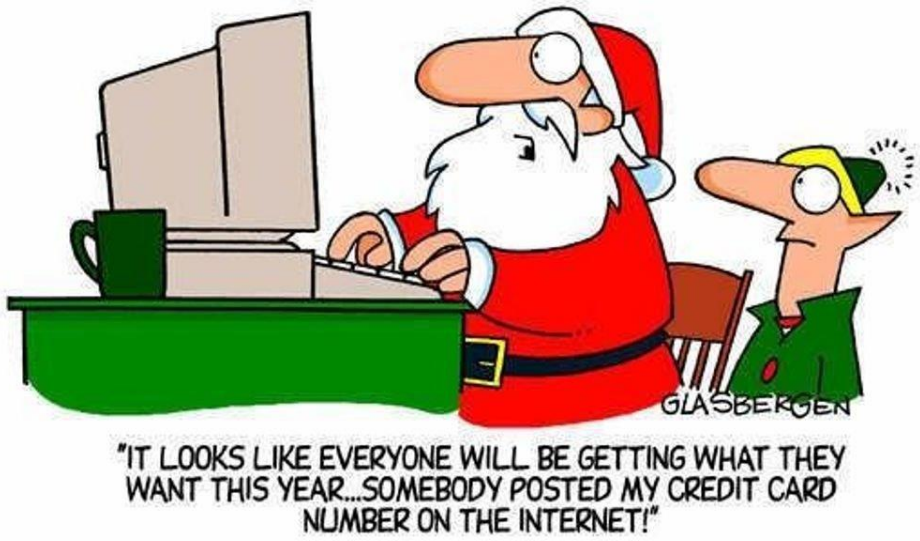
# Human in-the-Loop Learning for Anomaly Detection

**Jana Doppa**
Huie-Rogers Endowed Chair Associate Professor
School of EECS, Washington State University

twitter
@janadoppa

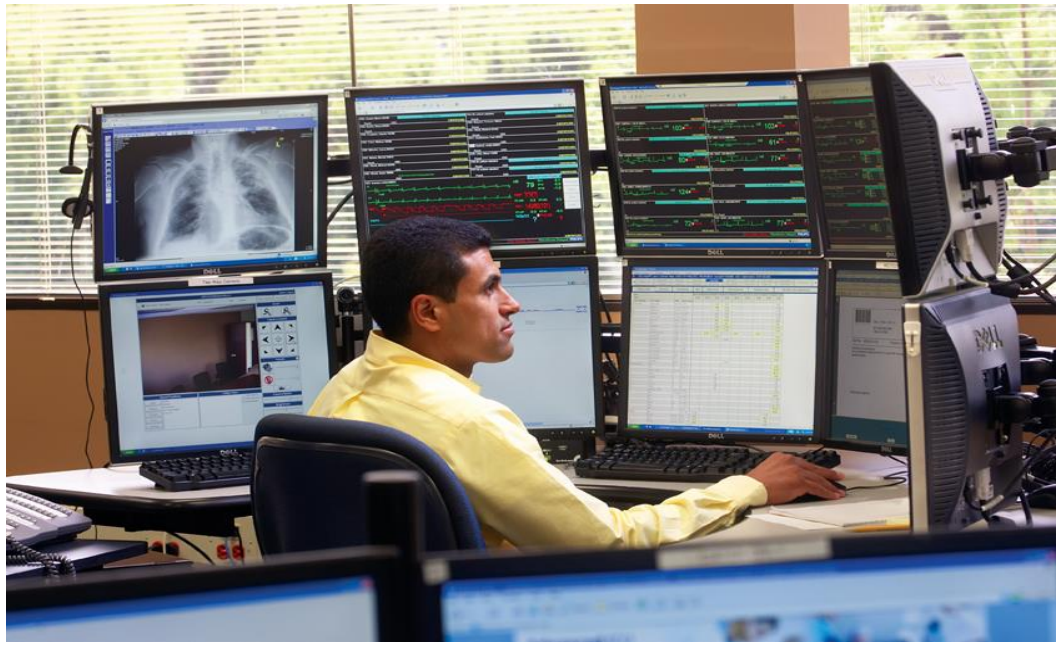
Joint work w/ Rakibul Islam and Shubhomoy Das

# Motivating App #1: Credit Card Fraud

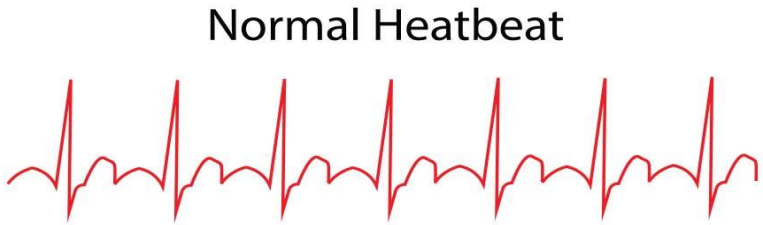




- Unusual transactions
- False alarms are common
- High false positive rate → wasted human effort

# Motivating App #2: ICU Patient Monitoring



- Monitor patients' condition
- False alarms are common
- High cost of wrong decisions



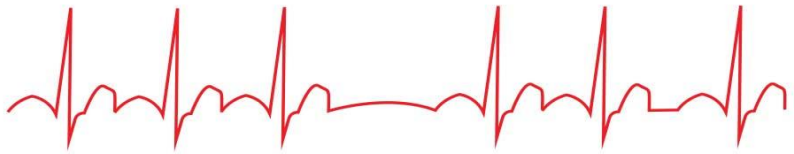
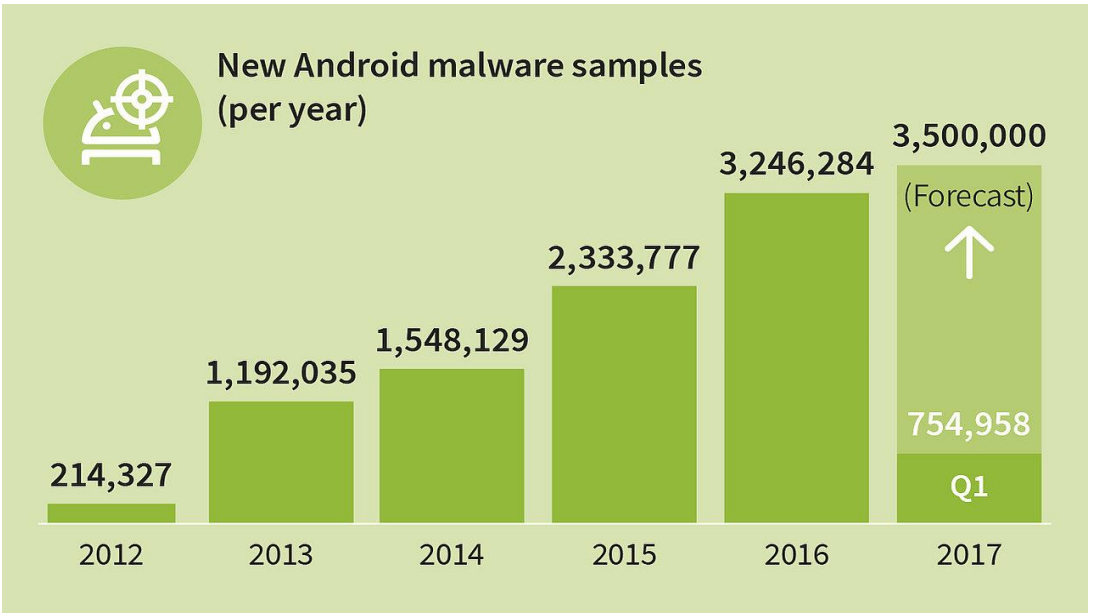




Photo credit: stock.adobe.com

# Motivating App #3: Android Malware



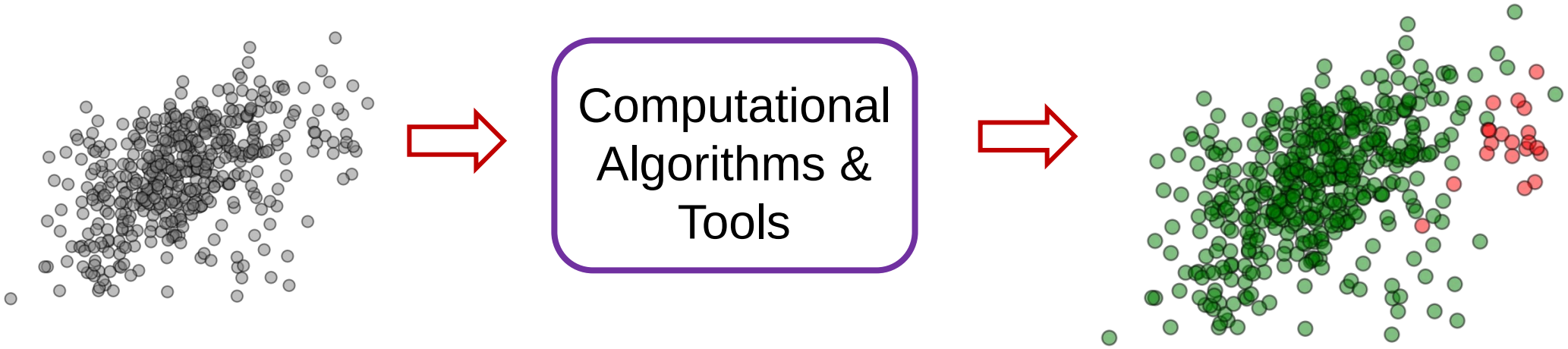


Anti-Malware Industry

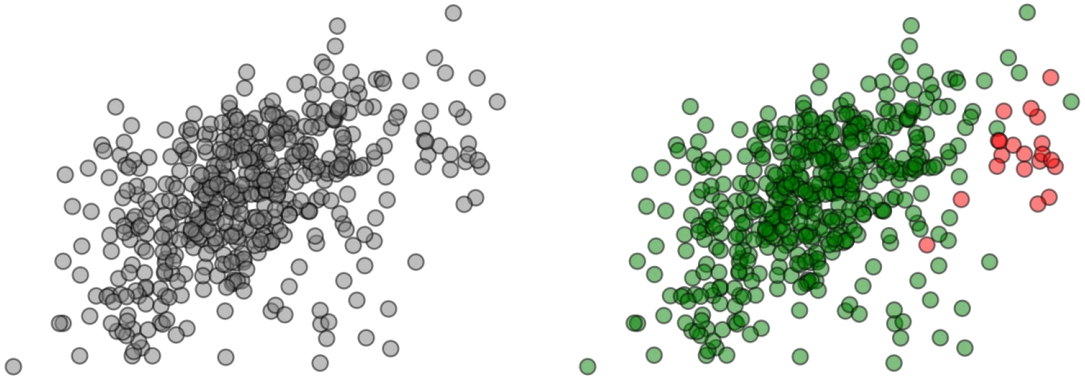
Malwares can potentially

- Spy
- Steal person information
- Make fake calls
- ….

# Anomaly Detection: The Problem



# Anomaly Detection: Challenges



- # of anomalies << # of nominals
- Knowledge discovery task involving humans
- High false-positive rate → wasted human effort

# Prior work on Anomaly Detection: Unsupervised Methods

- **Density-Based Approaches**
  - RKDE: Robust Kernel Density Estimation (Kim & Scott, 2008)
  - EGMM: Ensemble Gaussian Mixture Model
- **Quantile-Based Methods**
  - OCSVM: One-class SVM (Schoelkopf, et al., 1999)
  - SVDD: Support Vector Data Description (Tax & Duin, 2004)
- **Neighbor-Based Methods**
  - LOF: Local Outlier Factor (Breunig, et al., 2000)
  - ABOD: kNN Angle-Based Outlier Detector (Kriegel, et al., 2008)
- **Projection-Based Methods**
  - IFOR: Isolation Forest (Liu, et al., 2008)
  - LODA: Lightweight Online Detector of Anomalies (Pevny, 2016)

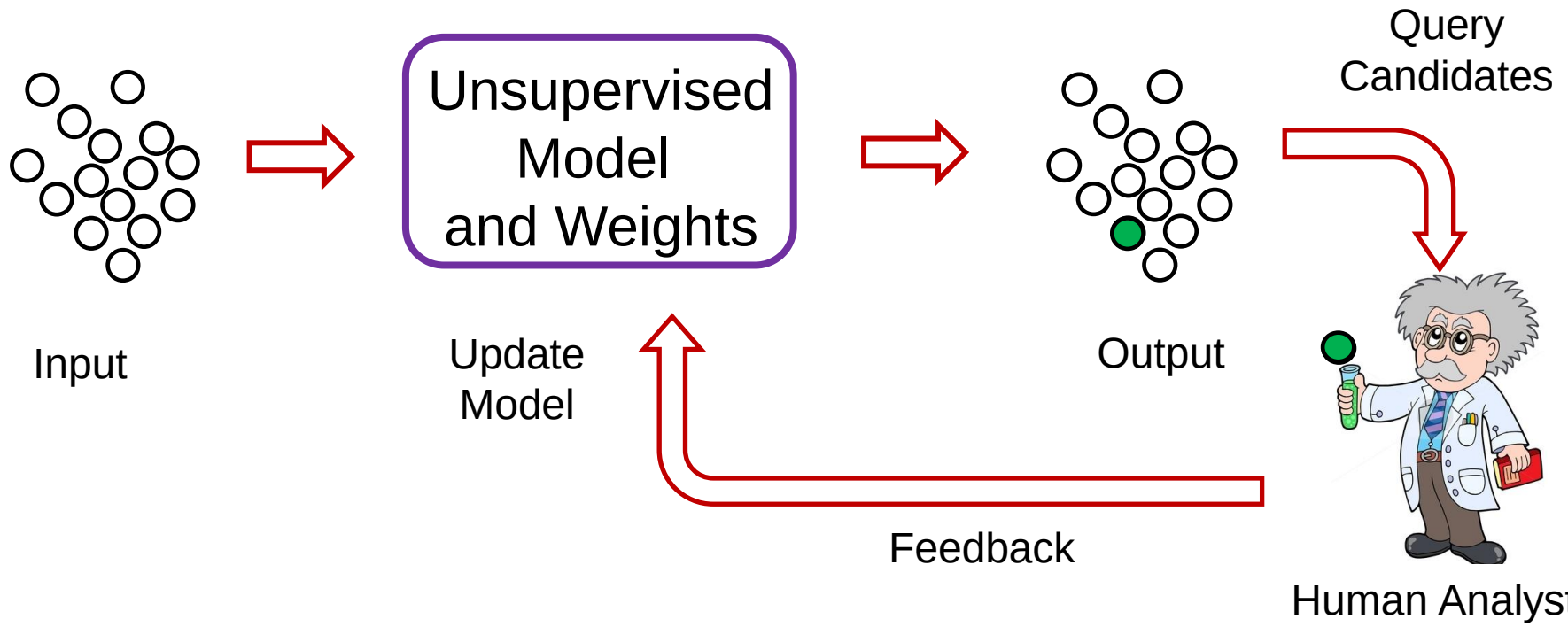
# Unsupervised methods: when they may not work?

- Underlying model assumptions are violated
- Nature/type of anomalies is not known beforehand (unknown unknowns)
- Only a subset of identified anomalies are relevant for real-world task

High false positive rate and wasted effort from human analysts

# Key Research Question

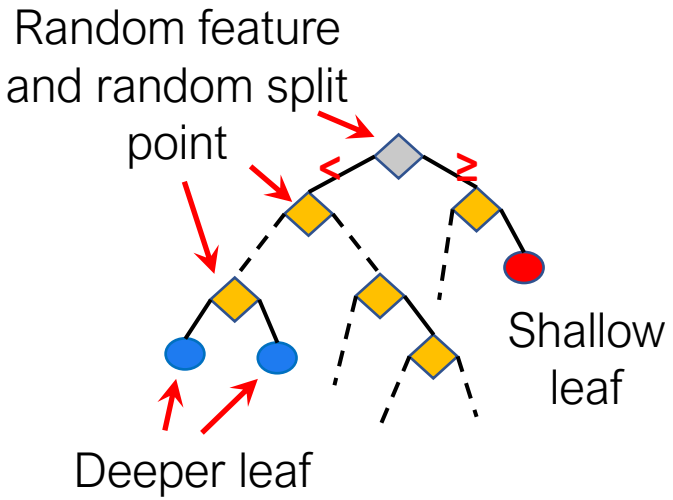
- How can we use human analyst efficiently to improve anomaly detection rate of unsupervised approaches?

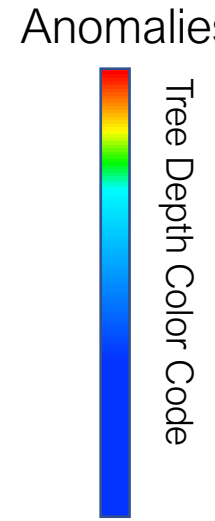


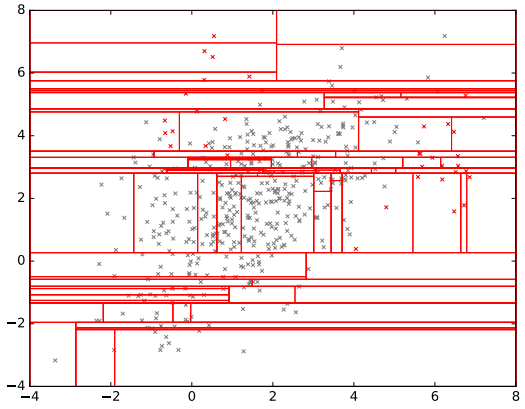

Discover all the anomalies with very small number of queries to human analyst (minimize human effort)

# Aside: Isolation Tree

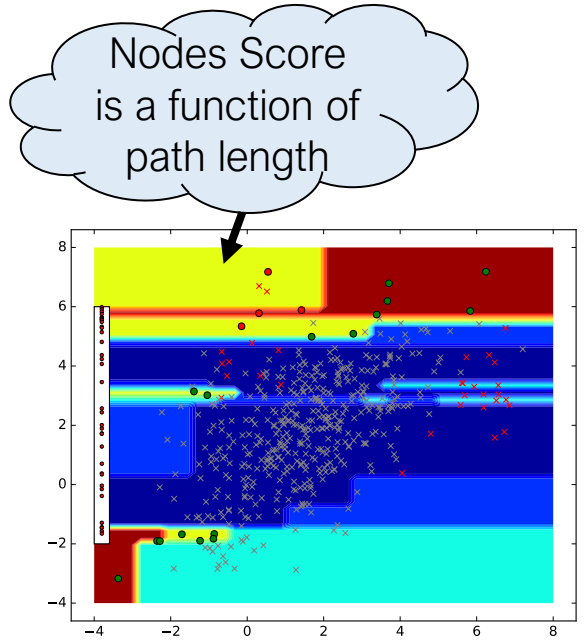
- Key Idea
  - Anomalies can be easily Isolated from nominals
  - Degree of anomaly is inversely proportional to depth



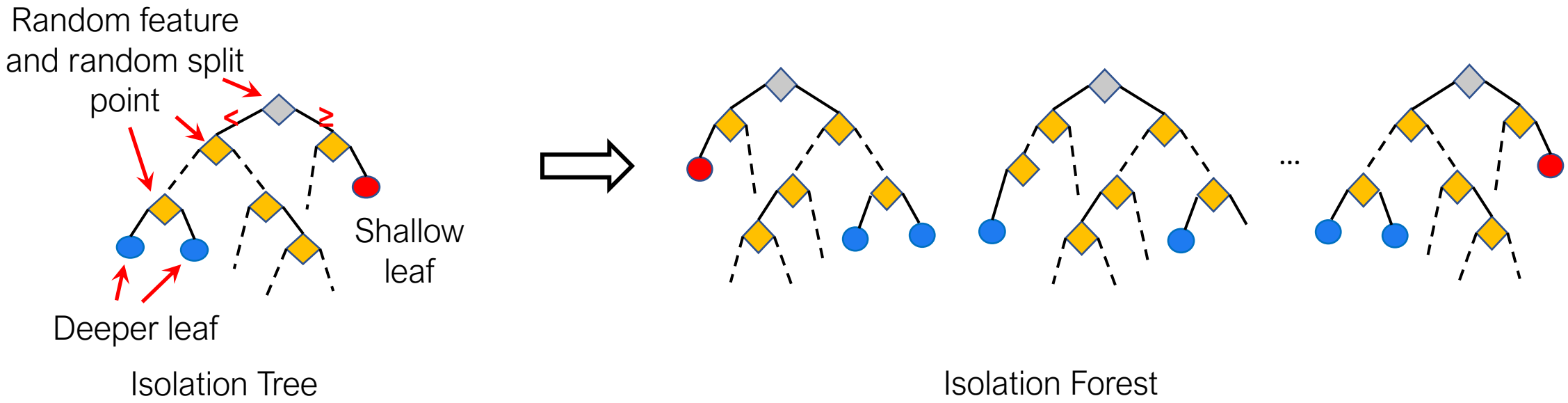



Partitioned
subspaces



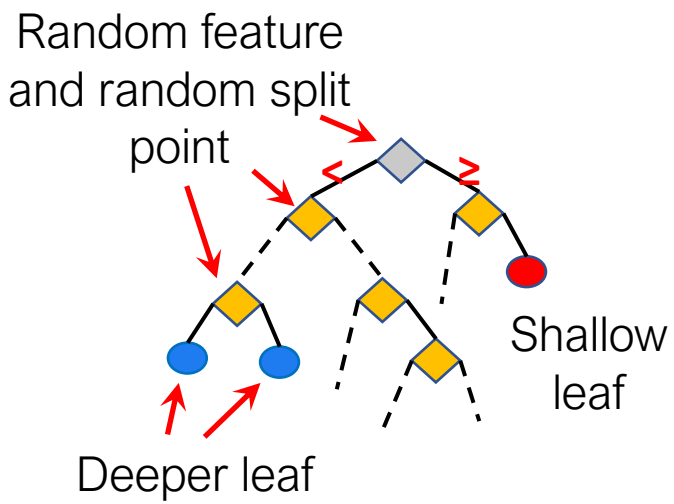

Depth Colored
subspaces

# Aside: Isolation Forest

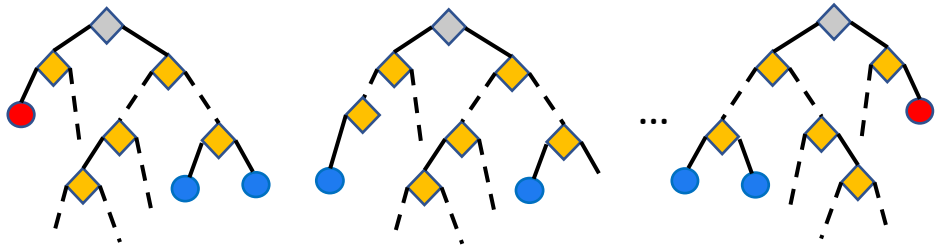



- State of the art unsupervised approach
- Assumptions
  - # of anomalies are small
  - Features are distinguishable
- Assigns uniform weights for subspace score

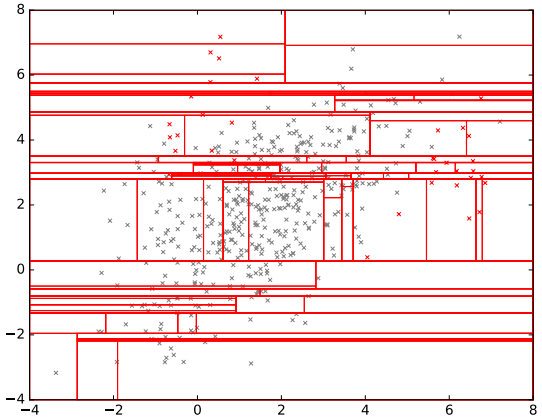
# Isolation Forest

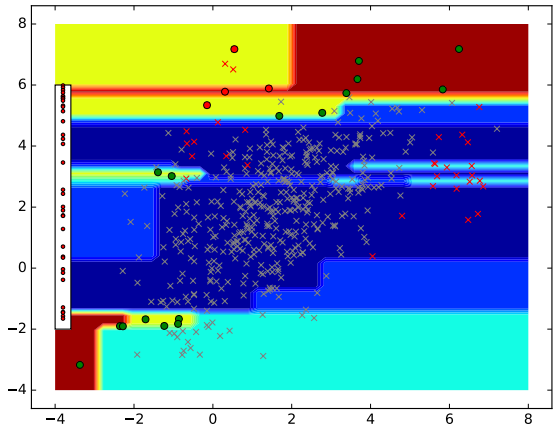


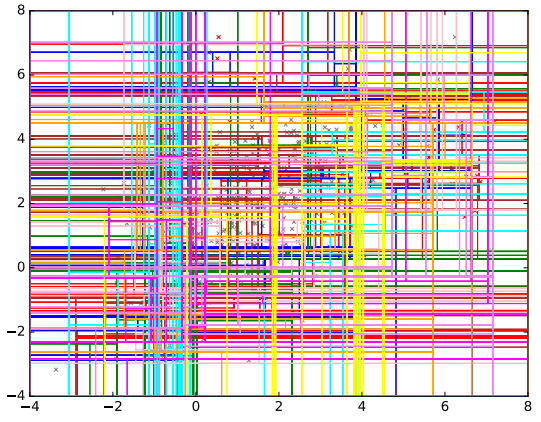

Isolation Tree

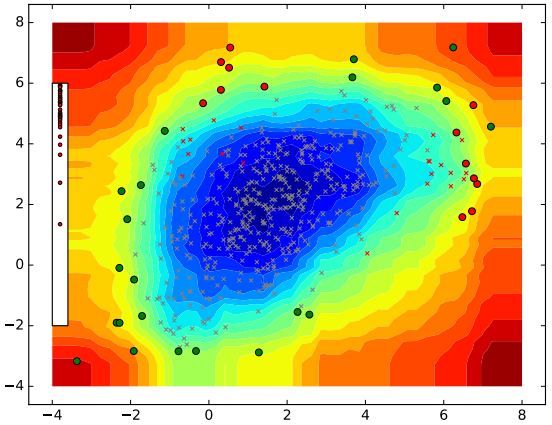


Isolation Forest









Space partition for 100 Trees

Contour Plot for 100 Trees

# Model Definition

- Isolation forest generates high number of subspaces/leaves (say $m$)

- We can map each data instance to this representation
  - $x \longmapsto IFor(x) \in R^m$
  - If the data point falls in a leaf, its feature value is equal to the adjusted depth based score. Otherwise, its feature value is zero

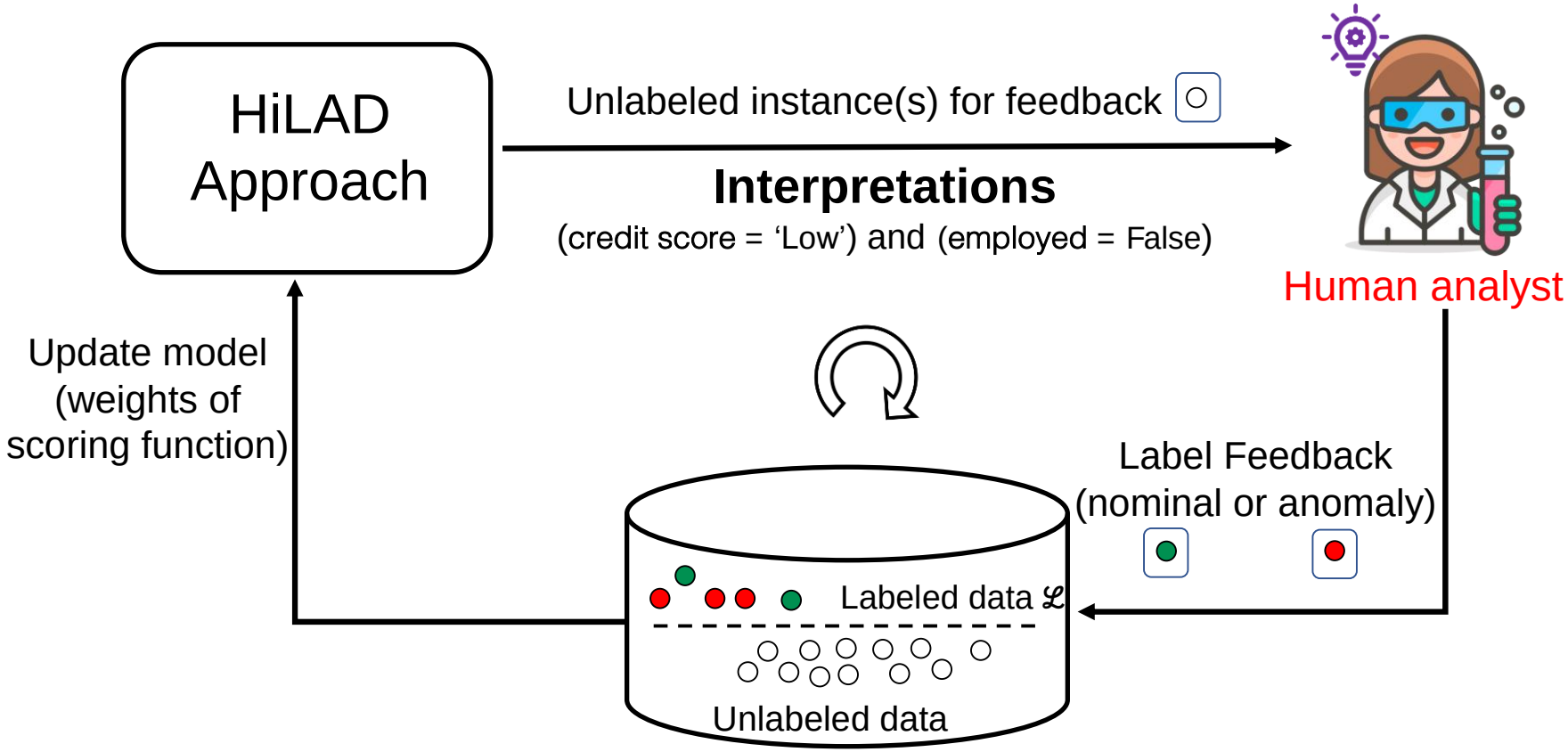
- All subspaces are equally weighted ($m$ weights)
  - $w_1 = w_2 = \ldots = w_m$

# Making Predictions

- Score all the data points
  - $\boldsymbol{score(x) = w.\mathbf{IFor(x)}}$
- Rank them based on the scores
- Pick top $\boldsymbol{\tau}$ candidates as anomalies

Anomaly detection accuracy depends on the weights of the model.
How can we learn the optimal weights?

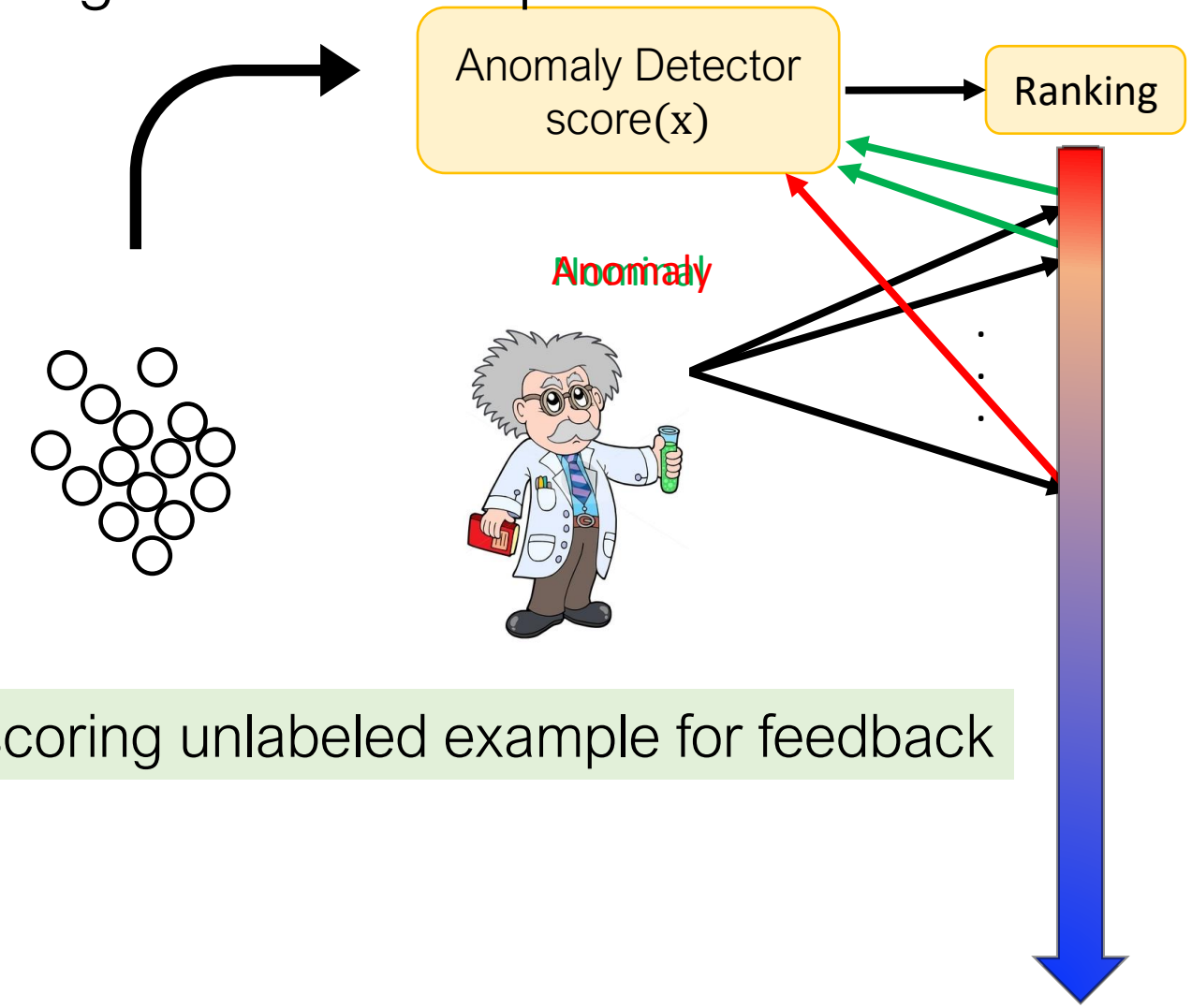
# HiLAD: Overview




Use **human feedback** to improve the anomaly detection performance

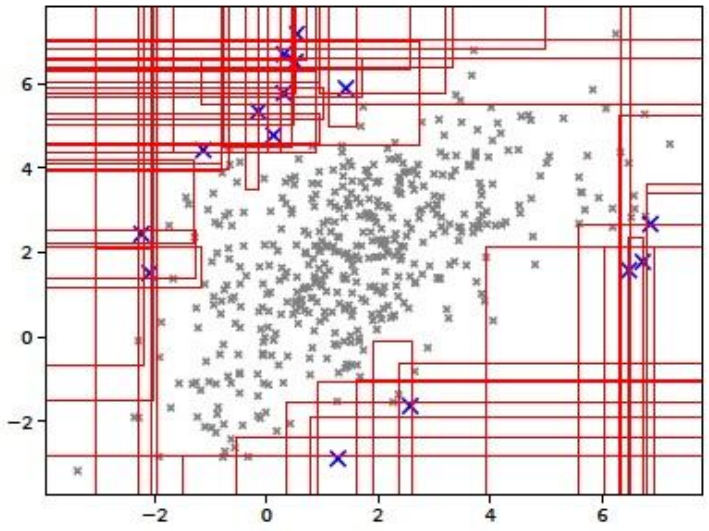
# Isolation Forest with Human Feedback

- Anomalies are pushed higher in score space

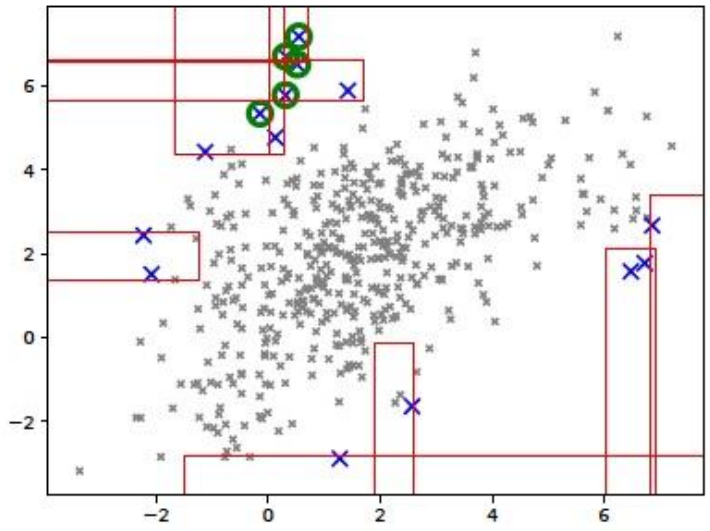



Greedily select the highest scoring unlabeled example for feedback

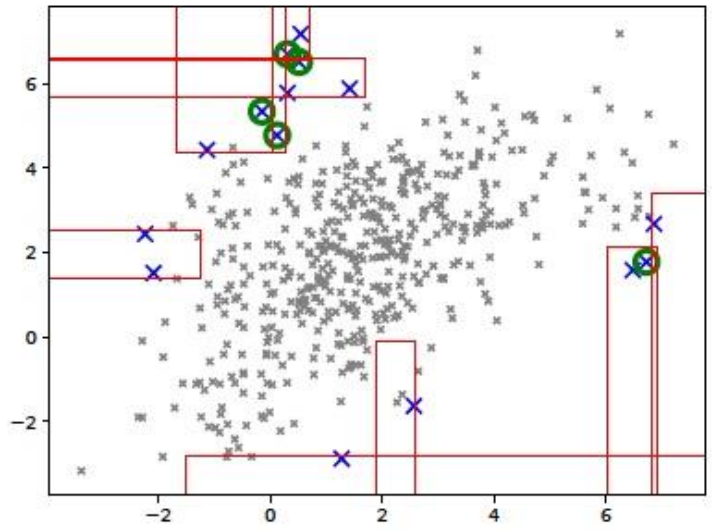
# Query strategy to discover diverse anomalies



Candidate Regions



Selecting the Top



Diverse Selection

- What if we want diverse anomalies?
  - The inherent structure of Isolation Forest can be exploited
  - Subspaces are selected to produce diverse queries

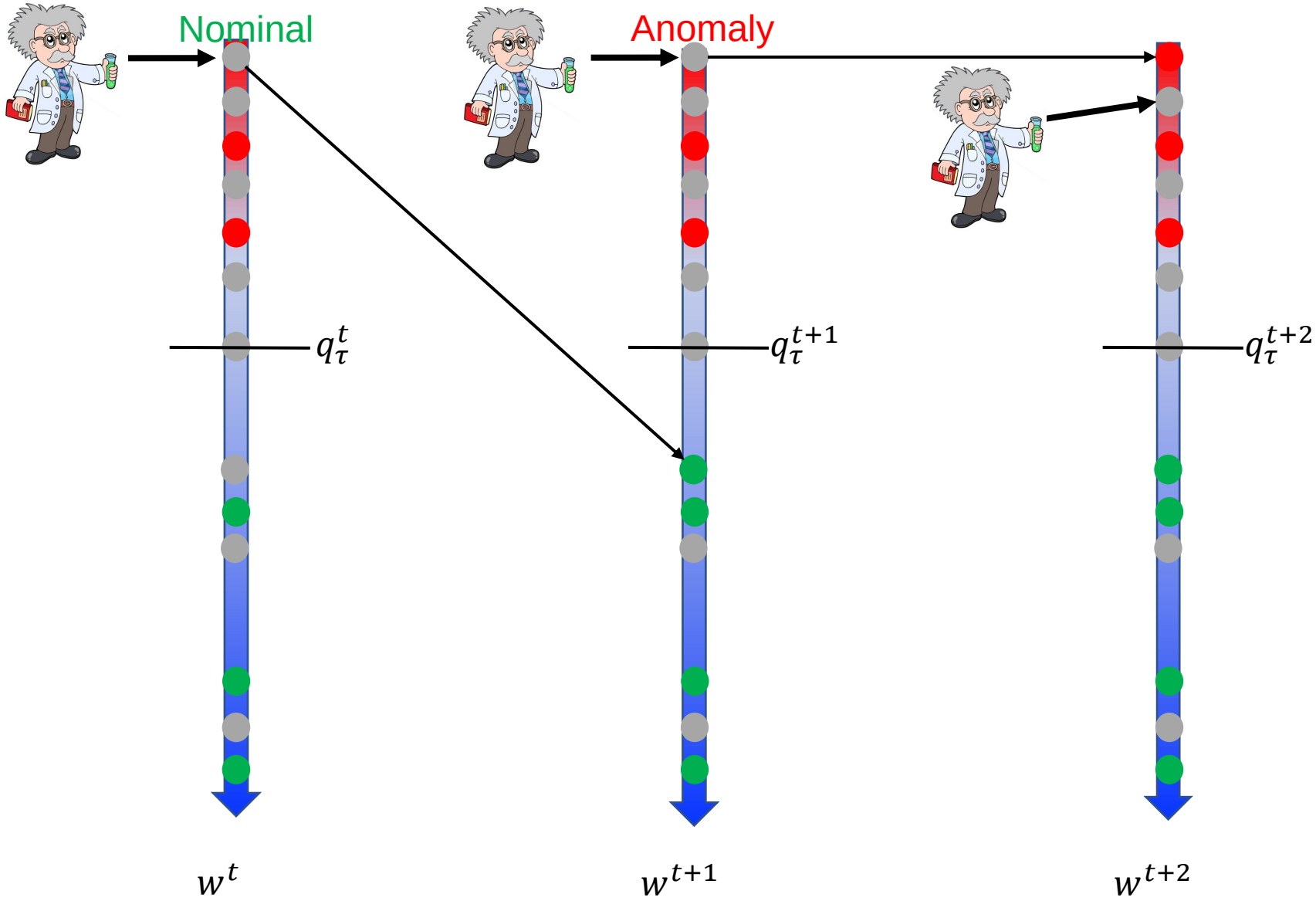
- Optimally pick queries from the most relevant compact subspaces
  - related to set covering problem

# Model Update via Online Optimization

- **Learning Goal**
  - Learn weights so that anomalies are ranked higher than the nominals
  - Score(anomaly) > Score(nominal)


- **Optimization to Update weights**
  - After feedback, nominals are ranked lower than top most $\tau$ fraction
  - A small change in the weights to satisfy the constraints

# Framework Illustration



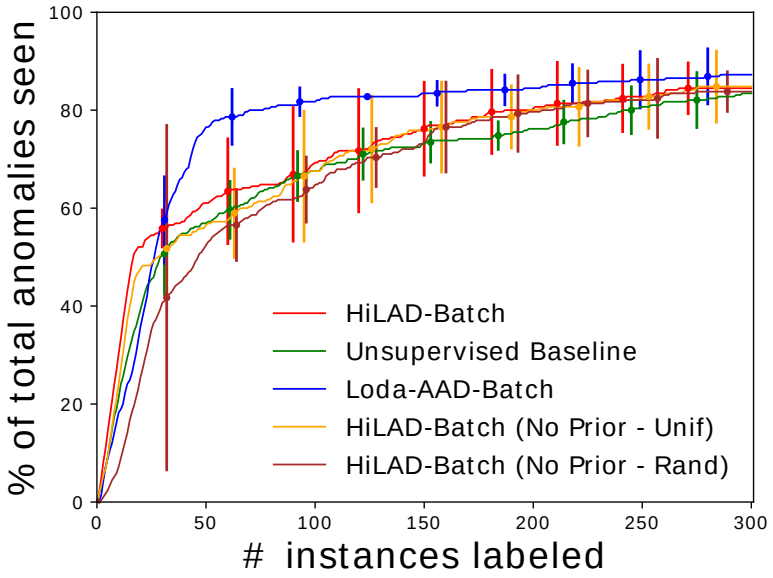
# Experimental Setup

- **Baselines**

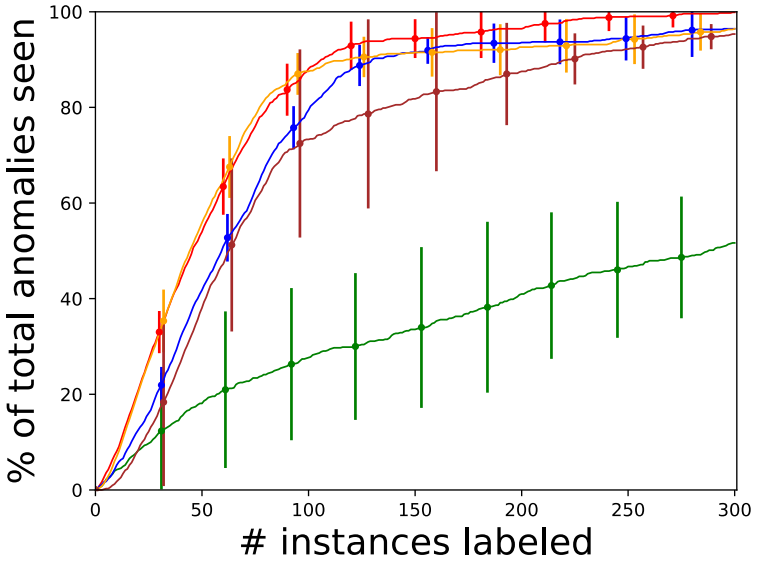
| Approach | Feedback | Prior | Influence Of prior |
|---|---|---|---|
| Unsupervised | NO | N/A | N/A |
| HiLAD (no prior-rand) | YES | Random | NO |
| HiLAD (no prior-uniform) | YES | Uniform | NO |
| HiLAD (Adaptive Prior) | YES | Uniform | YES |

- **Metrics**
  - What percentage of anomalies are discovered as a function of the number of queries?
  - AUC (Area Under ROC Curve)

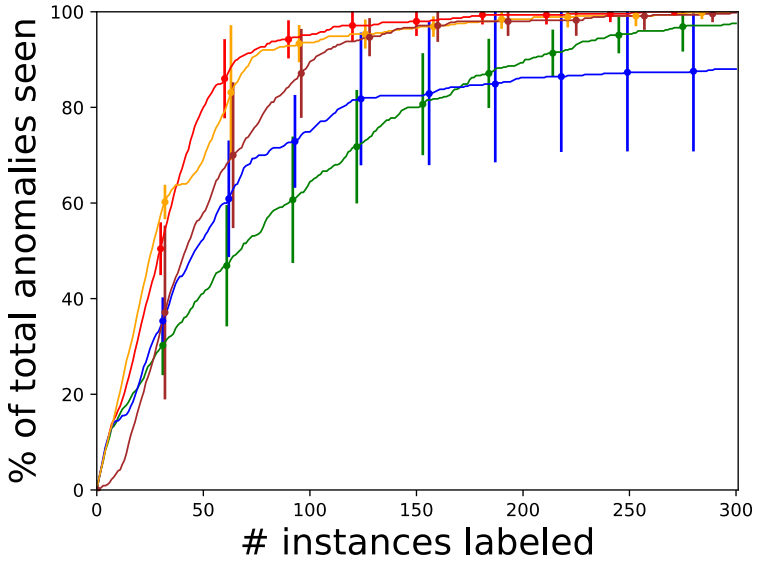
# Results for Single Queries




Abalone



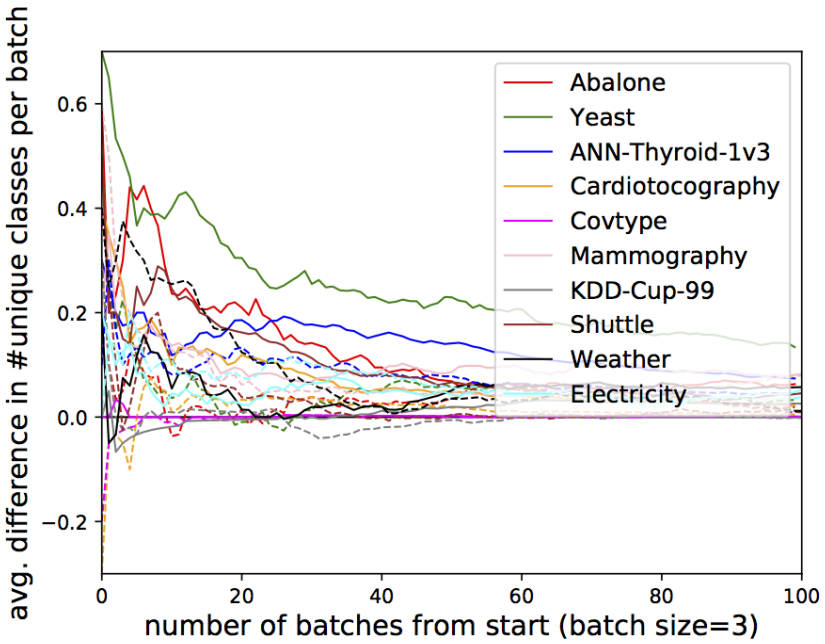

Thyroid



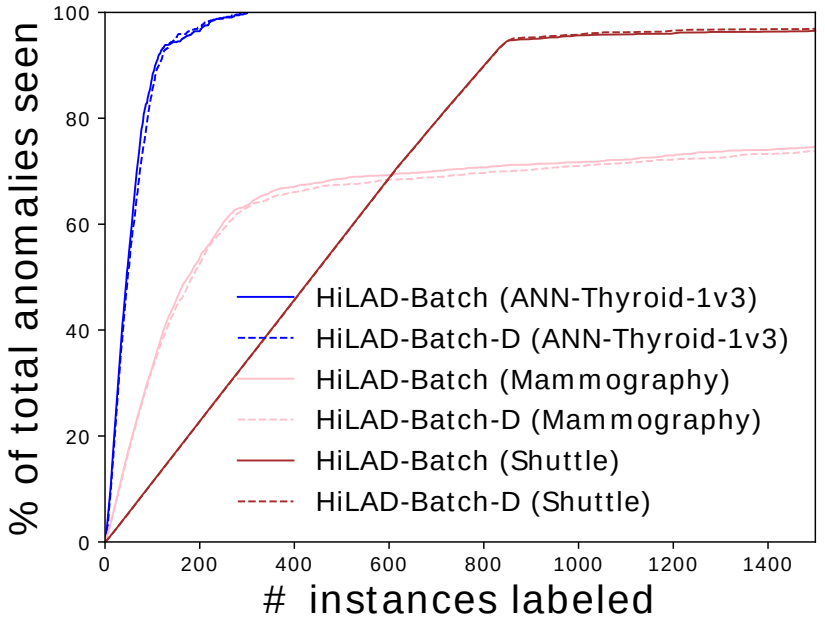

Cardiotocography

- Small amount of feedback significantly improves the accuracy
  - Updating weights help in finding new anomalies

# Results for Batch Queries




Diversity

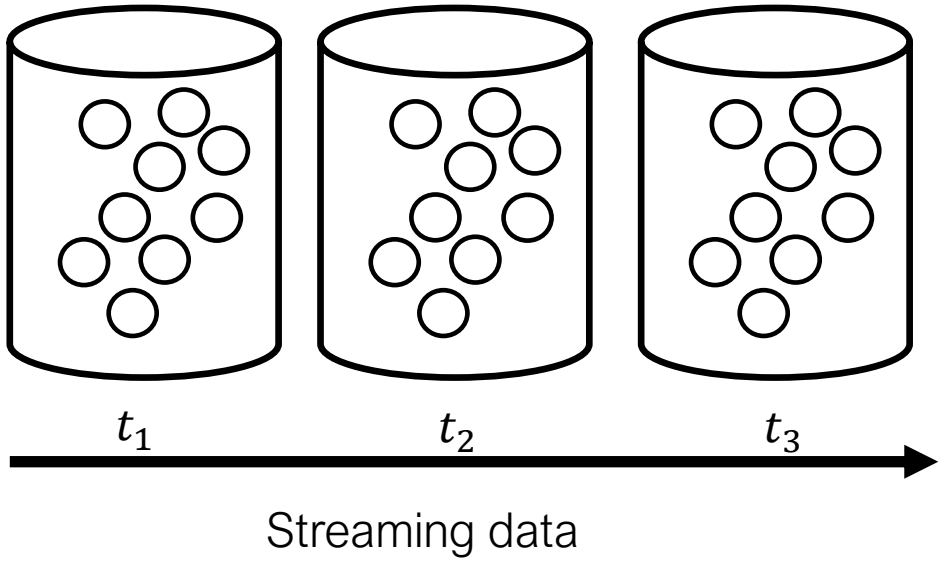



Detection performance

- Higher diversity
  - # of unique classes in query is higher than regular
- Little or no loss in anomaly detection accuracy

# Streaming Anomaly Detection

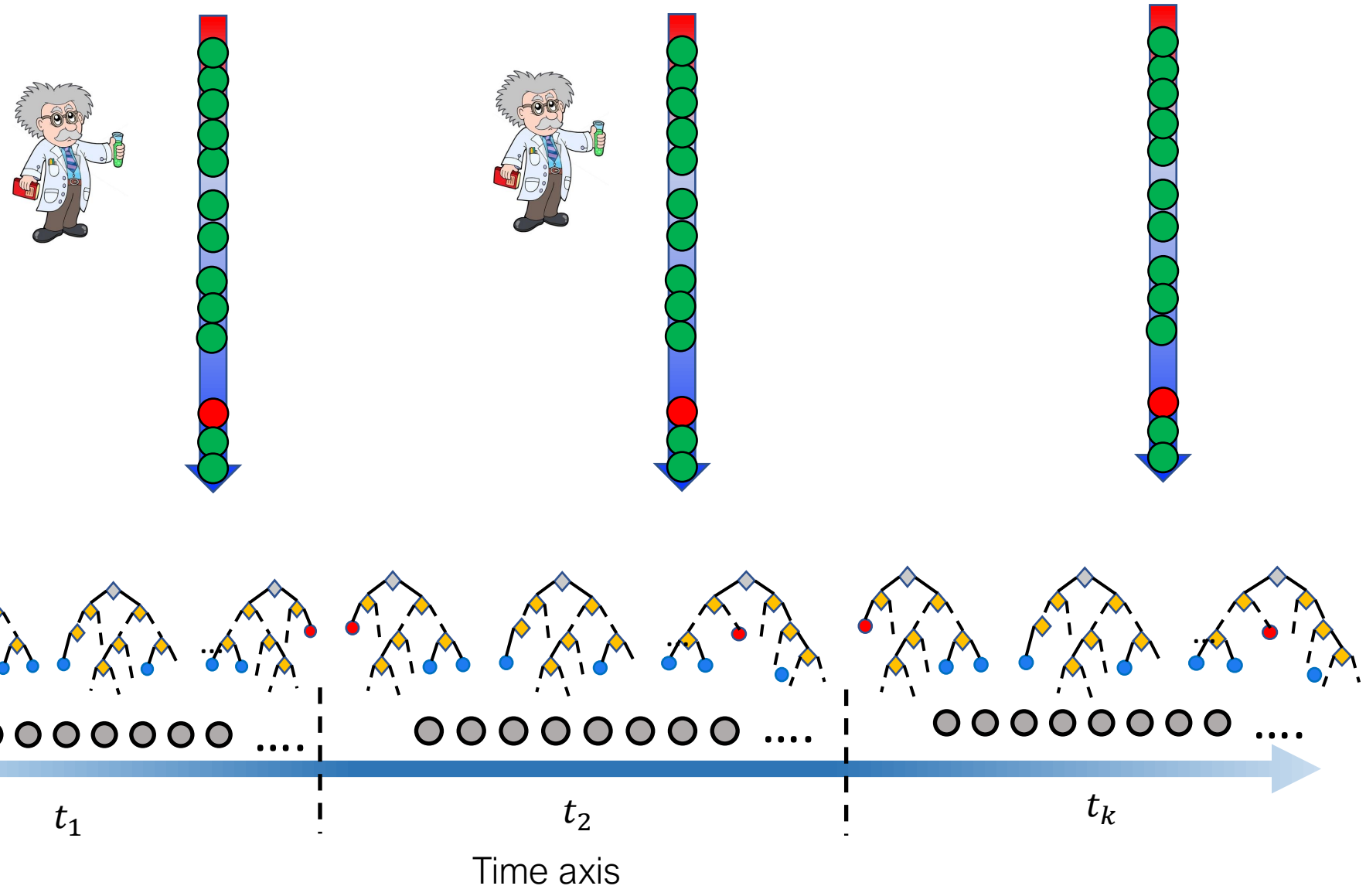
- Goal: Identify **“anomalies”** from the continuous stream of data




# Streaming Anomaly Detection: Challenges

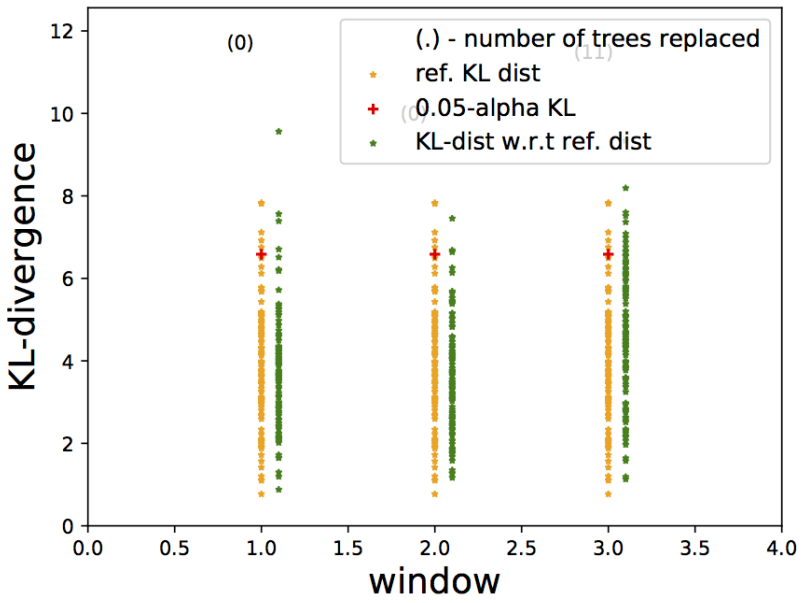
- Detecting concept drift?
- When and how to update the model?
- Memory constraints to store data?

# Streaming Anomaly Detection: Illustration

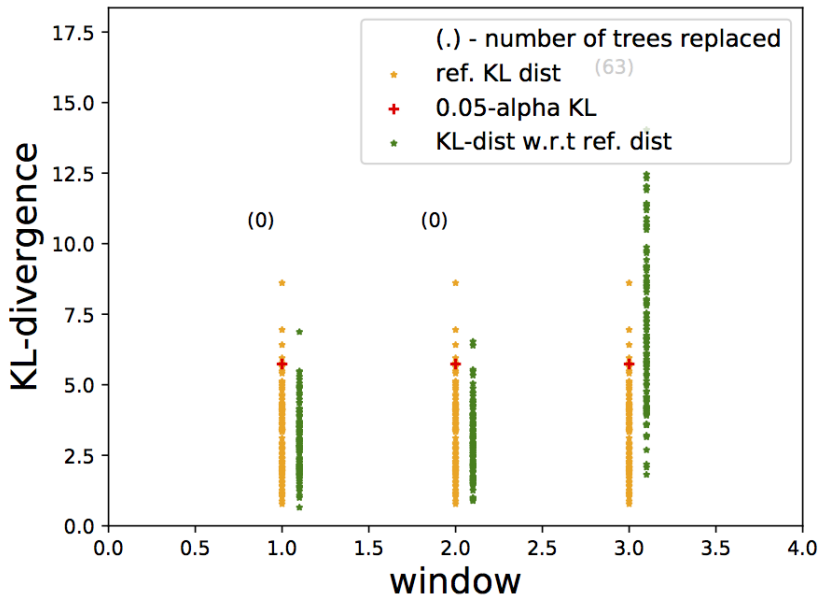


# Streaming AD via Drift Detection

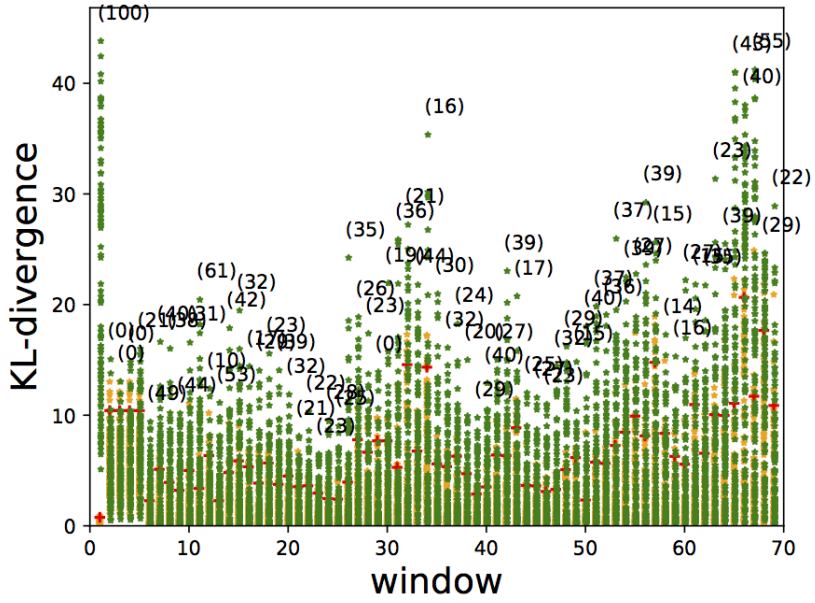
- Identify the data distribution of current window from ensembles
- Compare it with the data distribution of new window (via KL divergence)




Abalone




ANN-Thyroid-1v3




Covtype

Not much drift was observed

Drift detected

# Updating Ensemble of Trees for Streaming Data

- Limited memory and **minor concept drift**
  - Same as batch data setting and only requires retraining

- Limited memory with **major concept drift**
  - Replace a fraction of older trees
  - Include new trees from current window
  - Initialize the weights for the new trees with default (uniform) weights

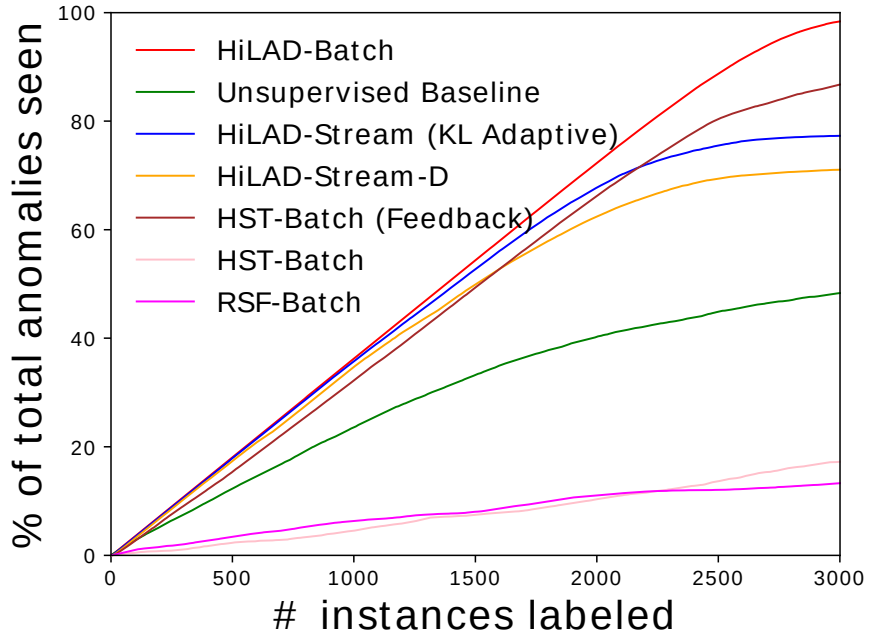
# Experimental Setup

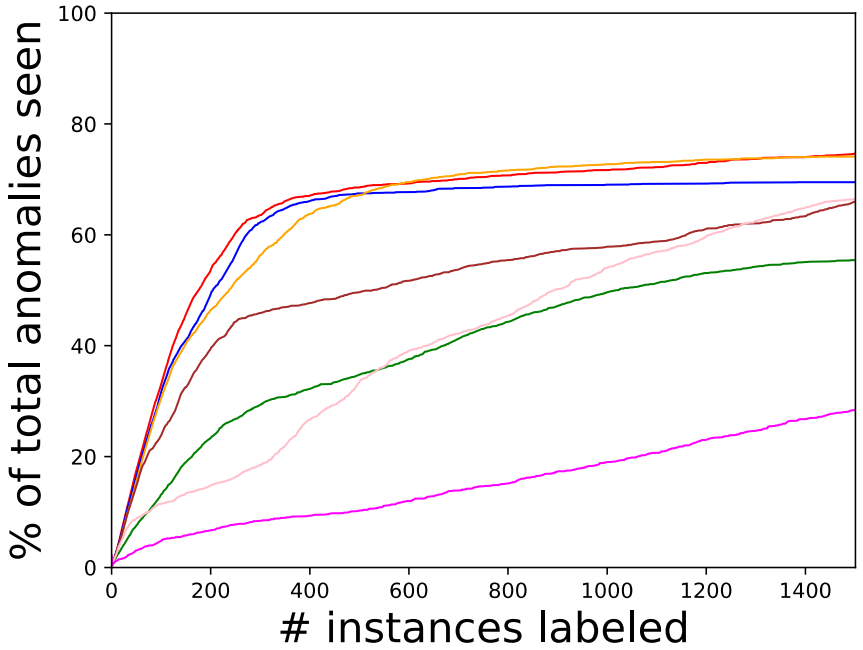
- When there is no concept drift
- Baselines

| Approach | Feedback | Prior | Query Strategy |
|---|---|---|---|
| Unsupervised | NO | N/A | Select Top |
| HiLAD-Batch | YES | Uniform | Select Top |
| HiLAD-Stream | YES | Uniform | Select Top |
| HiLAD-Stream-D | YES | Uniform | Select Diversified |

# Results for “No Drift”

- Limited memory settings

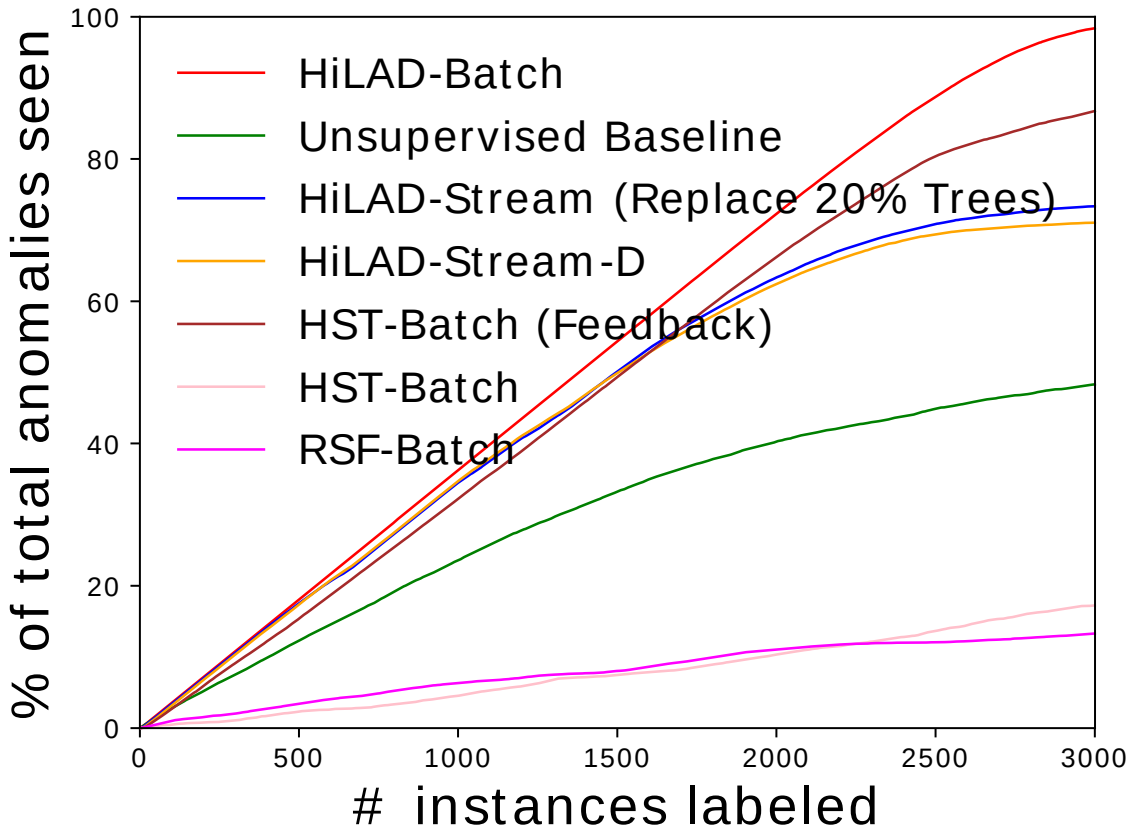


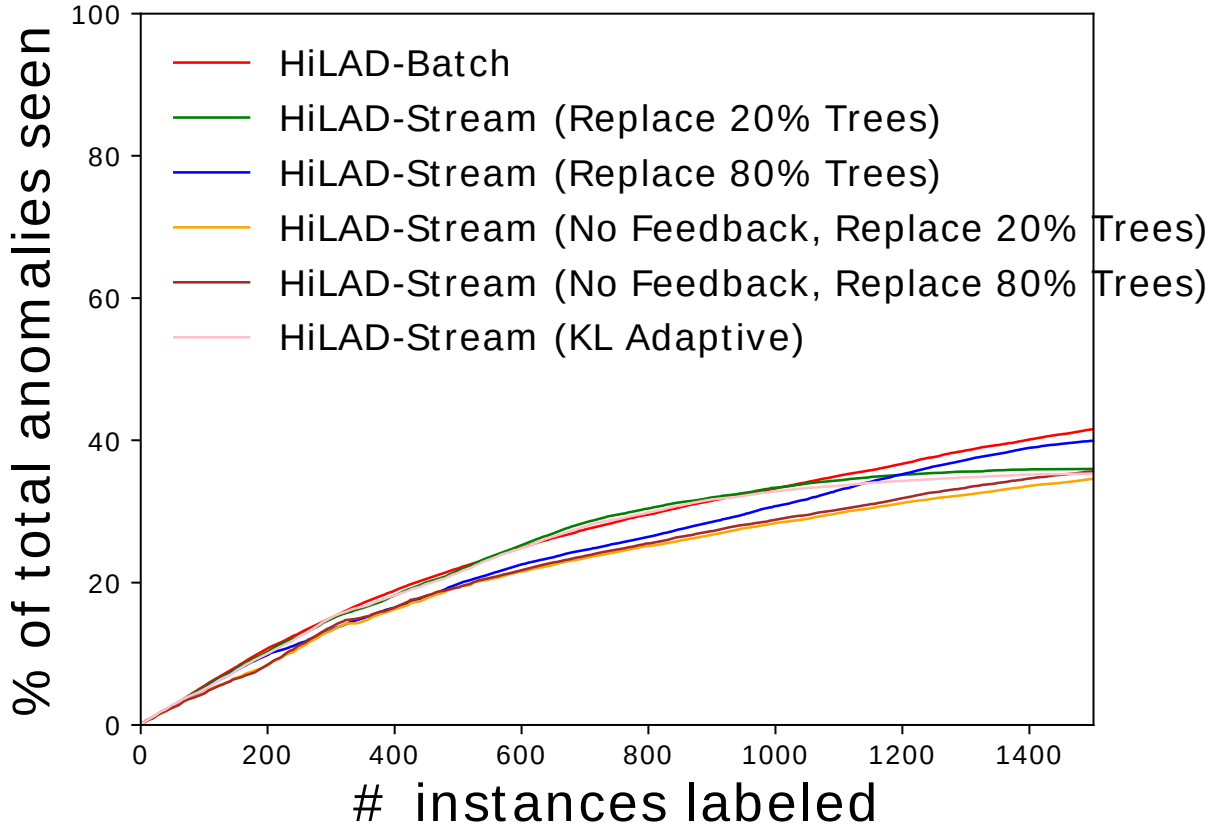

- With feedback, HiLAD-Batch is consistently the best performer
- Performance of HiLAD-Stream is close to HiLAD-Batch (**upper-bound**)

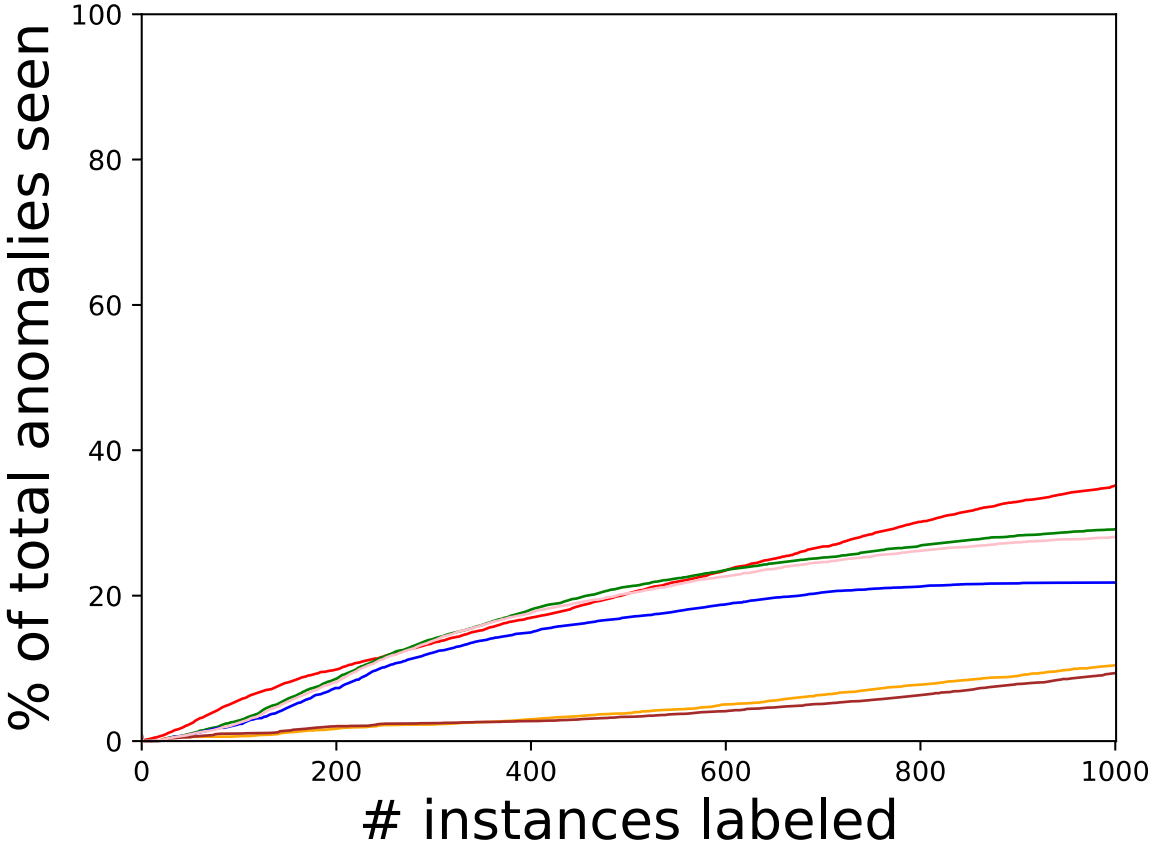
# Results for

- Updating ensemble of trees in a principled manner
  - Fixed threshold (10%, 20%, …)




# Streaming AD with drift detection




HiLAD-Stream(KL adaptive) model update is stable without knowing the drift amount prior.

# Summary

- Unsupervised ensembles and Isolation Forest in particular is a state-of-the-art approach for anomaly detection
  - High false-positive rate => wasted effort from human analyst

- Human feedback can be used to tune ensembles to reduce false-positives
  - Exploit the structure of Isolation forest to discover diverse anomalies
  - Handle streaming data via drift detection and updating ensembles