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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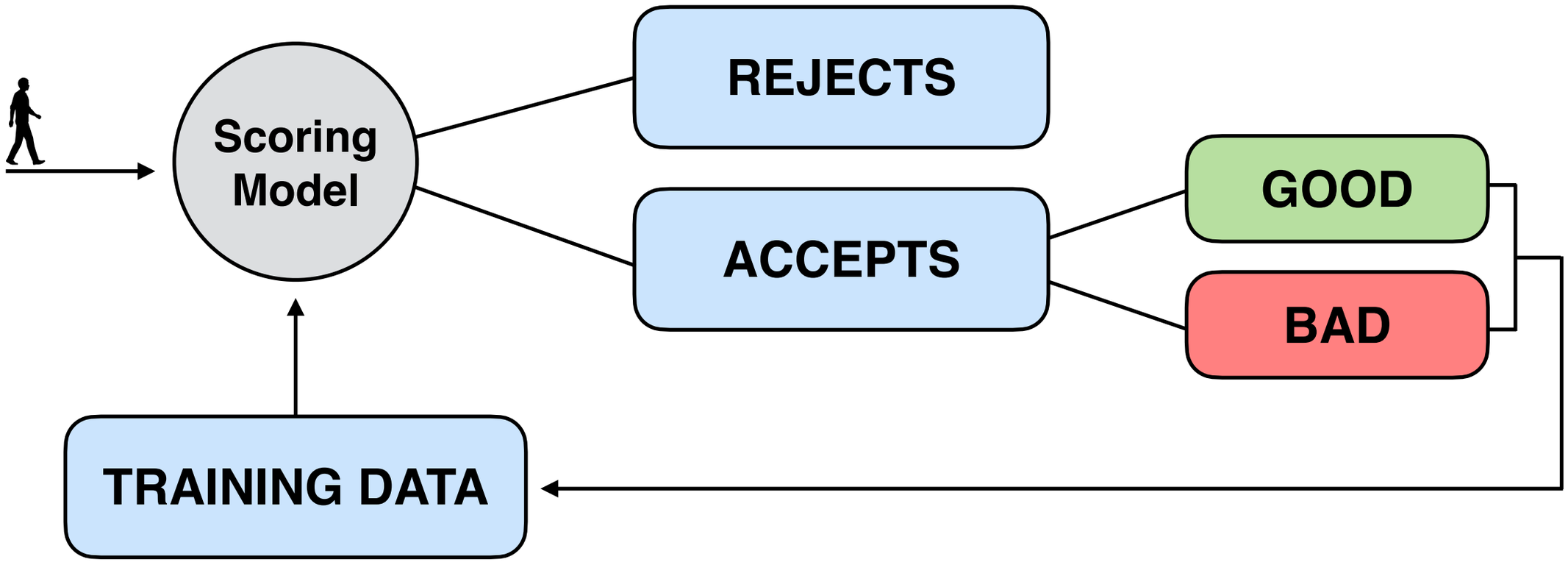
Acceptance Loop in Credit Scoring

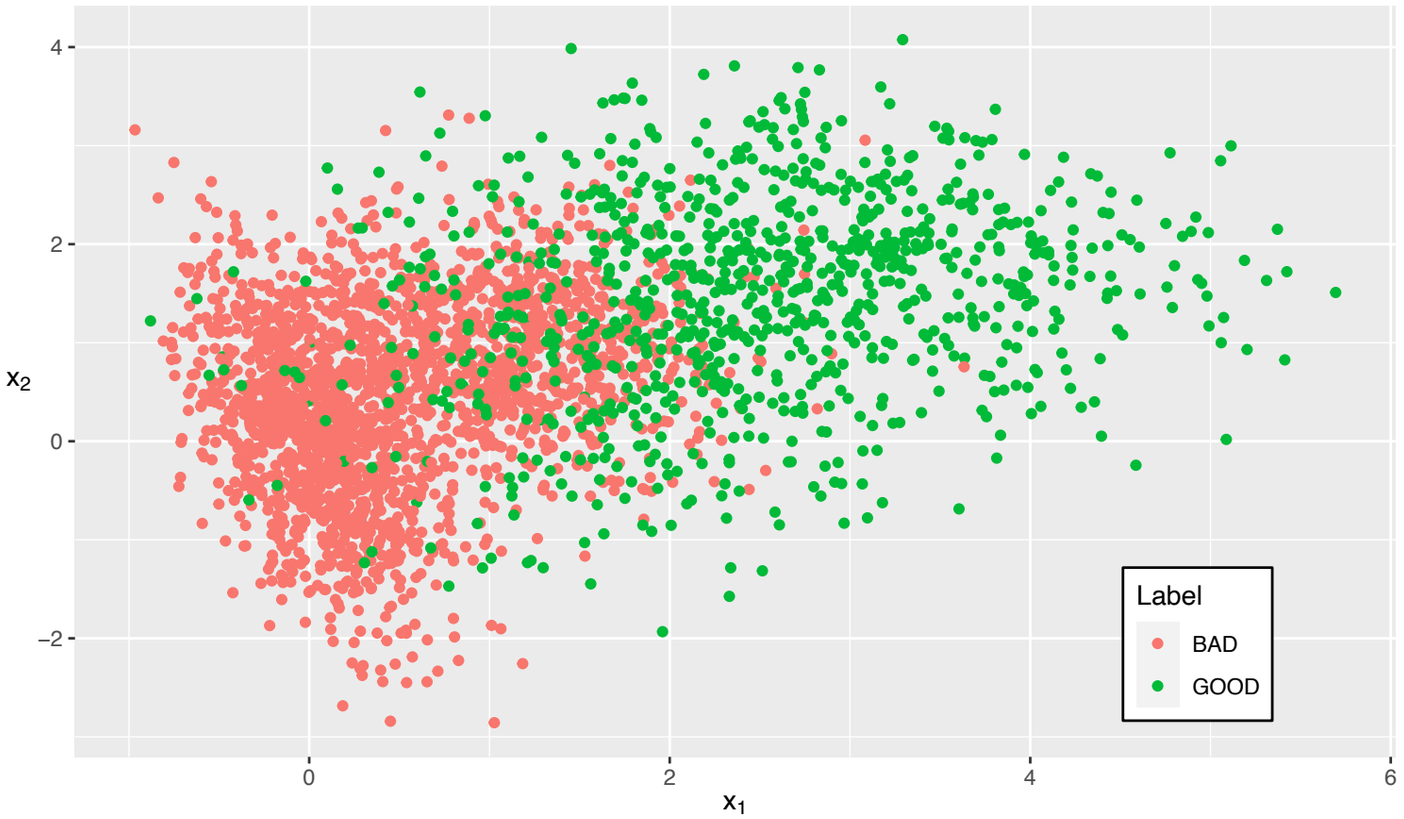


- **scoring model filters incoming loan applications**
  - ML model observes features of incoming applicants
  - predicts whether an applicant will repay the loan
- **training a model requires data with known outcomes**
  - repayment outcome is only observed for **accepted applicants**
  - application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

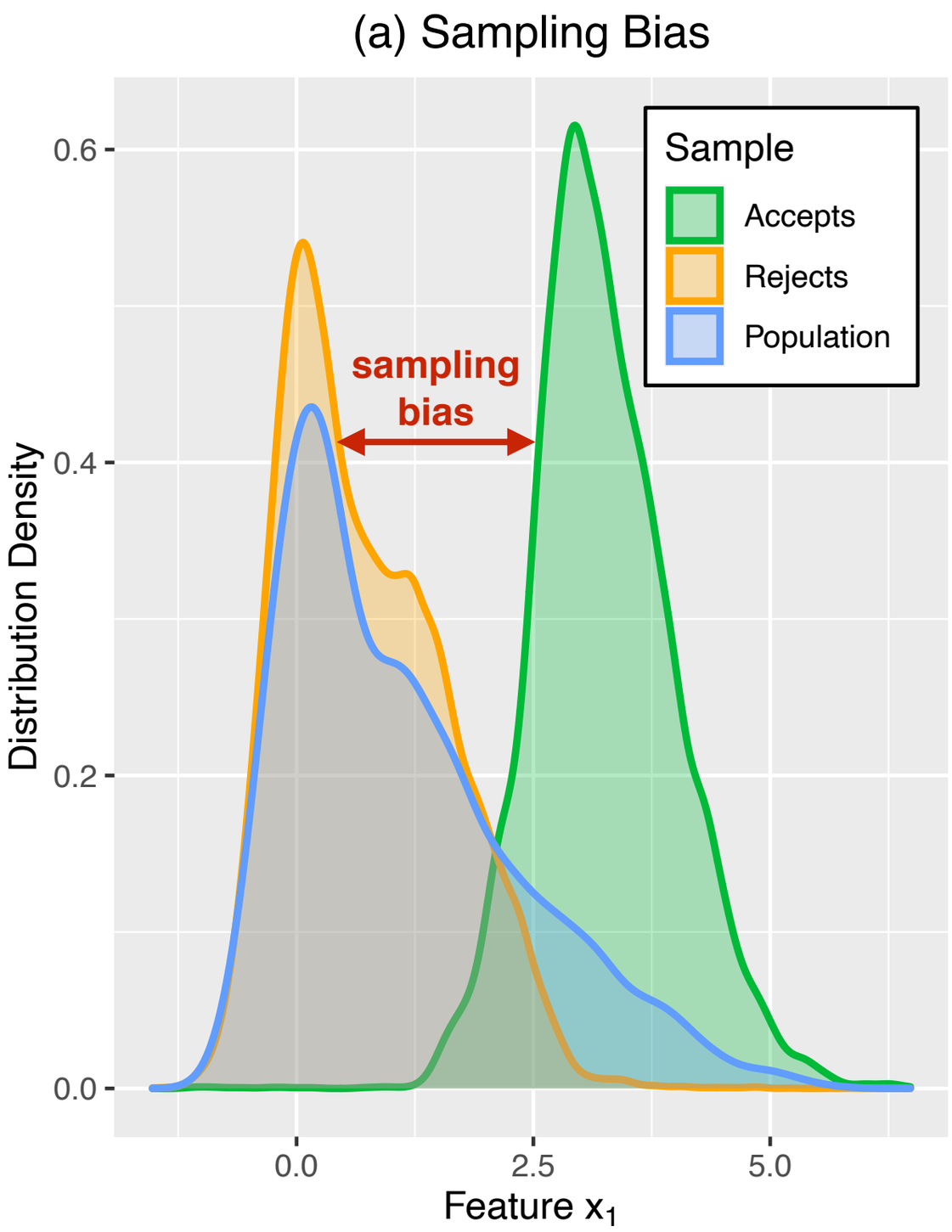
Sampling Bias Illustration [1/3]

Synthetic data:

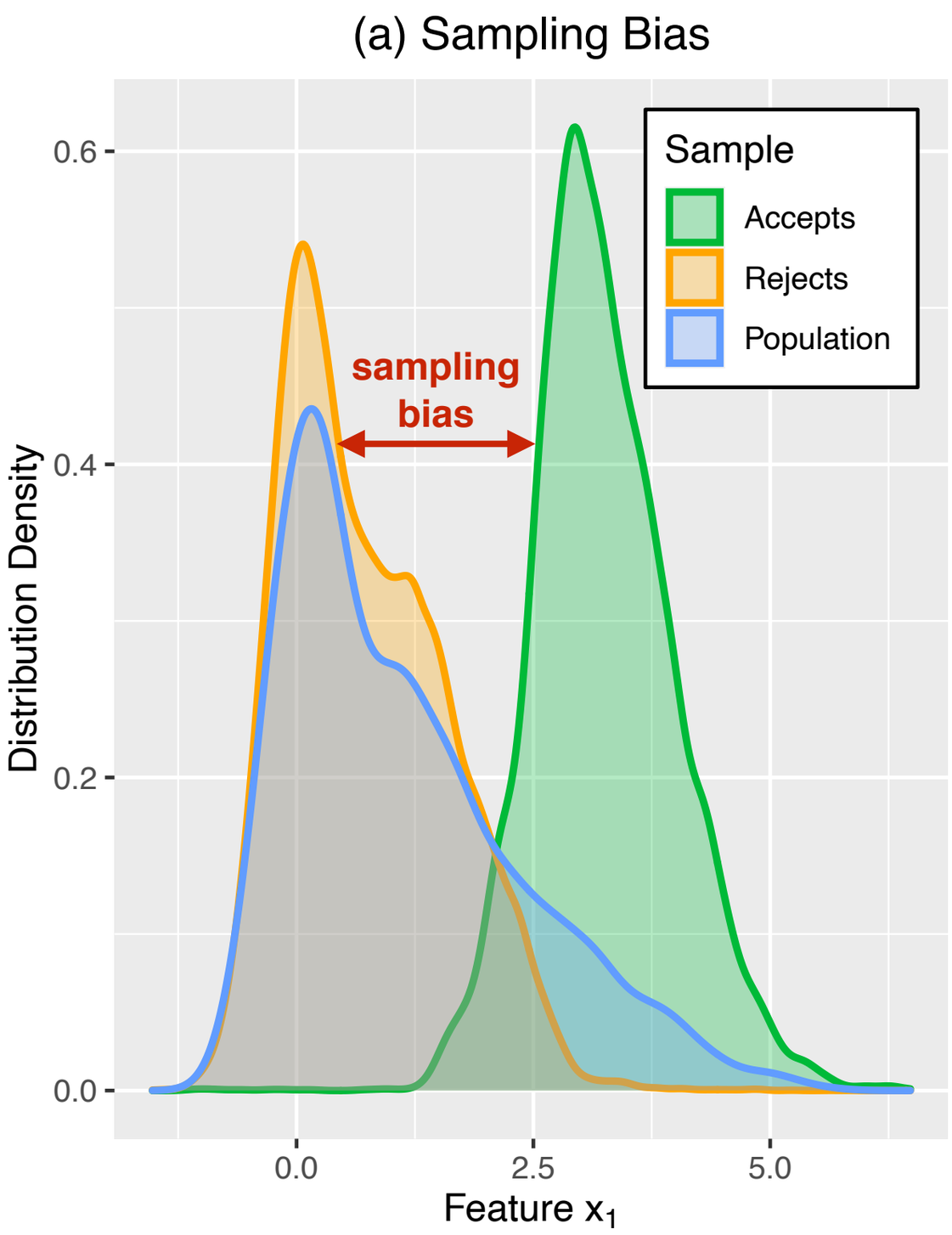
- sampling **GOOD** and **BAD** risks from multivariate Gaussian mixtures
- simulating real-world **acceptance loop:**
  - iteratively generating **batches** of new applications
  - using a scoring model to **accept** and **reject** new applications
  - **updating** the model after learning the labels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

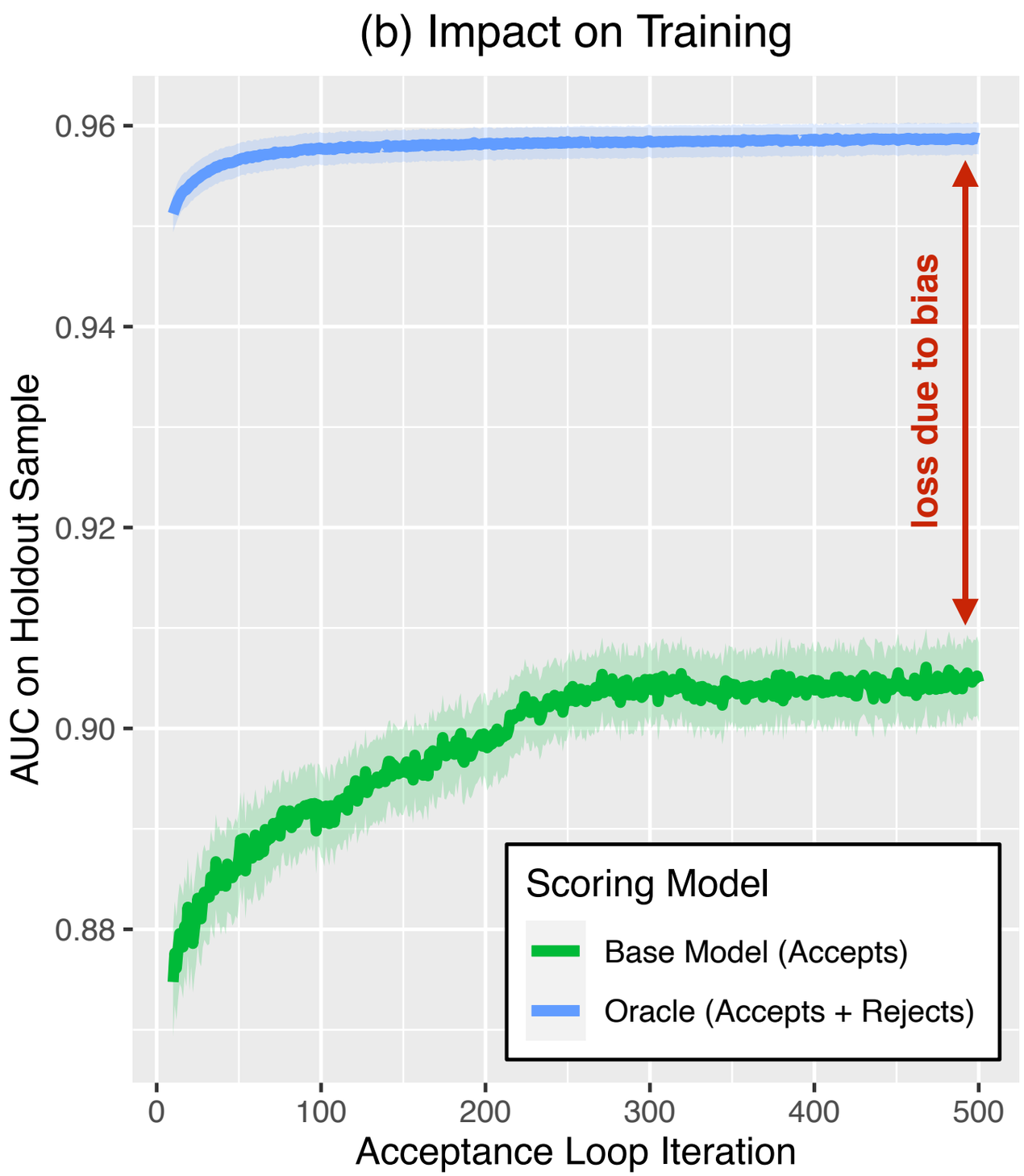


Sampling Bias Illustration [2/3]



Sampling Bias Illustration [3/3]





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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, parceling, Heckman model

Background on Reject Inference [2/2]

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, parceling, Heckman model

Hard cutoff augmentation (HCA):

- train a scoring model over **accepts**
- predict **P(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 <u>offline</u>**
  - sampling bias is mitigated by working with past **rejects**
- **<u>offline</u> reject inference has limitations**
  - actual labels of the past **rejects** are never observed
  - past 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]

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- **<u>offline</u> reject inference has limitations**
  - actual labels of the past **rejects** are never observed
  - past rejects become less relevant with dataset shift (e.g., business cycle)
  - regulation may prohibit using data on rejected customers
- **we propose <u>online</u> 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
- **<u>online</u> 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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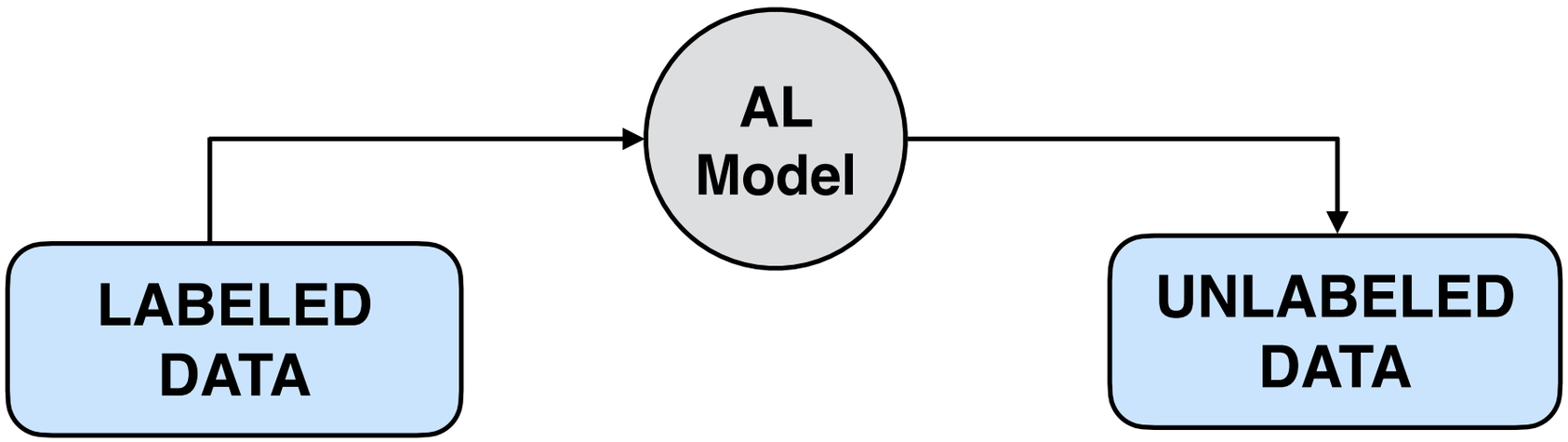
What is Active Learning? [3/4]

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

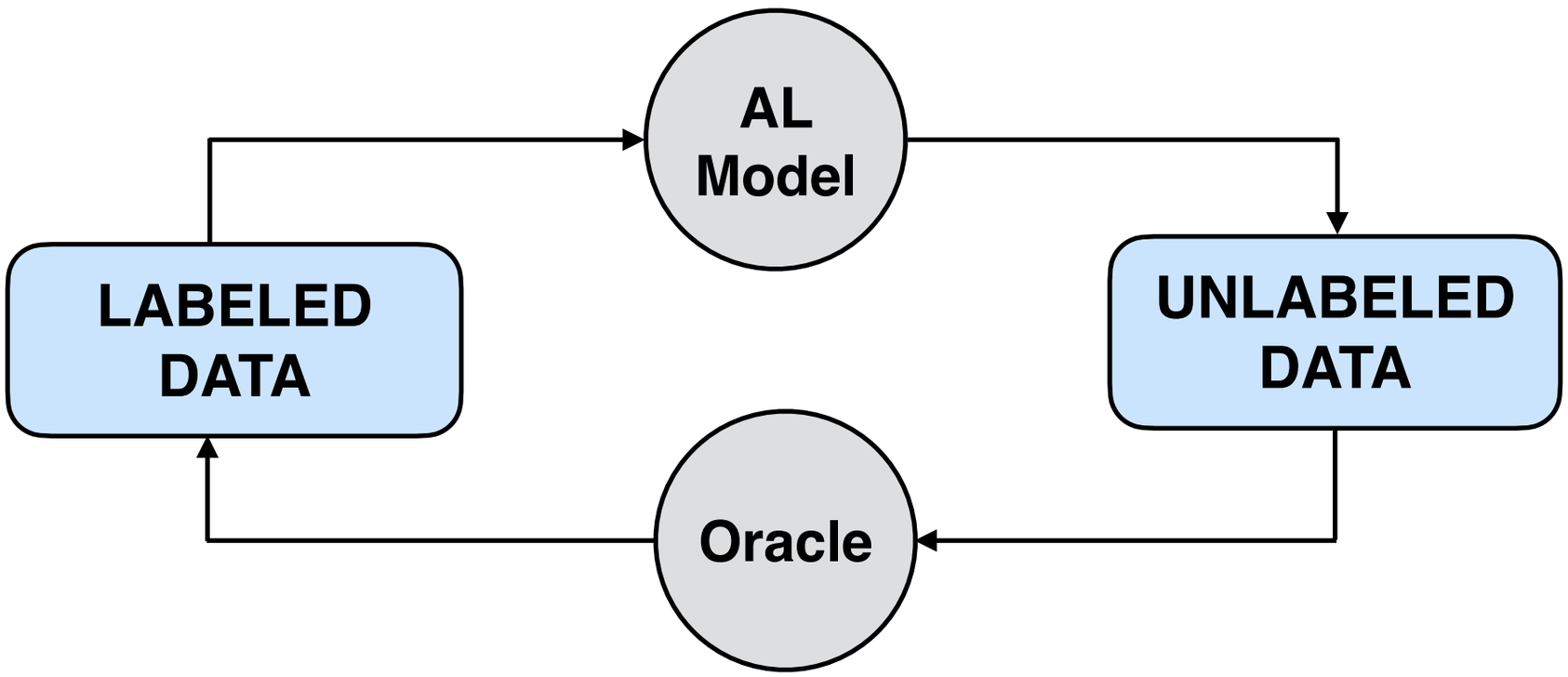
- consider a classification task with labeled and unlabeled data
- AL identifies **“most interesting”** unlabeled data points
  - which observations would improve classifier performance if they had labels?
  - can be measured as **uncertainty**, **correlation**, **expected error decrease**, etc.



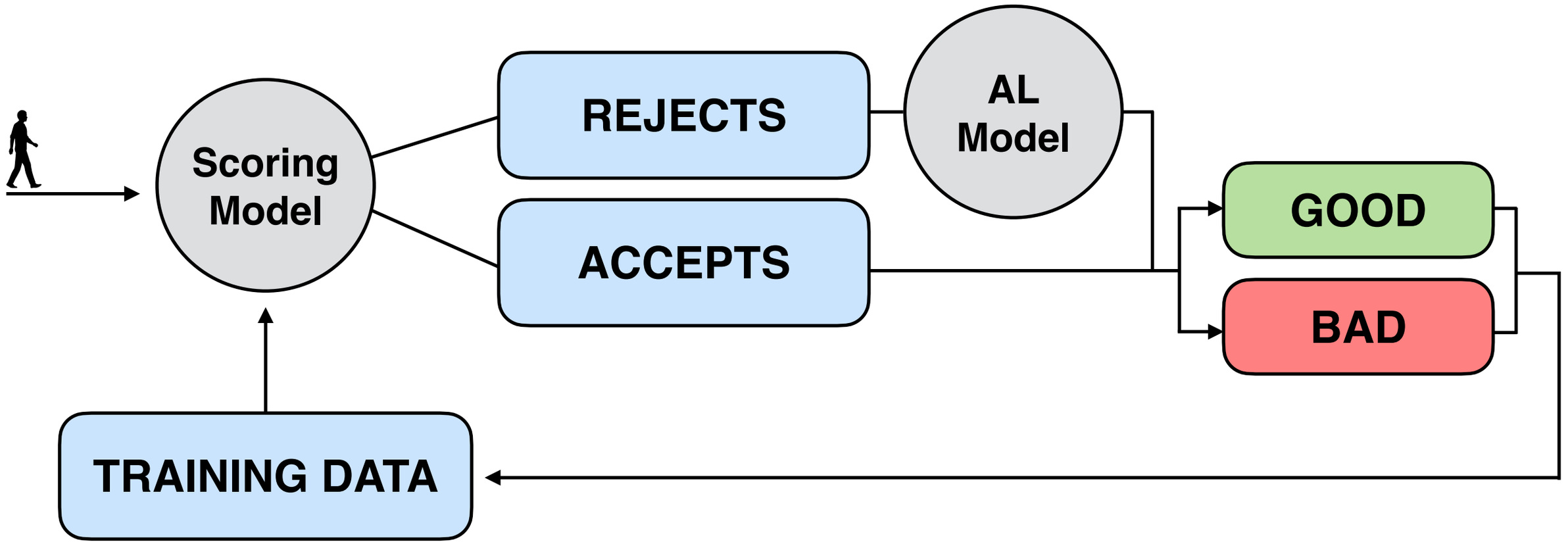
What is Active Learning? [4/4]

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»

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 a high-density neighborhood and high uncertainty

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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:

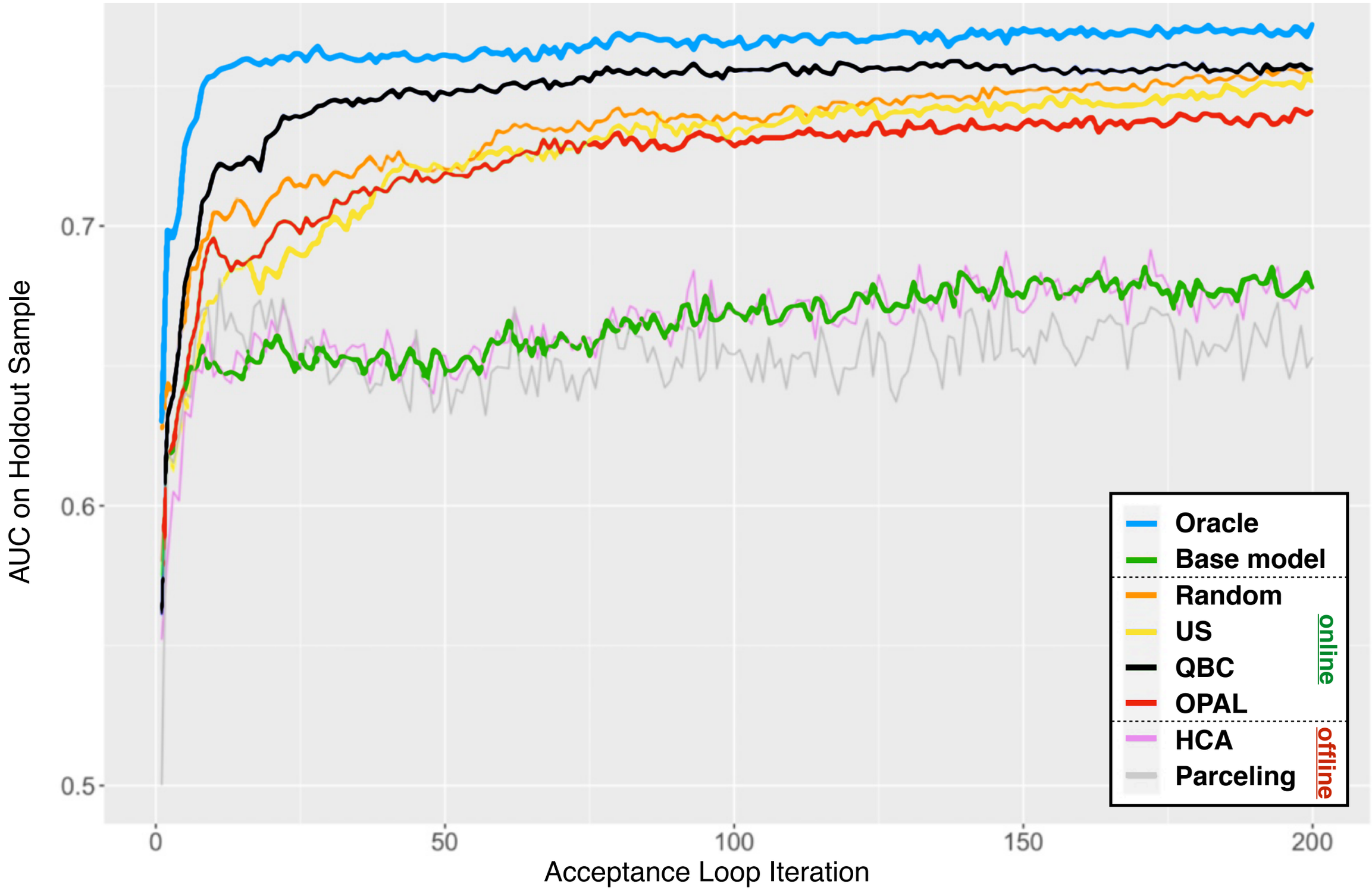
- draw / generate a batch of **new applications**
- **accept a subset** of loan applications
  - select 20% low-risk cases with **ML model**
  - select 10% «useful» cases with **AL model**
- **augment training data** with labeled accepts
- **retrain the scoring model** on new data
- **evaluate** performance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

repeat for 200 iterations

Performance evaluation:

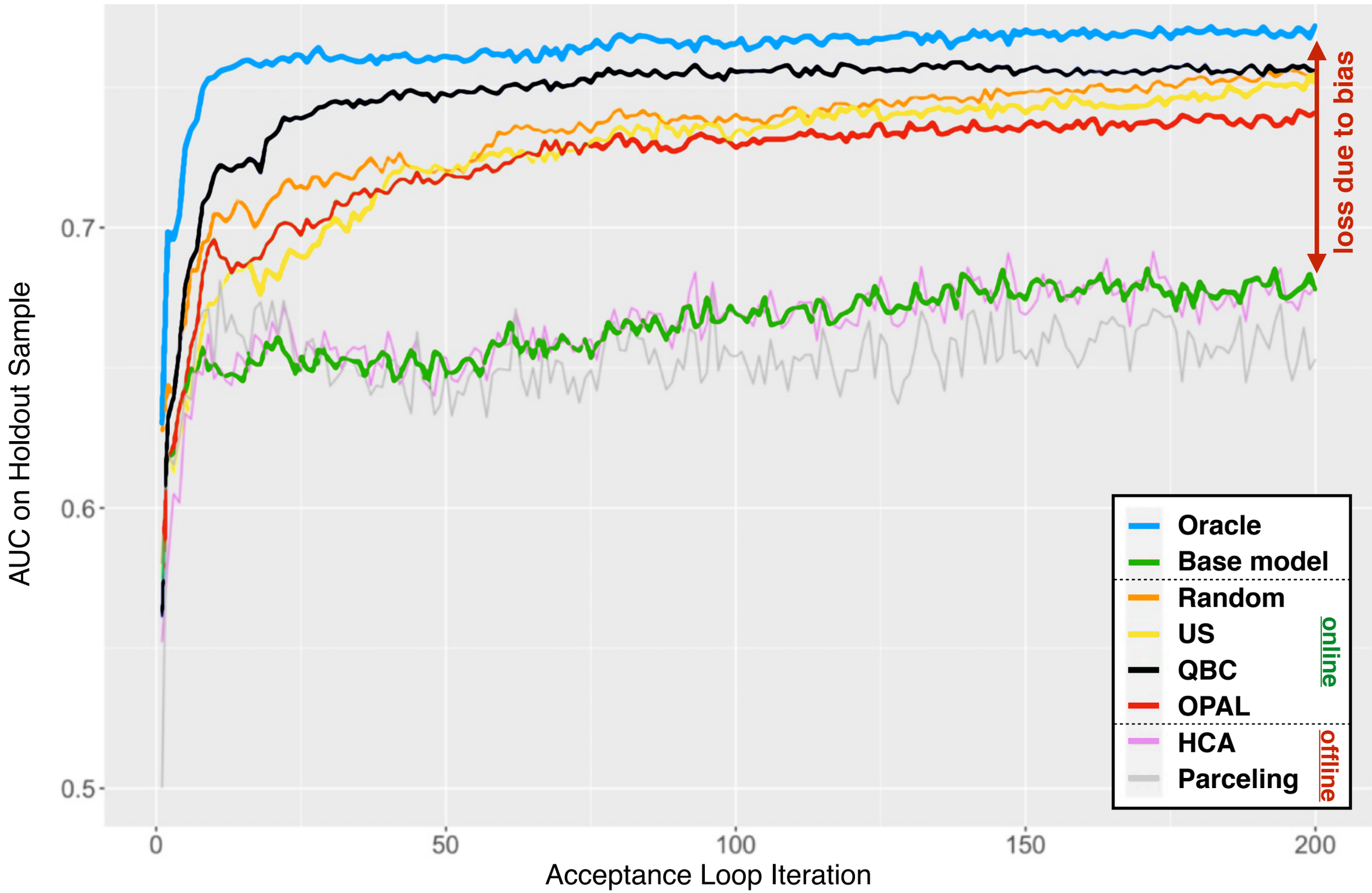
- **two cost / benefit components compared to base model:**
  - **model performance:** improved accuracy of the retrained **ML model**
  - **data augmentation:** accepting extra applicants with the **AL model**

Results: LendingClub [1/3]



AUC = area under the ROC curve; higher is better

Results: LendingClub [2/3]



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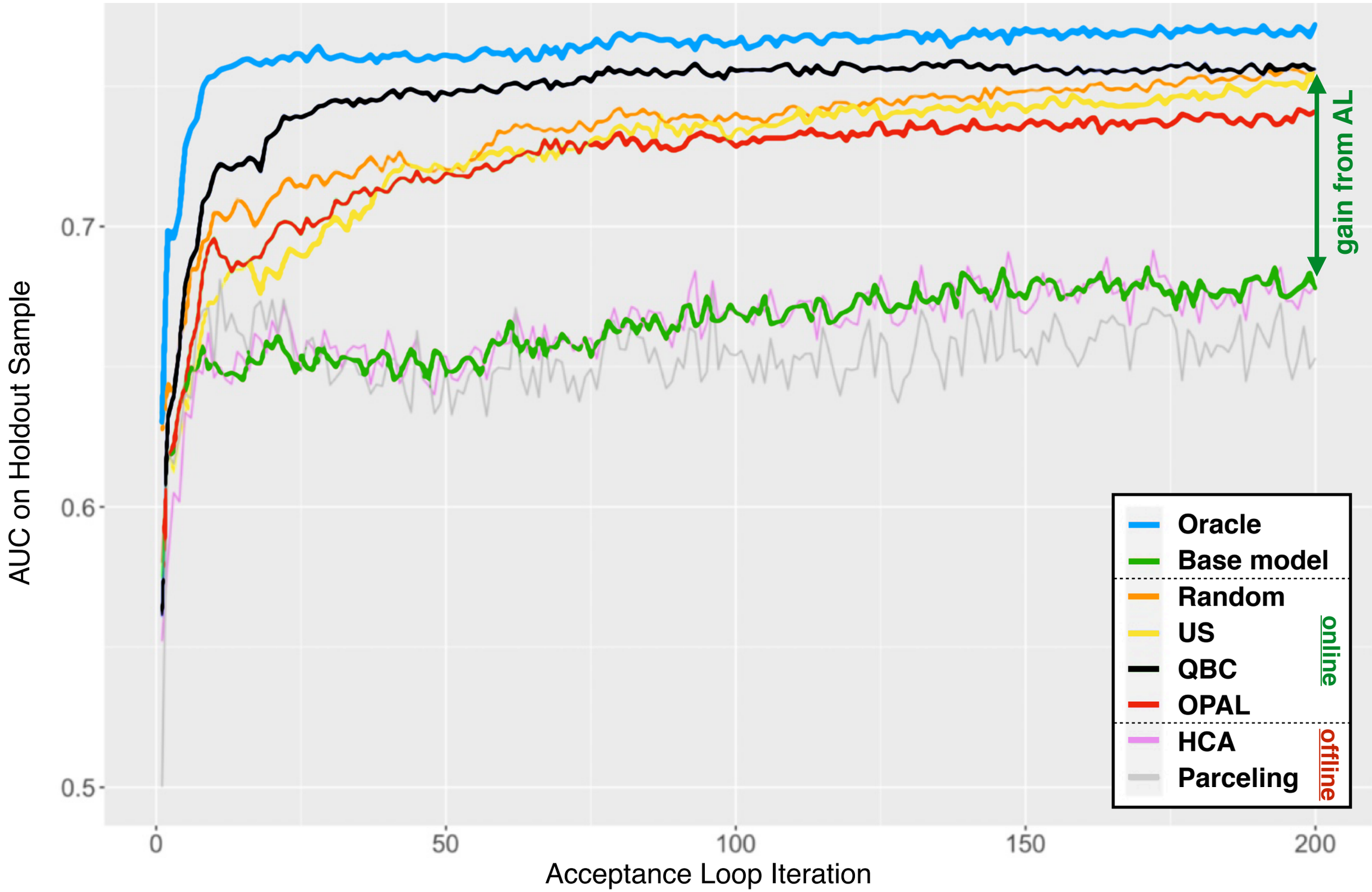

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Model Performance Gains [1/2]

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

Model Performance Gains [2/2]

LendingClub Dataset

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

Synthetic Dataset

Method	AUC gain	BS gain	ABR gain
Random	.025	**.009**	**.897**
US	.026	**.009**	.798
QBC	**.027**	.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
- bold numbers in green indicate the best method per metric

Overall Monetary Gains [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 report average profit per EUR issued

Overall Monetary Gains [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

- **data profit** = profit from assigning loans to applicants selected with AL
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- values report 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 substantially outweigh the model improvement
  - percentage of labeled cases is as 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?

References

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Slides