Selective Regression Under Fairness Criteria



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Prediction with a reject-option



Prediction with a reject-option

its predictions.

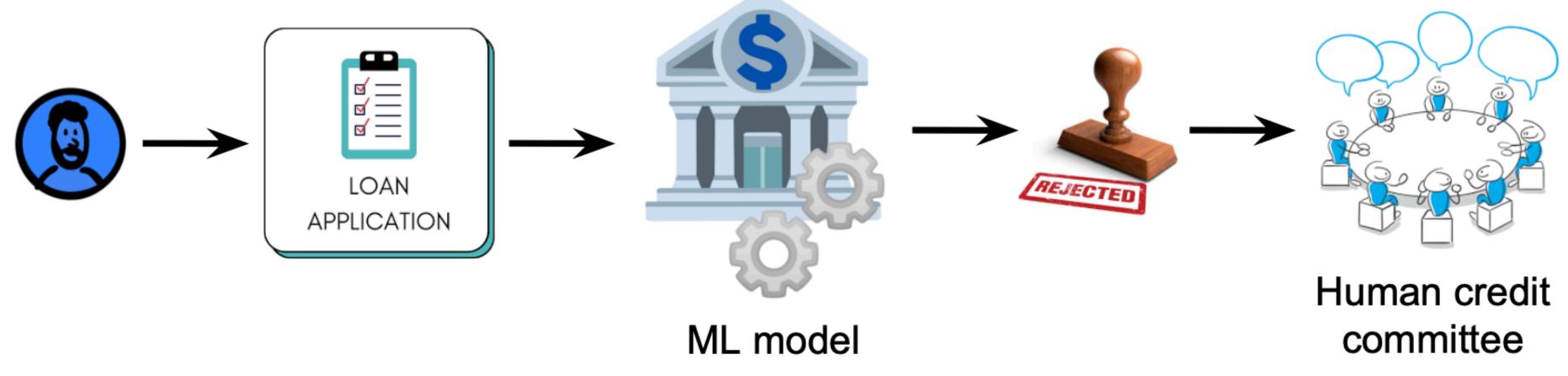
Selective Prediction

• A trustworthy machine learning system \rightarrow reliably communicate the uncertainty in



Prediction with a reject-option

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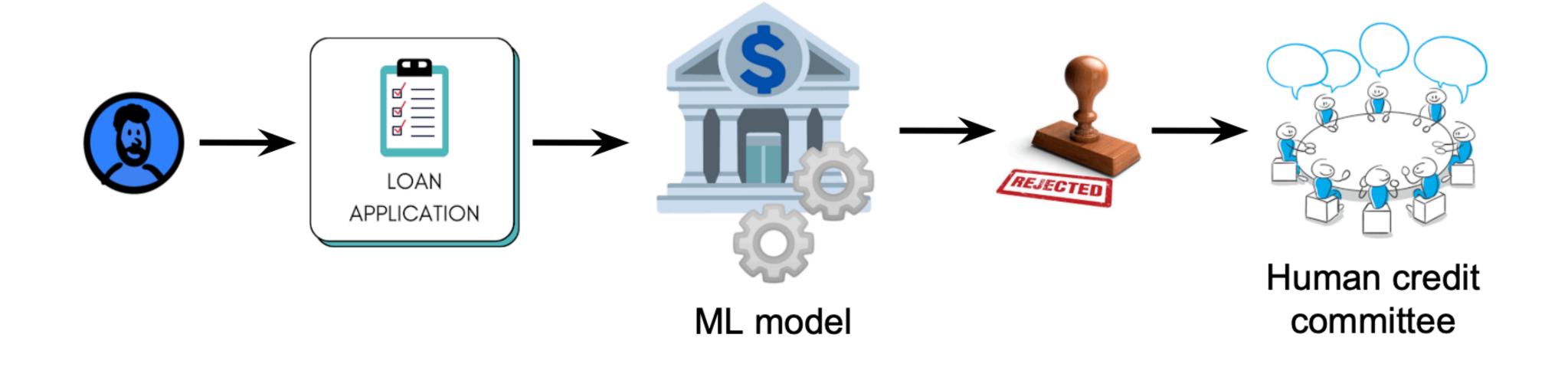
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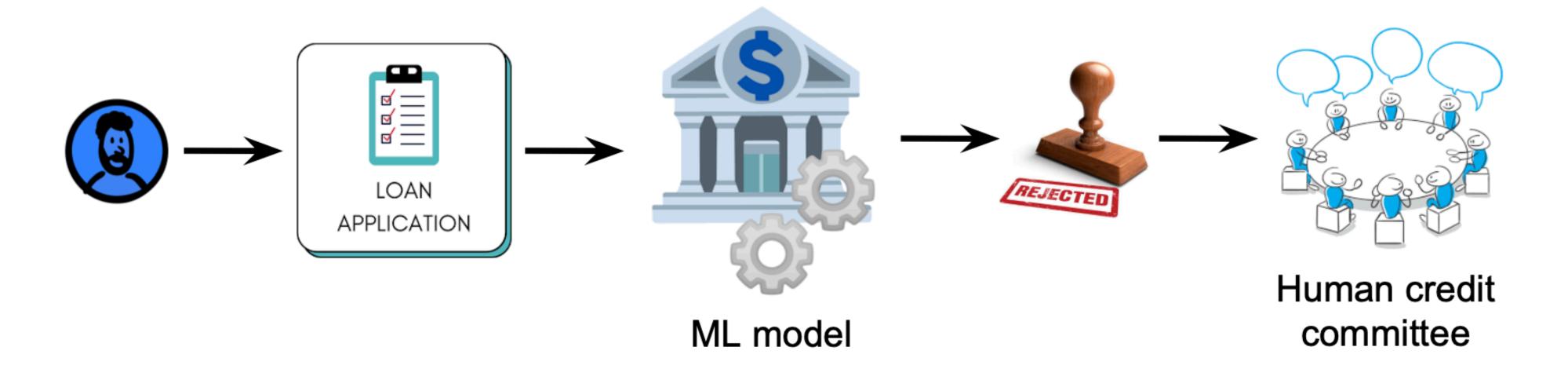


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- If the uncertainty in a prediction is high \rightarrow the prediction can be rejected to avoid potentially costly errors.
- Selective prediction \rightarrow can abstain from making a decision

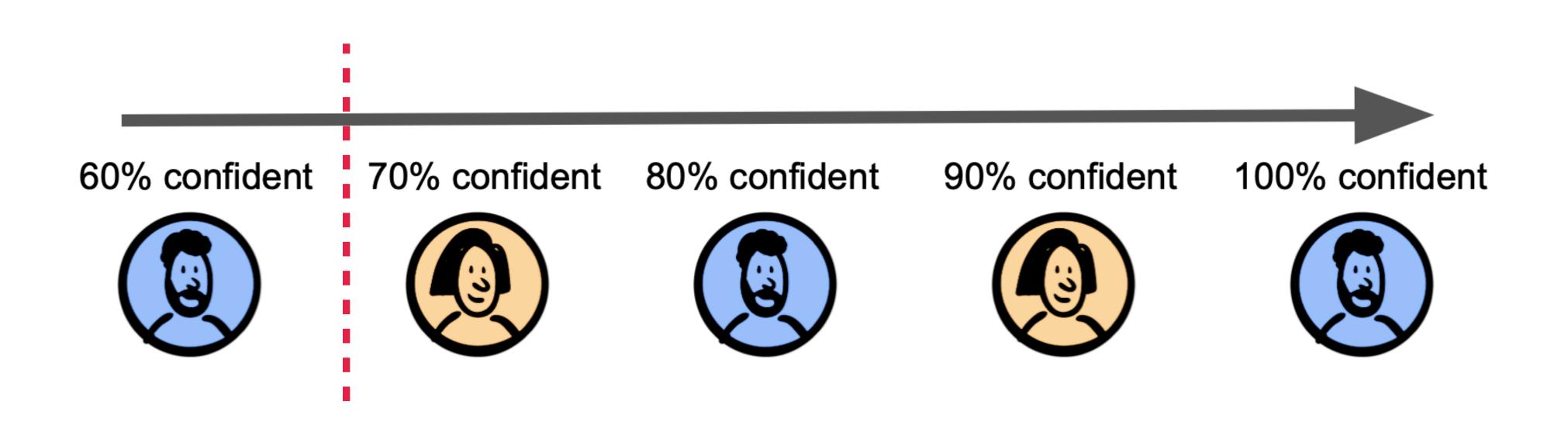


Prediction with a reject-option

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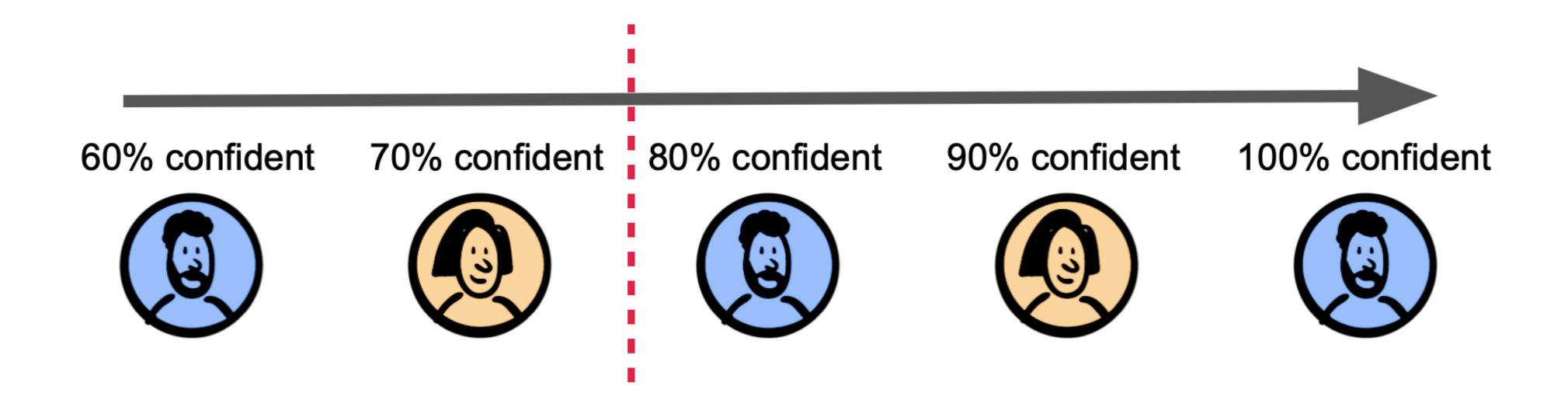


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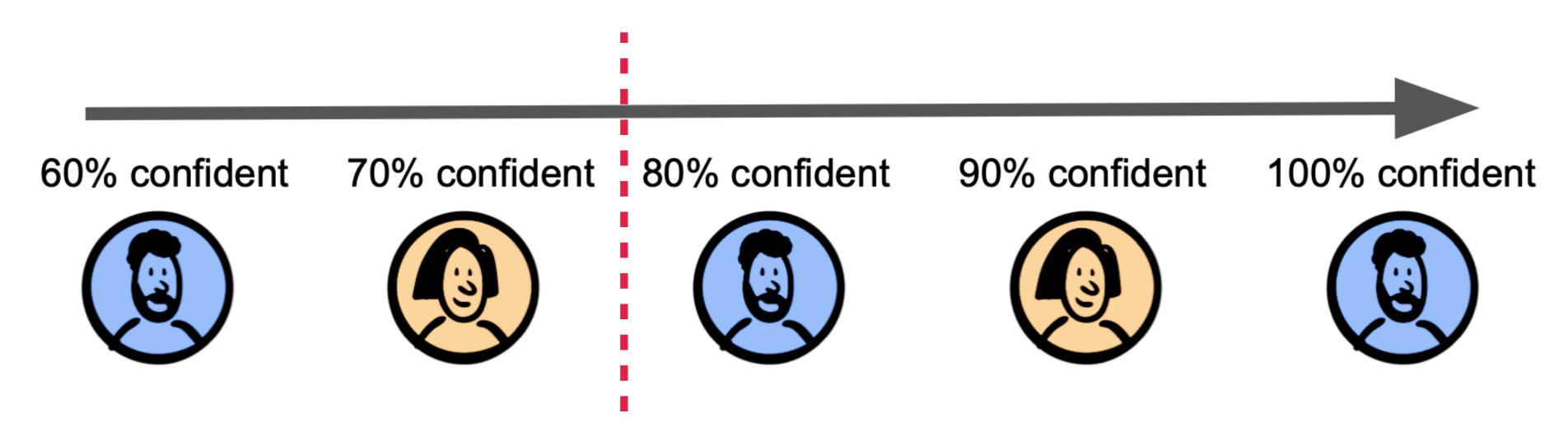


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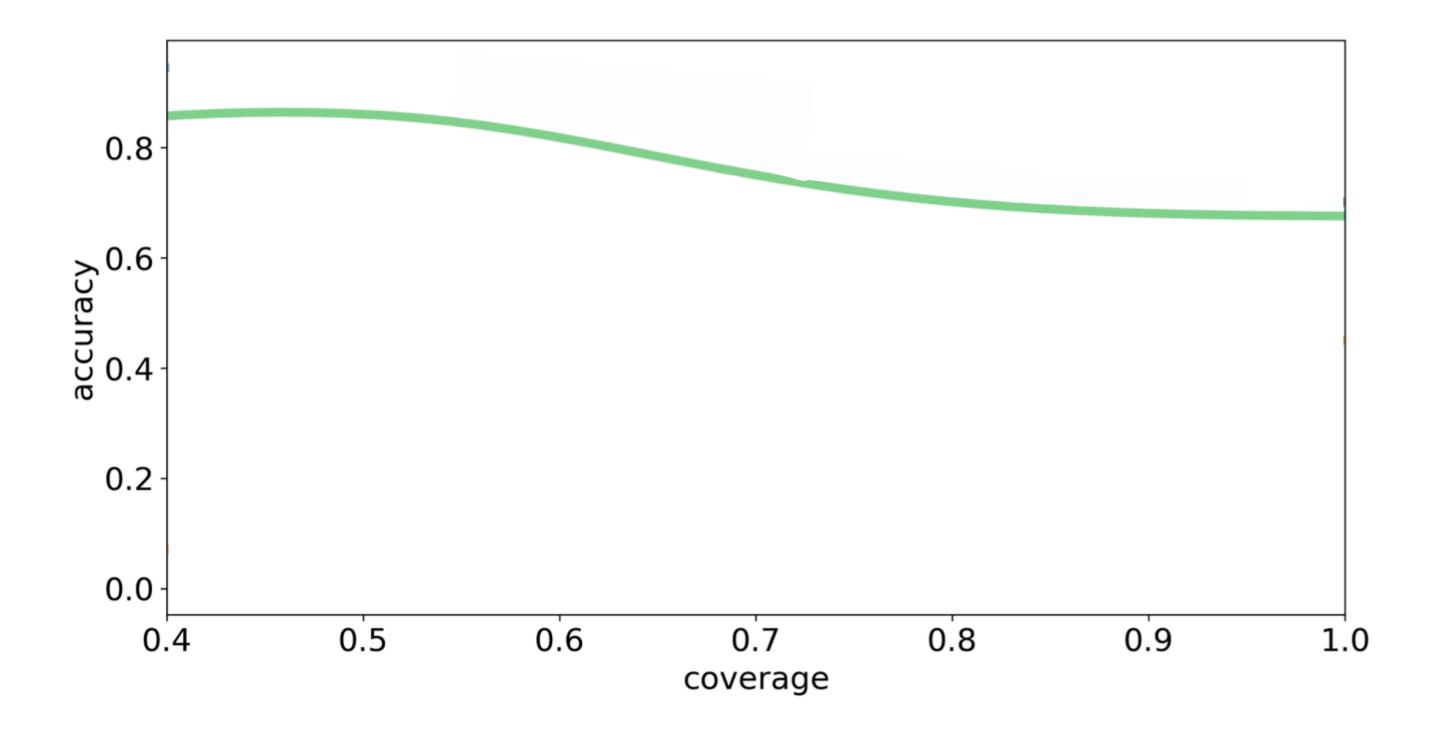
Prediction with reject-option

- confidence is below a certain threshold.
- With a good confidence measure \rightarrow increasing the threshold results in a better performance.
- Tradeoff \rightarrow we have predictions for a fewer samples (i.e., low coverage).



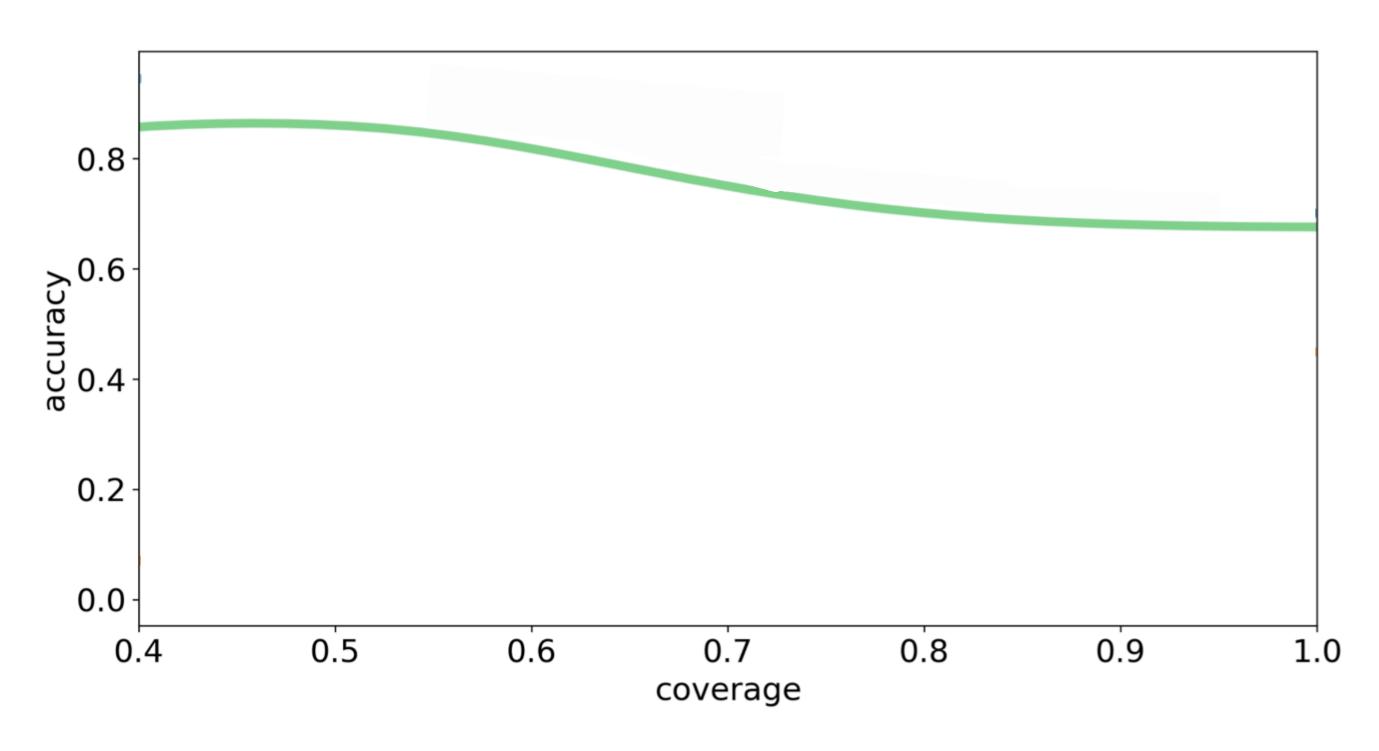
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Selective Classification Prior Work



Selective Classification

protected / sensitive groups [Jones et al. 2020].

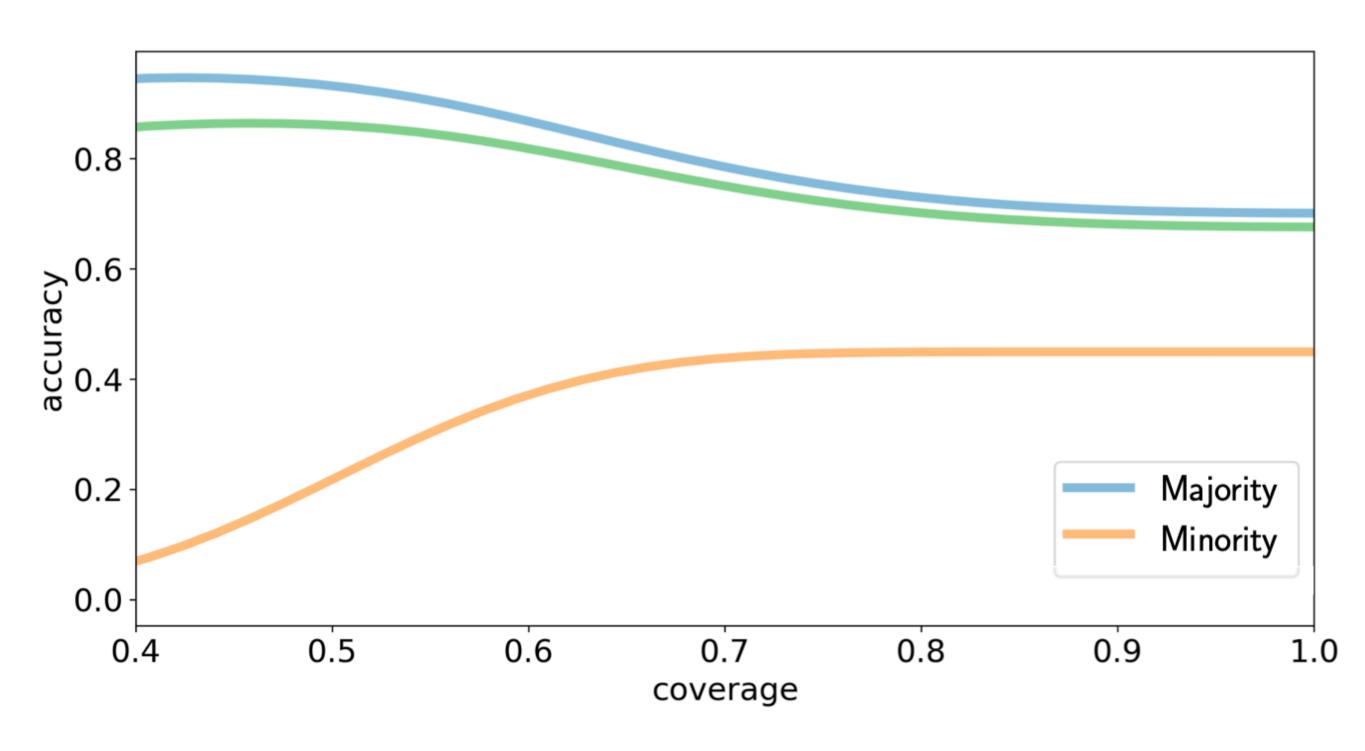


Prior Work

• Classifiers can have good average performance but may perform poorly on certain

Selective Classification

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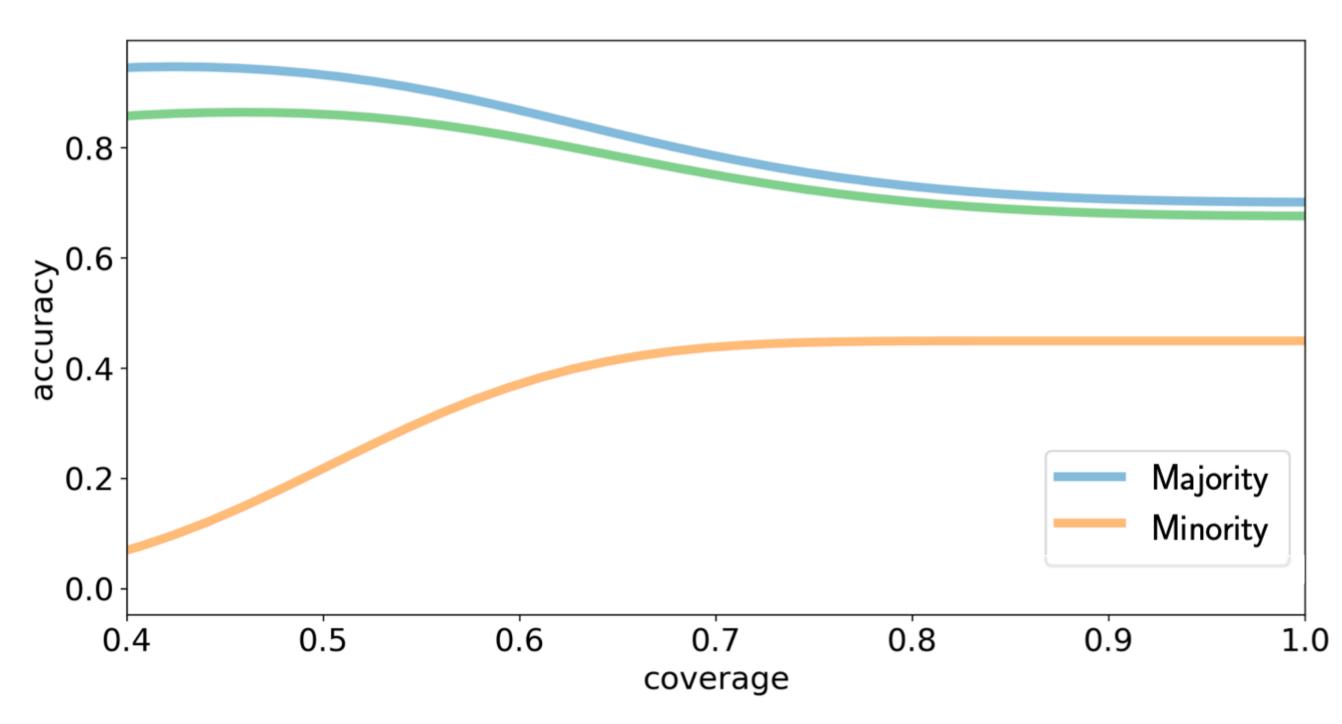


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proposed methods for performing fair selective classification.

Prior Work

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• To mitigate such disparities, recent works [Lee et al., 2021; Schreuder & Chzhen, 2021]

Designing an Uncertainty measure



Selective Regression Designing an Uncertainty measure

Classification \rightarrow learned using the softmax output (of an existing classifier)

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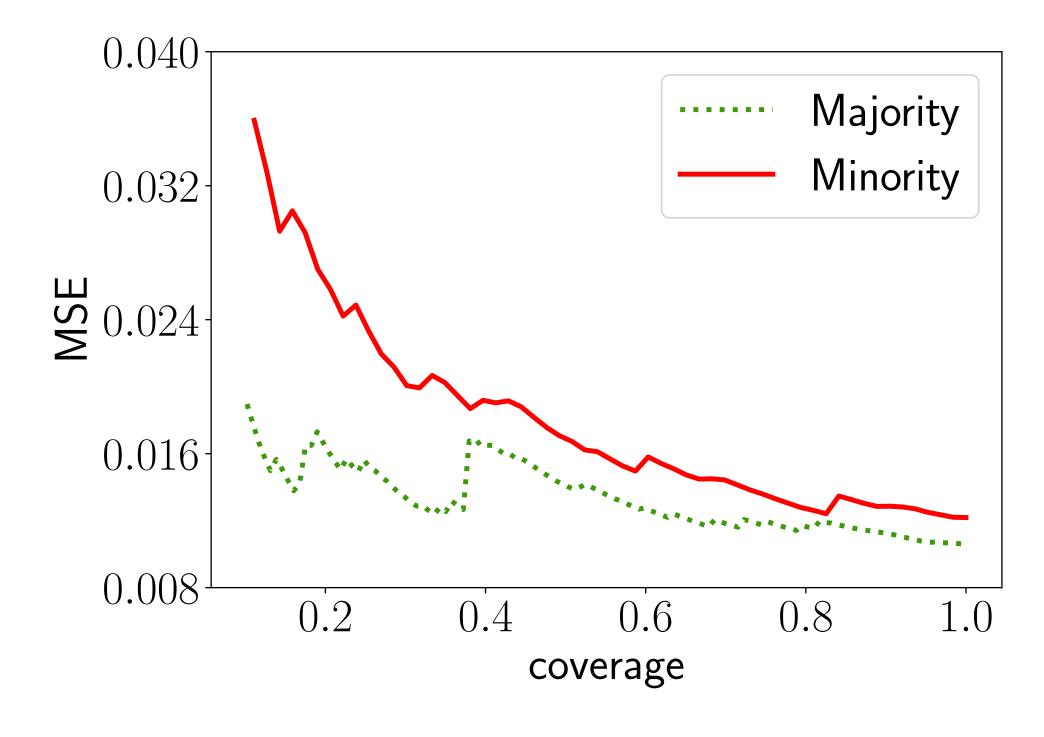
predict the conditional mean

- Regression \rightarrow no direct method to learn from an existing regressor designed only to

Biases in Selective Regression Contributions

Biases in Selective Regression Contributions

• We show that selective regression, like selective classification, can decrease the performance of some protected groups when coverage is reduced.



Insurance dataset

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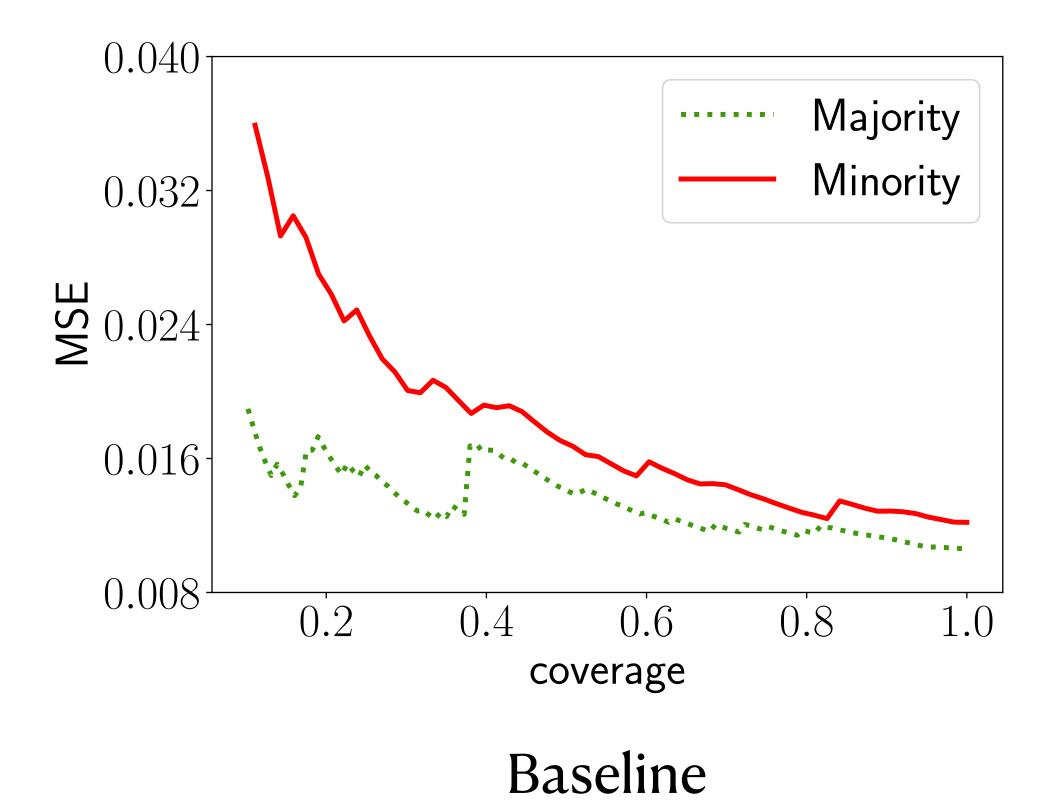
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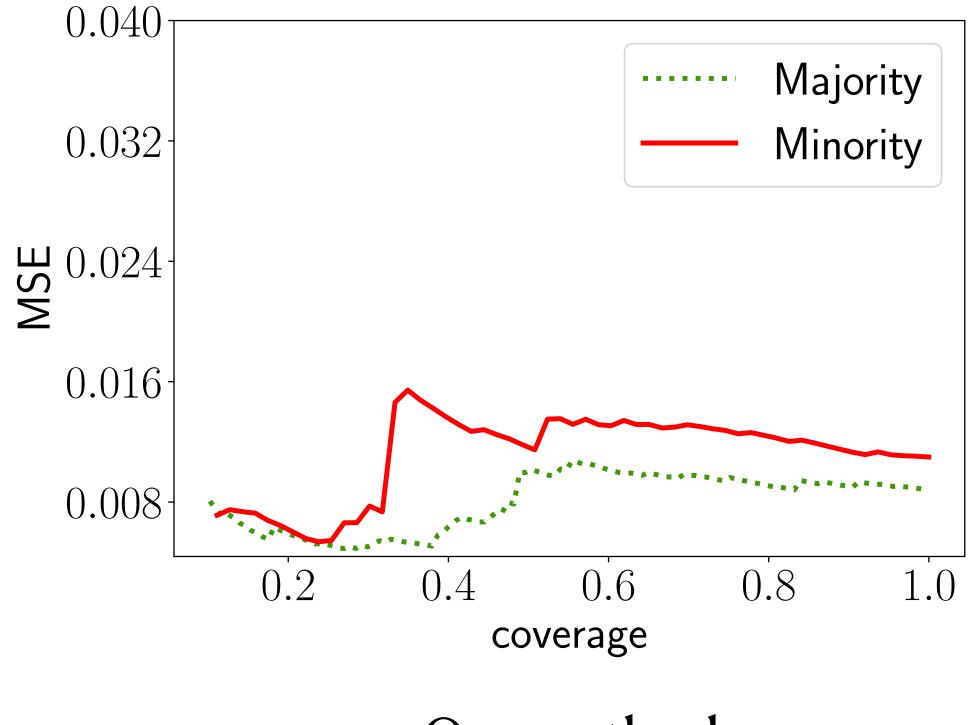
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- Two algorithms:
 - 1. impose the sufficiency criterion by regularizing an upper bound of conditional mutual information.
 - 2. impose the calibration for mean and variance by regularizing a contrastive loss.

Empirical Results Insurance dataset

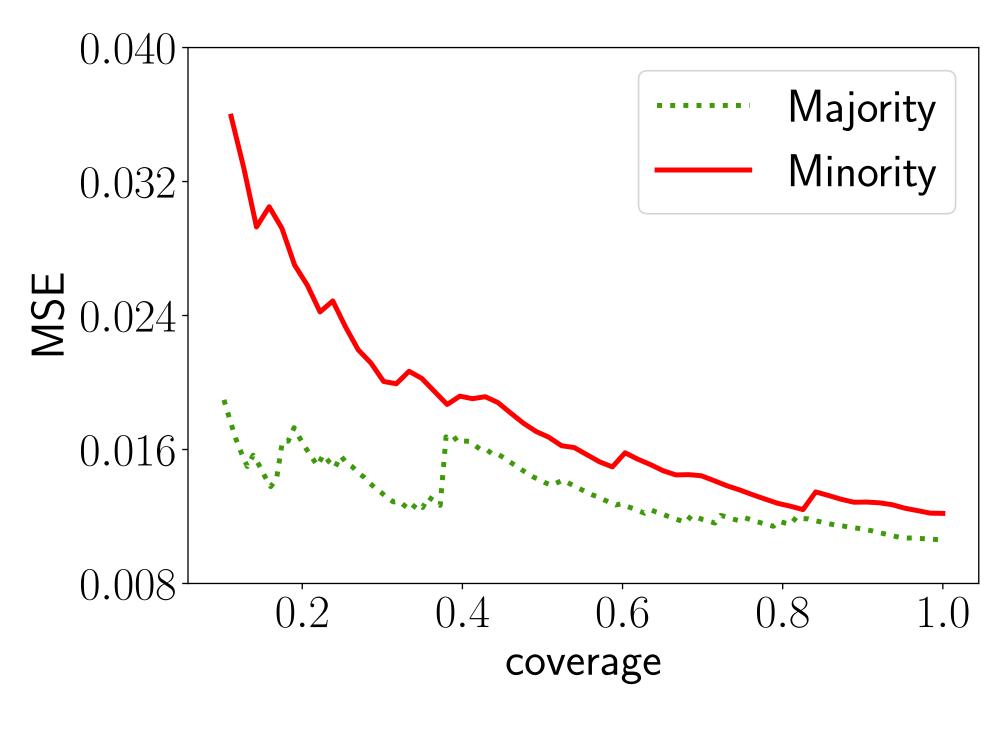
Empirical Results Insurance dataset



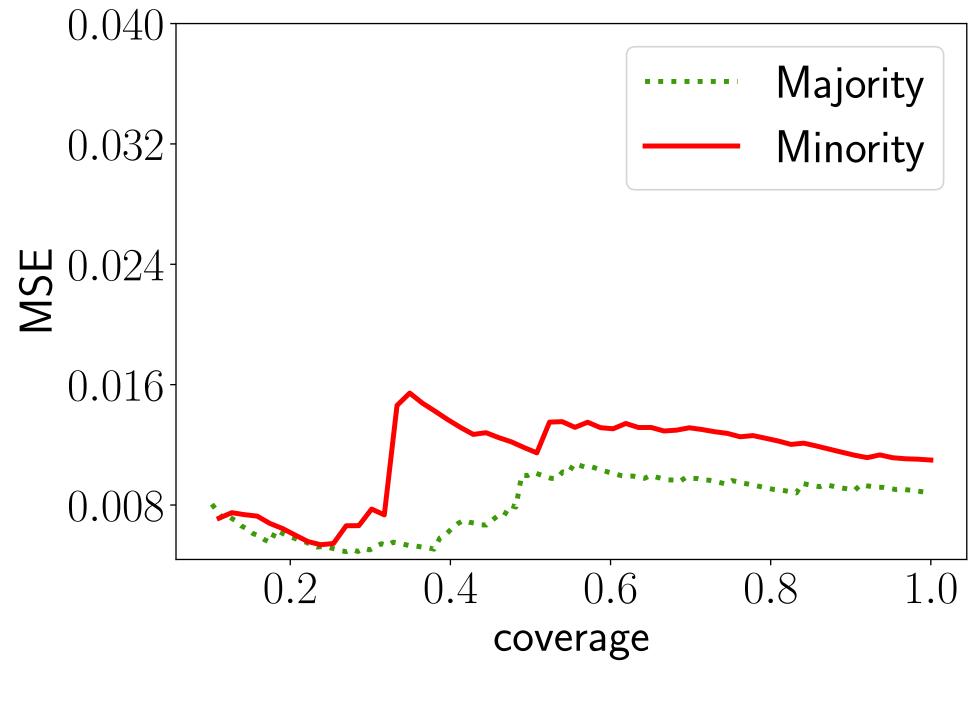


Our method

Empirical Results Insurance dataset



Baseline



Our method

Poster #1108