

Active Learning for Reject Inference in Credit Scoring

Nikita Kozodoi, Stefan Lessmann, Samantha Sizemore

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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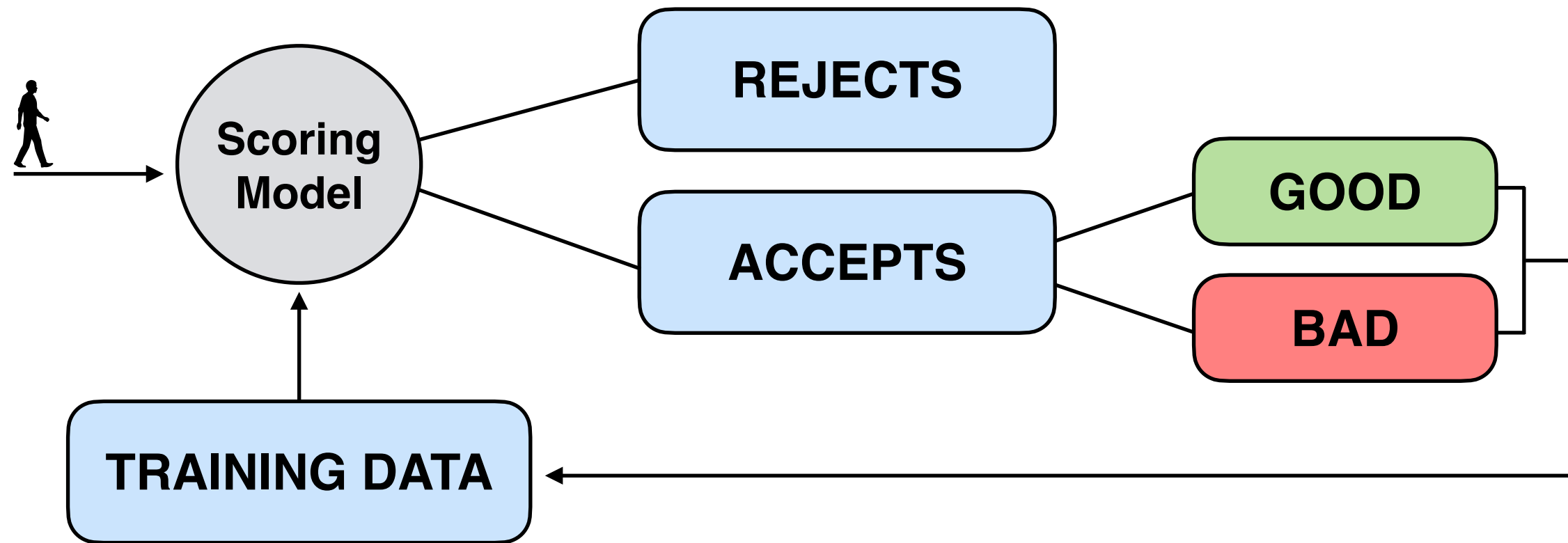
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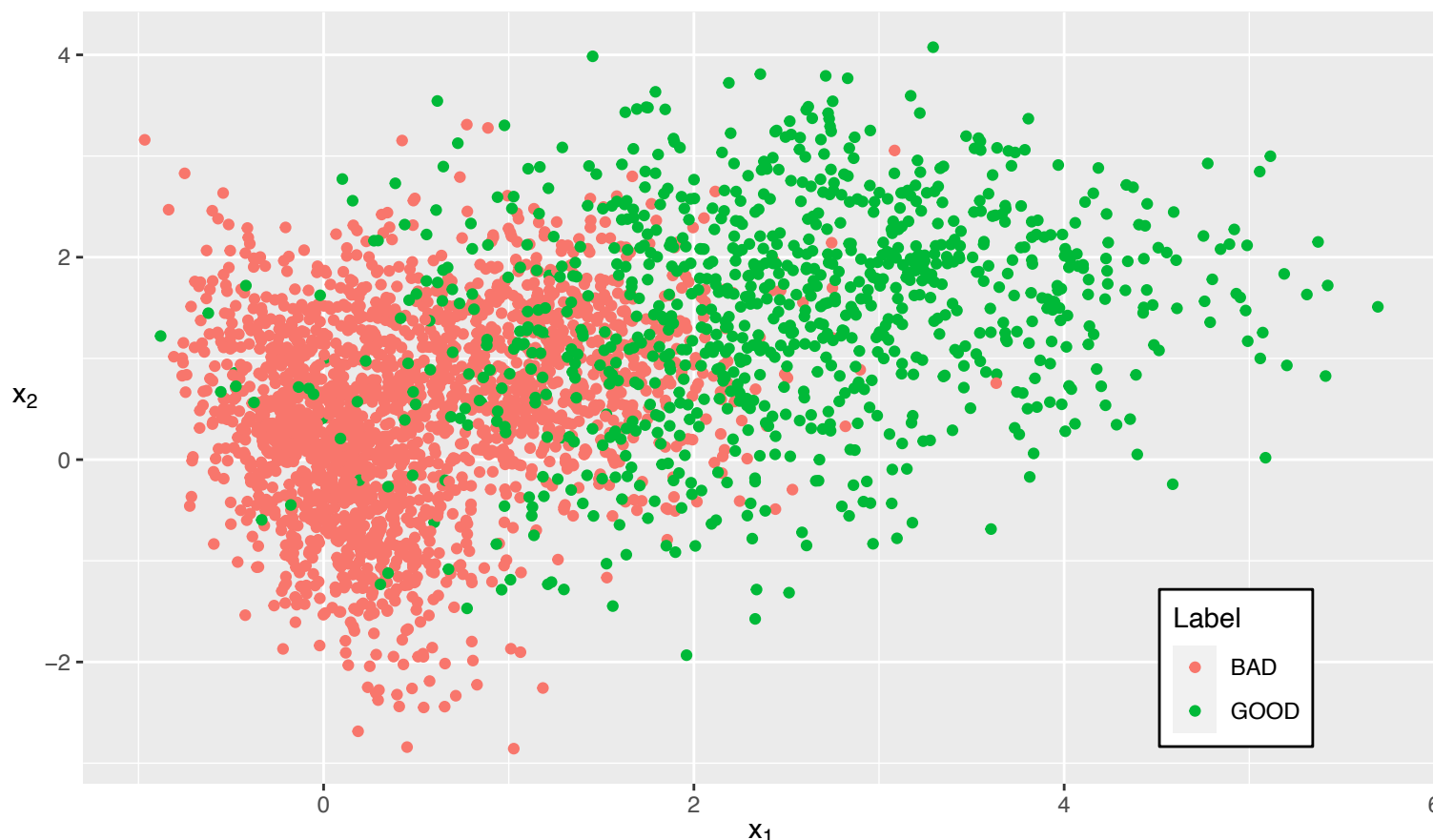
Acceptance Loop in Credit Scoring



- **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

Synthetic data:

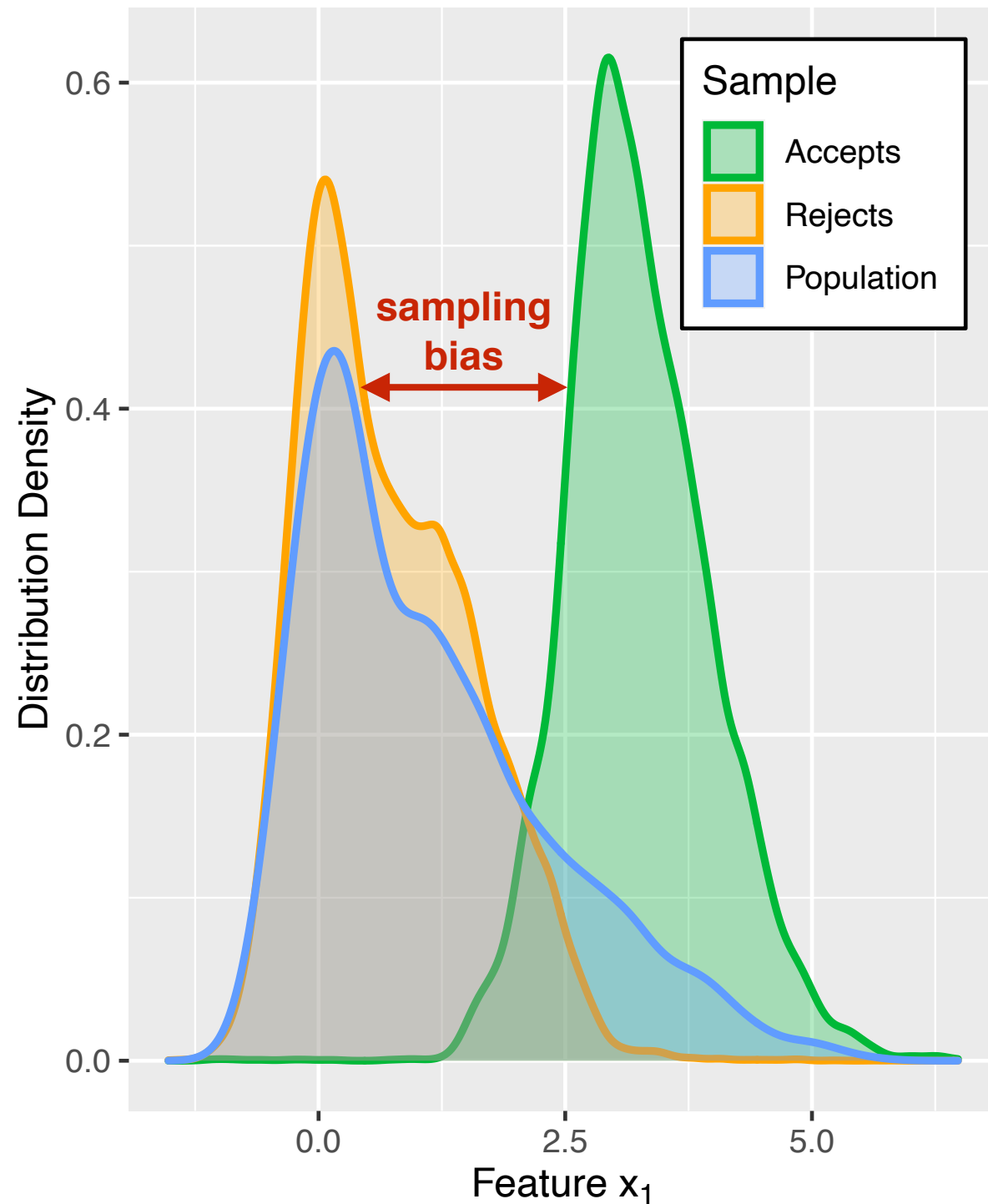
- sampling **GOOD** and **BAD** risks from multivariate Gaussian mixtures
- simulating real-world **acceptance loop**:
 - iteratively generating **batches** of new applications
 - using a scoring model to **accept** and **reject** new applications
 - **updating** the model after learning the labels of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



Sampling Bias Illustration [2/3]



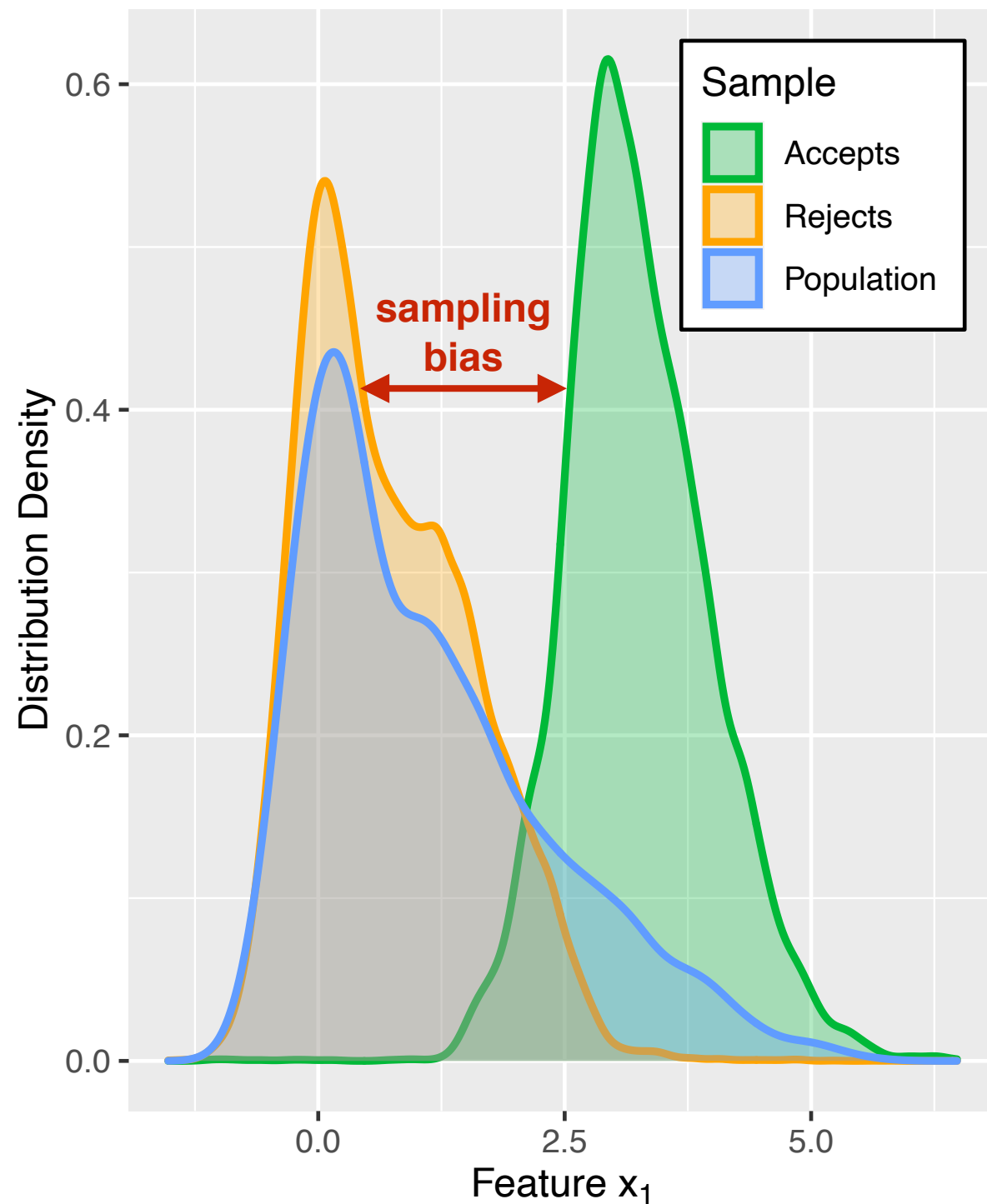
(a) Sampling Bias



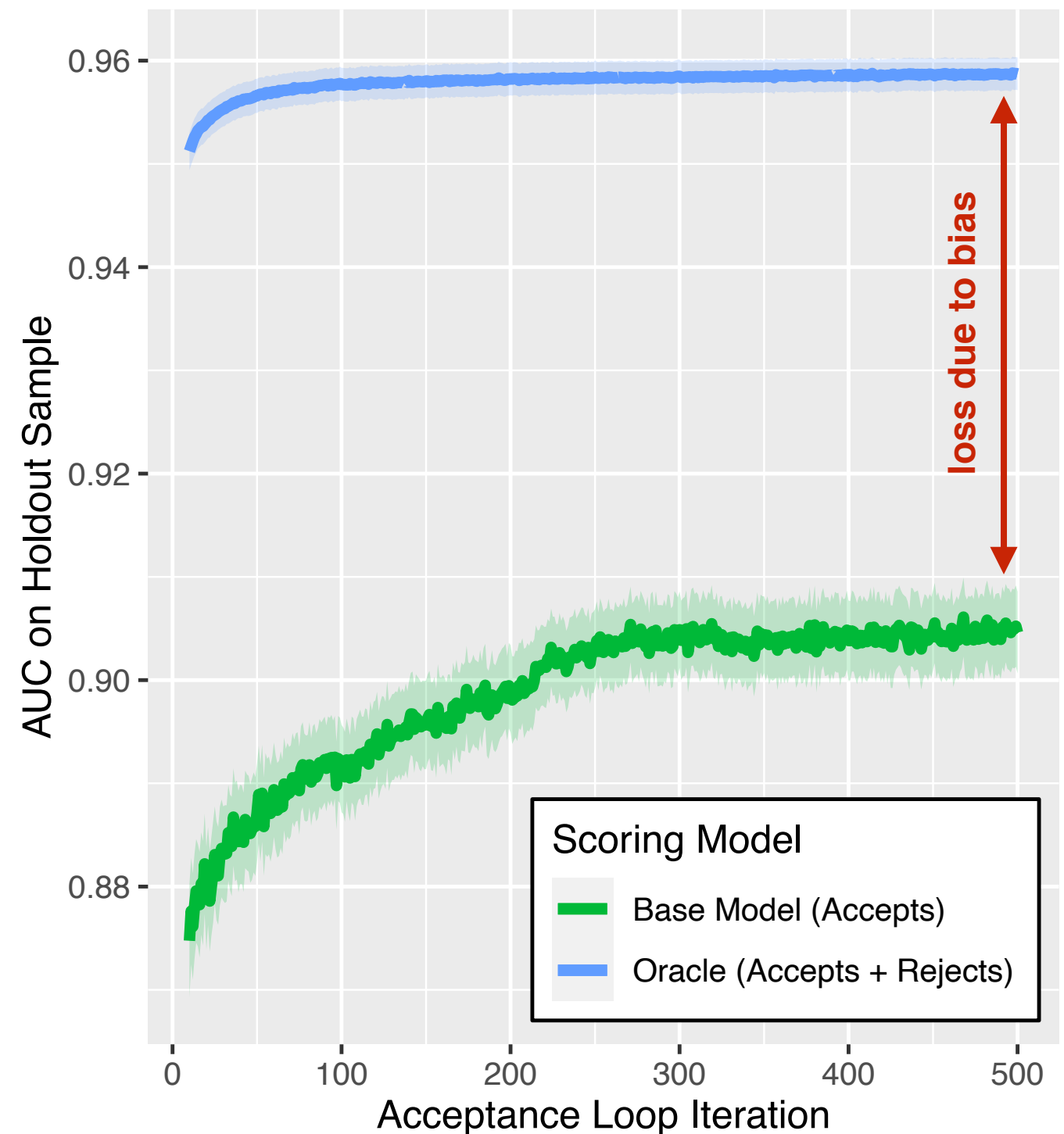
Sampling Bias Illustration [3/3]



(a) Sampling Bias



(b) Impact on Training



AUC = area under the ROC curve; higher is better

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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

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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**

- **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

- **traditional reject inference methods are offline**
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 - actual labels of the **rejects** are never observed
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 - 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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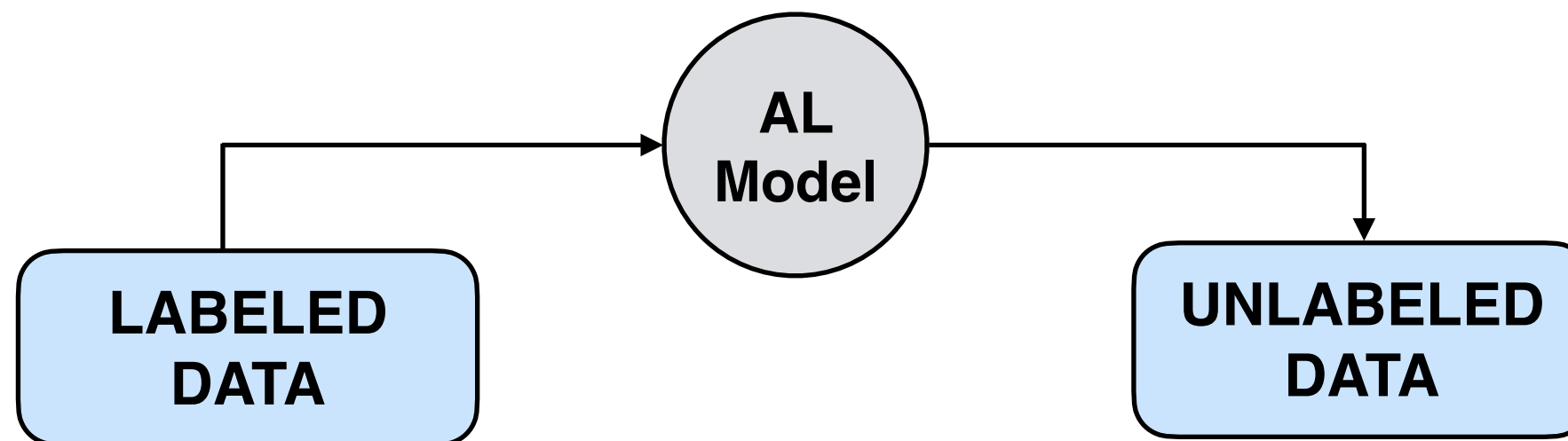
- consider a classification task with labeled and unlabeled data

**LABELED
DATA**

**UNLABELED
DATA**

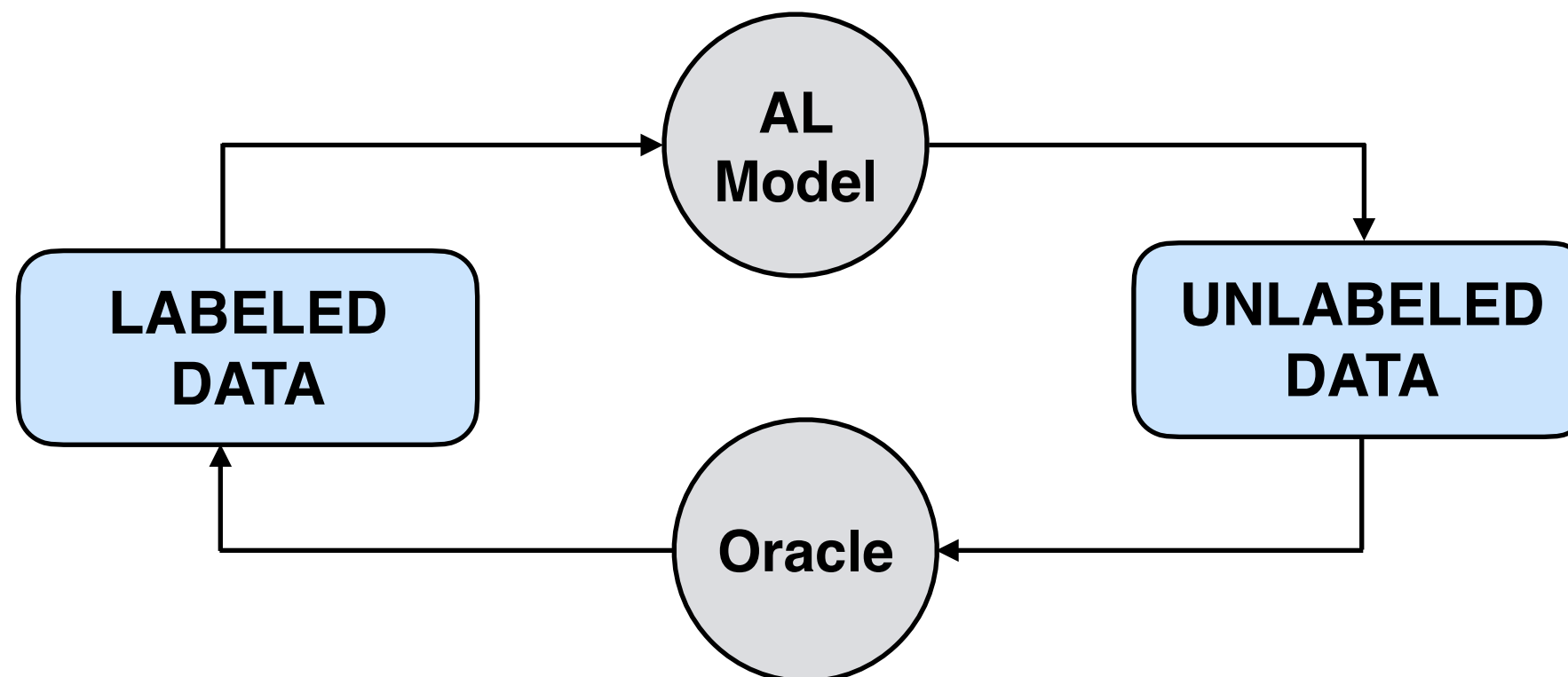
ML framework in which a learning algorithm interactively queries to label currently unlabeled data points

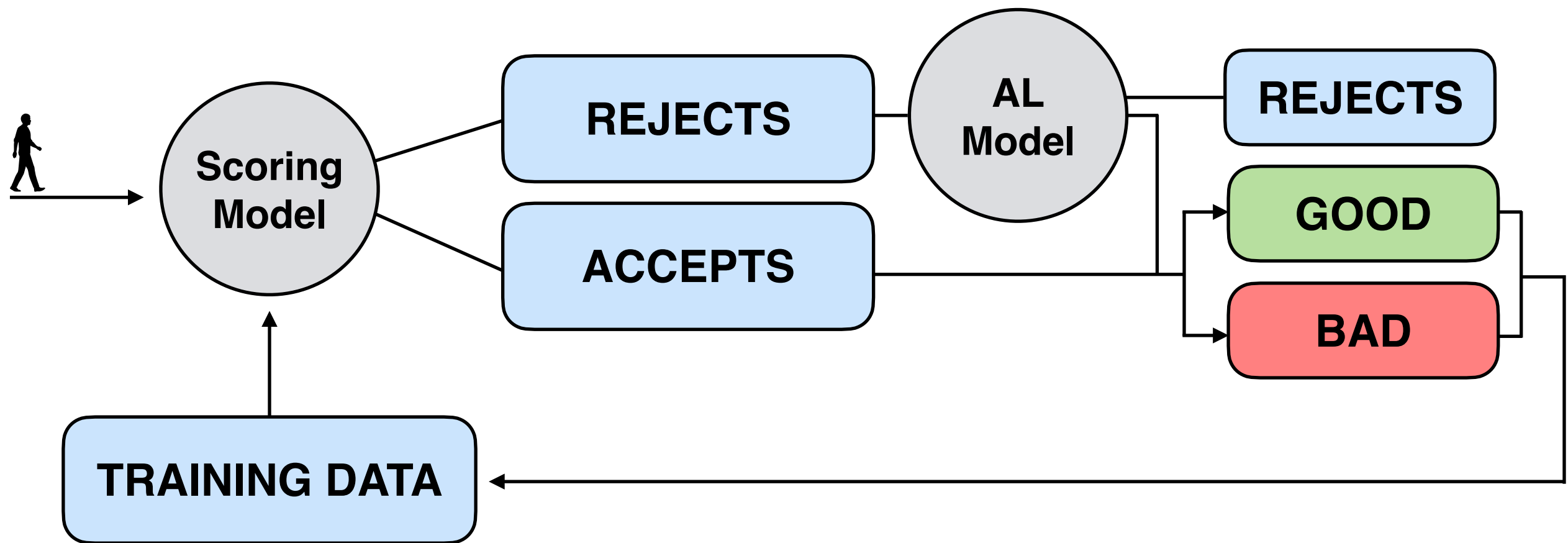
- consider a classification task with labeled and unlabeled data
- AL identifies “**most interesting**” unlabeled data points
 - which observations would improve classifier performance if they had labels?
 - can be measured as **uncertainty**, **correlation**, **expected error decrease**, etc.



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





- **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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- Active learning for «online» reject inference

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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 %

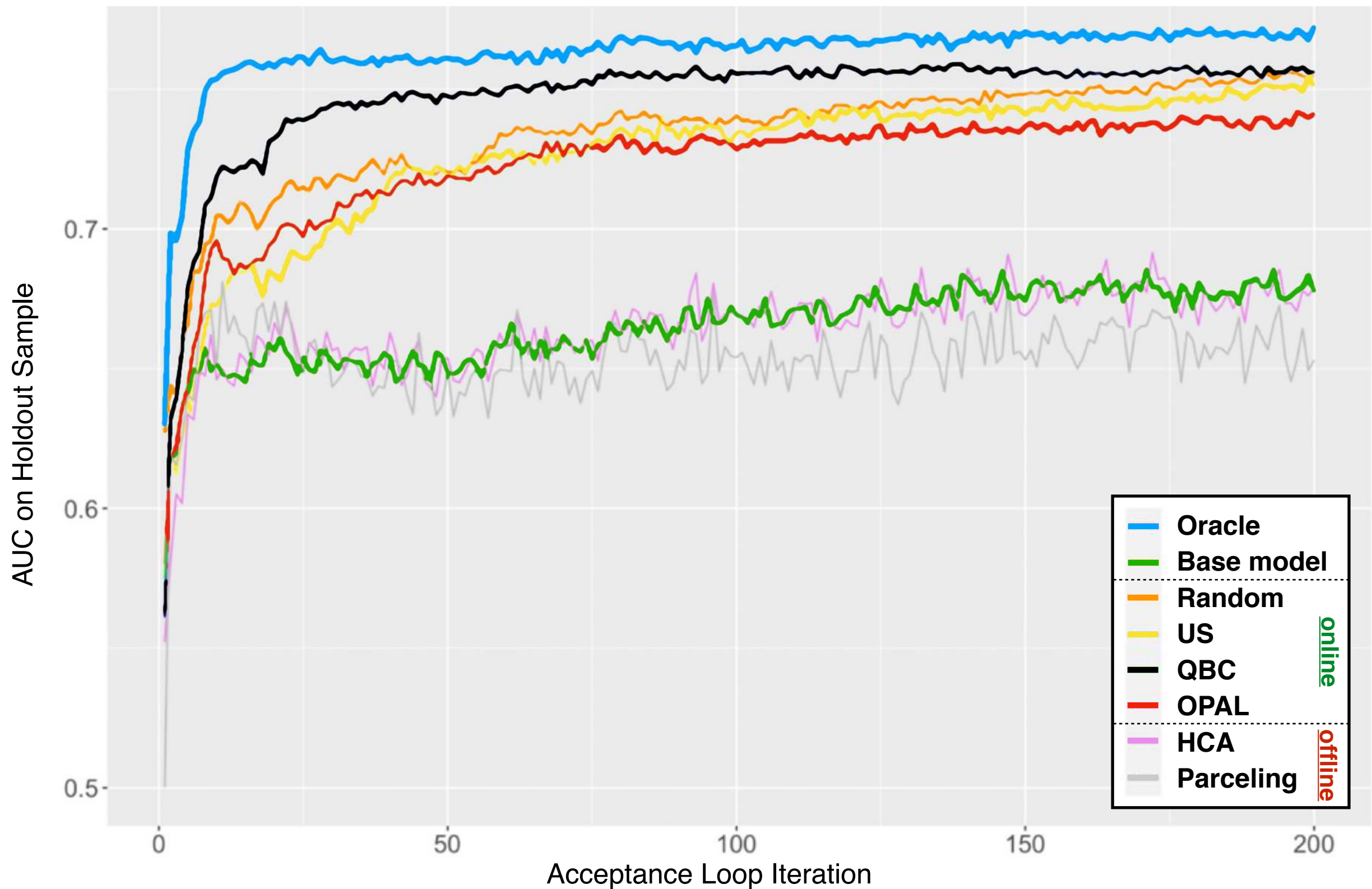
Acceptance loop:

- 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:

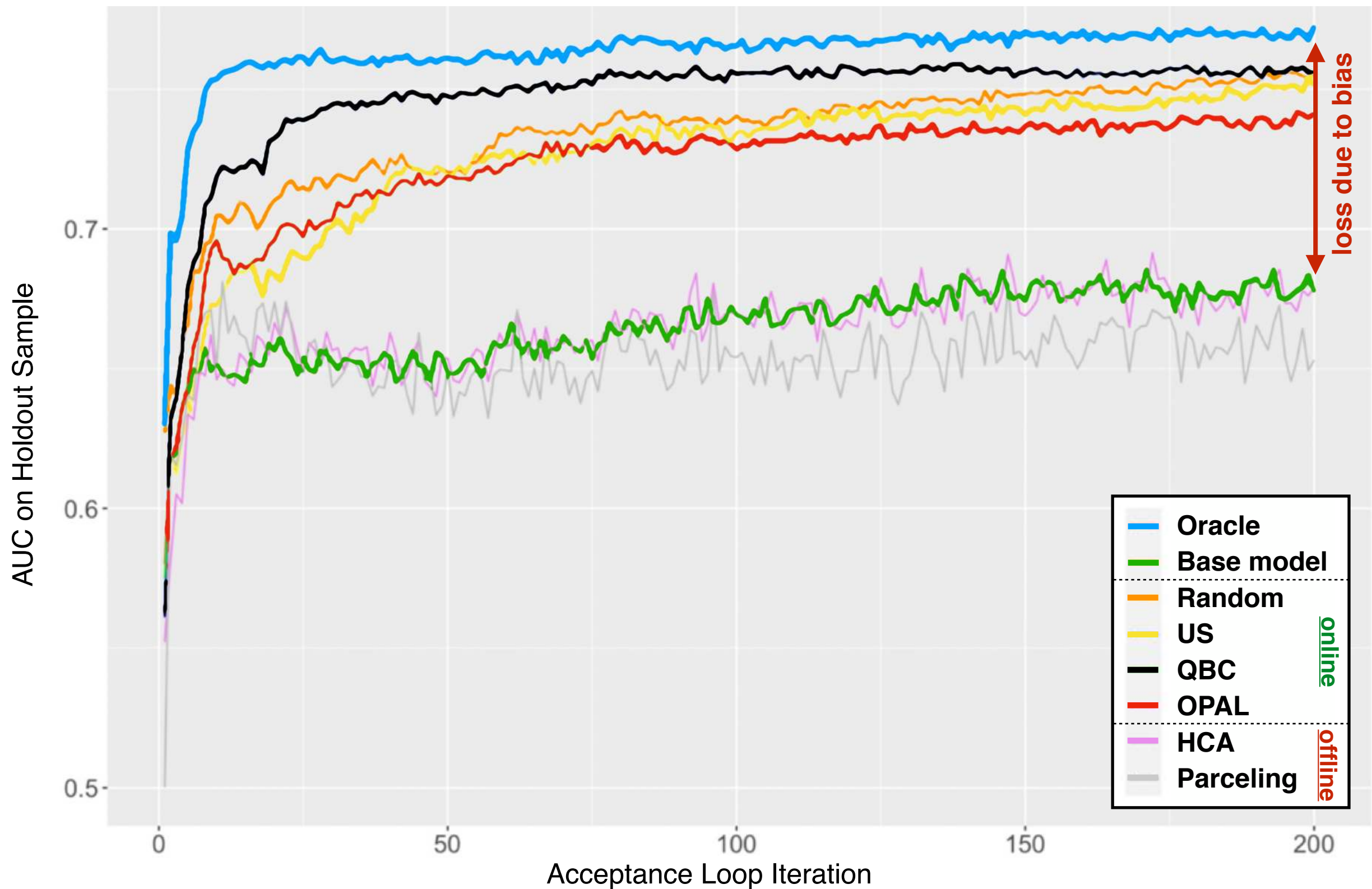
- **two cost / benefit components compared to base model:**
 - **model performance:** improved accuracy of the retrained **ML model**
 - **data augmentation:** accepting extra applicants with the **AL model**

Results: LendingClub [1/3]



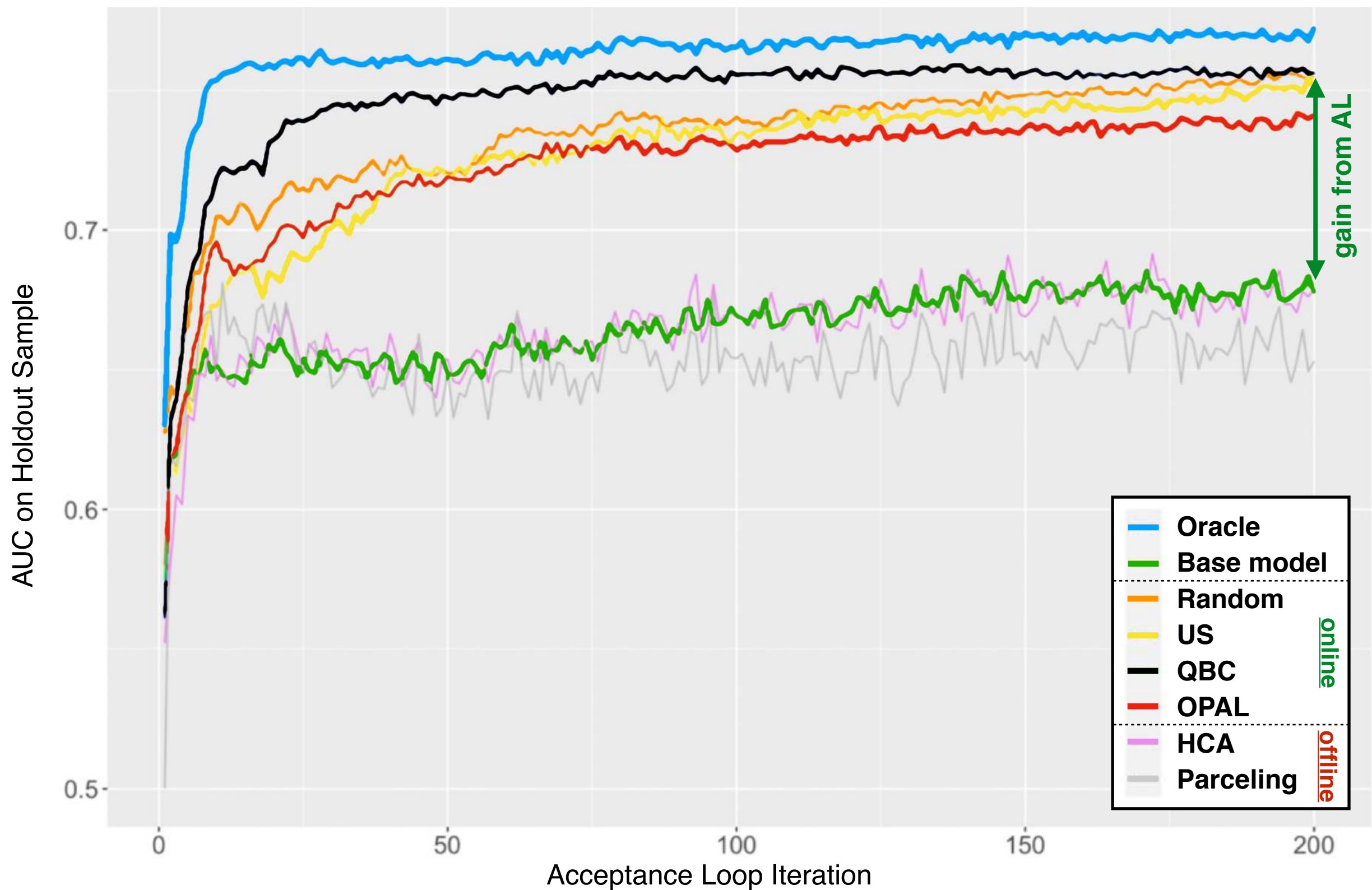
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Results: LendingClub [2/3]



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	.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
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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			
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- **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	.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

- **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?

Banasik, J., Crook, J., & Thomas, L. (2003). **Sample selection bias in credit scoring models.** Journal of the Operational Research Society, 54(8), 822-832.

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Slides

