Adaptive Query Algorithms for Efficiently Discovering Overconfident Unknowns

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Who am I?

Karsten Maurer

- Minnesota, Morris for BA in History and Statistics
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- Currently an Assistant Professor of Statistics at Miami University

- Teaching: Data Visualization, Predictive Modeling, Statistical Programming
- Research: Statistics Education, Machine Learning, Visualization, Collaborative Consulting

Overview of Today's Talk

Unknown Unknowns

- Exisiting Literature on Utility-Based Query Algorithms
- Deficiencies in Existing Methods

Facility Locations Search Algorithm

- Adapting Utility Objectives to Overcome Deficiencies
- Facility Locations Utility Function
- Greedy Adaptive Query Algorithm
- Empirical Experiment Results

Adversarial Distances for Unsupervised Query Set Selection

- Objective and Intuition
- Adversarial Distance-Based Query Algorithm
- Empirical Experiment Results

Discussion

- Conclusions, Current Work and Future Work

Unknown Unknowns

Unknown Unknowns

Context: You have a classifier that you wish to apply to a domaine in which you only have access to a large set of unlabeled test instances.

Problem: You know that the classifier was trained in a different domaine, or you suspect a bias in the training set relative to the testing

Goal: Select a set of instances from the unlabeled set that we will look up true labels which we use to evaluate the classifier performance. This is called a *query* of the unlabeled set.

An *oracle* is the person who will find the true labels. We don't want to waste the oracle's time, so we need a smart way to query the unlabeled set.

Unknown Unknowns

What are we looking for in the query set?

Attenberg et al. (2015) define *Unknown Unknowns* (UUs) as instances, x, from unlabeled test set where the classifier, $M(\cdot)$, is both:

- Highly confident. Above some threshold $\tau \in (0, 1)$. Thus, $C_x \geq \tau$
- Wrong. Misclassified with $y \neq M(x)$

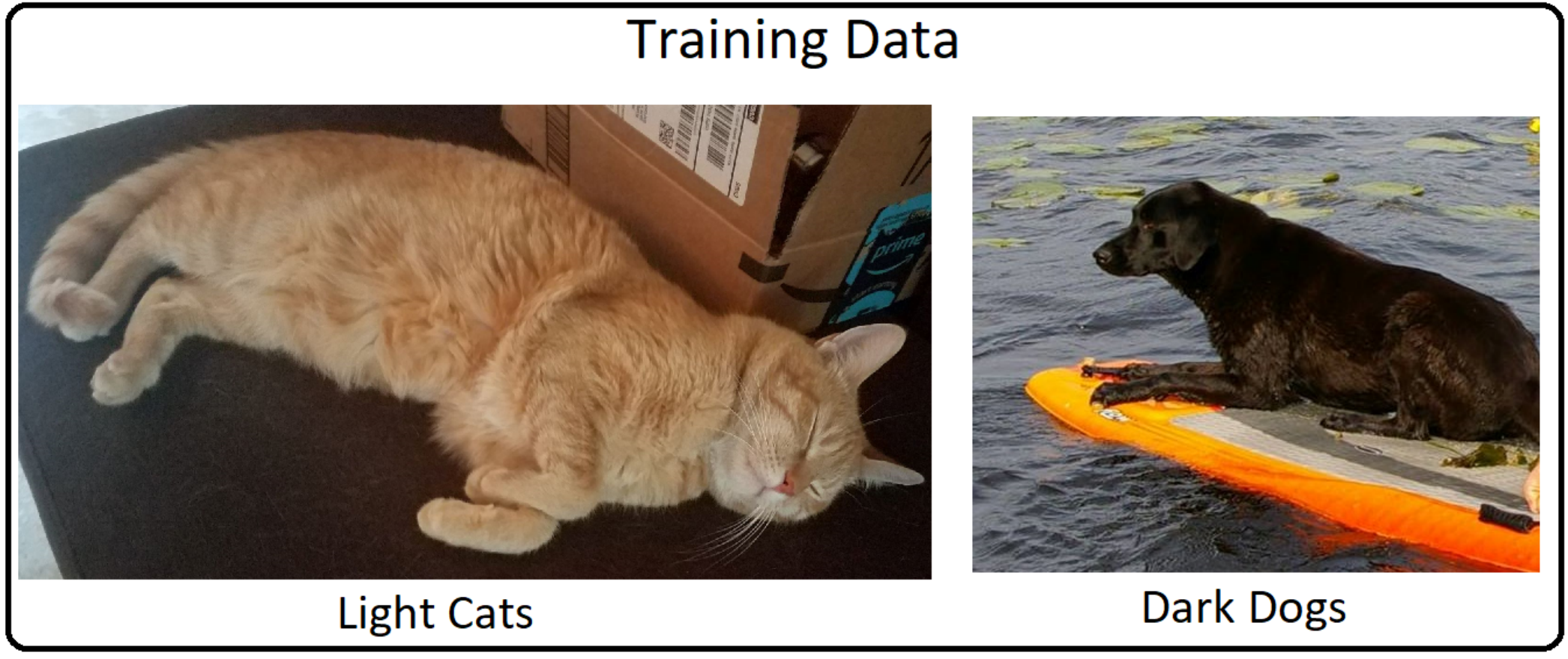
Why would we care about finding UUs in query set?

- High confidence mistakes lead to unmitigated risks in application of classifier
- Characteristics of the UUs may help analyst to understand classifier deficiencies

Unknown Unknowns

Example: Image Classifier for Cats and Dogs

- Bias in training set: Cats with light fur and Dogs with dark fur



Unknown Unknowns

Example: Image Classifier for Cats and Dogs

- Bias in training set: Cats with light fur and Dogs with dark fur
- Test set has all color fur for both cats and dogs
- Classifier likely to be highly confident but wrong about dark cats and light dogs
- A query set that finds these UUs could help us to identify the model deficiency from animal fir color

Exisiting Literature on Utility-Based Query Algorithms

Attenberg et al. (2015) - Crowdsource

- "Beat the Machine" game with monetary rewards for finding UUs
- Crowdsourcing as mechanism for learning classifier deficiencies
- Basically like using many oracles with large budget for labelling

Lakkaraju et al. (2017) - Multi-Armed Bandit

- Adaptive query algorithm that updates the optimal recommendation for next oracle query after evaluating the newly labeled instance
- Utility function provides a unit value for each discovered UU and penalizes by the cost of labeling

Bansal and Weld (2018) - Coverage-Based

- Another greedy query algorithm, but uses coverage-based utility
- Goal is to encourage both discovery of UUs and exploration of feature space

Coverage-Based Utility Details

$$U(Q) = \sum_{x \in \mathbb{X}} c_x \cdot \max_{q \in S} \{sim\,(x, q)\}$$

- $\mathbb{X} \subset \mathbb{R}^p$ is p-dimensional unlabeled test set
- $Q \subset \mathbb{X}$ is the set of points labeled by an oracle,
- $S = \{x | x \in Q, y_x \neq M(x)\}$ is the set of discovered UUs
- Classifier $M(x) : \mathbb{X} \rightarrow class$,
- c_x is the classifier's confidence in its prediction of x,
- $sim(x, q)$ is a distance-based similarity metric.

Deficiencies in existing methods

Attenberg et al. (2015)

- If the cost of oracle queries is the reason we need an algorithm, then crowd-sourcing the solution is not viable

Lakkaraju et al. (2017)

- Fundamentally place value on finding *any* UU, regardless of confidence
- This ignores the number of misclassification we **expect** based on the confidence scores

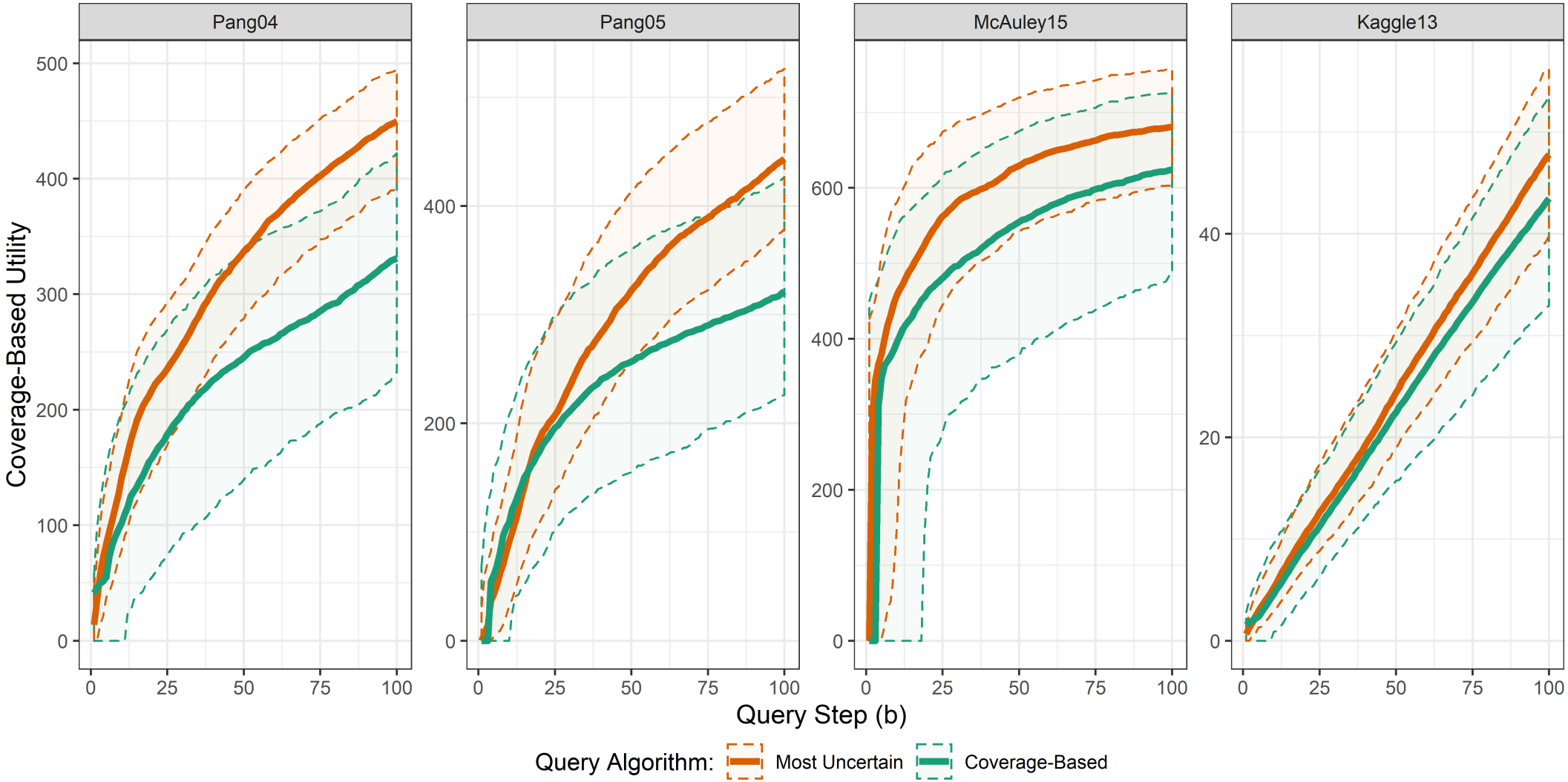
Bansal and Weld (2018)

- Places value on high confidence instances being *close to* UUs

Why is this a problem?

- The utility-based algorithms err toward instances that are "safe bets"; instances with confidence just above the τ threshold.
- The utility functions reward selection of the most-uncertain (least confident) UUs

Coverage-Based Query vs. Most-Uncertain Query



Facility Locations Search Algorithm

Adapting utility objectives to overcome deficiencies

Claims:

The focus on discovering Unknown Unknowns, as defined in current literature, is flawed.

High confidence should not be intepreted as an absolute. Misclassifications *should* be occuring.

The problem is when the rate of misclassification exceeds the rate expected based on classifier confidence.

Adaptated Objectives:

1. Our goal should be to query instances that demonstrate *classifier overconfidence*; containing more misclassification than should be expected based on classifier confidence.
2. Our query should also seek to thoroughly explore the feature space.

Thus, we propose a new utility function and associated greedy query algorithm that rewards both of these new objectives

Facility Locations Utility Function

$$W(Q) = \sum_{q \in S} r\left(c_q\right) - \frac{1}{n} \sum_{x \in \mathbb{X}} \min_{q \in S} \left(d\left(x, q\right)\right)$$

$r\left(c_q\right) = \log(1/(1 - c_q))$ is the *reward* function for finding a misclassification with confidence c_q

$d(x, q)$ is the Euclidean distance between points x and q.

Algorithm for Greedy Facility Location Search

Input:
Test set $\mathbb{X}$, prior $\hat{\phi}\left(x|Q=\emptyset\right)$, budget B
$Q=\{\}$ inputs that have been queried
$y_Q=\{\}$ oracle defined labels

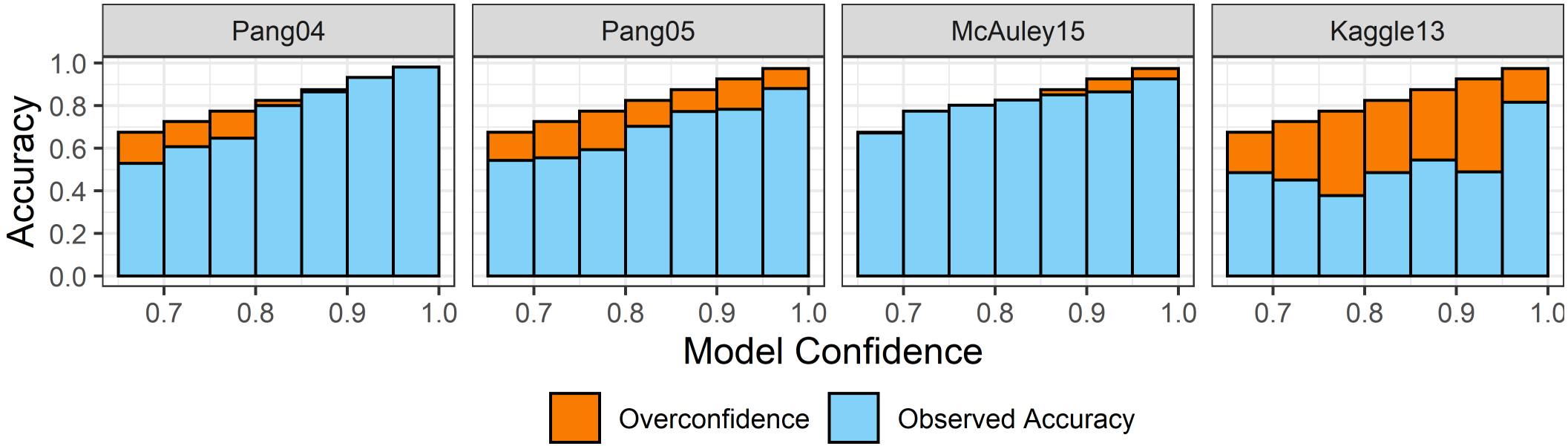
For: b = 1, 2, ..., B **do:**

> $q'=argmax_{q'\notin Q}E_{\hat{\phi}}\left[W\left(Q\cup q'\right)\right]$
>
> $Q\leftarrow Q\cup q'$
>
> $y_Q\leftarrow y_Q\cup y_{q'}$
>
> $S\leftarrow\{x|x\in Q\ \text{ and } y_x\neq M(x)\}$
>
> $\hat{\phi}\leftarrow\hat{\phi}\left(x|Q\right)$
>
> $b\leftarrow b+1$

Return: Q, S and y_Q

Empirical Experiment Results

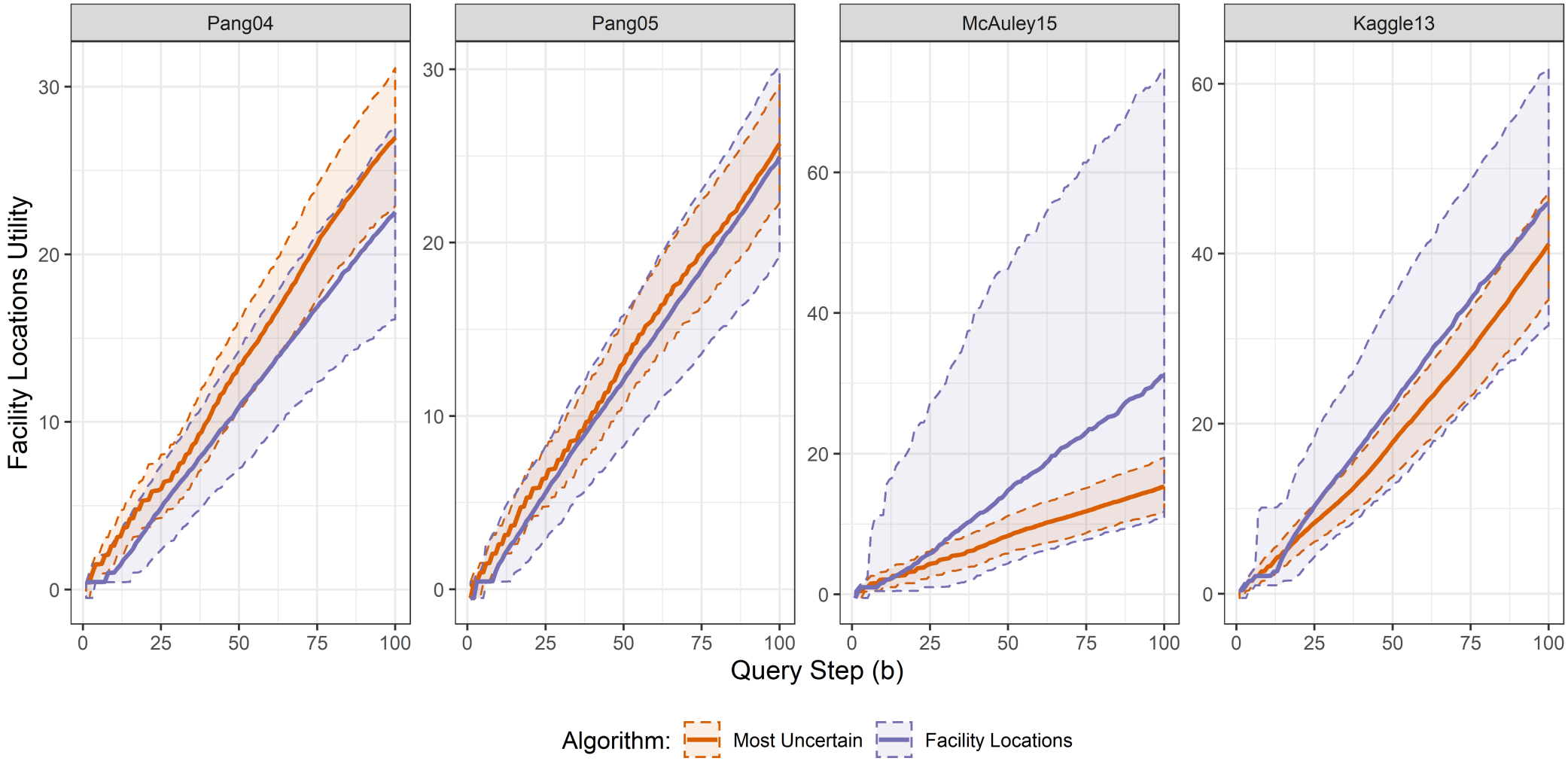
Datasets



1. Compare Facility Location Query vs. Most-Uncertain Query baseline

2. Evaluate the efficiency of query algorithms in finding misclassification relative to the confidence of the selected instances

Facility Location Query vs. Most-Uncertain Query



Comparing Apples and Oranges

Making comparison to a baseline on different utility outcomes is too indirect

Can't use the utilities on which the query algorithms optimize without obvious bias

Need a metric for comparison of query algorithms.

$$|S| / \sum_{x=1}^{B} (1 - c_x)$$

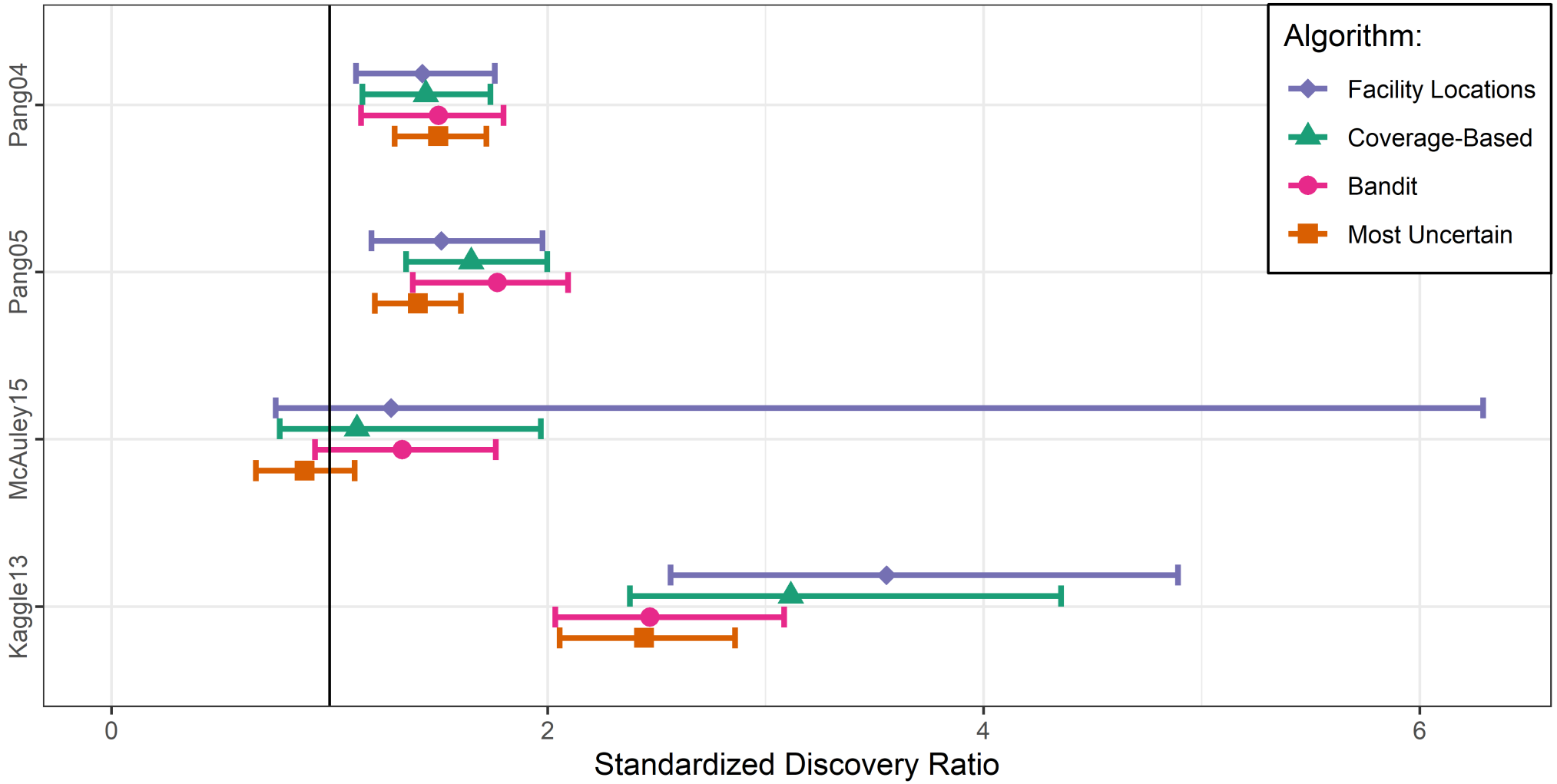
Standardized Discovery Ratio (SDR) is the ratio of discovered misclassifications to the expected number based on confidence

Numerator is count of discovered misclassification

Denominator is expected count based on confidence

Higher SDR values suggest higher efficiency of identifying overconfident instances

Facility Location Query vs. Most-Uncertain Query



Adversarial Distances for Unsupervised Query Set Selection

Leveraging Adversarial Learning Methods for Discovering Overconfidence

Problem: Adaptive query algorithms appear to discover overconfidence slowly and inconsistently

Goal: Initializing oracle query search with selection of "low hanging fruit" - a set of instances in the unlabeled test set that are *likely* to be overconfident

Need unsupervised method to extract more information about model confidence on unlabeled points

Adversarial instances are points that have been adapted to fool classifiers with malicious intent

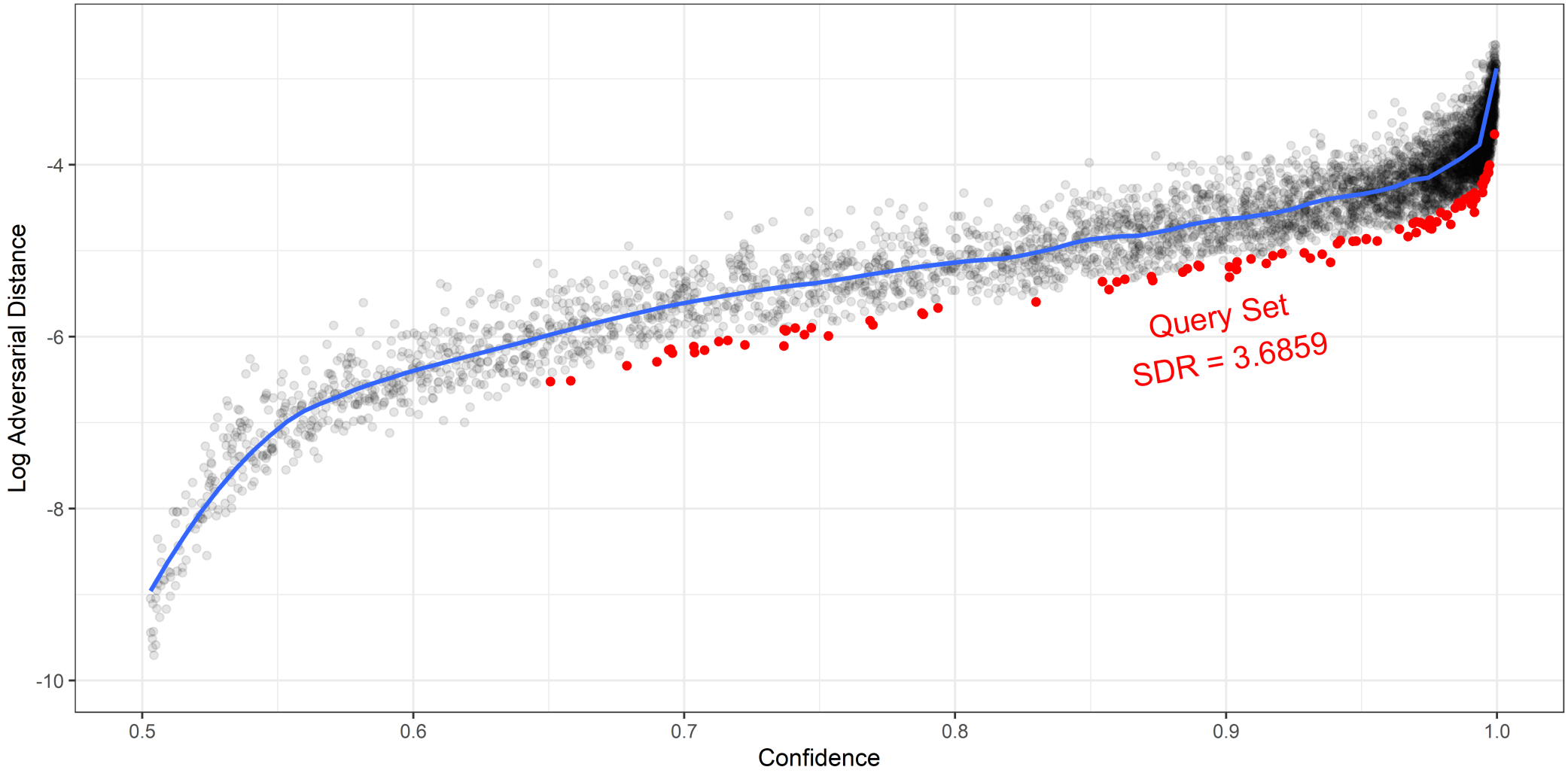
- This can involve minimally changing features until the instance is *misclassified*
- Images can be made adversarial by selectively adding noise in the pixels
- This is a supervised task, because it uses the true class labels

Proposal: Use adversarial methods to minimally change features until the instance *changes predicted class*.

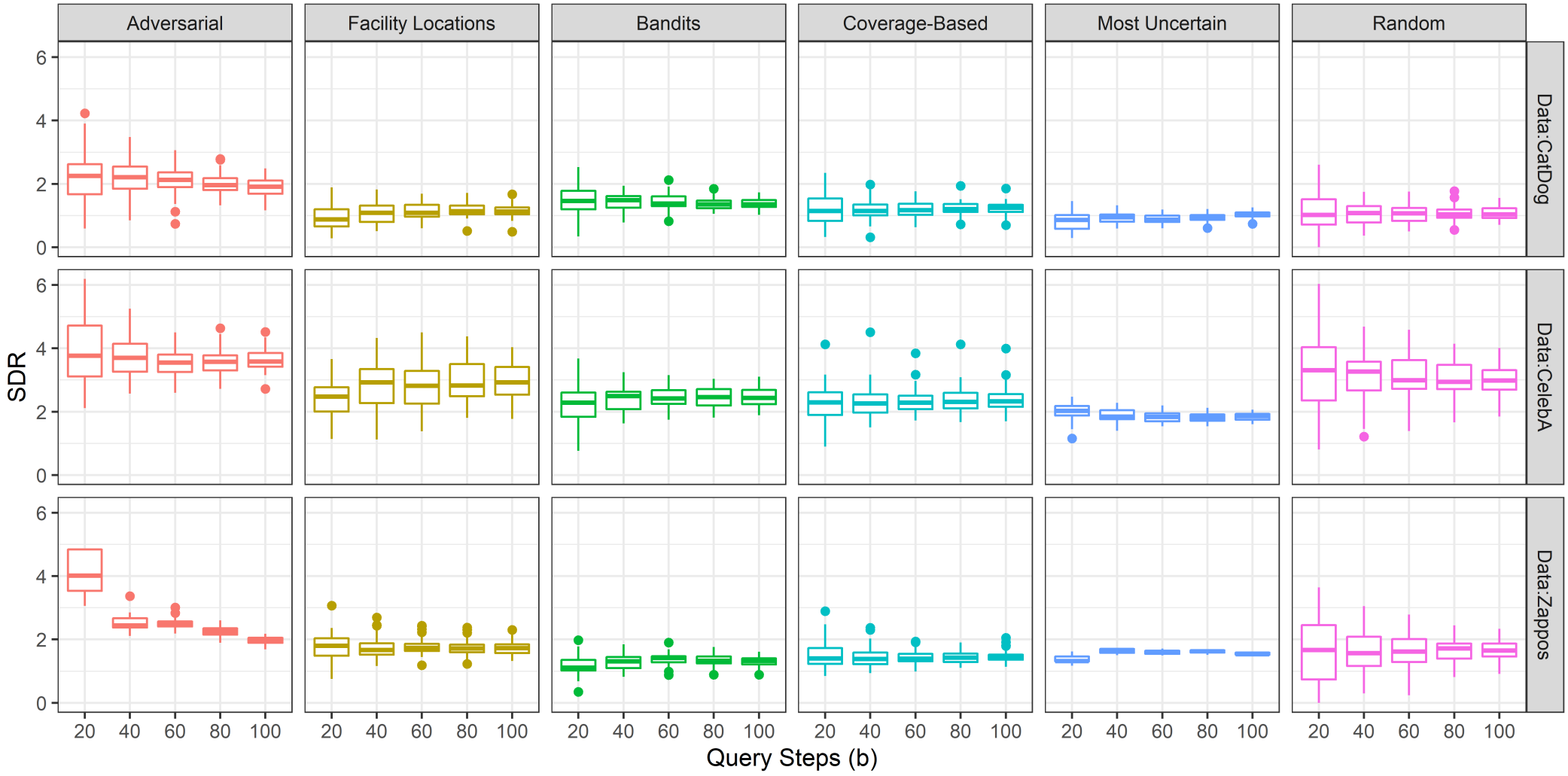
Define *minimal adversarial distance* (MAD) as the distance between an instance and the closest point in the feature space with different predicted class

We will query instances that have low MAD values relative to their confidence score.

Adversarial Distance-Based Query



Empirical Experiment Results



Discussion

Conclusions

Facility Locations Utility Methods

Performs well across all overconfidence profiles seen in empirical evaluations

SDR improves as budget increases, but this learning can be slow and inconsistent

Adversarial Distance Methods

Efficient in discovering instances that display classifier overconfidence with small budgets

SDR decreases as budget increases, decreasing returns on oracle investment

Implemented successfully in image classifier setting

Continuing and Future work

Student Research Projects:

- **Bunyod Tusmatov** extended adversarial methods to text classifiers, observed similarly strong SDR outcomes
- **Sally Dufek** currently working to extend adversarial methods to generalized feature space with black box classifiers
- Can envision **undergraduates** helping evaluate algorithms in a more extensive empirical experiment

Hybrid query algorithm

- Initialize query with set from adversarial distance method
- Continue with adaptive Facility Location utility method until budget

Resources

Code Repository

- These Slides: *https://github.com/kmaurer/search2020/tree/master/ResearchTalk*
- Facility Locations Utility: *https://github.com/kmaurer/uuutils*

Software and Data

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Thanks!

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