

A Discriminative Framework for Anomaly Detection in Large Videos



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1. MOTIVATION

- Our goal is to perform anomaly detection in a unique setting, removing the reliance on data and/or temporal assumptions.
- Our setting is largely unaddressed in vision-based anomaly detection, but appears often in practice







4. SYSTEM OVERVIEW

The framework from video to anomalies



First-time data: New systems and environments



Personalized results:Database sifting:Unique testingExploring a singledistributiondata chunk

Our setting involves two challenging restrictions

(1) Operate relative to the test sequence



(2) Score independent of ordering



2. APPROACH & KEY INSIGHTS Taking a discriminative, permutation-based approach allows us to operate in this setting

- No training data required
- Anomaly scores are independent of ordering

5. RESULTS This method ne

This method performs as well as other methods that require a training set

Avenue Dataset Similar frame- and pixel-based ROC, without using the training set UMN Dataset Higher AUC on all but 1 scene Example: Scene 7





Insight #1: Density ratios directly estimate discriminability, minimizing distribution assumptions

Density ratio concept





How we use density ratio estimation

Examples: Correct detections



panda sneeze

throwing

papers



crowd running

child

skipping



Examples: Failure cases



illumination

camera shake





subtle crowd movement single exitentrance

6. FUTURE WORK

Context-driven improvements could come from feature learning, active learning, and data





player

Insight #2: Permutation testing removes temporal assumptions, avoiding false positives

Scanning techniques Our method Ground truth: digit from MNIST Ground truth: digit from MNIST 100 100 150 150 50 One-class SVM, learned on frames 1-100 Our discriminative framework without shuffles 100 100 150 50 150 200 50 One-class SVM, fully online Our discriminative framework after 10 shuffles 150 200 150 200 50 100 50 100 frame number frame number





Feature learning: align with human notion of abnormality Active learning: incorporating feedback from humans

Datasets: developing larger, more realistic benchmarks

Acknowledgements. This research was supported through the US Department of Defense National Defense Science & Engineering Graduate Fellowship (NDSEG) Program and NSF grant IIS1227495.

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