Reviewer Integration and Performance Measurement for Malware Detection

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Google, UC Berkeley, ICSI, Intel Labs, DataVisor

Status Quo

- Malware detectors have room to improve
  - Only 66% of malware detected in first 24 hours*
  - 93% of malware detected in first month*

(*Damballa: State of Infections Report Q4 2014)

- ML research outperforms industry detectors
  - Multiple projects claiming >90% detection

Questions and Answers

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- **A:** Research is offline, accurate training labels

- **Q:** Can the performance gap be closed?

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- **Q:** Why does research outperform industry?
- **A:** Research is offline, accurate training labels

- **Q:** Can the performance gap be closed?
- **A:** Yes, by expert review of selected samples

Concrete Contributions

- Temporally consistent labels
  - Explains detection rate drop from 91% to 72%
- ML guided human reviewer integration
  - Increases detection from 72% to 89%
  - Detects 42% of previously undetected malware
- Open, scalable implementation & sample data

Overview

- Dataset analysis and design
  - Measure label shift; simulate reviewers at scale
- Experimental design
  - Accommodates time and integrated reviewers
- Experimental results
  - Demonstrated impact of labeling and reviewers

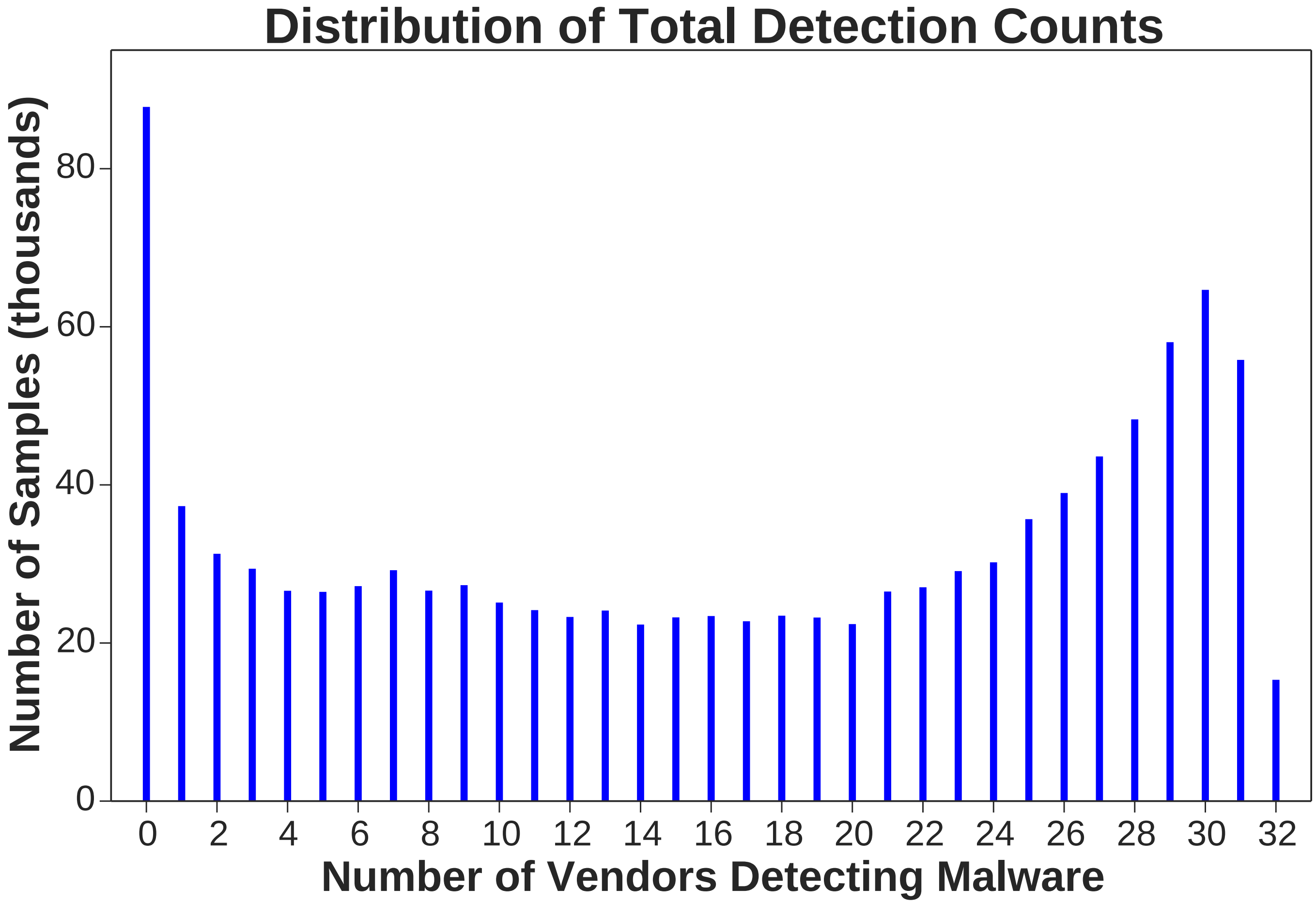
DATASET ANALYSIS AND DESIGN

Data Source

virustotal

- Scans submitted binaries with multiple AVs
- Each scan of a binary has a timestamp
- Re-scans occur upon request or re-submission
- 1M+ samples, 2M+ scans, spanning 2.5 years

Initial Detection Results



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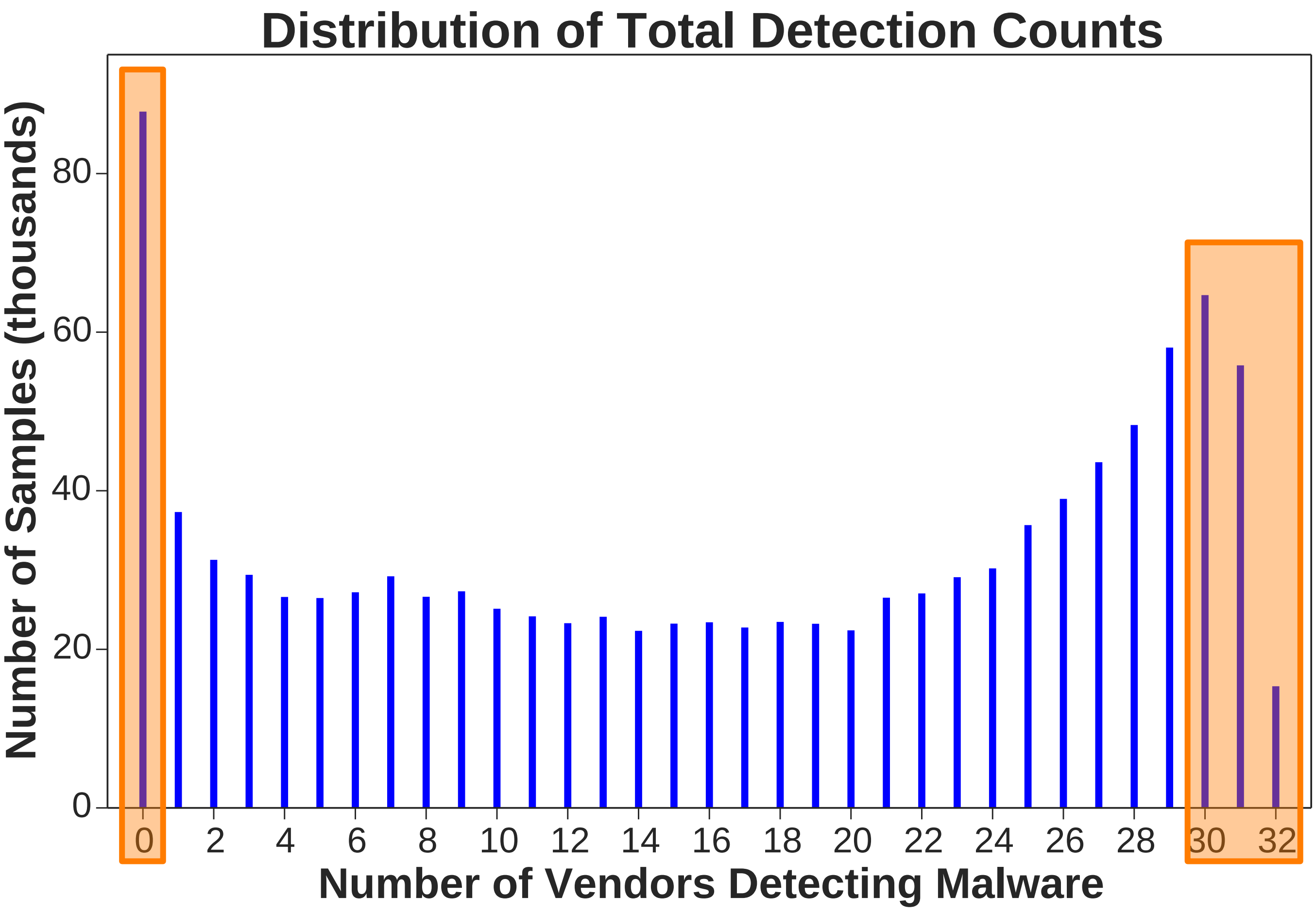

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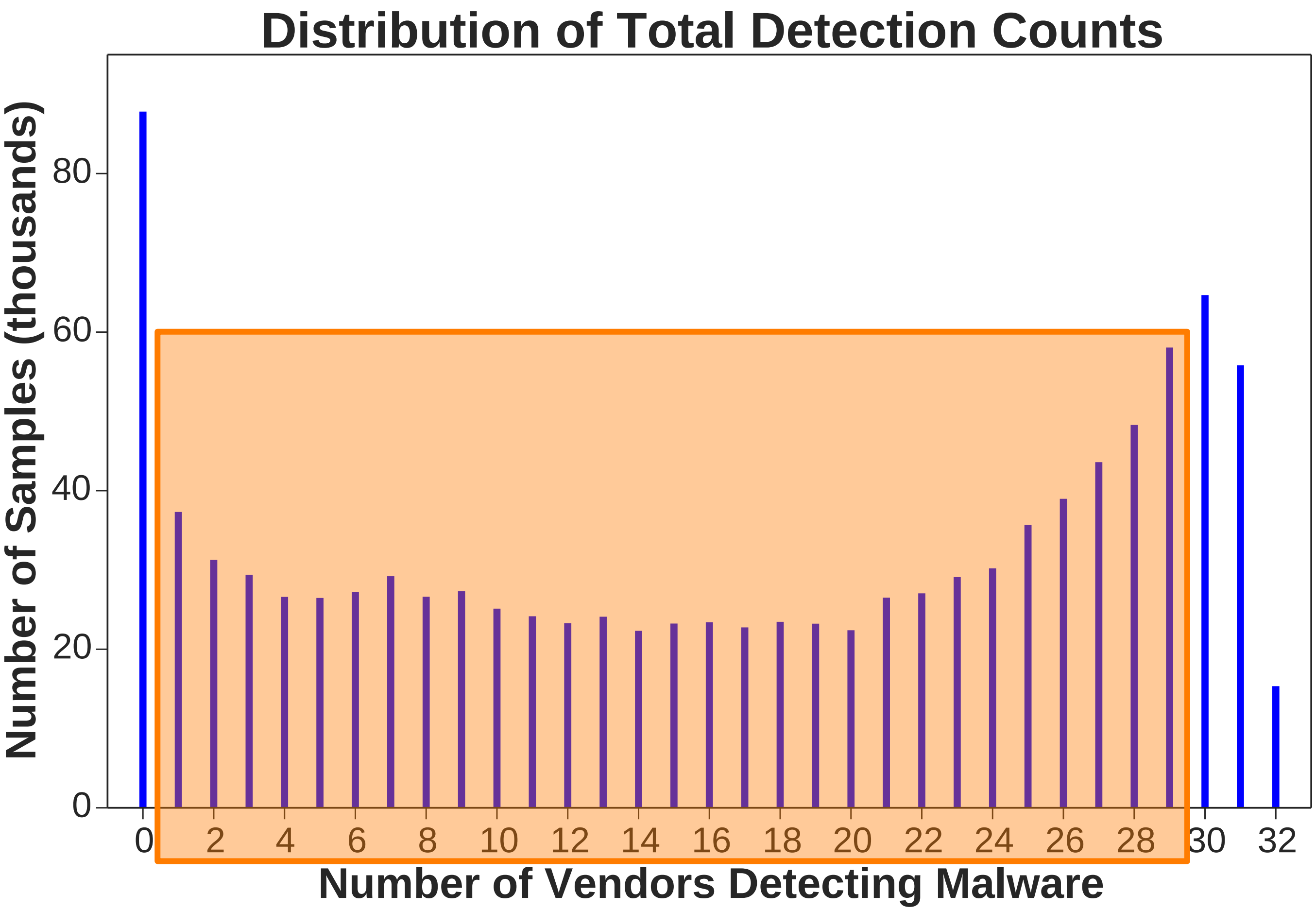
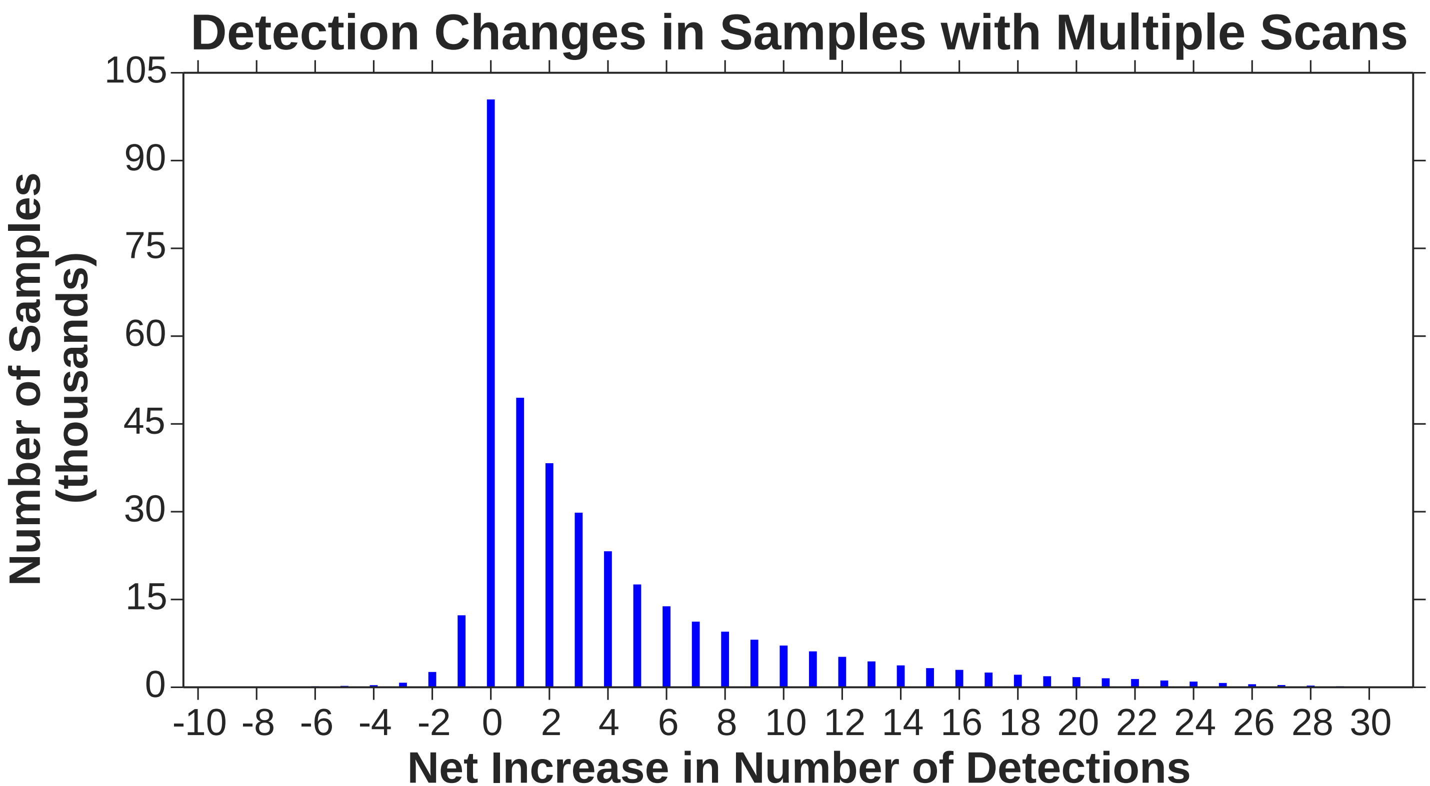


Detection Changes

- Detections generally increase with time



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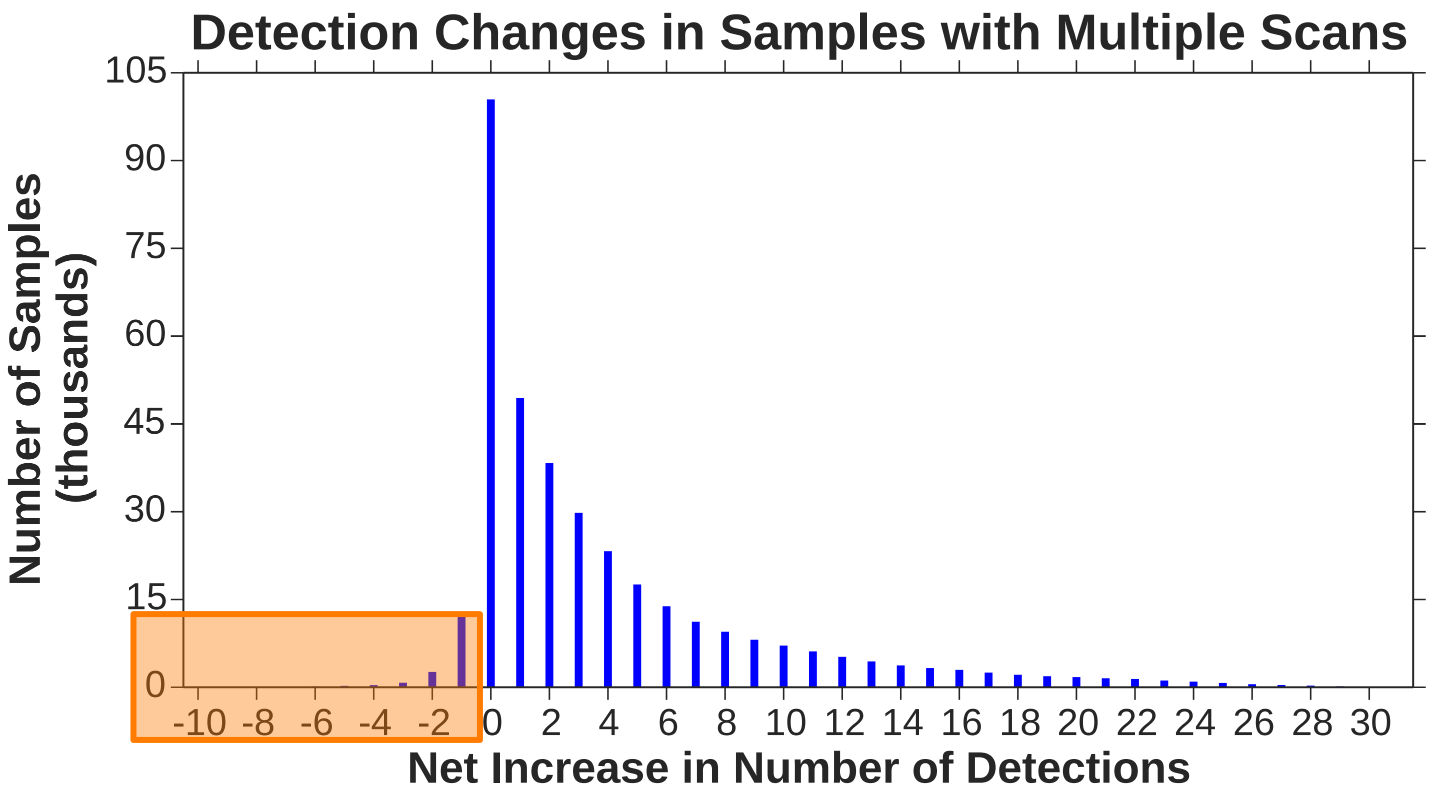
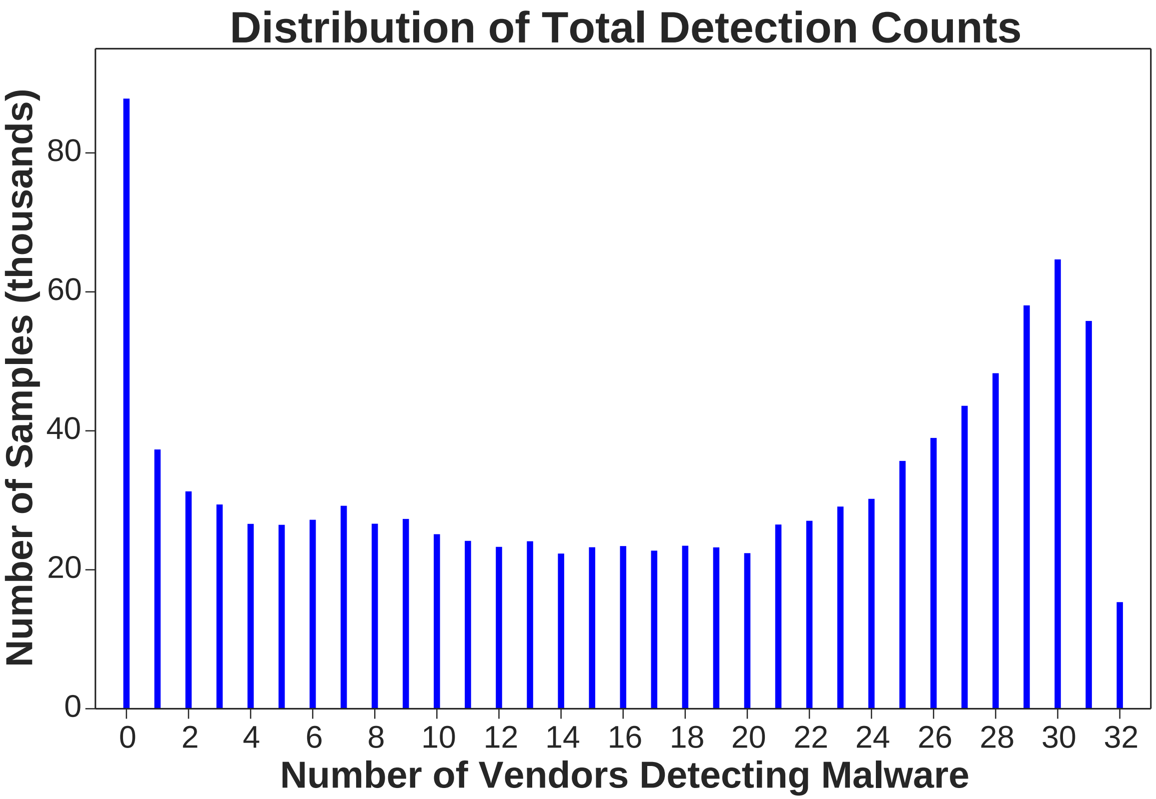


Final Detection Results

- Rescan ambiguous samples to clarify labels



Totals Before Rescan

Final Detection Results

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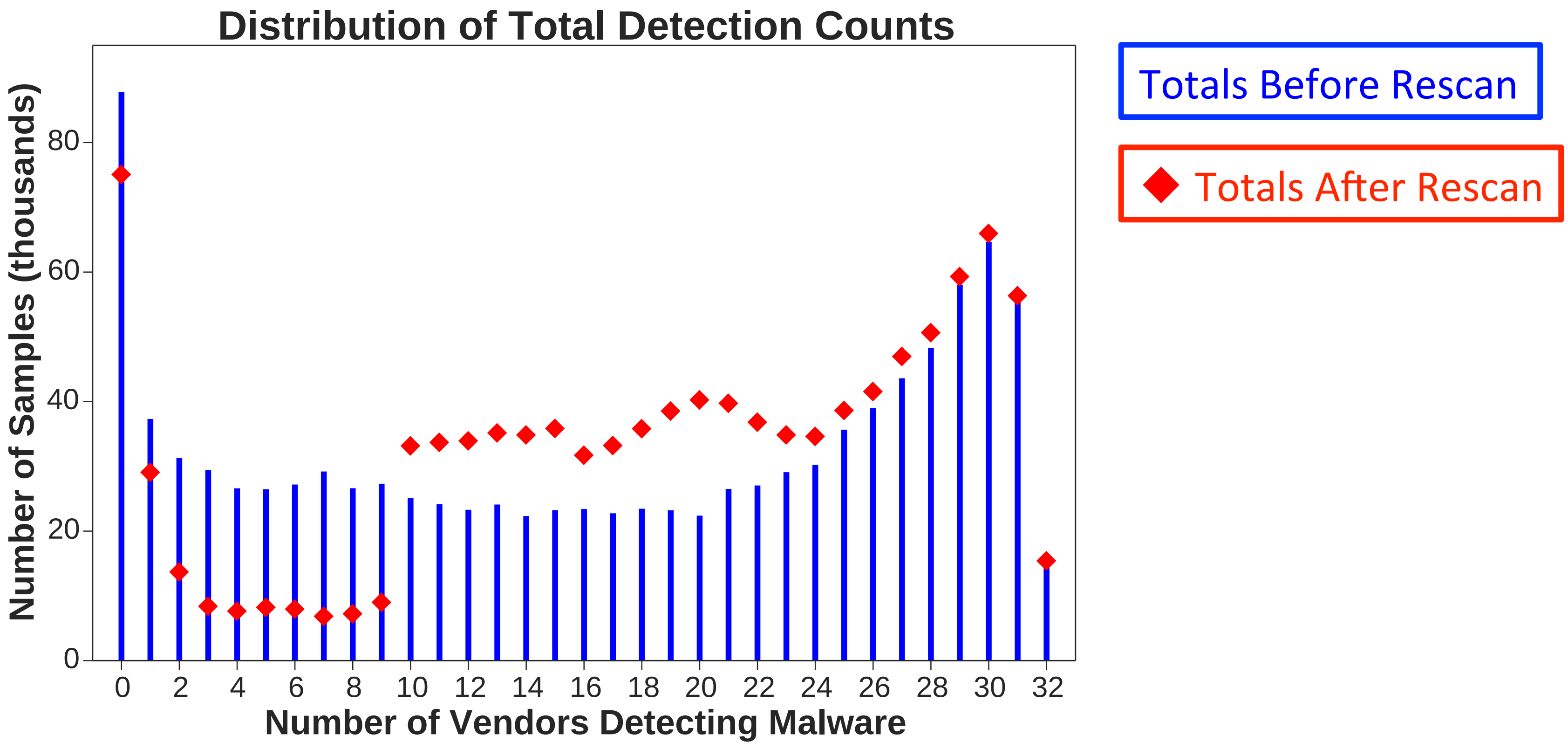

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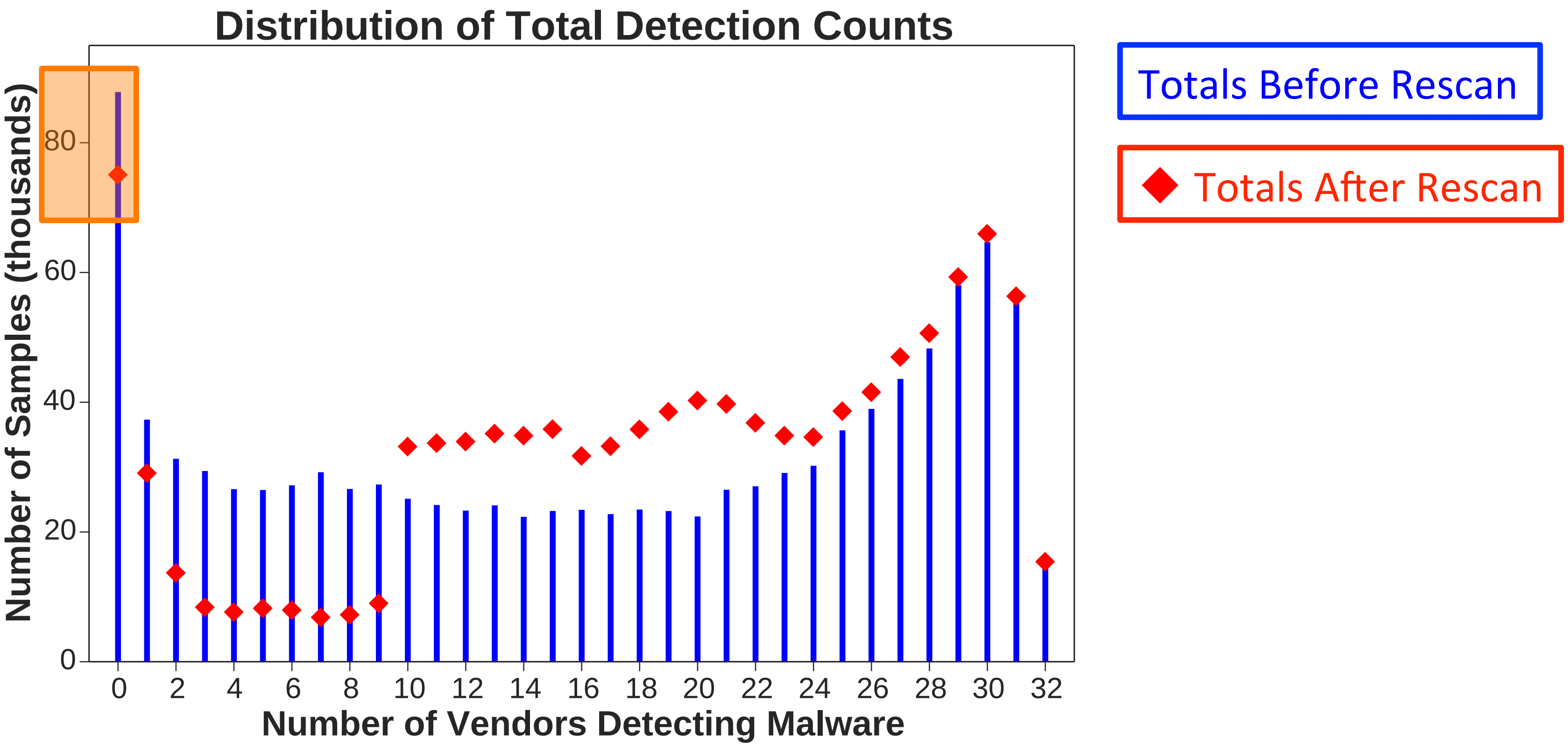

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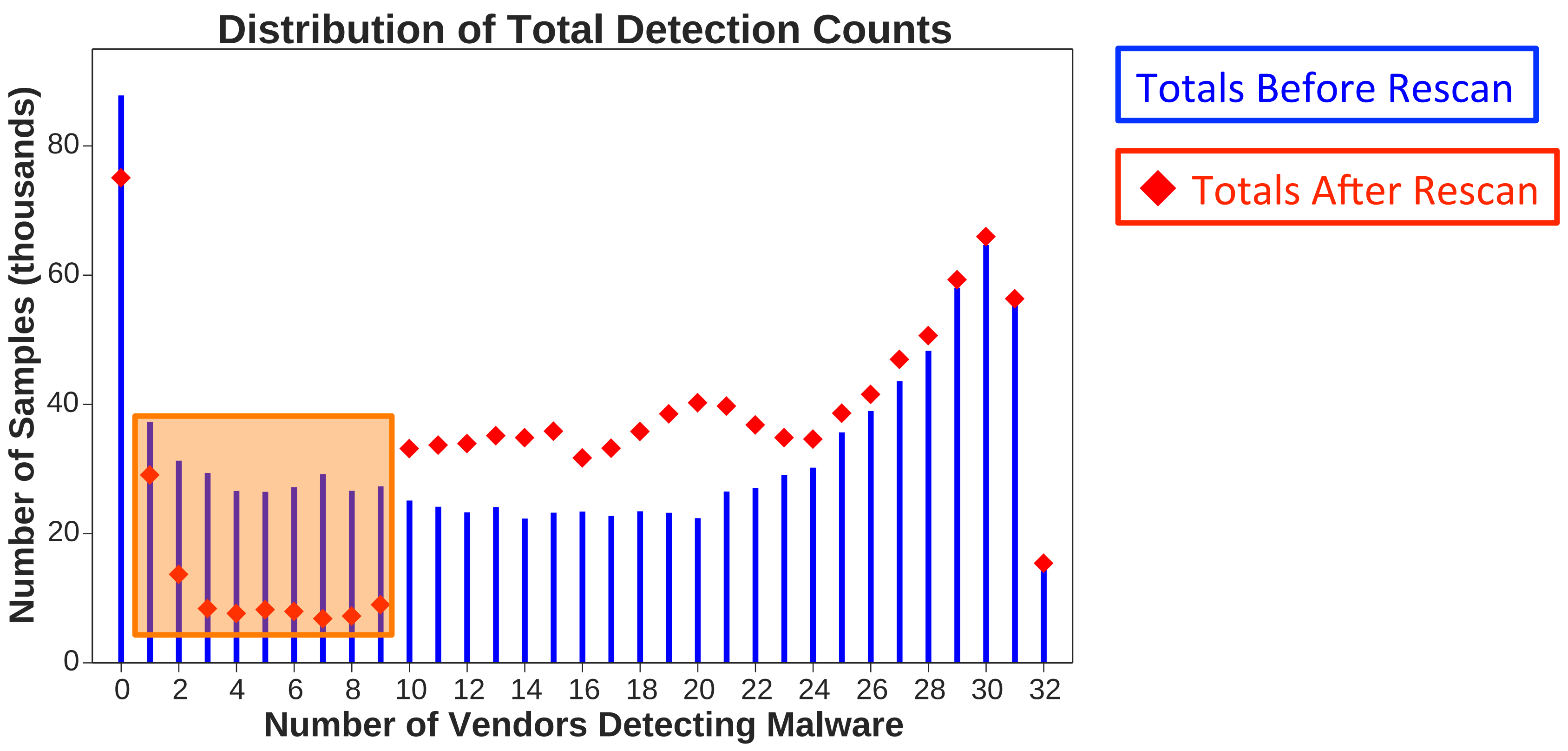

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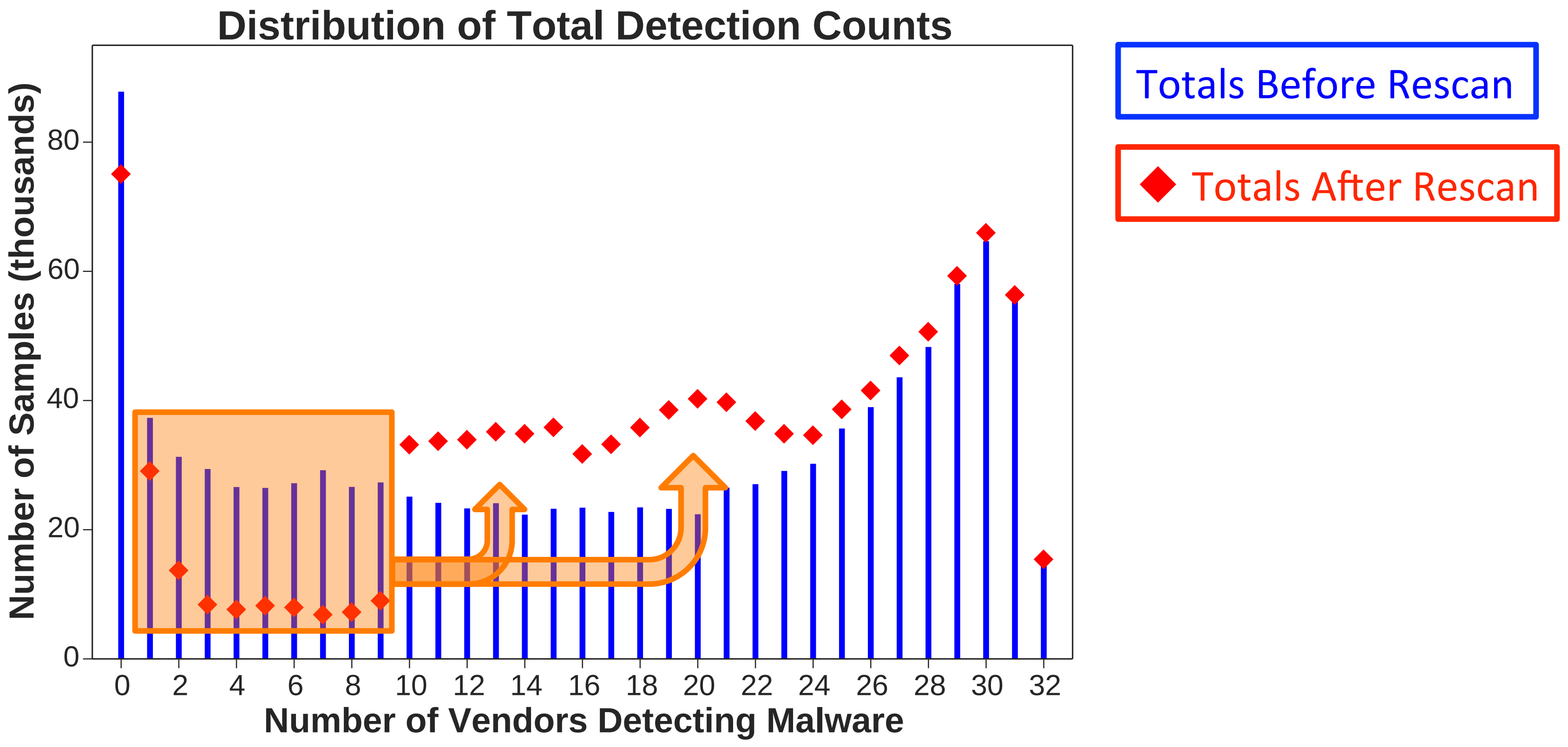

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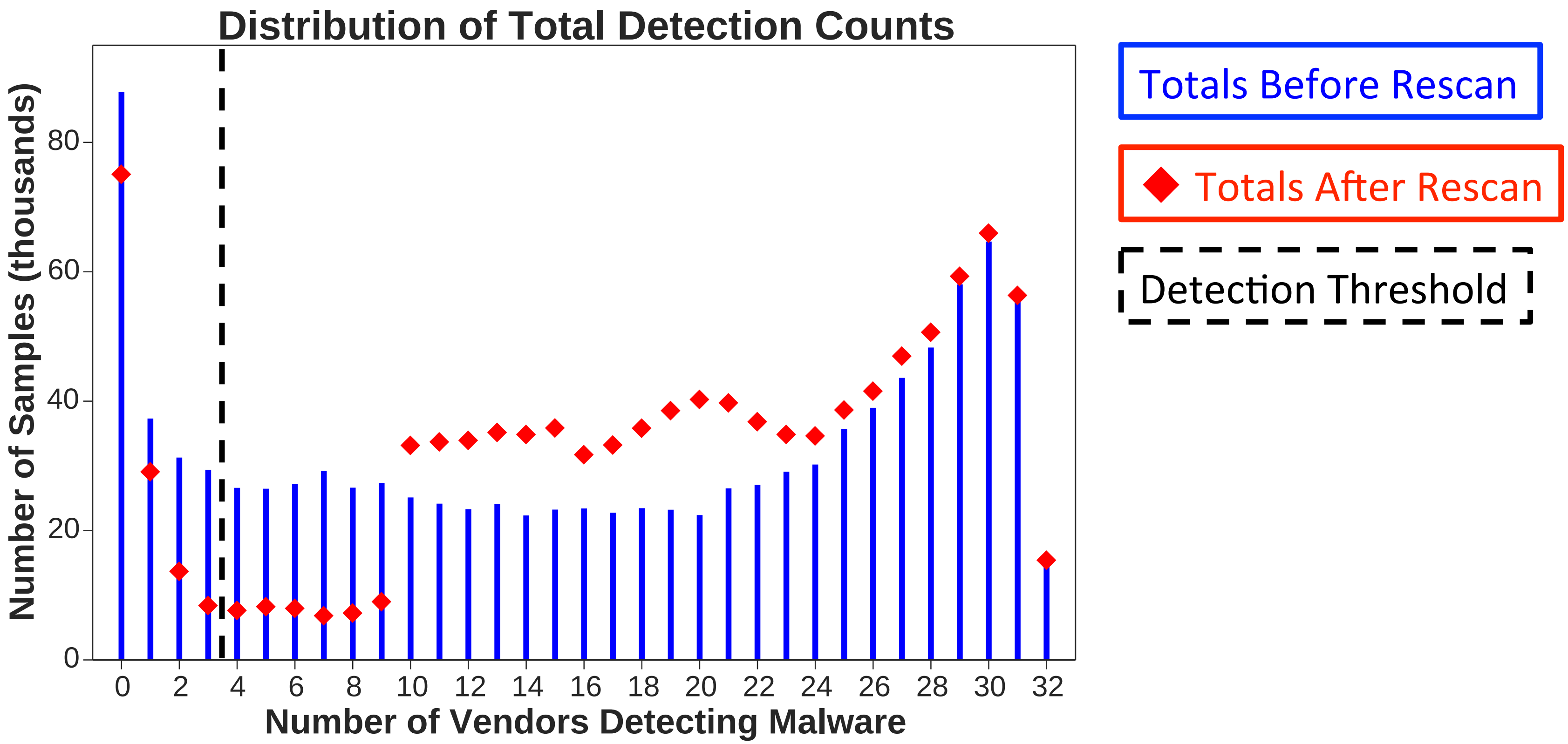


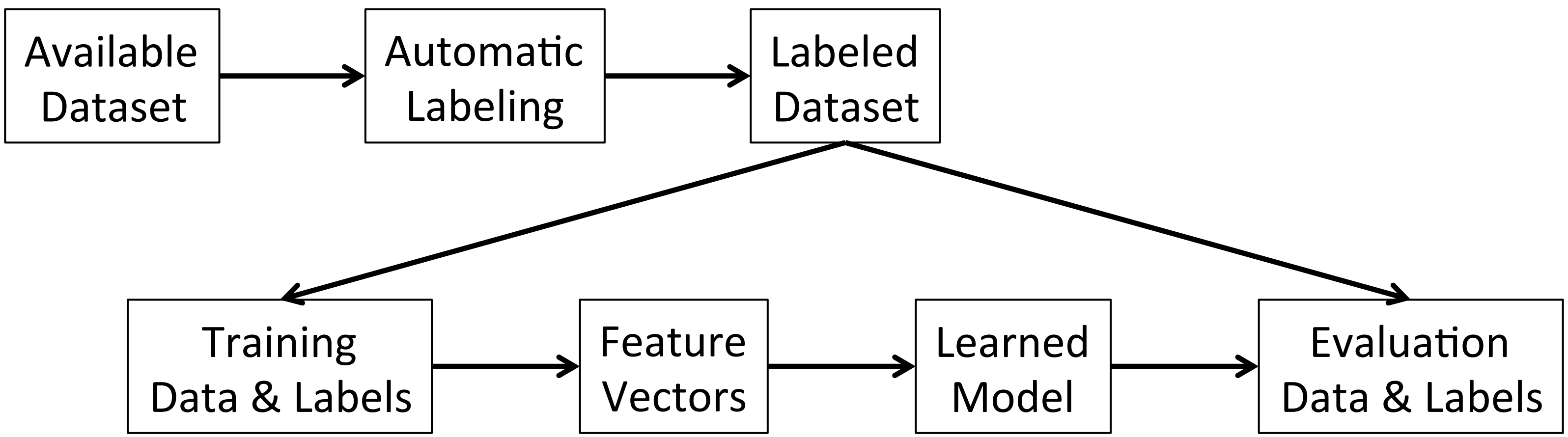
Reviewer Simulation at Scale

- Expert review not tractable for our scale
- We use simulation to study review at scale
- Final scan of sample simulates reviewer label
  - Added noise simulates imperfect reviewers

EXPERIMENTAL DESIGN

Classical ML Approach

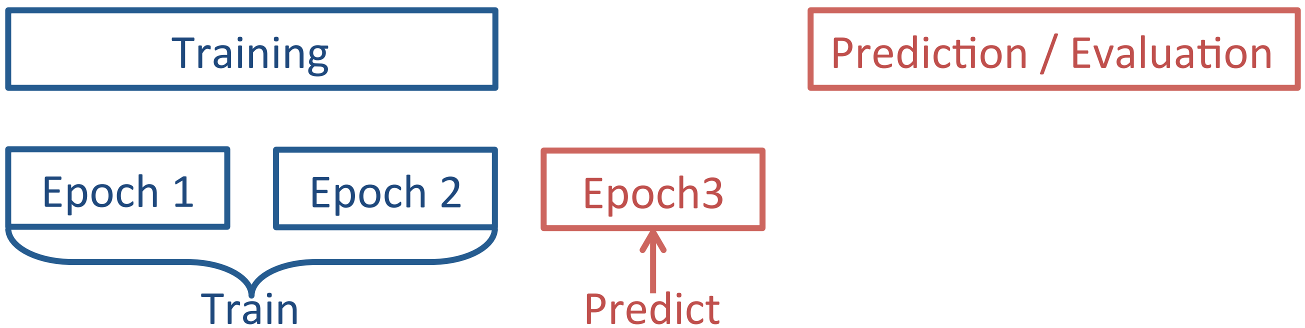
- Standard machine learning workflow



- Randomly divides training and evaluation data
- Training and evaluation labels are high quality

Chronological Sample Epochs

- Epochs provide sample temporal consistency



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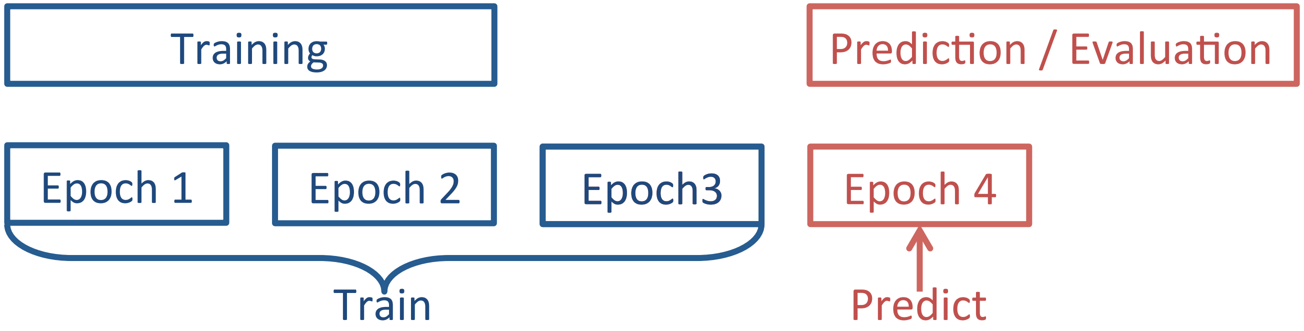

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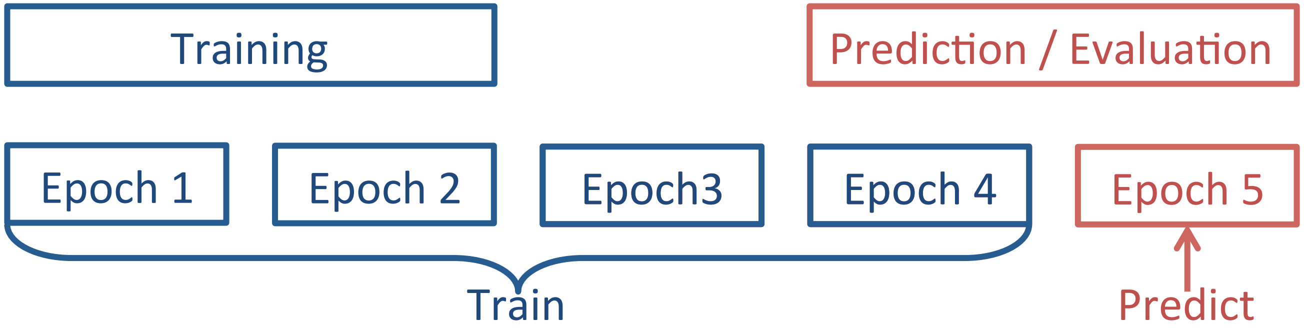

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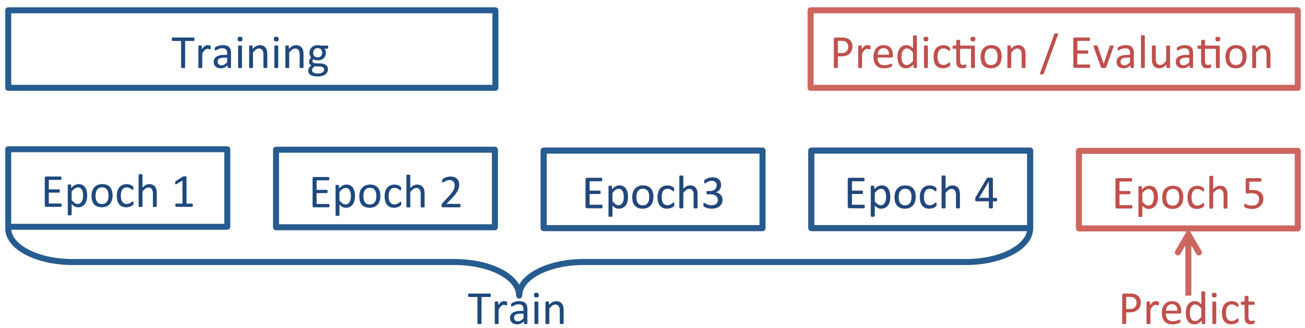
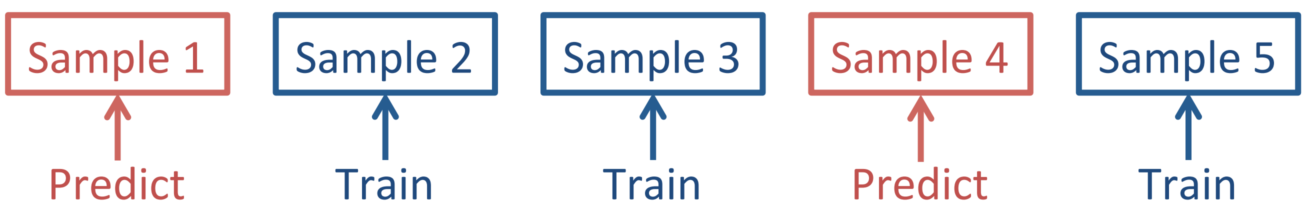
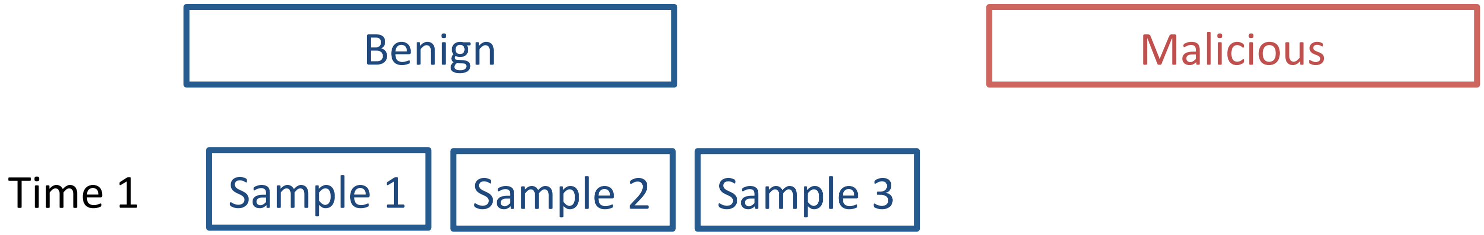


- Random division breaks temporal consistency



Temporally Consistent Labels

- Training labels must be known at training time
- Best possible labels used for evaluation



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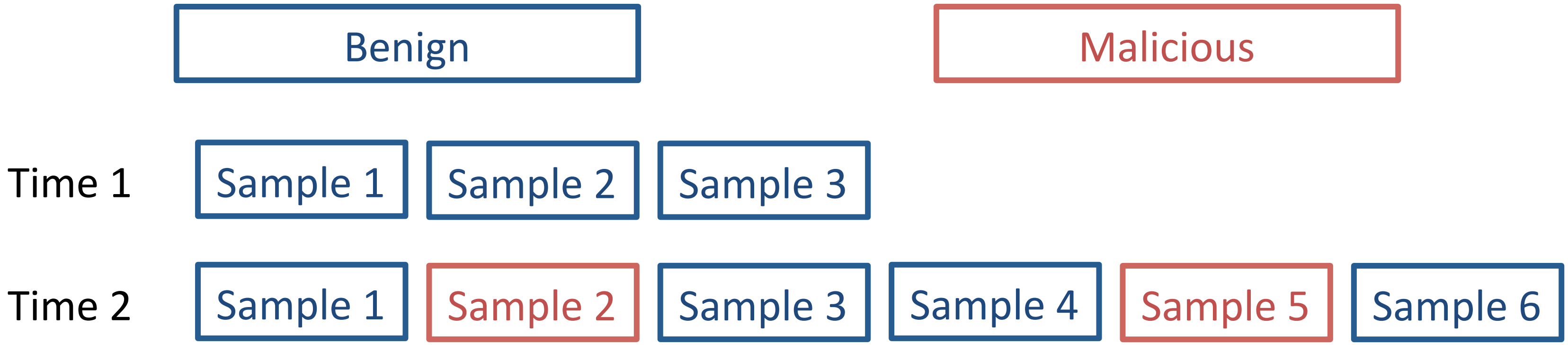

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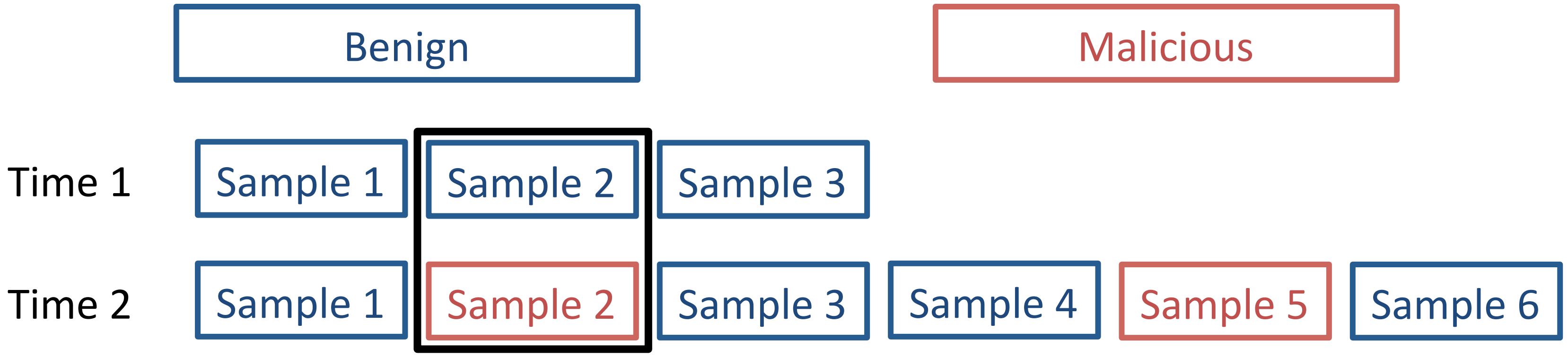

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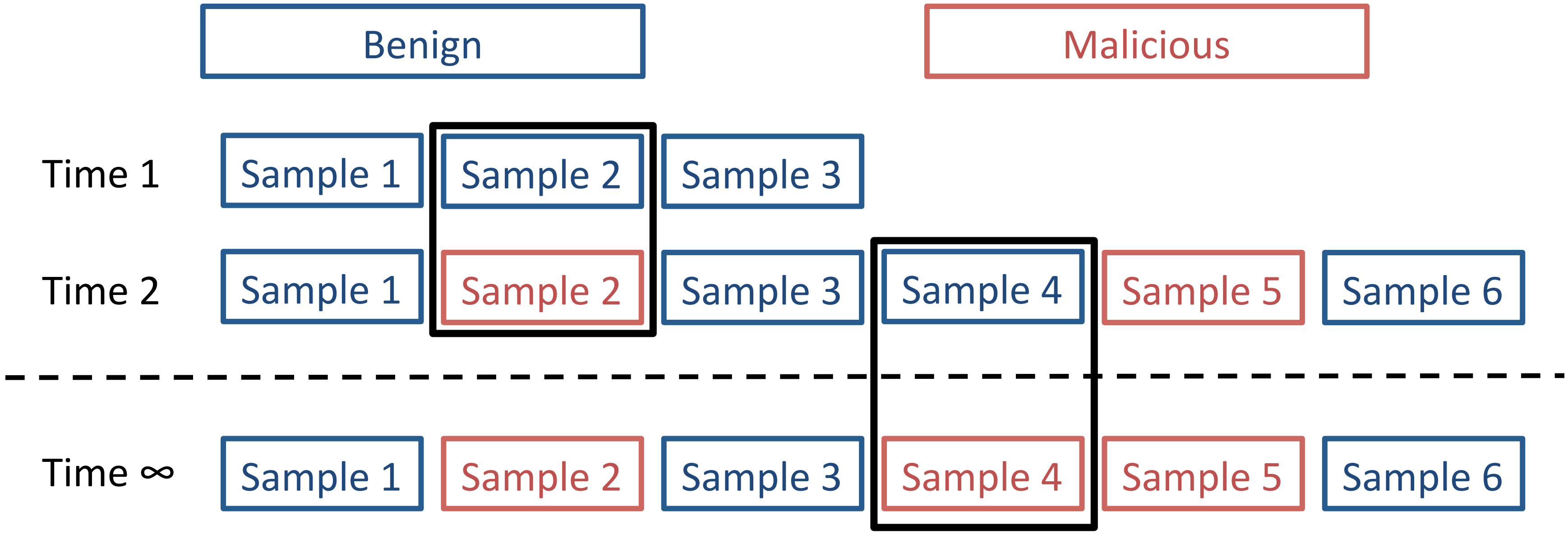
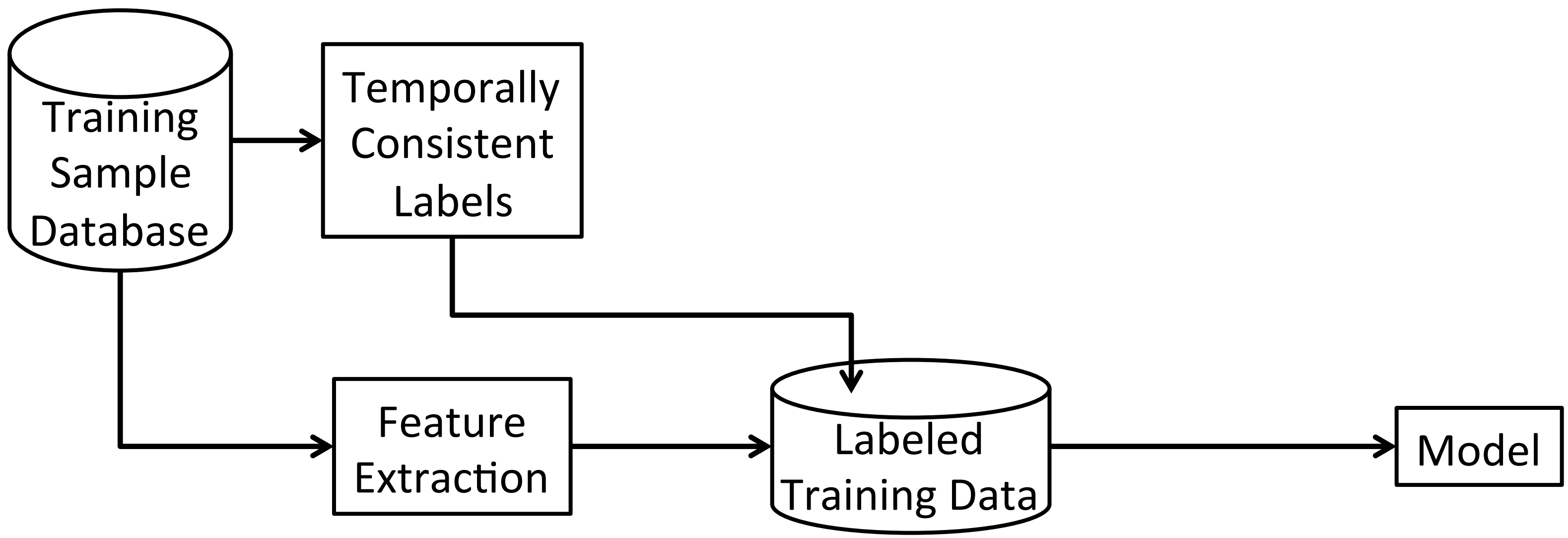


Design Overview



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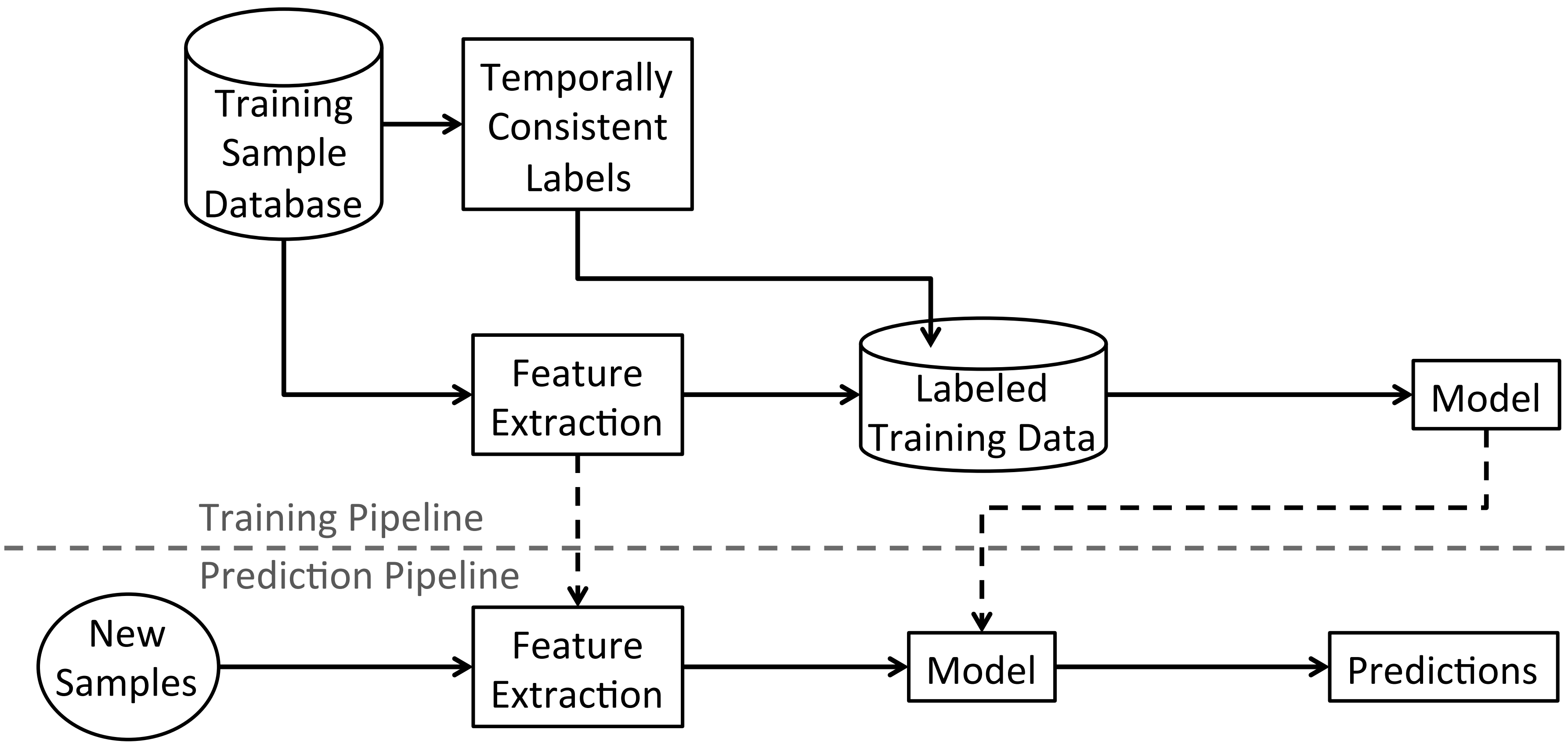

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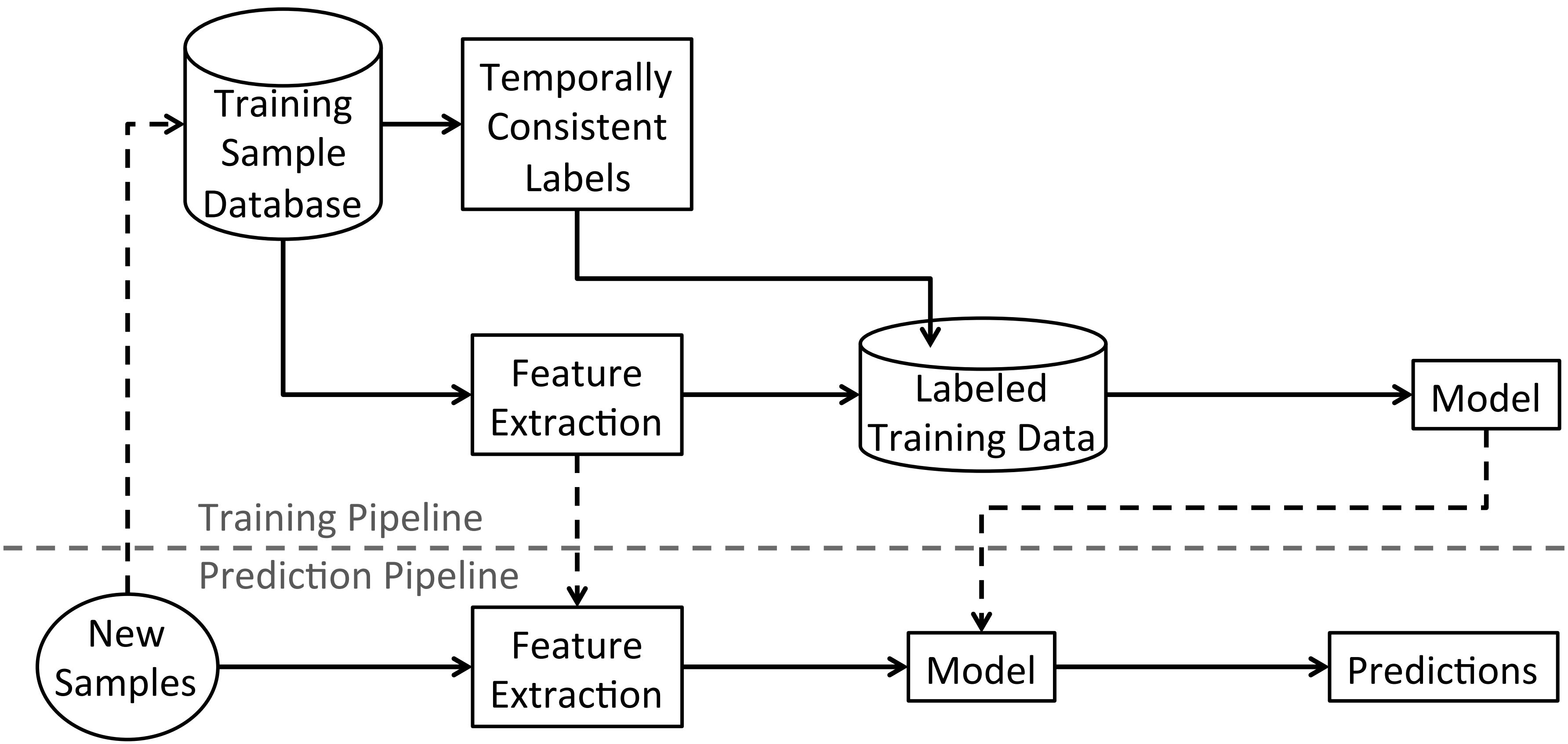

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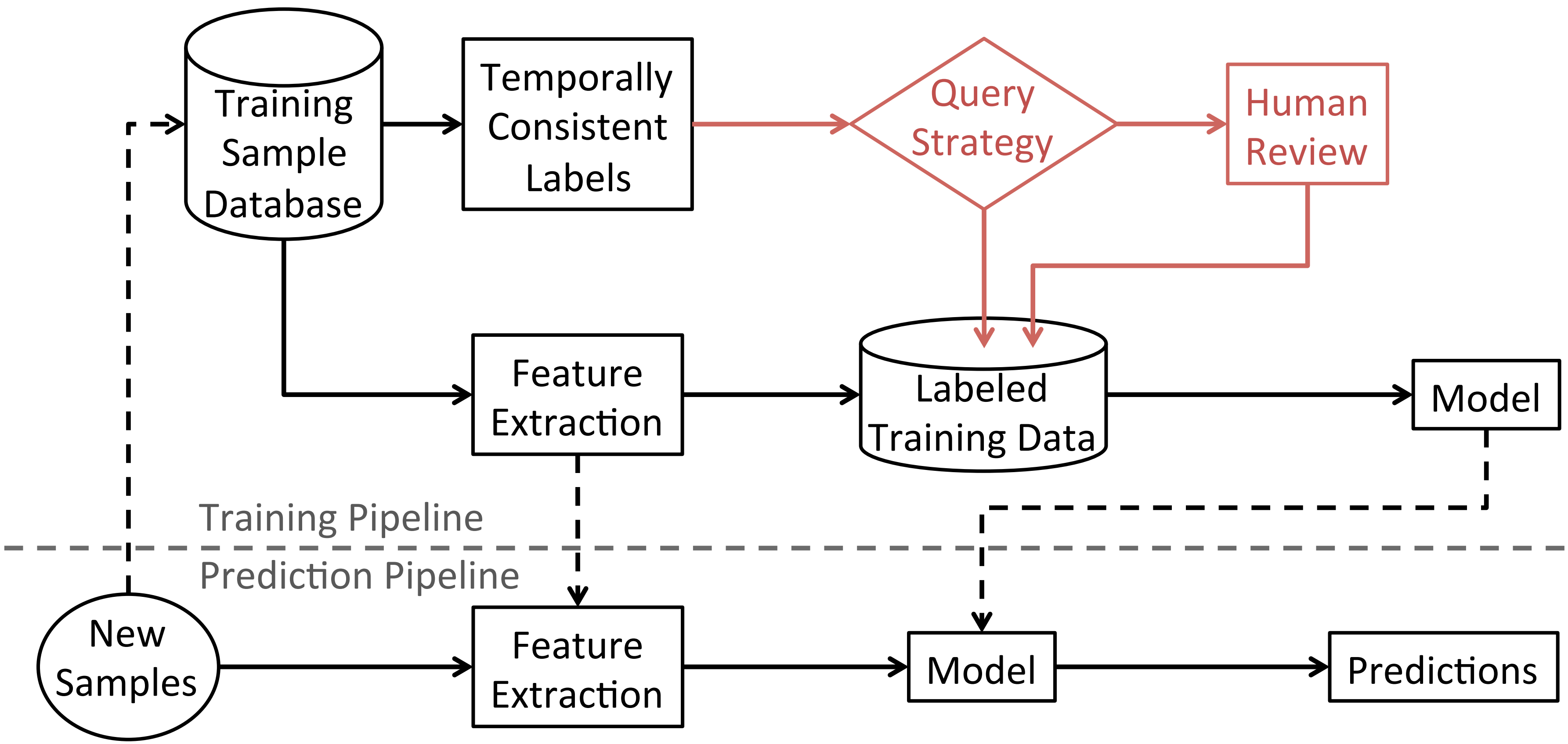

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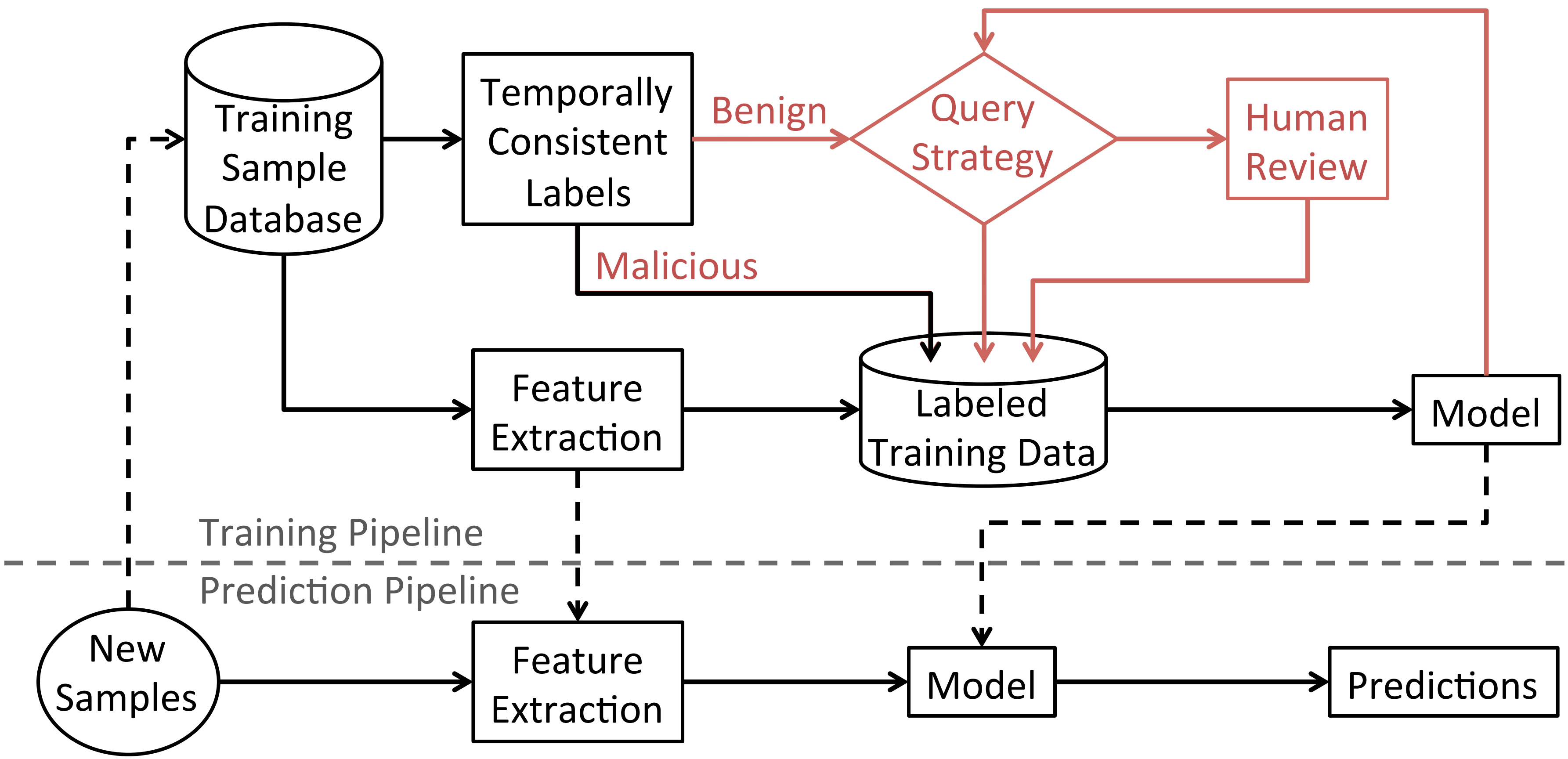

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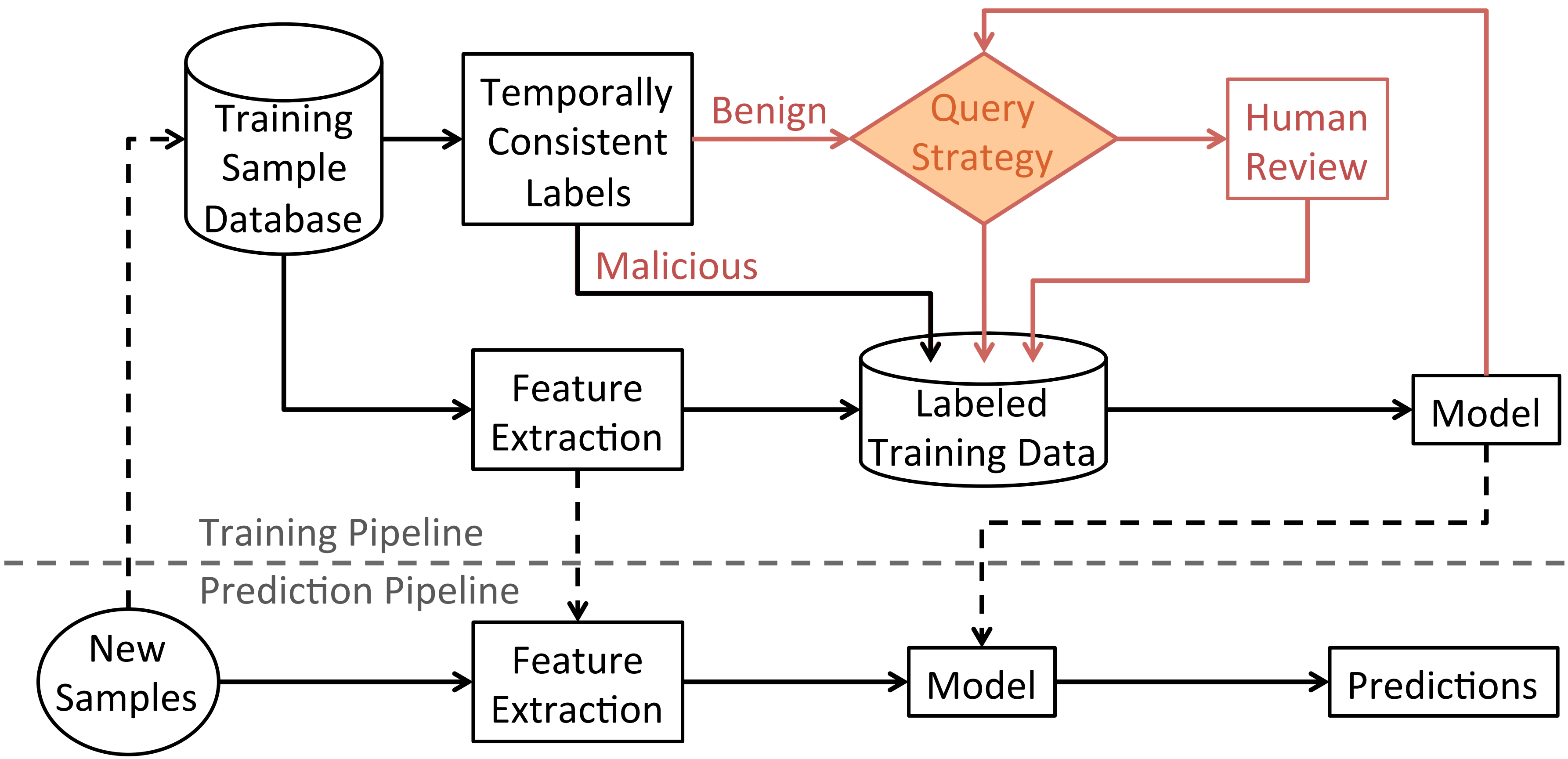
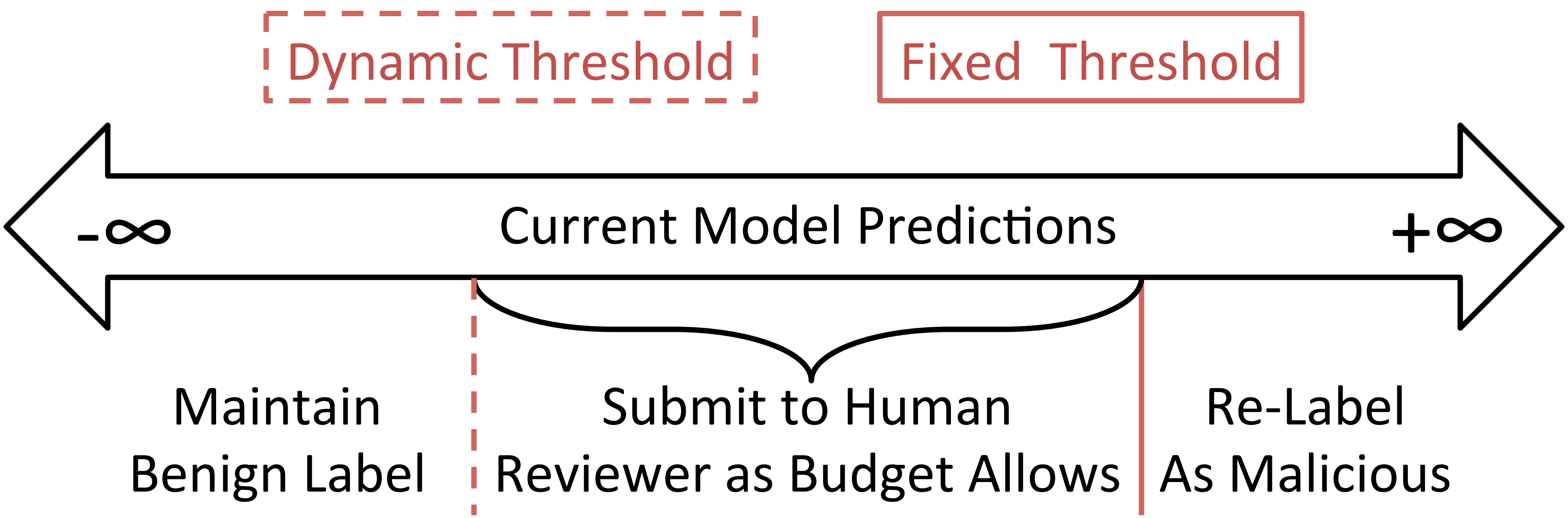


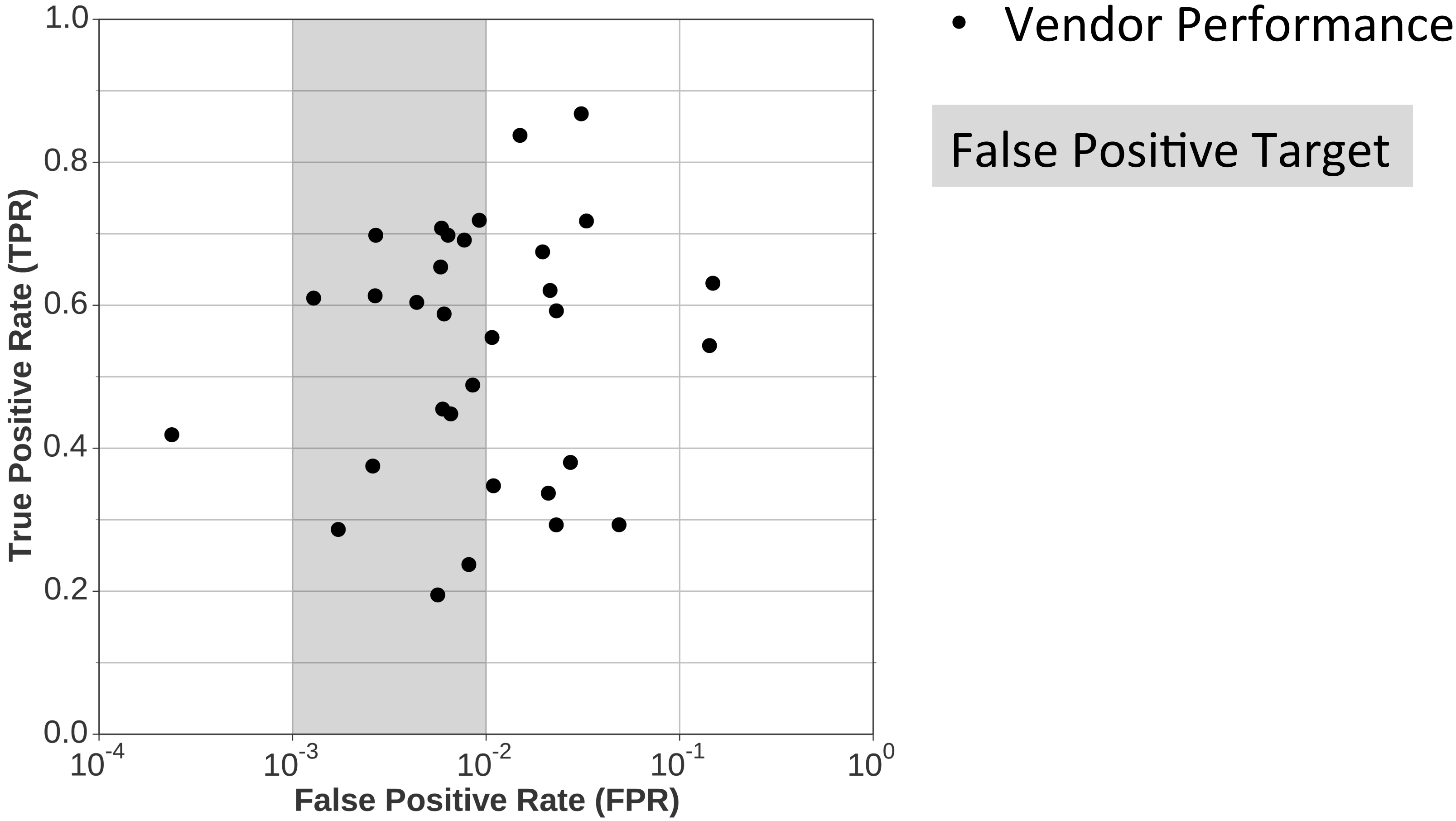
Reviewer Query Strategy

- Score candidate samples with current model
- Submit samples as query budget allows



EXPERIMENTAL RESULTS

Performance Overview



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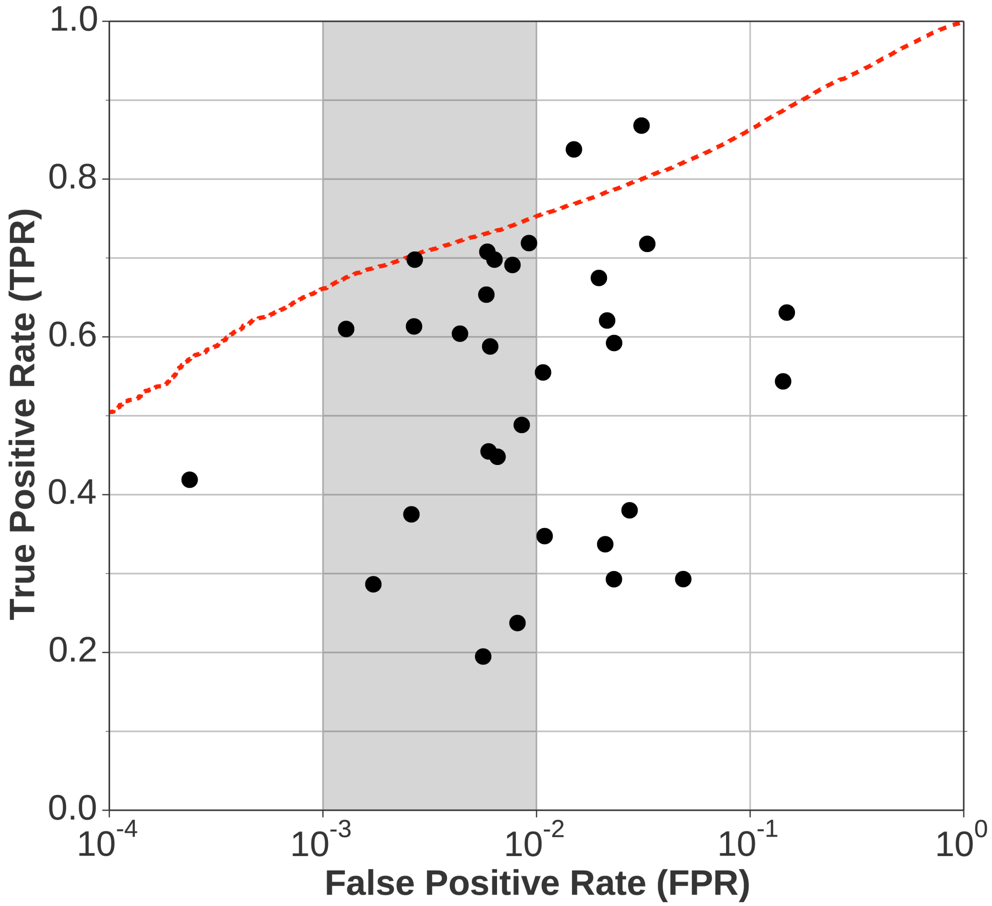

- Vendor Performance

False Positive Target

Online: Temporally Consistent (0 reviews)

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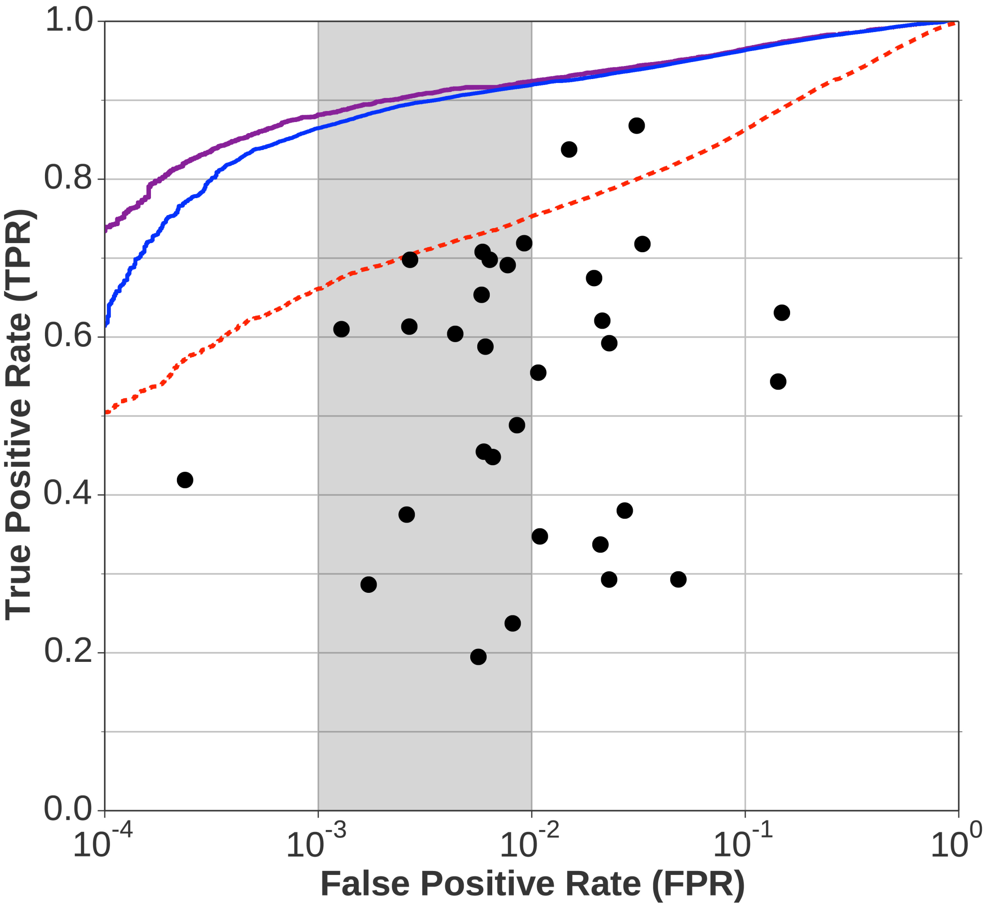

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Offline: Random Division

Offline: Temporal Samples

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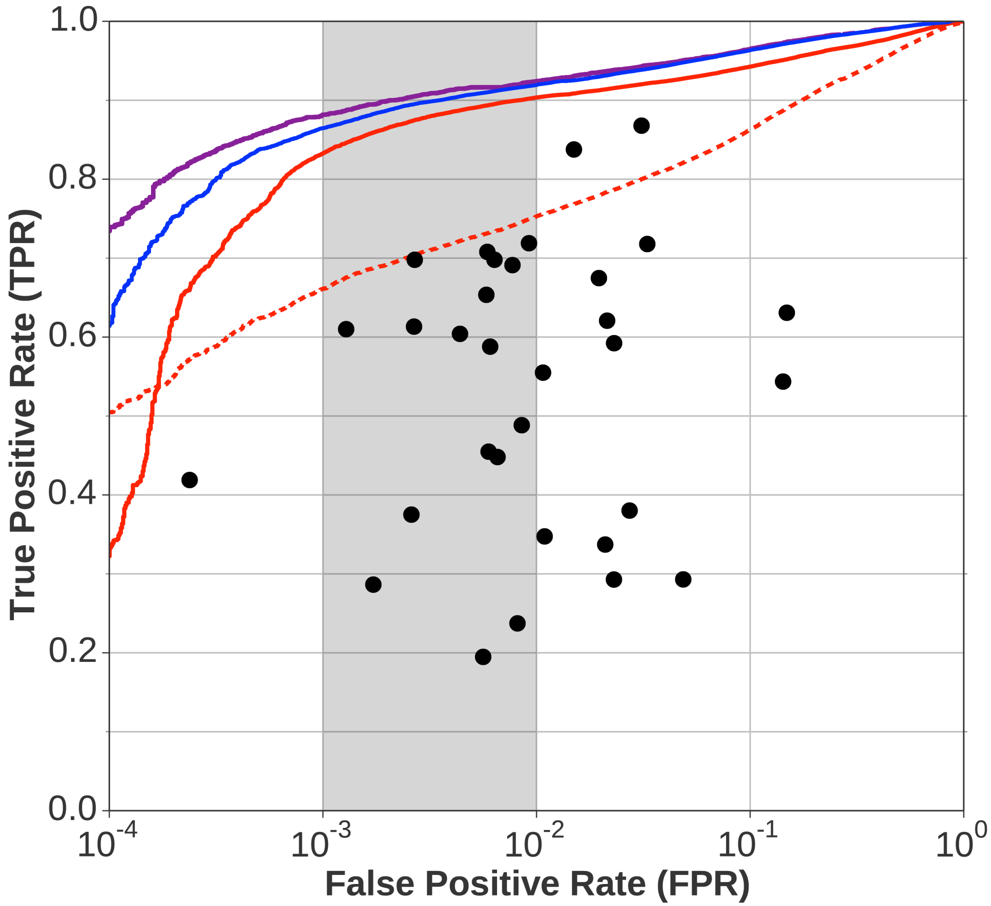

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Online: Temporally Consistent (80 reviews/day)

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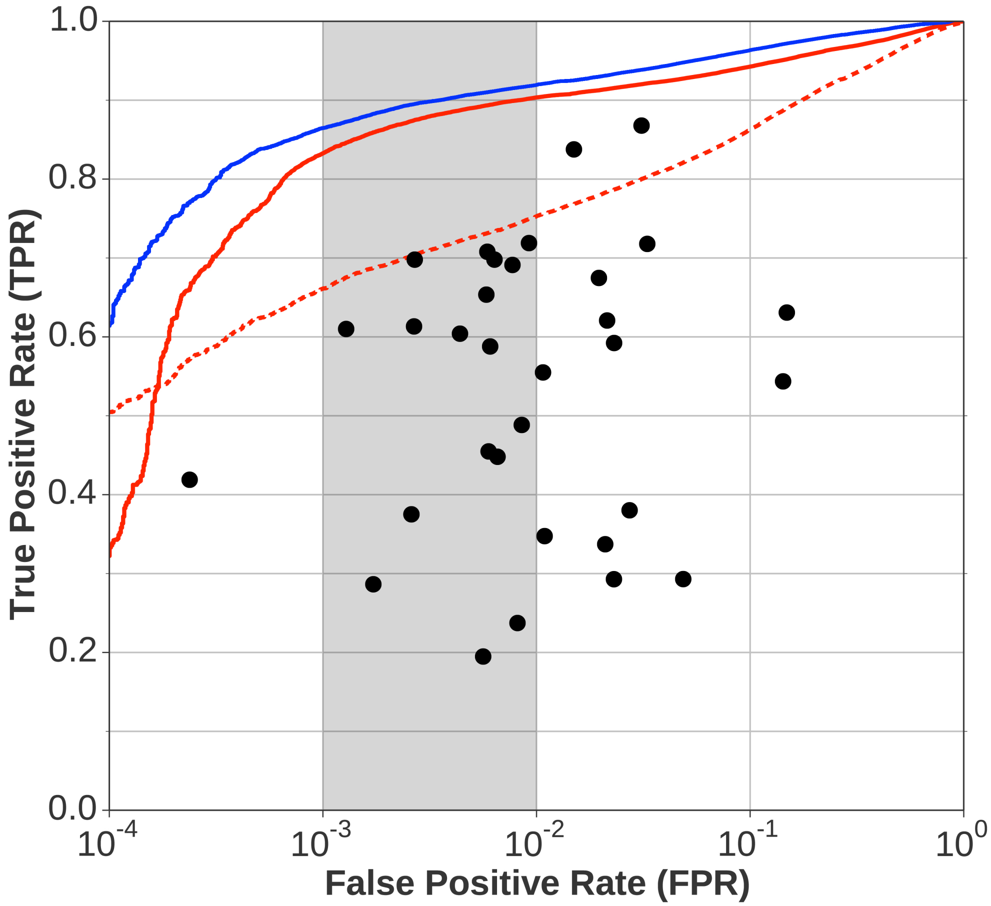

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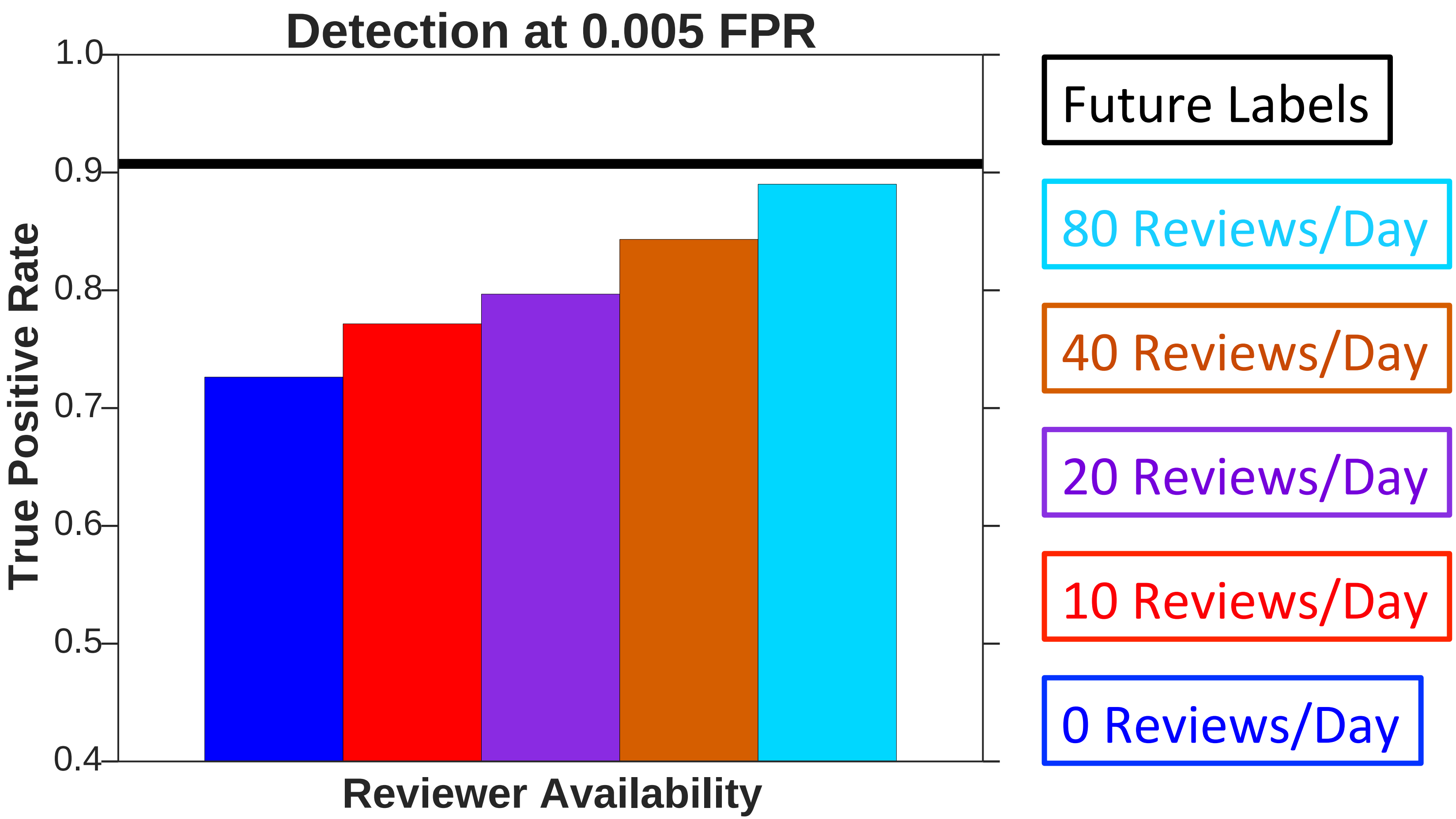
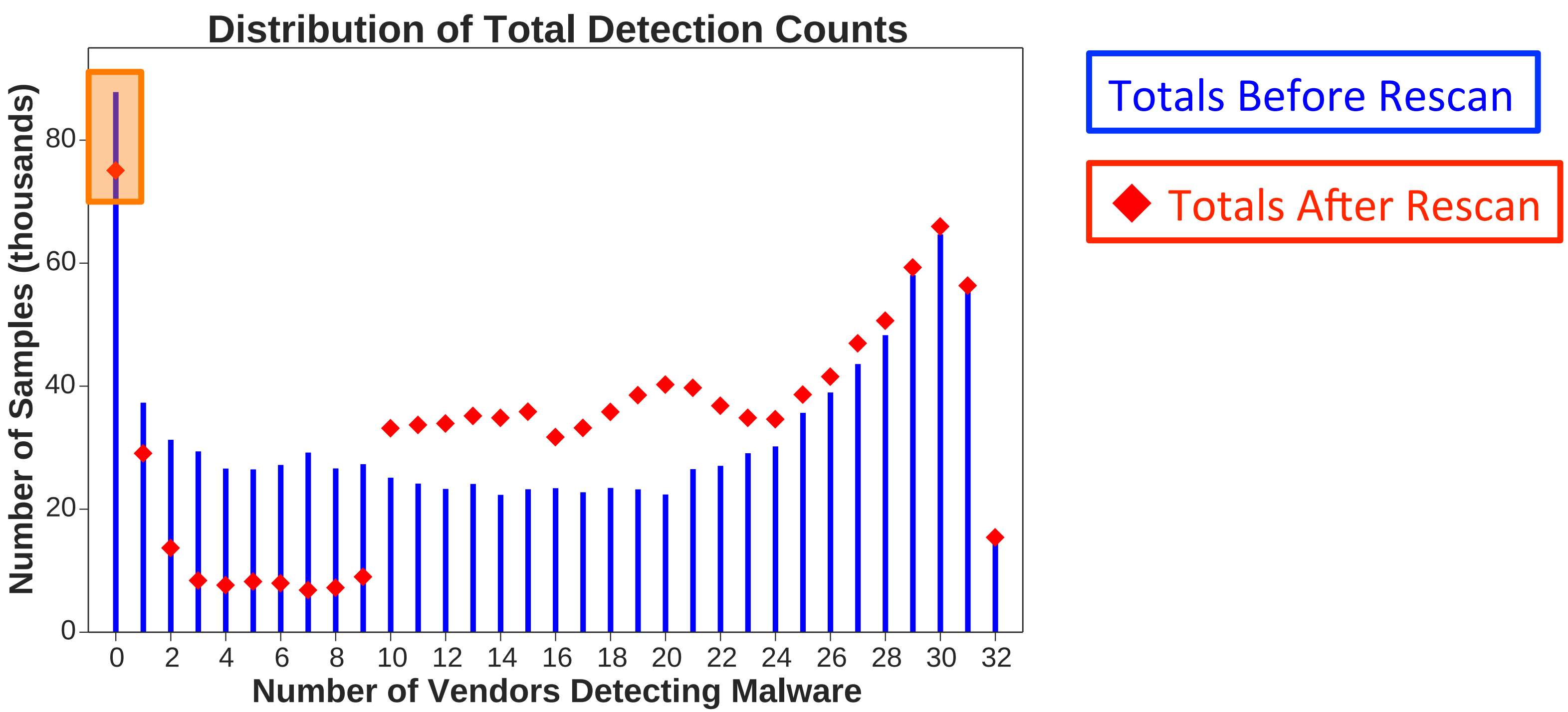
Impact of Reviewer Queries



Catching Undetected Malware

- ML + reviewers increases detector robustness
- Detects 42% of previously undetected malware



Open Source & Data Release

- Modular design facilitates future work
  - Portable across application domains
  - Agnostic to learning algorithm and label source
- Scales well to large amounts of data
  - 778GB of raw data in ~12 hours with 40 cores
  - Apache Spark manages computation
- Data release enables reproducible results
  - 3% of our entire data set
  - List of all hashes

CONCLUSION

Key Results

- Account for industry performance gap
  - Offer improved technique for academic evaluation
- Offer solution to improve performance gap
  - Increases detection from 72% to 89%
  - Detects 42% of previously undetected malware
- Publicly release implementation and data