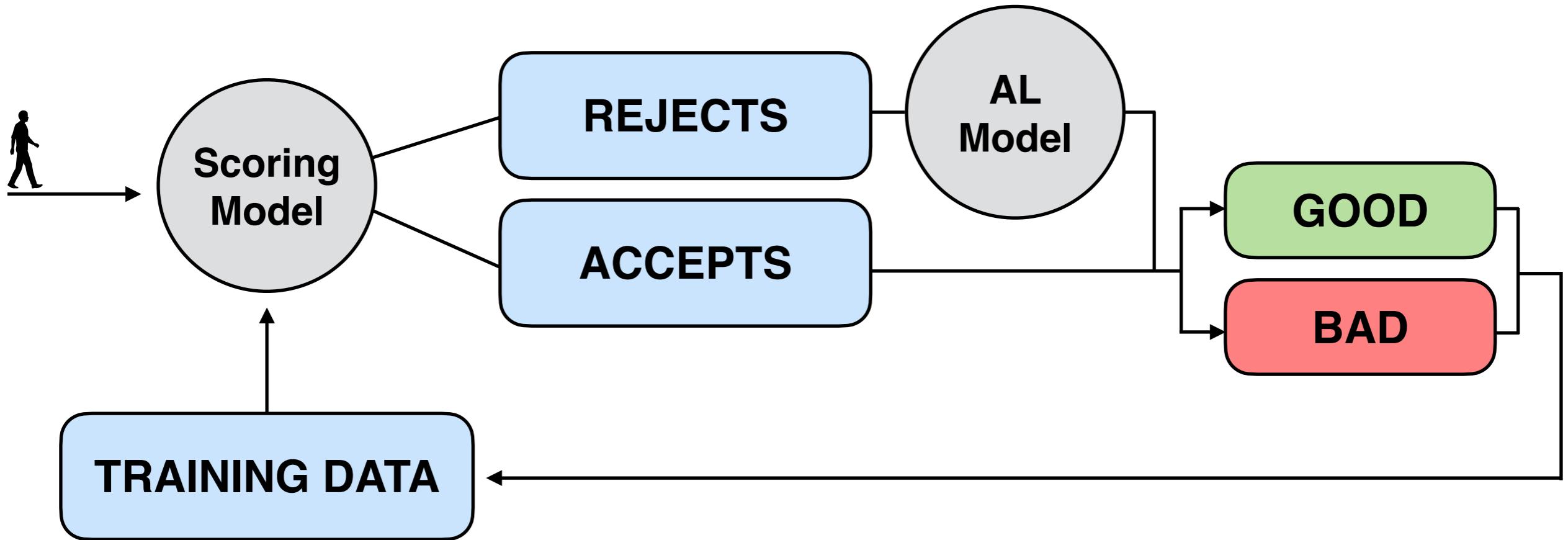
# What is Active Learning? [4/4]

ML framework in which a learning algorithm interactively queries to label currently unlabeled data points

- consider a classification task with labeled and unlabeled data
- AL identifies “**most interesting**” unlabeled data points
  - which observations would improve classifier performance if they had labels?
  - can be measured as **uncertainty, correlation, expected error decrease**, etc.
- identified data points are labeled by oracle
- the classifier is trained on augmented data



# 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»

## 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

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# Data Summary

## Real data:

- consumer credit scoring data provided by LendingClub
- repayment behavior of actual **rejects** is not available
- treating most risky **accepts** as «**rejects**»

## Synthetic data:

- full control over the data generation process
- repayment behavior of both **accepts** and **rejects** is available

Data set	Observations	Features	BAD rate
LendingClub	100,000	17	8 %
Synthetic Data	50,000	19	40 %

# Experimental Setup

## Acceptance loop:

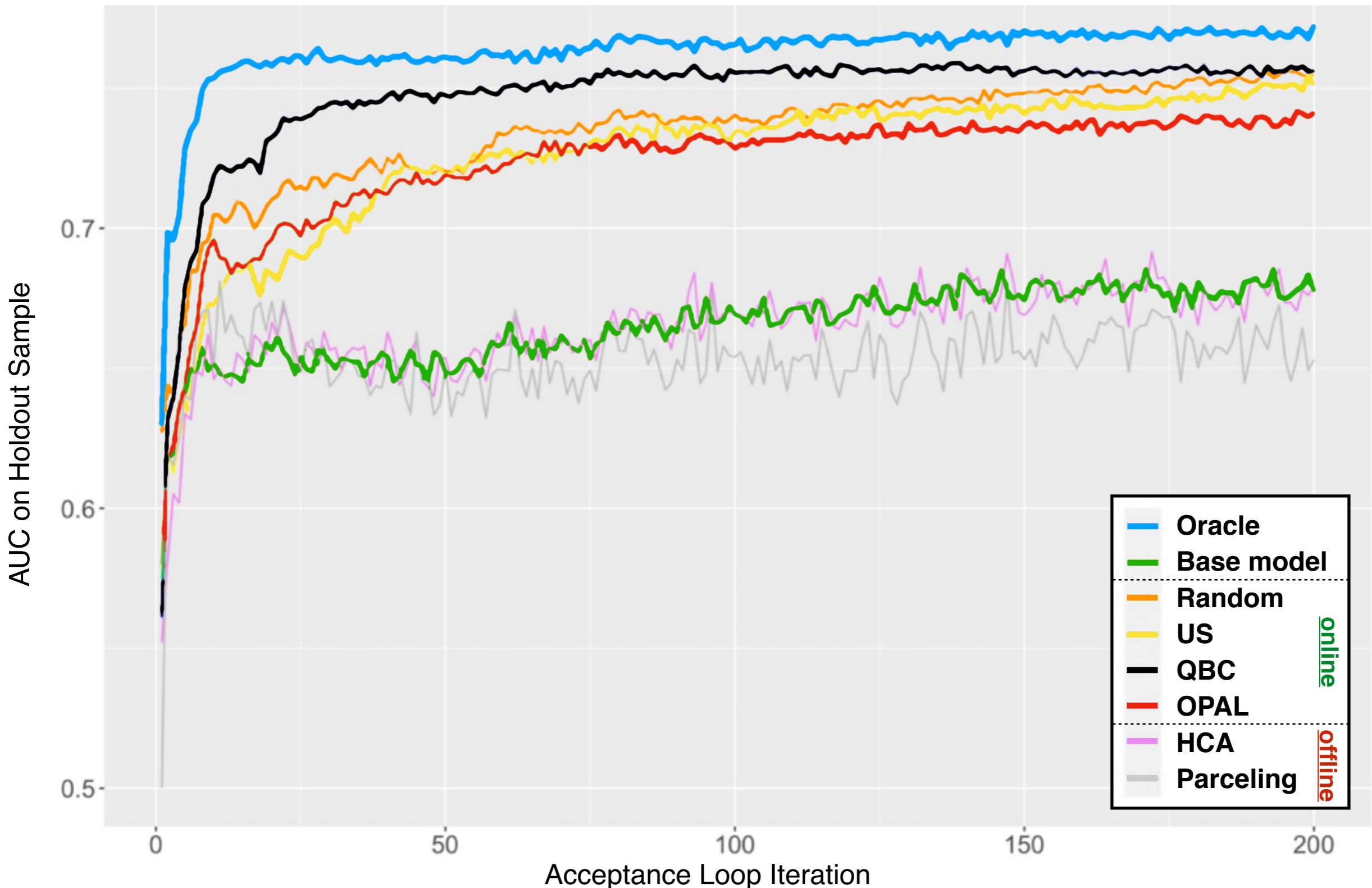
- draw / generate a batch of **new applications**
- **accept a subset** of loan applications
  - select 20% low-risk cases with **ML model**
  - select 10% «useful» cases with **AL model**
- **augment training data** with labeled accepts
- **retrain the scoring model** on new data
- **evaluate** performance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

repeat for 200 iterations

## Performance evaluation:

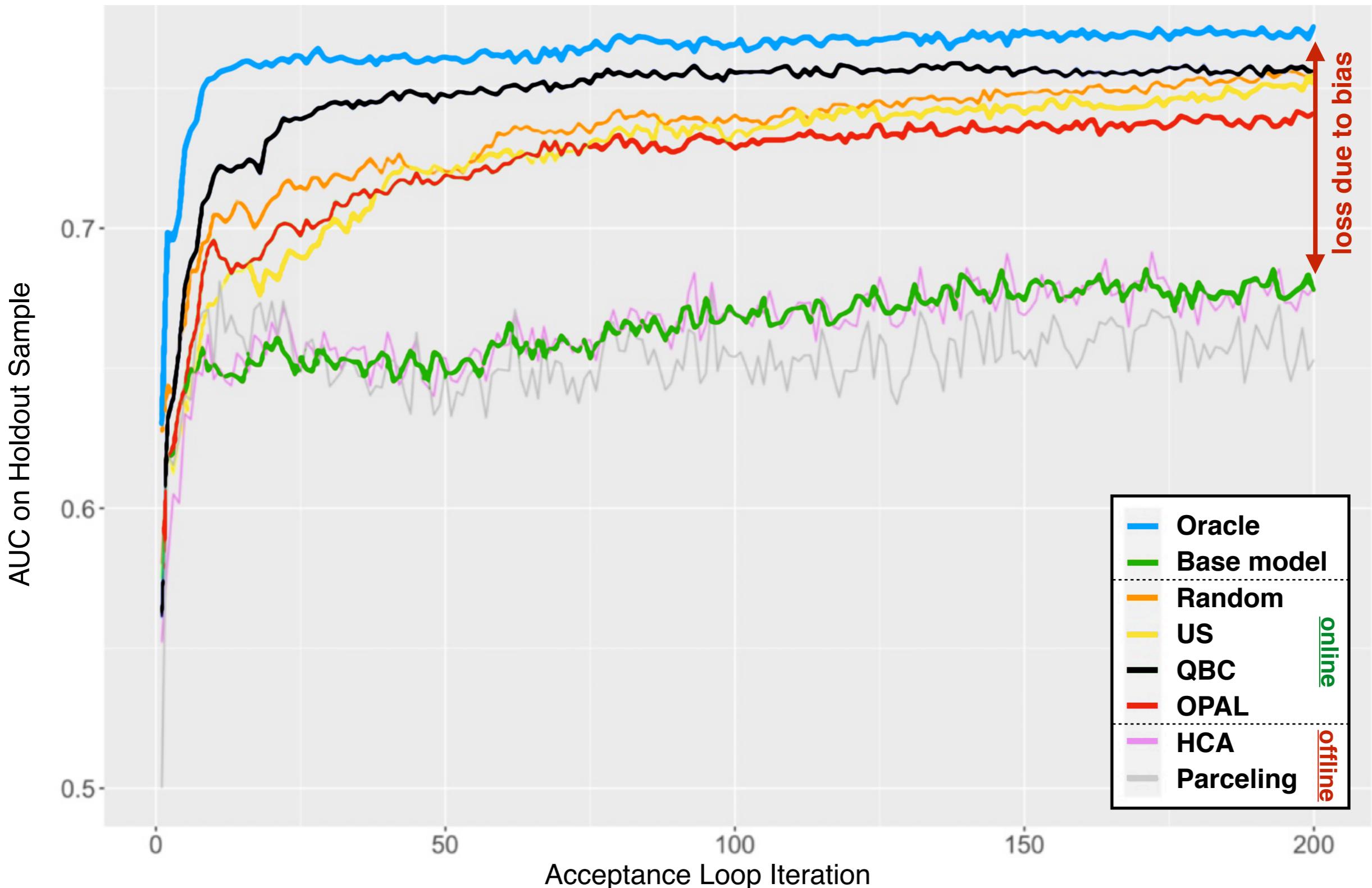
- **two cost / benefit components compared to base model:**
  - **model performance:** improved accuracy of the retrained **ML model**
  - **data augmentation:** accepting extra applicants with the **AL model**

# Results: LendingClub [1/3]



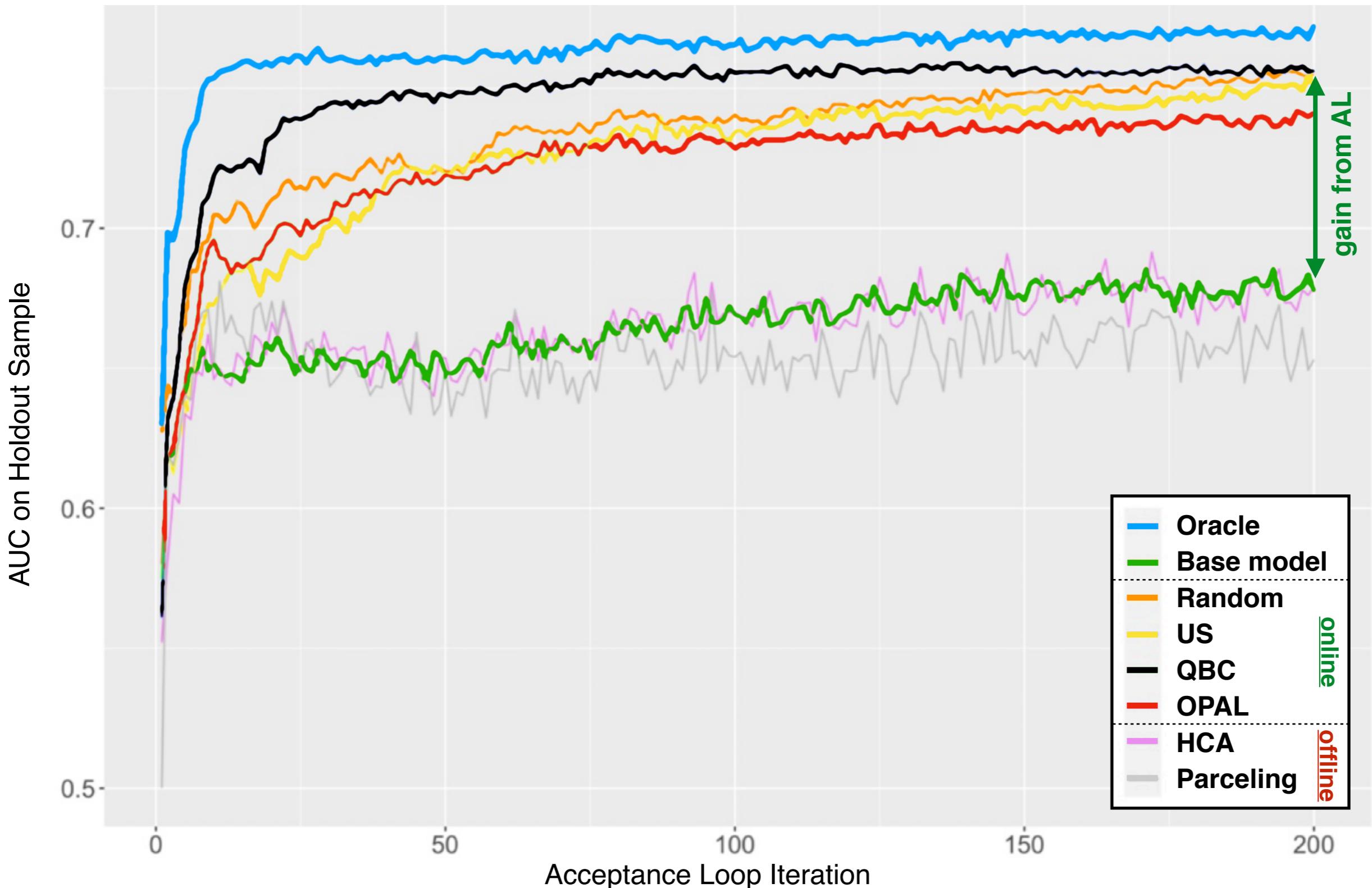
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# Results: LendingClub [2/3]



AUC = area under the ROC curve; higher is better

# Results: LendingClub [3/3]



AUC = area under the ROC curve; higher is better

# Results: Model Performance [1/2]

## LendingClub Dataset

Method	AUC gain	BS gain	ABR gain
Random	.069	.101	.057
US			
QBC			
OPAL			
Oracle	.098	.107	.405

## Synthetic Dataset

Method	AUC gain	BS gain	ABR gain
Random	.025	.009	.897
US			
QBC			
OPAL			
Oracle	.037	.013	1.380

- average gains per iteration in area under the learning curve relative to base model
- positive numbers indicate improvement over the base model

AUC = area under the ROC curve; BS = Brier score; ABR = BAD rate then accepting top-20% applicants

# Results: Model Performance [2/2]

## LendingClub Dataset

Method	AUC gain	BS gain	ABR gain
Random	.069	.101	.057
US	.061	<b>.103</b>	.245
QBC	<b>.082</b>	.097	<b>.264</b>
OPAL	.058	.094	.172
Oracle	.098	.107	.405

## Synthetic Dataset

Method	AUC gain	BS gain	ABR gain
Random	.025	<b>.009</b>	<b>.897</b>
US	.026	<b>.009</b>	.798
QBC	<b>.027</b>	.008	.830
OPAL	.025	.008	.857
Oracle	.037	.013	1.380

- average gains per iteration in area under the learning curve relative to base model
- positive numbers indicate improvement over the base model

AUC = area under the ROC curve; BS = Brier score; ABR = BAD rate then accepting top-20% applicants

# Results: Overall Profit [1/2]

## LendingClub Dataset

Method	Data profit	Model profit	Total profit
Random			
US			
QBC			
OPAL			
Oracle	1.271	.002	1.272

## Synthetic Dataset

Method	Data profit	Model profit	Total profit
Random			
US			
QBC			
OPAL			
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

# 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	.001	.096
Oracle	1.271	.002	1.272

## Synthetic Dataset

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

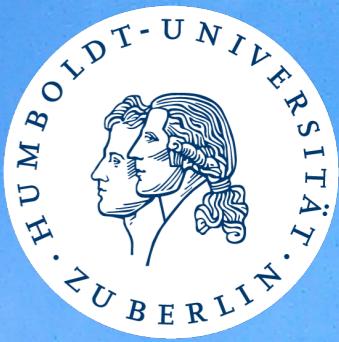
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# Summary

- **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?

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## Slides

