# ANOMALY DETECTION IN VIDEO FEEDS

**TEAM NAME:** Team Gabru

**PROJECT SUPERVISOR**

Prof. Pabitra Mitra

**PROJECT MENTOR**

Anirban Santara

**TEAM MEMBERS**

| | | |
|---|---|---|
| Aishik Chakraborty | \| | 13CS30041 |
| Ashish Sharma | \| | 13CS30043 |
| Chinmaya Pancholi | \| | 13CS30010 |
| Jatin Arora | \| | 13CS10057 |
| Jeenu Grover | \| | 13CS30042 |
| Prabhat Agarwal | \| | 13CS10060 |

# INTRODUCTION

## ❖ Anomaly

- Unusual motion patterns of unusual objects in unusual locations


- **Objective:** Identify such **outliers** in video feeds using Machine Learning techniques

# MOTIVATION

- Requirement to **process high volumes of data automatically**

## USE CASES

1. Security
2. System Health
3. Old-age home monitoring
4. Child Monitoring

# CHALLENGES INVOLVED

1. **High Computational Complexity** : Have to deal with video feeds which may be several 100 GBs in size

2. **Online Detection of Anomalies :** May be required to detect anomalies in the videos in real time especially for surveillance tasks

3. **Anomaly is Context-Dependent** : Similar events and actions can be considered anomalous in some scenarios and regular in others

4. **Annotating extremely rare events** : Anomalies occur rarely making manually spotting and annotating them a tedious and difficult task

# DATASET

## ❖ UCSD Anomaly Detection Dataset [1]

- Stationary camera mounted at an elevation, overlooking pedestrian walkways

## ❖ Reasons for Anomaly

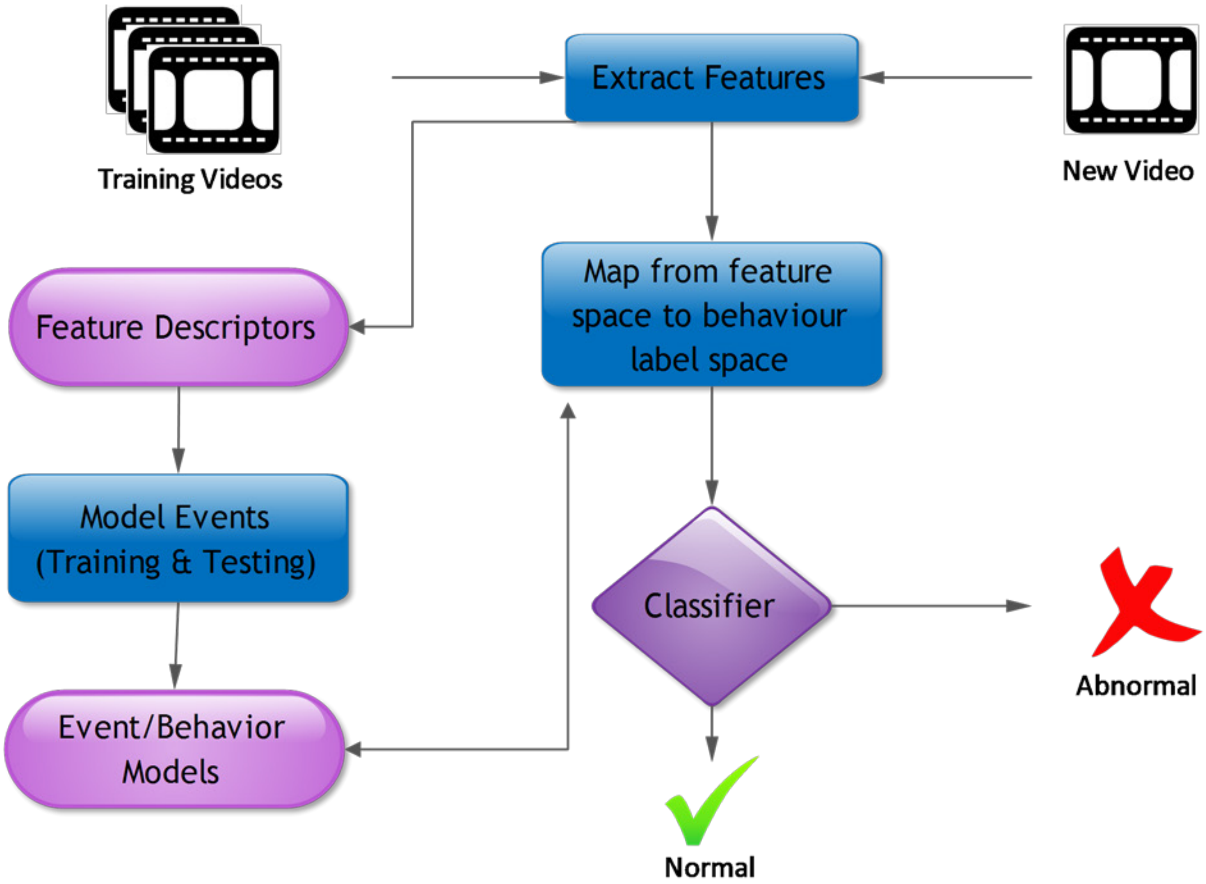
- Circulation of non-pedestrian entities in walkways
- Anomalous pedestrian motion patterns

## ❖ Dataset Composition

- **2 subsets** - Ped1 and Ped2
- **Ped1:** Contains **34 training** and **36 testing** videos
- **Ped2:** Contains **16 training** and **12 testing** videos
- 10 clips from Ped1 and 12 from Ped2 are provided with manually generated pixel level binary masks

[1] http://www.svcl.ucsd.edu/projects/anomaly/dataset.htm

# GENERAL APPROACH



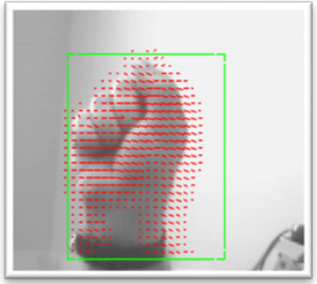
# APPROACH 1: Using Optical Flow

❖ Feature Extraction

Video

Convert to Pixels
and Frames

Background
Subtraction



Optical Flow

Feature Vector [ ● ● ● ● ● ]

# APPROACH 1: Using Optical Flow

- Classification using Decision Tree

| APPROACH | PED1 | | | PED2 | | |
|---|---|---|---|---|---|---|
| | F1-Score | ROC | EER | F1-Score | ROC | EER |
| **Optical Flow** (Threshold = 10) | 0.57 | 71.55% | 36.23% | 0.25 | 57.88% | 45.71% |
| **Optical Flow** (Threshold = 50) | 0.64 | 78.15% | 30.03% | 0.29 | 59.76% | 44.58% |

# APPROACH 2: Feature Extraction using AlexNet

- **AlexNet**
  - Object Classification using deep neural networks

- **BVLC Reference Caffenet**
  - Pre-trained AlexNet on the 1.2M image ILSVRC-2012 dataset

**Video**

Sample Frames

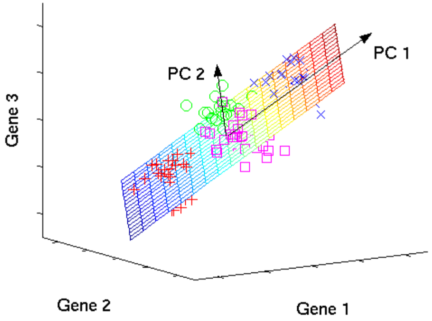
**Output of fc7 Layer**

**4096 dimensional Feature Vector**

# APPROACH 2: Feature Extraction using AlexNet

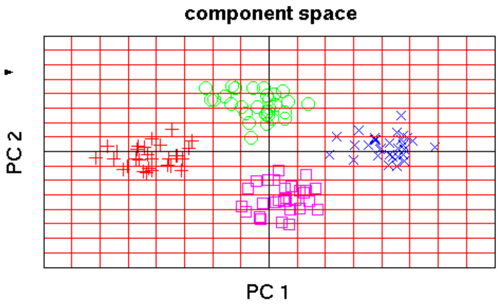
| APPROACH | PED1 | | |
|---|---|---|---|
| | F1-Score | ROC | EER |
| **AlexNet** | 0.39 | 58.05% | 45.08% |

# APPROACH 3: Time Series Analysis




4096 dimensional feature space for each frame

PCA




Dimensionality Reduction (300)

Time Series Analysis over each dimension

[ ]
1 2 3 4............No. of frames

No. of dimensions Anomalous in each frame

No. of dimensions with anomaly ?

>= threshold

< threshold

ANOMALY

Normal

**Precision:** 0.68
**Recall:** 0.60

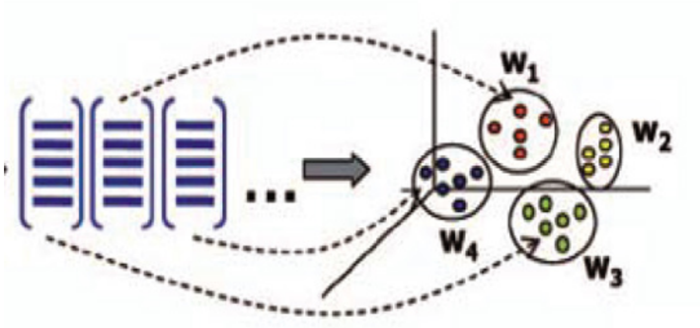
## ❖ Seasonal Hybrid ESD (S-H-ESD):

- Statistical Anomaly detection procedure in real valued time-series data

# APPROACH 4: Utilizing Topic Models

Set of Video Frames

Represented as
Bag of Words

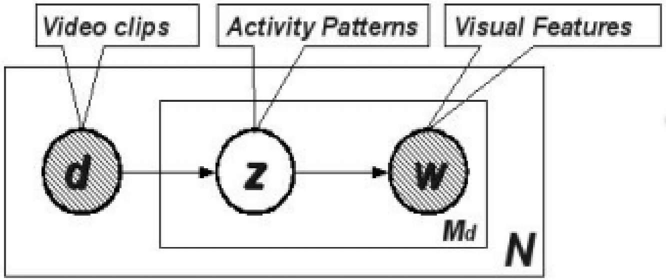



Cluster using K-Means

Extract
Cluster Centers

Cluster Centers as Words

# APPROACH 4: Utilizing Topic Models




pLSA over set of frames

$$L_d^{nl}(P(z|d)) = \sum_w \frac{n(d,w)}{n_d} \log \sum_z P(z|d)P(w|z) = \sum_w P_o(w|d) \log P_c(w|d)$$

Find Normalized log-likelihood

Test Frame

Determine Log-Likelihood

High → ANOMALY

Low → Normal

**Precision:** 0.55
**Recall:** 0.32

# Evaluation

| APPROACH | PED1 | | | PED2 | | |
|---|---|---|---|---|---|---|
| | F1-Score | ROC | EER | F1-Score | ROC | EER |
| AlexNet (Frame) | 0.39 | 58.05% | 45.08% | - | - | - |
| Optical Flow (Threshold = 50) (Pixel) | 0.64 | 78.15% | 30.03% | 0.29 | 59.76% | 44.58% |

| Algorithm | Ped1(frame) | | Ped1(pixel) | | Ped2 | |
|---|---|---|---|---|---|---|
| | EER | AUC | EER | AUC | EER | AUC |
| MPPCA | 40% | 59.0% | 81% | 20.5% | 30% | 69.3% |
| Social force | 31% | 67.5% | 79% | 19.7% | 42% | 55.6% |
| Social force+MPPCA | 32% | 66.8% | 71% | 21.3% | 36% | 61.3% |
| Sparse reconstruction | 19% | – | 54% | 45.3% | – | – |
| Mixture dynamic texture | 25% | 81.8% | 58% | 44.1% | 25% | 82.9% |
| Local Statistical Aggregates | 16% | 92.7% | – | – | – | – |
| Detection at 150 FPS | 15% | 91.8% | 43% | 63.8% | – | – |

# Conclusion

- Explored 4 supervised approaches of anomaly detection in videos:
  - **Optical Flow**
  - Feature Extraction from **AlexNet**
  - **Time Series Analysis** over Video
  - Utilizing **Topic Modelling**
- Our approaches include both frame level and pixel level detection
- Supervised Approaches outperform unsupervised ones

# THANK YOU !

"Ms. Jones, there are a number of big questions here to see you. They say they won't leave until they have some answers."