Analyzing Video and Audio from Body Worn Cameras

Description and Questionnaire

The Los Angeles Police Department (LAPD or the Department), Justice & Security Strategies Inc. (JSS), the University of California, Los Angeles (UCLA), and the Los Angeles Police Foundation (LAPF) are conducting a three-year study of the use of body worn cameras by law enforcement. Under a grant from the National Institute of Justice (NIJ), United States Department of Justice, the four organizations are evaluating the use of cameras and examining the way in which footage from cameras is analyzed.

Currently, the LAPD has over 420,000 videos covering over 60,000 hours of footage. Not all of these videos will be reviewed, nor should they be. But when they are reviewed, it is time-consuming and labor intensive. The Department is looking for analytics (video and/or audio) that can assist it in successfully searching, identifying, and tagging different situations using algorithms or formulae.

You have been invited to give us a presentation about your product(s) at the Police Administration Building, Los Angeles Police Department, 100 W. First Street, Los Angeles, CA 90012, Room 839. A projector, laptop, and screen are available.

We are interested in how you analyze video footage and how you analyze audio. You need not do both. Our primary interest is with the analysis of video. We are not interested in redaction or other aspects of body worn cameras. If you do not analyze video or audio, please let us know.

We are inviting 10-12 vendors, technologists, and academicians to demonstrate their products. You will be given a total of 90 minutes for your presentation and for questions and answers. We will select a small number to work with over the next 9-12 months.

Funding is unavailable at this time for travel or other compensation. You will be responsible for bearing those costs.

During your presentation please provide information regarding your background, areas of expertise, education, and current or previous law enforcement clients.

Prior to your visit, please fill out the following questionnaire and return it by July 20, 2016 to:

Dr. Craig D. Uchida	**Sgt. Daniel Gomez**
cduchida@jssinc.org	Daniel.Gomez@lapd.lacity.org

Questionnaire

Vendor Name: ____

Address: ____

____

Point of Contact: ____

Telephone Number: ____

Email Address: ____

Basic Questions:

Have you analyzed video footage using algorithms or mathematical formulae?
___Y ___ N

If yes, is the footage from a body-worn camera or a camera in motion? ___Y ___N

Is the footage from a fixed position video camera? ___Y ___N

Is the footage from other types of cameras? ___Y ___ N Please specify ______

Please indicate the sources of video that you have analyzed (check all that apply):

__ Law Enforcement
__ Military
__ Other government agencies
__ Medical industry
__ Other, please specify: _____________________

How long have you been involved in video analytics (years and/or months)?
____

Audio Analysis

Have you analyzed data from audio sources? ___Y ___N

Have you analyzed audio data from body worn cameras? ___Y ___N

How long have you been involved in audio analytics (months and/or years)?
____

Have you successfully sold/delivered your video or audio software analytic tool to a customer/client? ___Y ___N
Would you be willing to provide a list of customers/clients? ___Y ___N
(We can discuss this during your presentation)

Potential Scenarios/Items of Interest

We recognize that analyzing video footage is complex and requires examples of situations of interest. At this time we cannot provide you with LAPD body worn camera video footage. However, the following items are priorities for the Department and will be discussed at your meeting.

1. Supervisors reviewing video want to know if it is possible to determine when the cameras are on and off. Are there ways to determine when the camera has been activated and when the situation has ended? Can you analyze distinct movements (e.g., getting out of the patrol car) that may be of value?

2. Police agencies are interested in searching, identifying, and tagging foot pursuits. Have you analyzed these types of encounters?

3. Police agencies are interested in searching, identifying, and tagging traffic stops. Have you analyzed these types of encounters?

Research in Industrial Projects for Students

Sponsor

Los Angeles Police Department

Final Report

Change-point Detection Methods for Body-Worn Video

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Date: August 19, 2016

This project was jointly supported by the LAPD and NSF Grant DMS-0931852.

Abstract

Body-worn video (BWV) cameras are increasingly utilized by police departments to provide a record of police-public interactions. However, large-scale BWV deployment produces terabytes of data per week, necessitating the development of effective computational methods to identify salient changes in video. In this work, we present a novel two-stage framework for video change-point detection. First, we utilize state-of-the-art machine learning methods including convolutional neural networks and support vector machines for scene classification. We then develop change-point detection algorithms utilizing hidden Markov models, time series analysis, and maximum likelihood estimation to identify noteworthy changes. We test our framework on detection of vehicle exits and entrances in a BWV dataset provided by the Los Angeles Police Department and achieve over 90% recall and nearly 70% precision — demonstrating robustness to rapid scene changes, extreme luminance differences, and frequent camera occlusions.

Acknowledgments

First, we would like to thank our academic mentor, Dr. Giang Tran, for her guidance and continuous support. Her suggestions have helped us tremendously throughout this research. We would also like to thank Sgt. Javier Macias and Dr. Jeff Brantingham as our industry mentors; they have provided us with important context for this project. We also thank Dr. Susana Serna for her comments regarding our presentations and paper drafts. Finally, we would like to thank the Institute for Pure and Applied Mathematics for supporting us in this research.

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Chapter 1

Introduction

Body-worn video (BWV) has come about as another source of information regarding police-public interactions. To produce this video, police officers wear specially designed cameras on their chests to record their interactions with the public. This video then may be utilized when there is public disagreement about police conduct. Furthermore, these cameras have been shown to increase professionalism in the police force [6]. However, BWV creates large amounts of data—terabytes within a few weeks—which necessitates the use of automatic data analysis in order to help the police sort through the important and unimportant video clips.

The Los Angeles Police Department (LAPD) seeks to protect and to serve the residents and visitors of the city of Los Angeles via patrol, traffic, and specialized divisions. The Department is indeed a leader in the effort to equip police officers with body-worn cameras—having already deployed cameras to 1,200 officers and with plans for deployment to 7,000 officers in the next year to year and a half. Before the deployment, the Department undertook a pilot project in its Central Division whereby police officers received body cameras to document their work in the field. The Department gave police officers license to turn the cameras on when they felt their interactions should be recorded. The Research in Industrial Projects for Students (RIPS) LAPD student research group will work with a sample of this data to develop video processing, machine learning, and change-point detection methods to streamline the video analysis processes.

1.1 Problem Statement

From a broad point of view, we aim to create algorithms to detect change-points in body-worn video. Examples of these change-points include entering/exiting buildings or cars, arguments with the public, the drawing of a police officer's gun, a pursuit, etc. Detecting these change-points would greatly streamline the video review process because it would allow the police to flag the important points in the video, thereby streamlining the video review process. It would both greatly improve the efficiency of BWV analysis and reduce storage requirements. For this project, we focus specifically on the change-point of an officer's entry or exit from a car. This change is important because officers often exit their vehicles to interact with the public, which are the events most pertinent to BWV.

1.2 Review of Literature

In early architectures in the literature, image changes are detected using a variety of statistical and image processing techniques based on computing differences in image feature representations, and attempting to identify change-points by calculating where these differences pass certain thresholds [12]. Threshold calculation can be performed in an unsupervised way by applying principles of Bayesian decision theory [14]. A comprehensive overview of this approach and related research can be found in [55].

Extensions to the aforementioned strategies include wavelet-based hierarchical video decomposition methods to detect shot transitions, and clustering methods to segment videos [90, 87]. Use of statistical models to determine regime changes for video segmentation are also prevalent, as in [11]. These results generally attempt to detect the boundaries of cinematic transition effects or cluster videos, and are not directly related to our goals. However, they do account for some of the spatiotemporal features of videos.

Advanced methods extend these basic spatiotemporal models in interesting and unique ways. For example, In [56], the authors introduce a Bayesian method to segment videos containing specific places into clusters in an online, unsupervised way accompanied by confidence probabilities. In recent deep learning literature, the authors in [32] propose a convolutional network with a sliding frame window input capable of creating spatiotemporal features to classify videos. These methods, while complex and computationally demanding, are excellent inferential frameworks.

A balance can be struck between these methods by creating video and image representations, which are then recognized by classifiers and analyzed by change-point detection algorithms. This modular format allows our research to be extended to a variety of different change-points. In creating and classifying image representations, we turn to the computer vision literature, where state of the art image recognition generally uses either a bag-of-visual-words approach with classification performed by a support vector machine [83, 65, 37, 41], or convolutional neural networks [36, 63].

Change-point detection literature informs part of our approach as well. Classic statistical methods range from simple sum- and mean-based thresholding algorithms for single change-point detection in offline data [16], to nonparametric tests for changes in distributions [89, 39]. Other statistical methods use Bayesian priors to incorporate time-dependent information into the probability of a change-point occurring [3], or use kernel density estimation to detect when points are most likely to have been sampled from two different distributions [66, 68].

Non-statistical approaches to change-point detection include a variety of approaches. Graph theoretic methods utilize minimum spanning trees and mincuts to determine change-points [21, 15]. Approaches in machine learning use Gaussian processes to account for dependencies in data [60], kernel methods to select salient features [85], or manifold learning to interpret high-dimensional time series with missing data [84]. Some authors modify existing sum-based methods for robust, video-specific change-point detection [75].

1.3 Our Approach

In order to tackle this problem, we had to work on several discrete tasks, which are outlined by Figure 1.1 below.

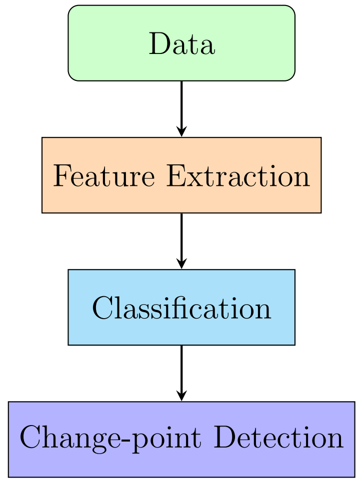

Figure 1.1: Project Workflow

First, we had to process the body-worn video data by labeling it for our purposes. We then sampled images from each video because we wanted to work on a *sequence of images* from the videos. Next, we simplified the matrix representations of the images via feature extraction methods. Then, we inputted these representations into support vector machines, which produced univariate data pertaining to if the officers were in or out of a car. We also used a convolutional neural network to extract fine-tuned convolutional features and to produce univariate data for our methods. Alternatively, we obtained multivariate data by applying dimensionality reduction methods — including principle component analysis, diffusion maps, and cluster analysis — to the representations created by the feature extraction methods.

Once we obtained this univariate and multivariate data, we ran a variety of change-point detection algorithms on this data in order to find the change-point(s) of an exit from or entry into a car in each video. These methods included mean squared error, hypothesis testing, density, graph-based, time series, hidden Markov model, and histogram comparison approaches.

1.4 Description of Data

Our data was provided by the LAPD, from their BWV pilot program in Los Angeles' Central Division in 2014-2015. The body-worn videos are recorded using cameras that have about a 130°field-of-view, a resolution of 640x480, and a fisheye lens. There were 691 videos in total, with an average length of 9 minutes. 420 of these videos contained some sort of change-point of interest (either a vehicle entrance or exit). Of these, 270 of them began from the driver's side, 176 were during the nighttime, and in 274 of them, the vehicle was moving at some point during the video. In addition, some videos contain occasional camera field-of-view occlusions from the officers' hands, arms, or clothing. The effect is that there was a fair amount of variance in the data set. All images are from the officer's point-of-view, as body cameras are mounted on officers' chests.

1.5 Overview of the Report

Chapter 2 will discuss the feature extraction methods used on the matrix representations of the images, while Chapter 3 will outline classifiers we used. Chapter 4 will discuss the change-point detection methods we used. Chapter 5 will present our results. Finally, Chapter 6 will summarize our work and propose additional avenues of research.

Chapter 2

Video Representations

Video is a sequence of frame, with each frame being an image. In this project, we converted an input video to a sequence of signals, which was input for our change point detection algorithms. There is a trade-off between expressiveness and dimensionality of these signals. While it is desirable for them to retain more information from the corresponding videos, defining and detecting a change-point in high-dimensional time series poses various challenges. Therefore, in the video and image processing step, our goal was to construct expressive image representations in a lower dimensional space. We used two feature description processes, the Scale-invariant Feature Transformation (SIFT) [42] and the Histogram of Oriented Gradients (HOG). Because the number of SIFT features extracted from an image is unknown beforehand, we used the bag-of-visual-words (BoVW) technique to reduce SIFT features to a fixed length representation. HOG features are fixed length, and require no preprocessing.

2.1 Keypoint Detection and Description

Intuitively, keypoints are distinctive image features. After a keypoint is located by a keypoint detector, image features in the keypoint's neighborhood can be described by a keypoint descriptor. Various papers in the computer vision literature [80, 86] have shown the effectiveness of representing images as sets of keypoint descriptors in object matching and scene recognition. One of the most desirable properties of a keypoint detector is repeatability, which expresses the ability of a detector to locate the same object under changes in perspectives. To ensure matching accuracy in the task of object regnition, it is desirable for such keypoint descriptor to be distinctive and robust to noise.

Various keypoint detectors and descriptors, for example, Speeded Up Robust Features (SURF) [8] and Oriented FAST and Rotated BRIEF (ORB) [57], have been proposed in recent literature. In this project, we decided to use SIFT because SIFT features are shown to be invariant to image scale and rotation, and it is partially invariant to changes in illumination. The major steps of SIFT feature detection and description in [42] can be summarized as:

- Keypoint detection and localization
    - Apply Gaussian filters with different standard deviations to the input image
    - In the differences of Gaussians, search for local extrema in scale and space
    - Remove potential keypoints that are located along edge or have low contrast

- Orientation assignment
  - Assign one or more orientations to each keypoint based on the directions of pixel gradients in the keypoint's neighborhood
- Keypoint description
  - Compute gradients of pixels relative to the keypoint orientation in the 16-by-16 neighborhood around keypoint
  - Divide this 16-by-16 patch into blocks of 4-by-4 in size
  - Create a 8-bin orientation histogram for each block
  - Concatenate histogram to get a 128 dimensional descriptor for each keypoint
  - Normalize descriptor using L^2 norm to improve robustness to illumination changes

Using this approach, each image can be represented as a SIFT matrix, with each row being a SIFT descriptor. Each matrix has 128 columns; however, we the number of rows is unknown beforehand, because it depends on the number of SIFT descriptor extracted from the corresponding image. Since the Support Vector Machine (SVM) classifier requires inputs to have the same size, we use BoVW as an additional step to construct image representations.

2.2 Bag-of-Visual-Words

After performing feature extraction on all video frames using SIFT, we took 20% of "in-car" and "out-car" training data and applied k-means clustering *separately* on their feature vectors. After all centroids were computed, we assigned each of feature vectors in images from the remaining part of the data set to closet centroids based on Euclidean distance. This is an example of vector quantization (VQ), which allows us to represent a feature vector by the indices of clusters to which it is assigned.

After VQ, for each image, we recorded the effective number of feature vectors assigned to each centroid, and the image can be represented as a histogram of frequency. This process is an example of orderless BoVW, in which the location of each keypoint is not taken into account. To introduce spatial information into BoVW, we also implemented spatial pyramid match kernel [38], which is explained in Chapter 3. Details of VQ and constructing histogram representations of orderless BoVW are discussed in the following subsections.

2.2.1 Clustering

k-means clustering requires K as a parameter, which in our project was the predetermined number of centroids for *each* of the two classes, "in-car" and "out-car". The values of K have a significant impact on performance of classifier, and there are two possible explanations. The first explanation is that, in cluster construction stage, over-fitting occurs with a relatively high value of K, and therefore the resulting model does not generalize well to new data points. Another explanation is, in the stage of assigning feature vectors to centroids, as K doubles, the total number of centroids quadruple. Thus, a new feature vector may be close to multiple centroids. This poses a challenge because if we assign a feature vector only to the closet centroid, the resulting model will be sensitive to noise in data set. Since our work only focused on the two cases: "in-car" and "out-car", a relatively low value of K was sufficient to get a decent classification accuracy around 85%; however, if we want to include other scene categories into our model, we would inevitably need to increase the total number of centroids. To further investigate the impact of K on classification accuracy and to improve our model's generalizability, we evaluated the effectiveness soft histogram as a remedy for the negative impacts of having a large number of centroids.

2.2.2 Vector Quantization

In the VQ step, our goal was to assign a feature vector to cluster(s), so that the feature vector can be represented by the index(indices) of the cluster(s). As explained in [80], in *hard* VQ, a feature vector is assigned to exactly one cluster, which corresponds to the closest centroid; whereas in *soft* VQ, a vector can be assigned to multiple clusters. In our project, a feature vector's membership in each cluster depends on the feature vector's distance to the corresponding centroid. We proposed the following technique to perform soft VQ.

Let $\{c_j\}_{j=1}^{C}$ be a set of centroids computed in the clustering stage, where $C = 2K$ is the total number of centroids, and let $\{f_i\}_{i=1}^{F}$ denote the set of all SIFT feature vectors extracted from an image. Given $\{f_i\}_{i=1}^{F}$, our goal was to construct $H \in \mathbb{R}^C$, where H_j measures the effective number of features assigned to cluster j for $1 \leq j \leq C$.

For each feature vector f_i, we computed its Euclidean distance D_{ij} to each of the centroids c_j. Then, the *relative* distance between centroid c_j and feature vector D_{ij} can be defined as

$$R_{ij} = \frac{D_{ij} - \min\limits_{1 \leq p \leq C}(D_{ip})}{\max\limits_{1 \leq p \leq C}(D_{ip}) - \min\limits_{1 \leq p \leq C}(D_{ip})},$$

where the centroid closest to the f_i has relative distance 0 whereas the farthest centroid gets relative distance 1. To control the contribution of f_i to clusters whose corresponding centroids are not the closest to f_i, a parameter E is introduced. We then defined the exponentially decayed relative distance R'_{ij} as $R'_{ij} = \exp(-ER_{ij})$, so that we essentially recover hard VQ as E approaches positive infinity. The contribution of f_i to H_j is normalized by summing over R'_{ij} over all j. This procedure is summarized in Algorithm 1 below.

Note that the idea of VQ is closely related to that of histogramming: assigning a vector to clusters is equivalent to incrementing the counts at the corresponding histogram bins. We refer to soft VQ and soft histogram interchangeably in subsequent chapters.

2.2.3 Histogram Representation

For a given image, we constructed a histogram representation by recording the effective number of feature vectors assigned to each cluster. This procedure is an example of orderless BoVW, in which histogram representations of images do not incorporate spatial information of keypoints.

One of the complications involved in the histogram construction stage is normalization. As mentioned in the previous section, the number of feature vectors extracted varies across images. Since the contributions of a feature vector to histogram bins add up to one in both soft histogram and hard histogram, the norm of vector representation of a histogram also varies across images. The authors in [86] suggest that if video frames have identical

Algorithm 1: Soft VQ

Inputs : set of centroids $\{c_j\}_{j=1}^{C}$,
set of feature vectors $\{f_i\}_{i=1}^{F}$ from an image,
a positive constant E

Output: $H \in \mathbb{R}^C$

For $i = 1 : F$
  For $j = 1 : C$
    $D_{ij} \leftarrow ||f_i - c_j||_2$
  For $j = 1 : C$
    $R_{ij} \leftarrow \frac{D_{ij} - \min\limits_{1 \le p \le C}(D_{ip})}{\max\limits_{1 \le p \le C}(D_{ip}) - \min\limits_{1 \le p \le C}(D_{ip})}$
    $R'_{ij} \leftarrow \exp\left(-ER_{ij}\right)$
  For $j = 1 : C$
    $H_j \leftarrow H_j + \frac{R'_{ij}}{\sum\limits_{p=1}^{C} R'_{ip}}$

size, normalization suppresses the information contained in each video frame and hurts the classifer's performance. The results of our experiments confirm this observation.

2.3 Histogram of Oriented Gradients

Image features are generally extracted in a dense or sparse fashion. SIFT extracts features in a sparse fashion at local keypoints determined by a Gaussian filtering scheme. The Histogram of Oriented Gradients (HOG) method, first introduced in [20], extracts feature descriptions at a dense set of points determined by tiling the image with a grid of rectangles. Like SIFT, HOG's expressiveness is predicated upon the assumption that significant image features can be well described by a histogram of local pixel gradients. This same underlying hypothesis gives both HOG and SIFT a degree of invariance to certain geometric transformations. Unlike SIFT, HOG is computed using a fixed set of histograms, leading to a feature descriptor with a fixed size that can be directly consumed by an image classifier.

2.3.1 Algorithm Description

The HOG feature extraction process starts by computing a gradient image for the image I. A gradient image conveys how pixel values change across local image pixels. In the HOG process, one-dimensional gradients are computed along the vertical and horizontal axes for each pixel by convolving the zero-padded image with a simple, discrete derivative kernel. The range of the convolution is restricted such that the kernel is centered and then applied at each pixel in the original image. The gradient for each pixel $I_{i,j}$ at row i and column j in an image I can be represented as a two-dimensional vector,

$$\nabla I_{i,j} := \begin{bmatrix} g_x \\ g_y \end{bmatrix}.$$

Each gradient in the horizontal and vertical direction is calculated as follows, using the convolution outlined above:

$$g_x := \frac{\partial I_{i,j}}{\partial x} = \left(I * \begin{bmatrix} -1 & 0 & 1 \end{bmatrix} \right)_{i,j} \qquad = -1 \cdot I_{i,j-1} + 0 \cdot I_{i,j} + 1 \cdot I_{i,j+1}$$

$$g_y := \frac{\partial I_{i,j}}{\partial y} = \left(I * \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} \right)_{i,j} \qquad = -1 \cdot I_{i-1,j} + 0 \cdot I_{i,j} + 1 \cdot I_{i+1,j},$$

where i and j range over the dimensions of the original, non-zero-padded image I. The unsigned pixel gradient orientation, or angle, θ is computed via the arctangent function,

$$\theta = \arctan\left(\frac{g_y}{g_x}\right).$$

After a gradient orientation has been computed for each pixel in the image, the image is divided into small contiguous rectangular regions called cells. In the literature, cells are generally chosen to be 9x9 image patches. Within each cell, a histogram of gradient orientations is computed. The orientations are grouped into a small number of bins that cover the range of possible angles (0–180°). Dalal and Triggs [20] use a bin size of 20°, resulting in a nine bin histogram for each cell. Each pixel's orientation makes a contribution (weighted by the magnitude of the gradient) to a bin in the histogram. This process forms the cell-level histogram vectors h_i.

After the cell histograms are computed, they are locally normalized to provide a degree of photometric invariance (to e.g. contrast and luminance changes). To compute the local normalization constants, cells are grouped into blocks, which are contiguous, typically overlapping rectangles containing a small number of cells. Each normalization constant is unique to a specific block. The histogram vectors h_i from each cell in a block are concatenated to form the block-level histogram vector v_j. This vector is divided by the normalization constant to form the block-level feature vector. The constant is computed using the ℓ^2 norm of the descriptor and a small regularization constant ϵ, to avoid dividing by zero:

$$v_j \leftarrow \frac{v_j}{\sqrt{\|v_j\|_2^2 + \epsilon}}.$$

The potential overlap of blocks means that the same cell histogram, normalized by a different constant, may be included in several different block-level feature descriptors. The HOG descriptor is simply the concatenation of all block-level feature vectors v_j.

Chapter 3

Classification Approaches

After deriving video representations or raw matrices of pixel values from body-worn videos, we would like to classify each representation as depicting an in car or out of car scene. Accomplishing this task required the use of *classification algorithms* that can learn to differentiate between each class of images.

3.1 Classification Overview

Classification algorithms are members of the set of algorithms used to perform *supervised learning*. Supervised learning is part of a field called *machine learning* (ML), which is generally concerned with the development of algorithms that learn from data. A dichotomy is traditionally drawn between algorithms that learn from human-annotated, or *labeled* data (supervised learning), and algorithms that learn from unlabeled data (unsupervised learning).

Formally, supervised learning algorithms process a set of input/output tuples from a dataset $(I, O) \in \mathcal{D}$ to learn a mapping Φ that relates an output to a given input. After Φ has been learned, similar but unseen tuples $(I', O') \notin \mathcal{D}$ should be related by the mapping such that $\Phi(I') \approx O'$. The definitions of "relate", "learn", "unseen", "$\approx$", and the form of the input and output objects themselves are interpreted and restricted in various ways by concrete algorithm implementations.

A subset of supervised learning called *binary classification* restricts the output object to be a binary value generally represented as one or zero. Binary classification then considers the labeling of inputs as true or false with respect to a valid question. For example, a classifier may learn to answer the question "Was this body-worn video frame taken inside an LAPD vehicle, or outside of one?" This is, of course, the question we consider in this section.

3.2 Our Classification Approaches

Our approaches to classification are inspired by literature in computer vision—specifically, image recognition. Current state of the art approaches use either the bag-of-visual-words approach with a classifier capable of comparing the histograms it produces [83, 65, 37, 41, 86], or a convolutional neural network on raw pixel values [36, 63]. We implemented and extended the first approach, used a neural network trained mainly on HOG vectors in preparation for implementing the second approach, and implemented the second approach using a publicly available convolutional network with pre-trained weights. Details are described in the following sections.

3.3 Support Vector Machines

A support vector machine (SVM) is a discriminative classifier. Its operation is based on finding the hyperplane that gives the maximum margin between training examples from two classes of data. Let x_n be a D-dimensional representation of image X_n ($1 \leq n \leq N$), where N is the total number of training examples. Let $t_n = 1$ if x_n corresponds to an "out-car" image, and $t_n = -1$ otherwise. As shown in [9], the task of finding the optimal hyperplane can be achieved by solving the following optimization problem:

$$\begin{aligned} &\min_{w \in \mathbb{R}} \quad C \sum_{n=1}^{N} \xi_n + \frac{1}{2}||w||^2 \\ &\qquad \text{subject to} \quad t_n(w^T \phi(x_n) + b) \geq 1 - \xi_n, \quad n = 1, 2, ..., N, \end{aligned} \tag{3.1}$$

where $\xi_n = 0$ if x_n is within the correct side of margin boundary, and $\xi_n = |t_n - (w^T \phi(x_n) + b)|$ otherwise. Here $\phi(x)$ is a feature space mapping, $b \in \mathbb{R}$ is a bias term, and parameter C controls the trade-off between maximum margin and lowest total penalty $\sum_{n=1}^{N} \xi_n$.

As shown in [9], the optimization problem in equation (3.1) can be written in a dual form, which facilitates the formulation of kernel function:

$$\begin{aligned} &\max_{\{a_n\}_{n=1}^N} \quad \tilde{L}(a) = \sum_{n=1}^{N} a_n - \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{N} a_n a_m t_n t_m k(x_n, x_m) \\ &\qquad\qquad \text{subject to} \quad 0 \leq a_n \leq C \quad \text{and} \quad \sum_{n=1}^{N} a_n t_n = 0. \end{aligned} \tag{3.2}$$

In equation (3.2), $k(x_n, x_m)$ is the kernel function, and it is defined by $k(x_n, x_m) = \phi(x_n)^T \phi(x_m)$. The inner product of feature space mapping essentially quantifies the similarity between observations x_n and x_m.

After solving the optimization problem above, we obtained weight coefficients $\{a_n\}_{n=1}^N$. For each new input histogram x in the testing set, a prediction for its class label can be calcuated:

$$\begin{aligned} Score_{outCar}(x) &= \sum_{n=1}^{N} a_n t_n k(x, x_n) + b \\ Score_{inCar}(x) &= -Score_{outCar}(x) \\ \widehat{Class}(x) &= \begin{cases} 1 \quad (\text{“out-car”}), & \text{if} \quad Score_{outCar}(x) \geq 0 \\ -1 \quad (\text{“in-car”}), & \text{otherwise.} \end{cases} \end{aligned} \tag{3.3}$$

In the first line of equation (3.3), b is a bias term that can be computed from weight coefficients $\{a_n\}_{n=1}^N$. Since the only difference between $Score_{outCar}(x)$ and $Score_{inCar}(x)$ is their opposite signs, inputting only $Score_{inCar}(x)$ to our change point detection algorithms did not result in loss of information.

The choice of kernel function has a significant impact on prediction accuracy, and a kernel function with high discriminative power is expected to give a high accuracy despite noise present in the data set [91]. Kernel functions that we experimented with are discussed in the following subsections.

3.3.1 Linear Kernel

The linear kernel can be written as $k_{linear}(x, y) = x^T y$. SVM equipped with linear kernel finds the hyperplane that gives the maximum separation in the original feature space. While our results indicate linear kernel did not give the highest classification accuracy in this project, we nevertheless used linear kernel as a benchmark to evaluate the effectiveness of other kernels.

3.3.2 Gaussian and χ^2 Kernel

χ^2 distance is a bin-by-bin similarity measure between histograms, and it can be defined as [91]:

$$\Lambda(x, y) = \frac{1}{2}\sum_{i=1}^{D}\frac{(x_i - y_i)^2}{x_i + y_i}.$$

To integrate χ^2 distance into our SVM framework, we extended the Gaussian kernel function:

$$k_{\chi^2}(x, y) = \exp\left(-\frac{1}{A}\Lambda(x, y)\right).$$

Here we took A as the average χ^2 distance between all pairs of training examples.

3.3.3 Pyramid Match Kernel

To include spatial information of each keypoint, we experimented with pyramid match kernel[38], which works by partitioning an input image into increasingly fine grids. At level l, 2^l cells are placed on each side of an image, so there are 4^l grids in total, and no partition occurs at level 0. After VQ, we were able to represent each feature vector by indices of clusters and to construct a histogram of cluster memberships for feature vectors within each grid. These histograms are then weighted by the level at which the grid is located before being concatenated. Because matches of features at finer spatial resolutions are expected to yield more information about the similarity between two images, histograms at finer grids are weighted more heavily.

Let D be total number of centroids, L be the maximum level, X and Y be two images, and $G_l = 4^l$ be the total number of grids at level l. Let $H^l_{X_d}(i)$ be the number of features from image X assigned to centroid d and fall into cell i at level l, where $i = 1, 2, ...G_l$. The match between images X and Y at level l and at centroid d can be defined using histogram intersection:

$$\mathcal{L}(H^l_{X_d}, H^l_{Y_d}) = \sum_{i=1}^{G_l}\min(H^l_{X_d}(i), H^l_{Y_d}(i)).$$

For convenience, we let $\mathcal{L}^l_d$ denote $\mathcal{L}(H^l_{X_d}, H^l_{Y_d})$. Since a match at level $l+1$ double-counts match at level l, new match at level $l+1$ is $\mathcal{L}^{l+1}_d - \mathcal{L}^l_d$. The pyramid match kernel[38] at centroid d is defined as

$$\begin{aligned} k_d^L(X,Y) &= \mathcal{L}_d^L + \sum_{l=0}^{L-1} \frac{1}{2^{L-l}}(\mathcal{L}_d^l - \mathcal{L}_d^{l+1}) \\ &= \frac{1}{2^L}\mathcal{L}_d^0 + \sum_{l=1}^{L} \frac{1}{2^{L-l+1}}\mathcal{L}_d^l. \end{aligned}$$

The final kernel[38] is the sum of pyramid match kernel over each centroid c:

$$K^L(X,Y) = \sum_{d=1}^{D} k_c^L(X,Y). \tag{3.4}$$

After combining equations (3.4) and (3.2), the optimization problem in SVM can be written as:

$$\begin{aligned} \max_{\{a_n\}_{n=1}^N} \quad \tilde{L}(a) &= \sum_{n=1}^{N} a_n - \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N} a_n a_m t_n t_m K^L(X_n, X_m) \\ \text{subject to} \quad & 0 \le a_n \le C \quad \text{and} \quad \sum_{n=1}^{N} a_n t_n = 0. \end{aligned}$$

For each new input image X, a prediction for its class label can be calculated by combining equations (3.4) and (3.3):

$$\begin{aligned} Score_{outCar}(X) &= \sum_{n=1}^{N} a_n t_n K(X, X_n) + b \\ Score_{inCar}(X) &= -Score_{outCar}(X) \\ \widehat{Class(X)} &= \begin{cases} 1 \quad (\text{“out-car”}), & \text{if} \quad Score_{outCar}(X) \ge 0 \\ -1 \quad (\text{“in-car”}), & \text{otherwise.} \end{cases} \end{aligned}$$

In practice, one only needs to compute $H_{X_d}^l$ only for $l = L$: to derive $H_{X_d}^l(i)$, it is sufficient to sum up 4 cells from $H_{X_d}^{l+1}$. This is the case because each grid at level l can be decomposed into 4 grids at level $l+1$.

We previously defined x_n to be a D dimensional histogram representation of image X_n. What is the relationship between x_n and $H_{X_{nd}}^l$ for some d and l? At $l = 0$, no partition occurs and the spatial information of each keypoint is not considered, and therefore $x_n(d) = H_{X_{nd}}^l$ and $H_{X_{nd}}^l \in \mathbb{R}$. As we proceed to higher levels, the contribution of a keypoint to $H_{X_{nd}}^l$ depends not only on the clusters to which it is assigned, but also on its location within image X_n; therefore, the connection between x_n and $H_{X_{nd}}^l$ is less explicit.

The major advantage of spatial pyramid match kernel is that it considers locations of keypoints in constructing histogram representations of images. This comes at a cost – the resulting histograms have dimensionality of $D\sum_{l=0}^{L} 4^l$, while the orderless BoVW gives histograms of D dimensions.

3.4 Deep Neural Networks

Deep neural networks (hereafter simply referred to as “neural networks”) are machine learning algorithms that jointly learn a feature representation and discriminative classifier over a data set [23]. Nonlinear computational nodes called *neurons* are stacked on top of one another in layers to form complex, richly informative sets of features that have highly discriminative characteristics. At the last layer of a neural network classifier, outputs from the previous layer are normalized to form a probability distribution or a decision function over possible classes. They are generally considered "deep" when they have more than two layers between the input layer and output layer. Neural networks are trained by changing weights, thresholds, and other parameters, generally through the use of an iterative optimization algorithm like stochastic gradient descent [23].

In our work, we use two types of neural networks to classify video frames into in and out of car classes. Our first process uses a fully connected, two-layer neural network classifier, which is fed image representations extracted from video frames using traditional image processing techniques. Our second process uses a popular pre-trained convolutional neural network architecture to extract image features from raw video frames and classify them as in or out of car. Implementation details can be found in Chapter 5. In the following subsections, we discuss the structure of an artificial neuron, the architecture of the fully connected neural network classifier, the architecture of the convolutional neural network, and the use of networks with pre-trained weights.

3.4.1 Artificial Neuron Structure

Neural networks provide a complex and extensible framework for machine learning, and it is not easy to describe them in full generality. However, generally, operations within a neuron consist of multiplying inputs by weights, passing them to a *transfer function*, and passing the result through a nonlinear, thresholded *activation function*. This process has a biological metaphor: the neuron only fires (passes along its activation to neurons in the downstream layer) if its activation passes a certain threshold; otherwise, it outputs a different value or none at all. Although true neurons are vastly more complex than this simple example, the architecture is partially biologically inspired. Figure 3.1 displays this process for a single neuron [18].

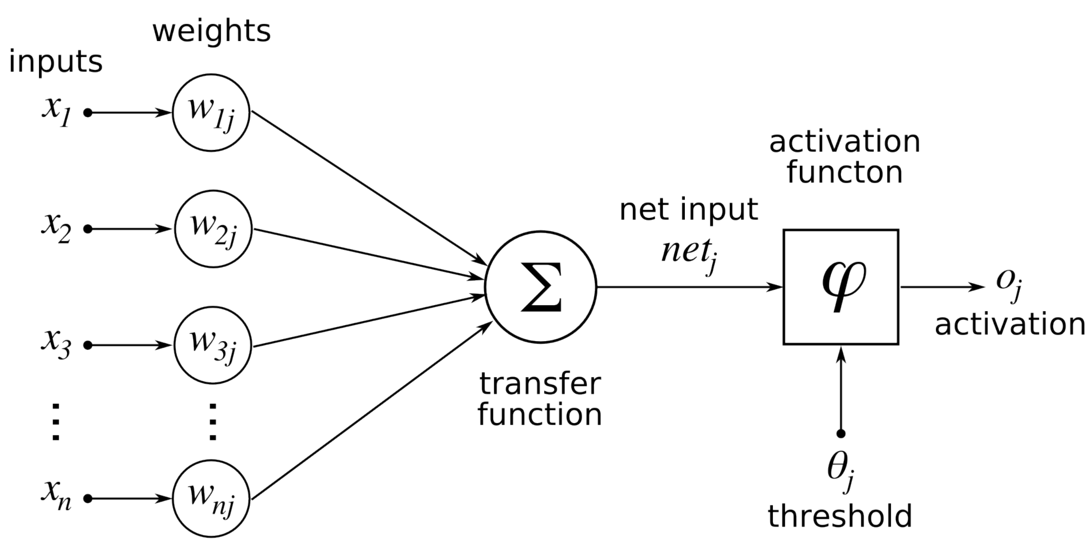

Figure 3.1: Computations performed in an artificial neuron, used under GFDL license from [18]

In modern fully connected networks used for classification, the summation function generally takes the place of the transfer function, and the threshold (also known as the bias) is the product of a scalar and a vector of ones. This threshold is generally added to the output of the summation function, before application of the nonlinear activation function.

More variation exists in the type of activation function used. There are a wide variety of activation functions used in the literature, although in fully connected networks for binary classification, two classes of functions are generally used. The first class is squashing functions, which tend to asymptotically "squash" their input x to a small range, typically between -1 and 1.

The second class of functions, called rectified functions (because they "rectify" a portion of the activation), have recently gained attention in the literature by enabling the training of very deep neural networks [23]. Experimental support for their superiority over squashing functions in both training and forming predictions has sustained interest in them, and a number of variations exist. However, the most popular version is the rectified linear unit (ReLU) [45], which is simply $\max(0, x)$. The simplicity of the ReLU function has many attractive features: it is biologically plausible, having gained inspiration from the functions created to model the firing of real neurons; it encourages sparse activations; it does not encounter various training difficulties that are present when using squashing functions; and it is computationally simple to evaluate [22]. We use ReLU activation functions in both of our neural networks.

3.4.2 Fully Connected Network Architecture

All neural networks are organized in a network-like architecture constructed from a series of layers. In the most common type of neural network architecture, "fully connected" networks, each layer except the output layer forms a complete bipartite graph with the layer downstream from the input layer. This type of connection between one layer and the next is called a fully connected layer. This structure can be observed in a sample fully connected network architecture in Figure 3.2 [47].

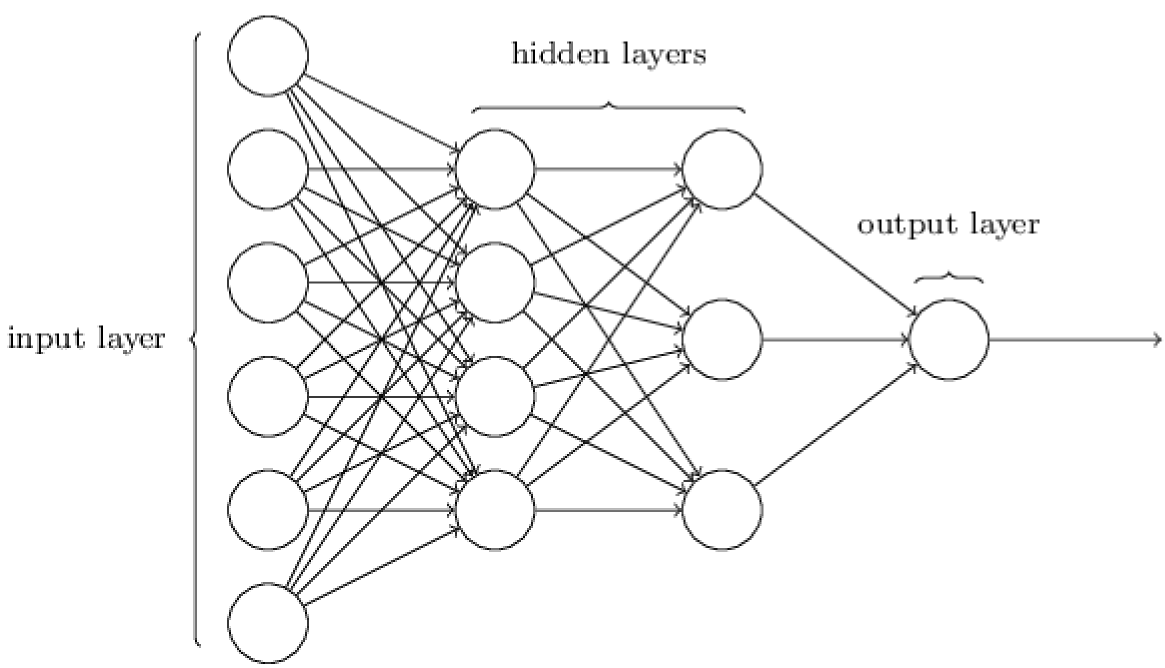

Figure 3.2: A typical neural network architecture, from [47]

In this architecture, each neuron in the hidden layer applies a nonlinear function to the outputs from the neurons in the upstream layer. For example, the top neuron in the second layer (first hidden layer) computes a function of the six features from the input layer. It then passes its output to every neuron in the second hidden layer, which does the same. This process continues up to the output layer, which receives inputs from every neuron in the last hidden layer and computes a nonlinear function. If the network is being used for a classification task, at this point, the output is normalized to form a valid probability distribution over the classes. This process is carried out through use of the softmax function, which consumes a vector of outputs $\mathbf{o}$ from the output layer, and produces a probability p_i for the ith class of N classes,

$$p_i(\mathbf{o}) = \frac{\exp(\mathbf{o}_i)}{\sum_{i=1}^{N} \exp(\mathbf{o}_i)}.$$

For networks with one output node such as the example in Figure 3.2, the formula is instead modified to output a probability of zero for negative results, and one for non-negative results. In our work, classes correspond to probabilities for in and out of car states. We use a network with the input layer proportional to the number of features we have, and an output layer of size two. Each class label is one-hot encoded into a two-dimensional column vector representing in car $[1, 0]^T$ or out of car $[0, 1]^T$ states. This format was chosen so that it can be easily adapted to generalize to more classes later without rewriting parts of our implementation.

A choice must be made in the number of hidden layers and the number of hidden units per layer when deciding on a neural network architecture. These and other settings described in future subsections are called *hyperparameters*, and the process of setting them to ensure an optimal prediction error is called hyperparameter tuning. Theoretical results [29] guarantee that only a single hidden layer with an appropriate number of hidden units and a large class of activation functions is necessary to approximate any function to an arbitrary degree. Experimental results agree that, in fully connected networks, only a few layers are needed to gain significant accuracy scores on various test data sets [25].

Various heuristic rules and formulas offer advice on choosing the number of hidden units per hidden layer, but common ones take into account the number of input and output layers, as well as the number of training samples. A commonly used process is to set the number of hidden units in a layer to the square root of the dimensionality of the layer upstream [25]. In our work, we use this heuristic, as well as cross-validation, to decide on a number of hidden units for a two-hidden layer fully connected network.

3.4.3 Convolutional Neural Network Architecture

Convolutional neural networks (sometimes referred to as "ConvNets", "convolutional networks", or "CNNs") replace the sums of weight-input products in fully connected networks with overlapping convolutions. Each convolution operation consists of "sliding" a feature detector over input data, which generates an output of similar dimensionality. Each feature detector looks for one specific feature, and is made up of a number of trainable weights. Features are dependent on data; for example, image features may include edges, color blobs, or simple shapes. Multiple convolutions are performed in a single *convolutional layer*, and the output of a convolutional layer is transformed by nonlinear activation functions. Convolutional layers are stacked and interspersed with *pooling layers*, which subsample their input (e.g. by taking averages over various input sections) and produce an output with lower dimension.

Like fully connected networks, convolutional networks can be used to perform classification. However, the trainable feature maps in CNNs make them especially well-suited to data with spatial and/or temporal structure. Their use in large-scale object recognition competitions like the ImageNet Large Scale Visual Recognition Challenge [59] has led to widespread agreement that convolutional networks represent the current state of the art for image classification. For these reasons, we use a convolutional network to classify video frames as in or out of car—without performing any feature extraction beforehand.

Convolutional Layers

Convolving an image with various hand-crafted feature detectors (properly called filters, *feature maps*, or *convolutional kernels*) is a common practice in traditional image processing. For example, the first step in SIFT involves convolution with Gaussian filters to detect keypoints (see Section 2.1 for complete details). ConvNets extend this basic idea by convolving images with tens or hundreds of trainable feature maps at each convolutional layer.

A convolutional layer is made up of several different feature maps, which take the form of tensors, in the sense that they are (small) multi-dimensional arrays of numbers. The feature maps require this definition because the two-dimensional input image requires the first convolutional layer to contain two-dimensional feature maps. Because there are multiple feature maps in the first layer, the output matrices are concatenated to form output tensors—three-dimensional arrays that are convolved with the feature maps in the next convolutional layers. This structure means that convolutional networks pass tensors in between their intermediate layers.

Convolutional computations. The mechanics of the discrete convolution process that produces an output tensor is best explained using an alternative view of neural networks that emphasizes their computational implementation.

In traditional fully connected networks, computing the output $\mathbf{o}_n$ of the nth layer can be represented as a matrix-vector product followed by a nonlinearity σ, where the matrix $\mathbf{W}_n$ contains the layer's weights and the vector $\mathbf{o}_{n-1}$ represents the outputs of the immediate upstream layer:

$$\mathbf{o}_n = \sigma(\mathbf{W}_n \mathbf{o}_{n-1})$$

Convolutional layers replace this matrix-vector multiplication with convolutions of multiple feature maps. For an input pixel matrix I, a set of feature map matrices $F_1, ..., F_n$, and a set of activation matrices $A_1, ..., A_n$ in a convolutional layer, convolution proceeds as follows:

1. Each F_i is centered at a pixel $I_{j,k}$, where j and k are chosen such that all indices of the feature map correspond to indices of the image (i.e. the feature map does not extend beyond the bounds of the image).

2. The numbers at each index of F_i (which are the weights of the convolutional network) are pointwise multiplied by the numbers in I which overlap with those of F_i.

3. The results of the pointwise multiplication are summed to produce an output, which is then placed at $A_{i_{j,k}}$, the index of the activation matrix corresponding to the same location the feature map was centered at in I.

4. The feature map is moved such that it is centered at a new index $A_{j',k'}$, and the process is repeated from step 1. This process continues until all indices of A_i have been filled.

5. After all indices of each A_i have been filled, all of the A_i matrices are concatenated to form a three-dimensional tensor. This tensor constitutes the input to the next layer of the convolutional net.

The set of indices $\{(j_m, k_m)\}$ used for each feature map are determined by a parameter known as the *stride*. The stride indicates the number of pixels skipped between centerings of the feature map. A stride of one indicates that the feature map will be centered, and the product-sum computed at each pixel of the input image. A stride of three indicates that a faeture map will be centered and the product-sum computed only at every third pixel (in the x and y direction) of an input image. In our work, we use a stride of one for greater feature granularity.

It is important to note that this convolution operation will decrease the dimensionality of an image, or locate the feature map in an invalid area. The solution is to zero-pad the image (i.e. extend in the border of the image matrix with zeros) such that the convolution is valid.In our work, we zero-pad the input image, as well as a number of tensors throughout the convolutional layers of the network, in order to maintain dimensions.

First convolutional layer. In the first convolutional layer of a CNN used for image classification, each feature map is "slid over" (i.e. convolved with) the input image to produce an output of similar dimensionality. If the feature map "matches" a section of the image that it is convolved with, the numbers located at the indices corresponding to that section in the output tensor will take on significant values. Because the size of each feature map is generally small (on the order of three to fifteen pixels wide and high), significant values in the output tensor are able to represent points in the input image in a fine-grained way.

The diagram from [5] in Figure 3.3 illustrates a convolution of a feature map (referred to as "kernel" in the figure) with a partially zero-padded image. In this scenario, the 3×3 feature map detects embossed edges. The output of the feature map becomes the activation matrix. Activation matrices for each feature map are stacked to create the tensor output of a single convolutional layer.

Later convolutional layers. As noted above, the output of the first convolutional layer is a three-dimensional tensor that consists of individual activation matrices. This tensor is further convolved by downstream, convolutional layers that have feature maps of height and width similar to those in the first layer. However, because the input is now three-dimensional, the feature maps are three-dimensional as well; as such, they have a depth component. This depth is generally set to the number of feature maps in the immediate upstream layer. For example, if there are 64 3×3 feature maps convolving a 224×224 image in the first layer, the output of the first layer will be a $224 \times 224 \times 64$ tensor. If this layer is followed by a second convolutional layer, the feature maps in the second convolutional layer may be of size $3 \times 3 \times 64$. This pattern carries on for any downstream convolutional layer as well.

The diagram in Figure 3.4, taken from [51], illustrates a simple convolutional architecture. Each feature map's output is concatenated into a tensor (denoted by a graduated stack of individual matrices). The subsampling layers are explained in the Pooling Layers subsection below, and the layer denoted as "classification" is explained in the Fully Connected and Output Layers in ConvNets subsection below.

Like HOG, the ability to apply a feature detector (or map, in the CNN case) at a dense set of points (e.g. every pixel in the input image, if the stride is one) is what gives ConvNet features translation invariance. In addition, at each convolutional layer, activation tensors are transformed by nonlinear activation functions that provide great discriminative power.

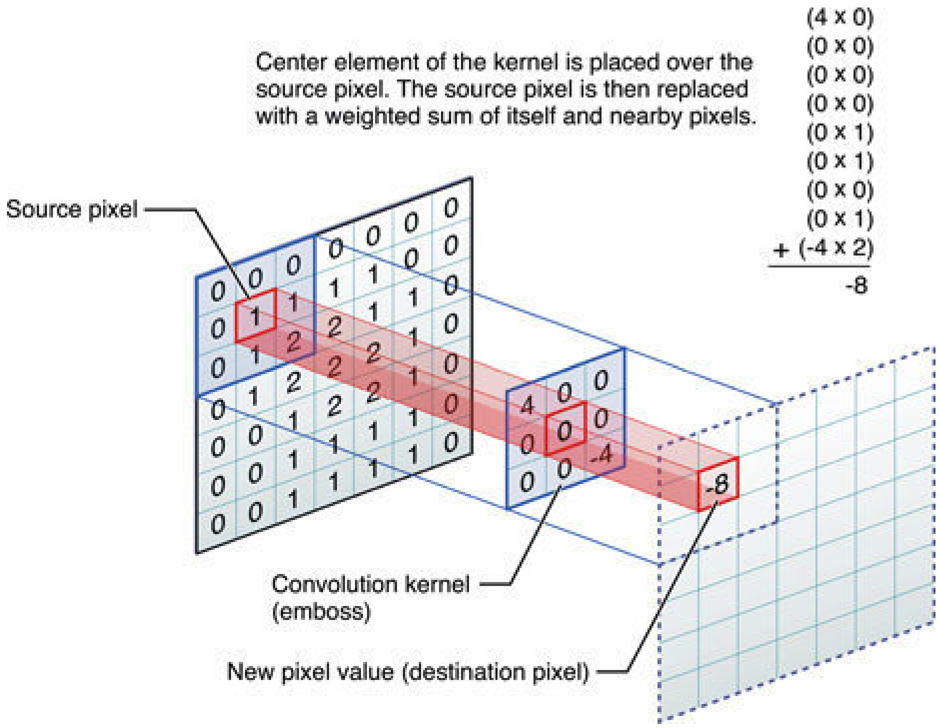

Figure 3.3: A product-sum operation at a pixel $I_{j,k}$, from [5]. Several of these operations make up a single feature map's convolution with an input image.

Pooling Layers

Convolutional layers are interspersed with layers that subsample the input to reduce dimensionality. The most common form of pooling, and the form that we employ, is called *max pooling*. Max pooling convolves a small kernel over the input tensor, with stride often equal to the size of the kernel (or at least small enough such that the resulting output tensor dimensionality is lower than the input tensor dimensionality). This kernel simply takes the max over the input that it receives. The input tensor is not zero-padded for max pooling, and nonlinearities may be applied before or after max pooling.

Although some information is lost during max pooling, it is required to keep the number of weights in downstream convolutional layers manageable. Subsampling schemes like max pooling allow or deeper networks to be formed, thus increasing the quality of the feature maps located at the last layers of a CNN.

Fully Connected and Output Layers in ConvNets

At the last pooling or convolutional layer, the activation tensor produced is generally flattened into a single vector, and connected to a fully connected layer. This fully connected layer is followed by one or two more fully connected layers, and an output layer. The output layer may use the traditional softmax normalization to form a probability distribution over class labels as described in Section 3.4.2. Alternatively, in the case of binary classification, we use a different function to output a score for an input image instead of probabilities. This function, known as *hinge loss* is described in Section 3.4.5. The combination of convolutional layers, which create high-quality, deep feature representations of images, and fully connected neural networks, which are excellent classifiers, make convolutional neural networks very effective at most computer vision tasks.

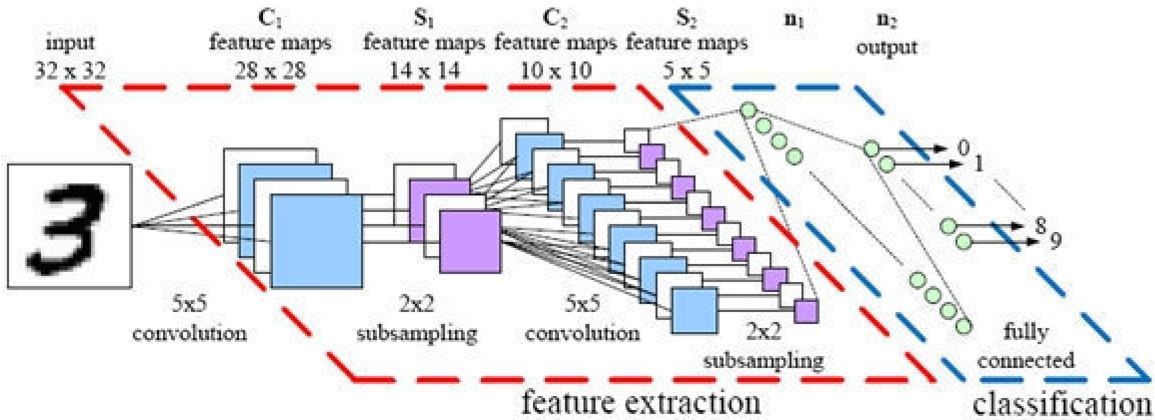

Figure 3.4: As the tensor output of each layer propagates through the network, each feature map in a downstream layer is convolved with the output of every matrix in the output tensor it receives from an upstream layer, [51]. This architecture has two convolutional layers, two subsampling layers, and a fully connected layer. The first convolutional layer convolves four 5x5 feature maps over the image to produce four 28x28 outputs. The first subsampling layer subsamples 2x2 squares of each 28x28 input to produce a four 14x14 outputs. The fully connected output layer performs 10-way softmax to classify handwritten digits.

3.4.4 Pre-trained Networks

Unfortunately, deep neural networks (especially convolutional networks) have one negative feature: they take large amounts of time and computational power to train. One way to bypass this problem is to re-use a popular, well-known network configuration for which trained weights already exist. These pre-trained neural networks are created by neural network researchers, and consist of a known architecture (e.g. a number of convolutional layers, specific sizes of feature maps, etc.), and a file containing the numbers for each weight in the network.

Pre-trained networks have been released for ILSVRC, a competition in which participants aim to classify images into one of 1,000 classes. It has been found that the weights and structure of these networks provide excellent starting points for classifying images into a different set of classes. For example, in [49, 88], it is reported that simply removing the output layer of a popular pre-trained ConvNet and replacing it with a new output layer trained to detect a different set of classes provides state of the art accuracy on several computer vision problems.

VGG-16 Architecture

The pre-trained VGG-16 network of [63] was initially conceived and publicly released in 2014. It was a top-performing model in the 2014 ILSVRC, and has been used widely in the literature to achieve excellent results on image classification problems. The original training process of the VGG-16 network can be found in [63]. The main reason we use the VGG-16 convolutional network is for its very deep architecture, which is what allowed it to perform so well in the 2014 ILSVRC competition. The architectural details can be found in the appendix.

The diagram in Figure 3.5 displays the VGG-16 architecture. Multiple layers of convolutions and max pooling using ReLU nonlinearities produce a $7 \times 7 \times 512$ cube of "bottleneck features", which are numbers representing complex textures and patterns that exist in the input image. This cube is flattened into a vector, and used as input to a two-hidden layer fully connected network. The fully connected network ends at a 1,000-dimensional output layer, which performs softmax to create a probability distribution. In the next section, we explain the modifications we make to the VGG-16 architecture in order to adapt it to the task of in/out of car scene classification.

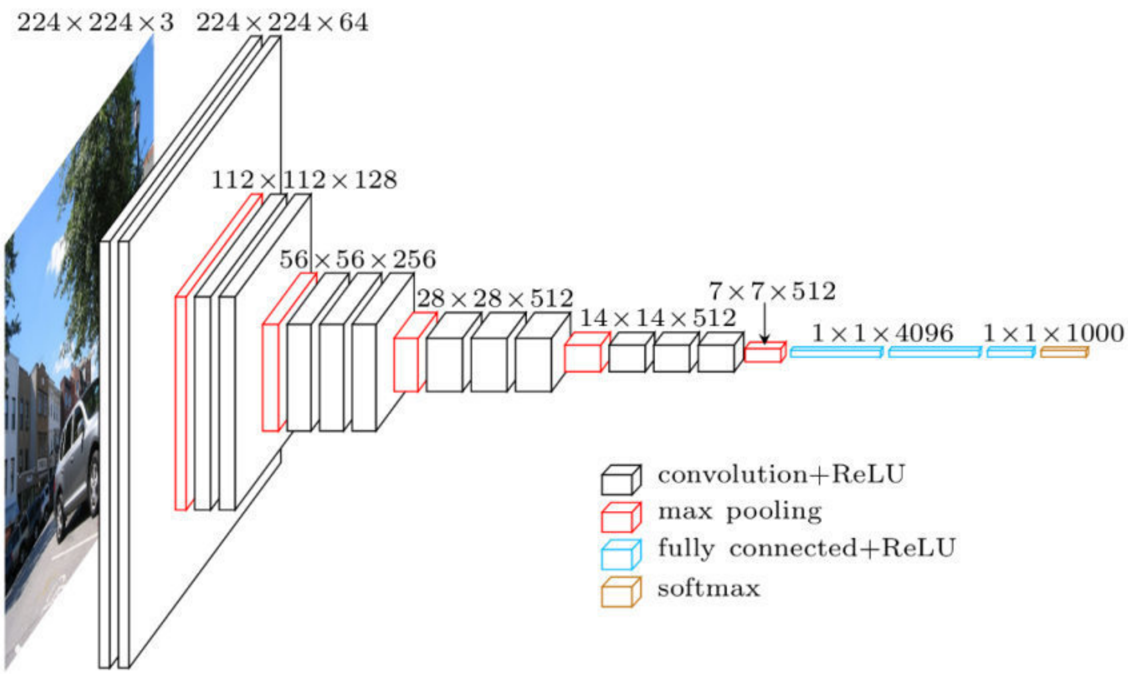

Figure 3.5: This figure shows the dimensionality of the *outputs* (not the feature maps) of each layer of the VGG-16 network. The network reduces an input image with three color channels to a $7 \times 7 \times 512$ cube of richly informative features, before passing these features to a fully connected network for classification. We modify this architecture by using a single-channel grayscale image as input, and replacing the second fully connected layer and output layer with a output layer customized for detecting in and out of car scenes.

Adapting VGG-16

Although VGG-16 ends with a 1,000-dimensional output layer, this layer can be removed and replaced with a layer made for a binary classification task such as detecting whether a video frame is set in or out of a car. To facilitate this, we weights were downloaded from the authors' website, and the network was implemented using two software libraries, Keras and TensorFlow [17, 1]. Because the weights of the last fully connected layer are often tuned to the task of the next (output) layer [49], we removed this layer as well as the output layer. We replaced the two layers with a single output layer that uses the hinge loss function, which is explained in Section 3.4.5. This new layer, once the weights are trained, produces a univariate scalar score for each image that conveys the "in-carness" or "out-of-carness" of the image. The use of a hinge loss function is reported in [72] to produce excellent results on different classification problems. To train this network, we first froze the weights of the non-modified layers so that they would not be changed. Training then proceeded using mini-batch stochastic gradient descent, which is outlined in Section 3.4.5. Our results are located in Chapter 5.

3.4.5 Training Neural Networks

Neural networks need to be trained by setting weights, biases, and other parameters to values that will produce low prediction errors on an unseen, test data set. Training encompasses a variety of topics, but those relevant to our interests are weight initialization, weight regularization, normalization, loss function selection, and optimization algorithm selection. We try to intelligently make choices in these areas so that the network can learn only the most important, generalizable features from the video frames it has been given.

Weight Initialization

The first step in training is to initialize weights to values that will not "oversaturate", that is, cause large activation values, in the early stages of training. We want to avoid oversaturation so that neither in car nor out of car frames produce activations with vastly different magnitudes, because this disparate behavior can cause unstable training and poor predictions. Like many design choices in the literature, weight initialization is set via a combination of heuristic methods, layer-local statistical arguments, and experimental guidance. Generally, weights are initiated to small values sampled from a Gaussian distribution with small variance, such as $\mathcal{N}(0, 0.1)$, or with variance proportional to the dimensionality d of the upstream layer: $\mathcal{N}\big(0, \frac{1}{\sqrt{d}}\big)$ [70]. Along with standardizing features by e.g. their mean and standard deviation, these small values ensure that the network commences training without relatively large influence given to any one feature. In our work, we both standardize input features by scaling them by the magnitude of their maximum absolute value (to preserve sparsity), and initialize weights following the second scheme outlined above.

Weight Regularization

While weight initialization ensures a steady starting state for training, weight regularization is an attempt to control the size, sparsity, or distribution of weights, thereby reducing the tendency for a network to "overfit" to the training data (i.e. be unable to generalize to the test data set). In our work, weight regularization forces neurons to learn features that are common to a variety of in and out of car LAPD videos, instead of features that are common only to the videos that are used to fit the neural network. Common regularization schemes generally restrict the L^p norm or a similar function of the layer weights during training, in order to keep weights small or sparse [23]. In our work, we use a technique based on a convex combination of the L^1 and L^2 norm, known as elastic net regularization [92], to regularize the top-level weights of the convolutional neural network. Elastic net regularization R of a set of weights $\mathbf{w}$ is parameterized by α, the convex coefficient of the L^1 norm:

$$R(\mathbf{w}) = \alpha\|\mathbf{w}\|_1 + (1-\alpha)\|\mathbf{w}\|_2^2 \qquad 0 \leq \alpha \leq 1$$

Details concerning the use of this regularization can be found in Chapter 5.

Dropout is a regularization scheme that has become very popular in recent work [67]. With dropout, a probability p is chosen such that each neuron in a dropout layer has chance p of being "turned off" during training. That is, the neuron's connections are severed: it receives no input, it outputs nothing, and receives no weight update. The theory behind dropout has two interpretations: in the language of ML, dropout trains a random subset of the network during each propagation of an example through the network, and therefore trains an ensemble of networks with greater resistance to overfitting; in biological metaphor, dropout reduces the tendency of the neurons to co-adapt to one another, which forces them to learn more expressive features that allow for greater generalizability. We use dropout to help our fully connected neural network avoid learning features that are just noise from the training data set. This allows our fully connected network gain a degree of resilience to noisy frames like camera occlusions, and transition periods between in and out of car frames. For example, dropout will, in theory, force neurons that have learned to recognize an occluded camera view as a feature of in car frames to change and learn more predictive features, like steering wheels and car mirrors.

Loss Functions

Neural networks only learn what they are optimized to learn. The most sophisticated architectures and weight schemes are only useful if they are being considered with respect to some objective function. This objective function (often called a loss function) is what a neural network is trained to optimize. In our work, the loss function represents the average level of frame misclassification in the training data set, which the network is trained to minimize. Loss functions can take a variety of forms based on the predictive task at hand, but for binary classification we use two of the most popular choices: cross-entropy loss [23] and hinge loss.

Cross-entropy is a measure of distributional divergence, and is used to compare the "distance" between the output probability distribution and the true output class label. The network is trained by attempting to minimize the average divergence over all training examples. Intuitively, the cross-entropy H between two probability distributions p and q measures the average cost in bits required to encode an event from the true probability distribution p in the form of an event from the approximated probability distribution q, where p_i and q_i are the probabilities of the ith event in each distribution,

$$H(p, q) = \mathrm{E}_p[-\log q] = -\sum_i p_i \log q_i.$$

In the case of binary classification, cross-entropy takes the following form, where y is the true class label and $\hat{y}$ the predicted class label probability,

$$H(y, \hat{y}) = -y \log \hat{y} + (1 - y) \log(1 - \hat{y}).$$

The loss for an individual example in the training set is thus near zero when the predictions agree with the true values, and gets worse as the values diverge.

In our work, we consider out of car to be the label we're predicting. So, for example, we can compute the cross-entropy between the true label $[1, 0]$ (for in car) of a frame, and the probability distribution over the labels for the frame that has been predicted by the network, say $[0.6, 0.4]$. In this case, we're encoding the labels as two-dimensional vectors, but this encoding is equivalent to the binary encoding in $H(y, \hat{y})$ above if we consider the prediction of the "out of car" label as 1. In this case, we would take the second element of each vector (true and predicted) above in order to compute our cross-entropy. In this format, the true class label for this example is 0 (for in car), and the prediction is 0.4. The cross-entropy is $-0 \log 0.4 + (1) \log 0.6 \approx -1.32$. We can do better, however: if the prediction was 0.1 (or $[0.9, 0.1]$ in the two-dimensional encoding), the cross-entropy would be $-0 \log 0.9 + (1) \log 0.1 \approx -3.32$, which is much lower. In our work, we use a fully connected network with cross-entropy to classify HOG features. Details can be found in Chapter 5.

Hinge loss is similar to cross-entropy loss, but penalizes misclassifications differently. It also uses labels that are encoded in a slightly different way, and classifiers using it compute *confidence scores* instead of probabilities. Optimizing hinge loss corresponds to optimizing the same objective that an SVM optimizes: finding the hyperplane that maximizes the margin between two classes of data. Hinge loss finds its roots in SVMs [79], but has been shown to be a very effective loss function in deep learning scenarios as well [73].

In hinge loss, labels y represent class membership, and are drawn from the set $\{-1, +1\}$. Confidence scores $\hat{y}$ vary in value, but generally remain in the $[-10, 10]$ range for zero-mean variance-normalized data. The confidence score represents the distance from the separating hyperplane found by optimizing hinge loss, which is defined as

$$\ell(y, \hat{y}) = \max(0, 1 - y \cdot \hat{y}).$$

Hinge loss thus increases as the predicted confidence score $\hat{y}$ deviates from $y \in \{-1, +1\}$, but does not increase when the confidence score is larger in absolute value than the true label y. Optimizing hinge loss thus tries to move points away from the hyperplane and toward the sign of the label, resulting in a margin around the hyperplane into which only a few points are classified. In our work, we use hinge loss in the convolutional network outlined in Section 3.4.3.

We want to aggregate all losses for each training example into the *total* loss function, which is the value we minimize during training. The total loss function for the neural network (given N training examples and the weights of the network $\mathbf{w}$) is

$$J(\mathbf{w}) = -\frac{1}{N} \sum_{i=1}^{N} \left[c(y_i, \hat{y}_i) \right],$$

where c is a loss function. The total loss function can be interpreted as the "cost" of using the weights $\mathbf{w}$, yielding yet another name for the loss function (i.e. cost function). To minimize this cost, we train the network using backpropagation of errors and an incremental optimization algorithm.

Backpropagation & Optimization

For binary classification (and most other tasks), neural networks are generally trained using the backpropagation algorithm. Although a full description of backpropagation is beyond the scope of this paper, a summary suffices to relay the intuition required to understand our frame classifier. Backpropagation is ultimately an algorithm for credit assignment. After propagating an example forward through the network to generate a prediction, the loss of the prediction is computed, and backpropagation is used to determine the change in each weight ∇w required to correct the error. Backpropagation works by incrementally computing the discrete gradients of the error in reverse, propagating the error back through the network to the weights of the nodes responsible. Each weight is assigned a gradient, ∇w, by which it must change to generate a better prediction.

If a network always used the gradients calculated by backpropagation to determine new weights, it would overfit to each training example, and become largely useless. For example, if we changed the weights completely in order to perfectly predict the last frame correctly, any other frame would likely be given very bad predictions. Instead, backpropagation works with an optimization algorithm like gradient descent to determine the optimal weight update after each example is propagated forward through the network. Because these updates tend to be very small, the training examples are often fed through the network multiple times until prediction error on a test set is at a stable level. Each full iteration of the training data set is called an *epoch*. In our work, an epoch is the full set of frames that we train on.

Traditionally, neural networks are trained in the manner described above. However, deep networks can be trained in a more efficient fashion using better optimization algorithms and intelligently combining gradients before executing updates. One method in particular, called mini-batch stochastic gradient descent (often shortened to "stochastic gradient descent" in the literature) has gained wide acceptance for its stability and improvements over traditional methods [23]. In mini-batch stochastic gradient descent, a small number of examples (in our work, 100 frames) is randomly drawn without replacement from the training examples, and the gradients are collected for the propagation of each example in the mini-batch. The gradients are then combined (usually by averaging), and then a gradient descent-like algorithm is used to calculate the weight update. In this way, training is stabilized by smoothing large or noisy gradients using many others. This combination of computing gradients based on random subsets of the data and combining the gradients of small batches has allowed neural network researchers to train very large and deep networks in recent years. For our purposes, it allows us to reach a stable and near optimal level of error on the training data set in the presence of noisy gradients like those from occluded cameras and transition periods between in and out of car frames. Ultimately, mini-batch stochastic gradient descent allows us to speed up training and converge more quickly to a stable test data set error rate as well.

Chapter 4

Change-point Detection

Given a time series $X_i, i = 1...n$, we assume one, multiple, or zero change-points exist. We define a change-point c as a place in the series where the underlying distribution of the X_i changes. That is, in the case of one change-point:

$$X_i \sim F_1 \ \forall \ i \leq c, \ X_i \sim F_2 \ \forall \ i \ > c$$

for some distributions $F_1 \neq F_2, c \in \{1...n\}$.

Since we did not know where the change-point(s) existed in the time series, we had to consider each value in the time series as a potential change-point. Therefore, we constructed objective functions and/or test statistics, evaluated these functions at all potential c and, depending upon the function, we looked for the c in the series which either optimized the objective function or produced test statistic values above a threshold [24, 16]. For some of our methods described below, there are parameters that can be adjusted so, with some of the methods, we include a list of these parameters.

In this chapter, we discuss a whole spectrum of methods—including mean squared error, hypothesis testing, density estimation, graph-based, time series, hidden markov model, BoVW histogram comparison, and maximum likelihood estimation methods.

4.1 Mean-Squared Error

The mean-squared error method (MSE) is straightforward - we divide the data into two portions (at every c), find the mean of each portion, and compute the squared differences between the points before the division and their mean and the points after the division and their mean. These squared differences are then summed up to produce the MSE for a particular c. This statistic is computed for all possible change-points in the data - where the possible change-points are all of the points in the data set - so the change-point will be the partition which minimizes the mean squared error [74]. The formula for this method is as follows:

$$MSE(c) = \min_{1 \leq c < n} \sum_{i=1}^{c} \left(x_i - \bar{x}_1\right)^2 + \sum_{i=c+1}^{n} \left(x_i - \bar{x}_2\right)^2,$$

where

$$\bar{x}_1 = \frac{1}{c} \sum_{i=1}^{c} x_i, \ \bar{x}_2 = \frac{1}{n-c} \sum_{i=c+1}^{n} x_i,$$

Through algebraic manipulation, we can reduce this to the following (in the univariate case):

$$MSE(c) = \sum_{i=1}^{n} x_i^2 + c\bar{x}_1^2 + (n-c)\bar{x}_2^2.$$

As $\bar{x}_1$ and $\bar{x}_2$ are sample means, we can take them to be normally distributed for large enough samples. That is, for sample size c from distribution X, we can say that $\bar{x}_1, \bar{x}_2 \sim \mathcal{N}(\mu_x, \frac{\sigma_x^2}{c})$. Without loss of generality, let us assume our data has mean zero, i.e. $\mu_x = 0$. Then, the squared normal variable $\bar{x}_1^2$ is from the gamma distribution $\Gamma(\frac{1}{2}, \frac{2\sigma_x^2}{c})$, and $\bar{x}_2^2$ is from $\Gamma(\frac{1}{2}, \frac{2\sigma_x^2}{n-c})$, meaning that $c\bar{x}_1^2 \sim \Gamma(\frac{1}{2}, \frac{2c\sigma_x^2}{c}) = \Gamma(\frac{1}{2}, 2\sigma_x^2)$ and $(n-c)\bar{x}_2^2 \sim \Gamma(\frac{1}{2}, \frac{2(n-c)\sigma_x^2}{n-c}) = \Gamma(\frac{1}{2}, 2\sigma_x^2)$ as well. Therefore, $c\bar{x}_1^2 + (n-c)\bar{x}_2^2 \sim \Gamma(1, 2\sigma_x^2)$. Let us call this variable G_c. We then have

$$MSE(c) = \sum_{i=1}^{n} x_i^2 + G_c$$

$$MSE(c) - \sum_{i=1}^{n} x_i^2 = G_c \sim \Gamma(1, 2\sigma_x^2).$$

Since $\sum\limits_{i=1}^{n} x_i^2$ is a constant for each sequence, we can now calculate a p-value for $MSE(c)$, using the cumulative distribution function (CDF) for a gamma distribution with shape $k = 1$ and scale $\theta = 2\sigma_x^2$. The CDF is as follows:

$$\begin{aligned} CDF(x) &= \frac{1}{\Gamma(k)}\gamma(k, \frac{x}{\theta}) \\ &= \frac{1}{\Gamma(1)}\gamma(1, \frac{x}{2\sigma_x^2}) \\ &= \frac{1}{1}\int_0^{\frac{x}{2\sigma_x^2}} t^0 e^{-t} dt \\ &= -e^{-\frac{x}{2\sigma_x^2}} + 1 \end{aligned}$$

where $\Gamma(k)$ is the gamma function, and $\gamma(s, x)$ is the lower incomplete gamma function. Therefore, $p - value(x) = 1 - CDF(x) = e^{-\frac{x}{2\sigma_x^2}}$. We now can construct a hypothesis test for a given univariate series x_i and potential change-point c. Let H_0 be that X_i does not have a change-point at c. We can reject this null hypothesis if $p = e^{-\frac{x}{2\sigma_x^2}} < \alpha$, for significance level α.

This hypothesis test allows us to extend our MSE method to the multiple change-point case - naively, we can take all points with a p-value below our threshhold to be change-points. However, this does not quite work, due to the highly correlated nature of the time series. At the very least, we need to filter out stretches of consecutive points with low p-values. We also filter points which do not have a wide range of SVM scores in a local neighbourhood. To pre-smooth our data, we use a median filter. Our parameters are as follows: Median filter window size, threshold t below which MSE values are considered significant, maximum recursive depth for our extension to the multi-change-point case, and max/min window filter size K and max/min filter threshhold (the neighbourhood K around each window in which we search for two values separated by a certain amount M). K and M are only used when classifier output is non-binary (so they are used for SVM score output, but not CNN predictions).

Figure 4.1 shows an example of parameter tuning - the x-axis is recall, the y-axis is precision, and the color represents the value of the parameter K, the size of the neighbourhood around each change point in which we search for a wide range. Each point on this graph represents a different parameter setting for MSE. We can see that, given the options, the lower value of K is stronger in general, since those parameter settings achieve stronger precision and recall.

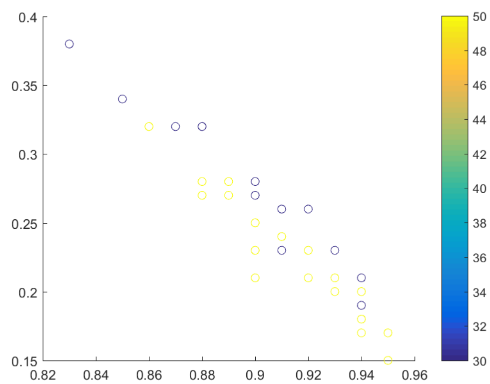

Figure 4.1: Precision vs Recall for various values of K

However, in Figure 4.2, the trade-off is clear - lower values of M result in better recall, high result in better precision. This parameter tuning becomes a value judgment - the parameters we choose depends on whether we value precision or recall more highly. For our problem, we prefer recall.

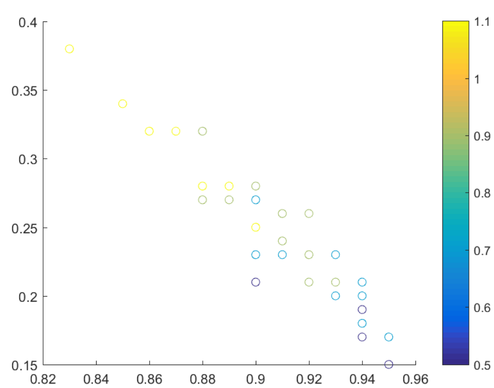

Figure 4.2: Precision vs Recall for various values of M

Our method for MSE in the multiple change point case is recursive. First, take the point with the lowest MSE across the series. If that point satisfies various filtering conditions (length of interval long enough, a high and low point in its neighbourhood), split the series into two halves, before and after this point. Then, recursively run MSE on each of those halves. The results can be found in Table 5.4 and Table 5.5.

4.2 Pettitt and Simple CUSUM

Pettitt's method [53], similar to the MSE method, divides the inputted data along all possible cut points. For each possible cut point (that preserves the order of the data), the method finds all of the signed differences (via the sign function) between each of the data points before the cut point (including the cut point) and each of the data points after the cut point. Then, for each cut point, the algorithm sums the result – which we will call the aggregate sum. This sum is divided by the total number of differences to account for the fact that the number of signed differences will vary from cut to cut. Finally, the change-point is the cut point that maximizes the absolute value of the normalized aggregate sum [53]. The formula for the method can be written as

$$\max_{1 \leq t < n} \Big| \sum_{i=1}^{t} \sum_{j=i+1}^{n} \operatorname{sgn}(x_i - x_j) \Big|,$$

where $\operatorname{sgn}(x) = 1$ if $x > 0$, $\operatorname{sgn}(x) = 0$ if $x = 0$, and $\operatorname{sgn}(x) = -1$ if $x < 0$. Given the code we have produced, this method only works for video segments with one change-point. However, it could be extended to multiple change-points if a threshold was set and if an iterative process were to be constructed. The results from this method can be found in Table 5.2.

Our Simple CUSUM method was adopted from [50]. This approach takes a sample mean for the time series, finds the cumulative summed differences between the time series points and the mean, and then identifies the change-point as the point in the series where the difference between a sum and the minimum of the sums that came before it is maximized. Therefore, the formula is

$$\max_{1 \leq r \leq n} \Big\{ S_r - \min_{0 \leq i < r} S_i \Big\},$$

where

$$S_r = \sum_{j=1}^{r} \big(x_j - \bar{x} \big), \ \ \bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i.$$

Our source paper assumes knowledge of the population mean, where here we take the sample mean of the time series. The method also compares the maximum to a threshold, while we just take the maximum of the objective function [50]. Therefore, the method has only been coded to deal with one change-point in a video. The results from this method can be found in Table 5.2.

4.3 Hypothesis Testing

The Kolmogorov-Smirnov (K-S) Two-Sample test [89] is a popular method of determining similarity of the underlying distributions of two samples, even when these distributions may be non-parametric. Given two samples, S_1 and S_2, we can define the *empirical cumulative distribution functions* F_i, for $i = 1, 2$, such that

$$F_i(x) = \frac{1}{n} \sum_{j=1}^{n} I_{[-\infty, x]}(X_{j,i})$$

where n is the number of data points and $I_{[j,k]}(x)$ is 1 if $j \leq x \leq k$, and is 0 otherwise. The Kolmogorov-Smirnov test statistic is

$$D = \sup_x |F_1(x) - F_2(x)|,$$

where the null hypothesis (that two samples are drawn from the same distribution) is rejected for high values of D.

Given a time series $X_i, i = 1...n$, we can use the K-S test as follows. For each point X_i, let $S_1 = \{X_1...X_i\},\ S_2 = \{X_{i+1}...X_n\}$, and define F_1, F_2 over these samples. Given these functions for each i, we can calculate the K-S test statistic for this data split - call it D_i. We calculate D_i for each point i in our sequence, and our change-point is the i that maximizes D_i. Therefore, based on this set-up, this method only deals with one change-point. It could, however, be extended to multiple change-points.

However, the K-S test is only defined for univariate data, and there have been few attempts to extend it beyond two-dimensional input. For a multivariate change-point method of a similar spirit to the K-S test, we turn to Leach [39], who proposed a multivariate and non-parametric two-sample test.

In Leach's test, we first rank the data on each variable separately. Then our test statistic $U^* \sim \chi^2_p$ is calculated as

$$U^* = U'(NV)^{-1}U,$$

where U is a vector of test statistics, N is the size of the combined sample, and V is a covariance matrix defined below. There is one element of U for each variable in our data, and U_i is defined as

$$U_i = \frac{R_i}{N+1} - \frac{n}{2},$$

where n is the size of the smaller of the two samples, and R_i is the sum of the ranks in this smaller sample. Finally, V is defined as follows. The diagonal entries are

$$v_{ii} = \frac{mn}{12N(N+1)}$$

and the off-diagonal entries are

$$v_{ij} = \frac{mn}{N^2(N-1)(N+1)^2} \sum_{t=1}^{N} R_{it}R_{jt} - \frac{N(N+1)^2}{4}$$

where m, n are the sizes of the two samples and R_{it} is the rank of variable i in data point t. This test only works for videos with one change-point. The results for the K-S and Leach tests can be found in Table 5.2 and Table 5.3.

4.4 Density Estimation

After a change-point, we assume there is a change in the distribution of the data — whether it is in a parameter or in the equation of the distribution itself. The ability to compare these two distributions in a meaningful way for all potential change-points allows us to see which potential change-point leads to the most dissimilar distributions; in theory, distribution comparison would allow us to detect many types of changes in the distribution. However, reaching an estimation for these distributions is a very difficult task and could lead to huge errors. Therefore, we decided to use kernel density estimation to develop a non-parametric representation of the before change-point and after change-point distributions.

Kernel density estimation (KDE) fits a continuous distribution to data whose true distribution is unknown. The method relies upon kernel functions, which are simpler representations of probability functions; we use Gaussian kernel functions. KDE centers a kernel function at every point in the data set and then sums these functions to produce an estimate of the data's distribution. The summation is scaled by the number of data points in the set and is a function of the bandwidth, which is essentially the standard deviation of the distribution. The bandwidth is constant for each kernel function, and its computation greatly impacts the shape of the KDE [62, 44, 19, 35]. We use Silverman's rule to compute the bandwidth, which uses the number of observations and the spread of the data in its computation [26]. Since we use Gaussian kernel functions that are second order, the Silverman's rule equation is

$$h = \min\{\sigma, \mathrm{IQR}\}1.06n^{\frac{-1}{5}},$$

where σ is the standard deviation, IQR is the inter-quartile range, and n is the sample size. The use of the IQR came as a result of a Google Search and, in fact, there are multiple ways to define Silverman's rule. The formal representations of the KDE and the Gaussian kernel function are

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right),$$

$$K(x) = \frac{1}{\sqrt{2\pi}}e^{-\frac{|x|^2}{2}},$$

where h is the bandwidth and n is number of points in the data set. It should also be noted that the resulting KDE functions have an area of one underneath them.

After establishing the estimation of the density function, we need to compare the two distributions in a scientific way. We computed the Kullback-Leibler divergence, the CUSUM, and a parametric test statistic for each potential change point and, then, determined the change-point as the one which maximized these values.

The Kullback-Leibler (KL) divergence is often used in information theory to give an indication as to the difference between two distributions. However, this value is difficult to interpret – especially because the KL Divergence is not symmetric (The KL divergence between P and Q is not the same as between Q and P) [48]. Nevertheless, the method has been used before in change-point detection [54]. Its formula can be seen here:

$$D(q||p) = \sum_{i=1}^{n} q(x_i) \ln\left(\frac{q(x_i)}{p(x_i)}\right),$$

where $p(x_i)$ and $q(x_i)$ are the two distributions we are comparing and x_i are the data points. The method only detects one change-point but, if a threshold was established, it could be used for multiple change-point detection. Due to time constraints and computing power, we were not able to test this method on our final image representations.

The CUSUM statistic takes the natural log of the ratio of the two estimated distributions $f_0(x)$, which is the distribution before the change-point, and $f_1(x)$, which is the distribution after the change-point. For each potential change-point, we input the values that come *after* the potential change point into the ratio of $f_1(x)$ to $f_0(x)$. We sum the result of the log of this ratio for all points after the potential change-point. We are looking for the potential change-point where the distributions are the most different – meaning that the ratios of the probabilities of these values under the two functions will be (ideally) greater than one because the values will produce higher probabilities in the function estimated on their values ($f_1(x)$) than on the function estimated on the values before the change-point ($f_0(x)$). Because the natural log of a number greater than 1 is a positive number, then we know the values we are looking for are positive numbers. If we find the potential change-point that maximizes the sum, then this means we have found the point at which the values that come after the change-point are the most probable in the second distribution *as compared to* the first – signifying that is the point at which the distributions are the most different and thus where the change-point is located [24, 16, 76]. We write the test statistic as

$$\max_{1 \leq n_c \leq n} \sum_{i=n_c}^{n} \ln\left(\frac{f_1(x_i)}{f_0(x_i)}\right), n_c \in \{1, 2, ..., n\}.$$

This test statistic can deal with videos with a single change-point and ones with multiple change-points. During the course of this research, we proved the CUSUM statistic, under certain assumptions, follows a normal distribution, but this did not lead to a practical application because the normal distribution that the CUSUM statistic follows changes for every new observation in the series. The proof has been included in Appendix C for reference. The final results for this method can be found in Table 5.2.

The parametric test statistic as derived by [66] carries out KDE on part of the data before the potential change-point and then uses this kernel density estimation to create a test statistic that relies upon the remaining part of the data before the change-point and on the data after the change-point. The test statistic is essentially a weighted difference between the results of the computation of probabilities with the kernel density function on the first part of the data and the results on the second part of the data. This test statistic follows a normal distribution whose variance can be computed using bootstrapping methods, which in the future should allow us to compute p-values [64]. If we assume the set B represents the values before the potential change-point, $B = B_1 \bigcup B_2$, and the set C represents values after the change-point, then the test statistic is:

$$Y = \log\left\{\prod_{x \in B_2} \mathrm{KDE}_{B_1}(x)\right\} - \frac{|B_2|}{|C|} \log\left\{\prod_{x \in C} \mathrm{KDE}_{B_1}(x)\right\},$$

where the kernel density function is computed on B_1. This method deals with single change-points. Due to time constraints and computing power, we were not able to test this method on our final image representations.

Finally, we used the Kullback-Leibler Importance Estimation Procedure (KLIEP), which allows us to estimate the CUSUM *ratio of the density distributions* directly without estimating the density distributions individually. To explain how this is done, first imagine that $f_0(x)$ is the distribution before the change-point, and $f_1(x)$ is the distribution after the change-point. The KLIEP process minimizes the KL Divergence between $\hat{f}_1(x) = \hat{w}(x) f_0(x)$ – where $\hat{w}(x) = \frac{f_1(x)}{f_0(x)}$ – and $f_1(x)$. Since we assume we don't know the formulas of these functions, we have to take an indirect route to minimize the divergence. First, we write $\hat{w}(x) = \frac{f_1(x)}{f_0(x)}$ as a linear combination of "basis functions"; we choose to use Gaussian kernel functions centered at the points after the potential change-point for the basis functions as the paper suggested. The actual values to be solved for in the KL divergence problem are the coefficients in front of these kernel functions. In order to achieve this, we notice that the expanded form of the KL divergence of $\hat{w}(x)p_1(x)$ and $p_2(x)$ actually is a difference of two terms. Therefore, if we maximize the second term (which involves $\hat{w}(x)$) with respect to the coefficients, we minimize the KL Divergence. This turns into a convex optimization problem. The KLIEP paper provides code for MATLAB to implement this method, which we took advantage of and made some slight modifications to for our purposes [69, 34]. Due to time constraints and lack of computing power, we were unable to test this method on our final video representations.

4.5 Graph-based Methods

Density estimation is highly flexible—using kernel methods, we can approximate all sorts of non-parametric distributions. However, it is notoriously difficult. Graph-based methods provide a simpler framework for working with non-parametric distributions [15, 21]. Given a series $X_i, i = 1...n$, we can imagine plotting these points in space. These X_i would then act as nodes for a graph G. We can connect every two nodes X_i, X_j by an edge with weight $\|X_i - X_j\|$ (the Euclidean distance between X_i and X_j, to make G fully connected. Then, we can find a minimium spanning tree (MST) T of G - this reveals structure in the graph, such as which nodes are in close groups to each other.

Once we have T, we try a series of successive partitions P_i of the graph. In partition P_i, we separate nodes $S_1 = X_1...X_i$ from nodes $S_2 = X_{i+1}...X_n$. Each of these partitions P_i represents a possible change-point occurring at the ith point in the sequence. We then count the number of edges E_i of T which cross this partition - that is, edges which have ends $X_j, X_k, 1 \leq j \leq i, i + 1 \leq k \leq n$.

Let us define the size of the partition $\|P_i\|$ to be a pair of numbers: the size of the two groups formed by the partition. Therefore: $\|P_i\| = (\|S_1\|, \|S_2\|) = (i, n - i)$. For any given partition size, a partition which cuts many edges of is likely separating many nodes which are close in space, since most edges of T are among the shortest in G. By the same token, if we were to compare all partitions of the same size on G, the partition which cuts fewest edges of T is most likely to be dividing the points into well-separated groups.

We want to compare all P_i to see which is the most likely candidate for a change-point. If all $\|P_i\|$ were equal, we could simply see which one cut the fewest edges of T (minimize E_i). However, $\|P_i\|$ changes with the value of i. This is a problem: a partition which only separates one node from the graph will probably cut fewer edges of T than a partition which divides the nodes into equal groups. Therefore, we need a way to compare partitions of different sizes.

To remedy this, we find an expected value for edges cut by a partition of a given size, $\mathbb{E}[E_i \,\big|\, \|P_i\| = (m, N - m)]$, with N the number of nodes in the graph. This calculation proceeds as follows. Note, a tree has $\|E(G)\| = (N - 1)$.

$$
\begin{aligned}
&\mathbb{E}[E_i \,\big|\, \|P_i\| = (m, N - m))] \\
&= \|E(G)\| \cdot P((X_i, X_j) \in S_1 \times S_2 : \; e_{ij} \in E(G), \|P_i\| = (m, N - m)) \\
&= (N - 1) \cdot \frac{\#\ partitions\ P_i : (X_i, X_j) \in S_1 \times S_2, \|P_i\| = (m, N - m)}{total\#\ of\ partitions} \\
&= (N - 1) \frac{1}{\binom{N}{m}} \cdot 2\binom{N-2}{m-1} \\
&= \frac{2m(N - m)}{N}
\end{aligned}
$$

There are $\binom{N}{m}$ possible partitions of size $(m, N - m)$ since we need to choose m nodes for the smaller group. There are $2\binom{N-2}{m-1}$ partitions of size $(m, N - m)$ with $X_i \in S_1$ and $X_j \in S_2$ because there are $N - 2$ other nodes in G, and we need to choose $m - 1$ of them to fill up the smaller partition. We can also have $X_i \in S_2$ and $X_j \in S_1$, hence the factor of 2. The final step is achieved through algebra.

Now that we have a way to compare expected E_i for different partition sizes, we return to the problem of comparing the P_i. We can say that the P_i with the fewest edges cut *compared to expectation* is the most likely candidate for a change-point. So, for each P_i, we take $E'_i = \frac{E_i}{\mathbb{E}[E_i \mid \|P_i\|=(i,N-i)]}$. The smallest E'_i leads us to our change-point prediction.

We extended this method to the multiple change point case in a similar manner as MSE - by recursively finding the most likely change-point in each side of the previous change-point.

4.6 Time Series Methods

As stated in the introduction to this chapter, change-point detection operates on time series data. For most of the methods, we made the assumption that each X_i was independent, which was not in keeping with the nature of time series data. Indeed, the elements in a time series often are not independent because, when phenomena are measured over time, the current value of the time series often has a relationship with the previous values; in other words, values in the time-series are correlated with each other.

Consequently, to take this correlation into account, we utilized an autoregressive model, which took as an input the previous observation(s) in order to predict the current observation. Via this process, we accounted for the correlation among successive observations. Autoregressive models can have one or more lags — meaning that, to predict the current observation, we can regress the time-series on itself one or more times. To employ this model for change-point detection, we estimated a one lag model based on a set number of observations in the beginning of the series (under the assumption that there will not be a change-point right in the beginning of the time-series),

$$X_t = B_0 + B_1 X_{t-1}.$$

We then used this model as a baseline to see if the actual data was different from the model's predictions. To find potential changes, we predicted the next value in the series based on the initial model. We then compared the prediction to a set number of future observations – call this a "future window." If the difference between the predicted value and the observed values – for all the values in the window – was greater than the standard deviation (which acts as a threshold) of the entire time series, then we called the value at the beginning of this window of observations the change-point. If a change-point was established, a new autoregressive model was estimated based on these five observations. This process was repeated for every point in the time-series, except for the last few where it would have been impossible to take a full future window into account. This methodology of estimating future observations based on a current model lines up with the framing of the change-point problem, which assumes that there is a shift in the model after a change-point, and the methodology enables the handling of cases where there are multiple change-points and cases where there are no change-points [71, 77]. The parameters to be varied in this model were the threshold, the future window, and whether or not we updated our model with future observations. The results of the AR(1) model can be found in Table 5.4.

The mean model/intercept model also relies upon a future window in order to make its predictions. The method assumes the time-series is stationary between all potential change-points, meaning the data retains the same mean and variance between potential change-points [4]. Therefore, in applying the method, we computed a mean of a set number of observations and, for the observations in the future window after this, we found the absolute difference between the established mean and the observations. For all of the observations in the future window, if the difference between the established mean and the value was greater than the standard deviation (the threshold) of the time-series, we determined that the beginning observation of this window was the change-point. A new sample mean was then evaluated from this observation window; if there was not a change-point, the current mean was maintained. We repeated this process for all future observations, until the last few for which there were not enough future observations. With this model, we were able to detect multiple change-points. The parameters to be varied in this model were the threshold, the future window, and whether or not we updated the sample mean with future observations [46]. The methods can also be modified to integrate successive observations into the model — meaning that, even if there is not a change-point declared at an observation, the observation can be integrated into the model. The results of this method can be found in Table 5.4 and Table 5.5.

In order to work with multivariate data, we extended the mean/intercept model so, instead of working with one dimensional means, we worked with centroids – which can be thought of as the multivariate equivalent to a univariate mean. To find the centroid of a group of vectors, we simply added the vectors and divided each component of the resulting vector by the number of elements that went into the sum. The standard deviation was found by summing the squared deviations of each element of every time series in the multivariate series from its respective mean – which was the element in the centroid corresponding to the time-series with which one was dealing [2, 13]. The rest of the method followed the one previously outlined by the mean model. The parameters to be varied in this model were the threshold, the future window, and whether or not we updated the sample centroid-mean with future observations. The results can be found in Table 5.4 and Table 5.5.

4.7 Hidden Markov Model

In a Hidden Markov Model (HMM), the system being modeled is a sequence of discrete latent states, which, in our project, are the ground truths of whether the officer recording these frames is inside or outside of a car. Such sequence is modeled using a Markov chain, in which the conditional probability of the future state only depends on the present state. Each type of state has an associated emission probability, according to which an output is assumed to be generated. While each latent state is not directly observable, the associated output is observable. Our goal was to construct the most probable sequence of latent states, given the sequence of associated SVM scores. Let $\{z_n\}_{n=1}^N$ be a sequence of latent states, where $z_n = (1 \quad 0)^T$ if the frame is taken inside a car and $z_n = (0 \quad 1)^T$ otherwise. Let $\{o_n\}_{n=1}^N$ be the associated sequence of SVM scores. The initial distribution $p(z_1)$ is given by $\pi = (\pi_1 \quad \pi_2)$, so that

$$p(z_1) = \begin{cases} \pi_1 & \text{if} \quad z_1 = (1 \quad 0)^T \\ \pi_2 & \text{otherwise.} \end{cases}$$

The transition matrix of latent states is denoted as A, where $A_{ij} = p(z_{n,j} = 1 | z_{n-1,i} = 1)$ and $i, j \in \{1, 2\}$. We modeled the conditional distributions of observed variables using Gaussian distribution:

$$p(x_n | z_n, \Phi) = \left(\frac{1}{\sqrt{2\pi\sigma_1}} \exp(\frac{1}{\sigma_1}(x_n - \mu_1)^2) \right)^{z_{n,1}} \left(\frac{1}{\sqrt{2\pi\sigma_2}} \exp(\frac{1}{\sigma_2}(x_n - \mu_2)^2) \right)^{z_{n,2}},$$

where $\Phi = \{\sigma_1, \sigma_2, \mu_1, \mu_2\}$ is the set of emission parameters. The structure of HMM is illustrated in Figure 4.3.

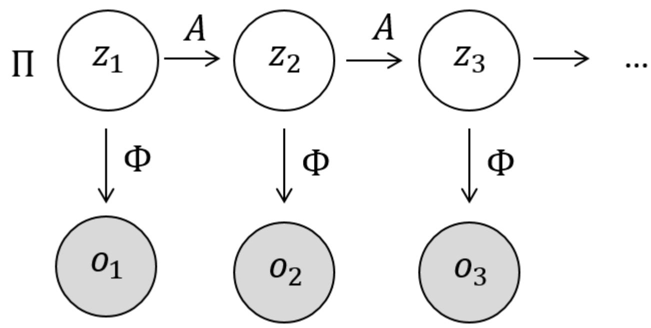

Figure 4.3: Structure of HMM

Estimates of parameters π, A, and Φ were computed by applying Expectation-Maximization (EM) algorithm and the Baum-Welch algorithm[7]. After this step, the most likely sequence of latent states were inferred using the Viterbi algorithm[81].

HMM is an unsupervised method, in which training examples are unlabeled. Thus, in principle, one can train a HMM and perform inference on the same sequence of scores extracted from a given video. In this project, however, we were more interested in evaluating how well a trained HMM can generalize to a new video. Our training and testing data sets were designed in the following way.

Videos that have at least one exit or entrance into five folds were split into five folds. A HMM model was trained on four folds, and we applied a Savitzky-Golay filter[61] on the sequences of scores from videos in the remaining folds before inputting them to the trained HMM model. We declared a change point occurred if two adjacent latent variables were inferred to have different states. This process was repeated five times, and we were able to predict change points for all of these 420 videos.

In another experiment, the goal was to estimate the precision of HMM on all videos, including those without exit or entrance. To get predictions for these additional 291 videos, we applied a HMM trained on the 420 videos that contain at least one actual change point. The results are presented in Table 5.5.

4.8 BoVW Histogram Comparison

The BoVW histograms gave us a succinct representation of an image by counting the number of keypoints associated with each visual word found in the image. However, the centroids, which each characterize a visual word, can be located within close proximity to each other – meaning the assignment of a keypoint to a visual word can be, to a certain degree, arbitrary or trivial. Therefore, it can be useful to group these visual words further — especially if one uses hard thresholds for the BoVW histograms. Even when we used soft thresholds for the BoVW histograms, this method still generated abbreviated representations without hurting the change-point detection results. Similarly to [31], we made use of the agglomerate clustering algorithm to simplify the histograms by grouping the BoVW centroids that were within close proximity to each other. In an iterative fashion, the agglomerate clustering algorithm groups the two closest centroids to form a new cluster (which takes on a new centroid value – call it the "cluster centroid") and continues to do this between the original centroids and the cluster centroids until all of the centroids have been connected to each other [31, 43]. For our specific application, we applied the algorithm to the first one-hundred centroids and then to the second set of one-hundred because the first one-hundred centroids dealt with in-car features and then the second one-hundred dealt with out-of-car features. A representation of the cluster tree can be seen below in Figure 4.4.

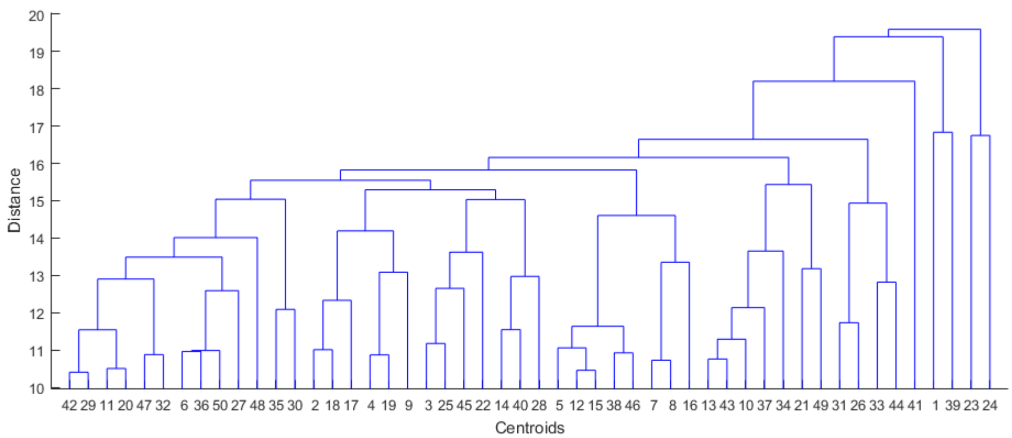

Figure 4.4: Representation of Cluster Tree using the Agglomerative Clustering Algorithm

Although the Euclidean distance is very popular, there are multiple ways of calculating the distance between the feature centroids. Furthermore, there are many ways of finding the distance between the clusters as one creates the cluster tree. We chose the distance metrics based on the cophenetic correlation coefficient and based on the need to generate a monotonic tree. With the cophenetic correlation coefficient, we sought to maximize this coefficient because it measured the degree to which the groupings made by the tree actually reflected the distances between the *individual* elements/centroids. When there is a grouping of centroids, there has to be a new representation for this cluster and, although this representation takes into consideration distance information from all of the elements in the cluster, it cannot represent all of the exact distances in that cluster. Monotonicity refers to the idea that clusters become "less similar" as the grouping process is undertaken [10]. The standardized Euclidean distance between the two points and then the average distance between clusters produced the highest cophenetic correlation coefficients and ensured the trees were monotonic [43, 10].

Once the tree was constructed, we needed to decide which clusters we wanted to use in the tree to simplify our BoVW histogram representations – meaning we wanted to see which bins/visual words of the histogram could be grouped together. Although we wanted to make the histogram simpler, we also did not want to group bins/visual words that were not related; in other words, we didn't want to greatly reduce the amount of information contained within the histogram. Consequently, we employed the inconsistency coefficient, which compares the height of the linkages (the horizontal bars in the diagram above) with the ones below them — the heights being a representation of the distances between the elements the cluster is joining. When links are not too different in height from each other, then they are fairly "consistent." As a result, we want to cluster centroids when the distances between the elements they group are not too large. Otherwise, we would be in danger of grouping centroids that are actually not very close together. Through trial and error, we decided to use an inconsistency coefficient value of 0.7 , which meant that we kept clusters that had this inconsistency value or lower [43].

Once the grouping were established, for each image, we aggregated the keypoints into each of these new "bins" and, then, we moved onto histogram comparing. To compare the results, we utilized the chi-squared goodness-of-fit test, which computes the squared differences between the bins of two histograms (call one the "observed" and one the "expected") and, for each bin, divides the squared difference by the number of elements in the "expected" histogram's bin, as demonstrated below

$$\chi^2 = \sum_{i=1}^{k} \frac{(o_i - e_i)^2}{e_i},$$

where o_i is the number of elements in the ith bin of the "observed" histogram, e_i is the number of elements in the ith bin of the "expected" histogram, and k is the number of bins. The degrees of freedom is $k - 1$. We use the same "future window" technique as was utilized in the time series methods and, after each iteration of the future window, we reset the "expected" histogram to the next observation. The parameters to be varied here are the alpha value, the future window length, and the histogram against which we compare the "future" histograms [82]. Besides the chi-squared statistic, we also used the match distance between histograms, which calculates the sum of the absolute valued differences between cumulative histograms at each bin — meaning that, for each bin, we find the cumulative sum for each histogram and, then, subtract those sums. This can be summarized by this equation:

$$d_M(H, K) = \sum_i |h_i - k_i|,$$

where h_i is the cumulative histogram of the elements of h at bin i [58]. As with the chi-squared statistic, we use the "future window" method and, after each iteration of the future window, we reset the "expected" histogram to the next observation. Each match distance is compared to a threshold and, if all the match distances for the elements in the window are greater than the threshold, a change-point is established. The parameters to be varied here are the threshold for the match distance, the future window length, and the histogram against which we compare the "future" histograms. The methods can also be modified to integrate successive observations into the model — meaning that, even if there is not a change-point declared at a histogram in the series, the histogram can be integrated into the model. Both of these histogram methods were applied to the raw histograms and the cluster reduced histograms, and the results can be found in Table 5.7.

4.9 Maximum Likelihood Estimation

Solving problems through maximum likelihood estimation is a common technique in the machine learning literature. The goal in maximum likelihood estimation is to find the values of some parameters which are most likely given the data available. Here, we develop a maximum likelihood formulation of the change-point detection problem, and parameters we are trying to find are the true in/out labels. Let $L_i \in [0, 1]$ be the ground truth labels (in/out of car) of a series and x_i the predictions from a classifier with accuracy p. Then, we can find the likelihood of a series of labels given the data as follows.

$$
\begin{aligned}
\mathcal{L}(L|X) &\sim P(X|L) \\
&= \prod_{i=1}^{n} P(X_i|L_i) \\
&= \prod_{i=1}^{n} p^{I[x_i=L_i]}(1-p)^{I[x_i \neq L_i]} \\
&= \sum_{i=1}^{n} I[x_i = L_i]\log(p) + I[x_i \neq L_i]\log(1-p) \\
&= \log(p)\sum_{i=1}^{n} I[x_i = L_i] + \log(1-p)\sum_{i=1}^{n} I[x_i \neq L_i]
\end{aligned}
$$

Using linear programming, we maximize this quantity. The main addition in the linear programming formulation is a constraint on the number of change-points allowable; otherwise, the program will change labels far too often. The linear program optimizes over values of L as follows:

$$
\begin{aligned}
\text{maximize} \quad & log(p)\sum_{i=1}^{n} I[x_i = L_i] + log(1-p)\sum_{i=1}^{n} I[x_i \neq L_i] \\
\text{w.r.t} \quad & \sum_{i=1}^{n-1} |L_i - L_{i+1}| < \; M \\
& L_i \in [0,1]
\end{aligned}
$$

The expression to maximize is the likelihood, the first constraint limits the number of change points, and the second constraint ensures that there are only two labels - in and out of car. The results can be found in Table 5.4 and Table 5.5.

Chapter 5

Results

5.1 Training and Testing Sets Description

We train and test our classifiers on LAPD body-worn video data. Out of the 691 videos provided, 420 of them contain at least one entrance or exit of a car. We use 200 of these 420 videos to train and cross-validate classifiers. These trained classifiers then compute a *Score* for each frame in the remaining 491 videos. To evaluate classifiers' performances, we randomly assign these 200 videos into 10 folds. In each trial, a classifier is trained using nine folds and tested on the remaining fold. This process is repeated ten times, and each fold is used as the testing fold exactly once. The testing accuracy on the ten trials are then averaged to give one estimate. Although we have had labeled each frame as either "in-car" or "out-car" before constructing classifiers, we select frames that go into training and testing sets manually, and the resulting data set has 515 "in-car" examples and 529 "out-car" examples. Our decision to manually construct training and testing is based on the following considerations:

- Redundancy in training set negatively impacts cluster construction and SVM training. Since consecutive frames usually have similar content, we expect them to have similar (if not the same) sets of feature vectors and therefore histogram representations. In the clustering stage, the repeated feature vectors essentially receive heavier weights and the centroids computed are likely to be biased. Redundancy in training set will also shift the learned decision boundary in SVM. Our SVM use a *soft* margin, which allows some training data points to be on the wrong sides of margin boundaries. This is achieved by imposing penalty on such training examples. However, if there is much redundancy in the training set, penalty may be applied to the repeated samples lying outside of the correct boundaries for multiple times.

- It is not always possible to tell whether an occluded frame is taken inside or outside of a car. An occluded frame is produced in video when the officer wearing the camera covers the camera lens by hand. Such frames usually do not contain enough information for even human eyes to identify the corresponding context. Since correct labels are not available for occluded images, we do not include them in training or testing set.

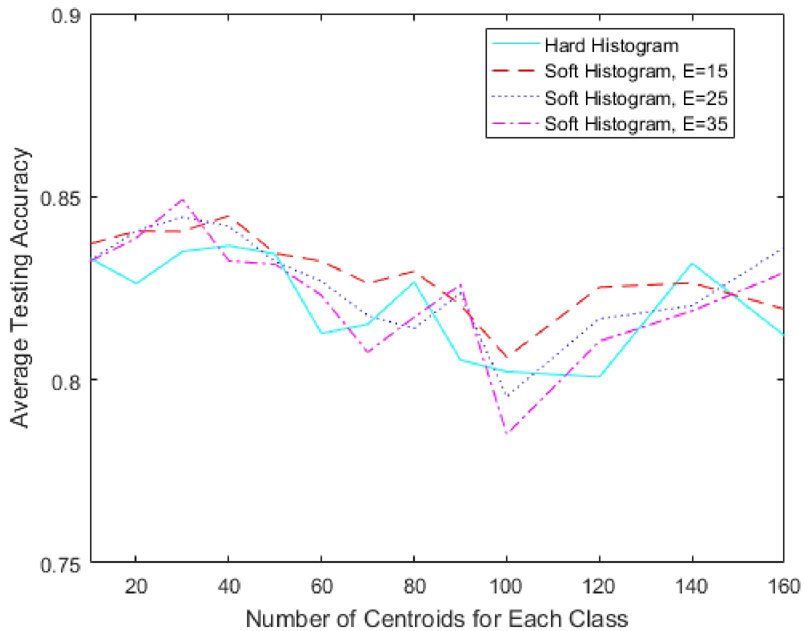

Figure 5.1: Classification Accuracy of Support Vector Machine with Linear Kernel. Parameter E of soft histogramming is set to 15, 25, and 35.

5.2 Results of Support Vector Machine

We study the classification performances of SVM with different number of centroids, histogram configurations, and choices of kernel function. The following subsections summarize our results.

5.2.1 SVM with Linear Kernel

As mentioned in Chapter 3, we used SVM with linear kernel as a benchmark to evaluate the performances of SVM equipped with other types of kernel function. The testing accuracy of linear SVM is displayed in Figure 5.1. As shown in the figure, there is a decreasing trend in testing accuracy as the number of centroids increases. In addition, in the case of linear SVM, using soft VQ technique with a relatively small value of E led to a general improvement in classification accuracy.

5.2.2 SVM with Gaussian-χ^2 Kernel

Figure 5.2 shows the relationship between testing accuracy of SVM with Gaussian-χ^2 kernel and number of clusters. We experiment with hard and soft histogram configurations, and the results are plotted. It is evident that the size of visual vocabulary has impact on classification accuracy, and SVM with hard histogram is more sensitive to variations in number of clusters. There is no significant difference in terms of classification accuracy among SVMs with hard and soft histogram configurations with a relatively small size of visual vocabulary. As the number of clusters increases, SVMs equipped with soft histograms tend to outperform SVM with hard histogram.

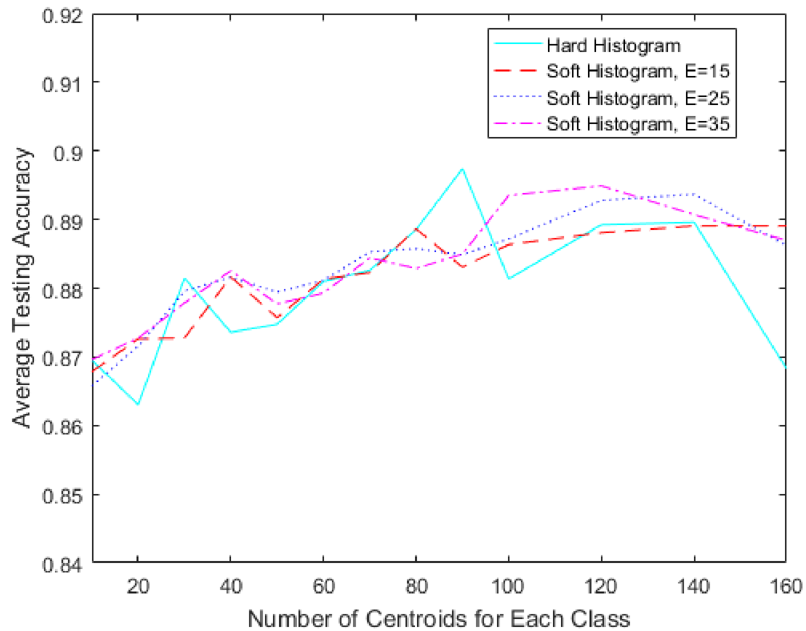

Figure 5.2: Classification Accuracy of Support Vector Machine with Gaussian-χ^2 Kernel. Parameter E of soft histogramming is set to 15, 25, and 35.

5.2.3 SVM with Spatial Pyramid Match Kernel

Figure 5.3 plots classification accuracy of SVM with spatial pyramid match kernel and hard histogram configuration versus number of clusters. The choice of L, which determines the total number of levels, has significant impact on classifier's performance. As L increases from 0 to 1, which implies the spatial information of each keypoint is now taken into account, classifier's performance improves greatly. As L increases from 1 to 2, each image is partitioned into finer cells, and the extra spatial information also contributes to improvements in classification accuracy. This observation also holds on the counterpart with soft histogram configuration, as shown in Figure 5.4.

Figure 5.5 compares performance of SVM with hard and soft histogram configurations. To obtain these results, parameter L is fixed at 2 and we let parameter E vary. As shown in the figure, soft VQ technique generally improve classification accuracy. For $E = 35$, SVM with soft histogram outperform that with hard histogram at every size of visual vocabulary.

5.2.4 Learning Curve

In machine learning literature, a learning curve plots the relationship between number of training examples and testing accuracy. To compute learning curves, we randomly selected training folds to construct new training sets of a given size, and the trained classifier output predictions for all remaining folds. For each given size of training set, the process is repeated five times, and classification accuracy are averaged to give one estimate. As shown in Figure 5.6, for a fixed size of training examples, the SVM with spatial pyramid generally outperforms the SVM with Gaussian-χ^2 kernel. Such gap in classification accuracy is more noticeable with a smaller size of training set.

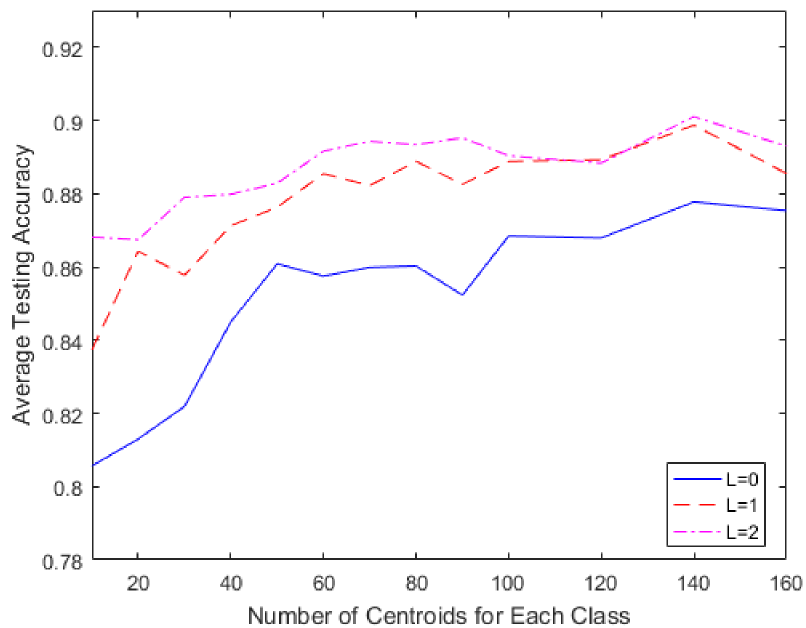

Figure 5.3: Classification Accuracy of Support Vector Machine with Spatial Pyramid Match Kernel using Hard Histogram. The maximum number of levels L is set to 0, 1, and 2 respectively.

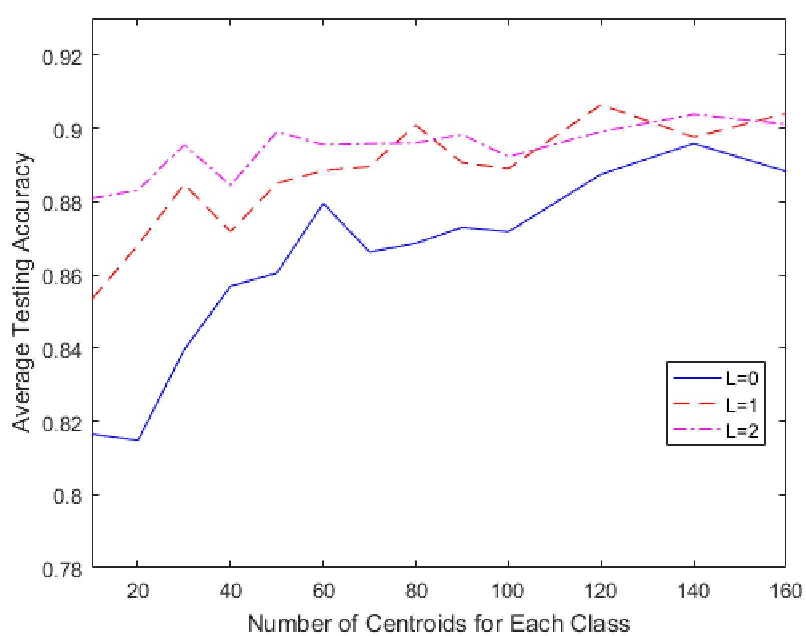

Figure 5.4: Classification Accuracy of Support Vector Machine with Spatial Pyramid Match Kernel using Soft Histogram $E = 35$. The maximum number of levels L is set to 0, 1, and 2 respectively.

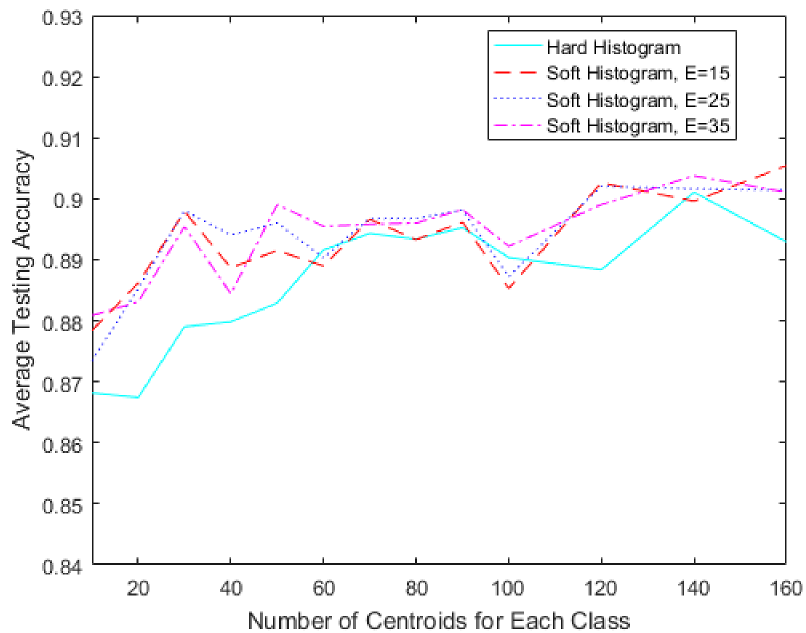

Figure 5.5: Classification Accuracies of Support Vector Machine with Spatial Pyramid Match Kernel using Soft and Hard Histograms. Parameter E of soft histogramming is set to 15, 25, and 35.

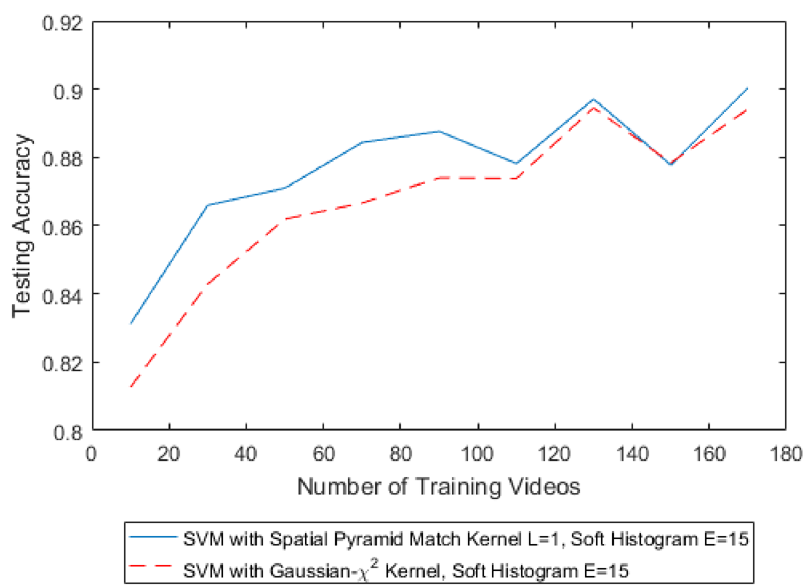

Figure 5.6: Learning Curves of Support Vector Machine. Parameter E of soft histogramming is set to 15.

5.3 Results of Deep Neural Networks

We created two deep neural networks for classifcation of video frames. A two-layer fully connected network was created to classify extracted HOG features to produce probabilities. Our modification of the VGG-16 convolutional neural network described in Section 3.4.3 classifies raw video frames using an output score similar to that of the SVMs described in Chapter 3.

5.3.1 Fully Connected Neural Network

The fully connected neural network classifier described in Section 3.4 required some modifications to the input data before deciding on the classifier's hyperparameters. First, each frame was converted to a single-channel greyscale image and downsampled to a resolution of 320x240, in order to keep the dimensionality of the resultant 7280-dimensional HOG feature vector relatively low. Next, the HOG feature vector was concatenated with a simple 256 bin pixel intensity histogram computed using the downsampled greyscale image. Each feature in the 7536-dimensional feature vector was then scaled by the inverse magnitude of the largest-magnitude value that feature took in the data set. Finally, the feature vectors were reduced in dimensionality to 400 dimensions using randomized PCA. This vector formed the input layer to the neural network.

After this preprocessing step, the neural network was tuned via cross-validation using a small variety of layer numbers, layer sizes, activation functions, regularization schemes, and optimization parameters. Hyperparameters were restricted to small range of numbers during tuning to reduce computation time. The most consistently effective model used two hidden layers, one of size 20, and the next of size 5. The network was trained with tuples of vectors of dimension $(400, 2)$, where each label is a two-dimensional one-hot encoded vector for the in car $[1, 0]$ or out of car $[0, 1]$ class. Consequently, the input layer was 400-dimensional, and the output layer 2-dimensional. Each hidden layer used the rectified linear unit (ReLU) activation function, which has been shown to give good performance in practice [45, 22]. Each hidden layer was regularized during training by the dropout regularization scheme [67] with a dropout probability of 0.5.

Training proceeded by stochastic gradient descent using a mini-batch size of 100 frames, and a learning rate of 0.001. The loss function optimized was cross-entropy for binary classification. The network was trained for 2,000 mini-batches, and then stopped. Test set performances on each cross-validation fold were averaged to compute the test set accuracy and recall, which are displayed in Table 5.1. The implementation used the TensorFlow software library, described in [1].

5.3.2 Pre-trained Convolutional Neural Network

The VGG-16 convolutional network architecture was modified for generalization, and to use the hinge loss function, as described in Section 3.4.3. After this modification, all weights in all layers except for the last layer (the output layer) were frozen so that weight updates were not computed for them. The network was then trained via stochastic gradient descent with a mini-batch size equal to the size of the training set. Elastic net weight regularization, described in Section 3.4.5 was used with $\alpha = 0.15$ and a penalty coefficient of 0.0003. The learning rate was initialized and scheduled according to an adaptive scheme, and decreased at every epoch. The network was trained for six epochs. Results are shown in Table

5.1. Implementation was carried out using the TensorFlow [1], Keras [17], and scikit-learn software libraries [52].

Table 5.1: Classification Results

Classifier	Accuracy	Precision	Recall
Best convolutional NN	**94%**	**96%**	**95%**
Best SVM	90%	92%	89%
Best fully connected NN	77%	76%	82%

5.3.3 Discussion

These results show the large improvement in performance statistics gained by using deep feature represenations of an image (e.g. those computed by a ConvNet) as opposed to shallow feature representations (e.g. those computed by HOG or the BoVW process). We believe that with more sophisticated training methods, or without freezing the weights of the adapted VGG-16 network, we may have been able to produce even more accurate predictions.

5.4 Change-point Detection Results

We ran our change-point detection algorithms on sequences of features and scores generated by our classifiers. For videos that contain at least one occurrence of exiting or entering a car, we took two approaches — single change-point detection and multiple change-point detection. We also tested our algorithms on an augmented data set that contains videos without actual change points, and those results are presented in Table 5.5.

For single change-point, we clipped these videos into shorter clips of length 2-5 minutes, each containing at most 1 change-point. We then tested our algorithms on the clips which contained a change-point, predicting a single changepoint for each of the 451 clips. We report accuracy within 2, 5, and 10 second windows for single-change-point tests.

For multiple change-point, we ran our algorithms on full videos, predicting many change-points for each. We report recall and precision for multiple change point test — recall being the percentage of true change-points which we predicted correctly within a 10 second window, and precision being the percentage of predicted change-points which fell within a 10 second window of a true change-point. For our purposes, recall is far more important — we would rather predict several false change points than miss a real one.

The details of all of our change-point detection methods can be found in Chapter 4.

5.4.1 Single Change-point Detection Results on Univariate Data

Our methods were run on series' of SVM output scores. The results are shown in Table 5.2 below, where the column labeled '2s' shows the percentage of the time that we correctly predicted the change-point within a 2 second margin of error on either side. Here we see that MSE, the simplest method, produces the best results. However, many other methods are fairly close in performance.

Table 5.2: Single Change-Point Detection Results - Univariate

Method	Within 2s	Within 5s	Within 10s
MSE	**50%**	**69%**	**78%**
Graph	49%	68%	**78%**
KS Test	49%	66%	74%
Simple CUSUM	41%	61%	72%
Pettitt	39%	59%	71%
CUSUM Density	39%	58%	68%

5.4.2 Single Change-point Detection Results on Multivariate Data

We also ran our change-point detection methods on multivariate series. This data was obtained through a dimensionality reduction on the BoVW histograms mentioned above. We tried many forms of dimensionality reduction [78], into 1, 3, 5, 10, 20, and 50 dimensions. The results below use a diffusion maps reduction to 10 dimensions, which achieved the best results. These methods are more generalizable, since the features were created in an unsupervised manner. However, unsupervised features are also more difficult to predict from.

Table 5.3: Single Change-Point Detection Results - Multivariate

Method	Within 2s	Within 5s	Within 10s
MSE	23%	**47%**	**60%**
Leach	**26%**	45%	57%
Graph	17%	36%	47%

5.4.3 Multiple Change-point Detection Results on Univariate Data

We then moved onto detecting *multiple* change-points in univariate data. We present results here for videos with change-points and then results for the entire dataset of videos we received from the LAPD. The results in Table 5.4 and Table 5.5 come from the optimal combinations of parameters for each individual method on the CNN scores, and details regarding these parameters can be found in Appendix A. The results in Table 5.6 come from the optimal combinations of parameters for each individual method on the BoVW-SVM scores, and details regarding these parameters can be found in Appendix A.

Table 5.4: Results of Univariate Multiple Change-Point Detection on Videos with Exit or Entrance

Method	Recall	Precision
HMM	**93%**	72%
MSE	88%	**75%**
Mean	88%	70%
MLE	88%	67%
AR(1)	85%	70%

Table 5.5: Results of Univariate Multiple Change-Point Detection on all Videos

Method	**Recall**	**Precision**
HMM	**93%**	65%
MSE	88%	**68%**
Mean	88%	61%
MLE	88%	58%
AR(1)	85%	60%

Table 5.6: Univariate Multiple Change-point Detection Results on BoVW-SVM

Method	**Recall (10 s)**	**Precision (10 s)**
MSE	**91%**	**30%**
Mean	96%	18%
HMM	90%	17%
AR(1)	90%	17%
MLE	66%	34%

5.4.4 Multiple Change-point Detection Results on Multivariate Data

Finally, we developed methods to detect multiple change-points in multivariate data. This multivariate data primarily came from the BoVW histograms. The parameter values for these methods can be found in Appendix A.

Table 5.7: Results of Multivariate Multiple Change-Point Detection on Videos with Exit or Entrance

Method	**Recall**	**Precision**
χ^2	**100%**	**20%**
Match	98%	13%
MSE	86%	17%
Centroid	88%	5%

Chapter 6

Conclusions and Future Work

To conclude, we will review the progress we have made on our project objectives, and we will propose directions for future research.

6.1 Progress on Objectives

First, we went through and annotated each video we received from the LAPD with information regarding the presence of an entry or exit from the police car, the time(s) of entry and exit from the police vehicle, the time-of-day of the video, if the officer was even in a car, if the officer was sitting on the driver's side or passenger's side to start in the video, and if the vehicle was moving. We then used this information to conducted exploratory data analysis where-in-which we computed the average length of the videos and counted the number of videos with an entrance or exit, the number where the officer starts on the driver's side, the number taken from a moving vehicle, and the number occurring at night/day. In dealing with this large amount of data, we created representations of the images and, then, built and tuned SVM classifiers to detect in car/out of car. We also used a convolutional neural network to extract fine-tuned convolutional features and to produced univariate data. To create the multivariate data, we used dimensionality reduction techniques and cluster tree to simplify the data – while still capturing more information than a univariate representation would capture. Finally, we developed change-point detection methods for univariate and multivariate data — some of which can detect one change-point per video and others that can detect multiple change-points or the absence of change-points in a video.

6.2 Future Work

If we were to continue this research, we would explore a variety of other elements. In the computer vision thread, we would try to account for the spatiotemporal structure of the data to create image representations that take into consideration the images before a given image. We would investigate key-frame selection methods to enable automatic construction of the training set. We would also move to unsupervised representations of the images, where the images would not be labeled when inputted into the SVM and Neural Net classifiers. This would hopefully make it possible for our process to generalize to other classes of change-points. Furthermore, we would explore labeling schemes to reduce state transition uncertainty; right now, there may be some confusion on the part of our classifiers of when the exit from a car actually occurs because the process of moving from in car to out of car (or vice-versa) takes a few seconds. We would want to notate that transition time.

On the change-point side, we would want to look into change-point detection methods which can detect changes in data as it is received (online data). We would also want to look at additional histogram comparing techniques and additional time series methods. In addition, we would like to explore ways to deal with the videos where-in-which the officers obscure the video. On the representation/classifier side of this project, we would potentially be able to give these images a separate label. On the change-point detection side, we would explore robust smoothing methods to deal with this noise. Finally, we would like to merge the machine learning and change-point aspects of the project via methods that integrate both approaches.

Appendix A

Optimal Parameters

The results for our change-point detection algorithms were a result of tuning parameters of our models. Therefore, for each model and each data-type, we describe briefly the optimal parameters. We give some short definitions before progressing into the tables:

1. Sign-change filter: The sign-change filter takes the average of the scores of the sections established by the change-point sequence and, then, turns these averages into 1s and -1s based on the sign of each average. If there is not a change from -1 to 1 or from 1 to -1 for each detected change-point, we eliminated the change-point from the final output. This filter significantly increased precision.

2. Rounding filter: The rounding filter rounds every input prediction to the nearest 10. We designed this filter because it is unlikely that an exit or entrance happens at least twice in any 10-second window. This filter gives cleaner output and can improve precision. However, based on how we have calculated precision, sometimes we generate better results without it.

3. Savitzky-Golay filter: The Savitzky-Golay filter [61] works by fitting a polynomial to the noisy data and minimizing least-squares error. The filter requires two parameters: polynomial order k and filter size f.

4. Median filter: For each value in the data set, the median filter takes a window centered at the point and finds the median in that window.

Table A.1: Optimal Parameter Values for Change-Point Detection Algorithms Applied to Univariate CNN Scores

Methods	**Parameter Values and Values**
HMM	Savitzky-Golay filter frame size = 15
	Savitzky-Golay filter polynomial order = 1
MSE	Median filter window = 30
	Threshhold t = 1 with Bonferroni correction
	Maximum recursive depth = 3
Mean	Threshold = sample standard deviation of video scores
	Future Window = 5
	Baseline for comparison = first 5 observations
	Integration of new observations = false
	Sign-change filter
MLE	Max number of changepoints = 20
	Classifier accuracy p = 0.9
AR(1)	Threshold = sample standard deviation of video scores
	Future Window = 5
	Baseline for comparison = first 5 observations
	Integration of new observations = false
	Sign-change filter

Table A.2: Optimal Parameter Values for Change-Point Detection Algorithms Applied to Univariate BoVW-SVM Scores

Methods	**Parameter Values and Values**
HMM	Savitzky-Golay filter frame size = 15
	Savitzky-Golay filter polynomial order = 1
MSE	Median filter window = 30
	Threshhold t = 1 with Bonferroni correction
	Maximum recursive depth = 3
	Max/min filter window K = 30
	Max/min filter threshhold M = 0.7
Mean	Threshold = sample standard deviation of video scores
	Future Window = 7
	Baseline for comparison = first 10 observations
	Integration of new observations = false
	Simple Rounding Filter
MLE	Max number of changepoints = 20
	Classifier accuracy p = 0.9
AR(1)	Threshold = s of raw data
	Future window = 5
	First baseline on 5 observations
	Existing Model does not integrate new observations

Table A.3: Optimal Parameter Values for Change-Point Detection Algorithms Applied to Multivariate BoVW Histograms or CNN Output

Methods	**Parameter Values and Values**
MSE	Median filter window = 30
	threshhold t = 0
	Maximum recursive depth = 3
Match	Threshold = 20 times the sum of the mean difference between successive observations for each feature
	Future Window = 10
	First histogram as baseline
	Simple rounding filter
χ^2	Alpha = 0.001
	Future Window = 7
	Baseline for comparison = first histogram

Appendix B

VGG-16 Network Details

This appendix outlines the VGG-16 architecture described in Section 3.4.4. The VGG-16 architecture consists of five sets of convolutional layers separated by max pooling layers. Each convolutional layer is followed by a ReLU nonlinearity. The first set contains two convolutional layers of 64 3×3 feature maps. The second set contains two convolutional layers of 128 3×3 feature maps. The third set contains three convolutional layers of 256 3×3 feature maps. The fourth and fifth set contain three convolutional layers of 512 3×3 feature maps. This is followed by two 4,096-dimensional fully connected layers, and a 1,000-dimensional output layer. Although each feature map is only of size 3×3, the stacked convolutional layers and great depth of this network mean that the filters at the end of the network can receive input processed by multiple upstream feature maps at multiple image points.

In the diagram in Figure B.1, the first set of convolutional layers is displayed under the $224 \times 224 \times 64$ callout text. It contains 64 3×3 feature maps. As noted in the above paragraph, all feature maps in the network are of size 3×3, and transformed by a ReLU nonlinearity. After this set, the first max pooling layer is applied to reduce the height and width dimensionalities of the output tensor created by the prior convolutional layer to $112 \times 112 \times 64$. Each max pooling layer only pools along height and width—not depth—in order to maintain the information created for the feature maps. After this, the second set of two convolutional layers is applied, each of which contains 128 feature maps. Another max pooling layer reduces the dimensionality to $56 \times 56 \times 128$. Then, the third set three of convolutional layers is applied, each of which contains 256 feature maps. The third max pooling layer reduces the dimensionality to $28 \times 28 \times 256$, and is followed by three convolutional layers each containing 512 feature maps. The second to last max pooling layer then reduces the dimensionality to $14 \times 14 \times 512$, and another three convolutional layers containing 512 feature maps each is applied. The output is reduced by a final max pooling layer to a $7 \times 7 \times 512$ cube of "bottleneck features". This cube is flattened into a vector, and connected to a fully connected network with two 4,096-dimensional hidden layers. The fully connected network ends at a 1,000-dimensional output layer, which performs softmax to create a probability distribution.

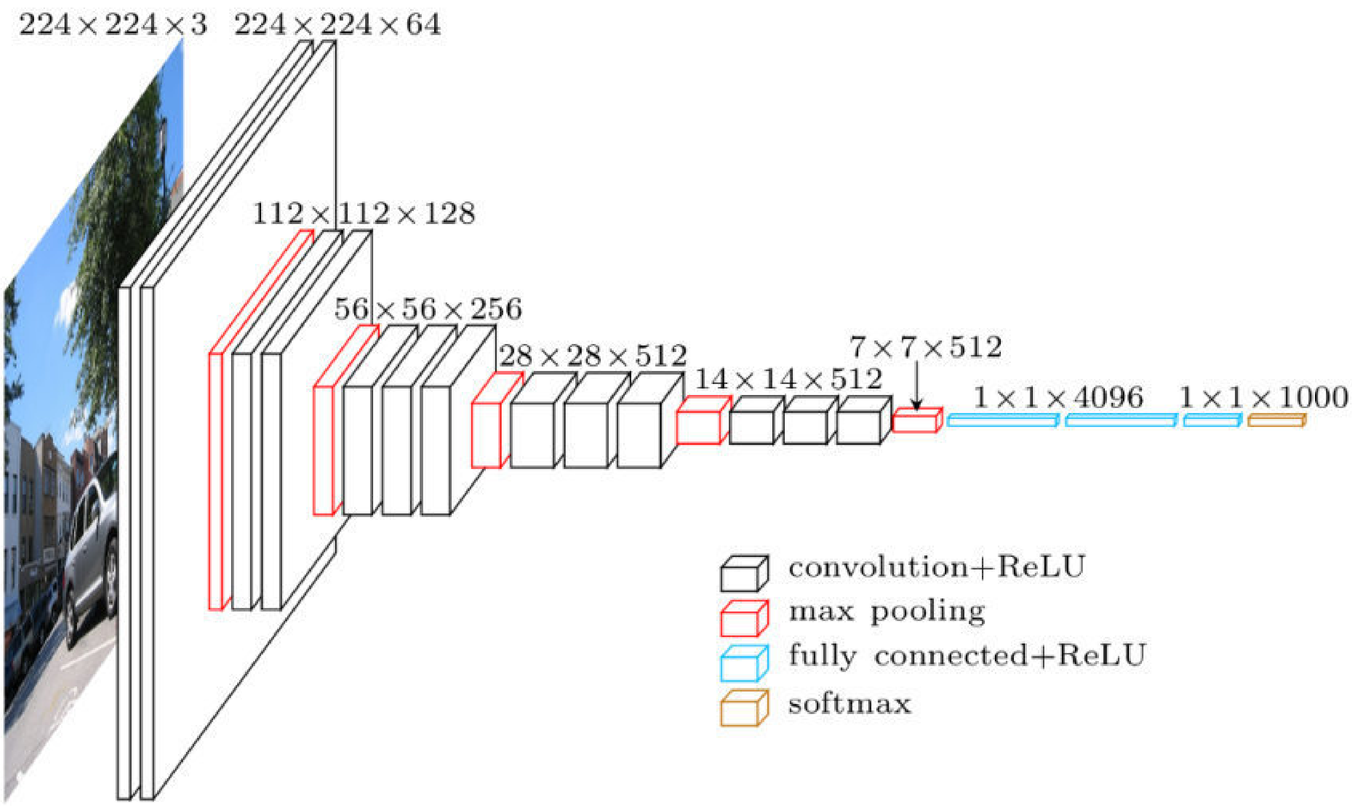

Figure B.1: This figure shows the dimensionality of the *outputs* (not the feature maps) of each layer of the VGG-16 network. The network reduces an input image with three color channels to a $7 \times 7 \times 512$ cube of richly informative features, before passing these features to a fully connected network for classification.

Appendix C

Proofs

This appendix includes proofs generated during the course of this project which were not used in our code.

C.1 CUSUM Statistic Proof

Based on the proof used by [66] to demonstrate that their statistic follows a normal distribution, this proof demonstrates that, given some assumptions, we can show the CUSUM statistic follows a normal distribution.

Proof: Assume that we have a series of independent, identically distributed (iid) random variables X_i. We know that, if we input iid random variables into a "measurable function," we will still have a series of iid random variables. We also know that the sum of iid random variables, given a sufficient number of variables, will eventually approximate a normal distribution. Therefore, if we have the CUSUM statistic:

$$\begin{aligned}
\text{CUSUM} &= \sum_{i=m}^{n} \ln \frac{f_1(x_i)}{f_0(x_i)} \\
&= \sum_{i=m}^{n} \ln f_1(x_i) - \ln f_0(x_i) \\
&= \sum_{i=m}^{n} \ln f_1(x_i) - \sum_{i=m}^{n} \ln f_0(x_i) \\
&= \sum_{i=m}^{n} g(x_i) - \sum_{i=m}^{n} h(x_i) \\
&= N_1 - N_2
\end{aligned}$$

Finally, since we know the sum of two independent normal random variables is normal random variable [82], $N_1 - N_2$ is a normal random variable. Therefore, we have shown that the CUSUM test statistic follows a normal distribution. QED

Since we do not know the equations for $f_1(x)$ and $f_0(x)$, we have used KDE to find approximations for them. If one replaces $f_1(x)$ and $f_0(x)$ with $KDE_1(X)$ and $KDE_0(x)$, the proof follows very similarity as the proof above and yields the same result. However, the problem becomes that, since we re-estimate these KDE functions each time, the CUSUM statistic at each potential change-point would follow a different normal distribution. Furthermore, the non-parametric nature means that the KDEs are all different from each other and do not have a consistent form. Consequently, any attempt to utilize the normality property would become very unwieldy — hence our decision not to pursue the use of this property.

In theory, if we knew $f_1(x)$ and $f_0(x)$, we might have been able to use the normality property to our advantage.

Appendix D

Abbreviations

AR(1). Autoregressive with One Lag

BoVW. Bag of Visual Words.

BRIEF. Binary Robust Independent Elementary Features.

BWV. Body-Worn Video.

CDF. Cumulative Distribution Function.

CNN. Convolutional Neural Network.

HMM. Hidden Markov Model.

HOG. Histogram of Oriented Gradients.

ILSVRC. ImageNet Large Scale Visual Recognition Competition.

KLIEP. Kullback-Leibler Importance Estimation Procedure.

K-S Test. Kolmogorov-Smirnov Test.

MLE. Maximum Likelihood Estimation.

MSE. Mean-Squared Error.

ReLU. Rectified Linear Unit.

SIFT. Scale-Invariant Feature Transform.

SURF. Speeded Up Robust Features.

SVM. Support Vector Machine.

VGG-16. Visual Geometry Group 16.

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Change-point Detection Methods for Body-Worn Video

Stephanie Allen, *SUNY Geneseo*
David Madras, *University of Toronto*
Ye Ye, *UCLA*
Greg Zanotti, *DePaul University*

Academic Mentor: Dr. Giang Tran
Consultant: Dr. Jeff Brantingham, *UCLA*
Industry Mentor: Sgt. Javier Macias, *LAPD*

August 18, 2016

LAPD & Body-Worn Video

- Third largest USA municipal police department, with 9,843 officers
- A leader in the effort to equip police officers with body-worn cameras

Body-worn Video (BWV)

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- Cameras worn on officers' chests used to record police-public interactions
  - Currently deployed to 1,200 officers; will be scaled up to 7,000
- **Benefits**:
  - Provide video record in the case of public disagreements
  - Shown to increase police professionalism
- **Challenge**:
  - Create large volumes of data, necessitating automatic data analysis

Problem Statement

- **Goal:** Create algorithms to detect change-points in body-worn video
  - This will greatly streamline the video review process

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  - **The moment at which an officer exits or enters their car**

Images from www.youtube.com

Data Analysis - In Car Examples

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Data Analysis - Out of Car Examples

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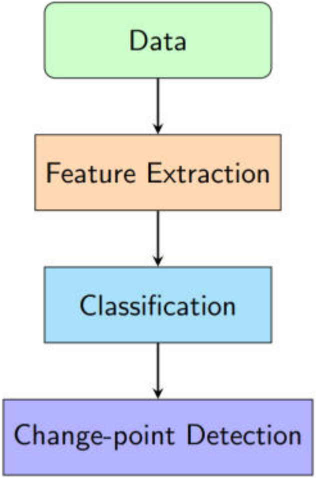
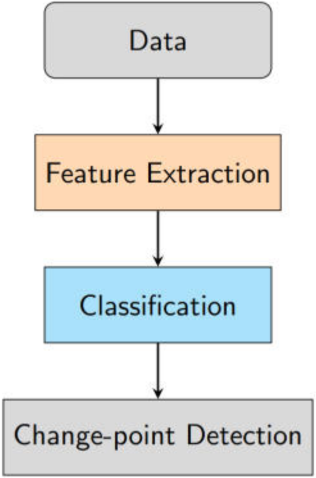
Data Analysis

- Sample of data taken from BWV pilot program (Dec '14-May '15)
- 691 videos, average length 9 minutes
- 420 contain either an entrance or exit from vehicle
- Of these:
  - 270 are taken from driver side
  - 274 are taken from a moving vehicle
  - 176 occur during nighttime

Overview of Methods



Overview of Methods - Feature Extraction & Classification



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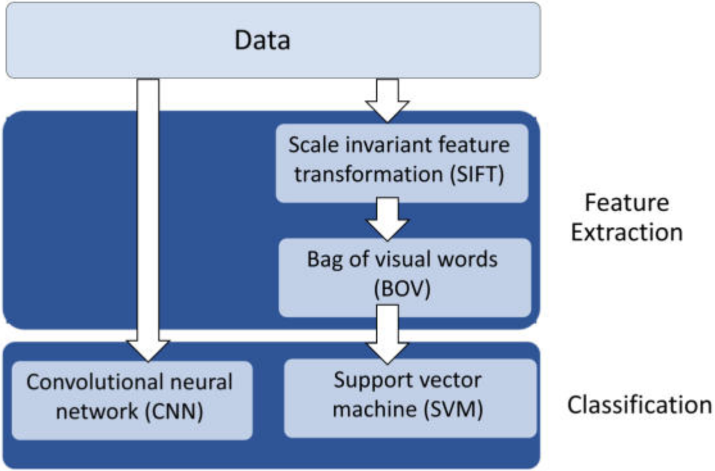
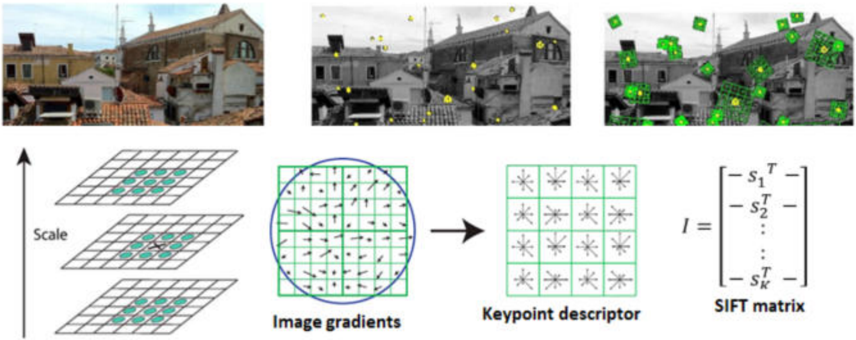


Keypoint Detection and Description – Scale-Invariant Feature Transformation (SIFT)



Images from Lowe, "Distinctive Image Features from Scale-Invariant Keypoints", and VLFeat.org

Image Representation - Bag of Visual Words

- Sample 20% of images in the training set, extract SIFT descriptors
- Apply *k*-means clustering, where the centroid of each cluster is a 'visual word'

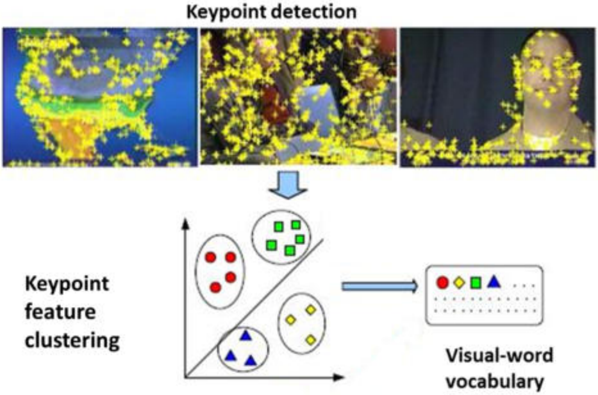
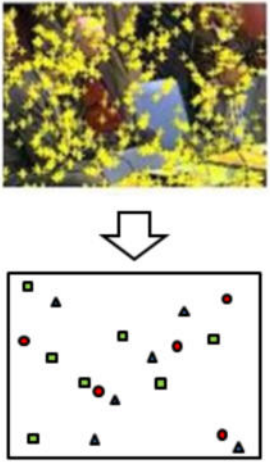


Image from Zhang et al., "Evaluating Bag-of-Visual-Words Representations in Scene Classification"

Bag of Visual Words and Spatial Pyramid

For each new input image

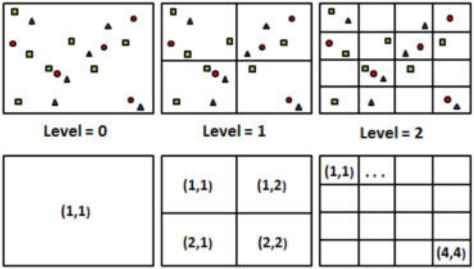
- Assign keypoint descriptors to nearest centroids



Bag of Visual Words and Spatial Pyramid

For each new input image

- Assign keypoint descriptors to nearest centroids
- Subdivide image into three levels of spatial resolution



Bag of Visual Words and Spatial Pyramid

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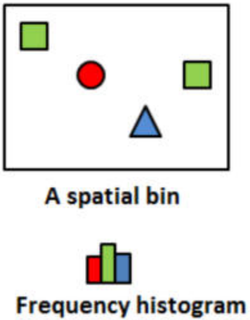
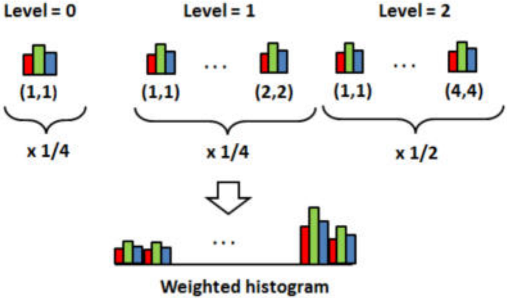
- Count # of descriptors for each spatial bin



Bag of Visual Words and Spatial Pyramid

For each new input image

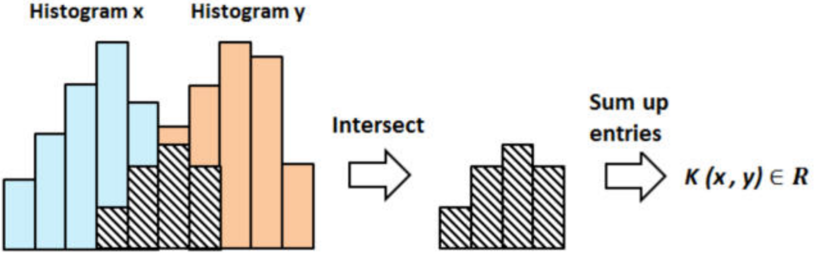
- Assign keypoint descriptors to nearest centroids
- Subdivide image into three levels of spatial resolution
- Count # of descriptors for each spatial bin
- Weight and concatenate spatial histograms



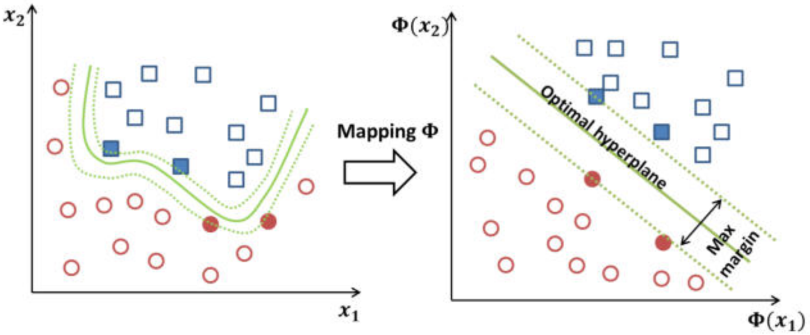
Histogram Intersection Kernel

- Goal: quantify similarity between two weighted histograms
- For two histograms $x, y \in \mathbb{R}^D$, kernel is defined as

$$K(x, y) = \sum_{i=1}^{D} \min(x_i, y_i).$$



Classifier - Support Vector Machine (SVM)



- Kernel function $K(x, y) = \Phi(x)^T \Phi(y) = \sum_{i=1}^{D} \min(x_i, y_i)$.
- Maximize margin and obtain weight coefficients
- For a new image histogram x, $Score(x) = \sum_{n=1}^{N} a_n t_n K(x, x_n) + b$

Classifier - Neural Network

- An artificial neural network jointly learns a **feature representation** and **discriminative classifier** over data
- Neurons are stacked on top of one another in **layers** to form complex, highly informative features
- At the last layer, outputs are normalized to form **class predictions**

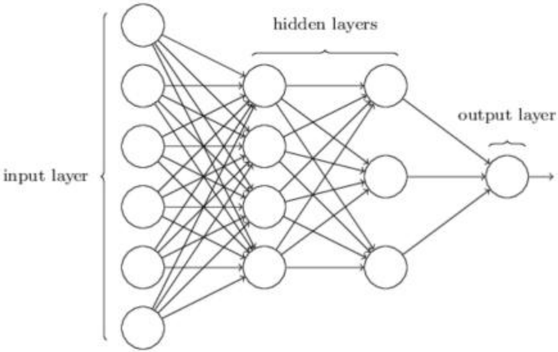
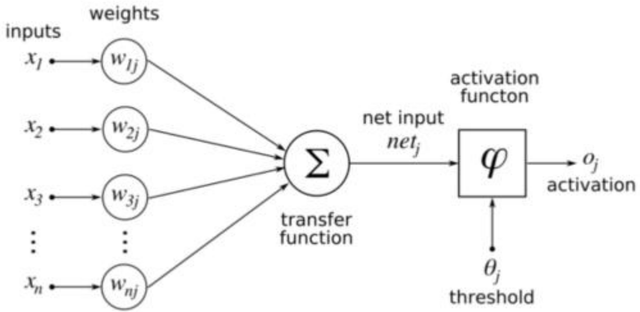


Image from Nielsen, *Neural Networks and Deep Learning*

Neural Network Detail

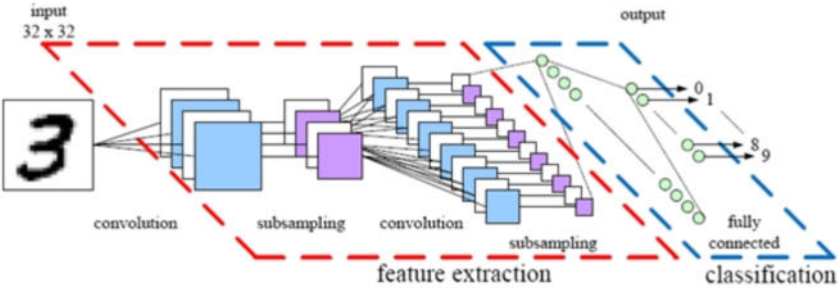
- Generally, operations within a neuron consist of **multiplying inputs by weights**, passing them to a **transfer function**, and passing the result through a **nonlinear, thresholded "activation" function**



- Neural networks are trained by changing the weights according to an iterative optimization algorithm like gradient descent

Image from https://en.wikibooks.org/wiki/File:ArtificialNeuronModel_english.png

Convolutional Neural Networks

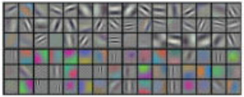


- Convolutional neural networks, or ConvNets, learn hierarchical filter banks for images. Architectures consist of alternating convolutional and pooling layers—some with nonlinearities.
- Convolutional layers slide a filter over an input to detect a certain pattern. Pooling layers subsample upstream outputs.

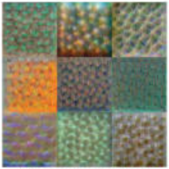
Image from Parallel Architecture Research Eindhoven

ConvNet Features

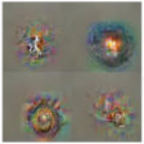
- As ConvNets are trained, the filters change what they detect and "learn" important features.
- Filters at early layers detect edges and blobs. Filters in later layers combine output of lower level filters to detect more complex patterns.



Conv 1: Edge+Blob



Conv 3: Texture



Conv 5: Object Parts

Fc8: Object Classes

Image from `http://www.cc.gatech.edu/~hays/compvision/proj6/`

Using and Finetuning ConvNets

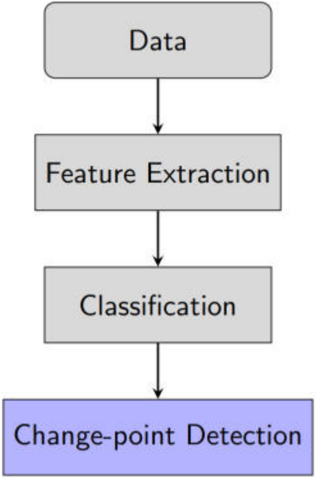
- Although ConvNets are extremely powerful, training them can be incredibly computationally intensive
- General convolutional networks for image recognition are created and released by researchers, and can be "finetuned" to specific problems
- We modify the popular VGG-16 architecture, and change only the top two layers to classify scenes as in/out of car

Classification Results

- Change-point detection depends on strong classification results
- Our predictions were made using 10-fold cross-validation on a large sample of or all of the videos
- Precision: How many of our out of car **predictions** were truly out of car?
- Recall: How many of our out of car **frames** did we correctly identify?

Classifier	Accuracy	Precision	Recall
SIFT-BOV-SVM	90%	92%	89%
ConvNet	**94%**	**96%**	**95%**

Overview of Methods - Change-point Detection



Change-point Methods Overview

- Given a time series $X_i, i = 1...n$, there may be one or more **change-points** c where the underlying distribution of the X_i changes.

- In the case of one change-point:

  $$X_i \sim F_1 \ \forall\ i \leq c,\ X_i \sim F_2 \ \forall\ i\ > c$$

  for some distributions $F_1 \neq F_2, c \in \{1...n\}$

- **Goal**: To find c
  - Evaluate an objective function or test statistic for each X_i for $i \in \{1...n\}$
  - Find i to optimize the objective function or all i which produce a test statistic value greater than a threshold

Five Change-point Methods

1. Forecasting/Time Series Analysis
2. BoVW Histogram Comparison
3. Hidden Markov Model
4. Mean-Squared Error
5. Maximum Likelihood

Method 1: Forecasting/Time Series Analysis

- Elements in a time series often are correlated with each other.

$$\text{Autoregressive One Lag (AR(1))} : X_t = B_0 + B_1 X_{t-1}$$

- Assume the sequence of scores is stationary between change-points — meaning the mean is constant during those intervals

- We can forecast the next observation in a given interval based on a mean of the previous observations.

$$\text{Mean Model} : X_t = \bar{X}$$

Method 1: Forecasting/Time Series

- "Future window" technique: Enables the application of forecasting methods to change-point detection
  - Estimate a model based on data-points from the beginning of the series
  - Forecast a set number of future values using the established model
  - If the forecasting error for **all of these observations** is larger than a set threshold, declare a change-point.
  - Re-estimate the model based on the observations in this window

Method 2: BoVW Histogram Comparison

- Establish a baseline histogram and compare successive histograms in the series to this baseline via the future window technique:
  - χ^2 Method: $\chi^2 = \sum_{i=1}^{m} \frac{(o_i - e_i)^2}{e_i}$,
    where e is the baseline histogram and o is a histogram in the future window
  - Match Distance: $d_M(H, K) = \sum_{i=1}^{m} |h_i - k_i|$,
    where h_i is the cumulative histogram of the elements of h up to bin i, h is the baseline histogram, and k is a histogram in the future window

Method 3: Hidden Markov Model

- **Goal:** given a sequence of observations, infer the most probable sequence of hidden variables.
- **Change-point** = transitions in the inferred states of hidden variables

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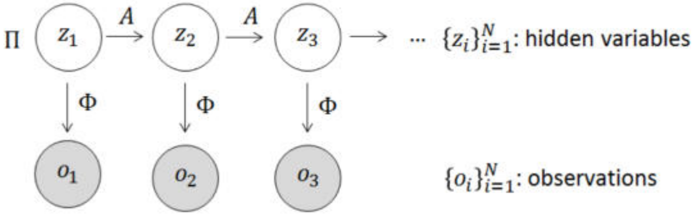
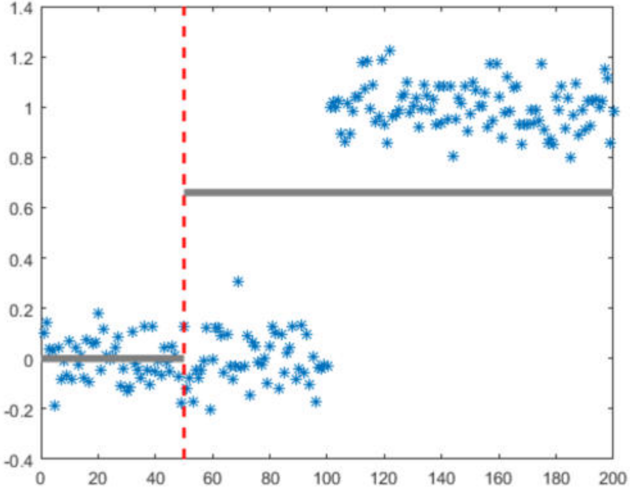


Π: initial distribution
A: transition matrix
Φ: emission parameters of observations' distributions

Method 4: Mean-Squared Error



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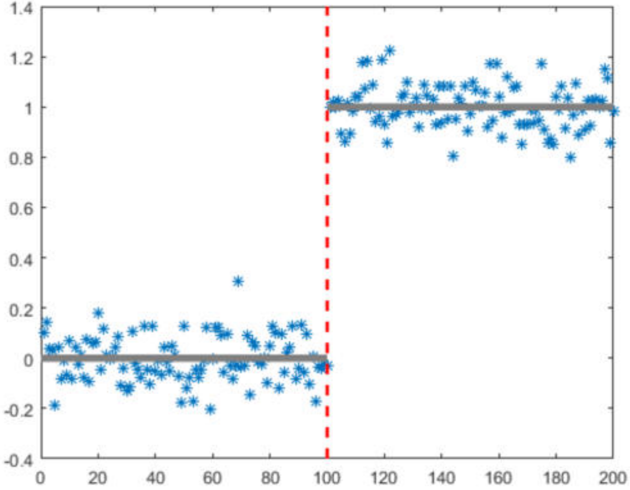


Method 4: Mean-Squared Error

- For large enough sample size, the sample mean $\bar{x}_i$ will be a **normal random variable** by the Central Limit Theorem
- Therefore, $\bar{x}_i^2$ will be a **gamma random variable** and:

$$MSE(c) - \sum_{i=1}^{n} x_i^2 = c\bar{x}_1^2 + (n-c)\bar{x}_2^2 \sim \boldsymbol{\Gamma(1, 2\sigma_x^2)}$$

- We can then derive a p-value for a measurement of mean-squared error

$$p = \frac{MSE(c) - \sum_{i=1}^{n} x_i^2}{2\sigma_x^2}$$

- Where p-value is low, we are near a change-point

Method 4: Mean-Squared Error

- We can now recursively extend mean-squared error to sequences with multiple change points
  1. Given sequence x_i, find x_j with smallest MSE.
  2. Calculate p-value for $MSE(j)$, then if $p \geq \alpha$ threshhold, stop.
  3. Run MSE again on sequences $x_1 ... x_{j-1}$ and $x_{j+1} ... x_n$.
  4. Return x_j, and the outputs of $MSE(x_1 ... x_{j-1})$ and $MSE(x_{j+1} ... x_n)$ as change-points.

Method 5: Maximum Likelihood Estimation

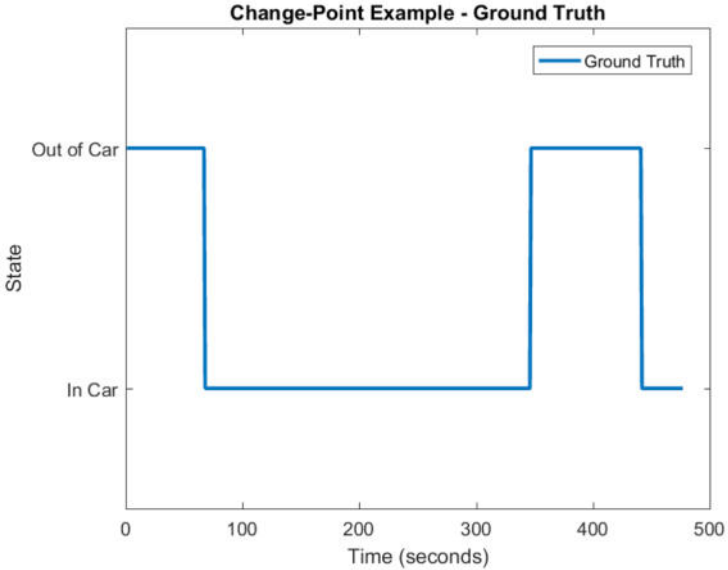
- We find the log-likelihood of the true labels given the data

$$\log \mathcal{L}(L, X) \sim \log \prod_{i=1}^{n} P(X_i | L_i)$$
$$= \log(p) \sum_{i=1}^{n} I[x_i = L_i] + \log(1-p) \sum_{i=1}^{n} I[x_i \neq L_i]$$

where $x_i \in \{0, 1\}$ is classifier output, $p \in [0, 1]$ is classifier accuracy

- We maximize this likelihood by formulating it as a linear program, and constraining the number of possible change-points

Change-point Detection Results



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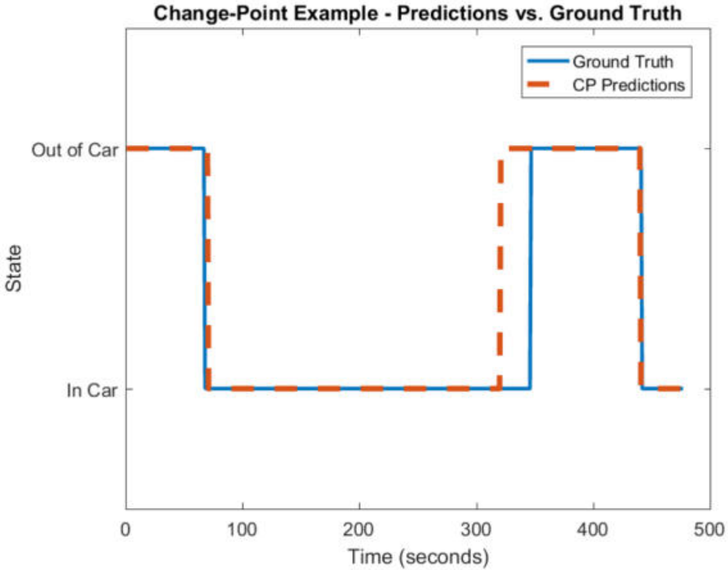

Change-point Detection Results

- Using 691 LAPD videos (420 contain at least one change-point)
- Our methods ran on scores from the convolutional neural network

Table: Univariate Multiple Change-point Detection Results (All Videos)

Method	Recall (10 s)	Precision (10 s)
Autoregressive: One Lag	85%	60%
Maximum Likelihood	88%	61%
Mean Model	88%	61%
Mean-Squared Error	88%	**68%**
Hidden Markov Model	**93%**	65%

Change-point Detection Result - Multivariate Data

- Tested methods on BoVW histogram representations and CNN representations
- Representations were made in an **unsupervised** way—didn't need to train a classifier with labeled data (i.e. frames labeled in/out of car)
- **Benefits:** these methods are much more generalized
- **Challenges:** high-dimensional space is extremely complex, unsupervised methods are difficult to assess

Table: Multiple Change-point Detection Results for Multivariate Data

Method	**Recall**	**Precision**
Mean-Squared Error	86%	17%
Match Distance	98%	13%
χ^2 Test	**100%**	**20%**

Summary

- Annotated data, conducted data analysis
- Built and tuned classifiers to detect in car/out of car images with 90%+ accuracy, 95%+ precision and recall
- Developed a variety of change point detection methods for univariate and multivariate data
- Achieved 90% recall and nearly 70% precision on change-points in univariate data
- Methods work well on a variety of videos
  - With or without change-points
  - Driver or passenger side
  - Indoor or outdoor driving
  - Daytime or nighttime driving

Questions?

Future Work

- Improve unsupervised methods for multivariate time series
- Exploit the spatiotemporal structure of the data
- Explore applicability of change-point detection to other domains

Difference of Gaussians

- Subtract one blurred image from another less blurred image
- Increase visibility of edges

Original image

Image after difference of Gaussian filtering in black and white

Image from https://en.wikipedia.org/wiki/Difference_of_Gaussians

Histogram Intersection Kernel Proof

- Let $x, y \in \mathbb{R}^D$ be two histogram representations, and let M be the number of pixels in each image. Then, M is also an upper bound for the maximum number of keypoints in any image.
- Claim: A mapping function Φ can be found such that

$$\Phi(x)^T \Phi(y) = \sum_{i=1}^{D} \min(x_i, y_i).$$

- Proof by construction:

$$\Phi(x) := (\overbrace{1, 1, ..., 1,}^{x_1} \underbrace{0, 0, ..., 0,}_{M-x_1} \overbrace{1, 1, ..., 1,}^{x_2} \underbrace{0, 0, ..., 0,}_{M-x_2}$$

$$... \overbrace{1, 1, ..., 1,}^{x_D} \underbrace{0, 0, ..., 0}_{M-x_D})$$

VGG-16 Architecture

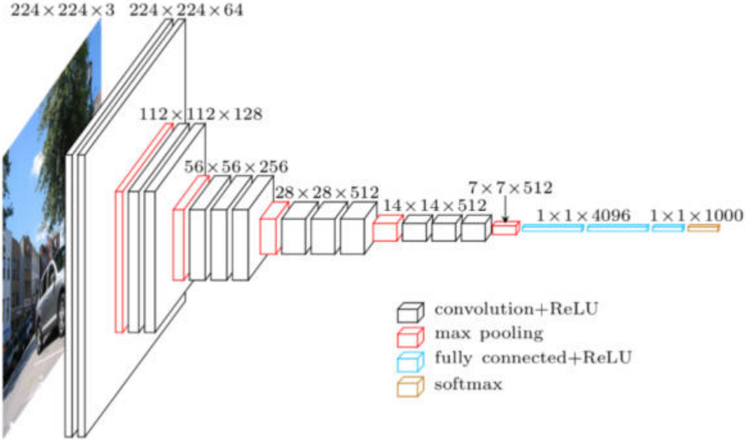

Image from
https://blog.heuritech.com/2016/02/29/a-brief-report-of-the-heuritech-deep-learning-meetup-5/

Hidden Markov Model

- Hidden variables $\{z_n\}_{n=1}^{N}$

$$z_n = \begin{cases} (1 \quad 0)^T & \text{if "in-car"} \\ (0 \quad 1)^T & \text{otherwise} \end{cases}$$

- Initial distribution $\pi = (\pi_1 \quad \pi_2)$
- Transition probability $A_{ij} = p(z_{n,j} = 1 | z_{n-1,i} = 1)$, where $i, j \in \{1, 2\}$
- Conditional distributions of observed variables:

$$p(x_n | z_n, \Phi) = \left(\frac{1}{\sqrt{2\pi\sigma_1}} \exp(\frac{(x_n - \mu_1)^2}{\sigma_1}) \right)^{z_{n,1}} \cdot \left(\frac{1}{\sqrt{2\pi\sigma_2}} \exp(\frac{(x_n - \mu_2)^2}{\sigma_2}) \right)^{z_{n,2}},$$

where $\Phi = \{\sigma_1, \sigma_2, \mu_1, \mu_2\}$ is the set of emission parameters.

Hidden Markov Model Coefficient Estimates

- Initial distribution: $\hat{\pi} = [0.667 \quad 0.333]$
- Transition matrix: $\hat{A} = \begin{bmatrix} 0.9883 & 0.0117 \\ 0.0044 & 0.9956 \end{bmatrix}$
- Emission parameters:
  - Gaussian distribution governs the prediction of observed scores, based on the current state
  - In-car: $\hat{\mu_1} = -1.85$, $\hat{\sigma_1} = 1.33$
  - Out-of-car: $\hat{\mu_2} = 1.96$, $\hat{\sigma_2} = 1.06$

SIFT-BoVW-SVM Results

- The SVM scores were outputted for videos with change-points.

Table: Univariate Multiple Change-point Detection Results

Method	**Recall (10 s)**	**Precision (10 s)**
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Autoregressive (1)	90%	17%
Hidden Markov Model	90%	17%
Mean Model	96%	18%
Mean-Squared Error	**91%**	30%

Change Point Detection Methods Applied to Body-Worn Video

Stephanie Allen, *SUNY Geneseo*
David Madras, *University of Toronto*
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August 18, 2016

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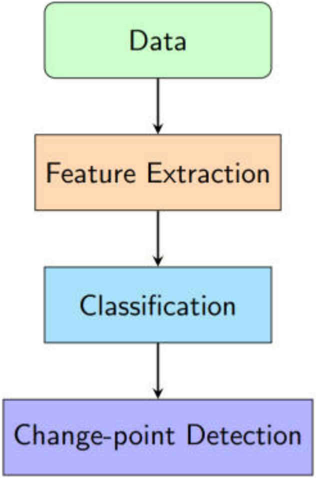
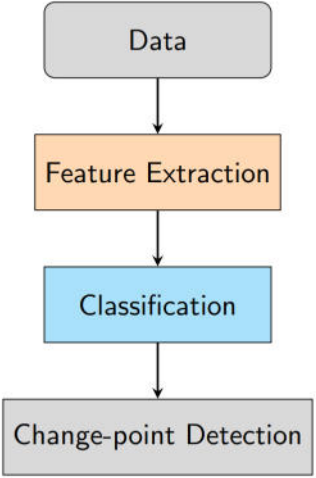


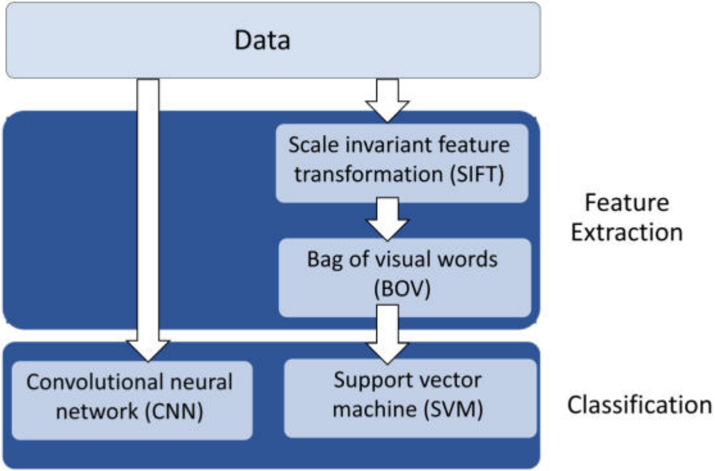
Overview of Methods

- **Feature extraction** methods take the sequence of images and reduce the images to compact representations that are then passed into **classifiers**.
- Other **classifiers** take raw images.
- **Change-point detection** methods have the ability to:
  - Take univariate or multivariate data
  - Detect any number of change-points per video

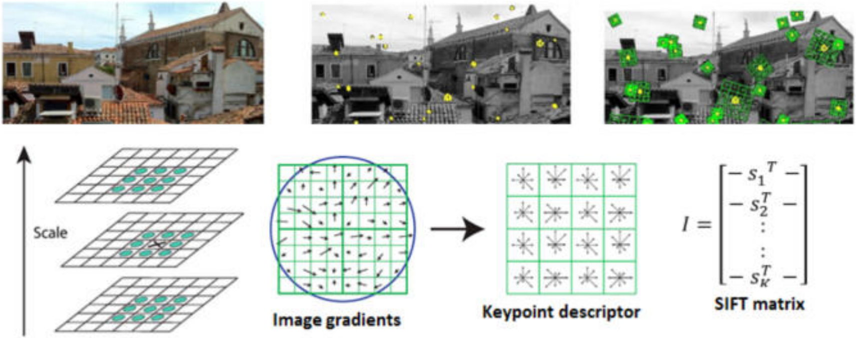
Overview of Methods - Feature Extraction & Classification



Overview of Methods - Feature Extraction & Classification



Keypoint Detection and Description – Scale-Invariant Feature Transformation (SIFT)



Images from Lowe, "Distinctive Image Features from Scale-Invariant Keypoints", and VLFeat.org

Image Representation - Bag of Visual Words

- Sample 20% of images in the training set, extract SIFT descriptors
- Apply k-means clustering, where the centroid of each cluster is a 'visual word'

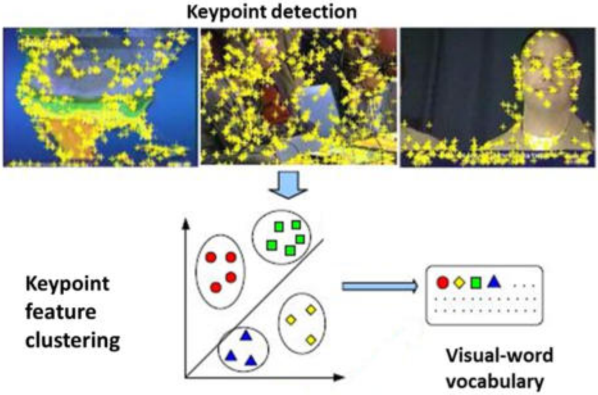
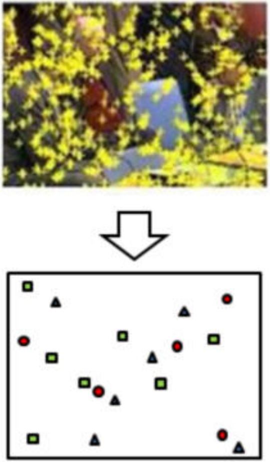


Image from Zhang et al., "Evaluating Bag-of-Visual-Words Representations in Scene Classification"

Bag of Visual Words and Spatial Pyramid

For each new input image

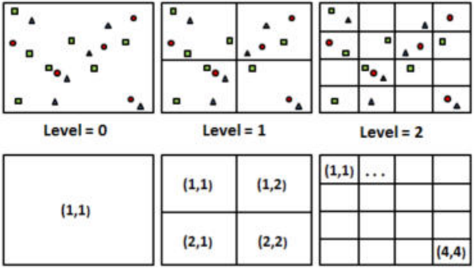
- Assign keypoint descriptors to nearest centroids



Bag of Visual Words and Spatial Pyramid

For each new input image

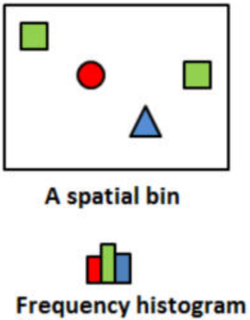
- Assign keypoint descriptors to nearest centroids
- Subdivide image into three levels of spatial resolution



Bag of Visual Words and Spatial Pyramid

For each new input image

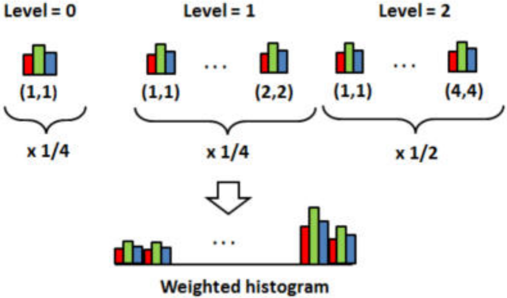
- Assign keypoint descriptors to nearest centroids
- Subdivide image into three levels of spatial resolution
- Count # of descriptors for each spatial bin



Bag of Visual Words and Spatial Pyramid

For each new input image

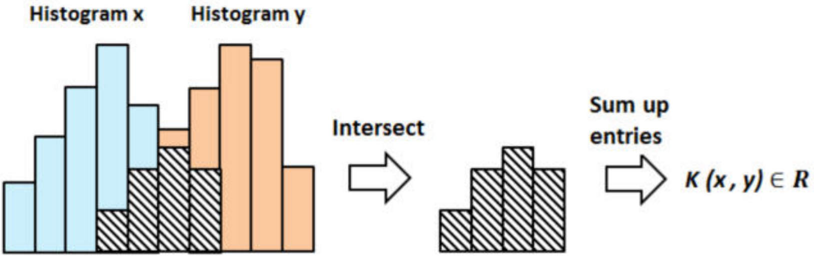
- Assign keypoint descriptors to nearest centroids
- Subdivide image into three levels of spatial resolution
- Count # of descriptors for each spatial bin
- Weight and concatenate spatial histograms

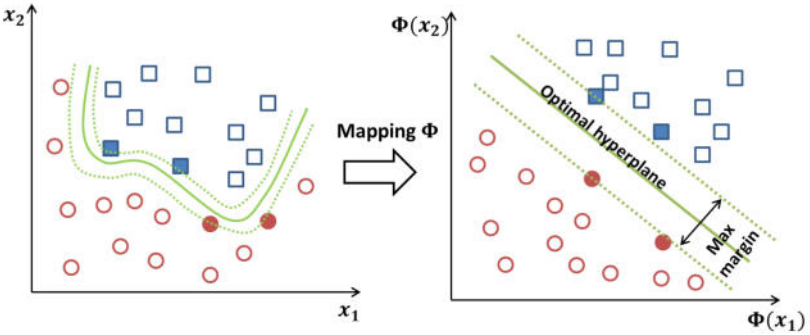


Histogram Intersection Kernel

- Goal: quantify similarity between two weighted histograms
- For two histograms $x, y \in \mathbb{R}^D$, kernel is defined as

$$K(x, y) = \sum_{i=1}^{D} \min(x_i, y_i).$$





- Kernel function $K(x, y) = \Phi(x)^T \Phi(y) = \sum_{i=1}^{D} \min(x_i, y_i)$.
- Maximize margin and obtain weight coefficients
- For a new image histogram x, $Score(x) = \sum_{n=1}^{N} a_n t_n K(x, x_n) + b$

Classifier - Neural Network

- An artificial neural network jointly learns a **feature representation** and **discriminative classifier** over data
- Neurons are stacked on top of one another in **layers** to form complex, highly informative features
- At the last layer, outputs are normalized to form **class predictions**

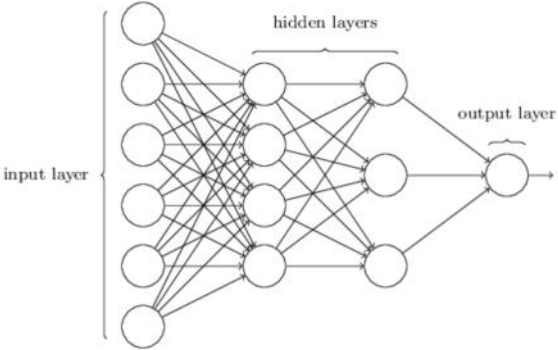
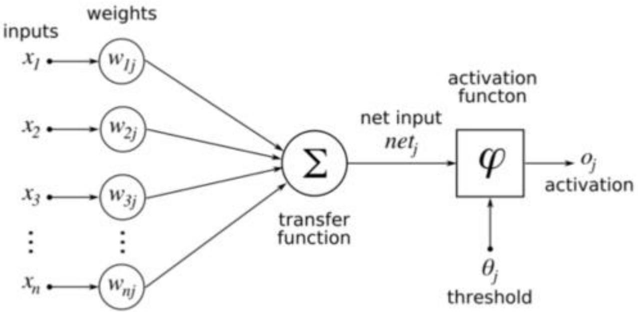


Image from Nielsen, *Neural Networks and Deep Learning*

Neural Network Detail

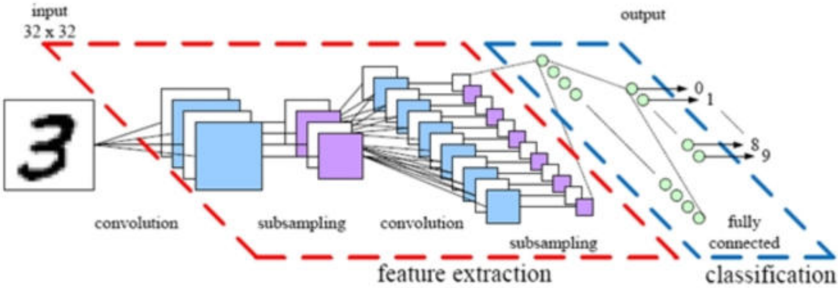
- Generally, operations within a neuron consist of **multiplying inputs by weights**, passing them to a **transfer function**, and passing the result through a **nonlinear, thresholded "activation" function**



- Neural networks are trained by changing the weights according to an iterative optimization algorithm like gradient descent

Image from `https://en.wikibooks.org/wiki/File:ArtificialNeuronModel_english.png`

Convolutional Neural Networks

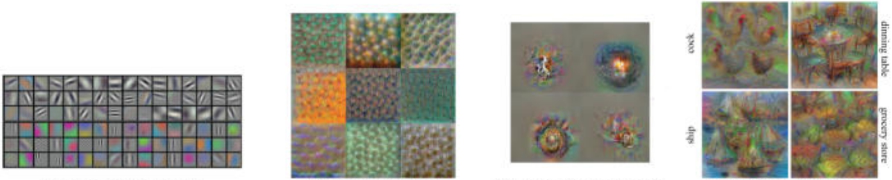


- Convolutional neural networks, or ConvNets, learn hierarchical filter banks for images. Architectures consist of alternating convolutional and pooling layers—some with nonlinearities.
- Convolutional layers slide a filter over an input to detect a certain pattern. Pooling layers subsample upstream outputs.

Image from Parallel Architecture Research Eindhoven

ConvNet Features

- As ConvNets are trained, the filters change what they detect and "learn" important features.
- Filters at early layers detect edges and blobs. Filters in later layers combine output of lower level filters to detect more complex patterns.



Conv 1: Edge+Blob **Conv 3: Texture** **Conv 5: Object Parts** **Fc8: Object Classes**

Image from `http://www.cc.gatech.edu/~hays/compvision/proj6/`

Using and Finetuning ConvNets

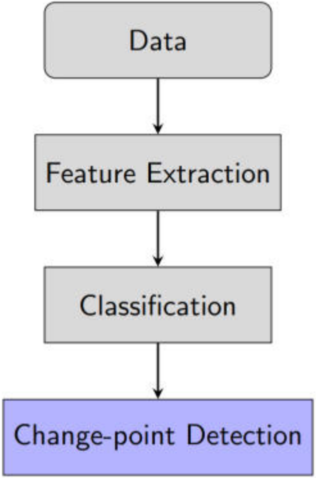
- Although ConvNets are extremely powerful, training them can be incredibly computationally intensive
- General convolutional networks for image recognition are created and released by researchers, and can be "finetuned" to specific problems
- We modify the popular VGG-16 architecture, and change only the top two layers to classify scenes as in/out of car

Classification Results

- Change-point detection depends on strong classification results
- Our predictions were made using 10-fold cross-validation on a large sample of or all of the videos
- Precision: How many of our out of car **predictions** were truly out of car? (complement of false pos. rate)
- Recall: How many of our out of car **frames** did we correctly identify?

Classifier	**Accuracy**	**Precision**	**Recall**
SIFT-BOV-SVM	90%	92%	89%
ConvNet	**94%**	**96%**	**95%**

Overview of Methods - Change-point Detection



Change-point Methods Overview

- Given a time series $X_i, i = 1...n$, there may be one or more **change-points** c where the underlying distribution of the X_i changes.
- In the case of one change-point:

$$X_i \sim F_1 \; \forall \; i \leq c, \; X_i \sim F_2 \; \forall \; i \; > c$$

  for some distributions $F_1 \neq F_2, c \in \{1...n\}$

- **Goal**: To find c
  - Evaluate an objective function or test statistic for each X_i for $i \in \{1...n\}$
  - Find i to optimize the objective function or all i which produce a test statistic value greater than a threshold

Five Change-point Methods

1. Forecasting/Time Series
2. BoVW Histogram Comparison
3. Hidden Markov Model
4. Mean-Squared Error
5. Maximum Likelihood

Method 1: Forecasting/Time Series

- Elements in a time series often are correlated with each other.

$$\text{Autoregressive One Lag (AR(1))} : X_t = B_0 + B_1 X_{t-1}$$

- If there are no change-points in a sequence of scores, we can assume the sequence is stationary and thus has a constant mean.

- We can forecast the next observation based on a mean of the previous observations.

$$\text{Mean Model} : X_t = \bar{X}$$

Method 1: Forecasting/Time Series

- "Future window" technique: Enables the application of forecasting methods to change-point detection
  - Estimate a model based on data-points from the beginning of the series
  - Forecast a set number of future values using the established model
  - If the forecasting error for **all of these observations** is larger than a set threshold, declare a change-point.
  - Re-estimate the model based on the observations in this window

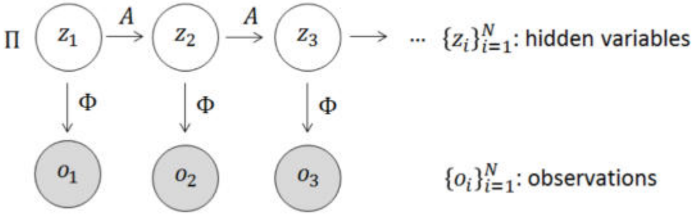
Method 2: BoVW Histogram Comparison

- Establish a baseline histogram and compare successive histograms in the series to this baseline via the future window technique:
  - χ^2 Method: $\chi^2 = \sum_{i=1}^{k} \frac{(o_i - e_i)^2}{e_i}$,
    where e is the baseline histogram and o is a histogram in the future window
  - Match Distance: $d_M(H, K) = \sum_{i=1}^{k} |h_i - k_i|$,
    where h_i is the cumulative histogram of the elements of h up to bin i

Method 3: Hidden Markov Model

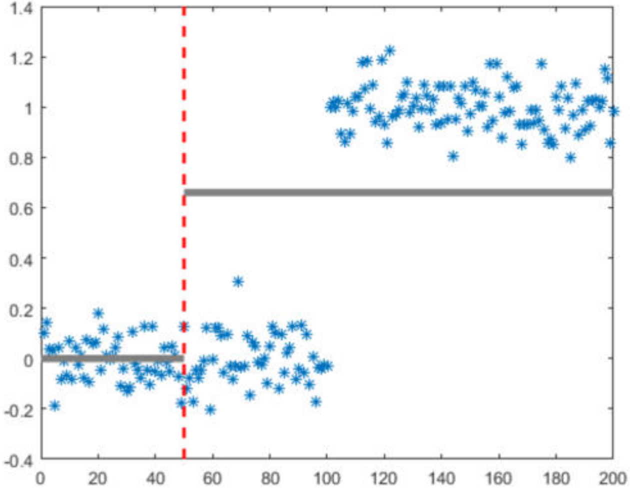
- **Goal:** given a sequence of observations, infer the most probable sequence of hidden variables.
- **Change-point** = transitions in the inferred states of hidden variables

- **Goal:** given a sequence of observations, infer the most probable sequence of hidden variables.
- **Change-point** = transitions in the inferred states of hidden variables

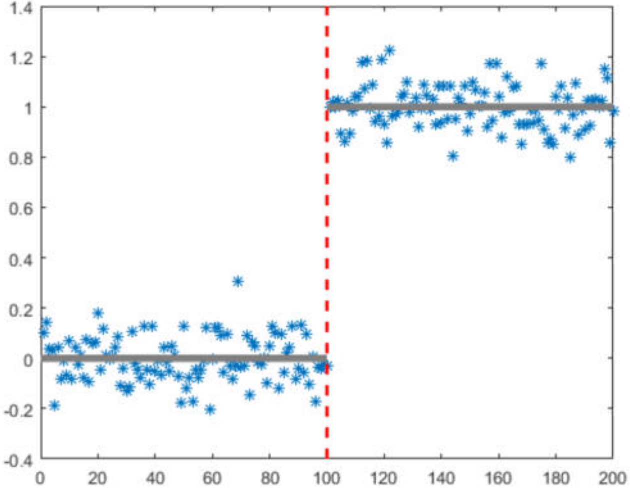


Π: initial distribution
A: transition matrix
Φ: emission parameters of observations' distributions

Method 4: Mean-Squared Error Change-point Detection



Method 4: Mean-Squared Error Change-point Detection



Method 4: Mean-Squared Error Change-point Detection

- For large enough samples, the sample mean $\bar{x}_i$ will be a **normal random variable** by the Central Limit Theorem
- Therefore, $\bar{x}_i^2$ will be a **gamma random variable** and:

$$MSE(c) - \sum_{i=1}^{n} x_i^2 = c\bar{x}_1^2 + (n-c)\bar{x}_2^2 \sim \Gamma(1, 2\sigma_x^2)$$

- We can then derive a p-value for a measurement of mean-squared error

$$p = \frac{MSE(c) - \sum_{i=1}^{n} x_i^2}{2\sigma_x^2}$$

- Where p-value is low, we are near a change-point

Method 4: Mean-Squared Error - Multiple Change-point Detection

- We can now recursively extend mean-squared error to sequences with multiple change points
  1. Given sequence x_i, find x_j with smallest MSE.
  2. Calculate p-value for $MSE(j)$, then if $p \geq \alpha$ threshhold, stop.
  3. Run MSE again on sequences $x_1 ... x_{j-1}$ and $x_{j+1} ... x_n$.
  4. Return x_j, and the outputs of $MSE(x_1 ... x_{j-1})$ and $MSE(x_{j+1} ... x_n)$ as change-points.

Method 5: Maximum Likelihood Estimation

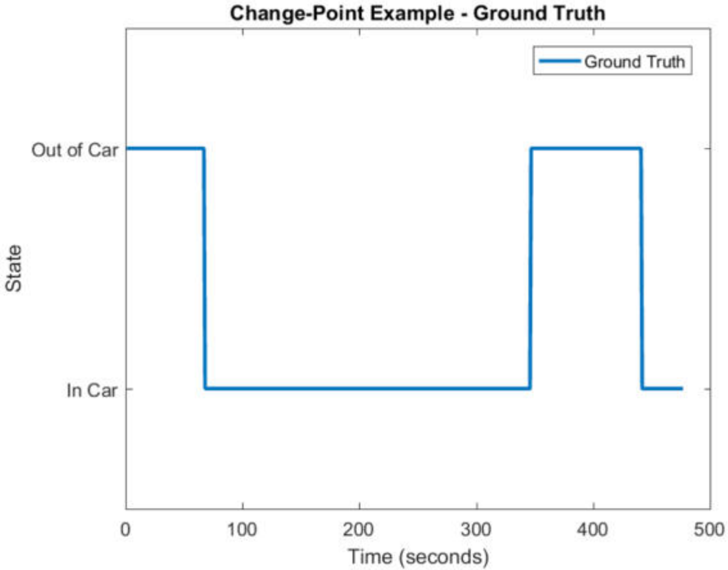
- We find the log-likelihood of the true labels given the data

$$\log \mathcal{L}(L, X) \sim \log \prod_{i=1}^{n} P(X_i | L_i)$$
$$= \log(p) \sum_{i=1}^{n} I[x_i = L_i] + \log(1-p) \sum_{i=1}^{n} I[x_i \neq L_i]$$

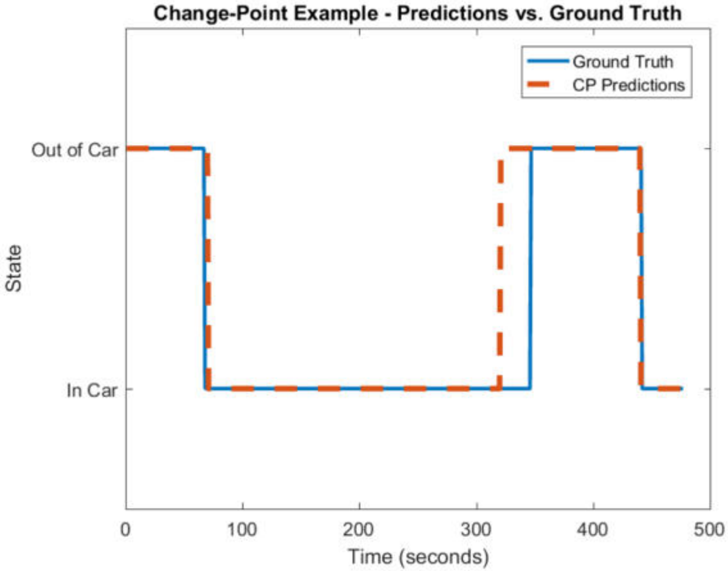
where $x_i \in \{0, 1\}$ is classifier output, $p \in [0, 1]$ is classifier accuracy

- We maximize this likelihood by formulating it as a linear program, and constraining the number of possible change-points

Change-point Detection Results



Change-point Detection Results



Change-point Detection Results

- Using 691 LAPD videos (420 contain at least 1 change-point)
- Our methods ran on output from the convolutional neural network

Table: Univariate Multiple Change-point Detection Results (All Videos)

Method	**Recall (10 s)**	**Precision (10 s)**
Autoregressive (1)	85%	60%
Maximum Likelihood	88%	61%
Mean Model	88%	61%
Mean-Squared Error	88%	**68%**
Hidden Markov Model	**93%**	65%

Change-point Detection Result - Multivariate Data

- Tested methods on BoVW histogram representations and CNN representations
- Representations were made in an **unsupervised** way—didn't need to train a classifier with labeled data (i.e. frames labeled in/out of car)
- Benefits: these methods are much more generalized
- Challenges: high-dimensional space is extremely complex, unsupervised methods are difficult to assess

Table: Multiple change-point detection Results for Multivariate Data

Method	**Recall**	**Precision**
Mean-Squared Error	86%	17%
Match Distance	99%	15%
χ^2 Test	**100%**	**21%**

Summary

- Annotated data, conducted data analysis
- Built and tuned classifiers to detect in car/out of car images with 90%+ accuracy, 95%+ precision and recall
- Developed a variety of change point detection methods for univariate and multivariate data
- Achieved 90% recall and nearly 70% precision on change-points in univariate data
- Methods work well on a variety of videos
  - With or without change-points
  - Driver or passenger side
  - Indoor or outdoor driving
  - Daytime or nighttime driving

Suggestions for RIPS 2017

- Improve unsupervised methods for multivariate time series
- Investigate methods for online data
- Exploit the spatiotemporal structure in the data
- Explore applicability of change-point detection to alternative domains

Questions?

Difference of Gaussians

- Subtract one blurred image from another less blurred image
- Increase visibility of edges

Original image

Image after difference of Gaussian filtering in black and white

Image from https://en.wikipedia.org/wiki/Difference_of_Gaussians

- Let $x, y \in \mathbb{R}^D$ be two histogram representations, and let M be the number of pixels in each image. Then, M is also an upper bound for the maximum number of keypoints in any image.
- Claim: A mapping function Φ can be found such that

$$\Phi(x)^T \Phi(y) = \sum_{i=1}^{D} \min(x_i, y_i).$$

- Proof by construction:

$$\Phi(x) := (\overbrace{1, 1, ..., 1,}^{x_1} \underbrace{0, 0, ..., 0,}_{M - x_1} \overbrace{1, 1, ..., 1,}^{x_2} \underbrace{0, 0, ..., 0,}_{M - x_2}$$

$$... \overbrace{1, 1, ..., 1,}^{x_D} \underbrace{0, 0, ..., 0}_{M - x_D})$$

VGG-16 Architecture

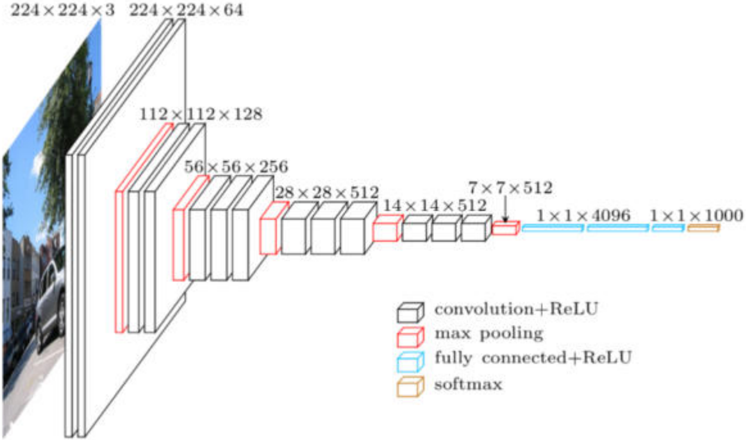


Image from
https://blog.heuritech.com/2016/02/29/a-brief-report-of-the-heuritech-deep-learning-meetup-5/

Hidden Markov Model

- Hidden variables $\{z_n\}_{n=1}^{N}$

$$z_n = \begin{cases} (1 \quad 0)^T & \text{if "in-car"} \\ (0 \quad 1)^T & \text{otherwise} \end{cases}$$

- Initial distribution $\pi = (\pi_1 \quad \pi_2)$
- Transition probability $A_{ij} = p(z_{n,j} = 1 | z_{n-1,i} = 1)$, where $i, j \in \{1, 2\}$
- Conditional distributions of observed variables:

$$p(x_n | z_n, \Phi) = \left(\frac{1}{\sqrt{2\pi\sigma_1}} \exp\left(\frac{(x_n - \mu_1)^2}{\sigma_1}\right) \right)^{z_{n,1}} \cdot \left(\frac{1}{\sqrt{2\pi\sigma_2}} \exp\left(\frac{(x_n - \mu_2)^2}{\sigma_2}\right) \right)^{z_{n,2}},$$

where $\Phi = \{\sigma_1, \sigma_2, \mu_1, \mu_2\}$ is the set of emission parameters.

Hidden Markov Model Coefficient Estimates

- Initial distribution: $\hat{\pi} = [0.667 \quad 0.333]$
- Transition matrix: $\hat{A} = \begin{bmatrix} 0.9883 & 0.0117 \\ 0.0044 & 0.9956 \end{bmatrix}$
- Emission parameters:
  - Standard deviations: $\hat{\sigma_1} = 1.3251$, $\hat{\sigma_2} = 1.0583$
  - Means: $\hat{\mu_1} = -1.8499$, $\hat{\mu_2} = 1.9646$

SIFT-BoVW-SVM Results

- The SVM scores were outputted for videos with change-points.

Table: Univariate Multiple Change-point Detection Results

Method	Recall (10 s)	Precision (10 s)
Maximum Likelihood	66%	34%
Mean Model	89%	18%
Autoregressive (1)	90%	17%
Hidden Markov Model	**90%**	17%
Mean-Squared Error	91%	**30%**

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LOS ANGELES, CA 90095-7121

June 29th, 2016

LOS ANGELES POLICE DEPARTMENT
Officer Benjamin Hong

Dear Officer Hong:

Enclosed are two copies of the Statement of Work (SOW) and two copies of this cover letter. The SOW outlines our team's current understanding of the problem and addresses our planned approach to a solution.

Please show your approval of the SOW by signing both copies of the cover letter in the space provided on this page, or by indicating your proposed changes, and returning one copy of each (SOW and signed cover letter) to me by Friday, July 8. Otherwise, after that date, we will assume the LAPD's tacit approval.

Sincerely,

Stephanie A. Allen

Stephanie Allen
RIPS Project Manager

Institute for Pure and Applied Mathematics (IPAM)
Attn RIPS: Stephanie Allen

Enclosure: Los Angeles Police Department RIPS Work Statement

Cc: Susana Serna, RIPS Program Director
Stacey Beggs, IPAM IPAM Assistant Director

Accepted this________day of June 2016

By: ______________________________

RIPS 2016 Project Work Statement
Sponsor: Los Angeles Police Department
Change Point Detection Methods Applied to Body-Worn Video

Stephanie Allen (Project Manager), ***SUNY Geneseo***
Contact: [redacted]
David Madras, ***University of Toronto***
Ye Ye, ***UCLA***
Greg Zanotti, ***DePaul University***

Academic Mentor: Giang Tran, gtran@math.utexas.edu

Academic Supervisors: Jeff Brantingham, UCLA Anthropology; Dr. Craig Uchida, Justice and Security Strategies

Industry Sponsor: Commander Sean Malinowski (LAPD Chief of Staff); Ms. Maggie Goodrich (LAPD CIO), Sgt. Javier Macias, Sgt. Dan Gomez, Mr. Arnold Suzukamo (LAPD-IT Bureau), Officer Benjamin Hong

June 29^{th}, 2016

1 Introduction

Body-worn video (BWV) has come about as another source of information regarding police-public interactions. To produce this video, police officers wear specially designed cameras on their chests to record their interactions with the public. This video then may be utilized when there is public disagreement about police conduct. Furthermore, these cameras have been shown to increase professionalism in the police force [1]. However, the video from the cameras has not been analyzed thoroughly because of the sheer quantity of data produced by them.

The Los Angeles Police Department (LAPD) seeks to protect and to serve the residents and visitors of the city of Los Angeles via patrol, traffic, and specialized divisions. The Department recently undertook a pilot project in its Central Division whereby police officers received body cameras to document their work in the field. The Department gave police officers license to turn the cameras on when they felt their interactions should be recorded. The Research in Industrial Projects for Students (RIPS) LAPD student research group will work with a sample of this data to develop change point detection methods that will help to streamline the video recording and analysis processes.

2 Problem Statement

In this project, we will work to develop change point detection algorithms to apply to video data. A significant change in the content of BWV may occur at the time an officer exits a car and engages in public interactions. However, it is not realistic to require an officer to record the time of exit from a vehicle—for example, in a dangerous situation. The same reasoning applies for other possible change points, such as entering or exiting buildings. Therefore, being able to automatically identify change points in a video stream would both greatly improve the efficiency of BWV analysis and reduce storage requirements. Our immediate goal is to identify the moment of exit from a car because this is a very clear change. We also seek to minimize the false alarm rate as we develop our identification algorithms.

3 Mathematical Background

The mathematical background required for this project is primarily statistical; specifically, it lies in the field of change point detection [3]. Change point detection methods exist to identify critical points in a series where the underlying distribution changes. A wide range of these methods exist. One popular and extensible change point detection method is the cumulative sum algorithm (CUSUM); one variation of this algorithm computes a log-likelihood ratio after each new data point, adds this ratio to the sum of the previous ratios, and tests this aggregate ratio against a chosen threshold [4, 16]. CUSUM is commonly used for change point detection and thus provides a good framework for exploration. The complex spatio-temporal inferential challenges posed by videos may require the use of other change point algorithms drawn from Bayesian methods and kernel methods. Bayesian methods like Gaussian processes are able to deal well with the temporal correlation in videos [5]. Kernel methods can identify interesting features in videos across space and time [6]. Video-specific algorithms also exist for scene labeling and change point detection; these may be applicable as well [7].

4 Computing Background

The bulk of the computing background for this project will involve methods of image and video representation and processing [2, 3]. The machine learning and the computer vision literature provide a variety of methods well-suited to our task. Within machine learning, representation learning algorithms are used to learn low-dimensional feature vectors from high-dimensional input like video. Many of these methods are framed in the theory of artificial neural networks. Specifically, networks such as denoising autoencoders and convolutional nets have seen great success in recent years [8, 9]. These methods work by hierarchically building an increasingly complex sequence of features from video patches. Other machine learning tools from nonlinear dimensionality reduction may be useful as well; for example, kernel principal component analysis finds a nonlinear map from a higher-dimensional set of data to a lower-dimensional one, where inference can be more tractable [10].

From computer vision approaches, we will explore a variety of image processing algorithms. These include methods for image segmentation and boundary detection, as well as local feature detection algorithms such as SIFT (Scale-Invariant Feature Transform) and SURF (Speeded Up Robust Features) [11, 12]. All these methods will provide different ways of describing the relevant features of our images compactly. Once derived from an image, these features can be intelligently consumed by a regularizing classifier like a support vector machines ("SVM") [13, 14]. SVMs work by finding a number of hyperplanes in n-dimensional space that optimally segment data into two or more classes [15].

5 Possible Solutions and Project Objectives

Our first objective is to build a classifier to detect if an image has or has not been taken within a car. We plan to use multiple machine learning algorithms such as convolutional neural networks and support vector machines. During the process, we will also perform data analysis on the body-worn video we receive. After developing this classifier, we plan to develop change point detection algorithms to identify the time at which the sequence of images changes from being inside a car to outside a car, which would indicate that the door has been opened. The method developed is intended to work with already recorded videos in storage (offline data). We hope that it will also work on sequentially received video frames (online data).

If time permits, we will work to generalize our change point detection methods to handle more complicated representations of the images. First, we will explore ways to extract multiple features from images, compute difference images, or use other methods of representing the images through time. Then, we will build upon established change point detection methods to write algorithms which can be applied on the extracted time series to identify the variation in the data that results from the opening of a door. If we are successful, we will then proceed to developing methods to deal with online data. The methods developed during this phase of the project may provide a framework for detecting additional change points beyond just the opening of a car door.

Our implementation will be carried out in *MATLAB* and/or *Python*. As we use and develop image processing and change point detection methods, we will also evaluate the efficacy of these methods.

6 Deliverables

In the following subsections, we will outline the materials we plan to provide to the LAPD and also the assistance from the LAPD required by this student research group.

6.1 RIPS to LAPD

- Thursday, July 21^{st}, 2016: We will give a Midterm Presentation regarding our progress on the proposed project.
- August 15^{th}, 2016 - August 19^{th}, 2016: We will present our final results during RIPS's Projects Day, which will be scheduled sometime between August 15^{th} and August 19^{th}.
- Friday, August 19^{th}, 2016: We will deliver our final project report. We will be sure to include our analysis of the video data and explanations of our change point detection algorithm(s) in this report.
- Friday, August 19^{th}, 2016: We will provide the code for our proposed algorithm(s).

  Any Code sent by the 2016 LAPD RIPS student research group to the LAPD will be in compliance with the Software Disclaimer attached to this Work Statement.

6.2 LAPD to RIPS

- Receipt of body-worn video data by Week 2 (June 27^{th}, 2016 - July 1^{st}, 2016)
- Timely response to RIPS LAPD student research group communications

- Weekly meetings and/or conference calls with a representative from the LAPD if necessary
- Site visit at LAPD

7 Timeline

Weeks 1-2 (6/20 - 6/24 and 6/27 - 7/1)

- Gather and review background reading
- Compose and submit work statement (by the end of Week 2)
- Begin data analysis and development of change point detection methods

Weeks 3-4 (7/5 - 7/8 and 7/11 - 7/15)

- Continue work on change point detection methods
- Visit the LAPD site during Week 3
- During the later half of Week 4, start to prepare for the Midterm presentation

Week 5 (7/18 - 7/22)

- Prepare and give Midterm presentation (date to be determined)

Weeks 6-8 (7/25 - 7/29, 8/1 - 8/5, and 8/8 - 8/12)

- Continue working on research
- During Week 8, work on the final report, code, and presentation

Week 9 (8/15 - 8/19)

- Finish research
- Finalize report and code for change point detection methods (for submission to LAPD)
- Present final presentation on RIPS's Projects Day to LAPD (date to be determined)

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Change Point Detection Methods Applied to Body-Worn Video

Stephanie Allen, *SUNY Geneseo*
David Madras, *University of Toronto*
Ye Ye, *UCLA*
Greg Zanotti, *DePaul University*

Academic Mentor: Dr. Giang Tran
Consultant: Dr. Jeff Brantingham, UCLA
Industry Mentor: Sgt. Javier Macias, LAPD

July 21st, 2016

Outline

LAPD & Body-Worn Video

- Third largest municipal police department in USA, employing 9,843 officers
- A leader in the effort to equip police officers with body-worn cameras

Body-worn Video (BWV)

Body-worn Video (BWV)

- Cameras worn on officers' chests used to record police-public interactions
  - Currently deployed to 1,200 officers; will be scaled up to 7,000
- **Benefits**:
  - Provides video record in the case of public disagreements
  - Shown to increase police professionalism
- **Challenge**:
  - Creates large volumes of data, necessitating the use of automatic data analysis

Problem Statement

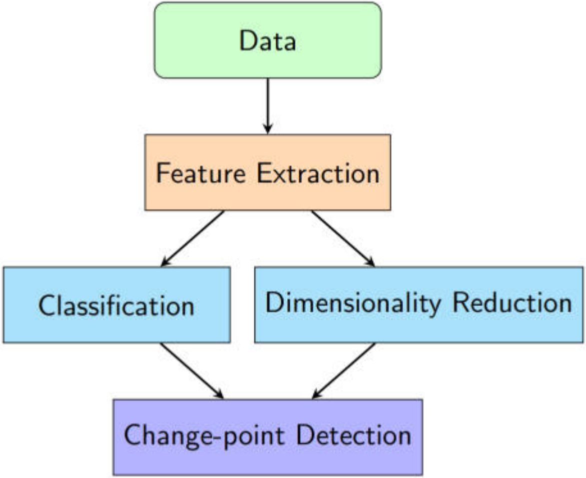
- **Goal:** Create algorithms to detect change-points in body-worn video
  - This will greatly streamline the video review process
- For this project, we focus on a specific class of change-points: **the moment at which an officer exits or enters their car**

Images from www.youtube.com

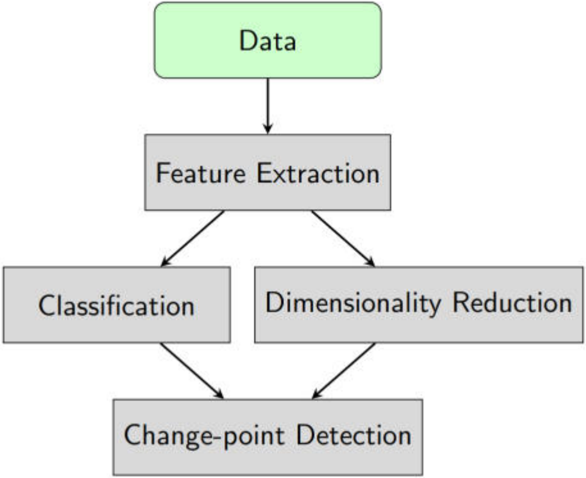
Video Change-point Detection - Related Work

- Three main approaches in the literature
  - Sequential comparison of **image differences**, with change points detected by thresholding schemes
  - Change-point detection methods run on time series of **image representations**
  - Combination of **spatiotemporal features** to generate video-specific change point detection methods
- To optimize time and accuracy constraints, we mainly consider the middle method

Overview of Methods



Overview of Methods - Data



Data Analysis - In Car Examples

Images from www.youtube.com

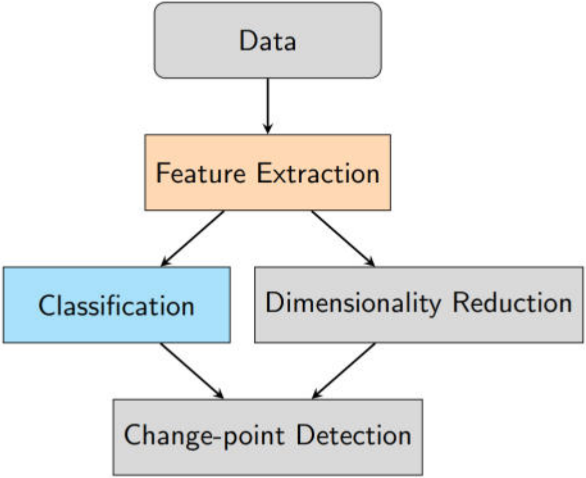
Data Analysis - Out of Car Examples

Images from www.youtube.com

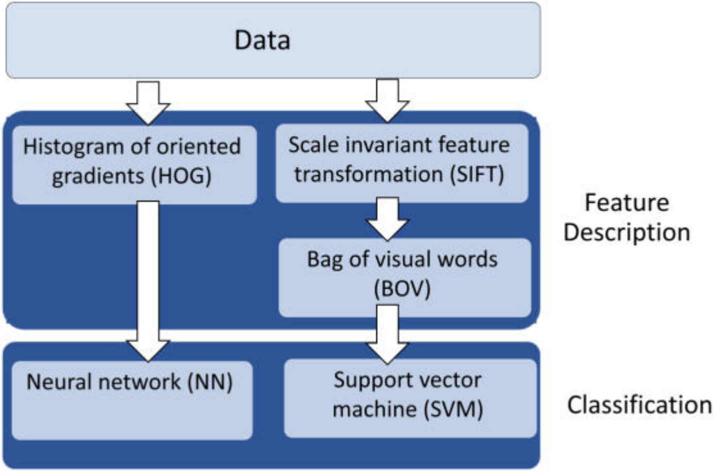
Data Analysis

- Sample of data taken from BWV pilot program (Dec '14-May '15)
- 691 videos, average length 9 minutes
- 421 contain either an entrance or exit from vehicle
- Of these:
  - 270 are taken from driver side
  - 274 are taken from a moving vehicle
  - 176 occur during nighttime

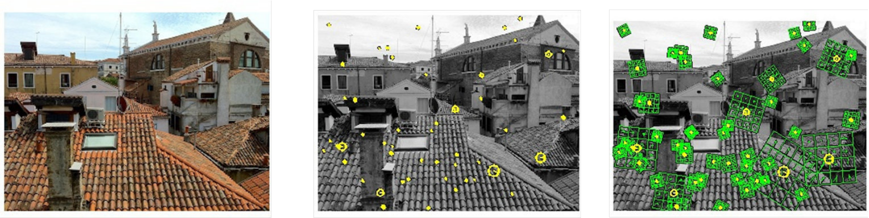
Overview of Methods - Feature Extraction & Classification

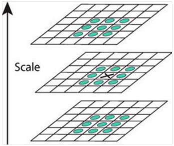


Overview of Methods - Feature Extraction & Classification



Keypoint Detection and Description – Scale-Invariant Feature Transformation (SIFT)





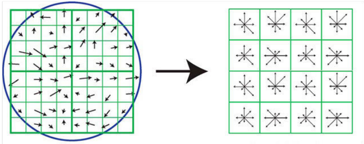


Image gradients

Keypoint descriptor

$$I = \begin{bmatrix} - & s_1^T & - \\ - & s_2^T & - \\ & \vdots & \\ & \vdots & \\ - & s_K^T & - \end{bmatrix}$$

SIFT matrix

Image Representation - Bag of Visual Words

- Sample 20% of images in the training set, extract SIFT descriptors
- Apply k-means clustering, where the centroid of each cluster is a 'visual word'

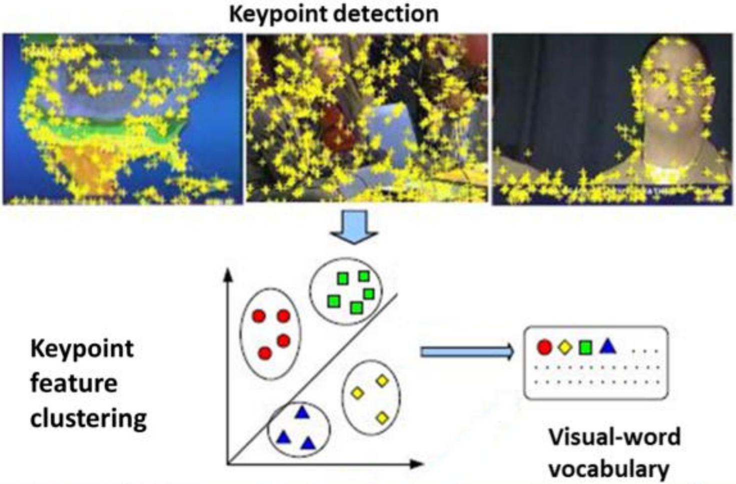
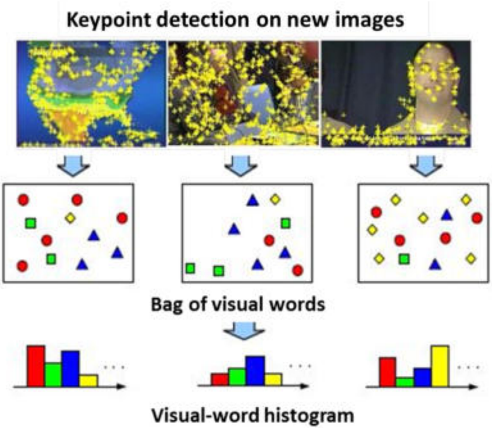
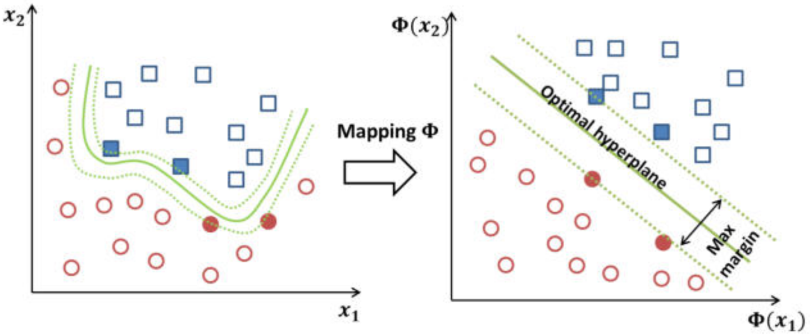


Image Representation - Bag of Visual Words

- For each new input image,
  - Assign its keypoint descriptors to nearest centroids
  - Count the number of occurrences for each centroid
  - Get a histogram representation

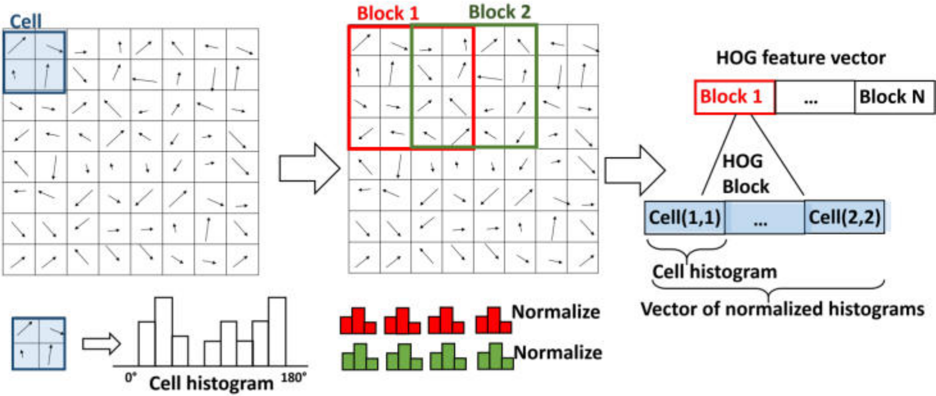


Classifier - Support Vector Machine (SVM)



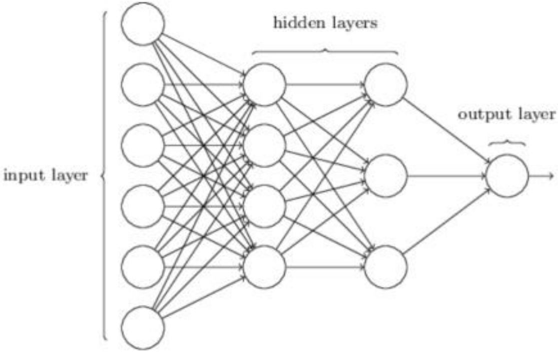
- Kernel function $k(x,y) = \Phi(x)^T\Phi(y) = \exp\left(-\frac{1}{2A}\sum_{d=1}^{D}\frac{(x_d-y_d)^2}{x_d+y_d}\right)$
- Maximize margin and obtain weight coefficients
- For a new image histogram x, $Score(x) = \sum_{n=1}^{N} a_n t_n k(x, x_n) + b$

Image Representation - Histogram of Oriented Gradients (HOG)



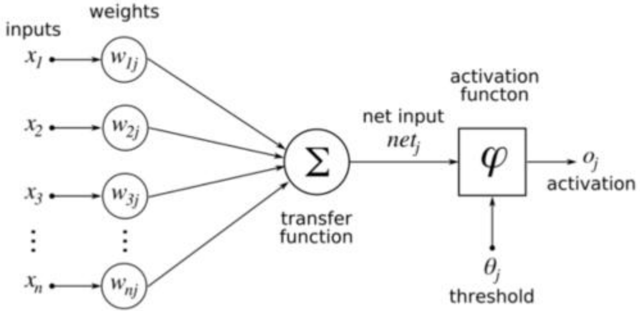
Classifier - Neural Network

- An artificial neural network jointly learns a **feature representation** and **discriminative classifier** over data
- Neurons are stacked on top of one another in **layers** to form complex, highly informative features
- At the last layer, outputs are normalized to form a **probability distribution** over classes



Neural Network Detail

- Generally, operations within a neuron consist of **multiplying inputs by weights**, passing them to a **transfer function**, and passing the result through a **nonlinear, thresholded 'activation' function**



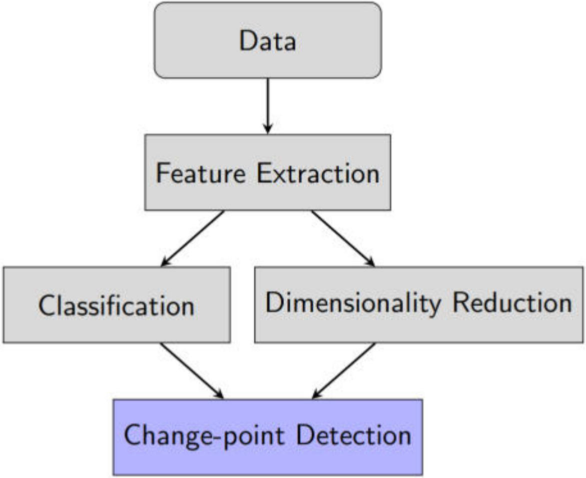
- Neural networks are trained by changing the weights according to a sequential optimization algorithm like gradient descent

Classification Results

- Change point detection depends on strong classification results
- Our dataset consists of $\sim 4,000$ labeled (in/out of car) frames
- $\text{Recall} := \dfrac{|\text{PredictedOut} \cap \text{Out}|}{|\text{Out}|}$
- 1st classifier: Frames $\Rightarrow$ SIFT vectors $\Rightarrow$ BOV $\Rightarrow$ SVM
- 2nd classifier: Frames $\Rightarrow$ HOG vectors + pixel hist. $\Rightarrow$ NN

Classifier	**Accuracy**	**Recall**
SIFT-BOV-SVM	88%	88%
HOG+PIXH-NN	77%	82%

Overview of Methods - Change-point Detection



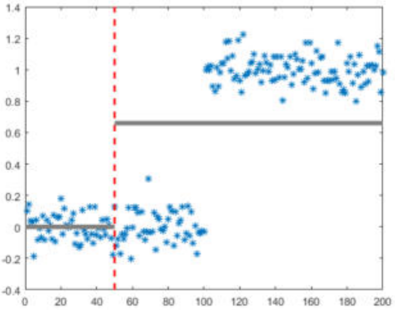
Change-point Methods Overview

- Given a time series $X_i, i = 1...n$
- We know there is some **change-point** c where the underlying distribution of the X_i changes
- That is:

$$X_i \sim F_1 \; \forall \; i \leq c, \;\; X_i \sim F_2 \; \forall \; i \; > c$$

  for some distributions $F_1 \neq F_2, c \in \{1...n\}$
- **Goal**: To find c
  - Evaluate some objective function for each $c \in \{1...n\}$
  - Find c to optimize this objective

Simple Change-point Detection - Example



- Minimize Mean Squared Error:

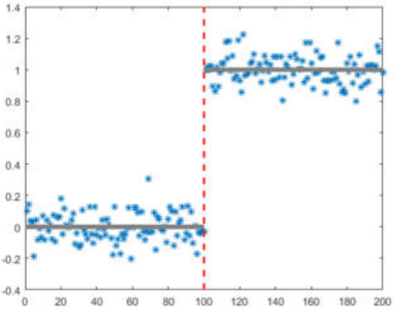
$$\sum_{i=1}^{m}\left(x_i-\bar{x}_1\right)^2+\sum_{i=m+1}^{n}\left(x_i-\bar{x}_2\right)^2$$

$$m\in\{1,2,...,n-1\}$$

$$\bar{x}_1=\sum_{i=1}^{m}\frac{x_i}{m}$$

$$\bar{x}_2=\sum_{i=m+1}^{n}\frac{x_i}{n-m}$$

Simple Change-point Detection - Example



- Minimize Mean Squared Error:

$$\sum_{i=1}^{m} \left(x_i - \bar{x}_1\right)^2 + \sum_{i=m+1}^{n} \left(x_i - \bar{x}_2\right)^2$$

$$m \in \{1, 2, ..., n-1\}$$

$$\bar{x}_1 = \sum_{i=1}^{m} \frac{x_i}{m}$$

$$\bar{x}_2 = \sum_{i=m+1}^{n} \frac{x_i}{n-m}$$

Kernel Density Estimation

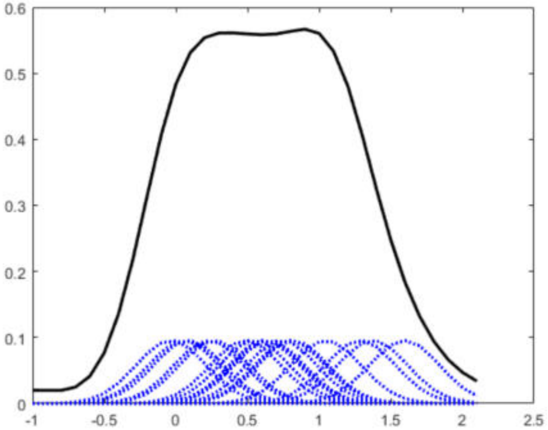
- Fits a continuous distribution to data whose true distribution is unknown
- Fits kernel functions to every point in the data set and then sums the functions to produce a fitted distribution

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)$$

$$K(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{|x|^2}{2}}$$

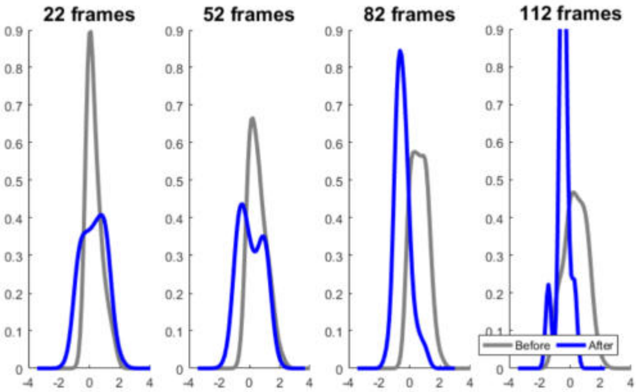
h = bandwidth, n = number of points in the data set

Density Estimation



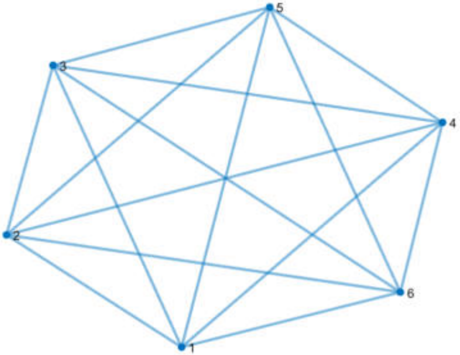
Density Estimation - Example

- CUSUM Density: $\max_{1 \le n_c \le n} \sum_{i=n_c}^{n} \ln\left(\frac{f_1(x_i)}{f_0(x_i)}\right), n_c \in \{1, 2, ..., n\}$



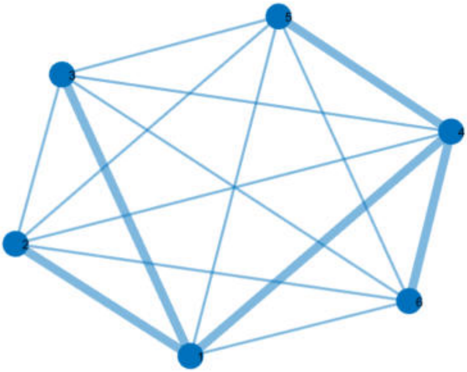
Graph-based Methods

- Given time series $X_i, i = 1...n$, create graph G where:
  - All X_i, X_j are nodes connected by an edge with weight $\|X_i - X_j\|$



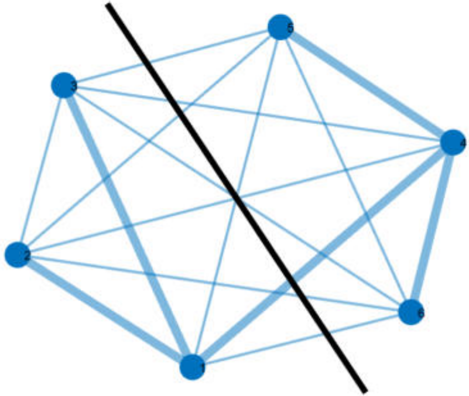
Graph-based Methods

- We can then use the minimum spanning tree (MST) of this graph to find structure in the data



Graph-based Methods

- Partition nodes while breaking relatively few edges in MST
  - Can normalize using mean and variance of edges cut w.r.t. partition size
- Non-parametric, generalizes easily to higher dimensions

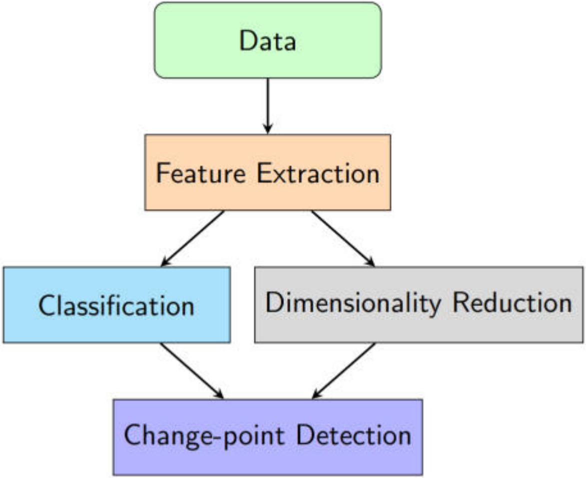


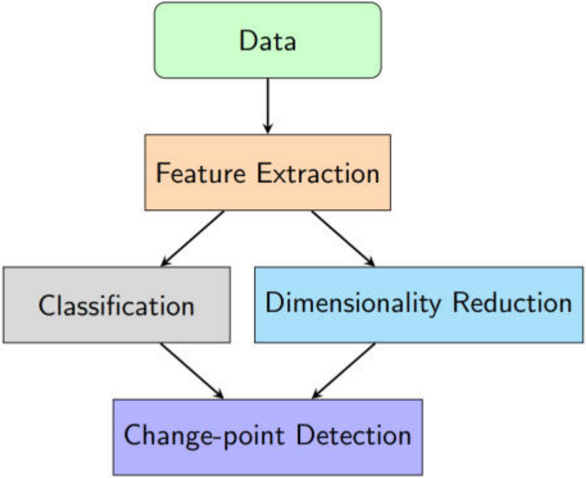
Change-point Detection Results

- Using 145 LAPD videos containing a car exit or entrance:
  - Clipped videos to smaller lengths (2-5 minutes)
  - Each clip contained exactly 1 change-point
  - 301 clips in total
- Our methods ran on a univariate series of SVM output scores

Method	Within 2s	Within 5s	Within 10s
MSE	46%	65%	74%
Graph	39%	57%	70%
CUDensity	34%	56%	65%

Overview of Methods - Univariate Data Workflow




Data
Feature Extraction
Classification
Dimensionality Reduction
Change-point Detection

Change-point Detection Result - Multivariate Data

- Also tested change-point detection methods on HOG and SIFT image representations (with dimensionality reduction)
- These representations were created in an **unsupervised** manner - meaning we didn't need to train a classifier with labeled data (i.e. frames labeled in/out of car)
- Due to the lack of need for labeled data, these methods are much more generalized

Method	Within 2s	Within 5s	Within 10s
MSE	23%	47%	60%
Leach	26%	45%	57%
Graph	17%	36%	47%

Conclusions and Progress

- Progress on project objectives
  - Annotated each video with change points
  - Conducted exploratory data analysis
  - Built and tuned classifiers to detect in car/out of car with 75-90% accuracy
  - Developed change point detection methods for univariate and multivariate data

Next Steps and Future Research

- Improve image representations
  - Use finetuned convolutional features
  - Improve spatial selection of bag-of-visual-words features
  - Use unsupervised representations for better generalization
  - Explore labeling schemes reduce state transition uncertainty
- Investigate better change-point detection methods
  - Implement thresholds for test statistics
  - Investigate methods for high-dimensional multivariate time series
  - Investigate methods for online data
  - Exploit the spatiotemporal structure in the data
  - Explore robust smoothing methods to avoid noise (e.g. from occlusions or outliers)

Questions?

Social Sciences
ZonMw

Call for proposals

Replication Studies

2016 1st round

ZonMw

The Hague, September 2016
Netherlands Organisation for Scientific Research

Contents

1 Introduction

1.1 Background

Content

Replication lies at the heart of the scientific method and makes it possible to build upon previously demonstrated and confirmed scientific findings. Many studies, however, have proved not to be reproducible. If research is not reproducible then this is often attributed to chance, or unintended errors, but p-hacking, publication bias and especially selective reporting will undoubtedly play a major role in this as well.[1]

By encouraging the realisation of replication research, NWO wants to make a contribution to increasing the transparency of research and the quality and completeness of the reporting of results. With this, NWO is joining initiatives such as the Reproducibility Project in psychology, and journals such as The Journal of Finance that has launched a section for publishing replications.2 NWO hopes that by encouraging replication research it can contribute to making replication research more commonplace and to improving insights into the reproducibility of research.

This programme is open to the submission of proposals for the replication of research within the disciplines of NWO Social Sciences and ZonMw. The programme may be modified in later rounds based on the results from earlier rounds.

There are three types of replication research:

1. Reproduction: replication with existing data - repeated analysis of the datasets from the original study.
2. Replication with new data: new data collection with the same research protocol as the original study.
3. Replication with the same research question: new data collection with a different design from the original study in which the research question remains unchanged compared to the original research.

In this pilot programme, only research that falls under the first two categories will be financed.

1.2 Available budget

For this funding round M€ 1 is available.[3] A maximum of €75,000 can be requested for a Type 1 project and a maximum of €150,000 for a Type 2 study.

[1] Reproducibility is not the only factor that can influence the quality, societal impact, integrity and efficiency of research. In this context we refer you to the programme Fostering Responsible Research Practices http://www.zonmw.nl/nl/programmas/programma-detail/bevorderen-van-verantwoorde-onderzoekspraktijken/algemeen/ (only in Dutch)

[2] http://dx.doi.org/10.1126/science.aac4716
http://www.afajof.org/SpringboardWebApp/userfiles/afa/file/Submissions/Replications%20and%20Corrigenda.pdf

[3] NWO has made M€ 3 available for the programme, for a period of three years. The funding for next calls will be decided on the basis of the experiences of the first call.

1.3 Validity of the call for proposals

This call for proposals is valid until the closing date **January 12, 2017.**

2 Aim

With this pilot programme NWO wants to encourage researchers to carry out replication research. NWO also wants to gain experience that can lead to insights into an effective way of including replication research in research programmes and to obtain insight into and a reflection on the requirements that NWO sets for research in terms of methodology and transparency.

3 Guidelines for applicants

3.1 Who can apply

Researchers from the following knowledge institutions can submit proposals:
- Dutch universities;
- NWO and KNAW institutes;
- University Medical Centres;
- the Netherlands Cancer Institute (NKI);
- the Netherlands institute for health services research (NIVEL)
- the Trimbos Institute (Netherlands institute for Mental Health and Addictions)
- the National Institute for Public Health and the Environment (RIVM)
- the Max Planck Institute for Psycholinguistics in Nijmegen;
- researchers from the DUBBLE Beamline at the ESRF in Grenoble;
- NCB Naturalis;
- the Advanced Research Centre for NanoLithography (ARCNL).

Expertise required and composition of the project group

Applicants are researchers who hold a PhD and are employed at one of the aforementioned institutions for the duration of the proposed project. They clearly possess the methodological competencies needed to carry out/supervise such a study. Applicants should also have demonstrable expertise in the research area of the study to be replicated. If the research will be carried out by several researchers then it must be clear from the composition of the project group that it contains the relevant expertise required. Besides research expertise there is a strong emphasis on methodological and statistical expertise.

There may be no history of collaboration with the original researchers (such as a supervisor-PhD student relationship, co-authorship, or another form of collaborative relationship). On the other hand there may also be no history of conflict. Applicants should provide convincing evidence that there is no prejudice or conflict of interest with respect to the original researchers. Further details about the types of conflict of interest can be found in Section 2.2 of the NWO Code of Conduct on Conflicts of Interest and section 3.4 of this call for proposals.

Where the design of the research deviates from or has been modified with respect to the original research, the applicant should state why these changes are necessary and why this is not a Type 3 replication study.

3.2 What can be applied for

For this pilot programme, funding can be requested for the replication of so-called cornerstone research: research that has had substantial consequences with respect to theory or policy and for which it is therefore important to assess whether the results on which these consequences are based are reproducible. In their proposal the applicants must argue why the original research that they want to replicate can be regarded as cornerstone research and why it is important to replicate this.

It should be noted that if the research has previously been replicated or if it is being replicated at the moment the proposal is submitted then the applicants will have to provide convincing arguments as to why an additional replication study is worthwhile.

Cornerstone research concerns one or more of the following types of research:

- studies that are frequently cited with far-reaching consequences for subsequent research. This can also include studies with theoretical and/or practical implications for which an intensive post-publication debate has arisen in the form of letters to the editor, on websites (for example https://pubpeer.com/) or in blogs (for example http://retractionwatch.com).https://pubpeer.com/http://retractionwatch.co m/
- research that plays a major role in policy formation, or studies on the basis of which important policy decisions have been taken: for example studies that have implications for the organisation and/or funding of healthcare or that play a crucial role or are expected to play a crucial role in a clinical guideline, with implications for the prevention of health problems.
- research that is part of the educational canon: research that is often cited in textbooks for students.
- research that has received a lot of media attention and therefore has a considerable impact on the public debate.
- studies with far-reaching consequences for legislation.

Explanatory note for proposals for ZonMw research

Examples of applications that can be submitted are proposals to replicate preclinical experimental animal research, stem cell and cell culture research, research aimed at models and human research aimed at prevention, diagnostics, therapy and prognosis. The replication of clinical trials falls outside of the scope of the pilot programme. Reproduction, reanalysing data from clinical trials, does however fall within the scope of the programme. See for ZonMw discipline codes the attachment to www.nwo.nl/replicationstudies.

Explanatory note for proposals for Social Sciences research:

Researchers can apply for funding for the replication of research that falls within the behavioural and social sciences, as included in the NWO discipline codes. Funding can be requested for the replication of experimental studies and for the reanalysis of survey data. Examples of research in the social and behavioural sciences that can be replicated in this programme are research that forms the basis for the development of teaching methods or research that forms the basis for interventions. See for social sciences discipline codes the attachment to www.nwo.nl/replicationstudies.

Type of replication, budget and-co-funding

As stated in Section 1.1 different types of replication studies can be distinguished. The most appropriate form for replicating the original study (Type 1 or Type 2) is described and substantiated by the applicants.

A maximum of €75,000 can be requested for a Type 1 project and a maximum of €150,000 for a Type 2 study. This amount can be freely allocated across personnel and material costs. The maximum duration of the research is two years. All costs for which funding is requested must be justified in the proposal. The reasonableness of the budget requested (value for money) is a heavily weighted assessment criterion and will be considered by the Executive Board when setting the amount awarded.

Within the category Type 1 research the preference is, where possible, for several replications to be carried out within a single project.

Co-funding is permitted as long as this remains limited to co-funding from the university/UMC, the Royal Netherlands Academy for Arts and Sciences (KNAW), NWO institutes, Netherlands Institute of Mental Health and Addiction (Trimbos Institute), Netherlands institute for health services research (NIVEL), National Institute for Public Health and the Environment (RIVM) and the health funds (Dutch Cancer Society, Dutch Heart Foundation, Asthma Fund, etc.). It is of paramount importance that the research is carried out independently; interests must also be clearly stated in the Conflict of Interests section in the application. Co-funding is not a requirement and gives no advantage during the assessment.

Role of the original researchers and information about the original research

The replication research must be carried out independently from the original researchers. It is however important that the relevant information, if possible, is requested from the original researchers and that they are informed about the intention to replicate the research.

In their application, applicants are requested to explain whether the original researchers have been informed and/or approached about the proposal and to state whether, and if so which, agreements have been made with the original researchers about access to the necessary information about the original research, the role of the original researchers (in an advisory capacity concerning the proposed replication for instance), and how the results of the research will be published and communicated. From this description it must be clear that the original researchers have no active researcher's role in the replication study.

Applicants must request the relevant data from the original study as comprehensively as possible: research protocol, logbook data collection, datasets, amendments, data analysis etc. In the application they must demonstrate that they have access/will obtain access to the data (Type 1) or the research protocol (Type 2). In some cases a research protocol will not be available. If this is lacking the applicants are requested to argue in the application how they will resolve this and in so doing to demonstrate the feasibility of their proposal.

Applicants are also requested to justify the choice of the sample they will take and to demonstrate that the sample size is large enough for the proposed research. Determining the required sample size can be justified in a number of ways.[4] Because reported effect sizes in the literature are often overestimations as a result of publication bias,[5] it is necessary to consider the required sample size well, and, if necessary, to determine this with the aid of a statistician.

If a proposal is awarded funding but the availability of the required data although likely has not been confirmed then the funding will be disbursed on the condition that these data are obtained. The project can only start once these data are clearly in the possession of the researchers.

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[4] Maxwell, S. E., Kelley, K., & Rausch, J. R. (2008). Sample Size Planning for Statistical Power and Accuracy in Parameter Estimation. Annual Review of Psychology, 59(1), 537–563. http://doi.org/10.1146/annurev.psych.59.103006.093735

[5] Open Science Collaboration, 2015: Estimating the reproducibility of psychological science. Science Vol 349, Issue 6251 28 August 2015. http://science.sciencemag.org/content/349/6251/aac4716

Button, Ioannidis, et al (2013): Power failure: why small sample size undermines the reliability of neuroscience. Nature Reviews Neuroscience 14, 365-376 (May 2013) http://www.nature.com/nrn/journal/v14/n5/full/nrn3475.html

3.3 When can applications be submitted

The deadline for the submission of proposals is **January 12, 2017**, 14:00 hours CE(S)T.

When you submit your application to ISAAC you will also need to enter additional details online. You should therefore start submitting your application at least one day before the deadline of this call for proposals. Applications submitted after the deadline will not be taken into consideration.

3.4 Preparing an application

- Download the application form from the electronic application system ISAAC or from NWO's website (on the grant page for this programme).
- Complete the application form.
- Save the application form as a PDF file and upload it in ISAAC.

The application must be written in English and contain information about the following points:

1. Research proposal
   - Why can the research to be replicated be viewed as cornerstone research? Has the research had substantial consequences, from a theoretical or policy point of view, and why is it, terms of methodology or content, important to test whether the results on which these consequences are based are reproducible?
   - Motivation for choosing Type 1 or 2 – why is this the most suitable form?
   - The methodological approach for the research
     - is the replication/reproduction as precise as possible and if not, where does the replication study deviate from the original study and why?
     - arguments supporting the sample size. If an improvement of the sample size is proposed then the need for this should be justified
   - If the research has been replicated in the past or is currently being replicated then why is carrying out an additional replication worthwhile?

2. Original research
   - Arguments to demonstrate the independence with respect to the original researchers – conflict of interest
   - Have the original researchers been informed and have any agreements been made about the research?
   - Are the relevant data[6] from the original research in the possession of the applicants and if that is not the case how do the applicants plan to deal with this?

3. Registration and dissemination
   - A plan for registering the research with a databank or repository
   - A data management plan that details the storage of measurement data and if data will not be stored in a public repository, then the reason for this choice must be given
   - A dissemination plan, with attention for the reporting guidelines, publications and other forms of knowledge utilisation used

[6] Type 1: original dataset and analysis plan, Type 2: the complete original protocol.

4. Team
   - Methodological competencies of the team
   - Expertise in the area of the study to be replicated
   - For each member of the team you can add a short CV as an attachment to illustrate the competencies and expertise stated above. For the CV please use the template provided with the application form.

You may want to use the services of DANS (www.dans.knaw.nl) when writing the application. DANS can advise about access to data via EASY, about access to data that is stored in repositories abroad, and provide help with the preparations for depositing data that emerges from the research (see also the section about data management under 3.5). For this you can contact Kees Waterman (kees.waterman@dans.knaw.nl).

3.5 Conditions on granting

NWO Regulation on Granting

The NWO Regulation on Granting applies to this programme. This regulation can be downloaded here: http://www.nwo.nl/en/documents/nwo/legal/nwo-regulation-on-granting-2015

Open Access

All scientific publications resulting from research that is funded by grants derived from this call for proposals are to be immediately (at the time of publication) and freely accessible worldwide (Open Access). There are several ways for researchers to publish Open Access. A detailed explanation regarding Open Access can be found at www.nwo.nl/openscience-en.

Data management

Responsible data management is part of good research. NWO wants research data that emerges from publicly funded research to become freely and sustainably available, as much as possible, for reuse by other researchers. Furthermore, NWO wants to increase the awareness among researchers about the importance of responsible data management. Proposals should therefore satisfy the data management protocol of NWO. This protocol consists of two steps:

1. Data management section
The data management section is part of the research proposal. Researchers should answer four questions about data management within their intended research project (see http://www.nwo.nl/datamanagement for further information). They will therefore be asked before the start of the research to think about how the data collected will be ordered and categorised such that it can be made freely available. This often means that measures will need to be taken when the data are produced and analysed to make its later storage and dissemination possible. Researchers are free to state which research data they consider relevant for storage and reuse.

2. Data management plan
After a proposal has been awarded funding, the researcher should elaborate the data management *section* into a data management *plan*. That plan must be submitted to NWO via ISAAC within four months of the proposal being awarded funding. NWO will approve the plan as quickly as possible. Approval of the data management plan by NWO is a condition for the grant being disbursed. The plan can be adjusted during the research.

Further information about the data management protocol of NWO and the form to be used can be found at:
http://www.nwo.nl/datamanagement.http://www.nwo.nl/datamanagement

Nagoya Protocol

The Nagoya Protocol became effective on 12 October 2014 and ensures an honest and reasonable distribution of benefits emerging from the use of genetic resources (Access and Benefit Sharing; ABS). Researchers who make use of genetic sources from the Netherlands or abroad for their research should familiarise themselves with the Nagoya Protocol (www.absfocalpoint.nl). NWO assumes that researchers will take all necessary actions with respect to the Nagoya Protocol.

Transparency: registration and publication

To increase transparency, the project should be registered with a databank or repository. During the registration prior to the start of the study the researchers will state what they will register and upload (research protocol, data management plan and data analysis plan) and they should substantiate this. After the completion of the study the logbook of the data collection (lab journal), the datasets, the data analysis (syntaxes and analysis files), and all outcomes will be uploaded. These data will be made accessible to other researchers and preferably be made publicly available. If there are reasons for not making the data publicly accessible then the applicants need to justify this choice in their proposal.

Researchers will explore the possibilities for registering the research protocol with journals and for publishing the research protocol, as well as the possibilities for publishing the research results and data from the research. Researchers should include a dissemination plan in their proposal in which they also describe how they will disseminate the results from the research within their own (sub)discipline(s). In this the researchers should also state which reporting guidelines they will follow. Where animal experiments form part of the proposed research then the ARRIVE guidelines must be adhered to.

How the registration takes place differs per field and discipline. Researchers are requested to act in accordance with the most recent and most progressive developments in the discipline concerned and to demonstrate this in their proposal.

At the end of the programme NWO will organise a scientific congress. Researchers will present their experiences, with a strong focus on the methodology and the practical aspects of replicating research.

3.6 Submitting an application

An application can only be submitted to NWO via the online application system ISAAC. Applications not submitted via ISAAC will not be taken into consideration.

A main applicant must submit her/his application via her/his own ISAAC account. If the main applicant does not have an ISAAC account yet, then this should be created at least one day before the application is submitted to ensure that any registration problems can be resolved on time. If the main applicant already has an NWO account, then she/he does not need to create a new account to submit an application.

When you submit your application to ISAAC you will also need to enter additional details online. You should therefore start submitting your application at least one day before the deadline of this call for proposals. Applications submitted after the deadline will not be taken into consideration.

For technical questions please contact the ISAAC helpdesk, see Section 5.2.1.

4 Assessment procedure

4.1 Procedure

The first step in the assessment procedure is to determine the admissibility of the application. This is done using the conditions stated in Chapter 3 of this call for proposals.

The NWO Code of Conduct on Conflicts of Interest applies to all persons and NWO staff involved in the assessment and/or decision-making process.

Once the admissibility has been checked by ZonMw and NWO Social Sciences, the proposals will be submitted to two external experts for review: one expert in the subject of the proposal and one methodological expert. The research expert will be asked to respond to the assessment questions about the cornerstone quality of the research be replicated and the assessment questions that are concerned with the research aspects of the proposal (is it a proposal that will yield a worthwhile replication, quality of the applicants, et cetera). The methodological expert will be asked to consider the methodological aspects of the proposal. Both reports will be submitted for a rebuttal to the main applicant. The selection committee will consist of methodological and statistical experts from the two fields, and will prioritise the proposals based on the proposal, the referees' reports and the rebuttal. The assessment committee will formulate the funding recommendation to the accredited board within NWO, who then takes the decision.[7]

Option for preselection:
Preselection will only take place if more than sixty proposals are received (in principle four times as many proposals as the expected number of proposals to be awarded funding). If this criterion is not satisfied then all proposals will be sent to the referees without preselection. If a preselection is carried out then the composition of the selection committee for this will be expanded: in addition to a core committee of methodological/statistical experts the committee will be enlarged to include ad hoc members who will assess the cornerstone value of the proposals.

The assessment in the preselection will be based on some of the assessment criteria – see below. Those criteria are: Criterion 1: justification cornerstone and relevance of the application, and Criterion 3: availability of data needed. During the preselection the committee will assess all proposals on a comparative basis and will prioritise these according to their chances of funding without making use of external referees. The candidates with the least chance will be informed that the committee does not intend to select their proposals for further consideration. If candidates have a valid reason to challenge the assessment of the committee then they can send a motivated response to the office. Following the response the committee can eventually still decide to select a proposal. If the proposal is not selected then the candidate will receive a formal rejection decision concerning the proposal.

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[7] In 2017, NWO will have a new governance structure with a central Executive Board and four domain boards (http://www.nwo.nl/en/news-and-events/news/2015/contours-new-nwo-announced.html). More details as to what the “accredited board” for this funding instrument is will be published in due course on the NWO Funding page for this call.

If the interest for the programme during the first round proves to be particularly large then a preproposal procedure for later rounds will be considered.

Qualifications
NWO gives all full proposals a qualification. The applicant is informed of this qualification when the decision about whether or not to award funding is announced.

Only proposals that receive at least the qualification excellent/very good/good will be eligible for funding.

For further information about the qualifications see www.nwo.nl/qualifications.

The allocation of funding between ZonMw and NWO Social Sciences will take place according to the ratio of proposals from both divisions that are identified as fundable so that the proposals awarded funding are a reflection of the proposals of good quality submitted.

Programme committee
The research-specific guidance of this pilot programme largely rests with subject experts in the area of replication research. To this end, NWO has appointed a programme committee that contains experts from the field of replication research. The programme committee will meet about twice per year to discuss the programming, the progress, the latest developments, bottlenecks and any interim adjustments needed for the pilot programme. The programme committee has not role in the assessment of the proposals. The programme committee will advise the boards of ZonMw and NWO Social Sciences/the ZonMw and NWO Social Sciences and Humanities domains and the Governing Board / Executive Board of NWO.[8]

Indicative timeline

The indicative timeline is as follows:

12 January 2017	Deadline submission proposals
January - April 2017	Consultation referees
May 2017	Obtaining rebuttal from applicants. Researchers will be given a week to give a response
June 2017	First meeting selection committee
July 2017	Decision Executive Board NWO
July 2017	NWO informs applicants about the decision

4.2 Criteria

1. Justification cornerstone and relevance of replication
   – Does the research that will be replicated form a cornerstone in the sense that important policy decisions have been or will be taken or because the research has or will have major theoretical consequences? Do the applicants provide convincing arguments about why this research in particular should be repeated?

[8] Dependent on the moment in the transition process of NWO and ZonMw.

- Does the replication have any methodological and/or subject-specific added value?
- Has the research been replicated in the past? If so, is the argumentation of the researchers as to why additional replication is needed convincing?

2. Exactness and feasibility of the replication
   - Is the proposed research a replication that is as precise as possible? If not, then are the points where the replication research deviates from the original study convincingly justified? If the applicants propose a specific improvement of sample size, for example, then are the reasons for this and the realisation of this sufficiently supported?
   - Is a justification of the sample size included in the proposal? Is it clear from this that the sample size is large enough? Have the underlying assumptions been sufficiently supported?

3. Availability necessary data
   - Is the required information available to carry out the application: for Type 1 research: is the dataset and the analysis plan available, and for Type 2 research: is the protocol available?
   - If applicable, do the researchers convincingly describe how they will deal with missing information?

4. Methodology, registration, publication, knowledge utilisation
   - Does the action plan proposed enable the researchers to draw a clear conclusion about the reproducibility of the original research?
   - Is there a clear plan for the registration of the research, publication of the results and the registration of the data, data analysis, protocols and other relevant details about the research? Is the study in line with the most recent and most progressive developments in the discipline?
   - Is there a concrete plan for dissemination? Is this realistic?
   - Does the plan miss out opportunities?

5. Quality of the applicants
   - Are the researchers capable of carrying out the proposed research?
   - Do the researchers possess the right subject-specific and methodological knowledge and experience required for the proposed research?

6. Budget
   - Is the budget requested reasonable for the realisation of the proposed research (value for money)?
   - Has the budget been allocated across personnel and material costs in such a way that the research can be carried out properly?

7. Relationship with the original researchers
   - Is the relationship with the original researchers clearly described?
   - Is there any form of involvement between the applicant and the original researchers?

In assessing the proposals, a 9 point scale will be used, on which 1 represents the highest/best score, and 9 the lowest/worst. All criteria will be scored (and in case of a preselection, a subset of the criteria).
On the basis of the scores and overall weighted average score will be calculated. This overall average score constitutes the final score. The final score will determine the position in the ranking. In calculating the final scores, the different weights allocated to the criteria will be taken into account. Criteria 1 to 3 contribute to the final score for 20% each, criteria 4 to 7 for 10% each.

5 Contact details and other information

5.1 Contact

5.1.1 Specific questions

For specific questions about Replication studies and this call for proposals please contact:

- Carlien Hillebrink, +[redacted], c.hillebrink@nwo.nl mailto:c.hillebrink@nwo.nl
- Guillaume Macor, +[redacted], macor@zonmw.nl mailto:macor@zonmw.nl

5.1.2 Technical questions about the electronic application system ISAAC

For technical questions about the use of ISAAC please contact the ISAAC helpdesk. Please read the manual first before consulting the helpdesk. The ISAAC helpdesk can be contacted from Monday to Friday between 10:00 and 17:00 hours CET on +31 (0)20 346 71 79. However, you can also submit your question by e-mail to isaac.helpdesk@nwo.nl. You will then receive an answer within two working days.

5.2 Other information

After the completion of the research projects, the programme committee will evaluate the outcomes of the pilot in order to formulate recommendations for NWO. This evaluation will concern the outcomes of the research funded, such as publications, preregistration, accessibility of data, and additional data about the research.

At the end of the programme a conference will take place to present the results of the programme. Researchers funded by the programme will present their experiences with carrying out their replication research and make a statement about the outcome of their replication research.

Published by:
Netherlands Organisation
for Scientific Research

Visiting address:
Laan van Nieuw Oost-Indië 300
2593 CE The Hague
The Netherlands

September 2016

Netherlands Organisation for Scientific Research

Homeland Security
Science and Technology

Press Release

June 7, 2016
Contact: DHS S&T Press Office at (202) 254-2385

DHS ANNOUNCES $40M FUNDING OPPORTUNITY FOR NEW CRIMINAL INVESTIGATIONS CENTER OF EXCELLENCE

WASHINGTON - The Department of Homeland Security (DHS), Science and Technology Directorate (S&T), today announced a $40M funding opportunity for an institution to lead a new DHS Center of Excellence (COE) for Criminal Investigations and Network Analysis. DHS S&T is additionally searching for potential partners to work with the lead institution in support of the Center's activities.

These two related funding opportunities, posted at www.grants.gov, are open to receive proposals from accredited U.S. colleges and universities. The deadline for submitting proposals is September 1, 2016. DHS intends to fund this new COE for 10 years for a total of approximately $40 million through a cooperative agreement.

This new COE will conduct end user-focused research to enhance investigation strategies of transnational criminal organizations' (TCO) activities and other homeland security-related crimes. The overarching goal of the Center will be to develop methods, tools, knowledge products, and technology-based solutions for agents, officers and investigators to better predict, thwart and prosecute these crimes.

DHS is soliciting proposals from multi-disciplinary research teams that have research experience and concentration in criminal investigations and network analysis. The research teams will work closely with DHS and other criminal investigators to develop successful innovations to dismantle TCOs. The teams will need to cover a variety of academic disciplines including criminology, engineering, and mathematics.

The S&T COEs are university consortia that work closely with DHS operating components to conduct research, develop and mission-relevant science and technology, and educate the next generation of homeland security technical experts. Each COE is led by a U.S. college or university and has multiple partners from universities, industry, DHS, federally funded research and development centers, and other federal state and local agencies.

The notice of funding opportunities for the Center for Criminal Investigations lead institution and partner institution are available at grants.gov.

For additional information about the DHS COEs, visit DHS S&T Centers of Excellence. DHS will conduct a webinar for interested applicants available at Informational Webinar on June 21, 2016 at 3 p.m. EDT.

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Giang Tran

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University of California, Los Angeles
✉ [redacted]
www.math.ucla.edu/ giangtran/

Research Interests

Computational Methods for PDEs, Image and Signal Processing, Medical Imaging, Inverse Problems, Scientific Computing, and Convex Optimization.

Education

Currently **Ph.D. Candidate in Mathematics**, *University of California, Los Angeles*.
Advisor: Stanley Osher
Thesis: Sparse-Inducing Methods in Imaging Sciences, Applied Harmonic Analysis, and PDEs.

2011 **M.A. in Mathematics**, *University of California, Los Angeles*.

2009 **M.S. in Mathematics**, *University of Strasbourg*, Strasbourg, France.

2006 **B.S. in Mathematics**, *Hanoi National University of Education*, Hanoi, Vietnam.

Honors and Awards

2014–2015 Beckenbach Dissertation Year Fellowship Award, UCLA.

2014 SIAM Student Travel Award.

2009–2014 Vietnam Education Foundation Fellow, Vietnam.

2004, 2005 Odon Vallet Scholarship, Vietnam.

Publications & Preprints

- **G. Tran**, H. Schaeffer, W. M. Feldman, and S. Osher. An L^1 Penalty Method for General Obstacle Problems. *SIAM Journal on Applied Mathematics*, to appear.
- R. Caflisch, S. Osher, H. Schaeffer, and **G. Tran**. PDEs with Compressed Solutions. *Communications in Mathematical Sciences*, to appear.
- D. Zosso, **G. Tran**, and S. Osher. Non-local Retinex - A Unifying Framework and Beyond. *SIAM Journal on Imaging Sciences*, to appear.
- J. Gilles, **G. Tran**, and S. Osher. 2D Empirical Transforms. Wavelets, Ridgelets and Curvelets Revisited. *SIAM Journal on Imaging Sciences*, 7(1): 157–186, 2014.
- **G. Tran** and Y. Shi. Adaptively Constrained Convex Optimization for Accurate Fiber Orientation Estimation with High Order Spherical Harmonics. *MICCAI*, 485–492, 2013.
- D. Zosso, **G. Tran**, and S. Osher. A Unifying Retinex Model Based on Non-local Differential Operators. *S&T / SPIE Electronic Imaging: Computational Imaging XI, San Francisco, USA*, 2013.
- **G. Tran** and Y. Shi. Fiber Orientation and Compartment Parameter Estimation from Multi-Shell Diffusion Imaging. *Submitted to IEEE Transactions on Medical Imaging*, 2014.
- J.C. Thomas, J.J. Schwartz, J.N. Hohman, S.A. Claridge, H.S. Auluck, A.C. Serino, A.M. Spokoyny, **G. Tran**, K.F. Kelly, C.A. Mirkin, J. Gilles, S.J. Osher, and P.S. Weiss. Defect-Tolerant Aligned Dipoles within Two-Dimensional Plastic Lattices. *Submitted to ACS Nano*, 2015.
- L.J. Larsson, G. Morin, A. Begault, R. Chaine, J. Abiva, E. Hubert, M. Hurdal, M. Li, B. Paniagua, **G. Tran**, and M-P. Cani. Identifying Perceptually Salient Features on 2D Shapes. *Submitted to Research in Shape Analysis*, Springer, 2014.

Research Experience

University of California, Los Angeles

2012–Present **Graduate Research Assistant**.
- Derived numerical solvers for partial differential equations using information science methods involving sparsity.
- Designed a new parameterless model for learning intrinsic features from images (Empirical Wavelet Transform).
- Proposed a unifying retinex model for image decomposition with applications in shadow detection, contrast enhancement, and nonuniform illumination correction.

2010–2012 **Graduate Teaching Assistant**.
- Conducted weekly discussion sections for 30 students in 5 math courses and an intermediate C++ programming class.
- Responsible for grading exams, holding office hours, and running general help sessions.

Collaborative Projects

2014–Present **California NanoSystem Institute (CNSI)**.
- Created a novel image analysis method to detect changes in dipole alignment based on a local maxima and block-matching algorithm, which allows the discovery of the self-assembly of carboranethiol monolayers.

2012–2013 **Laboratory of Neuro Imaging (LONI)**.
- Developed a new method for the analysis of HARDI and multishell diffusion imaging data for fiber orientation distribution reconstruction by solving an adaptively constrained optimization problem.

Talks

Mar. 2015 SIAM Conference on Computational Science and Engineering, Salt Lake City, Utah.

Aug. 2014 ICES Seminar, University of Texas, Austin.

Jun. 2014 Level Set Collective, University of California, Los Angeles.

Aug. 2013 Women in Shape Modeling (WiSH) Workshop, IPAM, University of California, Los Angeles.

Mar. 2013 Graduate Student Outreach Seminar, University of California, Los Angeles.

Jul. 2012 Level Set Collective, University of California, Los Angeles.

Teaching Experience

2010–2012 & Summer 2014 **GraduateTeaching Assistant**, *University of California, Los Angeles*.
- PIC 10B, Intermediate Programming
- Math 33A, Linear Algebra and Applications
- Math 33B, Differential Equations
- Math 32A,Calculus of Several Variables
- Math 31A, Differential and Integral Calculus
- Math 3A, Calculus for Life Sciences Students

Service and Academic Outreach

- Reviewed articles for: *SIAM Multiscale Modeling and Simulation, IEEE Transactions on Image Processing, Science Direct Computer and Geosciences*.
- UCLA Department of Mathematics First Year Graduate Mentor, 2014–Present
- UCLA Alumni Day Mathematics Outreach, Spring 2014

LAPD Project:

Change-point Detection for Police Body-Worn Video

Industry Sponsor: Commander Sean Malinowski (LAPD Chief of Staff); Ms. Maggie Goodrich (LAPD CIO), Sgt. Javier Macias, Sgt. Dan Gomez, Mr. Arnold Suzukamo (LAPD-IT Bureau).

Academic Mentor:

Academic Supervisors: Jeff Brantingham, UCLA Anthropology; Dr. Craig Uchida, Justice & Security Strategies

Introduction

Body-worn video (BWV) or on-body cameras provide a novel means to collect very fine-information about police-public interactions. The general use model requires officers to initiate recording of video whenever there is an encounter with a member of the public. During such interactions, BWV is recorded in real-time. Recording is terminated at the officer's discretion. BWV is not streamed or reviewed in real-time, but rather is uploaded to a secure cloud storage system at the end of an officer's shift.

BWV is designed to provide another line of evidence for the actions of individuals and the outcomes of interactions between police and members of the public. BWV is therefore evidence relevant to legal proceedings like any other form of evidence collected by police. In a limited number studies, BWV has been shown to reduce the likelihood that situations escalate to a point requiring use of force.

There are considerable challenges facing wide-spread use of BWV. Even small scale deployments are expected to lead to massive volumes of video data that will quickly outstrip the ability of law enforcement agencies to analyze. The resulting fallback position will be to review BWV footage only when it corresponds to adverse outcomes (e.g., use of force). Most video will go unused. Many of the potential benefits of BWV may therefore go unrealized.

The 2016 LAPD-RIPS Project

The 2016 RIPS-LAPD team will work to develop change-point detection methods for use with BWV. Change point detection represents a general class of mathematical problems that seek to identify significant shifts in the behavior of a temporal stochastic process. The process itself is often hidden and therefore changes in process can only be observed indirectly. For example, you might be interested in detecting whether an individual's disposition has changed from friendly (or neutral) to antagonistic given observations of their outward actions such as body position, direction of motion, arm gestures. Detecting changes is a necessary precursor to taking actions. For example, detecting changes in the disposition of an individual captured on video could be used for automated labeling or tagging of the video and, in some cases, automated initiation of some action. A key challenge is to produce change point detection methods that minimize false alarm rates.

The project will rely on a range of data types BWV metadata (e.g., time stamps), BWV audio, and the video images themselves. Computations may be done in Matlab, Mathematica, C, C++, R, Java, or other appropriate computational language.

Key Milestones:

1. Statistical assessment of LAPD BWV and other associated data.
2. Develop change point detection methods.
3. Testing of efficacy of methods.
4. Present to LAPD.

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Los Angeles, CA 90095-7121
[redacted]; Fax (310) 825-4756

INVOICE NO: 201606

DATE: JULY 6, 2016

TO:

Los Angeles Police Department
Attention: Ms. Maggie Goodrich, CIO
Regarding: Review of Video Analytics

FOR:

RIPS 2016 Sponsorship

DESCRIPTION	AMOUNT
RESEARCH IN INDUSTRIAL PROJECTS FOR STUDENTS (RIPS) 2016 PROGRAM AFFILIATION FEE AND IPAM SUPPORT	**$4,000.00 USD**
TOTAL	**$4,000.00 USD**

Make check payable to: **UC Regents**

Remit to:
UCLA Institute for Pure & Applied Mathematics
460 Portola Plaza, Suite 1158
Los Angeles, CA 90095-7121
Attn: Tom Nykiel

If you have any questions concerning this invoice, contact **Tom Nykiel, tnykiel@ipam.ucla.edu, or (310) 267-5247**

Thank you

RIDE ALONG REQUEST & WAIVER

Person Requesting Greg Zanotti			Date of Request 6/30/2016
Address 460 Portola Plaza, Los Angeles CA 90095		Day Phone No. [redacted]	Evening Phone No. Same
Dates(s)/Time(s) Available for Ride Along July 5th through 8th		Organization or Affiliation of Person Requesting IPAM UCLA	
Purpose of Ride Along Research		Driver's License No. or Other Identification [redacted]	
Approved ☐ Denied ☐	Area Commanding Officer		Area

RELEASE AND INDEMNITY AGREEMENT

For and in consideration of permitting Greg Zanotti to ride in a Los Angeles Police vehicle as a "ride along" or responding to a call for police services in the City of Los Angeles, I hereby voluntarily release, discharge, waive and relinquish any and all actions or causes of action for personal injury, property damage or wrongful death occurring to me which arise from or are related to the performance of the LAPD officers activity or any activities incidental thereto wherever or however the same may occur and for whatever period said activities may continue, and I for myself and my heirs, executors, administrators or assigns hereby release, waive, discharge and relinquish any action or causes of action, aforesaid, which may hereafter arise for myself and for my estate, and agree that under no circumstances will I or my heirs, executors, administrators or assigns prosecute, present any claim for personal injury, property damage or wrongful death against the City of Los Angeles or any of its officers, agents, servants or employees (hereinafter "Indemnified Parties") for any of said causes of action, whether the same shall arise by the negligence of any of said persons, or otherwise.

IT IS THE INTENTION OF Greg Zanotti **BY THIS INSTRUMENT, TO EXEMPT AND RELIEVE THE INDEMNIFIED PARTIES FROM LIABILITY FOR PERSONAL INJURY, PROPERTY DAMAGE OR WRONGFUL DEATH CAUSED BY NEGLIGENCE.**

I, for myself and for my heirs, executors, administrators or assigns agree that in the event any claim for personal injury, property damage or wrongful death shall be prosecuted against the INDEMNIFIED PARTIES, I shall indemnify and save harmless the same INDEMNIFIED PARTIES from any and all claims or causes of action by whomever or wherever made or presented for personal injuries, property damage or wrongful death.

No oral representations, statements or inducement apart from this written agreement have been made.

I acknowledge that I have read the foregoing paragraphs, and have been fully and completely advised of the potential dangers incidental to riding in police vehicles as a "ride along" or responding to requests for police services and the police activities that occur at the location of the incident, and I am fully aware of the legal consequences of signing the within instrument and voluntarily do so.

Scheduled Ride Along:

Requestor To Complete This Section

Ride Along's Name (Print)	Ride Along's Signature	Date
Greg Zanotti	[signature]	6/30/2016

[redacted]

L.A.P.D. Supervisor To Complete This Section

Supervisor	Serial No.	Date of Ride Along	Times (Start/Stop)
Supervisor's Comments			

 The completed original form shall be attached to and retained with the watch commander's log.

RIDE ALONG REQUEST & WAIVER

Person Requesting David Madras			Date of Request 29 June 2016
Address [redacted]		Day Phone No. [redacted]	Evening Phone No.
Dates(s)/Time(s) Available for Ride Along July 5–8, all day		Organization or Affiliation of Person Requesting Institute for Pure + Applied Mathematics	
Purpose of Ride Along Research		Driver's License No. or Other Identification [redacted]	
Approved ☐ Denied ☐	Area Commanding Officer		Area

RELEASE AND INDEMNITY AGREEMENT

For and in consideration of permitting David Madras to ride in a Los Angeles Police vehicle as a "ride along" or responding to a call for police services in the City of Los Angeles, I hereby voluntarily release, discharge, waive and relinquish any and all actions or causes of action for personal injury, property damage or wrongful death occurring to me which arise from or are related to the performance of the LAPD officers activity or any activities incidental thereto wherever or however the same may occur and for whatever period said activities may continue, and I for myself and my heirs, executors, administrators or assigns hereby release, waive, discharge and relinquish any action or causes of action, aforesaid, which may hereafter arise for myself and for my estate, and agree that under no circumstances will I or my heirs, executors, administrators or assigns prosecute, present any claim for personal injury, property damage or wrongful death against the City of Los Angeles or any of its officers, agents, servants or employees (hereinafter "Indemnified Parties") for any of said causes of action, whether the same shall arise by the negligence of any of said persons, or otherwise.

IT IS THE INTENTION OF David Madras **BY THIS INSTRUMENT, TO EXEMPT AND RELIEVE THE INDEMNIFIED PARTIES FROM LIABILITY FOR PERSONAL INJURY, PROPERTY DAMAGE OR WRONGFUL DEATH CAUSED BY NEGLIGENCE.**

I, for myself and for my heirs, executors, administrators or assigns agree that in the event any claim for personal injury, property damage or wrongful death shall be prosecuted against the INDEMNIFIED PARTIES, I shall indemnify and save harmless the same INDEMNIFIED PARTIES from any and all claims or causes of action by whomever or wherever made or presented for personal injuries, property damage or wrongful death.

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Scheduled Ride Along:

Requestor To Complete This Section

Ride Along's Name (Print)	Ride Along's Signature	Date
David Madras	David Madras	29 June 2016

[redacted]

L.A.P.D. Supervisor To Complete This Section

Supervisor	Serial No.	Date of Ride Along	Times (Start/Stop)
Supervisor's Comments			

15.83.00 (11/96) **The completed original form shall be attached to and retained with the watch commander's log.**

RIDE ALONG REQUEST & WAIVER

Person Requesting			Date of Request
Ye Ye			06/29/2016
Address		Day Phone No	Evening Phone No
[redacted]			
Dates(s)/Time(s) Available for Ride Along		Organization or Affiliation of Person Requesting	
July 5th to 8th, all day		Institute for Pure and Applied Mathematics	
Purpose of Ride Along		Driver's License No. or Other Identification	
Research		[redacted]	
Approved ☐	Denied ☐	Area Commanding Officer	Area

RELEASE AND INDEMNITY AGREEMENT

For and in consideration of permitting Ye Ye to ride in a Los Angeles Police vehicle as a "ride along" or responding to a call for police services in the City of Los Angeles, I hereby voluntarily release, discharge, waive and relinquish any and all actions or causes of action for personal injury, property damage or wrongful death occurring to me which arise from or are related to the performance of the LAPD officers activity or any activities incidental thereto wherever or however the same may occur and for whatever period said activities may continue, and I for myself and my heirs, executors, administrators or assigns hereby release, waive, discharge and relinquish any action or causes of action, aforesaid, which may hereafter arise for myself and for my estate, and agree that under no circumstances will I or my heirs, executors, administrators or assigns prosecute, present any claim for personal injury, property damage or wrongful death against the City of Los Angeles or any of its officers, agents, servants or employees (hereinafter "Indemnified Parties") for any of said causes of action, whether the same shall arise by the negligence of any of said persons, or otherwise.

IT IS THE INTENTION OF Ye Ye BY THIS INSTRUMENT, TO EXEMPT AND RELIEVE THE INDEMNIFIED PARTIES FROM LIABILITY FOR PERSONAL INJURY, PROPERTY DAMAGE OR WRONGFUL DEATH CAUSED BY NEGLIGENCE.

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Scheduled Ride Along:

Requestor To Complete This Section

Ride Along's Name (Print)	Ride Along's Signature	Date
Ye Ye	Ye Ye	06/29/2016

[redacted]

L.A.P.D. Supervisor To Complete This Section

Supervisor	Serial No.	Date of Ride Along	Times (Start/Stop)
Supervisor's Comments			

 The completed original form shall be attached to and retained with the watch commander's log.

RIDE ALONG REQUEST & WAIVER

<table>
<tr><td colspan="3">Person Requesting
Stephanie Allen</td><td colspan="2">Date of Request
6/29/2016</td></tr>
<tr><td colspan="3">Address
460 Portola Plaza</td><td>Day Phone No. [redacted]</td><td>Evening Phone No.</td></tr>
<tr><td colspan="3">Dates(s)/Time(s) Available for Ride Along
July 5th – 8th All day</td><td colspan="2">Organization or Affiliation of Person Requesting
Institute for Pure and Applied Mathematics</td></tr>
<tr><td colspan="3">Purpose of Ride Along
Research</td><td colspan="2">Driver's License No. or Other Identification
[redacted]</td></tr>
<tr><td>Approved ☐</td><td>Denied ☐</td><td colspan="2">Area Commanding Officer</td><td>Area</td></tr>
</table>

RELEASE AND INDEMNITY AGREEMENT

For and in consideration of permitting Stephanie Allen to ride in a Los Angeles Police vehicle as a "ride along" or responding to a call for police services in the City of Los Angeles, I hereby voluntarily release, discharge, waive and relinquish any and all actions or causes of action for personal injury, property damage or wrongful death occurring to me which arise from or are related to the performance of the LAPD officers activity or any activities incidental thereto wherever or however the same may occur and for whatever period said activities may continue, and I for myself and my heirs, executors, administrators or assigns hereby release, waive, discharge and relinquish any action or causes of action, aforesaid, which may hereafter arise for myself and for my estate, and agree that under no circumstances will I or my heirs, executors, administrators or assigns prosecute, present any claim for personal injury, property damage or wrongful death against the City of Los Angeles or any of its officers, agents, servants or employees (hereinafter "Indemnified Parties") for any of said causes of action, whether the same shall arise by the negligence of any of said persons, or otherwise.

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Scheduled Ride Along:

Requestor To Complete This Section

Ride Along's Name (Print)	Ride Along's Signature	Date
Stephanie Allen	Stephanie Allen	6/29/2016

[redacted]

L.A.P.D. Supervisor To Complete This Section

Supervisor	Serial No.	Date of Ride Along	Times (Start/Stop)
Supervisor's Comments			

15.83.00 (11/96) **The completed original form shall be attached to and retained with the watch commander's log.**

Change Point Detection Methods Applied to Body-Worn Video

Stephanie Allen, *SUNY Geneseo*
David Madras, *University of Toronto*
Ye Ye, *UCLA*
Greg Zanotti, *DePaul University*

Academic Mentor: Dr. Giang Tran
Consultant: Dr. Jeff Brantingham, UCLA
Industry Mentor: Sgt. Javier Macias, LAPD

July 21^{st}, 2016

Outline

LAPD & Body-Worn Video

- Third largest municipal police department in USA, employing 9,843 officers
- A leader in the effort to equip police officers with body-worn cameras

Body-worn Video (BWV)

Body-worn Video (BWV)

- Cameras worn on officers' chests used to record police-public interactions
  - Currently deployed to 1,200 officers; will be scaled up to 7,000
- **Benefits**:
  - Provides video record in the case of public disagreements
  - Shown to increase police professionalism
- **Challenge**:
  - Creates large volumes of data, necessitating the use of automatic data analysis

Problem Statement

- **Goal:** Create algorithms to detect change-points in body-worn video
  - This will greatly streamline the video review process

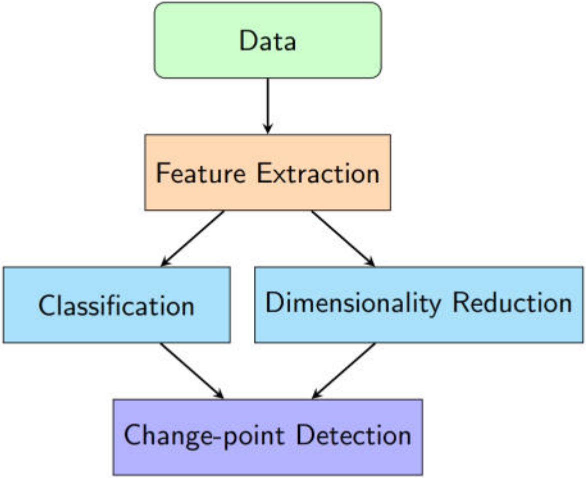
- For this project, we focus on a specific class of change-points: **the moment at which an officer exits or enters their car**

Images from www.youtube.com

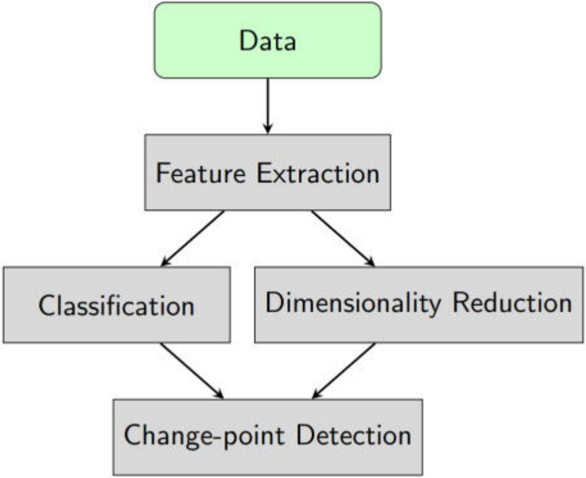
Video Change-point Detection - Related Work

- Three main approaches in the literature
  - Sequential comparison of **image differences**, with change points detected by thresholding schemes
  - Change-point detection methods run on time series of **image representations**
  - Combination of **spatiotemporal features** to generate video-specific change point detection methods
- To optimize time and accuracy constraints, we mainly consider the middle method

Overview of Methods



Overview of Methods - Data



Data Analysis - In Car Examples



Images from www.youtube.com

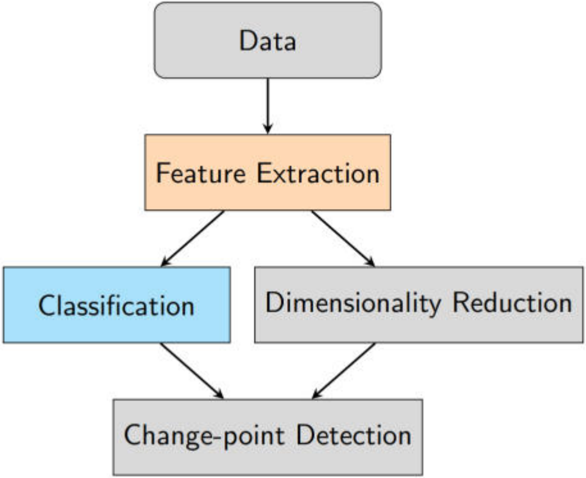
Data Analysis - Out of Car Examples

Images from www.youtube.com

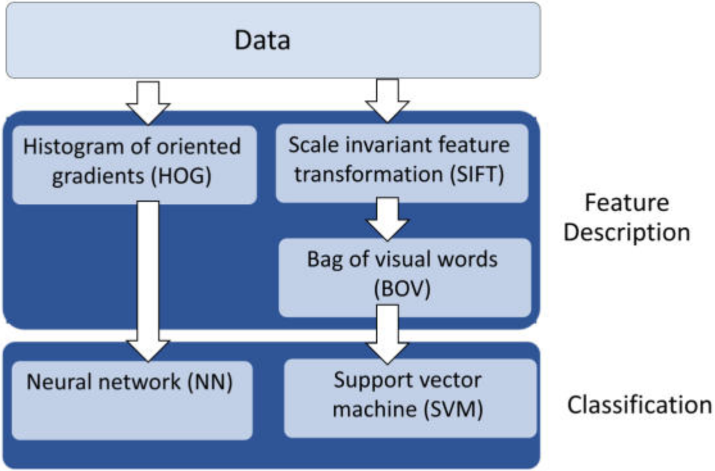
Data Analysis

- Sample of data taken from BWV pilot program (Dec '14-May '15)
- 691 videos, average length 9 minutes
- 421 contain either an entrance or exit from vehicle
- Of these:
  - 270 are taken from driver side
  - 274 are taken from a moving vehicle
  - 176 occur during nighttime

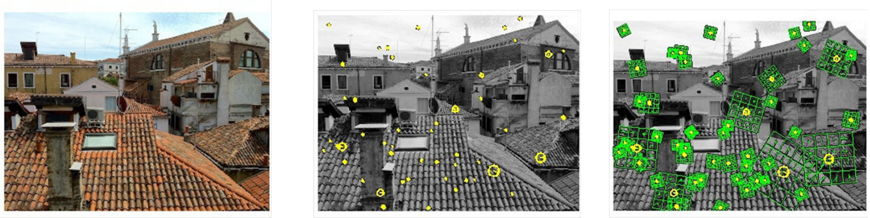
Overview of Methods - Feature Extraction & Classification

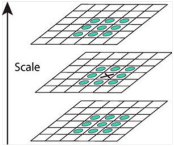


Overview of Methods - Feature Extraction & Classification



Keypoint Detection and Description – Scale-Invariant Feature Transformation (SIFT)





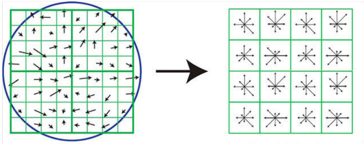


Image gradients

Keypoint descriptor

$$I = \begin{bmatrix} - & s_1^T & - \\ - & s_2^T & - \\ & \vdots & \\ & \vdots & \\ - & s_K^T & - \end{bmatrix}$$

SIFT matrix

Image Representation - Bag of Visual Words

- Sample 20% of images in the training set, extract SIFT descriptors
- Apply k-means clustering, where the centroid of each cluster is a 'visual word'

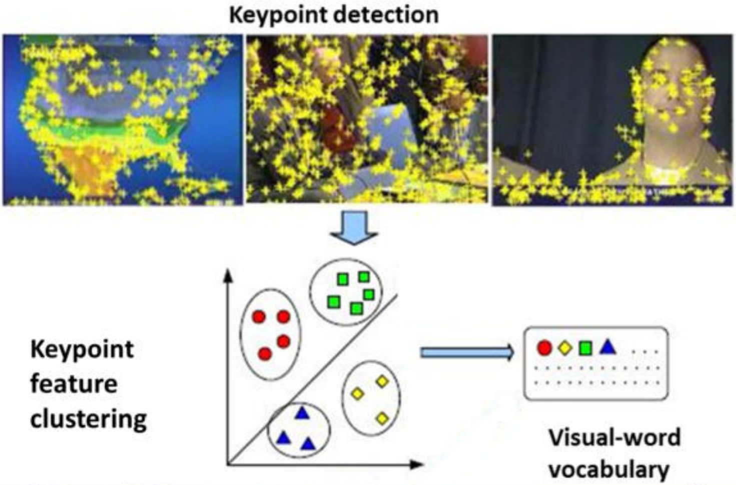
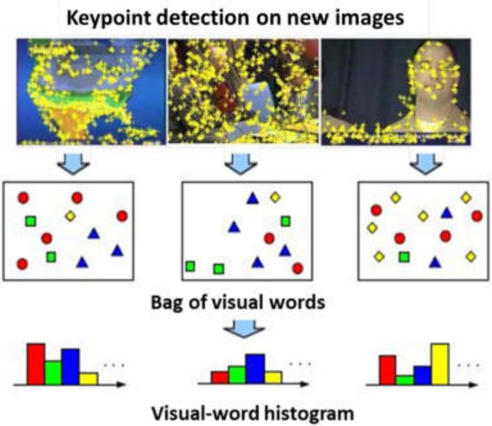
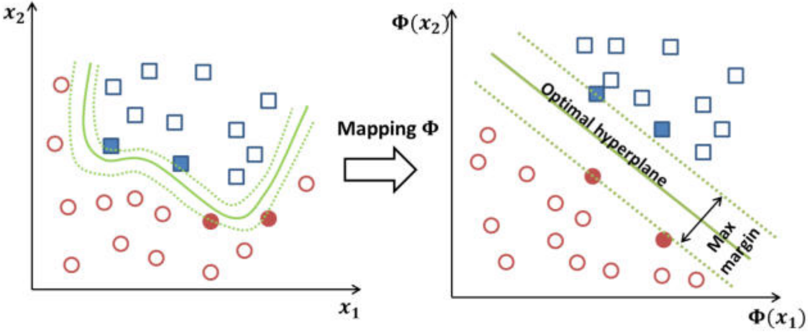


Image Representation - Bag of Visual Words

- For each new input image,
  - Assign its keypoint descriptors to nearest centroids
  - Count the number of occurrences for each centroid
  - Get a histogram representation

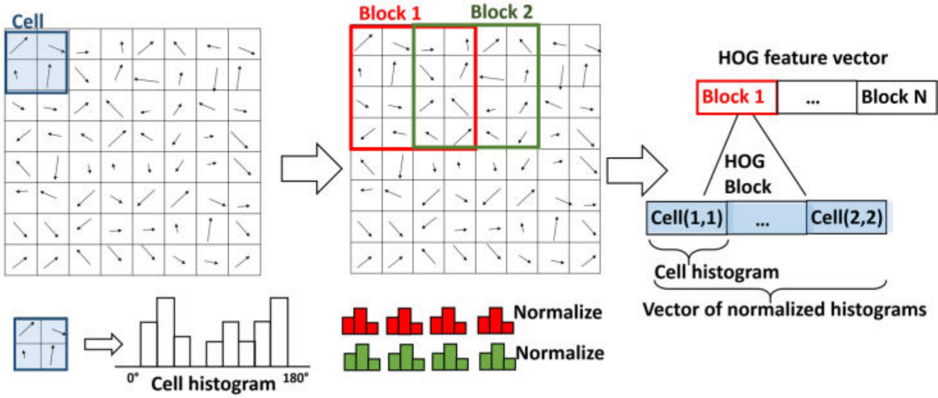


Classifier - Support Vector Machine (SVM)



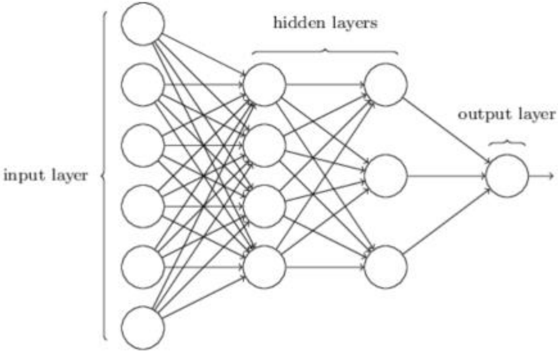
- Kernel function $k(x,y) = \Phi(x)^T\Phi(y) = \exp\left(-\frac{1}{2A}\sum_{d=1}^{D}\frac{(x_d-y_d)^2}{x_d+y_d}\right)$
- Maximize margin and obtain weight coefficients
- For a new image histogram x, $Score(x) = \sum_{n=1}^{N} a_n t_n k(x, x_n) + b$

Image Representation - Histogram of Oriented Gradients (HOG)



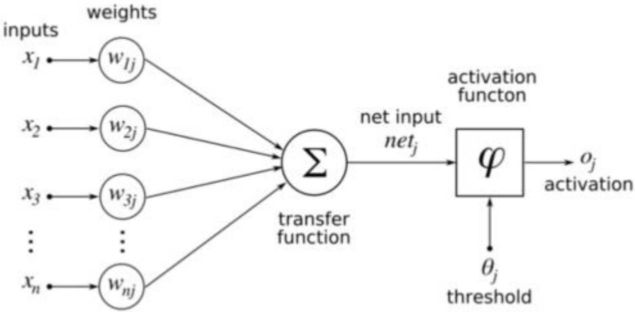
Classifier - Neural Network

- An artificial neural network jointly learns a **feature representation** and **discriminative classifier** over data
- Neurons are stacked on top of one another in **layers** to form complex, highly informative features
- At the last layer, outputs are normalized to form a **probability distribution** over classes



Neural Network Detail

- Generally, operations within a neuron consist of **multiplying inputs by weights**, passing them to a **transfer function**, and passing the result through a **nonlinear, thresholded 'activation' function**



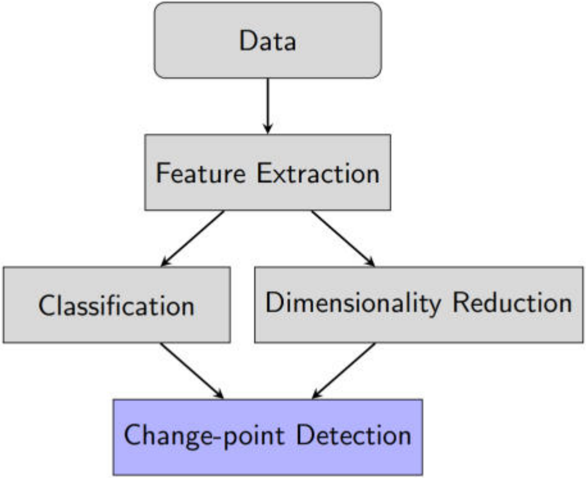
- Neural networks are **extensible**, and can be modified to handle image and time series data

Classification Results

- Change point detection depends on strong classification results
- Our dataset consists of $\sim 4,000$ labeled (in/out of car) frames
- Recall $:= \dfrac{|\text{PredictedOut} \cap \text{Out}|}{|\text{Out}|}$
- 1^{st} classifier: Frames $\Rightarrow$ SIFT vectors $\Rightarrow$ BOV $\Rightarrow$ SVM
- 2^{nd} classifier: Frames $\Rightarrow$ HOG vectors + pixel hist. $\Rightarrow$ NN

Classifier	Accuracy	Recall
SIFT-BOV-SVM	88%	88%
HOG+PIXH-NN	77%	82%

Overview of Methods - Change-point Detection



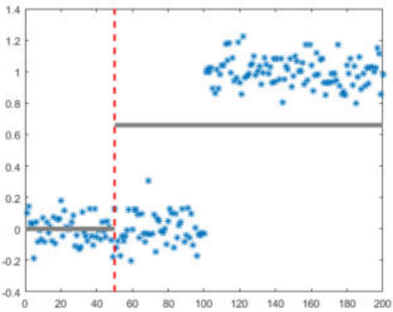
Change-point Methods Overview

- Given a time series $X_i, i = 1...n$
- We know there is some **change-point** c where the underlying distribution of the X_i changes
- That is:

$$X_i \sim F_1 \ \forall \ i \leq c, \ X_i \sim F_2 \ \forall \ i \ > c$$

  for some distributions $F_1 \neq F_2, c \in \{1...n\}$
- **Goal**: To find c
  - Evaluate some objective function for each $c \in \{1...n\}$
  - Find c to optimize this objective

Simple Change-point Detection - Example



- Minimize Mean Squared Error:

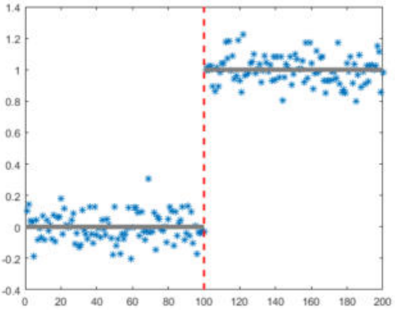
$$\sum_{i=1}^{m}\left(x_i-\bar{x}_1\right)^2+\sum_{i=m+1}^{n}\left(x_i-\bar{x}_2\right)^2$$

$$m \in \{1, 2, ..., n-1\}$$

$$\bar{x}_1 = \sum_{i=1}^{m} \frac{x_i}{m}$$

$$\bar{x}_2 = \sum_{i=m+1}^{n} \frac{x_i}{n-m}$$

Simple Change-point Detection - Example



- Minimize Mean Squared Error:

$$\sum_{i=1}^{m}\left(x_i - \bar{x}_1\right)^2 + \sum_{i=m+1}^{n}\left(x_i - \bar{x}_2\right)^2$$

$$m \in \{1, 2, ..., n-1\}$$

$$\bar{x}_1 = \sum_{i=1}^{m} \frac{x_i}{m}$$

$$\bar{x}_2 = \sum_{i=m+1}^{n} \frac{x_i}{n-m}$$

Kernel Density Estimation

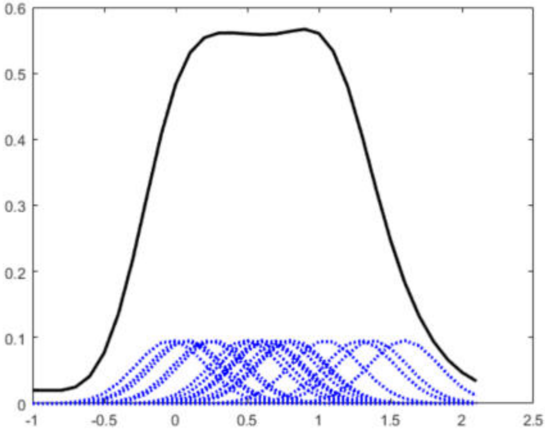
- Fits a continuous distribution to data whose true distribution is unknown
- Fits kernel functions to every point in the data set and then sums the functions to produce a fitted distribution

$$f(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)$$

$$K(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{|x|^2}{2}}$$

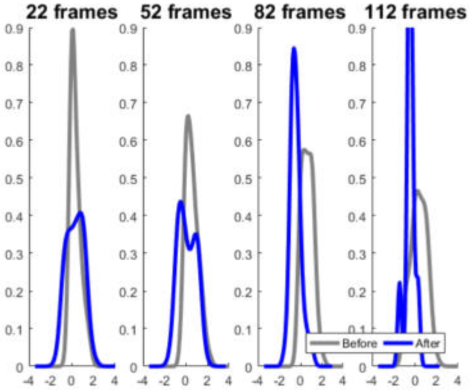
h = bandwidth, n = number of points in the data set

Density Estimation



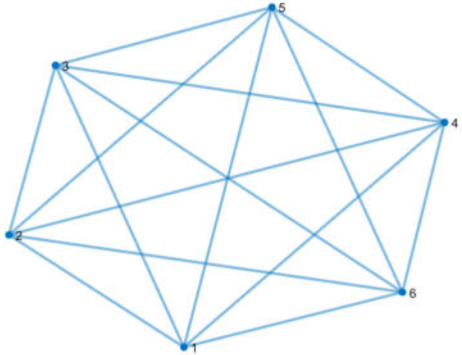
Density Estimation - Example

- CUSUM Density: $\max_{1 \leq n_c \leq k} \sum_{i=n_c}^{n} \ln\left(\frac{f_1(x_i)}{f_0(x_i)}\right), n_c \in \{1, 2, ..., n\}$



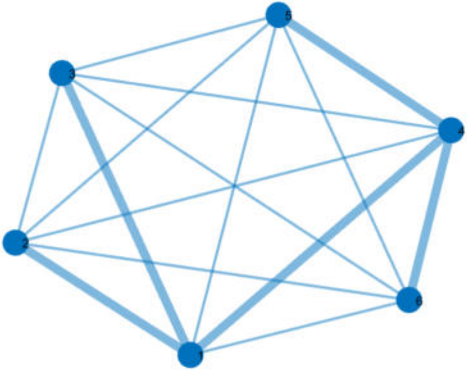
Graph-based Methods

- Given time series $X_i, i = 1...n$, create graph G where:
  - All X_i, X_j are nodes connected by an edge with weight $\|X_i - X_j\|$



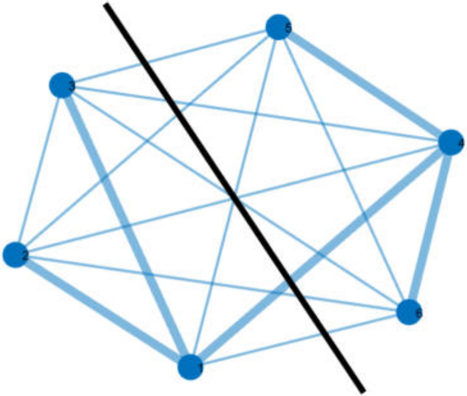
Graph-based Methods

- We can then use the minimum spanning tree (MST) of this graph to find structure in the data



Graph-based Methods

- Partition nodes while breaking relatively few edges in MST
  - Can normalize using mean and variance of edges cut w.r.t. partition size
- Non-parametric, generalizes easily to higher dimensions

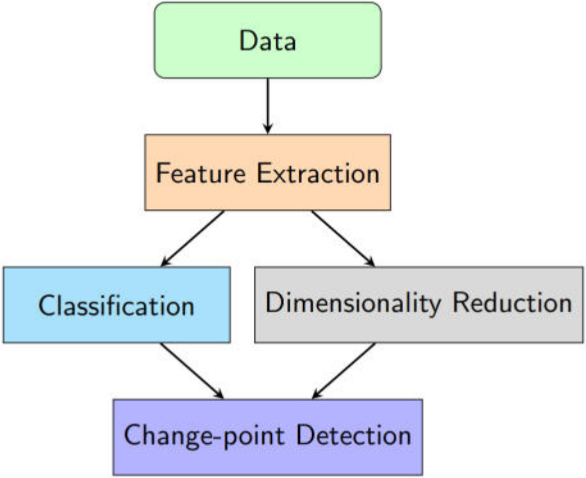


Change-point Detection Results

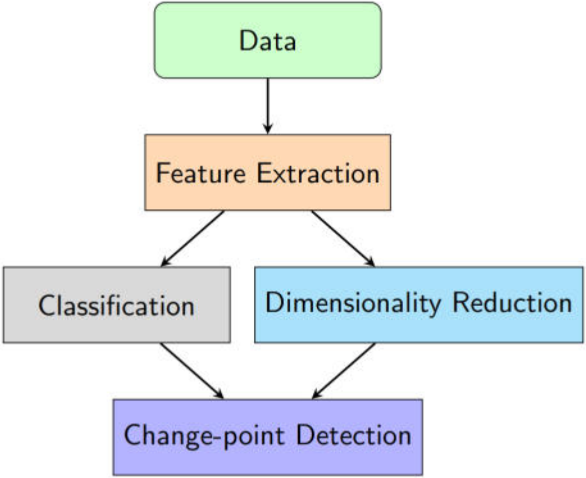
- Using 145 LAPD videos containing a car exit or entrance:
  - Clipped videos to smaller lengths (2-5 minutes)
  - Each clip contained exactly 1 change-point
  - 301 clips in total
- Our methods ran on a univariate series of SVM output scores

Method	**Within 2s**	**Within 5s**	**Within 10s**
MSE	46%	65%	74%
Graph	39%	57%	70%
CUDensity	34%	56%	65%

Overview of Methods - Univariate Data Workflow



Overview of Methods - Multivariate Data Workflow



Change-point Detection Result - Multivariate Data

- Also tested change-point detection methods on HOG and SIFT image representations (with dimensionality reduction)
- These representations were created in an **unsupervised** manner - meaning we didn't need to train a classifier with labeled data (i.e. frames labeled in/out of car)
- Due to the lack of need for labeled data, these methods are much more generalized

Method	Within 2s	Within 5s	Within 10s
MSE	23%	47%	60%
Leach	26%	45%	57%
Graph	17%	36%	47%

Conclusions and Progress

- Progress on project objectives
  - Annotated each video with change points
  - Conducted exploratory data analysis
  - Built and tuned classifiers to detect in car/out of car with 75-90% accuracy
  - Developed change point detection methods for univariate and multivariate data

Next Steps and Future Research

- Improve image representations
  - Use finetuned convolutional features
  - Improve spatial selection of bag-of-visual-words features
  - Use unsupervised representations for better generalization
- Investigate change-point detection methods further
  - Implement thresholds for test statistics
  - Investigate methods for high-dimensional multivariate time series
  - Investigate methods for online data
  - Exploit the spatiotemporal structure in the data

Questions?

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Research

Article submitted to journal

Subject Areas:
applied mathematics, behaviour, mathematical modeling

Keywords:
seasonal crime, stochastic modeling, SSA, human ecology

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Policing in a changing climate

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Most types of crime are known to exhibit seasonal oscillations, yet the annual variations in the amplitude of this seasonality and their causes are still uncertain. Using a large collection of data from the Houston and Los Angeles Metropolitan areas, we extract and study the seasonal variations in aggravated assault, break in and theft from vehicles, burglary, grand theft auto, rape, robbery, theft, and vandalism for many years from the raw daily data. Our approach allows us to see various long term and seasonal trends and aberrations in crime rates that have not been reported before. We then apply an ecologically motivated stochastic differential equation to reproduce the data. Our model relies only on social interaction terms, and not on any exigent factors, to reproduce both the seasonality, and the seasonal aberrations observed in our data set.

1. Introduction

Rising temperatures are inspiring various cities and nations to examine the expected results of global warming on social behavior, and generally the ability of mankind to thrive on a hotter planet. As an example Thriving in a Hotter LA, a UCLA sponsored program in response to the President's request for solving Grand Challenges, strives to pro-actively stem the negative effects of climate change through social change in Los Angeles. While there is evidence that large aberrations in temperature can lead to a measurable change in human hostility [1], the correlation between crime rates and seasonal temperature variations, believed to be important in the criminology literature [2], is poorly understood.

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Considering one of the most noticeable consequences of global warming is a shift in weather patterns, either locally warming or cooling, there is a need to understand how crime rates will change in response to the new weather patterns. Data collected from Los Angeles, controlled by the LAPD, and Houston [3] coupled with a stochastic model imply that the variations in crime's seasonal rates are strongly dependent on stochastic, and societal factors. The stochastic fluctuations are large compared to the dynamics and obfuscate the correlations between seasonal temperature fluctuations and seasonal crime rates. In some sense, the temperature dependence of crime's seasonal behavior, unlike those for large scale human conflict, are a higher order effect when compared to stochastic and sociological factors.

Crime rates change with the seasons. This well-known fact has been the subject of criminology research for over a century [4,5]. For example, every January burglary rates in Houston will be at a low, then during the summer they will peak. Though this is well known, the mechanism that produces this seasonality, the time of year that crime peaks, and whether all crimes display these oscillations is still debated [6–9]. These oscillations have implications in how police officers should be deployed, and how the success or failure of a police force in a particular district is measured [10]. Unfortunately the exact form of the oscillations is obscured by the nature of the data. First, crime in the United States has been in steady decline for the last few decades, and is at an exceptionally low level for most types of crime. Thus there is a very high level of noise compared to the average crime rate. This is one likely cause for the controversy in the seasonality of crime. For example, several studies have concluded rape is seasonal [2,10,11], while other studies find no strong evidence for a seasonal component [12]. Rape, however, is rarely reported and the number of daily cases is minimal. The decrease in crime can additionally obscure a seasonal peak or shift its location in time [13]. Our first goal is to separate the seasonal component from the long term trends in crime directly from the noisy data. Once the nonlinear trend is removed, we can see the variations in the seasonal amplitude from year to year. Once we have a seasonal component, we then apply an ecologically motivated stochastic differential equation (SDE) based on the Lotka–Volterra model for predator-prey relationships to reproduce the seasonal variations. From this, we draw the conclusion that stochastic noise of the order seen in the crime data overwhelms the dynamics in our simple SDE model and creates the same sort of annual variations that appear in the data. We then caution against trying to seek high order correlations between weather trends and the changes in the amplitude of these seasonal variations from year to year. The stochastic terms are strong enough such that they can easily change the underlying dynamics and overwhelm any actual weather or temperature dependence.

Considering the complexity of human behavior and the noisy crime data, correlating annual rises in crime with a single exogenous variable, such as temperature, is an optimistic oversimplification. Crime data has enough noise and variations that by looking at the right data set any desired correlation can be found. However, there is ample evidence that unusually large jumps in temperature, such as an unseasonably hot day, do lead to rises in human aggression [1]: this is related to temperatures above the normal average during a given era, rather than seasonal high temperatures that are gradual, expected, and adapted to by people every year. While we believe variations in crime rates will be effected by the weather, our goal is to show that variations in the amplitude of the seasonal oscillation in crime from year to year could arise solely from endogenous factors, stochasticity in the system, and large social catastrophes. The variations from the randomness are larger than those that would be induced by temperature alone. One clear example in the data is the dramatic rise in property crime rates and burglaries in the end of 2008 after the financial crisis. Our interest is in human behavioral response to these slow seasonal variations. For example, if unusually high average temperatures in one particular summer lead to unusually high aggravated assault rates in that summer and fall. We address this question in detail through a study of Los Angeles crime rates over a decade, as well as Houston crime rates over a three year period.

We compare the crime data to a minimalistic and ecologically motivated system of SDEs. Our goal is to show that a small amount of noise in these SDEs can produce the same annual variations in the amplitude of the seasonal component as is seen in the data. The SDEs serve as a model for human criminal behavior. The SDE system is based on the Lotka–Volterra equations [14,15], a standard predator-prey system that exhibits periodic behavior with the fewest possible species and that has been used in the criminology literature [16]. The random variations in our model are sufficient to explain the annual variations in the amplitude of the seasonal crime oscillation. While our model is simplistic, it helps illustrate that even small stochastic variations for an underlying system with periodic orbits can exhibit the same variability that is seen in the data even without external forcing. Specifically, no terms specifically related to changing weather patterns are needed to produce the aberrations in the data. This implies that seeking correlations with external factors may produce spurious results. Because of the low crime rate, temperature variations certainly are not the leading order effect in the data. The stochasticity of human behavior overwhelms the small effects from temperature fluctuations. Though an increase in violence and civil unrest is likely to occur once global temperatures adequately shift [1], the seasonal variations from changing weather patterns are unlikely to dominate yearly crime rates.

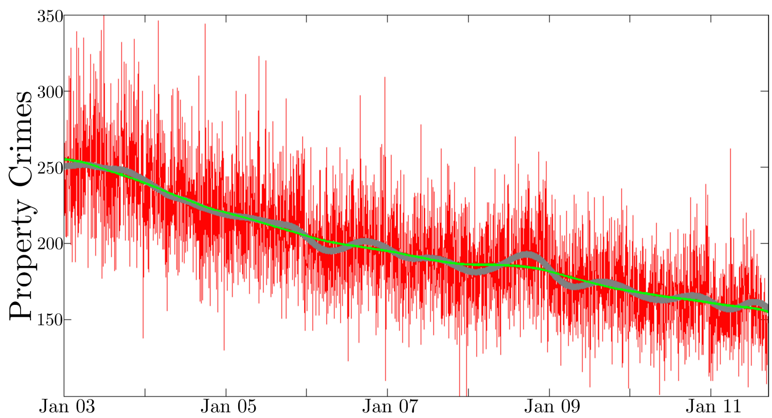

Figure 1. The daily aggregate property crime for Los Angeles is plotted in red. The gray curve is the SSA attained trend plus the seasonal term, and the green curve on top is the long term trend. Despite the relatively large number of daily crimes, the data is very noisy, and the seasonal variations are difficult to detect without applying some signal processing techniques. Throughout the rest of the paper, the plotted data will be smoothed with a moving window average after removing the trend to clarify and emphasize the seasonal oscillations in the later figures. Note that the SSA decomposition is always performed on the unsmoothed noisy data.

2. Extracting crime trends and seasonality

The raw crime data is exceedingly noisy. This noise completely obscures our ability to readily identify seasonal oscillations. Compounding the problem further, crime trends are falling in an inconsistent manner; over a single season, average rates can fall on the same order as the amplitude of the seasonal oscillations. There has been a long-term sustained reduction in crime [17,18] in the United States. This downward trend is obscured by the annual, or seasonal, oscillations in crime rates, the variations in crime by day of the week, and the stochasticity in crimes that occur from day to day. The total number of crimes on any given day is quite low. For example the total number of property crimes in Los Angeles over an eight year period never exceeds 350 events on a single day, and can vary by 100 events from day to day. Houston generally records less than ten rape cases a day. Thus there is a great deal of noise compared to the signal strength.

Extracting a seasonal component and long-term trend from such a signal is therefore non-trivial. Most studies rely on crime data binned into monthly totals over many years [8]. They

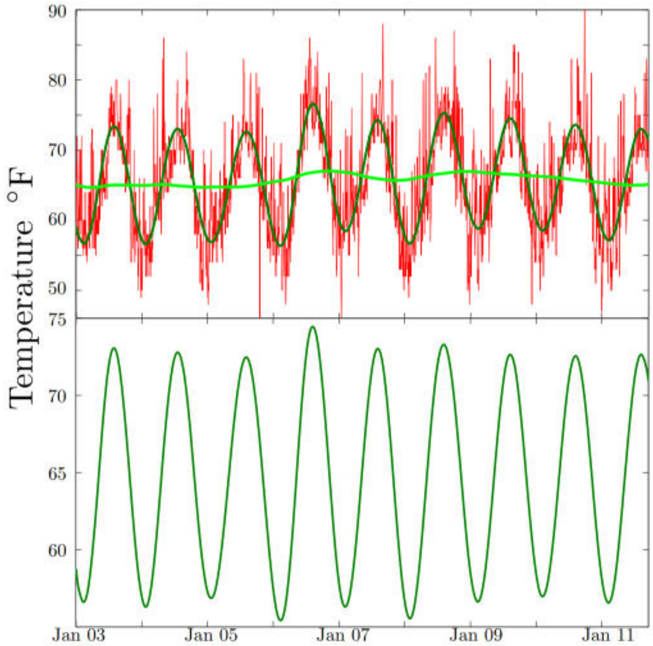

Figure 2. In the top panel, the daily average of high and low temperature for Los Angeles is plotted in red. The green curve is the SSA trend, and the dark grey curve is the seasonal component plus the trend. In the bottom panel, the seasonal component alone is shown. The temperature variations in Los Angeles are extremely regular, though the summer of 2006 does appear unusually warm. The aberrations in crime seasonality are far larger, and less consistent than the temperature variations.

then conclude that seasonality exists from consistent differences in the highest crime month to the lowest crime month across the entire data set. Our study necessitates directly extracting the seasonal variations and the long term general trends from the daily crime data. This enables a comparison between crime seasonality in Houston and Los Angeles, as well as a detailed study of the annual variations in the seasonal oscillations that is otherwise unfeasible from the monthly binned data.

Singular spectrum analysis (SSA), a nonparametric singular value decomposition (SVD) based technique, is used in meteorology to extract the long-term trends from noisy weather data. It also provides a natural decomposition of temporal data into components that vary on similar time scales [19]. SSA naturally separates time scales and allows us to differentiate between long term trends and the shorter term oscillations and noise in the crime data (figure 1). These techniques can also be used to forecast future states of noisy data sets [20]. We apply SSA to daily crime data for Houston and Los Angeles. The data consists of the number of crimes that occur each day over several years. It should be mentioned that crime is known to vary by day of the week, and certain crimes are more likely on weekends or weekdays. Though SSA will extract these changes, we consider them lower order oscillations for the current study as they vary on a far shorter time scale than we are interested in.

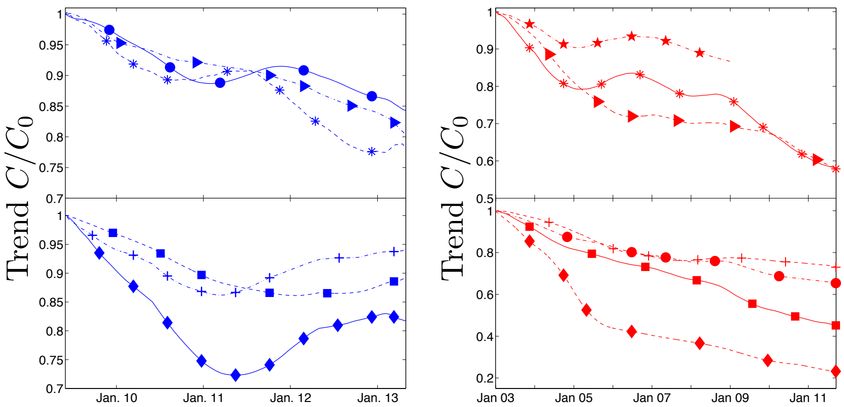

Figure 3. The long term crime trends $C(t)$, or first mode in the SSA decomposition, for Houston (blue on left) and Los Angeles (red on right). The data is normalized to be the fraction of the initial crime level for the first time point C_0. Top panel on left is aggravated assault (triangle), rape (asterisk), and burglary (circle). Top panel on right is break in and theft from vehicles (triangle), robbery (asterisk), and vandalism (star). On the bottom left is auto theft (+), theft (square), robbery (diamond). On bottom right is aggravated assault (diamond), burglary (circle), grand theft auto (square), and theft (+).

The first step in the SSA analysis involves creating a trajectory matrix. For a time series $X = (x_1, x_2, \dots, x_N)$ and a window length $L = 365$, we define the trajectory matrix as

$$\mathbf{X} = \begin{pmatrix} x_1 & x_2 & x_3 & \cdots & x_K \\ x_2 & x_3 & x_4 & \cdots & x_{K+1} \\ x_3 & x_4 & x_5 & \cdots & x_{K+2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_L & x_{L+1} & x_{L+2} & \cdots & x_N \end{pmatrix} \tag{2.1}$$

with $K = N - L + 1$. Then a singular value decomposition (SVD) is performed on the trajectory matrix, providing a decomposition $X = X_1 + \cdots + X_L$. Each of our modes then comes from averaging these matrices X_i along their anti-diagonal. The mode with the largest singular value always corresponds to the average crime trend. We then typically would look for any modes with an annual periodicity in the first twenty singular values and sum these to produce our seasonal component.

We emphasize that the most important term in our SSA decomposition is the trend, or first mode. Once this trend has been extracted, the data clearly exhibits seasonal oscillations once it has been smoothed with a moving window average. These same oscillations are not as clear without extracting the trend first. As is seen in figure 4, our seasonal component provides a reasonable smoothed approximation of the data but in many cases loses some of the structure of the annual oscillations.

In figure 3 the long term average crime trend from the SSA decomposition is plotted for Houston and Los Angeles. We see a general decrease in all types of crime in both cities, but there are several salient features of the data that are worth mentioning. First, crime decreases are not consistent in any sense. For every data set examined, the final level is lower than the initial level. However, this does not occur in a homogeneous fashion. Many crimes more recently seem on the rise in Houston. Second, the rate of decrease in Los Angeles seems to be slowing. After January 2006, the trend reduction appears comparatively small for all observed crimes. One possible cause is that crime is at a very low basal level, and it is hard to decrease it below this level. If this is the case, public funds applied towards lowering crime further will likely suffer from diminishing returns. Alternatively, police forces have not generally increased in size with respect

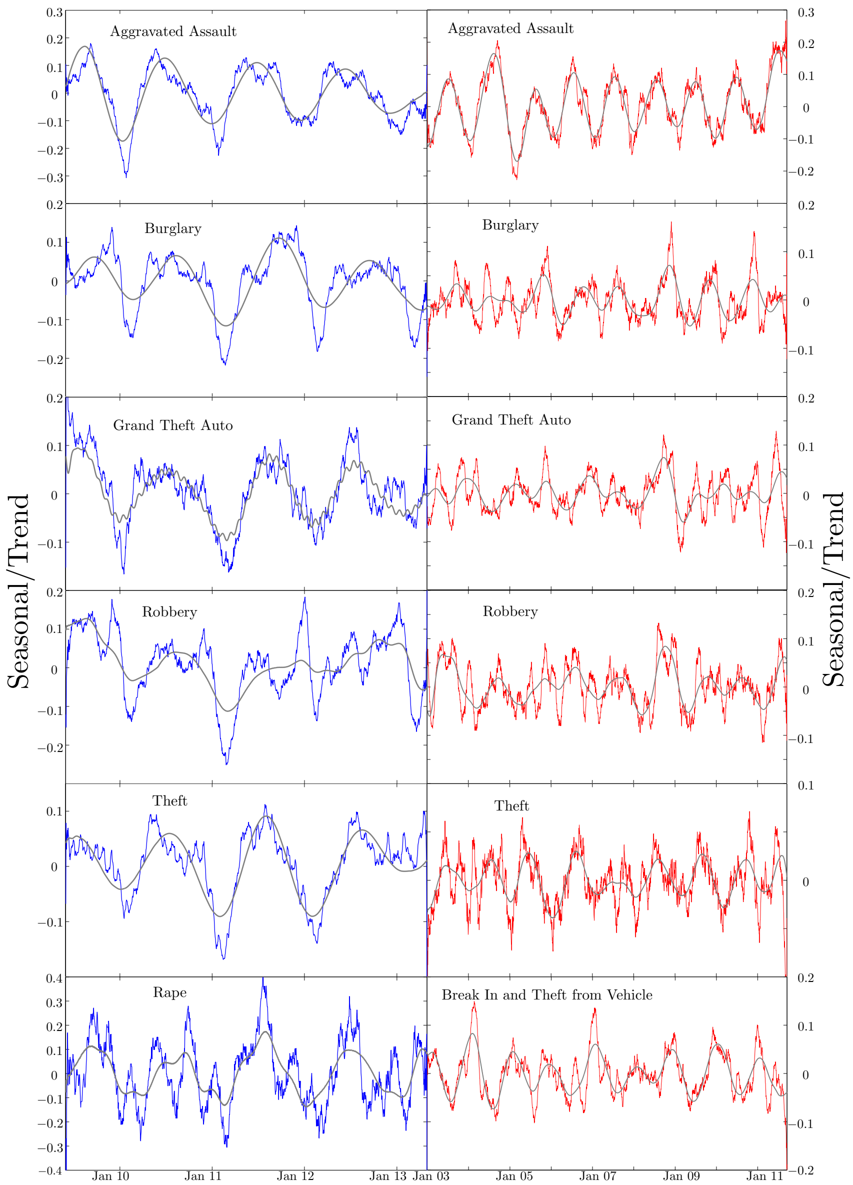

Figure 4. A comparison between the raw crime data and the SSA seasonal component (grey) for Houston (blue) and Los Angeles (red). The trend is subtracted from the data and then the data is smoothed using a moving window average. As the oscillations are related to the total amount of crime, the data and seasonal component have been divided by the trend pointwise in time to normalize the oscillations. Note that the seasonal oscillations are on the same order compared to the trend level of crime across all crime types. Even when the level of crime is low, a fairly consistent oscillation is seen. Note the large aberration in the Los Angeles data just after the 2008 crash. Such social catastrophes can override any seasonality and lead to dramatic changes in future crime rates.

to the population so it is likely difficult for the police to reduce the crime any lower without increased resources.

In figure 4, the seasonal components are compared to the data. Note that for the SSA derived seasonal components, we are generally keeping only the leading order modes in our reconstruction of the seasonal data. This dramatically smooths the data, but loses some of the higher order effects in the seasonal components. However once the data is flattened by removing the trend, the raw data smoothed with a moving window average clearly shows seasonal oscillations for comparison. We will eventually compare both this smoothed average from the raw data and the SSA derived seasonal components to the proposed SDE model. We see a seasonal oscillation across all of these data sets, though this can be a little deceptive. Rape in Houston appears to have a seasonal component, but this occurs at an incredibly low amplitude and is nearly impossible to see in the raw data. Figure 5 compares the extracted seasonal components from Los Angeles and Houston. It is clear from the figures that in some cases, such as aggravated assault and robbery, the seasonal amplitudes between the two cities are synchronized. Grand theft auto, burglary, and theft appear to have a different seasonality between the two cities. Grand theft auto in Los Angeles actually appears to have an oscillation on the order of half a year rather than annually. While Houston seems to have a fairly consistent peak around July for most crime types, the seasonal peaks for different crimes in Los Angeles vary significantly.

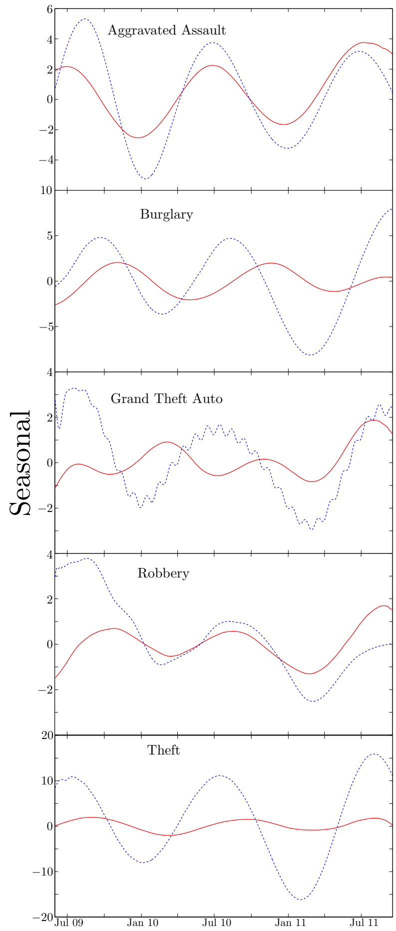

Figure 5. Comparison between the SSA derived seasonal component from Los Angeles (red) and Houston (blue).

3. An ecological model for seasonal crime rates

Criminal encounters have an analogous relationship to predator-prey interactions. Exploiting this analogy has led to great success in recent years. In fact, [21] has recommended that mathematicians exploit this analogy further by concentrating specifically on modeling crime occurrences rather than criminal behavior. The authors in [22] adapt a model for coyote territories from [23] to understand gang territories. Similarly, employing agent based models to criminals has led to a better understanding of gang rivalries [24] and hot spot formation for burglary [25–28]. Ecological models have also successfully deepened our understanding of gang activity and territorial boundaries [16]. In these studies, criminals are generally treated with the same mathematical formalism as predators.

The best known of these ecological models, the Lotka–Volterra predator-prey equations [14,15], exhibits periodically oscillating populations corresponding to a nonlinear center. In a nonlinear center, every possible initial condition leads to a periodic orbit, or in other words, to an oscillation similar to the seasonal oscillations in our crime data. The Lotka–Volterra equations are a two-component system of nonlinear, first-order equations. For a system of ordinary differential equations without external forcing, a two-component first order system is the simplest system that can exhibit periodic behavior and higher dimensional systems that exhibit periodic behavior can often be reduced to two-component systems on their center manifold. We use the Lotka-Volterra equations as the basis for our crime model because of their past appearances in the criminology literature and further note that they are a minimal ecological model that exhibits the requisite periodicity.

The analogy between this ecological model and crime is as follows. In a given time period, the predator population is the number of crimes that occur and the prey is the number of possible targets available. In any criminal event there is a victim and offender, and their interaction probability scales, according to standard mass action kinetics, like the product of the two populations. The multiplicative constants in our model β and δ account for the likelihood of losing possible victims after a criminal encounter and a crime being committed during the encounter, respectively. In the absence of targets, we assume the crime rate will decay to zero at rate $-\gamma$. Similarly, the number of available victims will grow in the absence of crime with rate α. In principle the number of available targets for victims is very large. However only a small fraction of them will occur in a suitable setting and display suitable characteristics to be victimized. For assault, rape, or robbery, the assailant only will encounter a limited number of suitable victims in a vulnerable location. Burglars are known to preferentially search a limited set of possible homes, generally within a block of previous successful burglary sites. In our model, the number of available targets, or prey animals, x is then generally kept small (on the order of 15). We note that this number must be estimated from sociological data, and cannot be directly measured from the daily crime data. The number of crimes that occur is then the predator variable y. In our analogy, victims disappear from the system after a crime occurs. When an area has recently hosted a number of crimes, people are far less likely to go out thus the number of possible victims will be decreased. Our model adds multiplicative noise, such as used in the derivation of the Black–Scholes equation for European Call options, onto the standard Lotka–Volterra equations:

$$\begin{aligned} dX_t &= X_t(\alpha - \beta Y_t)\,dt + \sigma_1 X_t\,dW_t, \qquad && X(0) = X_0 \\ dY_t &= -Y_t(\gamma - \delta X_t)\,dt + \sigma_2 Y_t\,dV_t, \qquad && Y(0) = Y_0. \end{aligned} \tag{3.1}$$

We note that this is in Itô form, with the standard interpretation that the system only has information about the past and not the future. This allows for modeling the random variations in the number of targets and crimes from day to day. The noise from the geometric Brownian motion is proportional to the total number of crimes and targets, and helps ensure positivity of the predator and prey populations. Positivity follows from the invariance of the X and Y axes under the SDE evolution, and continuity of sample paths. The dynamics of the deterministic Lotka-Volterra equations can be reduced to a one parameter family after non-dimensionalization. Using the change of variables $\tilde{X} = \delta X$, $\tilde{Y} = bY$, and $\tau = \alpha t$ we arrive at

$$\begin{aligned} \frac{\mathrm{d}\tilde{X}}{\mathrm{d}\tau} &= \tilde{X}(1 - \tilde{Y}) \\ \frac{\mathrm{d}\tilde{Y}}{\mathrm{d}\tau} &= -\tilde{\gamma}\tilde{Y}(1 - \tilde{X}) \end{aligned}$$

where our single parameter is $\tilde{\gamma} = \gamma/\alpha$.

In order to estimate the deterministic parameters, we first use least squares to fit the deterministic Lotka–Volterra equation to the seasonal component of the crime data as extracted from the SSA analysis. Our initial parameters for this minimization can be estimated as follows. The average crime rate $\bar{Y}$ determines the relation $\bar{Y} = \alpha/\beta$, and our estimate on average number of targets $\bar{X}$ (which we believe to be small and on the order of 15) determines $\bar{X} = \gamma/\delta$. We further reduce our parameters by assuming $\beta = \gamma$, or that a single crime will remove a single victim. Our periodicity should be on the order of a year, and we can estimate the time period by appealing to the linearization around the fixed point to find $T = 365 \approx 2\pi/\sqrt{\alpha\gamma}$. For the stochastic component, we fix $\sigma_1 = 0$ and only allow for stochastic jumps in the crime variable; these stochastic parameters could in principle be extracted using a maximum likelihood estimator. For the initial data, we assume the oscillations are approximately elliptical. This allows us to estimate where in the phase space of the deterministic system our initial data lies with respect to the oscillations in the crime Y variable.

In figure 6, a comparison between equation (3.1) and the smoothed experimental data can be seen for property crimes and aggravated assault in both Los Angeles and Houston. We see that the data can be reasonably reproduced with our stochastic model, including the large shift in annual amplitude for the seasonal component. Additionally, the target population remains relatively small, on the order of 10-30, rather than the hundreds or thousands, as was in line with our above interpretation. A typical run will produce noisy, periodic oscillations with varying amplitudes but will not reproduce the data nearly as well as the examples in figure 6. Individual runs of a stochastic system will generally exhibit a large degree of variability, but this does imply that our model can exhibit the variations seen in the data. These shifts in amplitude, as well as the missed periods seen in the Los Angeles data around 2004 to 2006 and in 2008 and 2010, are quite typical in our model. This implies that stochasticity is sufficient to produce the variations in crime seasonality; exogenous factors are not necessarily the cause of this variability in amplitude from one year to the next. External forcing should be an important factor in the seasonal trends, however it is not the only source of the variations in these crime rates. The social ecological terms alone are sufficient to explain the seasonal shifts in crime rates, and searching for correlations between varying seasonal crime rates and various weather patterns is likely to produce incorrect conclusions. Crime is simply too stochastic, and the data too noisy, for such correlations to be useful.

The Los Angeles property crime data, as seen in figure 6, illustrates another important feature for these systems. Frequently, an entire seasonal oscillation seems missing. This can easily be explained in terms of stochastic models with underlying periodic orbits. The stochastic terms can effectively overwhelm the deterministic evolution enough to push the system to very small periodic orbits near an equilibrium state. The periodicity is then masked by the random noise around the fixed point. Eventually, the random stochastic kicks will push the system back into a larger orbit and the deterministic terms will dominate. In our model, this is exhibited as periods of seasonal oscillations mixed with periods of near constant behavior. For a single limit cycle, [29] found that moderate noise, comparable to the strength of the limit cycle, can force the system to propagate opposite to the limit cycle rotation and can also stabilize an otherwise unstable equilibrium. For an entire family of periodic orbits, when the system is near the equilibrium any source of noise will dominate the deterministic system and drive the orbit towards larger oscillations. Eventually the deterministic oscillation and the stochastic noise will be comparable, and effects similar to those for the limit cycle from [29] will be observable. This balance between the periodic orbit and the stochastic forcing can persist for long times. Eventually the stochastic terms in the Lotka–Volterra model will become higher order and the system will slowly evolve towards a state exhibiting larger and larger oscillations.

4. Discussion

An underlying belief in the criminology community is that the seasonal oscillations are often driven by an external force, such as temperature or rainfall. The idea is that people are more aggressive during warmer seasons, and certainly that weather patterns like heavy rainfall can alter human behavior. Los Angeles, however, is extremely temperate with a short season for rainfall. The seasonal variations in weather are extremely consistent over the time period we study; see figure 2. Los Angeles still displays seasonal variations in crime rates with a significant amount of variation in the year to year swings. Additionally, different crimes peak at different times of the year, and the same crimes peak at different times in LA and Houston. Another salient feature of the data is pronounced shifts in the amplitude of the seasonal oscillation from year to year. The amplitude can shift significantly between two consecutive years, and this has been used as a basis to seek external factors that correlate well with these shifts. If an underlying factor such as temperature is responsible, then these variations can be explained by looking for correlations with these external factors. We see that this variation can be explained by a small amount of stochastic noise shifting the periodic cycles in the system and need not be derived from an external control parameter. Because such stochasticity can create dramatic variations in annual crime oscillations, we caution criminologists against seeking correlations between this data and exogenous factors.

One of the major difficulties in extracting the seasonality of crime for the United States is the low number of daily crimes and high variability in crime from day to day. As can be seen in figure 3, the drop in crime has not been monotone. Various lulls in crime reduction have been seen, such as from 2005 to 2009 in Los Angeles, and the rate of reduction is slowing. Some crimes have actually increased in prevalence during part of the examined time intervals. A standard technique to evaluate the effectiveness of police departments is to look at the changes in various crime rates over a quarter. Given crime rates are already so low and known to oscillate on such a time scale, this is not an ideal measure of success for the police. However using the SSA decomposition, the expected daily crime trends can be forecast from previous data and used as a benchmark against which to examine the actual crime rates. However, compounding the low level of crime and non-monotone trends with the seasonal shifts, it really is necessary to examine crime levels over several years to understand whether any policing strategy is effective. We see that the annual seasonal variations change significantly each year, and the overall trends change on a small enough scale that they can be overwhelmed by the oscillations and noise in the system.

When various different crimes peak in different seasons, the police can concentrate resources on limiting the crime that is most prevalent at any given point in time. This could help overtasked police forces engage with the criminal element. Unfortunately, some seasonal crimes, such as rape, vary so little and are so rarely reported that even targeted policing in this manner is unlikely to help. Reported rapes are extremely low, and the reduction in rape rates is very noisy though generally decreasing. Rape does seem to exhibit seasonality, as is shown in figure 4 but the size of the oscillation is too small to make a difference in policing strategy and is very noisy from the small amount of data. Uncovering seasonal variations in crime can help us to understand the expected crime rates at a given point in time, and aid in deploying police resources.

While exogenous factors in the form of external forcing are certainly important in pinning these oscillations to a yearly cycle, a stochastic ecological model based on predator-prey relationships, specifically the Lotka–Volterra equations, can successfully reproduce the oscillations and noise in these cycles. The predator, in this case a criminal act, feeds off of prey, or criminal targets, thus raising the crime rate but reducing the number of possible targets. As the criminals generally only encounter a small number of targets, the effective number of prey in the system should be quite small. As an example, burglars generally will choose targets off of past successful burglaries, and will limit their search to a fairly limited region in space [30,31]. Thus of the many thousands of homes in a metropolitan area, only a limited number of them are viable targets. By applying our model to several crime data sets, we demonstrate that ecological factors alone can reproduce the variability in crime's seasonality. However, we emphasize that external factors certainly play an

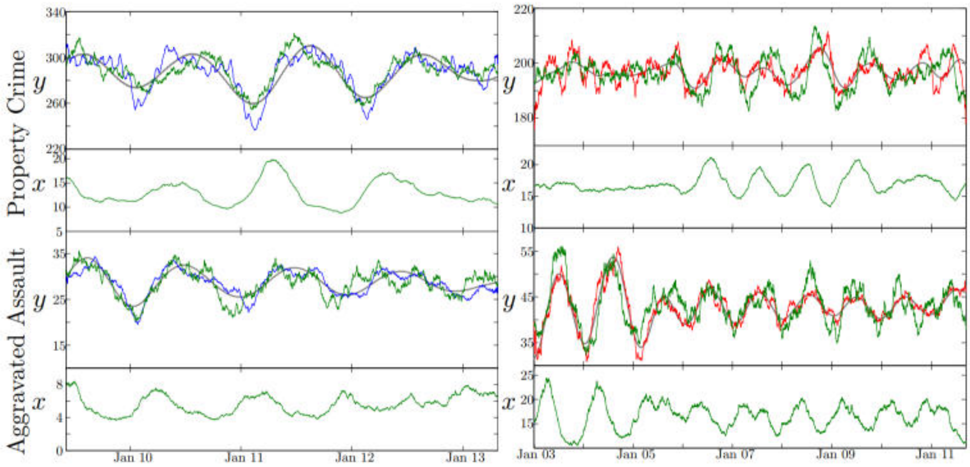

Figure 6. A comparison between equation (3.1) (green) and the moving window averaged aggravated assault and property crime data for Houston (blue on left) and Los Angeles (red on right). The stochastic differential equation is able to reproduce the seasonal component across various crime types and locations, as well as its annual variations without relying on any exogenous factors.

important part in the seasons of crime, but their effect can be overwhelmed by stochasticity and human ecology.

Stochastic and social factors create dramatic variations in crime rates from year to year. These effects, coupled with low levels of daily crime, can overwhelm the dependence that hostile behavior has on temperature fluctuations. Though mild correlations can be found between spiking crime rates and aberrations in temperature, crime's seasonality is not solely determined by the seasonal shifts in weather.

Competing Interests

We have no competing interests.

Authors' Contributions

KD performed the research and helped write the manuscript. YC, BS, and MW performed the research. SGM designed the research plan, performed the research, and helped write the manuscript. All authors gave final approval for publication.

Funding

This research originated as a summer REU in the California Research Training Program in Computational and Applied Mathematics at UCLA. This research was supported by NSF grants DMS-1045536, DMS-1312344, DMS-0968309, by ARO MURI grant W911NF-11-1- 0332, and by AFOSR MURI grant FA9550-10-1-0569.

Acknowledgment

We would like to thank P.J. Brantingham for leading us towards studying seasonal crime with a stochastic model. The Los Angeles data set was provided courtesy of P.J. Brantingham and the LAPD. Finally, we would like to thank J.H. von Brecht for his support in every aspect of this research program.

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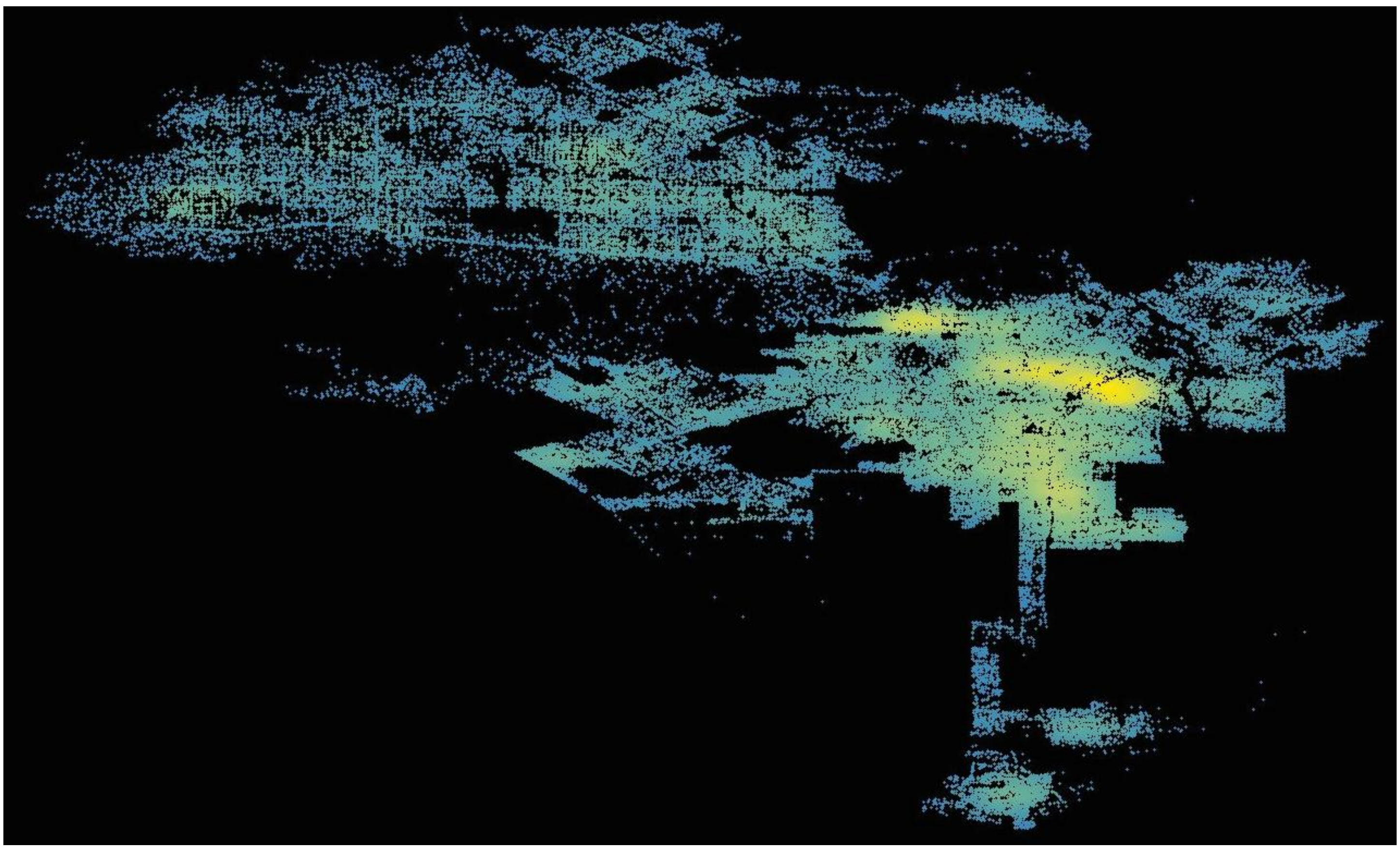

BJA Bureau of Justice Assistance
Office of Justice Programs ■ U.S. Department of Justice

NIJ National Institute of Justice
The Research, Development, and Evaluation Agency of the U.S. Department of Justice

Standard Functional Specifications for

Law Enforcement Records Management Systems (RMS)

Developed by the

Law Enforcement Information Technology Standards Council (LEITSC)

Law Enforcement Information Technology Standards Council

LEITSC

NOBLE

Police Executive Research Forum

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This document was prepared with the guidance, leadership, and funding of the Bureau of Justice Assistance, Office of Justice Programs, U.S. Department of Justice, in collaboration with the Law Enforcement Information Technology Standards Council. This project was supported by Grant No. 2003-MU-BX-0068, awarded by the Bureau of Justice Assistance.

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This document is the result of an extraordinary collaboration between many justice practitioners and industry experts. Thank you all for your commitment, time, energy, and patience.

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Executive Summary: Records Management System

History

The Law Enforcement Information Technology Standards Council (LEITSC) was created in 2002 with funding (Grant Number 2002-LD-BX-0002) from the U.S. Department of Justice, Bureau of Justice Assistance, and continued in 2003 with funding (Grant Number 2003-MU-BX-0068) through a collaborative effort between the Bureau of Justice Assistance and the National Institute of Justice. LEITSC is currently funded under the Bureau of Justice Assistance (Grant Number 2003-MU-BX-0068) and continues to work in cooperation with the National Institute of Justice. LEITSC brings together representatives from the International Association of Chiefs of Police (IACP), National Sheriffs' Association (NSA), National Organization of Black Law Enforcement Executives (NOBLE), and Police Executive Research Forum (PERF) to address law enforcement information technology standards issues.

The mission of the group is to foster the growth of strategic planning and implementation of integrated justice systems through the development and implementation of information technology standards. With guidance and leadership from BJA, LEITSC involves law enforcement partners to speak with a clear and consistent voice in shaping the course of crucial developments in information sharing.

The national initiatives include the Law Enforcement Information Sharing Program (LEISP), Law Enforcement National Data Exchange (N-DEx), and Law Enforcement Regional Data Exchange (R-DEx).

As law enforcement agencies move toward the procurement of computer aided dispatch (CAD) and law enforcement Records Management Systems (RMS), it is vital to recognize and consider the Law Enforcement Information Sharing Program (LEISP) developed by the U.S. Department of Justice (DOJ). The LEISP is designed to promote information sharing among all levels of the law enforcement community and to guide the investment of resources in information systems that will further this goal. The goals of LEISP are supported through the proliferation of the Global Justice Information Sharing Initiative (Global) Extensible Markup Language (XML) Data Model (Global JXDM). For additional information on the Global JXDM, visit www.it.ojp.gov. The Global JXDM is an XML standard designed specifically for justice information exchanges. It provides law enforcement, public safety agencies, prosecutors, public defenders, and the judicial branch with a tool to effectively share data and information in a timely manner. There are several ongoing DOJ initiatives incorporated into the LEISP.

One program currently being developed jointly between the Federal Bureau of Investigation (FBI) and state and local law enforcement is the Law Enforcement National Data Exchange (N-DEx)[1] System. A second program—the Law Enforcement Regional Data Exchange (R-DEx)[2] System—has been developed and implemented by the FBI. Both programs are new law enforcement information sharing systems based upon the above critical standards.

1 The N-DEx Program is an incident- and case-based information sharing system (e.g., RMS) for local, state, tribal, and federal law enforcement agencies that securely collects and processes crime data in support of the investigative and analytical process and will provide law enforcement agencies with strategic and tactical capabilities that do not currently exist on a national scale. An N-DEx concept of operations (ConOps) document is being finalized to aid in the design of the N-DEx system and to ensure that stakeholders understand and share the N-DEx vision.

2 The R-DEx Project seeks to securely share sensitive but unclassified crime information between federal agencies, while allowing for connection with several existing regionally based local and state information sharing systems to impede criminal and terrorist activities. R-DEx is now operational in several metropolitan areas.

Purpose

In 2003, LEITSC identified the need for a national standard for Records Management Systems (RMS) functional specifications with the following goals:

- Provide a starting point for law enforcement agencies to use when developing RMS requests for proposals (RFP).
- Streamline the process and lower the cost of implementing and maintaining an RMS.
- Promote information sharing.

With these goals in mind, the LEITSC Functional Standards Committee, composed of law enforcement practitioners and industry experts from around the country, was appointed to develop the Standard Functional Specifications for Law Enforcement Records Management Systems. The baseline document was developed from common elements found in the RFPs, technical documentation, and other RMS-related research. The document was then validated by the LEITSC Functional Standards Committee using a computerized modeling tool. Once developed and validated, the specifications were vetted through the law enforcement community via each of the participating associations, as well as through other stakeholder communities, in an effort to gain input from a number of different perspectives.

Document Scope

This document presents standard functional specifications for law enforcement RMS. The specifications found in this document are intended to be generic in nature rather than favoring one particular system or approach over another. They are at the functional level in that they define what is to be accomplished versus how it should be accomplished. These specifications were developed to depict the minimal amount of functionality that a new law enforcement RMS should contain. They are not intended simply to be substituted for an RFP but should be tailored to fit the specific needs of each agency or group of agencies looking to purchase or upgrade an RMS. These specifications should be used as a starting point to build a fully functional RMS, based on agency needs and open standards, to efficiently interface and share information with other systems both internally and externally.

It is expected that the process of defining detailed information exchanges in RMS will be addressed in future phases of this project. In addition, these specifications are intended to be used in conjunction with technical standards such as the U.S. Department of Justice's (DOJ) Global Justice Extensible Markup Language (XML) Data Model (Global JXDM) to streamline the process of sharing information.

It is intended that these standards will be updated and augmented on a regular basis.

Introduction

RMS is an agency-wide system that provides for the storage, retrieval, retention, manipulation, archiving, and viewing of information, records, documents, or files pertaining to law enforcement operations.

RMS covers the entire life span of records development—from the initial generation to its completion. An effective RMS allows single entry of data, while supporting multiple reporting mechanisms.

For the purposes of this document, RMS is limited to records directly related to law enforcement operations. Such records include incident and accident reports, arrests, citations, warrants, case management, field contacts, and other operations-oriented records. RMS does not address the general business functions of a law enforcement agency, such as budget, finance, payroll, purchasing, and human resources functions. However, because of operational needs, such as the maintenance of a duty roster, law enforcement personnel records and vehicle fleet maintenance records are included within an RMS.

This document addresses the following business functions:

- Calls for service
- Incident reporting
- Investigative case management
- Traffic accident reporting
- Citations
- Field contact
- Pawns
- Civil process
- Orders and restraints
- Permits and licenses
- Equipment and asset management
- Fleet management
- Personnel
- Internal affairs
- Analytical support (crime analysis)

In addition, the following support functions are addressed:

- Master indices
- Interfaces
- RMS administration
- RMS reports (general)

1 Business Function: General Requirements

The following are general requirements of RMS:

- Single entry (i.e., no duplicate data entry)
- RMS should automatically submit data to external sources as defined by the agency
- Maximum use of code tables
- Ability to enter and query narrative(s)/text fields
- Spell check and formatting capability on narrative(s)/text fields
- Ability to access multiple systems from a single RMS workstation
- Single database (i.e., virtual or physical)
- Validation on data entry (i.e., logical edits, edit checks for all fields)

Some functional specifications need to be addressed at the agency level, such as the identification of specific external agency interfaces. These unique functions are addressed within each applicable business function. For all exchanges generated by RMS, conformance with DOJ's Global JXDM is required.

Internal and External Databases:

An agency's RMS should provide the capabilities for users to generate inquiries to internal and external data sources—such as state Department of Motor Vehicles and criminal history files, as well as the National Crime Information Center (NCIC)—from within each module[3] where such inquiries make sense.

In addition, RMS should provide the user with the ability to reuse and/or import data returned from external sources to eliminate redundant data entry.

RMS also should provide the capability to electronically forward RMS data to external data sources, either automatically or upon the user's request (i.e., based on agency rules embedded within RMS).

The above capabilities should be based on existing and emerging criminal justice standards, including DOJ's Global JXDM; the National Information Exchange Model (NIEM); and the National Institute of Science and Technology (NIST), including the Electronic Fingerprint Transmission Specification (EFTS) and Facial Recognition Collection standards.

3 A module is an independent portion of an RMS software application which provides specific functionality, e.g., Arrest and Booking. Each module performs those procedures related to a specific process within a software package. Modules are normally separately compiled and linked together to build a software system. Single modules within the application can normally be modified without requiring change to other modules, so long as requisite inputs and outputs of the modified module are maintained.

2 Business Function: Master Indices

An agency's RMS should have basic master indices that correlate and aggregate information in the following areas: people, locations, property, conveyances (e.g., vehicles), and organizations (including businesses and gangs). Master indices eliminate redundant data entry by allowing the reuse of previously stored information and the automatic update of the master indices upon the entry of report information.

Master indices information can be captured in a variety of ways, including during the input of information from incident, traffic accident, and vehicle reports and citation, booking, arrest, juvenile, fingerprint, and mug shot subsystems. Prior to accepting an entry, RMS should automatically give the user the option of determining whether there is a match based on existing data.

The system should support the validation and linking of addresses, commonplace names, and street intersections.

Linkages among any information contained in the master indices (e.g., people to places or person to person) must be included in RMS.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Query and retrieval by name, vehicle, location, organization, and/or property to produce a comprehensive response displaying all related records in the system

Standard External Data Exchange:

- The master indices serve as an internal or external portal for information sharing
- Mobile computing system
- State databases
- NCIC

Standard Internal Data Exchange:

- Existing RMS data

2.1 Use Case Diagram[4] (see page 4)

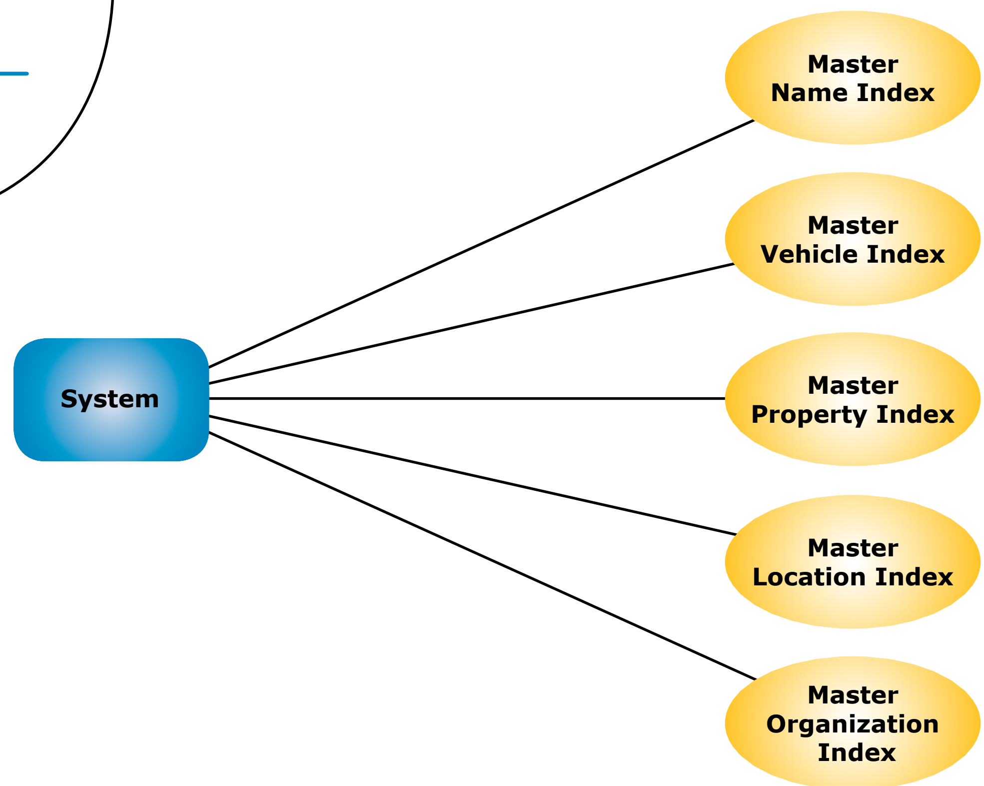
2.2 Use Case: Master Name Index

The RMS Master Name Index (MNI) function links an individual master name record to every event (e.g., incident report, arrest report, field interview, accident report, and license and permits) in which the individual was involved or associated. Every person identified within these events is given a master name record. Should that person become involved in another event, the single master name record is linked to all of the other events so that by querying that one name, the system can produce a synopsis of all the involvements associated with that one person. It also facilitates the linking of additional names to an individual master name record (i.e., alias information and relationship data). In querying an individual MNI record, the user also would be able to view all related records, as well as those associated with that individual.

When a record or report is added to RMS and a person is linked (i.e., indexed) to that event, the system should

4 URL Integration collaborated with LEITSC to assist in the development of the functional standards. URL Integration used an alternative method to requirements analysis with their RequirementsModeler software. RequirementsModeler is based on Uniform Modeling Language (UML), which is the defacto standard for documenting functional requirements. UML was created by the Object Management Group (OMG) in 1997 as a standard for visual object-oriented modeling. RequirementsModeler, consistent with UML principles, automatically generates diagrams and process flow (Use Case and Activity diagrams). URL Integration's Use Case and Activity diagrams were reproduced for use in this report.

Figure 2.1 Use Case Diagram—Master Indices



perform a very important matching function using a rule-based process defined by the agency. The purpose of this matching function is to either automatically link an existing MNI record or to present the user with a list of possible matches to the name so that the user can make the matching decision. RMS should provide a matching algorithm that will provide the ability to search the name file by a variety of criteria, such as sound-alike searching; phonetic replacement; diminutive first names (e.g., James/Jim/Jimmy, Elizabeth/Beth/Betty, and Jack/John); and other static demographic information, such as age, sex, and race.

Once a list of possible matches is provided, the user can decide whether the information should be linked to an existing master name record or whether a new master name entry should be added. This step is very important in maintaining the quality and integrity of the master name file in the system. In addition to names, the MNI should, at a minimum, capture and maintain information on:

- Physical characteristics (e.g., current and past descriptors)
- Race and ethnicity
- Location history (e.g., current and past residences)
- Employer information
- Telephone numbers
- Known associates
- Alias names/monikers
- Available mug shot(s) and photographs
- Scars, marks, and tattoos
- Modus operandi (i.e., unique method of operation for a specific type of crime)
- Identification (e.g., social security, driver's license, and local and county identification)
- NCIC fingerprint classification

Over time, and depending on the circumstances, this information may change, and new information will be made available. Additional information can be added, but older information should be maintained and viewable.

The RMS MNI should also provide maintenance functions that will permit a record or report to be unlinked from one MNI and relinked to another. Since it is not always possible to ensure that the correct MNI record is linked to an event record, it must be possible to correct it. Functions also should be provided that will allow two or more MNI records to be merged into one record.

2.3 Use Case: Master Vehicle Index

Like individuals, vehicles often are directly or indirectly involved in events. When a vehicle is linked to an incident in RMS, it should be added to the vehicle record in the Master Vehicle Index (MVI), which provides an agency with a detailed, searchable store of information about vehicles.

RMS should provide the capability to search on:

- Vehicle Identification Number (VIN)
- License plate number
- License plate state
- License plate year
- Registered owner
- Description (e.g.. make, model, year, color, style, and attributes)

When an inquiry is made on a vehicle, the system should return a list of all events in which the vehicle was involved.

In addition, RMS may require MVI to have external interfaces.

2.4 Use Case: Master Property Index

The Master Property Index (MPI) is the central access point that links all property records entered into RMS. Each record is catalogued by using unique property characteristics, such as make, model, brand, description, distinguishing characteristics, and serial number. Industry property coding standards, such as NCIC property codes, should be used during the entry of property records into RMS.

In addition, any property records entered throughout RMS should automatically cross-reference MPI to find potential matches based on the unique property characteristics outlined above.

2.5 Use Case: Master Location Index

The Master Location Index (MLI) provides a means to aggregate information throughout RMS based on a specific address, a range of addresses, an area (i.e., as defined in the agency geofile), and/or locations based on X/Y/Z coordinates. A geofile is the location information base file for emergency 911 computer aided dispatch (CAD) systems. It also provides a facility to store information about a specific location that may not be stored elsewhere in RMS. MLI should store or provide access to additional premise information, such as occupancy, elevation (e.g., floor), and premise type (e.g., residence versus business).

An assumption is made that all location information being processed in RMS is subject to stringent formatting rules. In addition, if the address is within the boundaries of the agency geofile, the actual location is validated. Typically, during the geovalidation process, key identification information, such as X/Y/Z coordinates and agency-defined reporting areas, is added to the location information.

The geovalidation process should allow an address to be accepted, even if it does not appear in the geofile. Unverified addresses should be flagged for possible review. Optionally, all addresses or only addresses within the jurisdiction are available in MLI.

2.6 Use Case: Master Organization Index

Many events also involve an organization, such as a gang, business, school, or shopping center. Information about these groups entered into RMS should be contained in a Master Organization Index (MOI). MOI provides an agency with a detailed, searchable store of information about organizations. An agency should be able to search on a variety of data elements and obtain a listing of all records associated with that organization. Organizations may change location and name, but these changes should be tracked in RMS. In addition, MOI also should permit the linking of aliases to organizations (e.g., M&M Associates, doing business as Joe's Pawn Shop).

3

Business Function: Calls for Service

All calls for service (CFS) are recorded in a structured records environment, providing the ability to run reports on these data, while also maintaining a historical record on all calls. The data are either segmented or identifiable by the agency.

Typically, data in this module cannot be modified after the call is closed because they serve as a formal audit trail of the information that started the law enforcement activity. If RMS is not integrated with a CAD system, this function must be able to serve as the initial point of data entry for a CFS. The basic call data (e.g. initial call time, units dispatched, and call disposition) can be available to facilitate the creation of an incident report. The data imported into the incident report can be modified, whether or not the call has been closed, to reflect the latest information known regarding the incident. Basic call data may be transferred at the time an incident number is assigned or at the initial closing of the call, depending on specified call types.

In the event that CFS data are transferred from CAD to RMS, RMS should receive the call number and associated incident number from the CAD system. If the call does not originate from a CAD system, this CFS module should be capable of generating or allowing manual entry of a sequential event number and an associated incident number to link CFS and incident records.

If the department is dispatched by a CAD system, an interface to the CAD system will be required to transfer the CFS data to RMS. The CAD workload[5] reports also should be available from the calls for service module.

5 Workload is the metric or metrics which accurately describe the amount of work performed by or within a process in a specific period of time. For example, the Calls for Service (CFS) module contains information about the number of calls received and the length of time needed to process those calls. The data on time and number of calls describes workload. A workload report in an RMS is a compilation of data that provides a user with statistics pertinent to the functions performed by or recorded within a module.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Daily log showing all calls received for the prior 24 hours from prior printing of the daily log
- Activity analysis by specified geographical area and time period
- CFS summary, by specified geographical area and time period
- Activity analysis by day of week
- Activity analysis by hour of day
- Activity analysis by day and hour
- Response time analysis by specified geographical area and time period (e.g., receipt of call, dispatch time, on-scene time, and time call cleared)
- Response time analysis by call type
- Time consumed by call type by hour of day
- Workload activity by resource assigned
- Workload activity by group assigned
- Time consumed by day of the week and hour of the day
- Time consumed by specified geographical area and by time period
- Calls that should result in the creation of an incident report

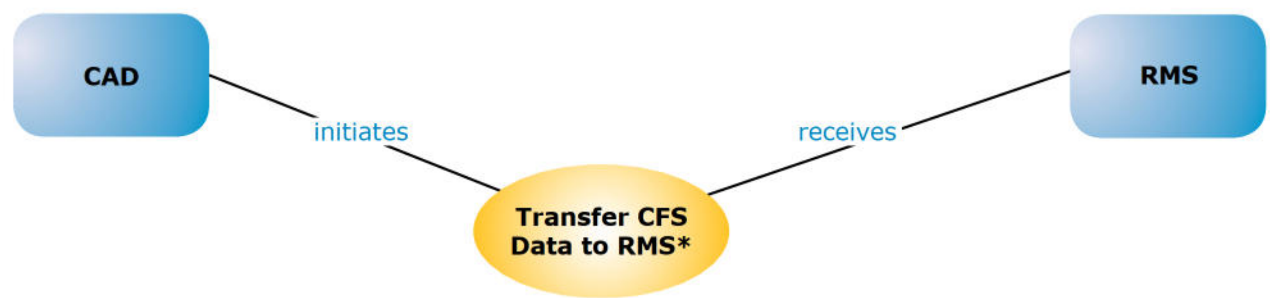
Standard External Data Exchanges:

- CAD

Standard Internal Data Exchanges:

- MNI
- Incident reporting

Figure 3.1 Use Case Diagram—Calls for Service



3.1 Use Case Diagram

3.2 Use Case: Transfer CFS Data to RMS

The call data are transferred to RMS when units are initially dispatched after an incident number is assigned or when the call is closed in CAD.

If CFS information is retransferred from CAD, the most current data will replace the information previously transmitted.

4 Business Function: Incident Reporting

Incident reporting is the function of capturing, processing, and storing detailed information on all law enforcement-related events handled by the department, including both criminal and noncriminal events. The incident reporting function collects sufficient information to satisfy the National Incident-Based Reporting System (NIBRS) or the Uniform Crime Reports (UCR). Incidents often are initially documented as CFS in a CAD system. The CFS record in RMS should be linked to the incident and should be easily accessible from the incident report.

Certain types of incident reports must be available to the public. Witness information, as well as the names of juveniles who are subjects or victims, may need to be redacted for public consumption. RMS must be able to recognize the age of the majority in the jurisdiction by the date-of-birth information entered into the system that is available to the public. The system should support the redaction prior to printing a public copy or making the report available online to the public.

The data captured in this module must support the preparation and submission of all required federal crime reporting and provide the capability to print a copy of both the completed department's incident report and the redacted incident report.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- All summary UCR reports and NIBRS reports
- Total incident reports based on period of time, area or beat, and incident type
- Location code (e.g., geocode)
- Initial call type
- Offense type
- Summary of incidents by a responsible officer

Standard External Data Exchanges:

- Federal databases to support electronic submissions
- State submission following NCIC standards
- Prosecutor
- Courts
- Jail Management System (JMS)
- Regional Information Sharing Systems (i.e., standards-based, such as Global JXDM, NCIC)

Standard Internal Data Exchanges:

- Mobile reporting system
- Investigative case management
- Property and evidence

4.1 Use Case Diagram (see page 10)

4.2 Use Case: Prepare Initial Incident Report

The incident report is prepared as soon as it is practical to do so following the incident and, depending on department procedure, may be updated throughout the initial investigation. Multiple officers may provide input once a single incident report is created and an incident number assigned. A primary officer will be assigned with overall responsibility for completing the report. This primary responsibility may shift to other officers during the life of the report. The incident report must contain sufficient information to comply with national reporting requirements.

Typically, an incident report contains factual information pertaining to the incident, including offense information, suspect information, and case status, as well as information pertaining to perpetrators, witnesses, victims, and complainants. Reporting requirements typically mandate the collection of certain elements of information.

In addition, incident reports have free-text fields, which allow the collection of an unlimited amount of narrative information. The system should provide the capability to search the narratives for a specific word or phase.

Once completed, officers submit the incident report to their supervisor for review.

4.3 Use Case: Create Supplemental Report

A supplemental report is used to add new information to the case after the initial incident report has been submitted and approved. The creation of a supplemental report may result from information gained during additional investigation and also may result in updating the status of the investigation, possibly bringing it to closure.

Investigators are typically the individuals within the law enforcement agency responsible for follow-up investigation and for creating supplemental reports. To that end, they must be able to query and retrieve the initial incident report and use it as a baseline document for the supplemental report. They also must be able to electronically submit the report to a supervisor for review and dissemination.

Multiple officers must be able to simultaneously create and add supplemental reports regarding the same event.

All supplemental reports are linked to the original incident report. The agency should be able to link all of the associated reports with a common report number. This may be done using the original incident report number, possibly with a suffix indicating supplementals or a case number.

Figure 4.1 Use Case Diagram—Incident Reporting

4.4 Use Case: Report Review

The incident report must be able to be locked from further edits at a point determined by the agency. This does not preclude the viewing of the document by those with access permissions, but the ability to block access should be a capability of the system.

Supervisors review incident reports and supplemental reports for accuracy and quality prior to their permanent, noneditable storage in the local RMS database and/or their distribution to the agency records bureau; to other agencies; and to local, state and federal criminal information repositories.

RMS must allow supervisors to receive, review, and approve incident reports online and to electronically respond to submitting officers and investigators regarding report quality and accuracy issues. The department's Standard Operating Procedures (SOP) also may require that the records division complete an accuracy review for compliance to reporting requirements prior to adding the information to the database. The system should support all required reviews and corrections prior to locking down the incident report.

5

Business Function: Investigative Case Management

Incidents that require further investigation or follow-up may be referred to an investigator before they are closed or submitted to the prosecutor for a charging decision. Depending on the department's size and policies, the assignment may be made to a patrol officer, generally the officer who responded to the original incident, or the department's investigative unit. The system should be able to assign case responsibility and task responsibility.

The assigned officer receives these referrals or cases electronically and records all of the subsequent case management-related activities in RMS. Case management functions include, but are not limited to, capturing and storing investigation data, requesting a warrant, conducting interviews and photo lineups, and producing supplemental reports. Investigators also may initiate criminal charges and obtain and execute both search and arrest warrants. The department should be able to define its specific activities, including a time allocation for each activity, so the system can generate alerts to both the assigned investigator and the supervisor.

Key products of the process are producing information for the prosecutor, assisting in managing case materials (i.e., including evidence), and preparing cases for prosecution.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Cases not assigned for investigation or follow-up
- Case summary
- Case aging report (list of cases by age range, days, weeks, month, etc.)
- Assigned cases (open cases by investigator and current status)
- Cases pending assignment
- Activity follow-up
- Alerts (e.g., overdue, case assignment, and task assignment)
- Pending activity (e.g., by investigator, case, and division)
- Case disposition (both law enforcement dispositions and court dispositions)
- Prosecutor charging documents

Standard External Data Exchanges:

- Prosecutor (case submission)
- Court (disposition exchanges)
- Regional Information Sharing Systems® (RISS) (i.e., standards-based, such as Global JXDM, NCIC)
- Jail Management System (JMS)

Standard Internal Data Exchanges:

- Incident reporting
- Property and evidence
- Warrant

Other Optional External Data Exchanges:

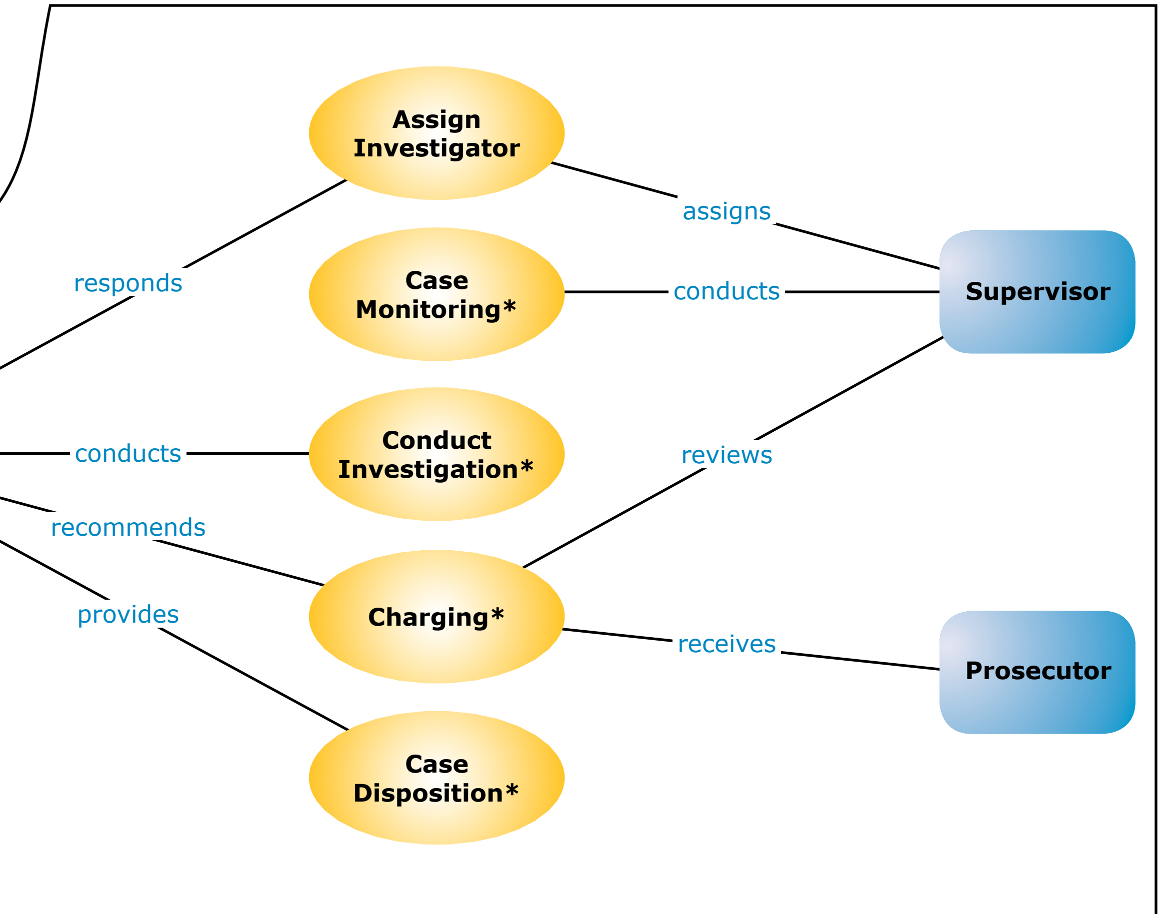
- Financial management system

5.1 Use Case Diagram (see page 14)

5.2 Use Case: Assign Investigator

The supervisor must be able to access and review unassigned cases. The supervisor will assign case responsibility to a primary investigator. Assignment factors may include the nature of the activity, type of follow-up required, the workload of available investigators, and cases already assigned.

Figure 5.1 Use Case Diagram—Investigative Case Management



5.3 Use Case: Case Monitoring

Supervisors monitor cases to ensure that progress is being made. The information used in case monitoring includes case status and activities, both pending and overdue, and investigator case workload.

Supervisors must be able to obtain workload information, assess all requests for new investigations, receive deadlines and reminders, and interact with investigators electronically. They must be able to view existing assignments, shift resources, and notify investigators of changes, as required.

5.4 Use Case: Conduct Investigation

Conducting an investigation involves following up on leads and documenting additional facts about the case. The activities associated with the investigation typically include collecting evidence, developing leads, conducting interviews and interrogations, requesting warrants, and writing supplemental reports. Each of these activities must be documented in RMS to confirm that proper department procedure was followed and that all potential leads were developed. This documentation may include case notes. Each activity during this process may result in an update of the status of the investigation.

During the course of the investigation, the primary investigator may assign tasks to others. The system should be capable of monitoring and tracking at both the case and task levels.

Several of the activities that are a part of conducting an investigation are detailed in other sections of this document. Investigators may need to create a supplemental report as defined in the Incident Reporting module. Warrants may be requested as defined in the Warrant module. Evidence collection and disposition is defined in the Property and Evidence and Management module. The arrest process is detailed in the Arrest module.

5.5 Use Case: Charging

In the situation where charges are to be filed, investigators and supervisors must assemble all relevant case information and reports, as well as their charging recommendations, for submission to the prosecutor. The system should support the development of charging recommendations and their electronic approval prior to the submission to the prosecutor. In some cases, the prosecutor may refer the case back for further investigation.

The prosecutor may decide to prosecute some, all, or none of the charges recommended by the law enforcement agency or decide to prosecute other charges. The prosecutor's charging decisions should be communicated to the law enforcement agency, and the system should capture the charging decisions.

In integrated justice systems, much of the communication between the prosecutor and the law enforcement agency happens electronically. If no interface is available, the data must be entered manually into RMS.

5.6 Use Case: Case Disposition

When the case is completed, a Law Enforcement Case Disposition is captured. This disposition is in addition to a case status. At this point, any property may be eligible for release to the owner as defined in the Property and Evidence Management module.

A court disposition (per person arrested and per charge) also should be included in the record as the court case is completed. With an integrated justice system, the disposition can be exchanged electronically. The system should support the ability to reopen a case, if necessary, based on new evidence.

6

Business Function: Property and Evidence Management

Property refers to any tangible item that can be owned, consumed, or otherwise used (e.g., stolen or recovered items, currency, narcotics, vehicles, animals, and evidence of any form) that is to be tracked by the agency. Property owned for use by the agency (e.g., department equipment) is typically not included in this module. Law enforcement agencies can take custody of property during the investigation of cases and preserve it for possible use at trial. Agencies also will receive property turned over by the public in which ownership is unknown or where circumstances of receiving the property are unknown or unrelated to an event or incident.

A property custodian is responsible for receiving property for the agency. Information about the property, including its source, is collected and recorded in RMS.

Law enforcement personnel can access property data to view detailed information about the item and historical information about the custody and control of the item, including the current status or location. Personnel also can follow links to related property items tracked in the system. The tracking system provides the ability to accurately track and verify that all property items and the evidentiary chain-of-custody requirements are met. The system also will track property that has been impounded or stored in remote facilities. Information about property and evidence must be linked to either a case file or a report that describes the property's involvement.

The disposition of property is managed by the system, with timed events to notify property custodians when property items will be released, destroyed, or sold at auction. The disposition history is maintained for a specified time period or may be indexed for future investigative purposes.

While many RMS include integrated Property and Evidence Management modules, many jurisdictions are using stand-alone programs to support the property and evidence function. Any stand-alone program should include an interface to RMS to minimize duplicate data entry. Links to appropriate RMS records should be made at the time the property record is uploaded.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Chain of custody
- Property summary report
- Property item detail
- Released property report
- Property inventory report
- Property disposition reports
- Form letter to inform the property owner of the pending disposition of property with instructions for filing a claim
- Vehicle impound forfeiture report
- Case closed evidence report
- Evidence location summary report
- Audit report

Standard External Data Exchanges:

- Regional Information Sharing Systems (RISS) (i.e., based on standards, such as Global JXDM, NCIC)
- State information sharing systems (i.e., based on standards, such as Global JXDM, NCIC)
- Prosecutor
- Court

Standard Internal Data Exchanges:

- Incident reporting
- Fleet management

Other Optional External Data Exchanges:

- Bar-code system
- Third-party property management systems, including a laboratory evidence processing system
- Pawn shops

6.1 Use Case Diagram

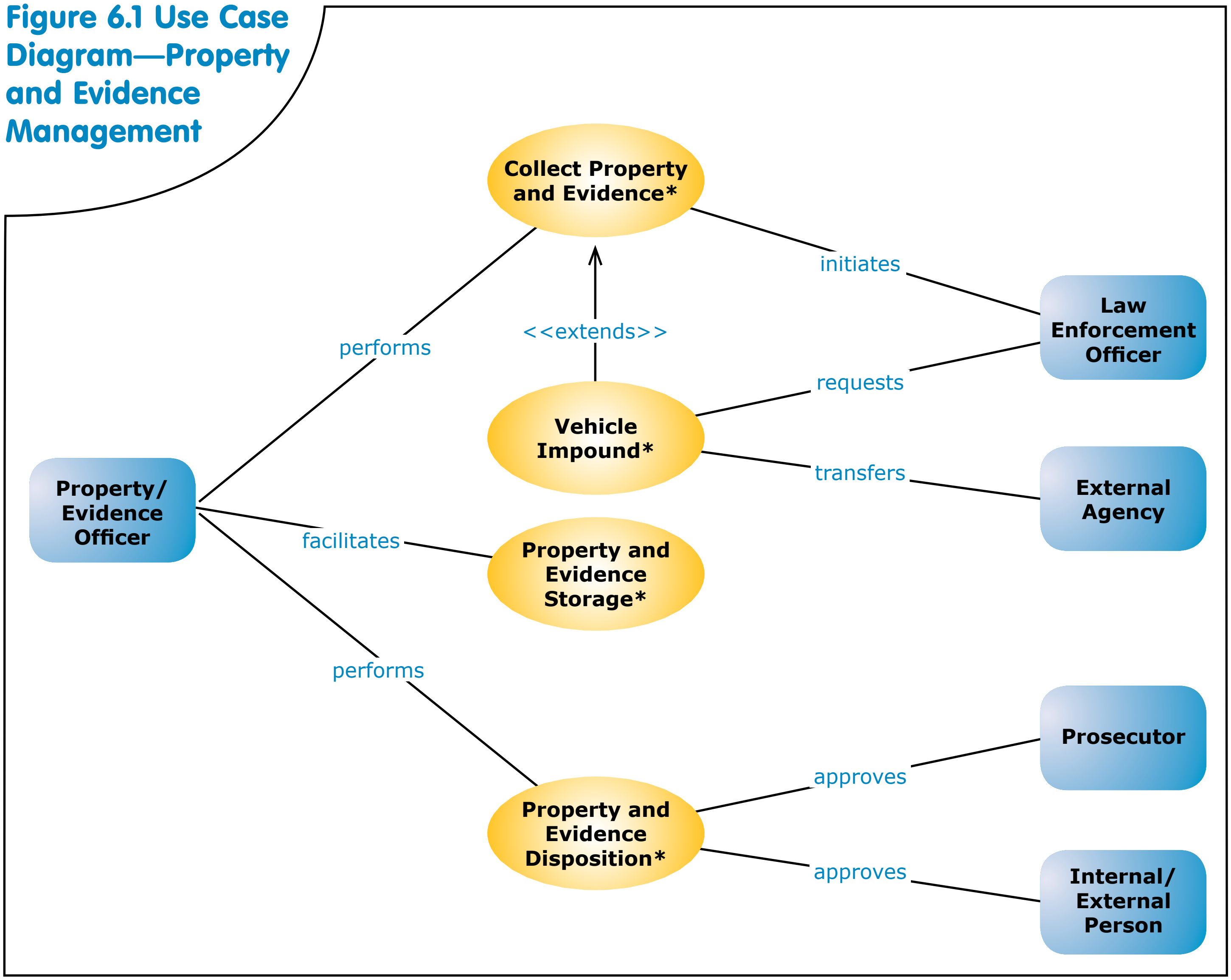
6.2 Use Case: Collect Property and Evidence

Property and evidence items are collected and processed into a physical location with established process and security controls. This is the point of entry into the system where descriptors and tracking identifiers (e.g., date/time received, contributing and receiving officers, and location) are recorded for both inventory control and chain-of-custody purposes. The property will be checked against internal and external databases for matches. RMS will link property/evidence information with the case and reports.

6.3 Use Case: Vehicle Impound

The law enforcement agency will impound vehicles in the normal course of operations. Vehicles might include boats, cars, motorcycles, airplanes, and other items used for transportation. The system should support the entry of all identifying information for all of these vehicle types. A vehicle may be impounded as evidence in an ongoing investigation or because the driver was driving under the influence. A vehicle may be impounded because it has been abandoned or because it was parked in a prohibited location.

Figure 6.1 Use Case Diagram—Property and Evidence Management



The officer who initiates the impound records the reason behind the impoundment and information about the towed vehicle, including the VIN, description, license number, and the condition of the vehicle, as well as information about the car owner and driver.

The vehicle should first be checked against the MVI in RMS and then automatically queried in both the state and federal repositories for wants and warrants.

The officer enters his estimate of when the vehicle will be available for release and includes the name of the tow company that will be moving the vehicle to the impound lot. A mobile computing system enables the information to be captured at the scene and made available at the time the vehicle arrives at the impound lot.

At the impound facility, the owner and driver information, as well as the vehicle identification and description information, are validated or updated, and the specific location within the facility is added to the record. Information related to the tow-and-impound process also is captured. An initial estimate of the vehicle's value may be entered. A general inventory is conducted to document items that may potentially be removed from the vehicle, including personal items, spare tires, gas caps, batteries, weapons, etc. This module should support a quick and easy way to capture that information.

If the vehicle has evidentiary value, it will be subject to the rules for chain of custody and should be protected and tracked by the system like other tangible evidence. RMS can treat the vehicle and most of its contents as one piece of evidence. However, if additional evidence is found during the impoundment process, it can be processed as a stand-alone piece of evidence.

6.4 Use Case: Property and Evidence Storage

Movement of property and evidence, regardless of how minor, is recorded to ensure that an accurate log of the activity is captured and all policies and chain-of-custody rules are followed. Bar-coding the property and using RMS during the check-in, checkout, and movement of the property will improve the accuracy of the chain-of-custody information in the system.

6.5 Use Case: Property and Evidence Disposition

Final disposition of property is essential to maintaining manageable storage capacities for the agency and making certain owners have their property returned in a timely fashion. The disposition process documents the disposition action and includes safeguards to ensure that procedures and laws governing the release, sale, or destruction of the item are followed. The system will use timed events by using system messages or providing access to lists of eligible property items to notify the property custodian when property can be lawfully disposed.

The prosecutor's approval will be required before the disposition of property with evidentiary value can go forward. The system should provide a means to store images of the item prior to the disposition. The system may include an interface or exchange capability with the prosecutor that affords officials an efficient and accurate means by which to review and grant or deny approval of disposition requests sent by the law enforcement agency.

Appropriate identification is required to verify the identity of the individual coming to claim a piece of property, and a search of information sources may be conducted where warranted. For example, if a person comes in to claim a weapon, a check of records should be conducted to ensure he or she can lawfully possess a weapon. An additional check against property databases (e.g., NCIC) should be conducted to determine if the property has been reported as being stolen. RMS should automate these queries and document that they were completed prior to the release of property.

After a prescribed period of time, property is eligible for sale or destruction. Only lawful property can be returned to the owner or sold at public sale. Any property deemed illegal for an individual to possess will be properly destroyed.

The system should generate automatic alerts when property is eligible for release or sale.

7

Business Function: Warrant

A warrant is an order of a court that directs a law enforcement officer to take specific action. For example, an arrest warrant would direct a law enforcement officer to arrest a person and bring that person before the court. A warrant may be issued for a person charged with a crime, a person convicted of a crime who failed to appear for sentencing, a person owing a fine, or a person that the judge has ruled to be in contempt of court.

The Warrant module is designed to track warrants that the law enforcement agency will be serving and that include the physical location of the warrant. It also tracks and records any warrant-related activity or status changes. The documentation of each activity includes the type of activity, contact with the subject (if any), the date of the activity, and the result of the activity.

In many departments, other papers (e.g., criminal summons) are handled using the process identified in the Warrant module.

The Warrant module should be able to create a warrant affidavit requesting that the court issue a warrant.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Warrants issued
- Warrants served or cancelled
- Warrant summary based on varying search criteria
- Attempts to serve by date or date range
- Warrant aging report
- Warrant affidavit

Standard External Data Exchanges:

- Court
- Regional, state, and federal warrant repositories following NCIC standards
- Jail Management System (JMS)
- Corrections

Standard Internal Data Exchanges:

- Booking
- Master Name Index (MNI)
- Master Vehicle Index (MVI)
- Master Property Index (MPI)

7.1 Use Case Diagram (see page 22)

7.2 Use Case: Receive and Process Warrant

Upon receipt of a warrant from the court, the warrant clerk enters the information into the Warrant module. An interface with the court system will reduce data entry. Entry into the local warrant system will update the appropriate regional or state warrant system. The warrant clerk reviews the warrant for completeness and ensures the subject information is up to date.

7.3 Use Case: Verify Warrant

Immediately prior to warrant service, the officer must verify that the warrant is still valid before the actual service takes place. This is especially important in serving an arrest warrant. The warrant verification process is important in determining whether the agency is willing to extradite the subject if the warrant is served.

If available, the verification can be done using a mobile data computer that has the appropriate interface. As an alternative, the officer can contact dispatch or another department facility to have the warrant verified.

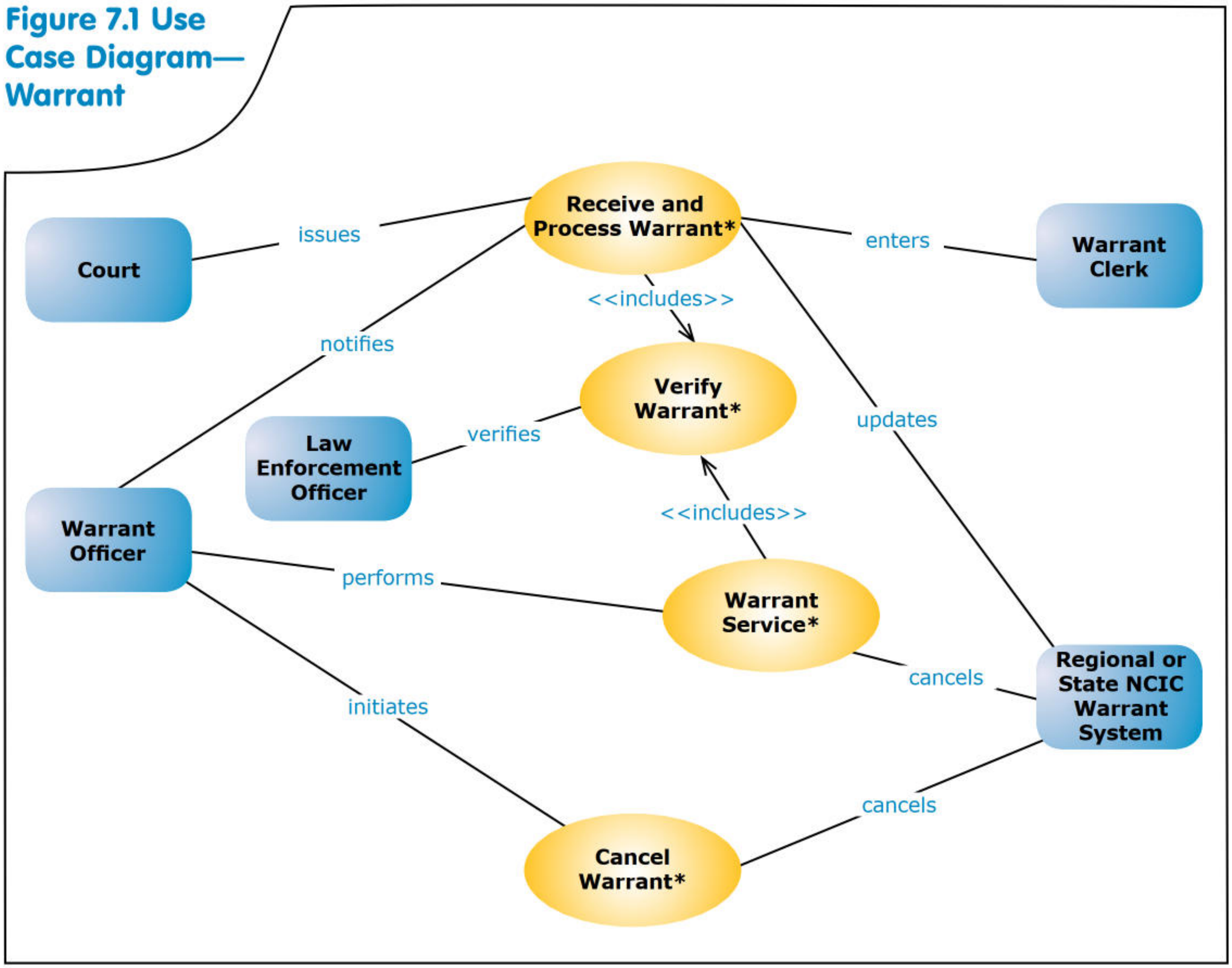
7.4 Use Case: Warrant Service

The process for warrant service will depend on the type of warrant. The Warrant module tracks and records any warrant-related activity or status changes. The documentation of each activity includes the type of activity, contact with the subject (if any), the date of the activity, and the result of the activity. Once the warrant is served, the module is updated and the warrant is cancelled in other appropriate warrant systems.

7.5 Use Case: Cancel Warrant

The court has the ability to cancel the warrant. The reason for the cancellation must be recorded in the Warrant module. Other appropriate warrant systems also must be updated to reflect that the warrant has been cancelled.

Figure 7.1 Use Case Diagram—Warrant



8

Business Function: Arrest

Law enforcement agencies arrest subjects suspected of having committed a crime. Arrest actions must be supported by either probable cause rules or definitions or a court warrant commanding the arrest of a subject. It is essential that the arresting officer follow well-defined procedures that include accurately documenting and recording every step in the arrest process. Both scenarios follow the same procedure when the person is arrested.

The Arrest module provides a place to document all of the steps taken in an arrest. This complete documentation may be used to defend the legality of an arrest.

The data from this report can then be used by the Booking module, the Jail Management System (JMS), and the court.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Daily arrests, by day and time, and date range
- Arrest report and/or affidavit
- Arrests by location
- Arrest log

Standard External Data Exchanges:

- Jail Management System (JMS)
- Court
- Prosecutor
- State criminal history system

Standard Internal Data Exchanges:

- Mobile field reporting
- Incident reporting
- Booking
- Master Name Index (MNI)
- Master Vehicle Index (MVI)
- Master Property Index (MPI)
- Property and evidence

8.1 Use Case Diagram (see page 24)

8.2 Use Case: Arrest Subject

When a law enforcement officer has control of a subject suspected of a crime, the officer will take the subject into custody if the circumstances support keeping control of the individual to maintain public safety and peace. The officer may be making a probable cause arrest, serving an arrest warrant, or making a driving-under-the-influence (DUI) arrest.

A probable cause or on-view arrest is based on immediate circumstances of an incident, where sufficient evidence supports the actions of the law enforcement officer. Examples include traffic violations and incidents when the officer witnesses the commission of a crime. In some cases, the arrest may trigger the detention process and booking.

The law enforcement officer must make every reasonable effort to confirm the identity of a subject prior to the person's being taken into custody. The Arrest module must allow the officer to capture the method of identification that was used. It also must capture the completion of other steps such as the issuing of the Miranda warning.

RMS must provide the capability to print the arrest report after all of the data have been entered into the system.

An arrest report will be required when the law enforcement officer takes the final step in the arrest process of transporting the person to jail. RMS should facilitate and document the agency's arrest report review process.

An interface with the appropriate booking and/or Jail Management System is desirable.

8.3 Use Case: Arrest Warrant Service

There are two situations that may trigger an arrest based on the serving of a warrant. The law enforcement officer may be serving an arrest warrant that was issued as a result of an ongoing investigation. Certain charges will have been approved by the prosecutor prior to the warrant being issued. These charges may or may not be updated prior to the service of the warrant. The arrest now follows the same process as a probable cause arrest.

The second trigger of a warrant arrest is when a law enforcement officer conducts a warrant check during a traffic stop or some other activity and finds that there is an active warrant on file for the person involved.

Prior to the warrant service, the officer must verify that the warrant is still valid. If the warrant was issued by another jurisdiction, the law enforcement officer must first confirm that the issuing agency is willing to extradite. This warrant verification process can be done using a mobile data computer that has the appropriate interface. Some agencies do not require an arrest report to be written if the warrant was issued by another jurisdiction.

After the warrant has been served, it is necessary to remove the warrant from all of the appropriate warrant systems.

8.4 Use Case: DUI Arrest

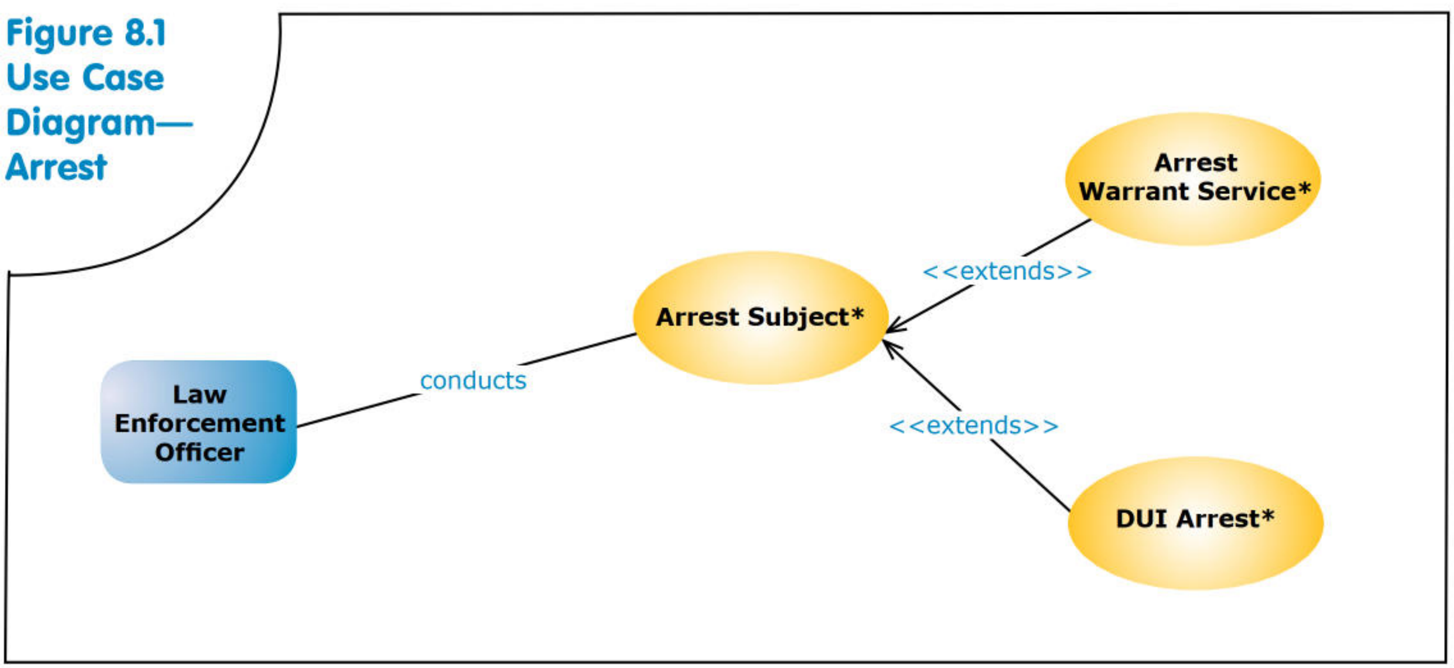
Driving under the influence of drugs or alcohol or while impaired in some other way is considered one of the most serious issues for traffic enforcement. Additional steps are required prior to the beginning of a DUI arrest.

This process may be initiated as part of a traffic stop or in response to an accident. If the law enforcement officer suspects that the driver was using drugs or alcohol, a chemical test will be conducted either in the field or under more stringent controls. The law enforcement officer will ask the subject if he or she is willing to submit to a chemical test. The response should be captured in RMS. When fatalities are involved, the law enforcement officer may be required to obtain chemical tests without the consent of the subject. All relevant information regarding the results from tests are gathered and recorded to supplement the report in RMS.

Based on the test results, the department's SOP for handling DUI arrests will be followed, and each step will be documented in RMS.

Evidence may be obtained from these types of traffic incidents, which require property handling and tracking.

Figure 8.1 Use Case Diagram—Arrest



9 Business Function: Booking

Booking data captured in a law enforcement RMS are eventually linked to the arrest report. The data to be captured include personal information of the subject.

The personal identification information provided by the subject will be checked against MNI to create a link to this booking and avoid unnecessary or redundant data entry. Personal information will include the subject's name and any known aliases; a physical description, including tattoos and other identifying marks; address and other contact information; date of birth; and identification data, such as a driver's license number or social security number. The subject's fingerprints will be taken as part of the booking process. A photo image also will be taken of the subject and may include images of any identifying attributes, such as tattoos and scars. RMS will provide the capability to store the images in the database linked to the booking record.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Booking form
- Booking summary, based on varying search criteria
- Daily court list by court and time
- Property received receipt
- Property released receipt
- Booking activity (e.g., intakes, releases, and transfers)

Standard External Data Exchanges:

- Jail Management System (JMS)
- Arrest
- Regional and state warrant and criminal history repositories, following NCIC standards
- Automated fingerprint identification system
- Mug-shot system

Standard Internal Data Exchanges:

- Master Name Index (MNI)
- Master Vehicle Index (MVI)
- Master Property Index (MPI)
- Property and evidence

9.1 Use Case Diagram (see page 26)

9.2 Use Case: Process Subject

The booking process includes collecting all relevant information on the subject and his or her arrest details, verifying the subject's identity, and addressing obvious physical and mental health needs.

This information may be obtained from the arrest report record within RMS. If the arrest report is available in RMS, a link should be established between the arrest report and the booking record.

If the booking record precedes the arrest record, the data from the booking record should prepopulate the arrest record. MNI acts as the primary key between the arrest record and the booking record.

Information about the arrest of the subject will be entered into the Booking module.

Agency officials perform an assessment during the course of the arrest and booking process. Generally, the assessment may follow a checklist of questions in RMS to capture noted medical needs and security risks. In an integrated environment, this information should be forwarded to appropriate external systems including the Jail Management System (JMS).

Property in the possession of the subject will be inventoried and stored in a secured area while the subject is in custody. If it is determined that the property will not be released to the subject at the time of his or her release, then the property should be handled following department procedures for property and evidence management. If the subject is in custody, agency officials should perform an assessment of the subject during the course of the arrest and booking process. Generally, the assessment follows a checklist of questions and captures in RMS noting medical needs and security risks. In an integrated environment, this information should be forwarded to appropriate external systems, including JMS.

The subject will be assigned to an appropriate facility and bed, based on gender, assessment needs, and space availability. Temporary holding areas may be used in cases where long-term accommodations are unavailable or where the subject's assessment warrants the assignment, such as when medical needs exist or intoxication is a factor.

9.3 Use Case: Verify Subject

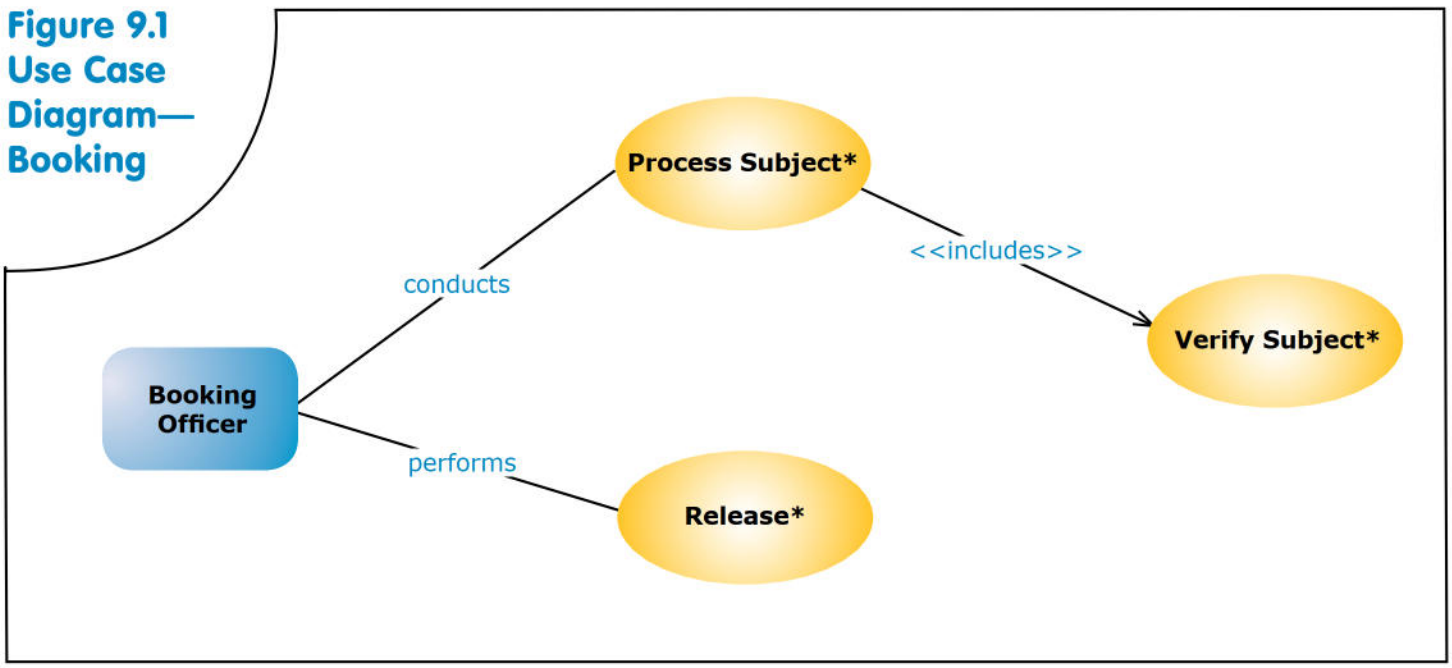
Personal information obtained from the subject will be used to obtain verification information from one or more sources to affirm or disaffirm the subject's identity. The personal information obtained from or about the subject will exist in many forms, including descriptive text, fingerprints, DNA, and photographic images. In most instances, the verification process will affirm or disaffirm the subject's identity electronically, but in some instances, a visual comparison will be necessary to make a determination. Fingerprints may be sent to an Automated Fingerprint Identification System (AFIS) and the Federal Bureau of Investigation's (FBI) Integrated Automated Fingerprint Identification System (IAFIS).

The system should check MNI plus state, regional, and federal databases for any information. The State Identification Number (SID), FBI number, and any other information returned from AFIS/IAFIS will be added to the report as they are received.

9.4 Use Case: Release

When a subject is released from custody, bond money will be collected, if required, and a check will be made to determine if the subject has any active warrants. Prior to release, subjects will have their personal property returned to them. The booking record will be updated, where applicable, to record all relevant information supporting the release of the subject from custody, including the reason, effective date, and time of release.

Figure 9.1 Use Case Diagram—Booking



10 Business Function: Juvenile Contact

The juvenile justice system requires special handling of information about juveniles. Paramount in this is the handling of their records, which must conform to legal requirements that specifically define privacy protections.

RMS must accommodate the need to access juvenile data distinctly from adult information.

As with all cases, information about juveniles disseminated externally also requires information entered into the system to be expunged when ordered by the court or statute. Access must be restricted to authorized law enforcement personnel with special privileges.

In some jurisdictions, the juvenile court is actively involved in juvenile intake and assessment activities. As such, there may be an interface between courts and RMS. Juvenile RMS modules also may provide notifications to external agencies, such as social services organizations and schools, based on certain activities involving juveniles.

RMS should have the ability to automatically archive juvenile information after a requisite amount of time (as governed by state law) has passed since the entry or when the subject reaches the age of 18 (whichever occurs first).

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Juvenile custody
- Juvenile contact report
- Name listing for juveniles separate from adults, based on varying search criteria

Standard External Data Exchanges:

- Prosecutor
- Juvenile assessment center
- Juvenile detention center
- Jail Management System (JMS)

Standard Internal Data Exchanges:

- Mobile reporting system

Other Optional External Data Exchanges:

- Social services
- Court
- Schools

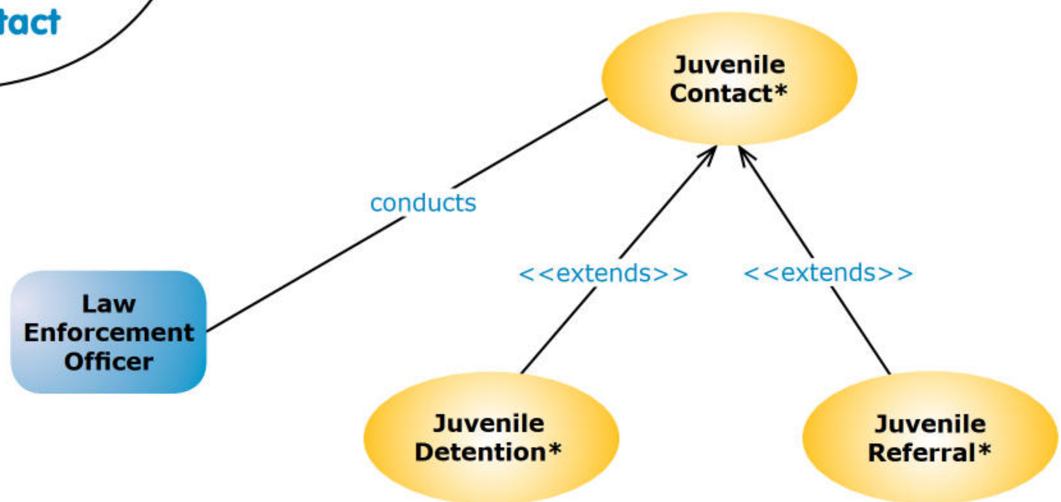
10.1 Use Case Diagram (see page 28)

10.2 Use Case: Juvenile Contact

A contact with a juvenile should be documented in RMS. The contact may result in a citation, referral, or detention. Taking the juvenile into custody allows the law enforcement officer to have the juvenile assessed and ensure the juvenile is not in danger. The law enforcement officer will gather information from the juvenile about the event to determine whether an offense (or status offense) occurred and whether to sanction the juvenile in any way.

In some jurisdictions, the law enforcement officer who takes the juvenile into custody will take the subject to a juvenile intake center for assessment. In other cases, qualified personnel at the law enforcement agency will make the assessment. Once the law enforcement officer has determined that the circumstances warrant more than admonishment, he or she will determine the appropriate recourse or referral. This evaluation is based on the nature of the incident, whether weapons were involved or narcotics were present, and the number of past contacts with the law and victims. In many jurisdictions, referral to juvenile intake is mandated if the juvenile has a pattern of delinquency over a period of time defined by law.

Figure 10.1 Use Case Diagram— Juvenile Contact



The juvenile may be released to a parent or guardian, a hospital, or other nonjudicial authority. Informal diversion might include requiring the juvenile to perform specific community service. RMS has a mechanism that allows for timed alert notices if follow-up contact or information is necessary.

RMS will support these activities by documenting the contact with the youth in a juvenile contact record. It also will guide the law enforcement officer to the appropriate remedy, sanction, or referral, depending on the circumstances.

In handling a juvenile contact, law enforcement officers must communicate with both the professionals conducting the assessment and the juvenile's parents or guardian. RMS must document these communications, as well as other information about the juvenile. The youth's full name, age, address, contact (i.e., family) information, physical description, gender, and name of school he or she attends, as well as information about the incident, are examples of information that will be entered into RMS.

RMS should have the ability to automatically archive juvenile contacts after a requisite period of time (as governed by state law) has passed since the entry or when the subject turns 18 years of age (whichever occurs first).

10.3 Use Case: Juvenile Detention

The juvenile is placed into the care of a custodial facility. The system must send appropriate notification to the court, the prosecutor, and all appropriate social services agencies involved.

10.4 Use Case: Juvenile Referral

Formal charges may be brought against the juvenile. The juvenile may be released to a parent or guardian, a hospital, or other nonjudicial authority. Informal diversion may include assigning required community services. RMS has a mechanism that allows for timed alert notices if follow-up contact or information is necessary.

11

Business Function: Traffic Accident Reporting

Traffic accident reporting involves the documentation of facts surrounding an accident. Typically, these are incidents that involve one or more motor vehicles but also may include pedestrians, cyclists, animals, or other objects. Traffic accident reporting also may be referred to by the terms “collision” or “crash.”

Most states require law enforcement to provide uniform documentation and reporting on all traffic and highway accidents. The information compiled in accident reports is used by the public, insurance companies, traffic analysts, and prosecutors to assist in prosecuting individuals where a criminal offense also may be included. The accident data can also facilitate analysis by identifying necessary road improvements and the elimination of traffic safety hazards.

Typically, Traffic Accident Reporting is a module within the agency RMS. The information is typically captured at the location of the incident; transcribed into electronic forms (e.g., in the field or office); transferred to and used by RMS for local analysis; and, in many jurisdictions, transmitted to the state transportation department. In some jurisdictions, traffic accident reporting is performed using a separate software system, which often is provided by the state transportation agency.

The module also should allow the officer to collect data on the demographics of the people involved, to collect statistics for reporting on bias-based policing evaluations.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- State accident report
- Accidents by location
- Accidents by time of day and day of week
- Accidents by violation
- Accidents by severity
- Accidents by driver demographic
- Statistical summary by intersection
- Statistics by area (e.g., beat, precinct), day, and time

Standard External Data Exchanges:

- State motor vehicle division
- Local, regional, and state transportation departments, using U.S. Department of Transportation (DOT) standards
- Traffic engineering using DOT standards
- Community development

Standard Internal Data Exchanges:

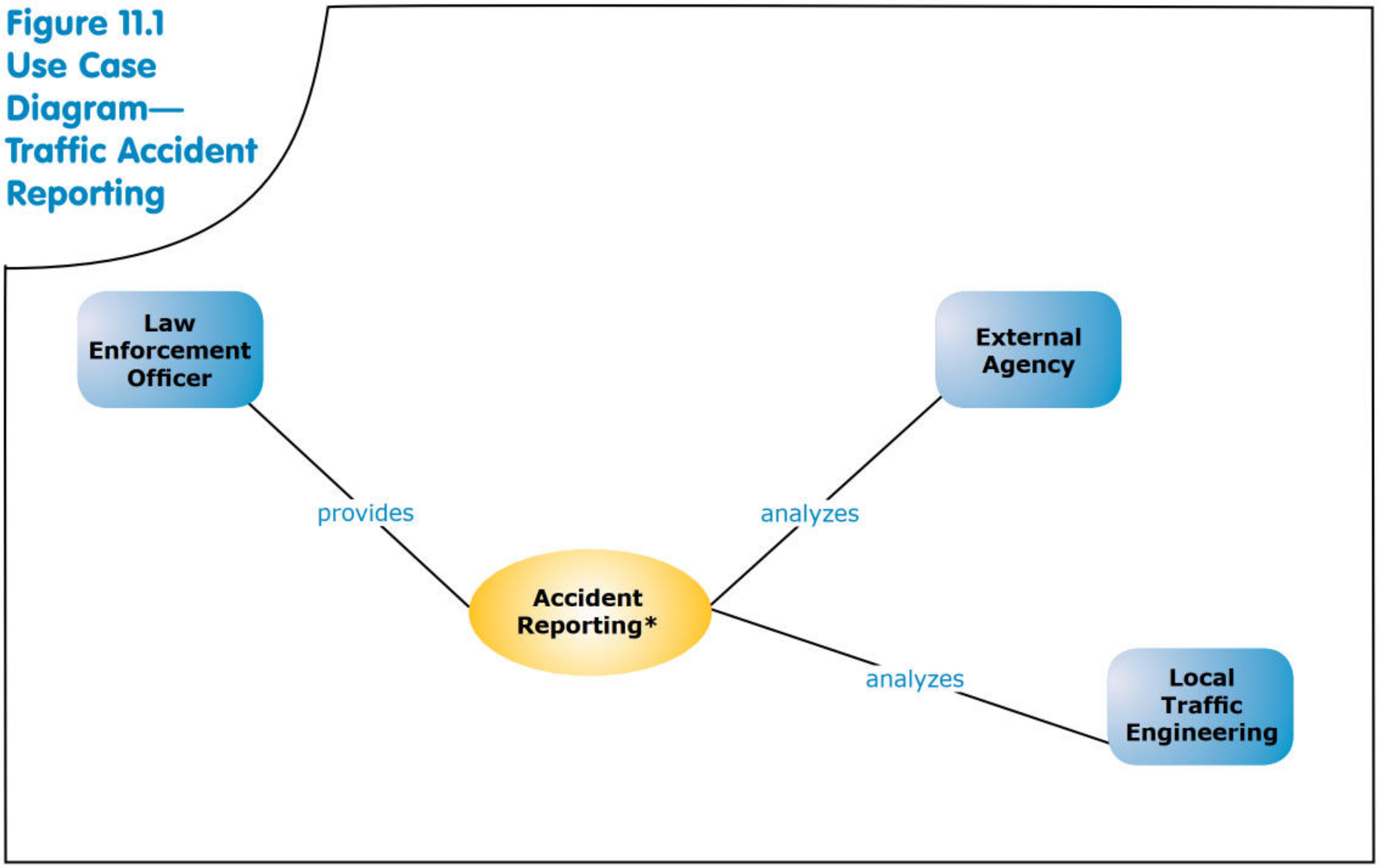
- Mobile reporting system
- Citation
- Master Name Index (MNI)
- Master Vehicle Index (MVI)
- Master Property Index (MPI)
- Arrest
- Citation
- Property and evidence
- Fleet management

11.1 Use Case Diagram (see page 30)

11.2 Use Case: Accident Reporting

Traffic accident reporting requirements differ from general criminal incident reports in that they emphasize the cause of the accident; weather, visibility, and road surface conditions at the time of the accident; and location information. Therefore, traffic accident reporting systems usually include drawing or diagramming tools to assist

Figure 11.1 Use Case Diagram— Traffic Accident Reporting



in accurately capturing accident scene and location information.

The system should support the ability to attach accident diagrams and photographs to the accident report. If a citation is issued as a result of the accident, the citation should be linked to the accident report.

12

Business Function: Citation

Individuals or organizations charged with minor offenses often are issued a citation or ticket, which requires them to pay a fine, post a bail amount, and/or appear in court on a specified date. Citations are commonly used in traffic and misdemeanor law enforcement.

The offender is given a copy of the citation that may contain a preassigned court appearance date. When the citation data are entered or uploaded into RMS, the appropriate links should be made to the master index records. The court clerk is notified of the charges, either by receiving a paper copy of the citation or an electronic copy of the citation data. Often, the offender can pay a fine or forfeit a bail amount to satisfy the fine. In the event that the court date is not assigned when the citation is issued, it is assigned at a later date. The Citation module should capture the court data and record the court's disposition of the citation.

In many jurisdictions, a uniform citation form is used by all law enforcement agencies. The application that supports the creation of the citation may be a module of RMS or a third-party solution designed for the creation of citations in the field.

If the subject is not issued a citation from a citation book, the application must be able to print the citation.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Citation and warnings summary based on varying search criteria
- Citation by location
- Citations and warnings by demographic data
- Citation audit (e.g., missing/voided numbers)

Standard External Data Exchanges:

- Court
- Jail Management System (JMS)
- Warrant
- Prosecutor
- Department of Motor Vehicles (DMV)

Standard Internal Data Exchanges:

- Mobile reporting system
- Traffic accident reporting
- Incident reporting (e.g., misdemeanor citations)
- Master Name Index (MNI)
- Master Vehicle Index (MVI)
- Master Property Index (MPI)
- Arrest
- Juvenile contact

12.1 Use Case Diagram (see page 32)

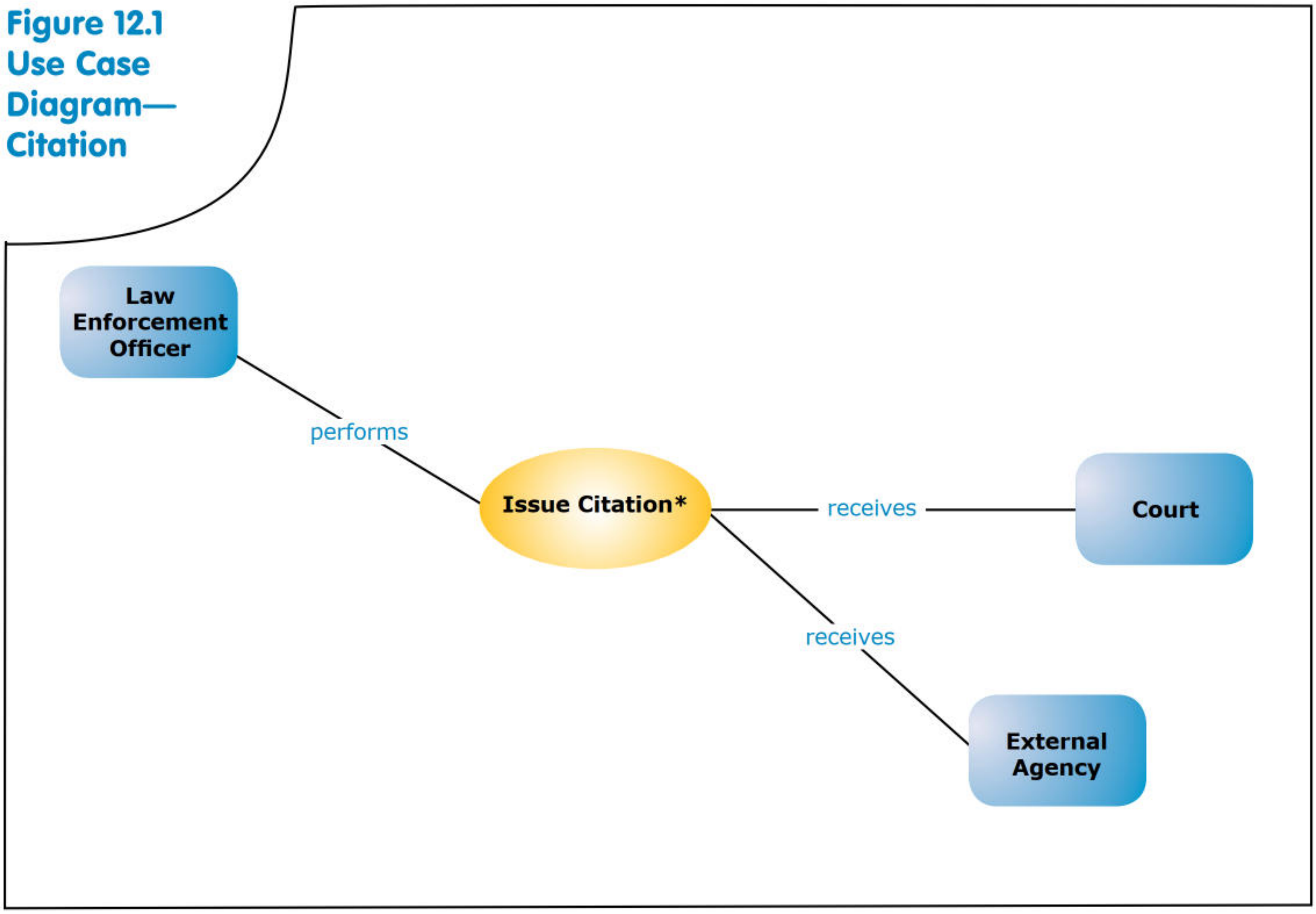
12.2 Use Case: Issue Citation

Citation information is stored and tracked in RMS. Officers will enter information about a violation or charge, as well as relevant court information, into RMS. The citation information will then be sent to the court, either electronically, if the appropriate interface is in place, or manually.

The officer issuing the citation needs to query state and local databases that contain information regarding previously issued citations and warnings. The query also should check for any outstanding warrants or alerts.

A law enforcement officer may decide to issue a warning

Figure 12.1 Use Case Diagram—Citation



instead of a citation. RMS must track warnings, as well as citations. Both must be linked to the subject's master name record.

The module also should allow the law enforcement officer to collect data on the demographics of the people involved, to collect statistics for reporting on bias-based policing evaluations.

13

Business Function: Field Contact

A field contact record is created by a law enforcement officer based on the department's SOP. Typically, this process is triggered by unusual or suspicious circumstances or any activity that is considered by the law enforcement officer to be of interest but would not otherwise be documented in RMS (see the Incident Reporting module for more details). The data in the Field Contact module are available for analytical support (crime analysis). It also can be searched by investigators to develop leads.

Field contacts are not subject to the same stringent review and approval process as incident reports.

The module also should allow the officer to collect data on the demographics of the people involved in order to collect statistics for reporting on bias-based policing evaluations.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Field contact summary, based on varying search criteria

Standard External Data Exchanges:

- State repositories, NCIC
- Mug shots
- Fingerprints

Standard Internal Data Exchanges:

- Mobile reporting system
- Master Name Index (MNI)
- Master Property Index (MPI)
- Master Vehicle Index (MVI)

13.1 Use Case Diagram (see page 34)

13.2 Use Case: Document Field Contact

A field contact is documented, usually at the discretion of the law enforcement officer, based on an observation or information indicating suspicious or unusual activity or circumstances, such as the following:

- A parked car in an area and at a time normally vacant of cars
- One or more people in an area and at a time normally vacant of people
- One or more people loitering in a vulnerable area
- People and vehicles that appear to be out of place for any particular reason

Specific areas may be targeted for field contact based on departmental policy. Such targeting may be for high-crime areas or in potentially sensitive areas, such as areas near schools and religious institutions.

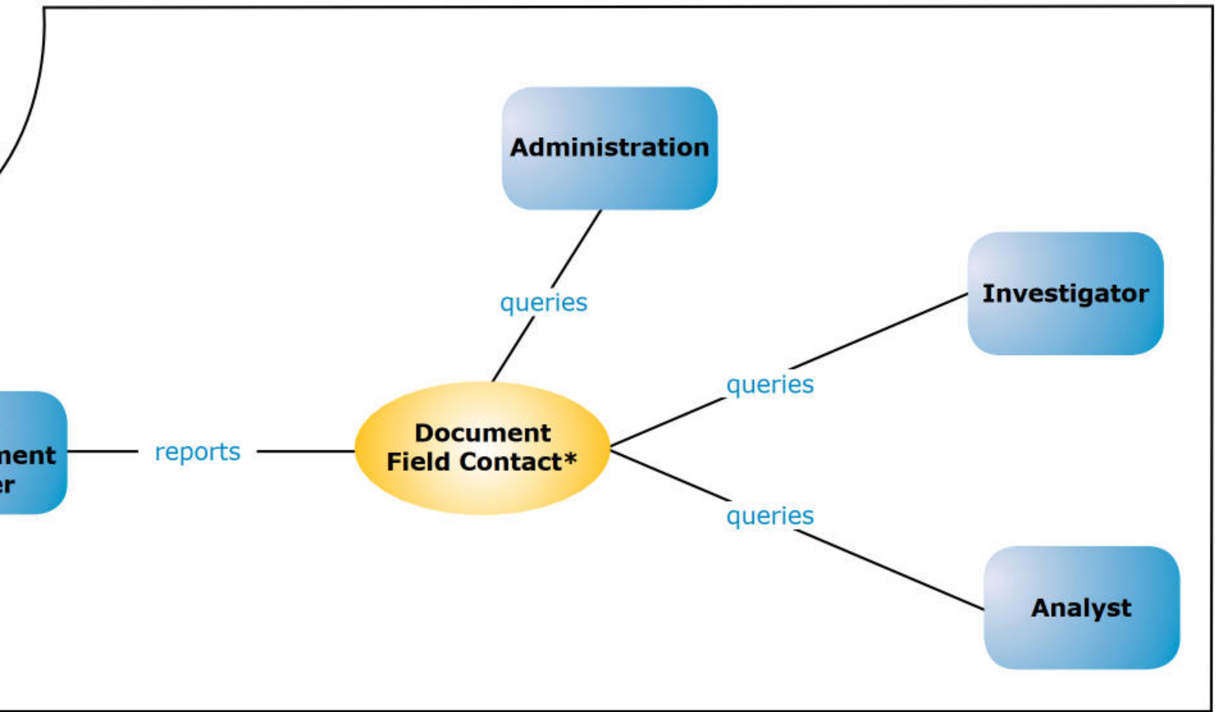
The information collected includes:

- Location and time
- General circumstances
- Names and descriptions of persons
- Identifying information on vehicles or other property

Field contact information serves as a key input to analytical support (crime analysis) and other investigative processes. It helps to establish links between persons, vehicles, and crime events. Because of this, field contact information should be consistent with data standards used in the analytical support/crime analysis process.

Field contact reports, unlike incident reports, are normally not subject to a stringent supervisor review and approval process. They are, however, reviewed to ensure the

Figure 13.1 Use Case Diagram—Field Contact



quality and adequacy of reporting and consistency with departmental policy and statute.

14

Business Function: Pawn

Pawn modules in RMS help law enforcement representatives identify and recover personal property that has been reported stolen. Many jurisdictions require pawnshops to register the items they receive and sell to facilitate this tracking process.

Specific functionality of the Pawn module includes:

- Collecting, storing, and tracking pawn data
- Comparing pawn data with lost or stolen property
- Supporting the investigative process for matches or patterns
- Running inquiries to external regional, state, and federal systems
- Providing data necessary to serve the needs of state pawn systems

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Pawn summary based on varying search criteria (e.g., date, time of sale, and property type)
- Frequent pawner list

Standard External Data Exchanges:

- State and regional pawn systems following NCIC property standards
- Local pawnshop computer systems following NCIC property standards

Standard Internal Data Exchanges:

- License and permits
- Master Property Index
- Property and evidence

14.1 Use Case Diagram (see page 36)

14.2 Use Case: Receive and Process Pawn Data

The pawn shop must submit pawn tickets to the law enforcement agency—either by paper or electronically. This information is then entered into the Pawn module. In the event the property record has a unique identifier, such as a serial number, inquiries may be made to local and external systems. In addition, the name of the person pawning the item and personal identity documentation information (e.g., driver's license number) should be included. Depending on the type of property being pawned, name inquiries may be made to state and national systems.

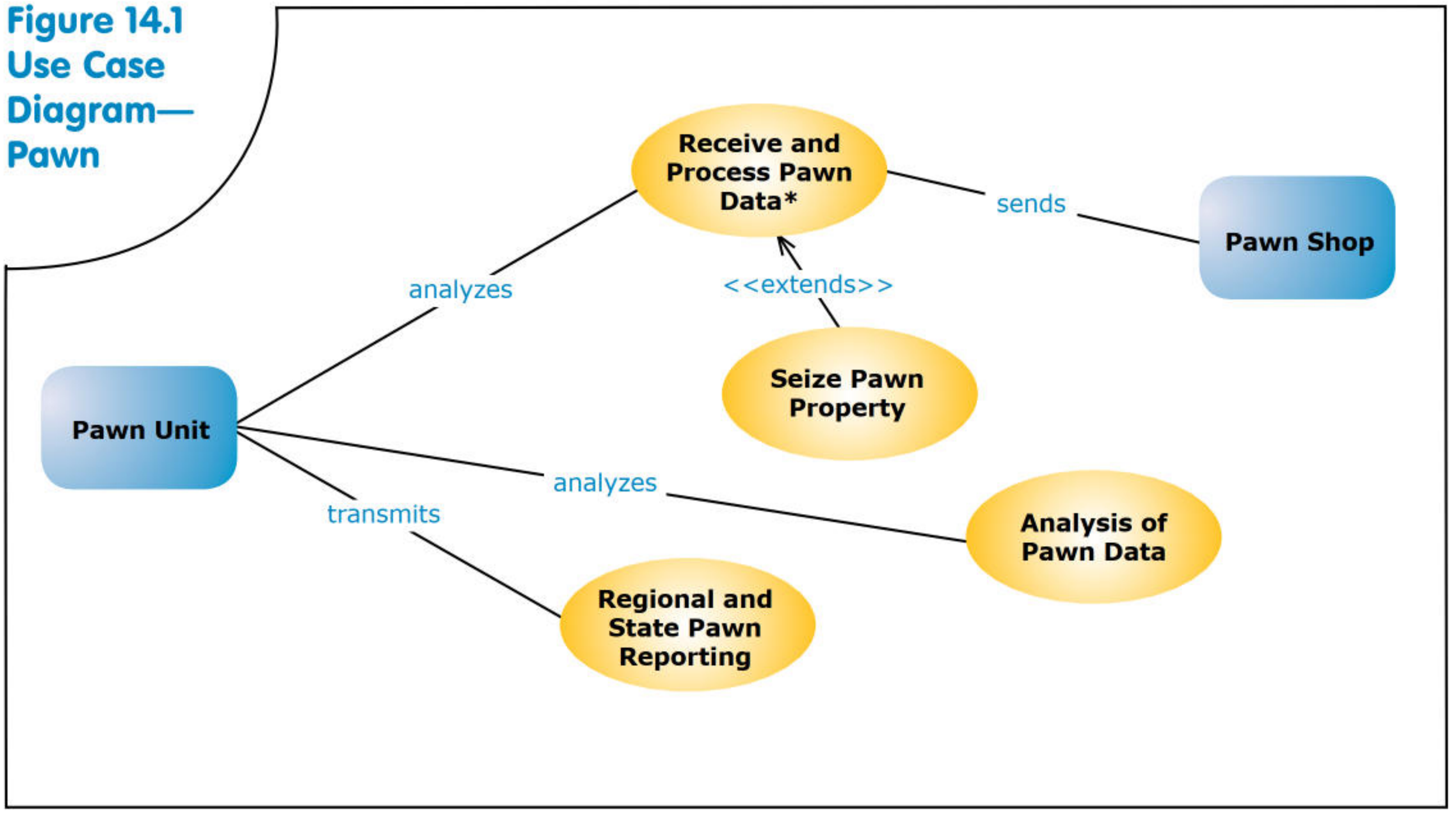
As new items are added to the stolen property database, the pawn database should be automatically queried to determine if the item was previously reported as being pawned.

Any positive hits that return from these external inquiries require follow-up on the part of the pawn unit. This follow-up could include seizing property or further investigation.

14.3 Use Case: Seize Pawn Property

When the pawn unit has identified pawned property that was reported stolen, the pawn record is updated to reflect that the article had been reported stolen and then seized. The pawn unit will take action to seize the property for evidentiary or safekeeping purposes. The property is then checked into the Property and Evidence Management module and, at this point, becomes part of an investigation.

Figure 14.1 Use Case Diagram—Pawn



14.4 Use Case: Analysis of Pawn Data

The Pawn module will analyze pawn data versus stolen data to identify trends and patterns. Examples of analysis include frequent pawn activity by location, person, type, etc. The module must create reports to support the analysis.

14.5 Use Case: Regional and State Pawn Reporting

If an external repository maintains pawn data, information from local Pawn modules may be transmitted to these systems electronically.

15 Business Function: Civil Process

Civil process describes the law enforcement agency responsibility to serve legal papers and execute legal processes as required to facilitate due process through the judicial system. These functions are commonly performed by sheriffs' offices, which are entitled to payment by private parties for such service. RMS modules should allow the data entry of papers to be served, as well as the capability to track the service of civil papers. There often is a data exchange with a billing or accounting system.

The agency may be required by statute to serve these court documents as prescribed and within specified time limits. These documents may include writs, summons, subpoenas, warrants, judgment orders, and civil protection orders. RMS will provide the ability to record the disposition of all actions required by the order, including court-ordered eviction, the seizure of property, and collection of court-ordered fees.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Active civil papers (e.g., by age, jurisdiction, and server)
- Served/returned civil papers
- Civil paper/civil paper jacket
- Expired civil papers
- Notice generation
- Letter generation
- General financial
- Civil summary (e.g., paper summary, assignments, and attempts to serve)
- Affidavit of service

Standard External Data Exchanges:

- Accounting system
- Court
- Jail Management System (JMS)

Standard Internal Data Exchanges:

- Master Name Index
- Master Vehicle Index
- Master Location Index (MLI)
- Master Property Index (MPI)
- Master Organization Index (MOI)
- Warrant

15.1 Use Case Diagram (see page 38)

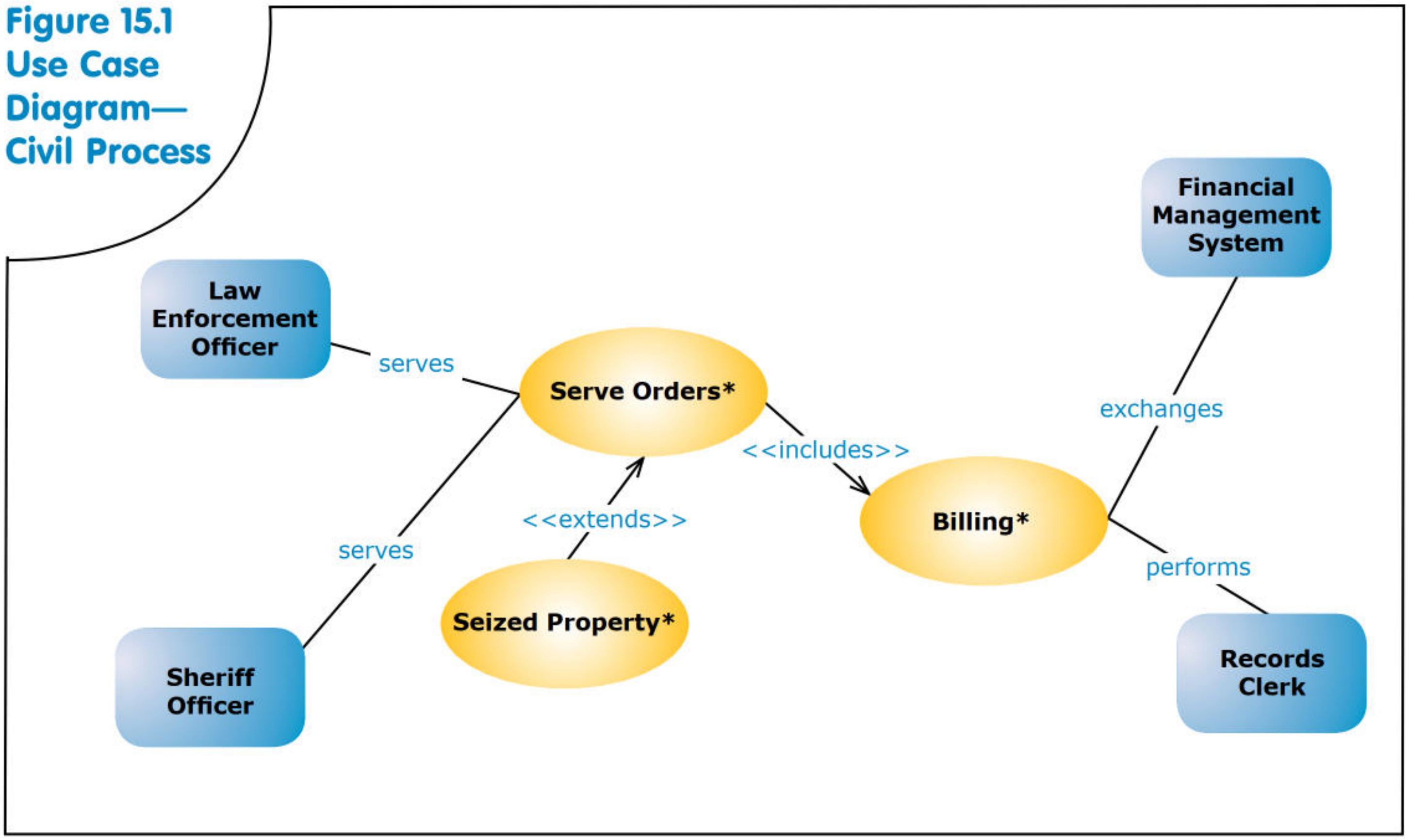
15.2 Use Case: Serve Orders

The service of orders to individuals, organizations, or other justice officials is based on court orders or subpoenas. Service of orders also includes evictions. There will be a good faith effort to serve the order as many times as necessary up to the expiration date. The service attempts and circumstances will be documented. The system generates an affidavit of service to the court on successful service or expiration of the order.

15.3 Use Case: Seized Property

Seized property describes the process and action of seizing personal property, based on a court order presented to a law enforcement officer. The individual or organization is served the order to voluntarily relinquish the property. On failure to relinquish property on a designated date, a property seizure will be scheduled and executed. All service attempts, as well as the order execution, will be documented in RMS.

Figure 15.1 Use Case Diagram—Civil Process



15.4 Use Case: Billing

An agency's RMS should collect the information pertaining to any fees associated with an order service and transfer billing data to the financial system for billing, collection, and distribution of funds. Billing information includes whom and when to invoice, billing amounts, and the allocation and disbursement of fees.

16 Business Function: Protection Orders and Restraints

Law enforcement agencies receive court orders for protection directly from the court or the protected party. This module is used to record protection orders and restraints, including antiharassment orders, protection orders, no-contact orders, and civil protection orders. All parties named in the orders and their relationship to the order must be stored in the system. The conditions of the order are stored as well. The conditions should include information such as the issuing authority, effective time period, location, distance, restrictions, and type of contact prohibited. This information must be readily available by name and location of the parties and also may be cross-referenced by vehicle.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Expired/soon-to-expire orders
- Active orders
- Orders that have been served
- Orders received, by source
- Cancelled orders
- No trespass order

Standard External Data Exchanges:

- CAD
- Court
- National Protection Order Registry (NPOR)
- Jail Management System (JMS)

Standard Internal Data Exchanges:

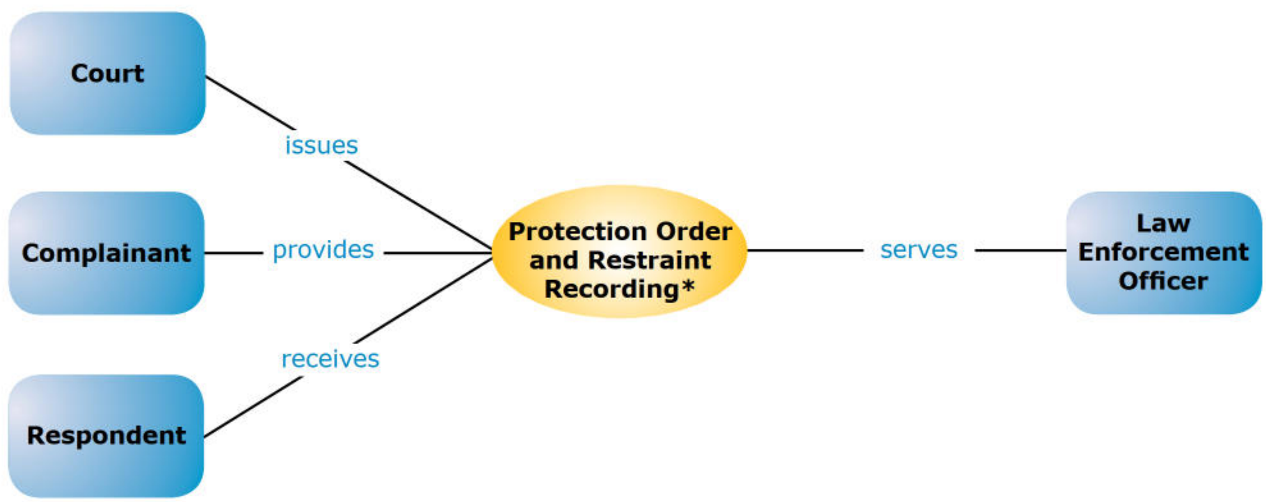
- Master Name Index (MNI)
- Master Location Index (MLI)
- Master Vehicle Index (MVI)
- Master Organization Index (MOI)
- Master Property Index (MPI)

16.1 Use Case Diagram (see page 40)

16.2 Use Case: Protection Order and Restraint Recording

A valid protection order or restraint is recorded in RMS.

Figure 16.1 Use Case Diagram—Protection Orders and Restraints



17 Business Function: Permits and Licenses

The Permits and License module records and tracks the issuance of licenses by agency. Examples of devices and activities that require a license include, but are not limited to, electronic alarms, firearm ownership, and operating massage parlors. Examples of permits include parade, race, or demonstration permits. Licensing is generally for an extended period of time, while permits provide authority for a shorter and specific period of time.

The status of licenses and permits is tracked, including application granting, denial, revocation, and expiration. The change of status or an upcoming expiration date generates appropriate alerts and notifications.

Applicant names are checked against the system MNI. Depending on the type of license or permit, there may be criminal history or other background information that precludes the applicant's eligibility to obtain the license.

Once a license is issued, if the licensee is arrested or is issued a traffic violation, the system will generate an alert to notify the permit and license group to determine whether the license should be revoked.

The system also must track the payments associated with the issuance of licenses and permits or link with a financial system to determine payment status.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Permits and license applications granted based on varying search criteria
- Permits and license applications denied with reason
- False alarm responses, for billing purposes
- Expiration notice

Standard External Data Exchanges:

- CAD (e.g., call data from alarms)

Other Optional External Data Exchanges:

- Financial management system

17.1 Use Case Diagram (see page 42)

17.2 Use Case: Application Processing

The application process includes reviewing the application to ensure all requirements are met. The review will result in either an approval or denial. The decision will be recorded in the RMS, and a notification will be generated by the system and sent to the applicant.

Guidelines for approval may include successful completion of specific training and/or passing a background check to verify the absence of relevant criminal history. There may be fees associated with the application process.

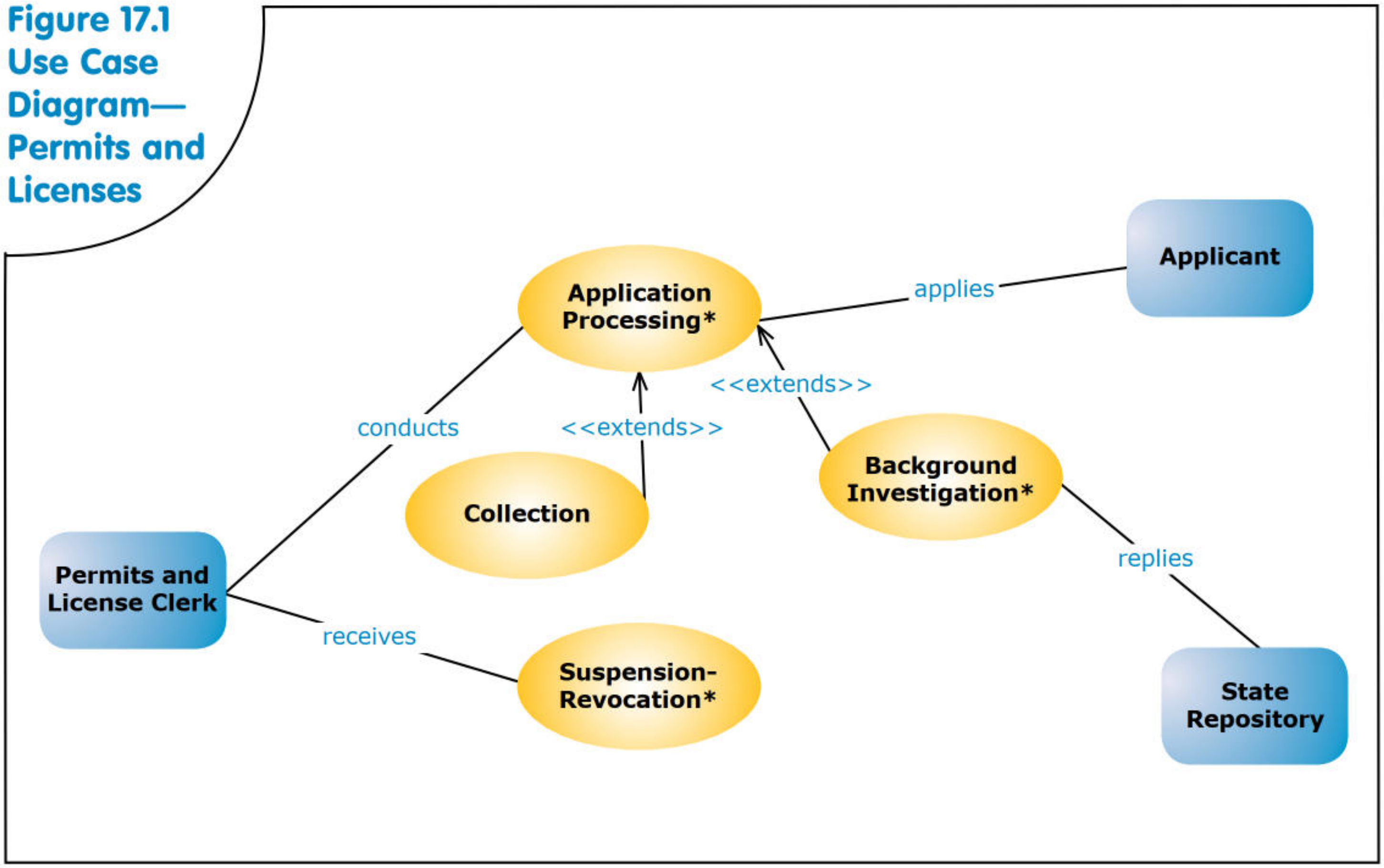
17.3 Use Case: Collection

The system will either receive notification of payment receipt from the financial system or record payment for the application. This module merely associates the payment with the application; it does not include cash drawer accounting.

17.4 Use Case: Background Investigation

The purpose of the background investigation is to determine whether the individual is eligible for the license or permit. The type of permit or license may require differing investigative steps and procedures, such as collecting fingerprints and criminal history checks.

Figure 17.1 Use Case Diagram—Permits and Licenses



17.5. Use Case: Suspension-Revocation

Once the license has been issued, if a licensee is arrested or has traffic violations, the system will generate an alert to notify the permit and license group to determine whether the license should be revoked.

The above situation can result in the generation of a notification letter to the licensee.

18

Business Function: Equipment and Asset Management

Equipment management describes the processes that the law enforcement agency uses to:

- Record the receipt of equipment
- Record the source of the equipment
- Issue equipment to an organizational element or individual
- Track equipment check-in or checkout

Management and tracking of equipment may be facilitated by the integration of bar-coding equipment, a Radio Frequency Identification Device (RFID), etc. The system should have the ability to store photographs of the equipment.

The Equipment and Asset Management module should generate reports to support the physical inventory and audits, which will assist in managing the repair, disposal, and maintenance of agency equipment.

In some agencies, inventory and control of agency property are regulated by authorities outside the law enforcement agency. If this is regulated by an outside agency, an interface between the two systems may minimize duplicate data entry.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Physical inventory report, based on varying search criteria (e.g., category, age, unit, and location)
- Physical inventory exception report
- Check-in/checkout log
- Equipment history

External Data Exchanges:

- Regulating authority (e.g., general services, facility services)

Other Optional External Exchanges:

- Financial management system
- Purchasing

18.1 Use Case Diagram (see page 44)

18.2 Use Case: Equipment Receipt

The Equipment and Asset Management module will allow the capture of descriptive characteristics of the equipment, associated identifiers on the equipment, and any agency-specific unique identifier, such as an inventory control number.

18.3 Use Case: Equipment Issuance

Equipment may be assigned to an organizational element (e.g., unit, division, or group) of the agency, a physical location, or an individual. In addition, equipment may be assigned on a check-in/checkout basis (e.g., daily basis, for patrol). The system must maintain a log of all activity.

Equipment may be authorized but not issued (e.g., a personally owned weapon). The authorization to carry that equipment must be captured.

18.4 Use Case: Equipment Checkout

When equipment is checked out to a unit or authorized person, information about the checkout (e.g., individual receiving equipment, date and time of equipment checkout, and condition of equipment) is recorded for tracking purposes.

This process may be facilitated by the use of bar-code or RFID equipment.

18.5 Use Case: Equipment Check-In

The return of equipment will include an evaluation of the condition of the item, performance of maintenance procedures, disposition of equipment deemed unfit for service, and the return of functional equipment.

The system must support the generation of reports for overdue, lost, stolen, or destroyed equipment.

18.6 Use Case: Physical Inventory/Audit

This function of the system must be able to generate reports about the physical whereabouts of agency equipment. The physical inventory will result in the identification of missing equipment, as well as equipment recommended for repair, replacement, or disposal. This process may identify that the location of the equipment has changed. All information gathered during the physical inventory is used to update the system.

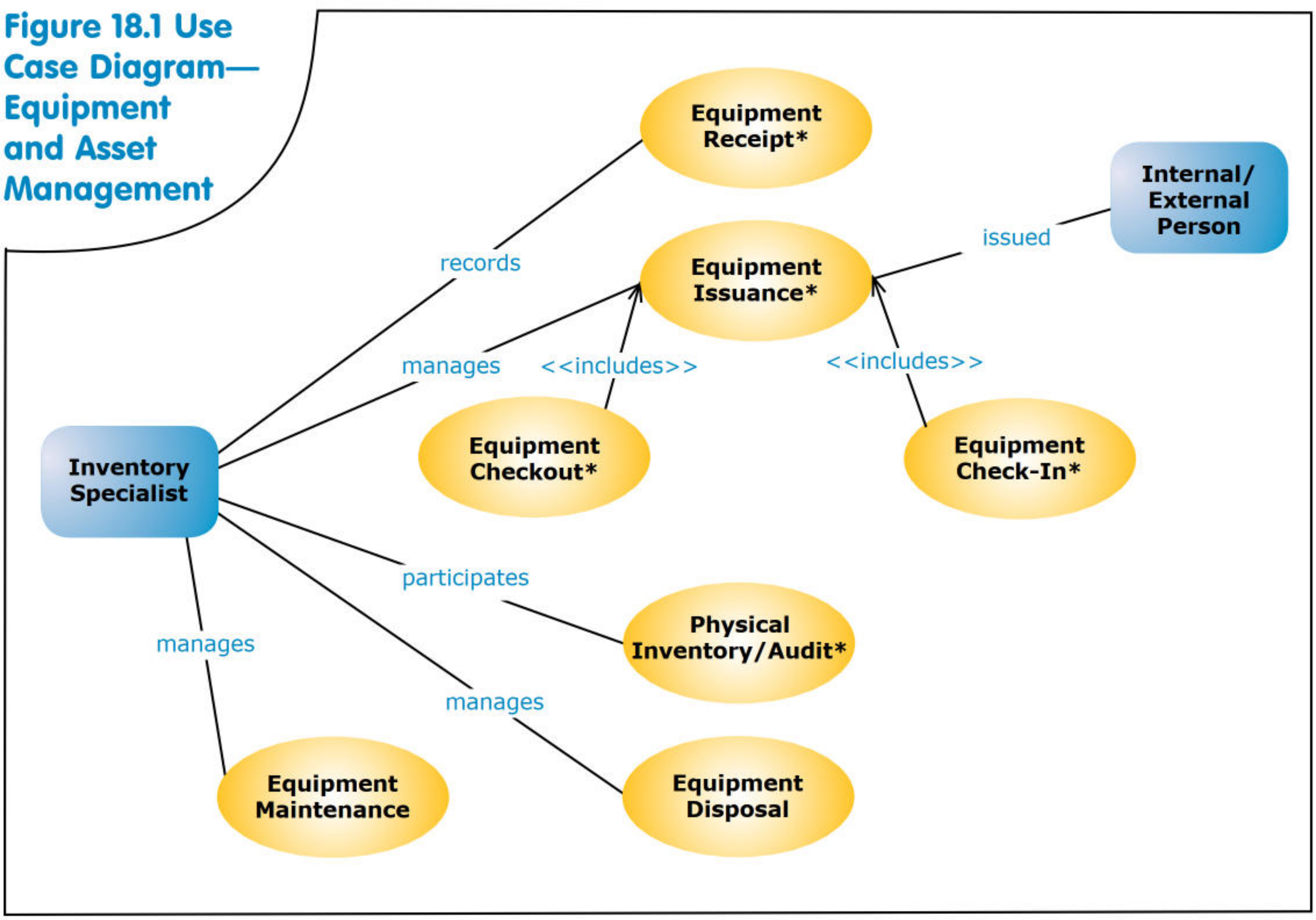
18.7 Use Case: Equipment Maintenance

The system shall record information about equipment condition and maintenance. The information recorded in this module includes reason for repair, cost of repair, date of repair, maintenance location, date expected back in service, date returned to service, and date of next scheduled maintenance.

18.8 Use Case: Equipment Disposal

This is the process associated with taking a piece of equipment out of service and disposing of it. The system changes the equipment status but will not delete or remove historical records associated with that item.

Figure 18.1 Use Case Diagram—Equipment and Asset Management



19

Business Function: Fleet Management

Fleet management includes all vehicle types (e.g., car, motorcycle, boat, and aircraft) and generally encompasses:

- Tracking and issuance of fleet assets
- Tracking service and maintenance schedules and history
- Parts inventory and warranties
- Fuel and oil inventory and usage
- Vehicle disposal

When maintenance or repair work is performed by a contractor, the fleet management module may include functions to track vendors and the services they provide.

Equipment assigned to vehicles may be associated with the identifiers issued by the Equipment and Asset Management module.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Fleet inventory
- Maintenance schedule
- Fleet repair log
- Fluid consumption/cost
- Vehicle repair cost
- Fleet equipment list

External Data Exchanges:

- CAD (e.g., for mileage and use information)

Other Optional External Data Exchanges:

- External fleet management system managed by city, county, or agency
- Fuel card system

19.1 Use Case Diagram (see page 46)

19.2 Use Case: Fleet Receipt

The Fleet module will allow the capture of:

- Descriptive characteristics of the vehicle (e.g., color, make, and model)
- Date the vehicle was deployed
- Starting mileage
- Identifiers (e.g., VIN and license plate number)
- Any agency-specific unique identifier

This module also will establish the service schedule, such as tune-ups and oil changes.

19.3 Use Case: Fleet Issuance

Fleet issuance refers to tracking events related to fleet asset issuance and where fleet is assigned. Vehicles are assigned to a particular organizational element or individual. The system should allow the ability to track the issuance history of the vehicle.

19.4 Use Case: Fuel Log

The Fleet module records the date, price, and amount of fuel purchased at each fill-up, as well as the vehicle's mileage at the time of fill-up. This assists the agency in tracking fuel-related costs.

If the agency uses a fuel card system, there may be an interface between it and the Fleet module to import the fill-up data directly.

19.5 Use Case: Fleet Maintenance

The system can be used to record information about vehicle maintenance and service. The information recorded in this module includes:

- Projected and actual maintenance schedule
- Fluid servicing
- Vendor providing service
- Repair schedule
- Repair and maintenance costs

In addition to periodic scheduled maintenance, a vehicle can enter this process if it is determined to be in need of unexpected repair.

19.6 Use Case: Damage Reporting

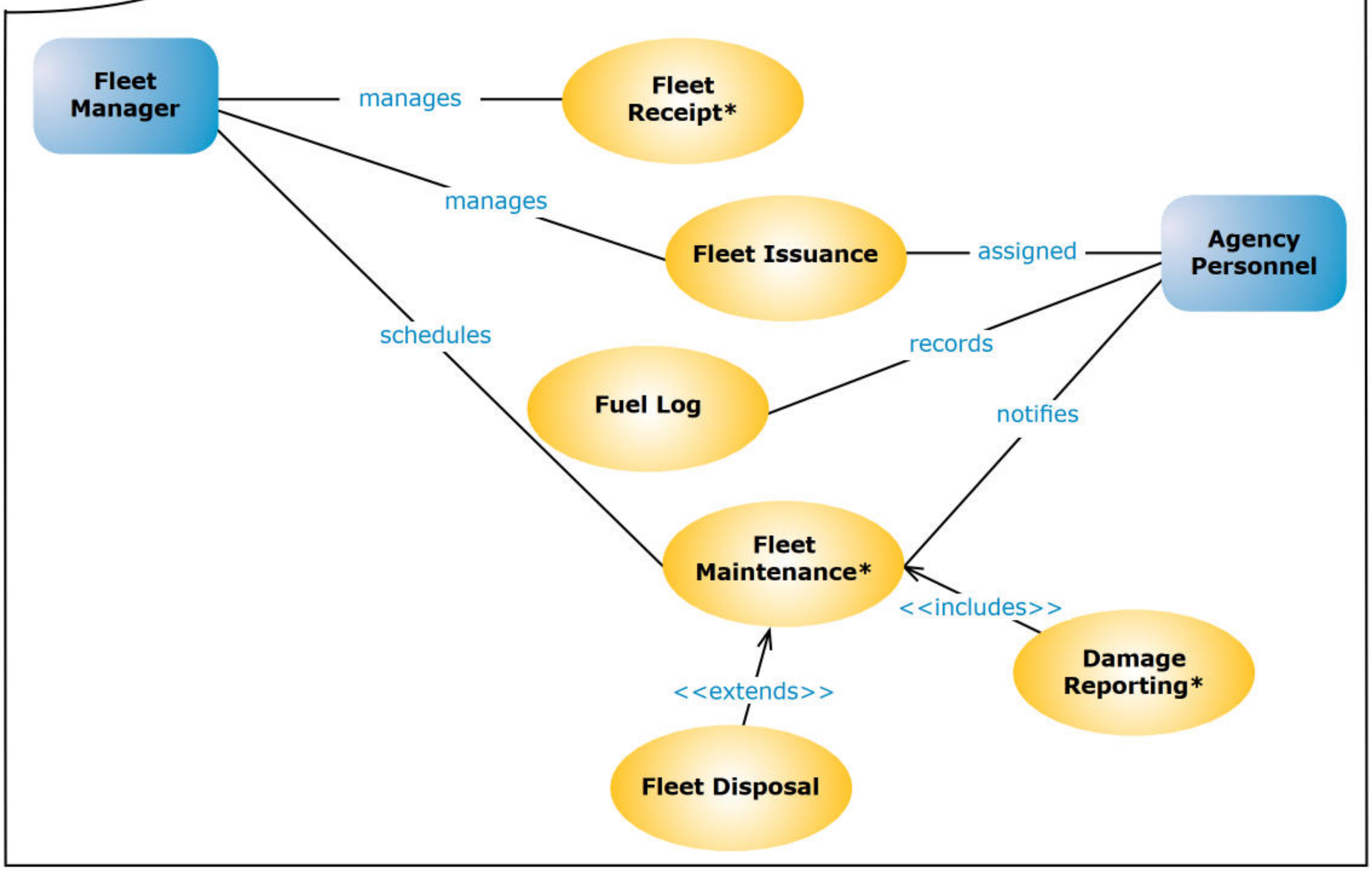
Agency personnel and the fleet manager will periodically assess the condition of the vehicle and record any damage.

This may or may not lead to a repair or maintenance activity. It also may lead to an assessment of officer performance.

19.7 Use Case: Fleet Disposal

This process is associated with taking a vehicle out of service and disposing of it. The system changes the vehicle status but will not delete or remove historical records associated with that item.

Figure 19.1 Use Case Diagram—Fleet Management



20 Business Function: Personnel

The Personnel module allows law enforcement managers to capture and maintain information on the individuals in their department, including volunteers. It also may include information on people outside the department who have received training from the department (e.g., people attending a citizen's academy). This information typically includes the person's basic information, such as emergency contacts, current and past assignments, education, training history, and certifications.

In most locations, information about the employee also is maintained in an external human resource system. To avoid duplicate data entry, an interface should be established between the personnel system and the law enforcement RMS personnel module.

This module addresses those functions that are unique to a law enforcement agency and/or are typically not found in a stand-alone human resources software program.

The Health Insurance Portability and Privacy Act (HIPPA) applies to those agencies that provide health care.

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Personnel summary, based on varying search criteria
- Personnel detail
- Duty roster
- Training and certification scheduling
- Pending certification and skill expiration
- Issued equipment based on varying search criteria
- Health maintenance requirements for duty status

Standard External Data Exchanges:

- Human resources
- Staffing deployment system
- CAD

Standard Internal Data Exchanges:

- Equipment and asset management
- Fleet management

20.1 Use Case Diagram (see page 49)

20.2 Use Case: Operational Management

RMS should be able to draw on RMS data to identify potential personnel and organizational issues. The information includes biased-based policing, uses of force, vehicle pursuits, vehicle crashes, employee injuries, citation data, field contact reports, citizen complaints, and civil and criminal actions.

Management should be able to conduct analyses, as well as ad hoc reporting on these parameters. Management should have the ability to define thresholds on data elements of interest and be notified when certain values, either above or below the thresholds, have been reached.

20.3 Use Case: Personnel Information

The system must allow for the gathering and maintenance of basic information for all personnel working for the department. Information may include names and addresses, physical characteristics, assigned equipment, emergency contact information, special skills, classifications (e.g. sworn/nonsworn), and rank histories.

Health maintenance is important to agency productivity, and some aspects of protecting employee health are mandated by law. The Personnel module will support tracking required vaccinations and medical baselines, such as titer tests for tuberculosis exposure. An agency-specific table should maintain information on vaccinations required by law or recommended by the agency and each vaccination's duration of efficacy. The Personnel module will collect information on date, type, and expiration date of vaccinations employees receive. Reports generated to supervisors will alert the agency to upcoming expirations and needed vaccinations. Similarly, the module will collect information on current health-related duty restrictions affecting employees, produce supervisor reports to ensure employee duties are assigned appropriately to prevent injury, and permit longitudinal tracking and analysis of medical limitations for risk management.

20.4 Use Case: Scheduling and Assignment

The scheduling portion allows for the creation and maintenance of schedule patterns (e.g., days on, days off, and assigned hours). The assignment portion records the officer assignment, shift, and location and associates the officer with a particular pattern. As assignments change, the personnel record is updated to reflect the new assignment. All exceptions to the officer assignment must be recorded.

The system creates the duty roster, which is based on the assignment, schedule, and exceptions to the schedule. To be able to generate past and future rosters, a complete history of assignments, patterns, and exceptions are maintained.

If the department uses a manpower deployment system, the system can be used for defining and finalizing changes in the overall plan for resource utilization, and changes in the assignment can be updated in the Personnel Information module. These automated updates will require an interface between the two systems.

20.5 Use Case: Exceptions

After schedules and assignments have been generated, it will then be necessary to document all conflicts with previously created work schedules. The exception can include any other duty or assignment outside the scheduled or assigned pattern (e.g., training; vacation or sick leave).

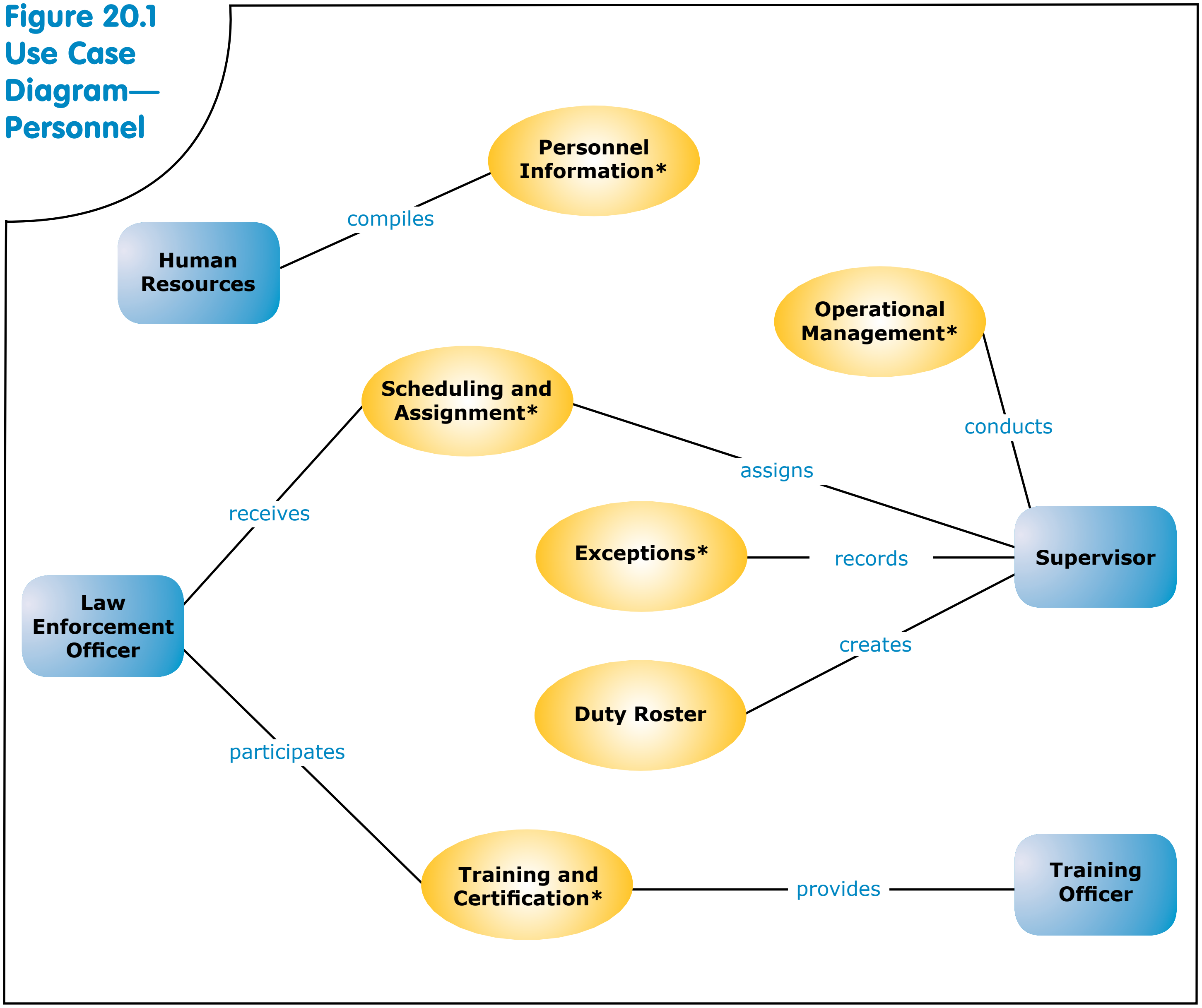
20.6 Use Case: Duty Roster

From the scheduling rotation, assignment, and exception information, the system generates the duty roster for a particular time period (e.g., past, present, or future) the supervisor selects.

20.7 Use Case: Training and Certification

The Personnel module tracks training history and the certification process. The certification process includes officer certification status; deadlines for maintaining certifications, including necessary hours of training, etc.; and student performance.

Figure 20.1 Use Case Diagram—Personnel



21 Business Function: Internal Affairs

A law enforcement agency's Internal Affairs (IA) Division thoroughly investigates allegations of misconduct on the part of employees of the department.

There are several common administrative requirements that help isolate the IA investigation information. The IA system must have multiple levels of security for the application itself, for individual records or groups of records, and for individual or groups of fields. Due to the sensitivity of the information collected in IA functions, the data could be encrypted.

RMS will store all information related to the IA investigation.

21.1 Use Case Diagram

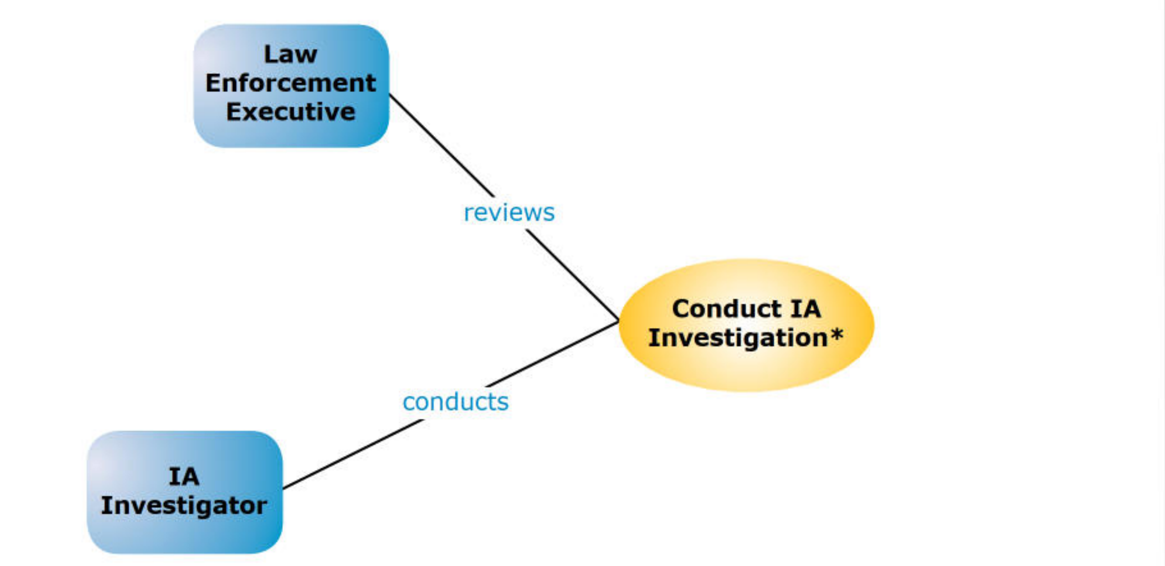
21.2 Use Case: Conduct IA Investigation

The purpose of an IA investigation is to ensure that department policy and procedures are followed and that agency standards of professionalism are adhered to by all department employees.

In many ways, IA investigations are conducted in a manner similar to criminal investigations. Subjects, witnesses, and complainants are interviewed and that information, along with the facts of the case, is recorded in the Internal Affairs module.

Security levels within the Internal Affairs module will limit the availability of information accessible through other RMS modules and indices. An agency-designated recipient will receive an alert whenever a party to an investigation is the subject of a query or if any other RMS activity occurs regarding that party.

Figure 21.1 Use Case Diagram—Internal Affairs



22 Business Function: Analytical Support (Crime Analysis)

Analytical support is the systematic process of collecting, collating, analyzing, and disseminating timely, accurate, and useful information that describes patterns, trends, problems, and potential suspects. RMS should support the tools used by the analyst in this work. Analytical support can be subdivided into four main types:

1. Tactical Analysis: Provides information to assist operations personnel in the identification of specific policing problems and the arrest of criminal offenders.
2. Strategic Analysis: Provides information concerning long-range crime problems. Strategic crime analysis provides information concerning crime rate variations and provides geographic, economic, social, and/or other types of general information to administrators.
3. Administrative Analysis: Provides information to support administrative decisions related to resource allocation and to support budget requests and decisions.
4. Forecasting Analysis: A combination of tactical, strategic, and administrative analysis; merging multiple sets of data.

In addition to being able to query and produce ad hoc reports on any number of indicators, analytical support also includes standardized reporting functionality. One example of a standardized report is crime statistics. Crime statistics are essentially comparative statistics on the community crime rate, which can be disaggregated by specified timeframes, offenses, and complaints by beat or zone.

RMS must interface with analytical support tools, such as crime-mapping software and link-analysis, data mining, spatial, and temporal tools. The results of these analyses should be stored in RMS for a time determined by the jurisdiction's SOP and can be used to assess agency performance and provide support for administrative decisions. RMS should have a variety of reporting functions attached to their Analytical Support modules and allow presentation of information in a variety of formats, such as bar graphs, pie charts, and line graphs.

RMS should support the ability to aggregate data on the various indicators, such as:

- Current period vs. previous period
- Current period vs. historical average
- Percentage of total crimes for period by:
  - Reporting districts
  - Areas/beats/zones
  - Teams/shifts
- Percentage change from prior periods (i.e., trend)

RMS should contain the ability to conduct crime distribution analysis based on a number of criteria, including:

- By area/beat or reporting district (i.e., ZIP codes)
- By time, date, and day of week
- Frequency of occurrence
- Citation
- Crime/incident report number
- Field interview data
- Search warrant data
- Vehicle information
- Type of offense (e.g., residential, auto, or business)

The system also should include standardized reports, such as general offense activity, offense activity by day of week, and offense activity by beat. Every field of operational data in RMS (i.e., data entered by the user in any form, not configuration or system control data) should be searchable, including narrative (e.g., text or memo) fields. This can be done by using query interfaces that are part of the application or, at a minimum, using third-party tools that can access the operational database via Open Data Base Connectivity (ODBC).

RMS should include an alert function related to analytical support to provide for the immediate transmission of information to law enforcement officers in the field.

RMS should support a quality control process on incoming reports to ensure that data are correctly and completely entered.

RMS should contain complete data elements that relate to time, such as the day, time of day, week, date, month, and year. It also should include a locally determined and previously validated geographic reference.

RMS should support crime/suspect correlations to show a relationship between a suspect and an offense. The correlations may be made by using any number of selected criteria in which unique and distinguishing characteristics, physical identifiers, modus operandi, and various other common traits of offenders are known. These identifiers may be captured as a part of multiple different business functions, including incident, field contact, arrest, accident, citation, MNI, MVI, MLI, and MOI.

Standard Output:

- Crime distribution analysis reports using the criteria listed above

Standard External Data Exchanges:

- Third-party mapping and graphing tools
- Regional Information Sharing Systems (RISS) (i.e., based on Global JXDM, NCIC standards)

22.1 Use Case Diagram (see page 55)

22.2 Use Case: Tactical Analysis

Tactical analysis provides information to assist personnel in the identification of specific, immediate crime or disorder problems and the arrest of criminal offenders. Tactical analysis provides information to assist personnel (e.g., patrol and investigative officers) in preventing and disrupting criminal behavior, identifying specific and immediate crime problems, and arresting criminal offenders. Analytical data are used to promote a quick response to field situations.

22.3 Use Case: Strategic Analysis

The purpose of strategic analysis is to provide information concerning long-range problems. Strategic analysis is primarily concerned with solutions to ongoing problems. It results in the ability to accomplish the agency mission more effectively and efficiently.

22.4 Use Case: Forecasting Analysis

The purpose of forecasting analysis is to prevent crime by analyzing information collected in RMS and correlating it with external sources. It can involve the application of advanced analytical methods to forecast the occurrence of specific crimes or trends.

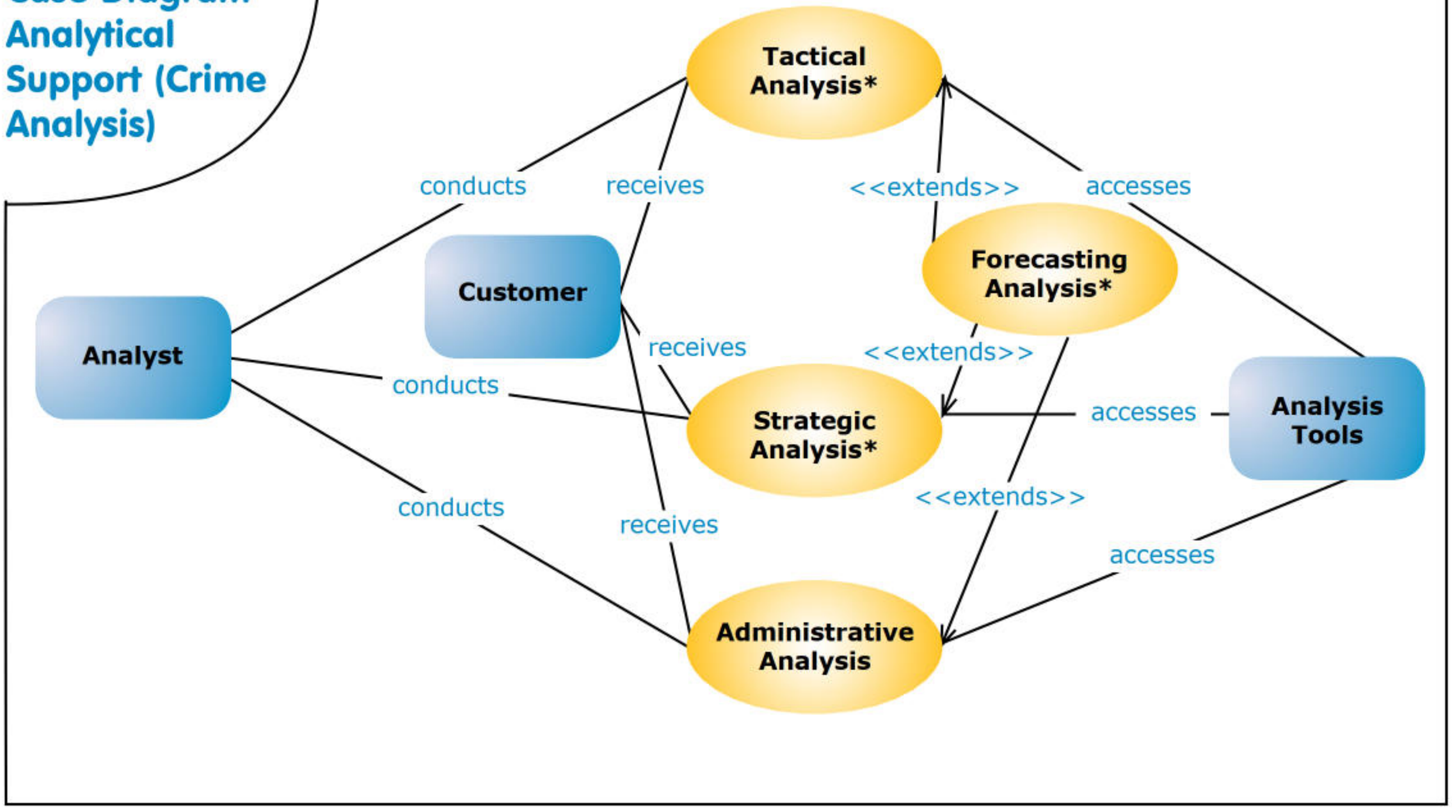
RMS should support the ability of the analyst to generate the Forecasting Analysis report. The report's format should be tailored to meet the particular requirements of the customers who receive the information, whether they are patrol, investigative, or administrative personnel.

22.5 Use Case: Administrative Analysis

Administrative analysis develops long-range (e.g., quarterly, semiannually, or annually), strategic comparisons and reports them externally. Examples of administrative crime analysis tasks may include providing economic, geographic, and law enforcement information to law enforcement management, neighborhood/citizen groups, other appropriate agencies, and the public.

Where required by the agency's SOP, RMS should support the ability to generate statistical reports on all law enforcement activities within that agency, allocate costs to those activities, and track performance measures as defined by the agency.

Figure 22.1 Use Case Diagram—Analytical Support (Crime Analysis)



23 Business Function: RMS Reports

RMS reports document officer and agency-wide activity or performance in a given area. Many reports are created over the course of conducting policing business (e.g., arrest report and incident report). Aggregated reports are conducted by line and supervisory staff and reviewed by law enforcement executives. Role-based security should restrict access to some reports.

Law enforcement personnel must be able to generate standardized reports and aggregate reports, as well as query RMS to produce ad hoc reports from the RMS reports module.

Examples of standardized reports from RMS business functions are:

- Incident reports
- Accident/crash reports
- Property/evidence reports
- Citation reports
- Field interview reports
- Uniform Crime Reports (UCR)/National Incident-Based Reporting System (NIBRS)
- Case management reports
- Billing reports
- Summary reports for warrants, citations, CFS, accidents, and employees

Typically, third-party products are used for ad hoc queries and reports.

23.1 Use Case Diagram (see page 58)

23.2 Use Case: Aggregate Reporting

Aggregate, agency-wide reporting allows law enforcement personnel to associate information in a variety of ways and among a number of different tables or fields, including CFS, warrants, incident reports, traffic data, property data, and weapons data.

Managers must be able to query, retrieve, and display information in a variety of ways. They must be able to query on indicators, such as date of the incident, case type, and assigned officer. They should be able to produce reports from a list of standardized reports or on an ad hoc basis.

The query and data retrieval system must be integrated with the RMS security system so that the department can designate search and query types and depths by password or groups of passwords.

23.3 Use Case: Standardized Reporting

Each module includes its own set of standardized reports, which also are available through the RMS Incident Reporting module.

23.4 Use Case: Ad Hoc Reporting

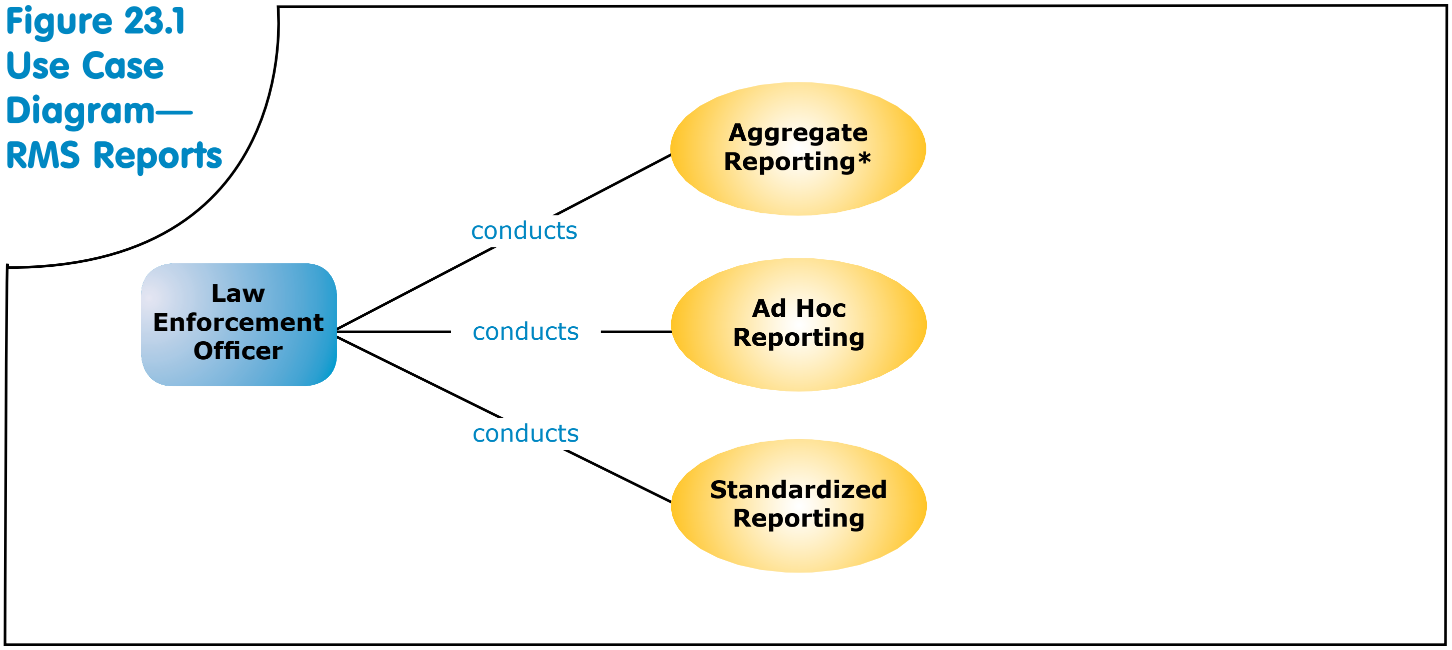
The agency may need operational reports and analysis that are not provided by standard RMS reports and queries. Ad hoc reporting will allow a user to define and create these additional custom reports. Once created, these custom reports can be saved and run as standard reports.

RMS should provide a tool that can be used to produce any number of ad hoc reports.

These ad hoc reporting tools may be provided using a third-party solution. This solution may be imbedded in the application or run as a stand-alone. Ad hoc reporting functions that are imbedded into the RMS solution may use existing RMS security controls. Stand-alone, ad hoc applications open the potential to bypass the RMS security controls (e.g., juvenile data, sealed records, and redacted records). The stand-alone approach may allow an agency to have a broader selection of ad hoc tools. However, there are trade-offs, such as the security issue noted above.

Another approach is to extract data, excluding secured information, into separate data warehouses. That way, stand-alone, ad hoc tools could be used to access the data without compromising RMS security controls.

Figure 23.1 Use Case Diagram— RMS Reports



24 Business Function: RMS System Administration

While most RMS systems are standard, they should be configurable so that they can be used to meet specific agency requirements. The RMS systems administration functions address RMS configurable aspects.

System administration encompasses a wide array of general functions that law enforcement agencies need from their RMS to be able to create and query information effectively; ensure appropriate access to information and systems security; and ensure effective departmental information, image, and document management.

Examples of administrative functions include:

- RMS table maintenance
- RMS configurations (e.g., parameters, defaults)
- Security (e.g., user role, jurisdiction)
- Geofile
- Data management (e.g., data dictionary, archive and purge)

Standard Outputs, External Data Exchanges, and Internal Data Exchanges

Standard Outputs:

- Report on users, sortable by names, access level, password age, and machine used
- Report on RMS use, sortable by user log-in, frequency, total time in system, number of concurrent log-ins, machine used, and duration time-outs
- Report on failed log-ins, sortable by log-in name, number of attempts, date/time of attempt, and machine used
- Report on subsystem security violations
- Alerts; user-definable security violations, which generate an external message to predefined locations

Standard Internal Data Exchanges:

- Agency network operating system
- E-mail system for alerts

24.1 Use Case Diagram (see page 60)

24.2 Use Case: Security

Systems should allow tiered access to information, based on passwords and other authentication and nonrepudiation practices. Role-based authentication and authorization must be a part of RMS. Other identification technologies such as biometrics, identification cards, and security tokens are emerging standards.

Systems should apply appropriate edits to all entered data to ensure data integrity and maintain activity logs and audit trails.

24.3 Use Case: RMS Table Maintenance

RMS should include the ability for the user agency to define and maintain codes and associated literals (i.e., plain English translation) for as many data elements as possible. The literals should be stored in the database, as appropriate.

Where available and applicable, RMS should use the authoritative code tables referenced in Global JXDM and NCIC.

24.4 Use Case: Data Management

Data management includes the following:

- Record expungement and sealing
- Data redaction
- Data dictionary

These topics are further described in the following paragraphs.

Record Disposition

RMS must be able to support expungement, sealing, and purging of whole records and partial records. To support this function, the system must be able to flag a record, flag data elements within a record, and delete a record. The flag should indicate why the record or data element is restricted.

Data Redaction

Redaction is the process of editing report information to filter sensitive or confidential information before the report is released to the public or for general use outside the department. The type of information that is edited includes victims' names in certain types of cases, juvenile information, or information that is considered by the agency to be sensitive to an investigation.

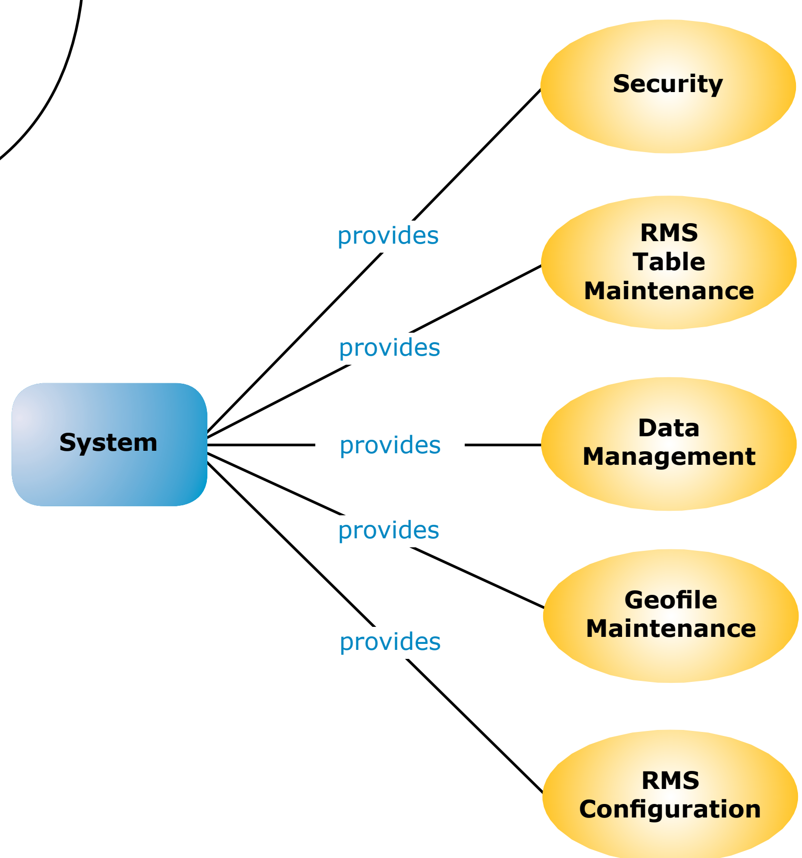
In the case of formatted and structured data, report output programs can produce a redacted version of specific report data. In the case of narrative or otherwise unstructured information, the redaction process requires a manual step to produce a public version of the report.

Generalized report tools, if employed to produce reports for public consumption, should be used only on data that have already been redacted.

Data Dictionary

RMS must provide a capability to display and/or print the database structures to allow the end user to access the database tables through third-party, ad hoc inquiry tools/utilities.

Figure 24.1 Use Case Diagram—RMS System Administration



The data dictionary may contain the following information for each field description:

- Field name (e.g., external representation)
- Database column name (e.g., internal representation)
- Data type (e.g., numeric, alpha, or date)
- Field size
- Field format (i.e., output format)
- Edit or validation criteria
- Associated code table
- Default value
- Description

24.5 Use Case: Geofile Maintenance

The geofile is used to validate and standardize location and address information. It also is used to cross-reference addresses and locations with law enforcement-defined reporting areas, X/Y/Z coordinates, ZIP codes, and other identifiers. The geofile contains sufficient information to ensure that an address is valid. Furthermore, it provides cross-references to addresses and locations using commonplace names (e.g., business names, parks, hospitals, and schools) and street aliases. It includes information such as direction of travel on particular streets and can identify the side of a street for a specific address. It is assumed that all addresses in RMS are validated using the system geofile.

The reporting area defined above should be used to define beats, sectors, command areas, neighborhoods, communities, etc.

The geofile contains the geographic information that is the basis for many decisions in a communications center. The system needs to provide the ability for an agency to enter and update all geofile data, including the physical address and the X/Y/Z coordinates.

The creation of a comprehensive geofile is a significant undertaking. The system should support the creation and maintenance of the geofile using an available mapping/Geographic Information System (GIS) database. Geofile information in CAD and RMS should be synchronized, based on established parameters.

24.6 Use Case: RMS Configuration

Some parameters of RMS should be configurable by the system administrator. For example, the system administrator should be able to modify the system variables, such as agency and chief's name, Originating Agency Identifier (ORI), address, and phone number. Changes to parameters, such as juvenile default age, X/Y/Z or state plane geography coordinates, and name match rules, should be allowed.

The system administrator also must have the ability to define the conditions under which an alert or notification is issued.

In a multijurisdictional RMS, the system administrator should be able to change the parameters for each participating agency.

Any configuration changes that could affect system integrity must be properly flagged with adequate warning to prevent inadvertent damage to the system.

25 Business Function: RMS Interfaces

RMS frequently requires functionality to exchange data with other systems. The exact nature of those exchanges will, in large part, be determined by local business practices and local agency work flows. All interfaces need to comply with national standards. Each business function includes examples of data exchanges.

25.1 Use Case Diagram

25.2 Use Case: CAD Interfaces

Information may be transferred from CAD to RMS when units are initially dispatched, an incident number is assigned, and/or the call is closed in CAD.

CAD users require the ability to retrieve information from RMS based on name, location, and vehicle descriptors.

25.3 Use Case: Local/Regional Interfaces

RMS users need to access and possibly update a variety of local and regional systems. Examples include courts, prosecutor, financial systems, Jail Management Systems, human resources systems, and multijurisdictional information systems. Data exchanges with many of these systems are identified in the specific business functions in this specification.

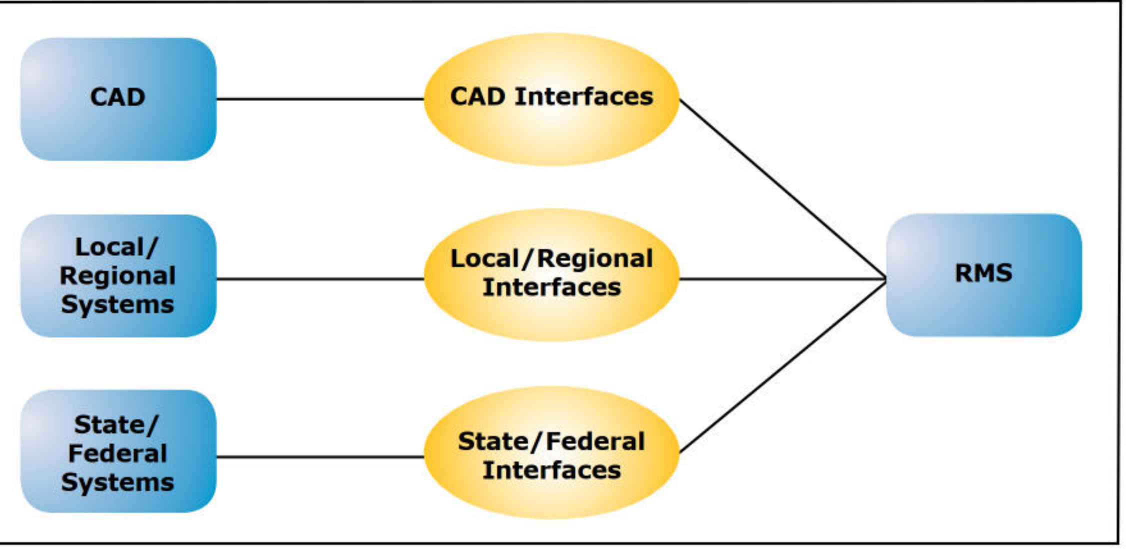
These interfaces should be based on national standards, such as Global JXDM and NCIC.

25.4 Use Case: State/Federal Interfaces

RMS needs to query, add, or modify information stored in state and federal systems. Examples include updates for wanted people, missing people, stolen vehicles/property, and state sex offender registries.

These interfaces should be based on national standards, such as Global JXDM and NCIC.

Figure 25.1 Use Case Diagram—RMS Interfaces



27 Conclusion

LEITSC had a mission to create a national standard for law enforcement RMS and has succeeded in carrying out this task.

The RMS functional standards are meant to describe the minimal amount of functionality that an RMS for law enforcement should contain. These standards should be used as a starting point to build a fully functional RMS, based on agency needs and open standards, to efficiently interface and share information with other systems, both internally and externally. They are designed to serve as a guiding tool for law enforcement agencies and should be tailored to fit the specific needs of each law enforcement agency or group of agencies looking to upgrade or purchase a new RMS. Although the RMS functional standards were not developed to substitute for an RFP, they can be used to supplement an RFP.

The functional standards found in this document are intended to be generic in nature and do not favor one particular system or approach over another. They are at the functional level, meaning that they define what is to be accomplished versus how it should be accomplished.

The RMS functional standards were developed by the LEITSC Functional Standards Committee and are now available to all law enforcement agencies.

Acronyms: RMS

AFIS	Automated Finger Print Identification System
BJA	Bureau of Justice Assistance
CAD	Computer Aided Dispatch
CFS	Calls for Service
DMV	Department of Motor Vehicles
DOJ	U.S. Department of Justice
DOT	U.S. Department of Transportation
DUI	Driving Under the Influence
EFTS	Electronic Fingerprint Transmission Specification
FBI	Federal Bureau of Investigation
GIS	Geographic Information System
Global JXDM	Global Justice XML Data Model
HIPPA	Health Insurance Portability and Privacy Act
IA	Internal Affairs
IACP	International Association of Chiefs of Police
IAFIS	Integrated Automated Fingerprint Identification System
IJIS	Integrated Justice Information System Institute
JMS	Jail Management System
LEITSC	Law Enforcement Information Technology Standards Council
MDC	Mobile Data Computer
MLI	Master Location Index
MNI	Master Name Index
MOI	Master Organization Index
MPI	Master Property Index
MVI	Master Vehicle Index
NCIC	National Crime Information Center
NIBRS	National Incident-Based Reporting System
NIEM	National Information Exchange Model
NIJ	National Institute of Justice
NIST	National Institute of Science and Technology
NOBLE	National Organization of Black Law Enforcement Executives
NPOR	National Protection Order Registry
NSA	National Sheriffs' Association
ODBC	Open Database Connectivity
OJP	Office of Justice Programs
ORI	Originating Agency Identifier
PERF	Police Executive Research Forum
RFID	Radio Frequency Identification Device
RFP	Request for Proposal
RISS	Regional Information Sharing Systems
RMS	Records Management Systems
SID	State Identification Number
SOP	Standard Operating Procedures
UCR	Uniform Crime Report
VIN	Vehicle Identification Number
XML	Extensible Markup Language
X/Y/Z	Longitude, latitude, and altitude

RIPS 2016 MIDTERM PRESENTATIONS

Thursday July 21 2016

Each team presents for 30 minutes (25 Talk and Q&A)

Morning Session

10:00-10:30 GumGum

10:30-11:00 Aerospace

11:00-11:30 Arete

11:30-12:00 LAPD

12:00-12:30 Google

Afternoon Session

14:00-14:30 LLNL

14:30-15:00 HRL

15:00-15:30 AMD

15:30-16:00 CSX

CONFIDENTIALITY AND NONDISCLOSURE AGREEMENT

Between

THE LOS ANGELES POLICE DEPARTMENT
And
UCLA
Institute for Pure and Applied Mathematics
Dr. P. Jeffrey Brantingham

(Hereafter "Requestor")

The undersigned hereby agrees to the following as conditions to the receipt and utilization of data from the Los Angeles Police Department ("LAPD"), for the purpose of assisting the LAPD with analyzing video footage. This project is titled, "Analyzing Body-Worn Camera Video in the Los Angeles Police Department". The purpose of this project is to identify specific features from video using machine learning algorithms. Researchers will examine video footage from LAPD to determine specific interactions between the police and the public.

1. Definitions

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2. Treatment and Use of Protected Confidential Material. Requestor hereby agrees that all Protected Confidential Materials to which he is given access shall remain the property of the City of Los Angeles. Such materials shall be used only for the Project and shall not be used for any other purpose not described in this Agreement. Requestor agrees not to copy, disseminate, or allow access to any Protected Confidential Material.

Requestor further agrees to secure any Protected Confidential Material received from the LAPD in such a way that unauthorized persons or entities cannot retrieve the information by any means, including but not limited to access via computer, remote terminal, or by any other electronic or non-electronic means.

Requestor acknowledges the confidential nature of the Protected Confidential Material supplied by the LAPD, and agrees that disclosure by the Requestor or any individual or group of individuals at the request or direction of the Requestor to anyone not directly identified in this Agreement is strictly prohibited.

Importantly, the Requestor assures that data identified to a specific individual will not be revealed under any circumstances and that the information is being used for research and statistical purposes only.

Project findings and reports will not contain information about individuals or private persons.

3. Return of Protected Confidential Materials. Upon completion of the Project, Requestor shall immediately return all Protected Confidential Material in their possession or control, including any and all copies (whether electronic or non-electronic), to the Los Angeles Police Department. Requestor shall certify in writing that all originals and copies of the material provided under this Agreement have been returned.

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C. Restrict access of all data supplied by LAPD to those individuals whose responsibilities cannot be accomplished without such access; and

D. Store all Protected Confidential Material received from LAPD in secure locked containers.

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I/We hereby agree to all conditions and requirements set forth in this Agreement:

FOR THE LOS ANGELES POLICE DEPARTMENT

MAGGIE GOODRICH, Chief Information Officer
Commanding Officer
Information Technology Bureau

Date: 5-31-16

FOR REQUESTOR

By:
P. Jeffrey Brantingham, Ph.D.
University of California, Los Angeles

Date: 5-9-16

<u>CONFIDENTIALITY AND NONDISCLOSURE AGREEMENT</u>

Between

THE LOS ANGELES POLICE DEPARTMENT
And
THE REGENTS OF THE UNIVERSITY OF CALIFORNIA LOS ANGELES, INSTITUTE FOR PURE AND APPLIED MATHEMATICS, RESEARCH IN INDUSTRIAL PROJECTS FOR STUDENTS 2016 ("UCLA IPAM RIPS")
(Hereafter "Requestors")

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FOR THE LOS ANGELES POLICE DEPARTMENT

____
MAGGIE GOODRICH, Chief Information Officer
Commanding Officer
Information Technology Bureau

Date: _________________________________

INSTITUTE FOR PURE AND APPLIED MATHEMATICS, RESEARCH IN INDUSTRIAL PROJECTS FOR STUDENTS 2016

By: ______________________________
Emily Loughran, Director of Licensing
Date: ______________________________

By: ______________________________
First Last Name, RIPS Academic Mentor
Date: ______________________________

By: ______________________________
First Last Name, RIPS Student
Date: ______________________________

By: ______________________________
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CONFIDENTIALITY AND NONDISCLOSURE AGREEMENT

Between

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And
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Information Technology Bureau

Date: _________________________________

THE REGENTS OF THE UNIVERSITY OF CALIFORNIA LOS ANGELES, DEPARTMENT OF MATHEMATICS, NATIONAL SCEINCE FOUNDATION, RESEARCH EXPERIENCE FOR UNDERGRADUATES 2016

By: ______________________________
Emily Loughran, Director of Licensing
Date: ______________________________

By: ______________________________
Matt Haberland, NSF REU Academic Mentor
Date: ______________________________

By: ______________________________
Alicia Figueroa, NSF REU Student
Date: ______________________________

By: ______________________________
Deborah Tonne, NSF REU Student
Date: ______________________________

By: ______________________________
Yun Liu, NSF REU Student
Date: ______________________________

By: ______________________________
Benjamin Lu, NSF REU Student
Date: ____________________________

CONFIDENTIALITY AND NONDISCLOSURE AGREEMENT

Between

THE LOS ANGELES POLICE DEPARTMENT
And
THE REGENTS OF THE UNIVERSITY OF CALIFORNIA LOS ANGELES, INSTITUTE FOR PURE AND APPLIED MATHEMATICS, RESEARCH IN INDUSTRIAL PROJECTS FOR STUDENTS 2016 ("UCLA IPAM RIPS")
(Hereafter "Requestors")

The undersigned hereby agree to the following as conditions to the receipt and utilization of data from the Los Angeles Police Department ("LAPD"), for the purpose of assisting the LAPD with analyzing video footage. This project is titled, "Analyzing Body-Worn Camera Video in the Los Angeles Police Department". The purpose of this project is to identify specific features from video using machine learning algorithms. Researchers will examine video footage from LAPD to determine specific interactions between the police and the public.

1. Definitions

A. "Protected Confidential Material" includes all written information, whether originals or copies, including but not limited to reports, documents, notes, interviews, electronically stored data, photographs, charts or any other information supplied by the LAPD to Requestors, and it to be treated as non-public and protected from disclosure or dissemination, in accordance with the terms of this Agreement.

2. Treatment and Use of Protected Confidential Material. Requestors hereby agree that all Protected Confidential Materials to which they are given access shall remain the property of the City of Los Angeles. Such materials shall be used only for the Project and shall not be used for any other purpose not described in this Agreement. Requestors agree not to copy, disseminate, or allow access to any Protected Confidential Material.

Requestors further agree to secure any Protected Confidential Material received from the LAPD in such a way that unauthorized persons or entities cannot retrieve the information by any means, including but not limited to access via computer, remote terminal, or by any other electronic or non-electronic means.

Requestors acknowledge the confidential nature of the Protected Confidential Material supplied by the LAPD, and agree that disclosure by the Requestors or any individual or group of individuals at the request or direction of the Requestors to anyone not directly identified in this Agreement is strictly prohibited.

3. Return of Protected Confidential Materials. Upon completion of the Project, Requestors shall immediately return all Protected Confidential Material in their possession or control, including any and all copies (whether electronic or non-electronic), to the Los Angeles Police

Department. Requestors shall certify in writing that all originals and copies of the material provided under this Agreement have been returned.

4. Monitoring of Compliance and Demand for Document Return. The LAPD may monitor, audit and review the Requestors' program activities and policies to ensure compliance with the requirements and conditions of this Agreement. If the LAPD determines that the requirements and conditions of this Agreement are not being satisfactorily met, it may require the immediate return of all copies of the Protected Confidential Material obtained under this Agreement, take such action as deemed appropriate to protect the security and privacy of this material, and refuse any future requests for information or records from the Requestors.

5. Protection of Personal Identifying Information. In order to protect the identities of any persons whose records are supplied to the Requestors under this Agreement, Requestors agree to:

A. Use the Protected Confidential Material furnished under this Agreement only for the purpose described by Requestors.

B. Replace the name and other personal identifiers with an alphanumeric or other appropriate code for purpose of conducting the necessary project analyses;

C. Restrict access of all data supplied by LAPD to those individuals whose responsibilities cannot be accomplished without such access; and

D. Store all Protected Confidential Material received from LAPD in secure locked containers.

6. Project Treatment. Requestors agree to insert into the preface of any report citing data analysis conducted on any of the Protected Confidential Material, a disclaimer that the analysis and report are solely the work product of the Requestors and do not represent the position or conclusions of the Los Angeles Police Department.

At the conclusion of the Project, Requestors will provide the LAPD with a copy of any written report derived from the Project. LAPD shall retain the discretion to use the report for whatever purpose or further analysis it deems appropriate.

Requestors acknowledge that any written or oral report generated pursuant to analysis of any of the Protected Confidential Material is not to be published or circulated in any manner other than as explicitly set forth under this Agreement. The City retains sole authority to approve disseminating to individuals, agencies, organizations or entities not parties to this agreement specific information regarding the services, reports, Deliverables and other materials resulting from this Agreement. "Dissemination" as used in this section includes, but is not limited to printed and online articles, reports or publications, and public relations and advertising materials for Requestor's services or participation under this Agreement.

7. **Release from Liability.** Requestors agree that the City of Los Angeles and any of its agents or employees shall not be liable for any acts or omissions arising from the production of the Protected Confidential Material to Requestors, its use by Requestors, or any and all resulting analyses or conclusions derived from the Materials. Requestors shall indemnify and hold the

City of Los Angeles and its employees and officers harmless for any and all claims, lawsuits, causes of action, damages or costs incurred in any adjudication or settlement of claims, including attorney's fees and costs, which may arise from any alleged use or misuse of documents provided by the LAPD pursuant to this Agreement, or by any negligent or willful act or omission on the part of Requestors.

This Agreement will become effective upon signature of the parties.

I/We hereby agree to all conditions and requirements set forth in this Agreement:

FOR THE LOS ANGELES POLICE DEPARTMENT

MAGGIE GOODRICH, Chief Information Officer
Commanding Officer
Information Technology Bureau

Date: 7-6-16

INSTITUTE FOR PURE AND APPLIED MATHEMATICS, RESEARCH IN INDUSTRIAL PROJECTS FOR STUDENTS 2016

By: ______________________
Emily Loughran, Director of Licensing
Date: 6-16-16

By: ______________________ Giang Tran
First Last Name, RIPS Academic Mentor
Date: 06/21/2016

By: ______________________
First Last Name, RIPS Student
Date: 21 June, 2016
David Madras

By: ______________________
First Last Name, RIPS Student
Date: 21 June 2016
Stephanie Allen

By: ______________________
First Last Name, RIPS Student
Date: 21 June 2016
Greg Zanotti

By: ______________________
First Last Name, RIPS Student
Date: 21 June 2016
Ye Ye

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LAPD

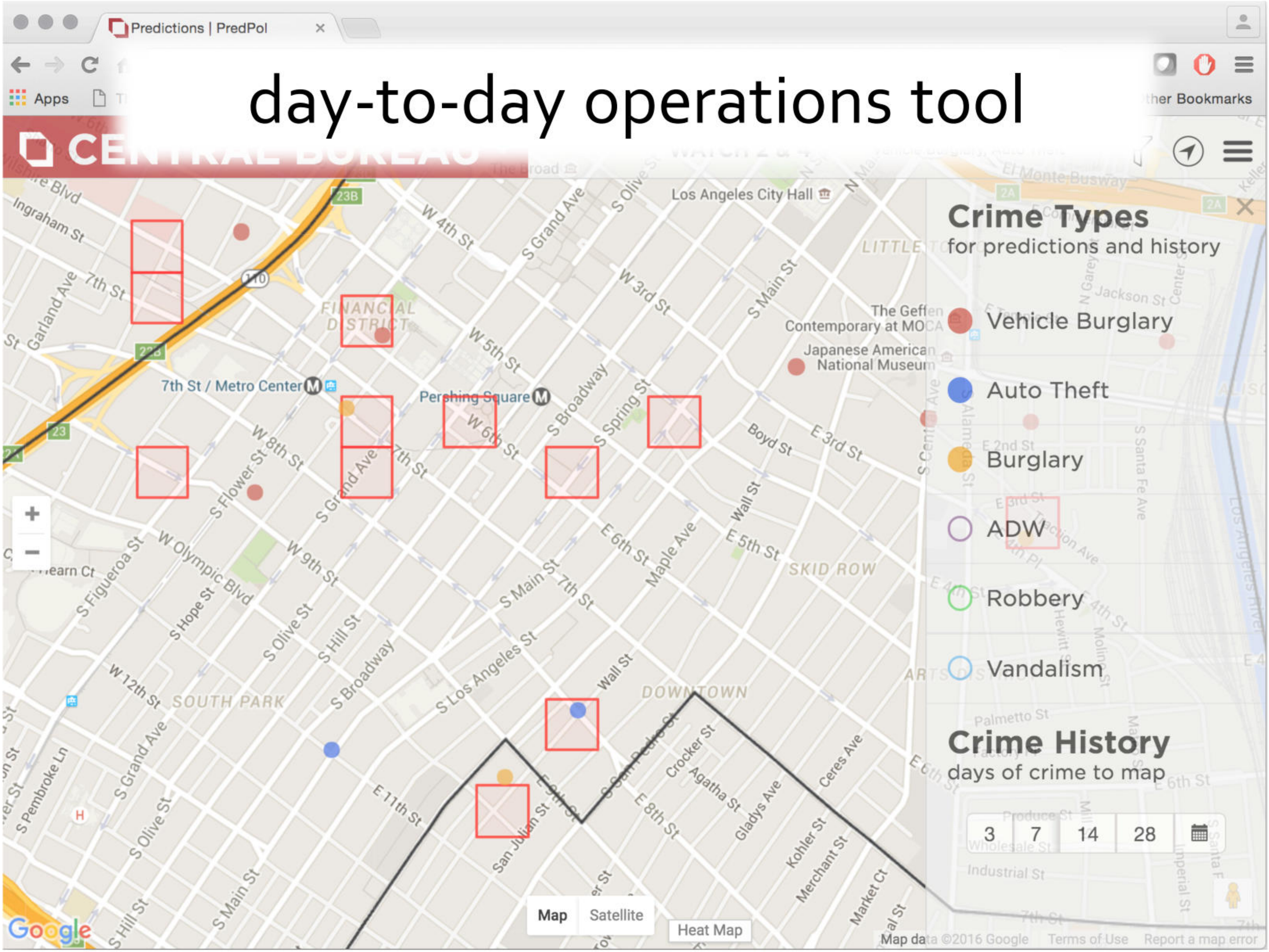
UCLA

Making Predictive Policing Work

Commander Sean Malinowski
LAPD Chief of Staff

sean.malinowski@lapd.lacity.org

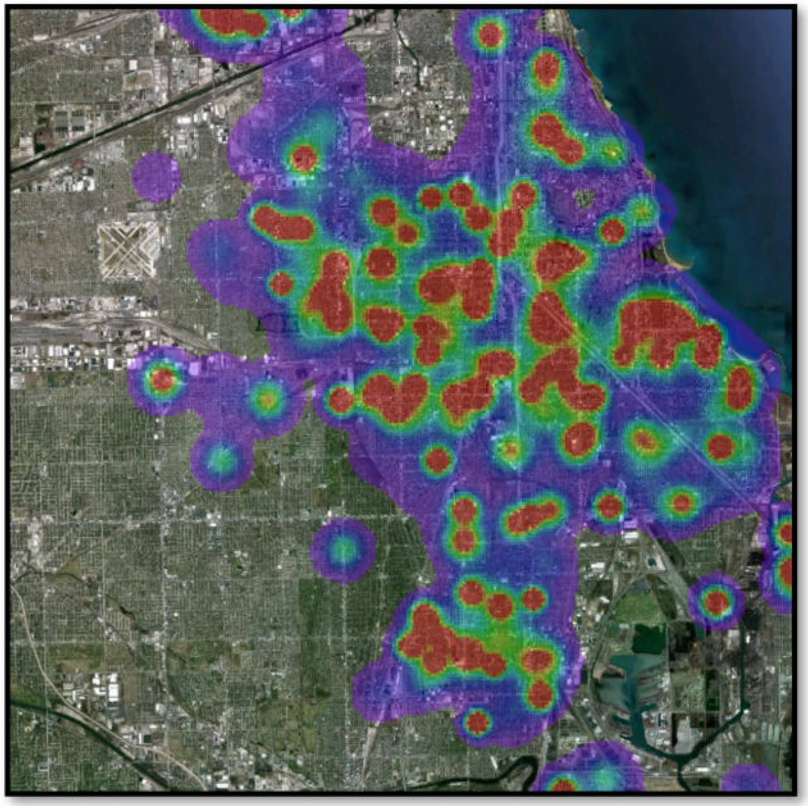
day-to-day operations tool



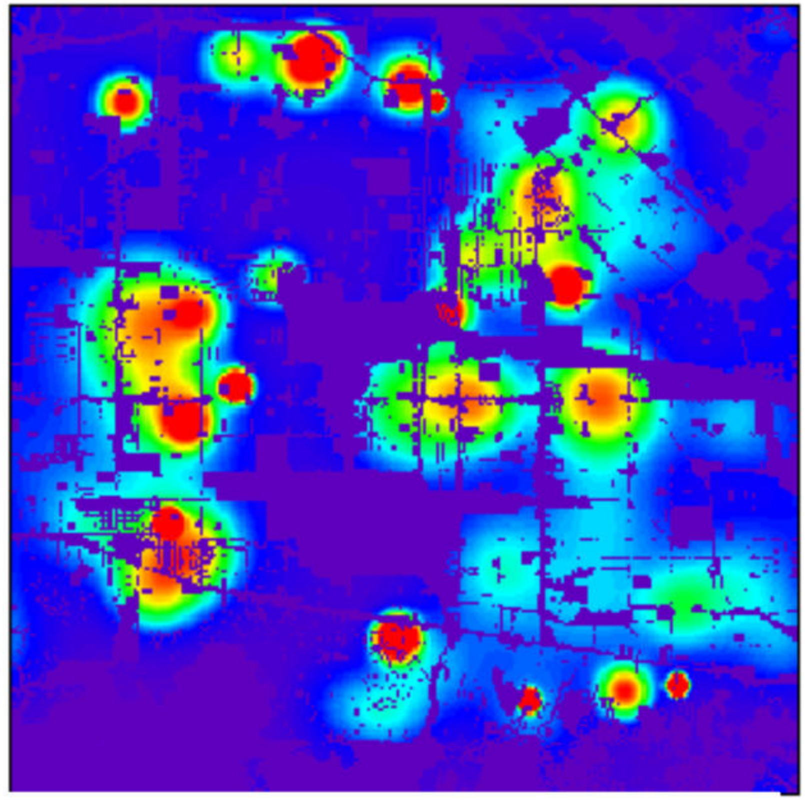
outline

1. Why is predictive policing needed?
2. What does predictive deliver?
3. How is it used?
4. What impact does it have?
5. Leadership & sustainability.

1. why is predictive needed?

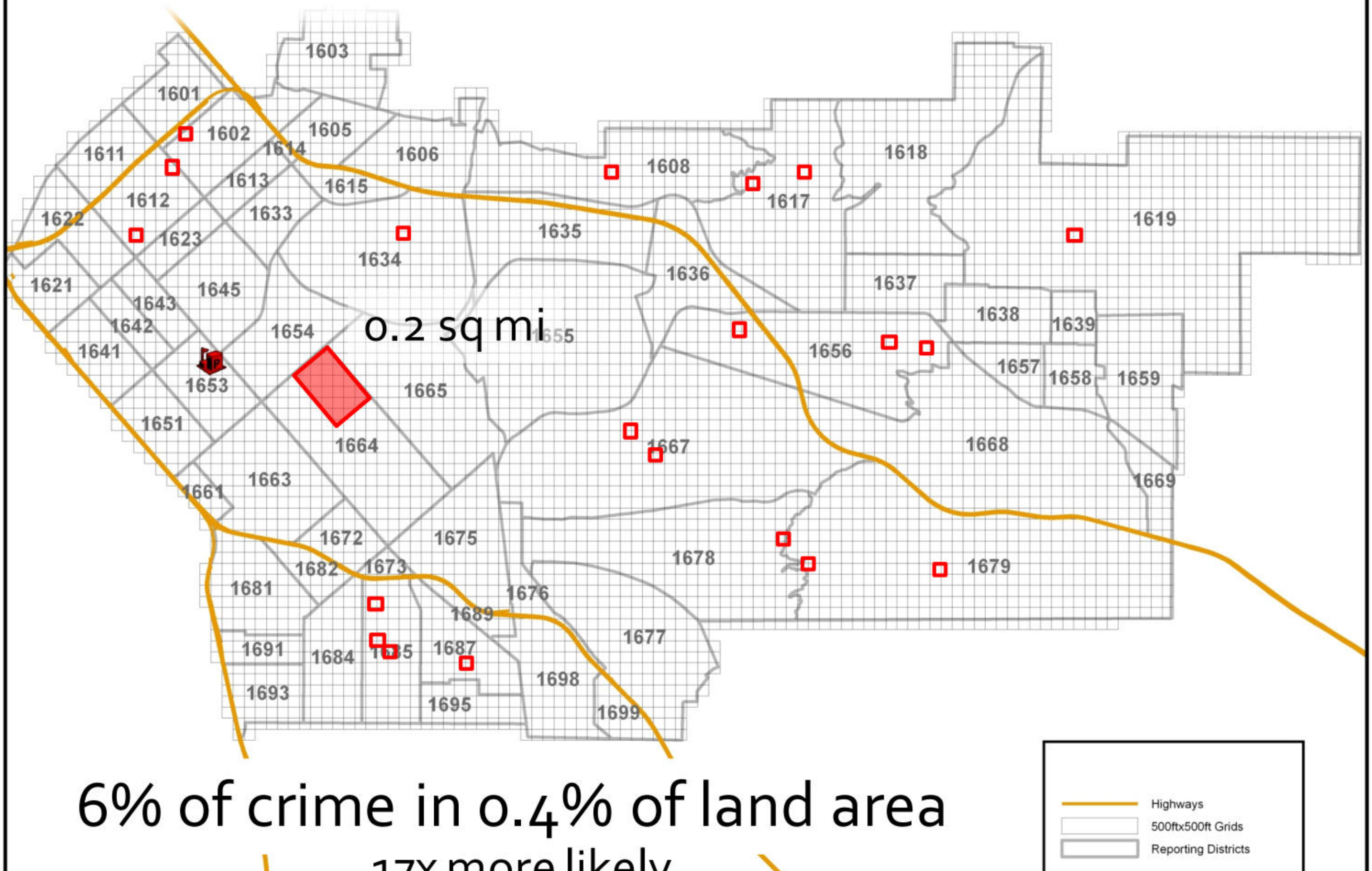


daily gun violence Chicago



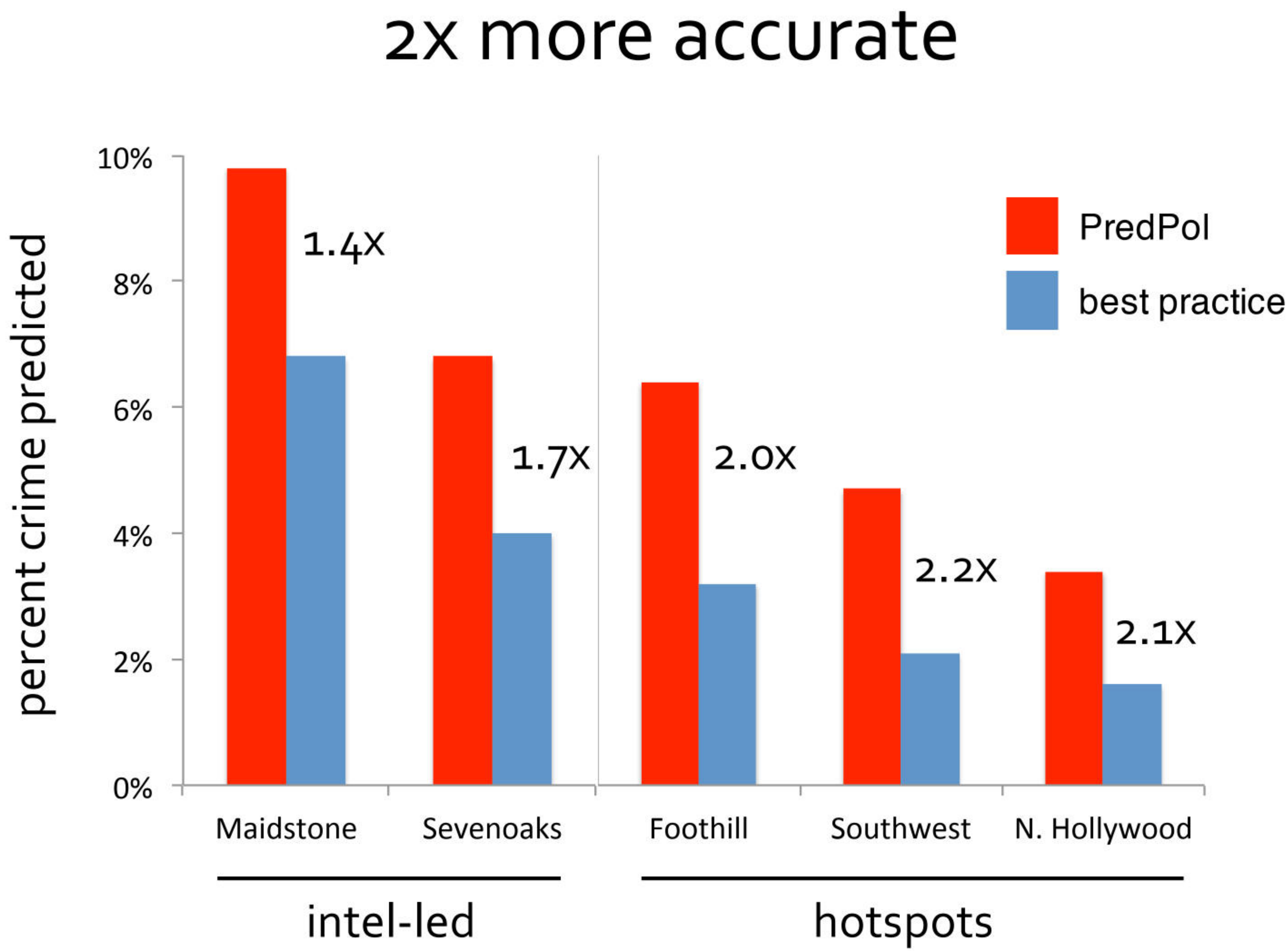
daily burglary Los Angeles

2. what does predictive deliver?

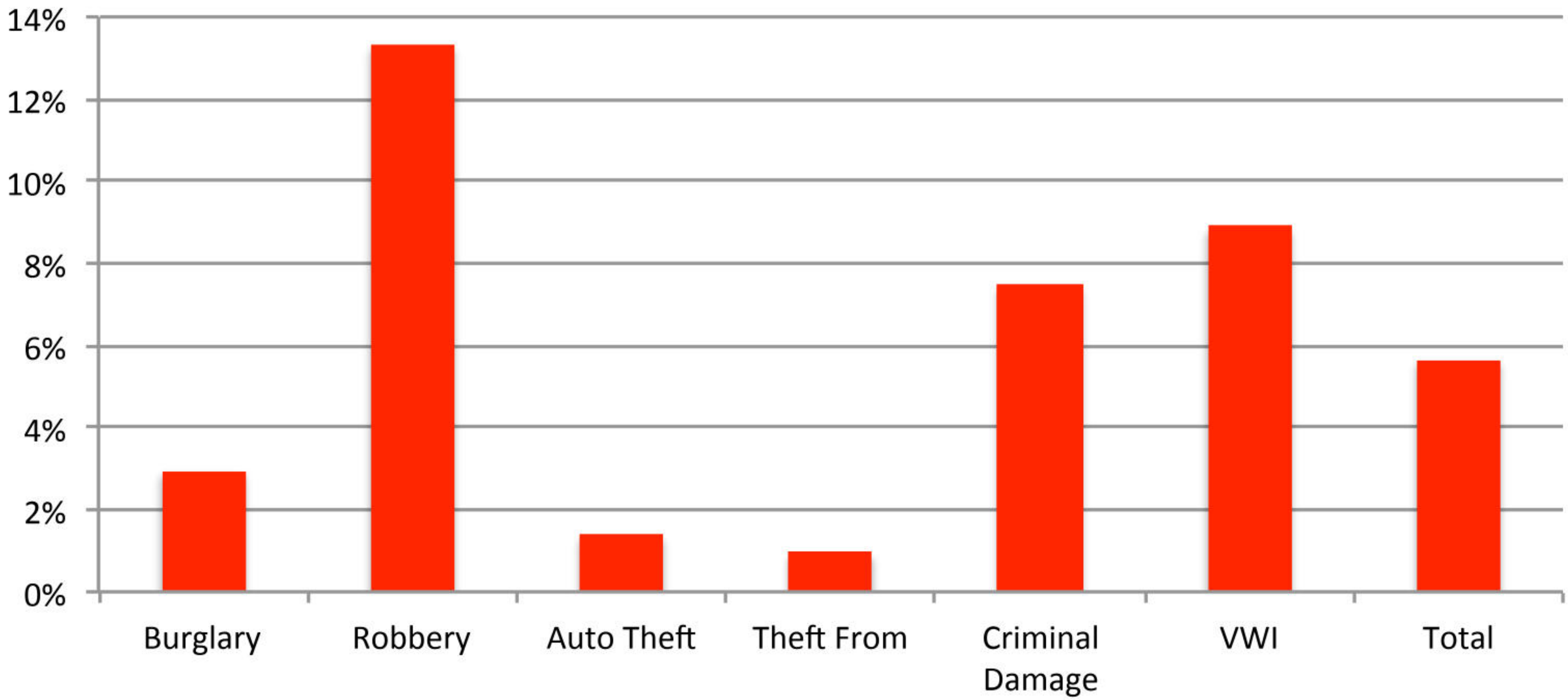


6% of crime in 0.4% of land area

17x more likely

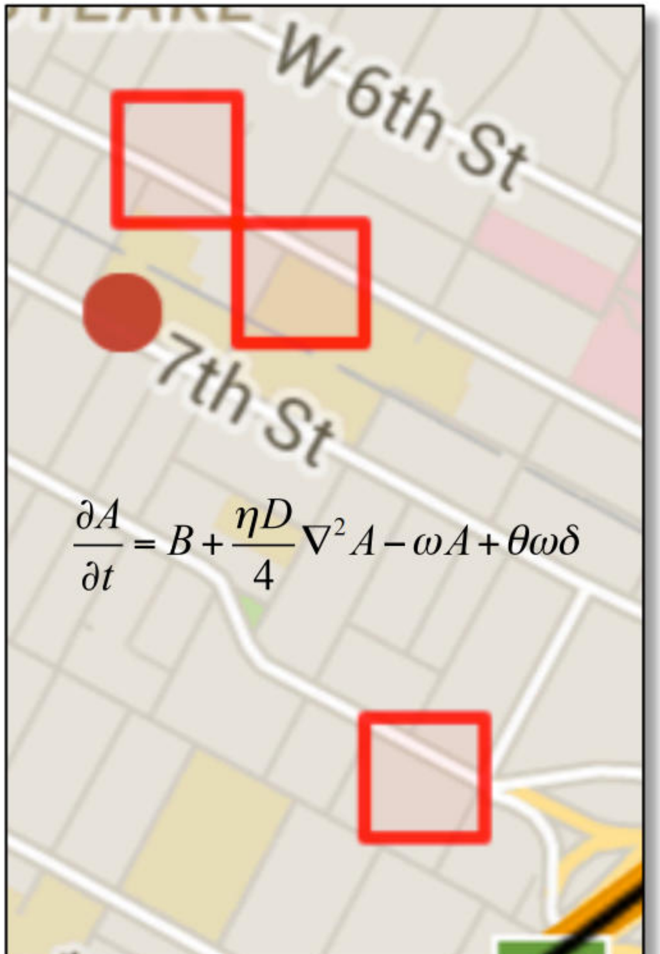

2x more accurate
percent crime predicted
10%
8%
6%
4%
2%
0%
PredPol
best practice
1.4X
1.7X
2.0X
2.2X
2.1X
Maidstone
Sevenoaks
Foothill
Southwest
N. Hollywood
intel-led
hotspots

accuracy by crime type

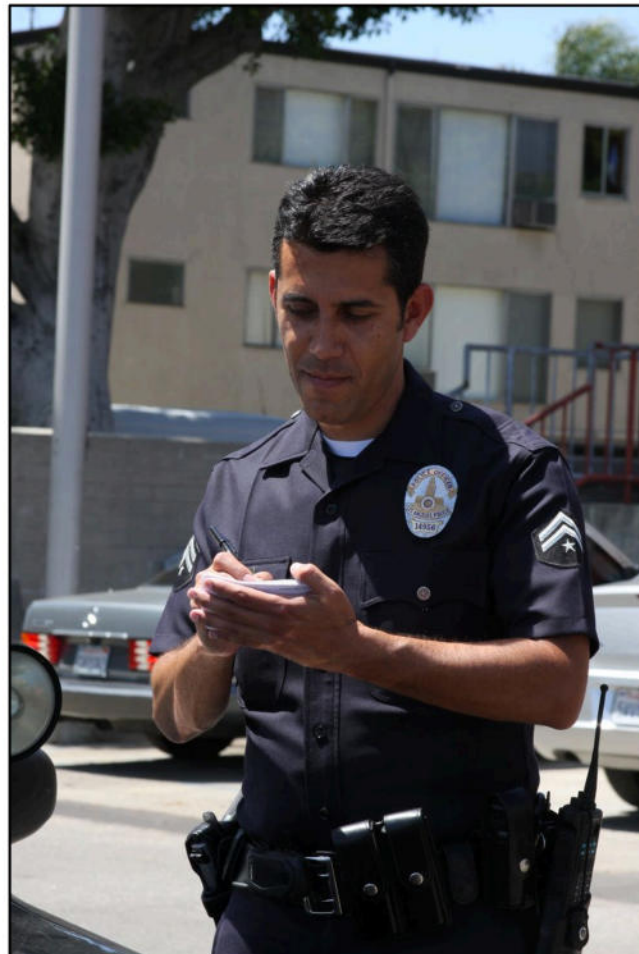


Large Urban European City

3. How is it used?



VS

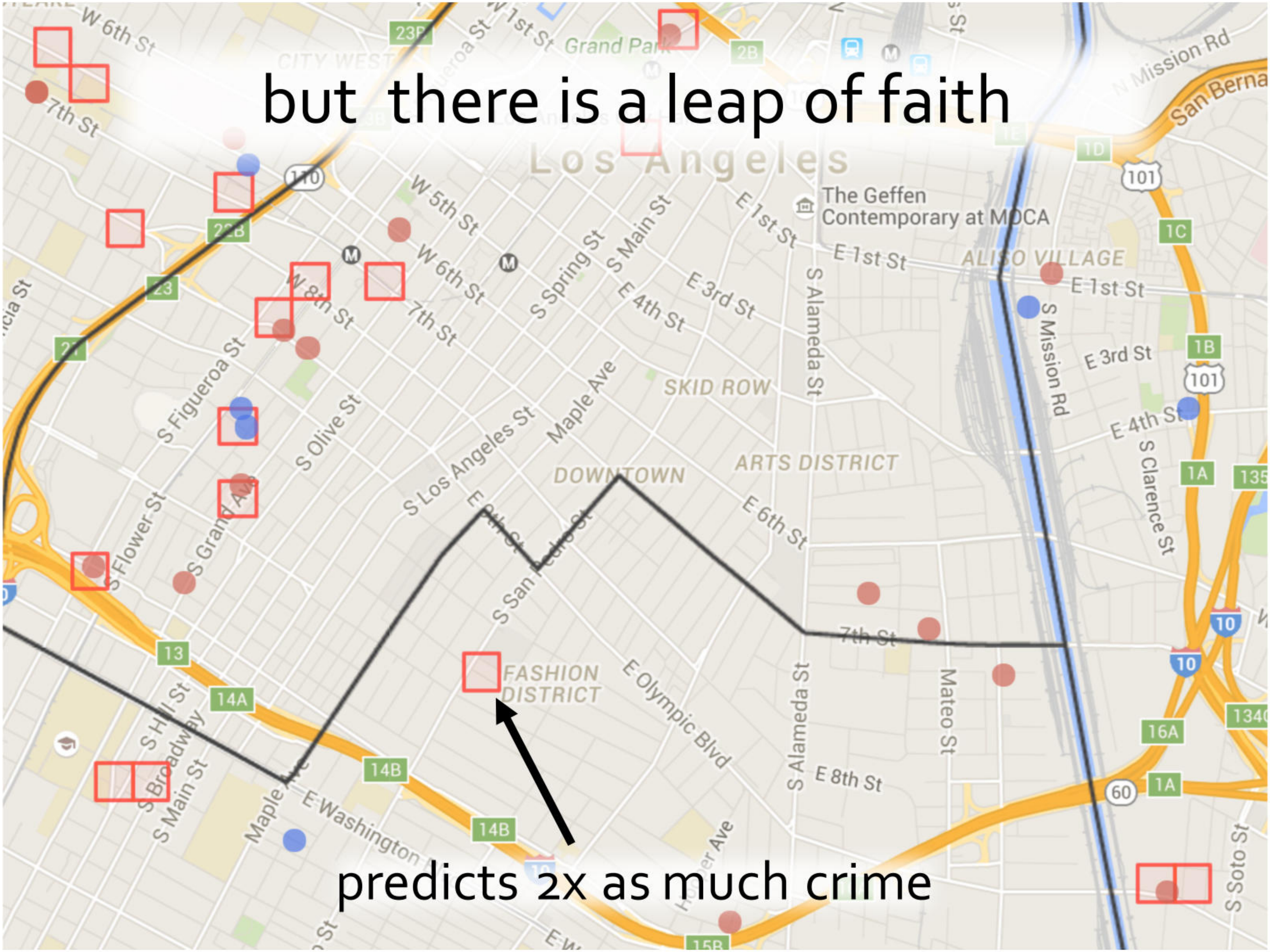


PREDPOL® LAPD UCLA

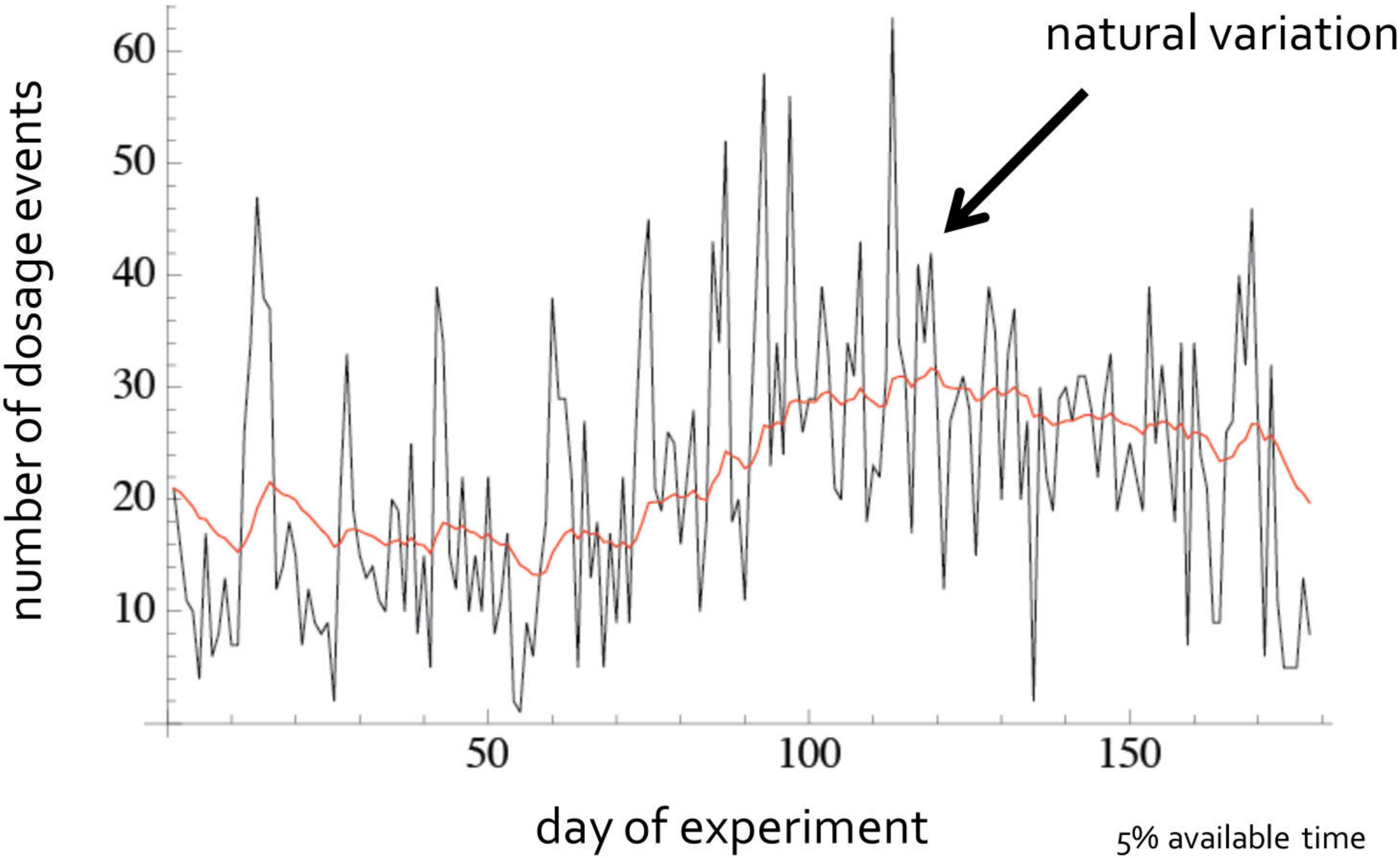
daily routine is simple

print hot sheet → brief to mission → minutes in the box

consistently playing the probabilities

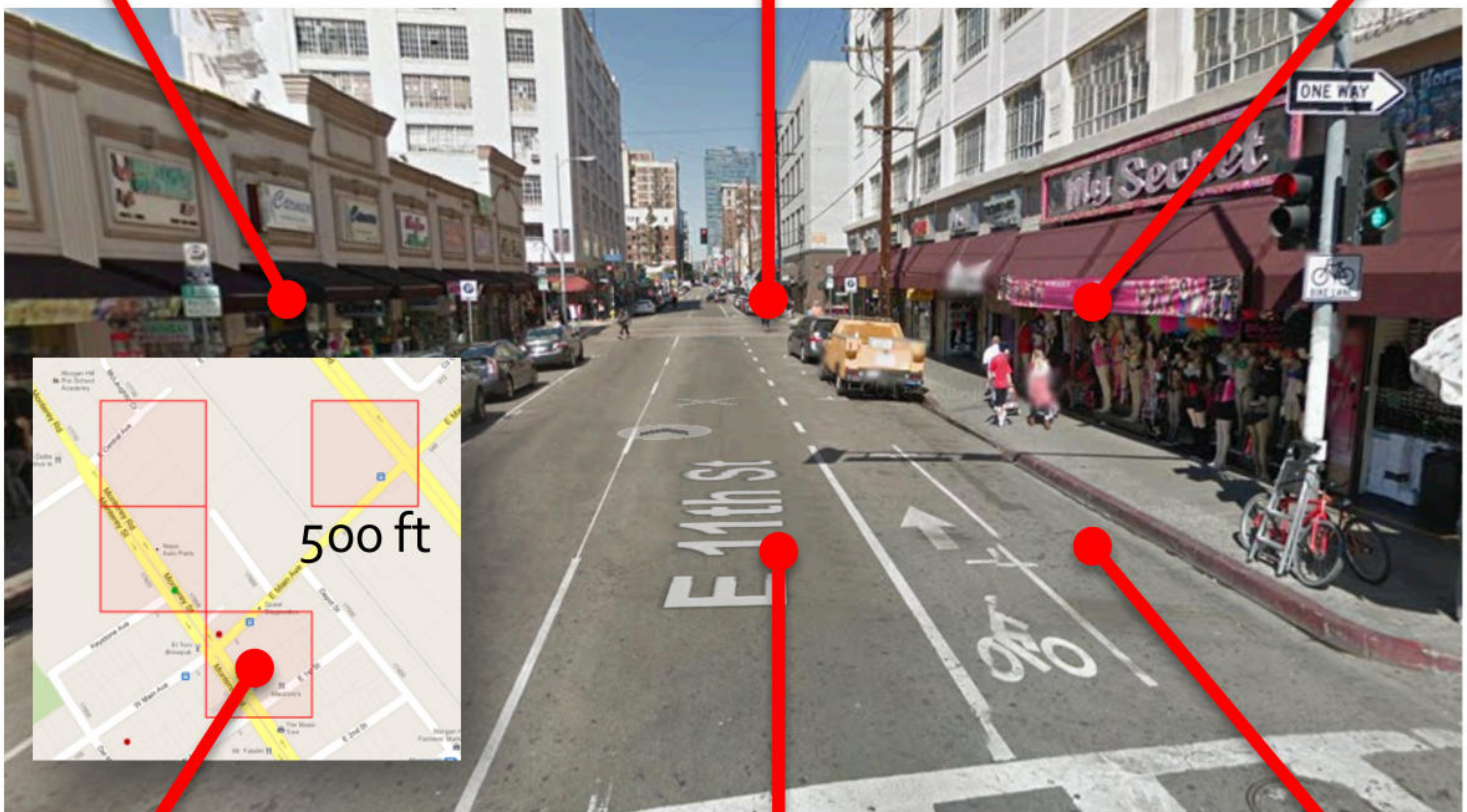

but there is a leap of faith
predicts 2x as much crime
Los Angeles
DOWNTOWN
SKID ROW
ARTS DISTRICT
FASHION DISTRICT
ALISO VILLAGE
CITY WEST
Grand Park
The Geffen Contemporary at MOCA
W 6th St
7th St
W 5th St
W 6th St
W 8th St
S Figueroa St
S Flower St
S Grand Ave
S Olive St
S Los Angeles St
S Spring St
S Main St
Maple Ave
S San Pedro St
E 1st St
E 3rd St
E 4th St
E 6th St
E 8th St
E Olympic Blvd
E Washington
S Alameda St
Mateo St
S Mission Rd
S Clarence St
S Soto St
N Mission Rd
E 1st St
E 3rd St
E 4th St
S Hill St
S Broadway
S Main St
110
101
10
60
23B
2B
22B
23
21
13
14A
14B
15B
1D
1C
1B
1A
16A

fits seamlessly into available time



knowledge, skills and experience

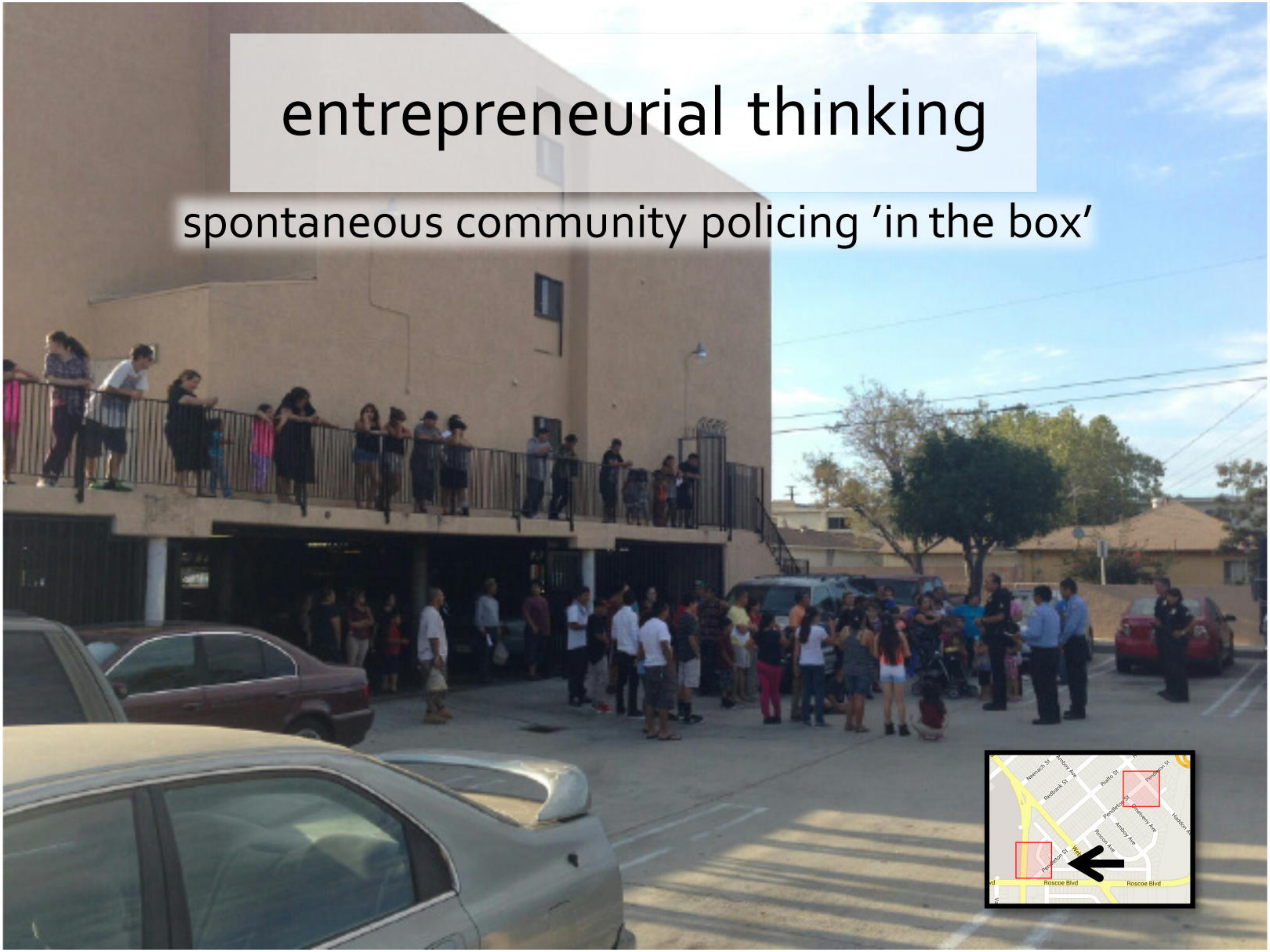
problem-oriented
environmental design
community policing



place-based
intelligence-led
broken-windows

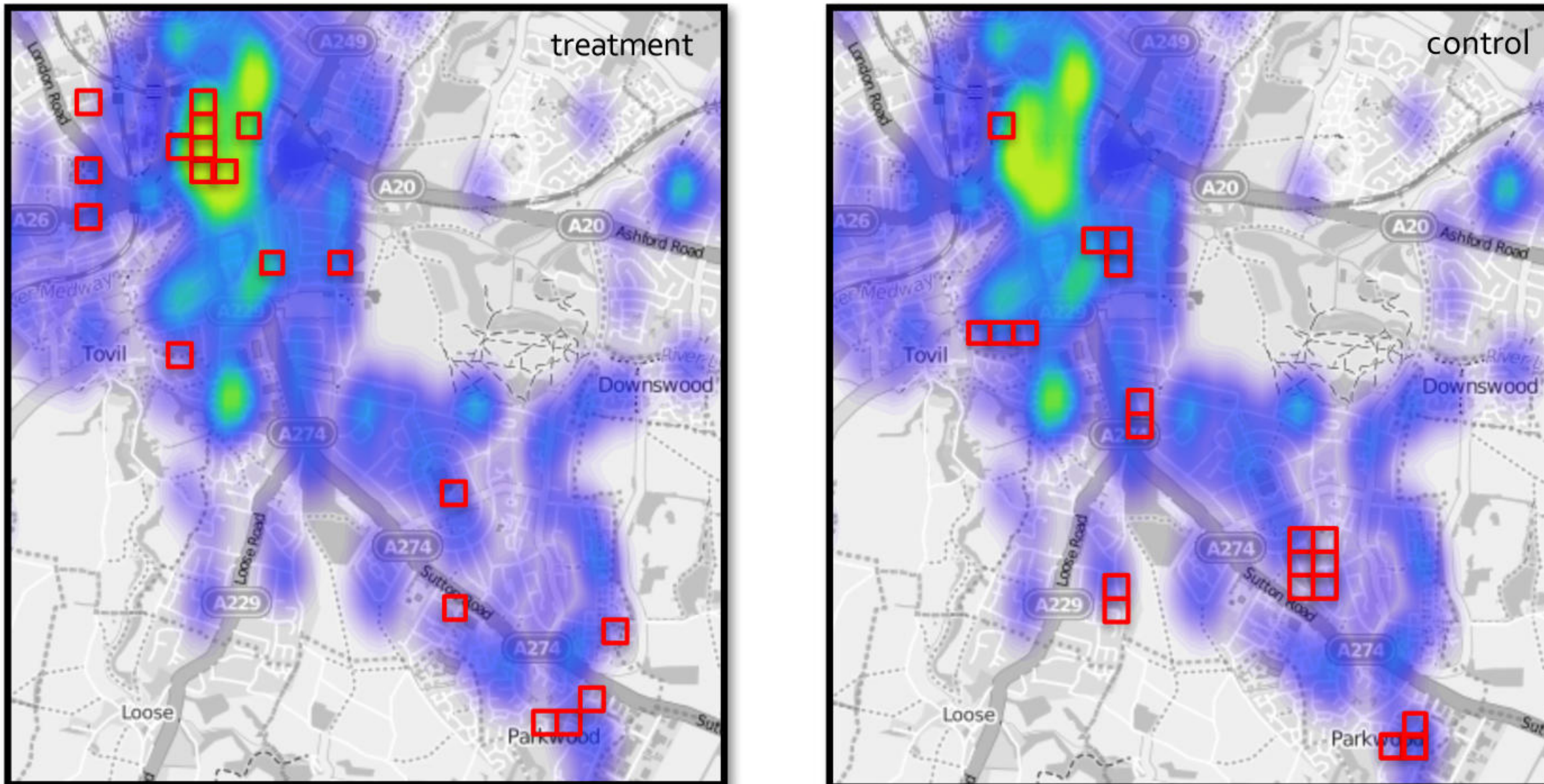
entrepreneurial thinking

spontaneous community policing 'in the box'



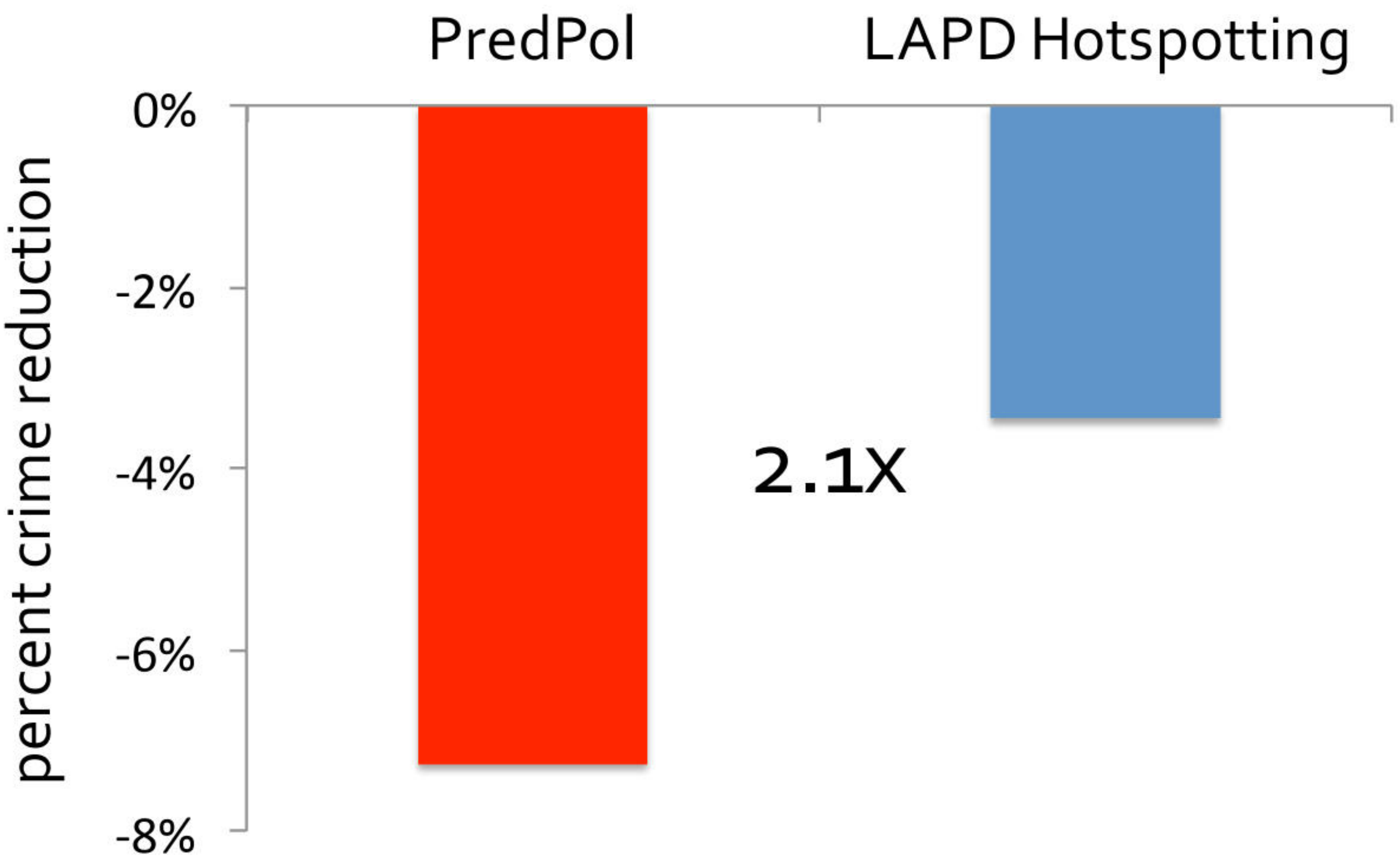
turns the arrest model on its head

4. impact on crime



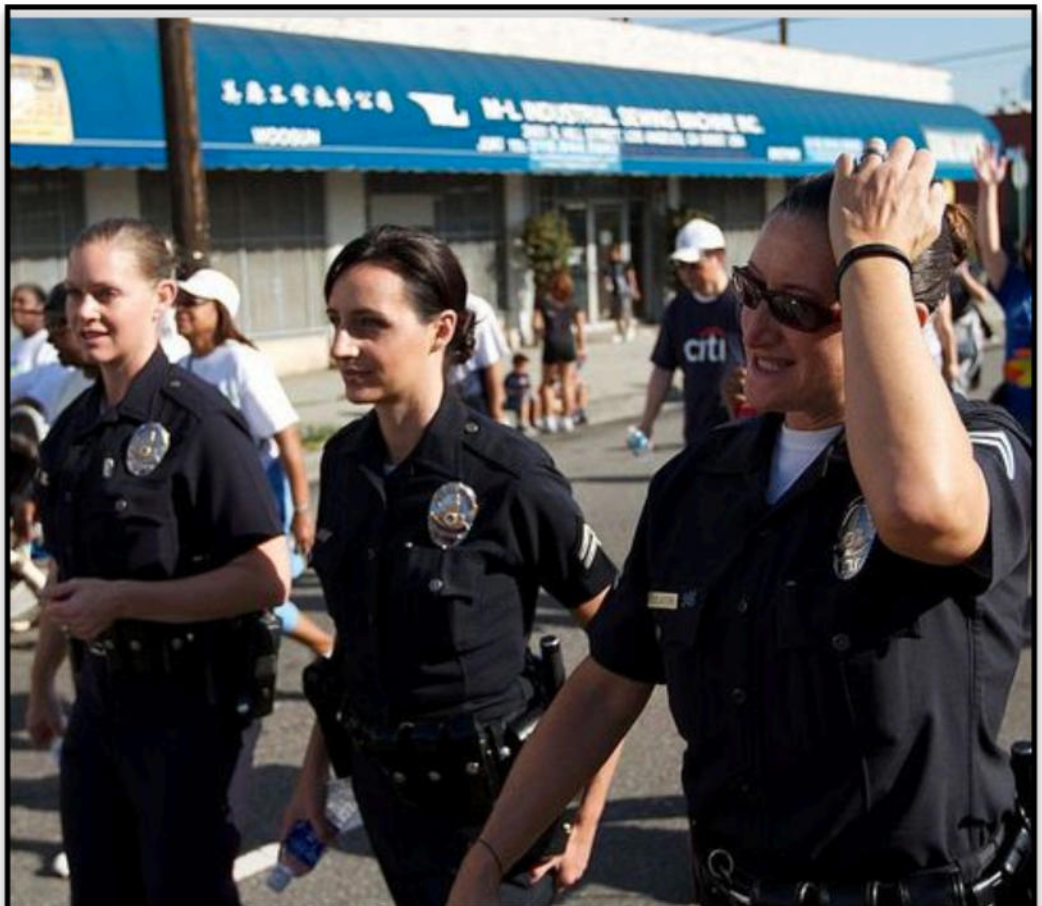
Mohler G, et al. (2015) Randomized Controlled Field Trials of Predictive Policing. *Journal of the American Statistical Association* 110(512):1399-1411.

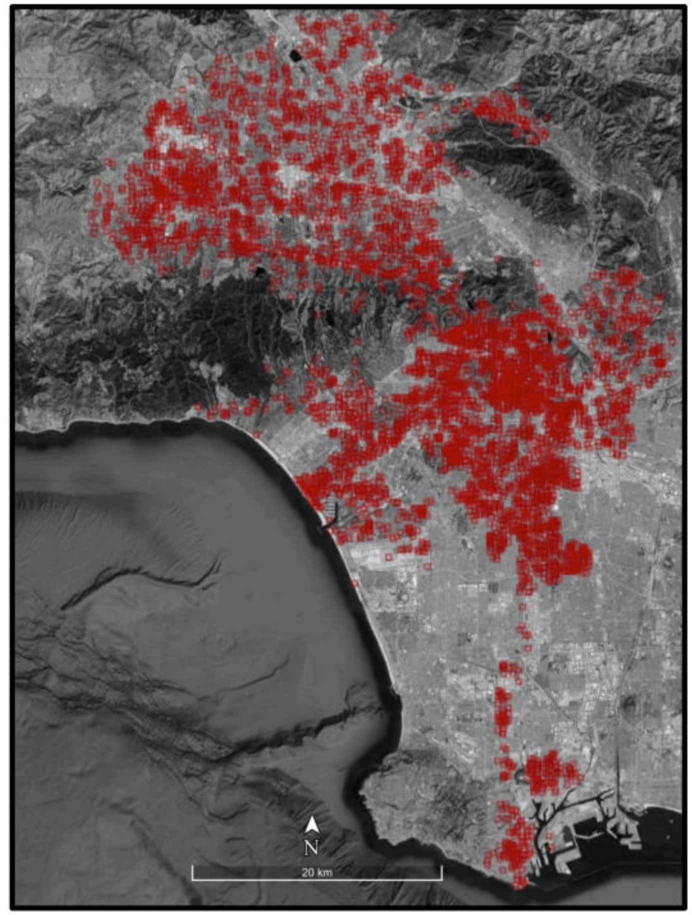
head-to-head crime reduction



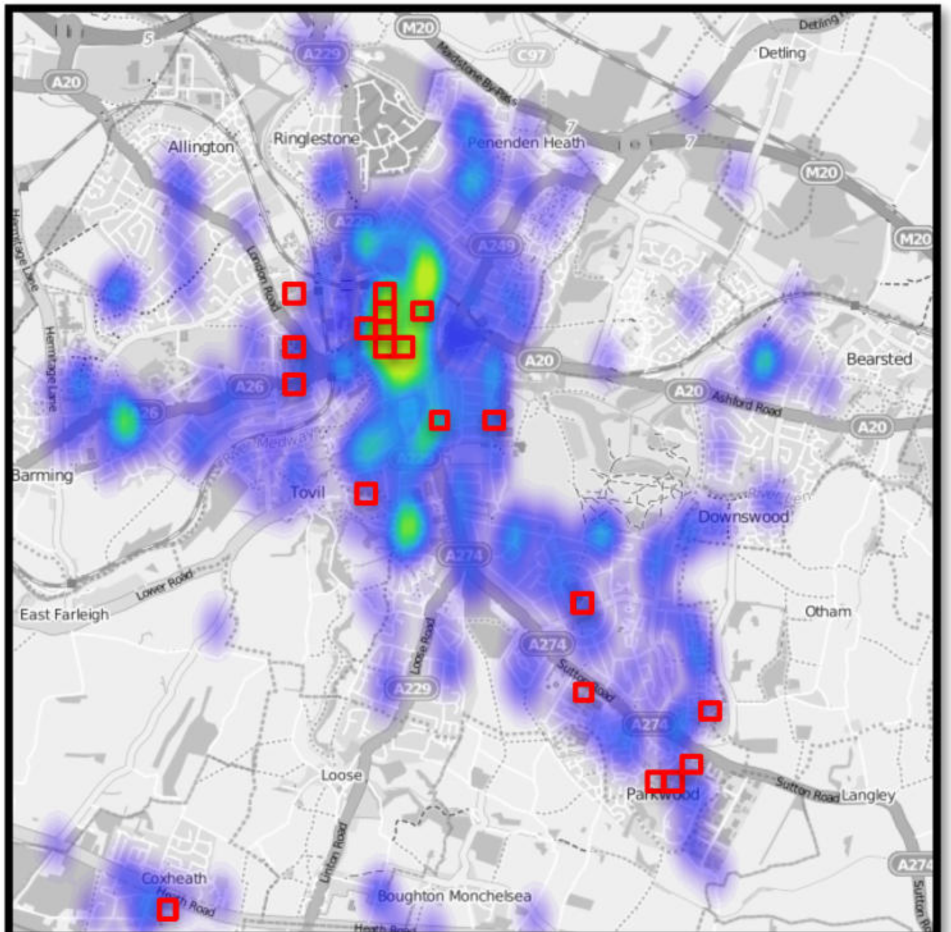
Mohler G, et al. (2015) Randomized Controlled Field Trials of Predictive Policing. *Journal of the American Statistical Association* 110(512):1399-1411.

5. leadership & sustainability





Questions?



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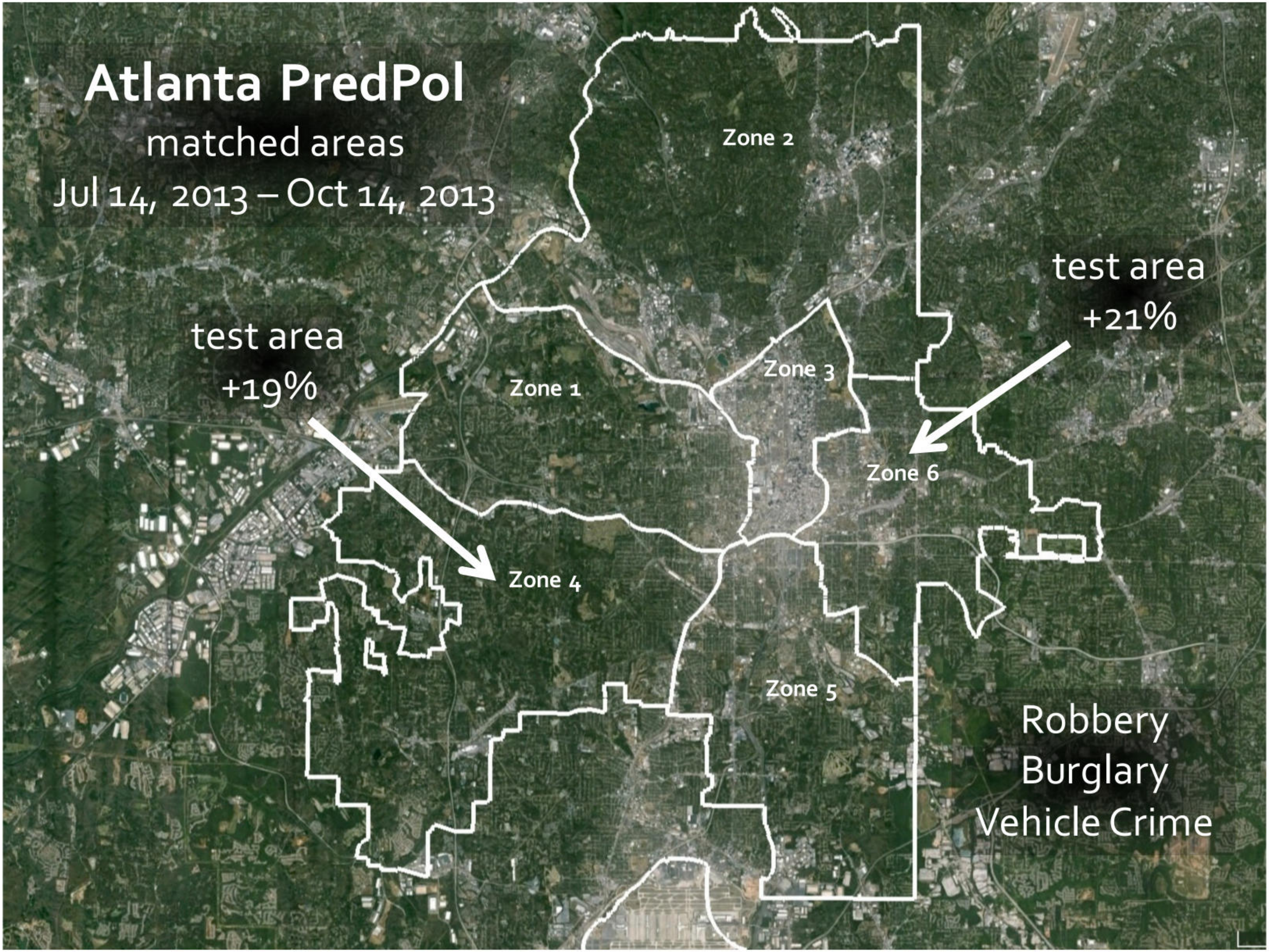
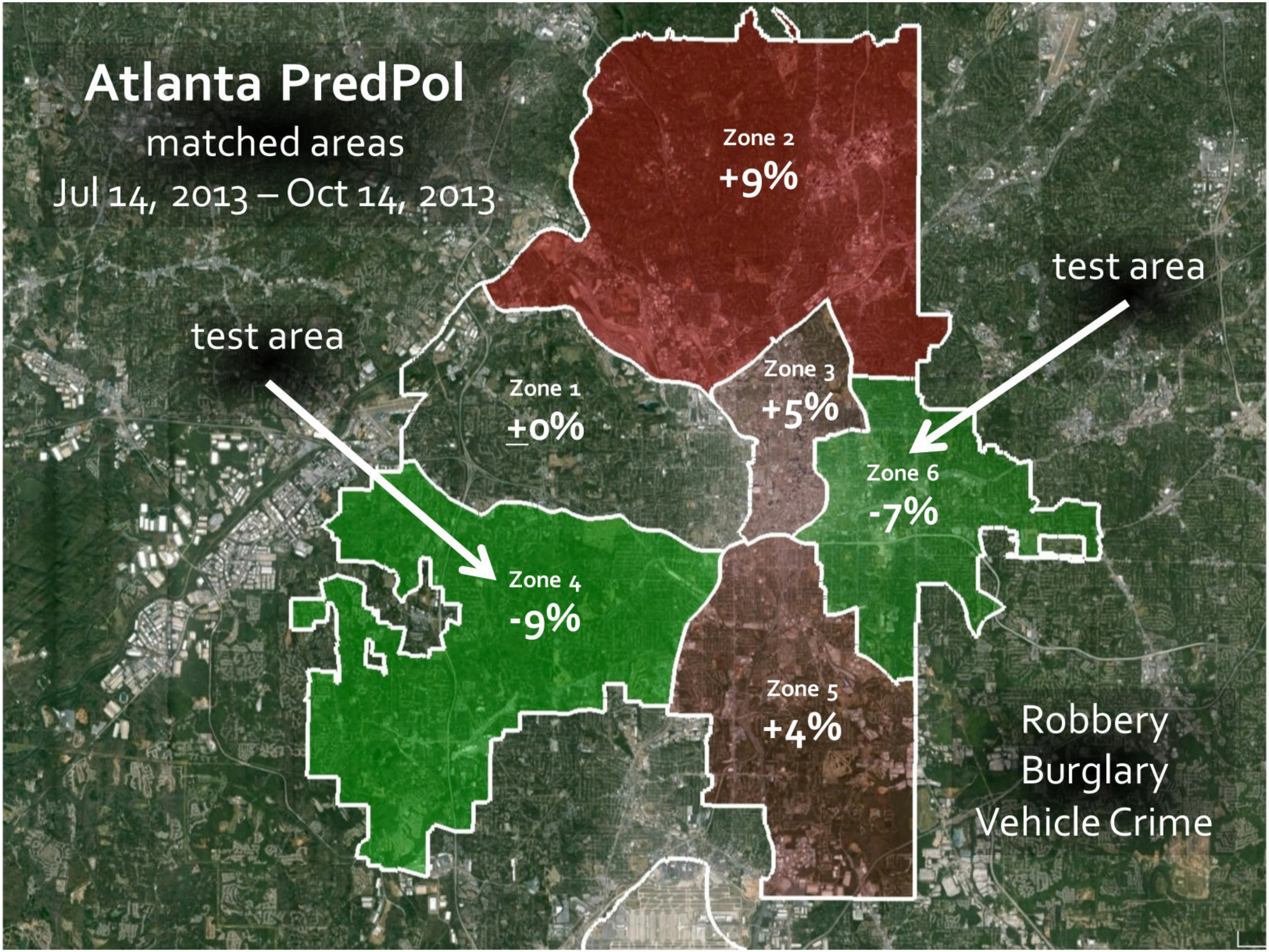

Atlanta PredPol
matched areas
Jul 14, 2013 – Oct 14, 2013
test area
+19%
test area
+21%
Zone 1
Zone 2
Zone 3
Zone 4
Zone 5
Zone 6
Robbery
Burglary
Vehicle Crime



Atlanta PredPol
matched areas
Jul 14, 2013 – Oct 14, 2013
test area
test area
Zone 2
+9%
Zone 3
+5%
Zone 1
±0%
Zone 6
-7%
Zone 4
-9%
Zone 5
+4%
Robbery
Burglary
Vehicle Crime

displacement or diffusion of benefits

	<500 ft	<1000 ft	<2000 ft
non-deployed	**13%**	**25%**	**48%**

Atlanta PredPol matched areas

no evidence of displacement

	<500 ft	<1000 ft	<2000 ft
non-deployed	**13%**	**25%**	**48%**
deployed	↑	↑	↑

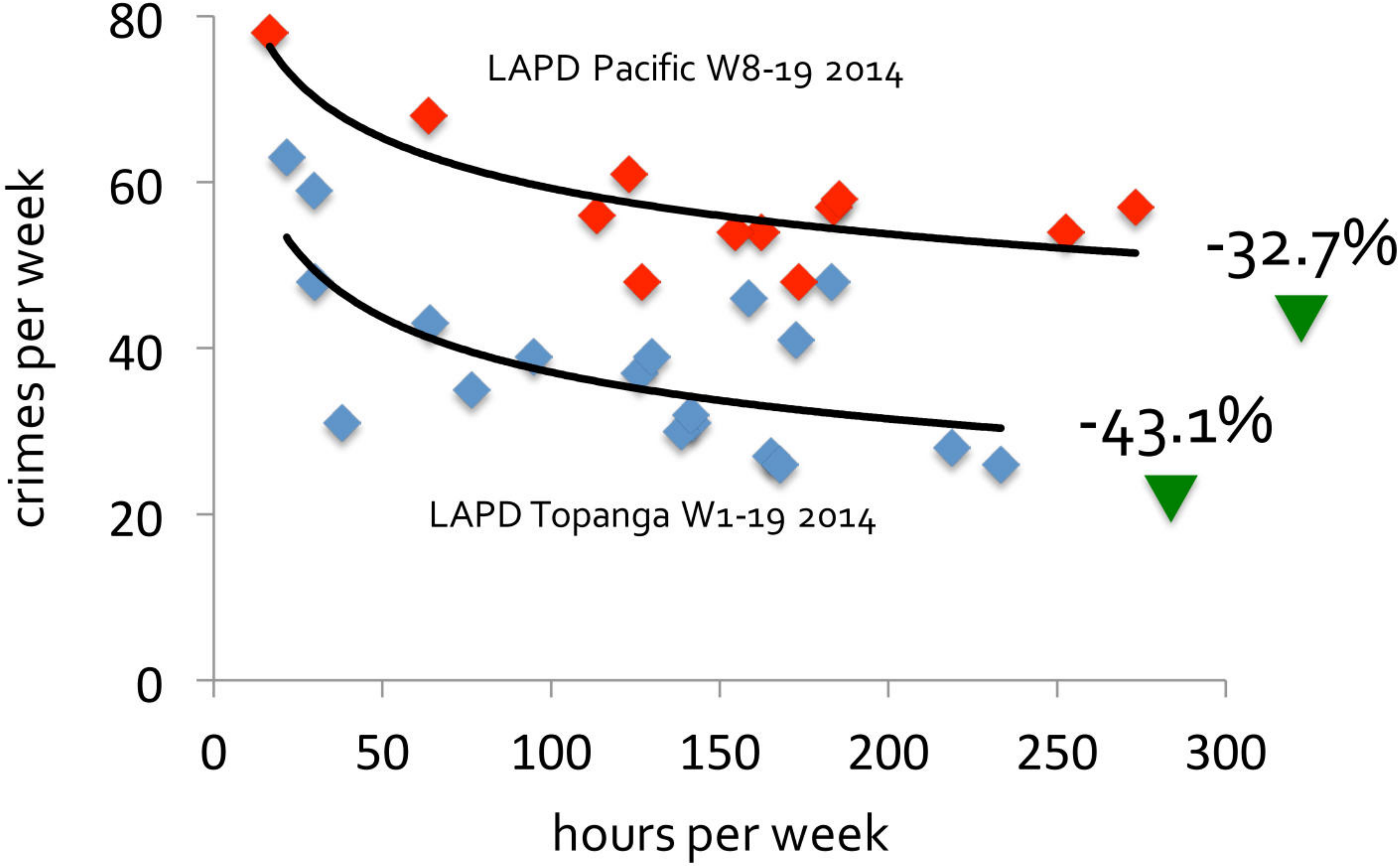
Atlanta PredPol matched areas

no evidence of displacement

	<500 ft	<1000 ft	<2000 ft
non-deployed	**13%**	**25%**	**48%**
deployed	**9%**	**19%**	**33%**

Atlanta PredPol matched areas

dosage and crime reduction



Nonadversial peer reviews of policing operations: fostering organizational learning

NIET VOOR VERPSREIDING!! In druk European Journal of Policing Studies

Otto M.J. Adang

This paper sets out to describe and explore experiences gained in the course of ten years with a non-blaming, nonadversarial learning methodology, as applied in the context of the policing of major events, where at the request of a host, peers gather data during events as they occur and a one-sided focus on errors is avoided. This peer review methodology appears to contribute to organisational learning in three different ways: hosts receive informed and constructive feedback, reviewers gain additional experience and insights and the exchanges taking place in the course of or following the reviews (e.g. in seminars) contribute to the identification of good practices and development of professional norms. Experiences show that the interactions taking place between participants also facilitate mutual understanding and cooperation. Interestingly, quite apart from the products obtained through the methodology, the peer review process itself proved to foster reflection and learning.

1. Introduction

In his paper "Suppose we were really serious about police departments becoming 'learning organizations'", Geller (1997) identified a number of obstacles to organizational learning within the police, most of them related to an organizational culture that has a "learning disorder". In high profile crisis-situations, even more barriers to learning exist (Elliot & Smith, 2000). In addition to an organizational culture averse to learning, Elliot & Smith point to (lack of) trust and scapegoating as intertwined and significant barriers to learning from crisis situations and:

> *In the immediate aftermath of a crisis, there will be an inevitable search for culpability and a scapegoating process will take place as the "survivors" seek to ensure their continued survival and project blame elsewhere. This phase is also typified by organisational turnaround and a re-alignment of corporate values and assumptions – or, as Turner put it "full cultural readjustment". It is within such a highly charged and emotive environment that organisational learning is supposed to take place*

Waddington (1994, p. 42) points out the enormous "in-the-job" trouble for senior police officers that may follow public disorder, arising from the threat of having to account for one's actions to superiors or to an independent inquiry. As Waddington (1996, p. 131) states: "*post-disorder analysis is an inherently political process in which various parties seek to reconstruct events so as to place blame on their opponents. It is a process in which the police have traditionally faired quite badly*".

Therefore, even though in theory, accountability and learning can go together, in practice they are often at odds with one another (Guijt, 2010) and there are numerous examples of senior police officers losing their jobs after high-profile incidents (in a recent example, the police chief of Cologne, Germany, was removed following criticism over his handling of allegations of sex assaults and violence by migrants on New Year's Eve [1]). The tension between accountability and learning all too often leads to considerable limitations for internal review processes (in the form of debriefings or after action reviews) that are supposed to contribute to learning (Elliot & Smith, 2000). Both Adang (1998, p. 126-7) and Elliott & Smith (2000) refer to the year before the 1989 Hillsborough stadium tragedy, where 96 football fans were crushed to death. A year before the tragedy, a near identical set of circumstances had arisen at the same location but tragedy was averted by an intervention from an experienced police officer. However, there was no effective debrief following this near-miss and no learning took place. Combined with latent error and a series of emergent properties associated with the event, disaster resulted a year later.

Aware of the need to distinguish between accountability and blame free organizational learning, the Task Force on 21st Century Policing (2015) established by US President Barack Obama recently came up with several recommendations to improve organizational learning within police departments, one of them being to encourage law enforcement agencies to implement nonpunitive peer review of critical incidents separate from criminal and administrative investigations (Recommendation 2.3). Such reviews already exist in medicine ("sentinel event" reviews), and other industries such as aviation ("near miss" reviews). Doyle (2014, p. 53) identified the following significant features of the sentinel events approach: the participation of all stakeholders, an emphasis on non-blaming, an approach that is routine and ongoing, findings that are publicly disseminated and an emphasis on being "forward-looking". These features fit quite well with a utilization-focused approach to evaluation as elaborated by Patton (1997), who states that "commitment to intended use by intended users should be the driving force in an evaluation". He argues that the primary determinant of the extent of evaluation utilization is not the level of methodological rigor employed but the extent to which stakeholders take ownership of the evaluation process and actively work to ensure that evaluation findings are utilized.

Doyle (2014) points to six issues that need to be addressed in sentinel reviews to avoid them becoming barriers to learning: system legitimacy (will they nourish public trust in the system and its operators?), resources (will it not take too long and cost too much?), liability and confidentiality (can they be done without increasing liability or compromising confidentiality?), risk management (how to deal with the trade-off between risk-reduction and liability?), leadership and collaboration (how to find innovative leaders that can initiate the necessary collaboration?) and the choice of sentinel events (big or notorious cases might hinder innovative efforts). It is not difficult to see many of these issues as related in one way or another to the need to avoid the in-the-job trouble that Waddington (1994) refers to. The problem is clear: how to overcome the barriers to learning?

To try and deal with this problem, Adang (2006) introduced a non-blaming, nonadversial peer review methodology used to learn from and for the policing of major events (initially international football matches) in several European countries. In contrast with the near miss/ sentinel events approach, that by definition takes place *after* an event almost got out of hand or disorder took place, the peer review methodology does not focus on near misses or errors, but observes and gathers data of actual policing operations *during* events, as they occur. The idea of this approach is to create a safe learning environment based on trust (by using trusted peers) and the avoidance of scapegoating (because the focus is on learning opportunities and not on blaming for any errors that might occur).

[1] http://news.sky.com/story/1618820/cologne-police-chief-removed-over-assaults

This paper sets out to describe and analyse the experiences gained in the course of ten years with the peer review methodology as applied in the context of the policing of major events (sports matches, festivals, political demonstrations). The analysis is exploratory and based solely on publicly available documents: no additional data were gathered. The experiences will be analysed both by using the features identified by Doyle (2014) as important to overcome barriers to learning and, following Patton (1997), identifying whether or not there was evidence of utilisation of the findings of the reviews. It should be noted that this paper solely deals with the *methodological* aspects of the peer reviews. Outcomes that are directly relevant to *policing of events* have no place here and are dealt with elsewhere (e.g. Adang & Brown, 2008).

First the peer review methodology is set out. Next, five different applications of the methodology are described, focusing on the way it is initiated and implemented, on evidence of utilisation (beyond reporting and dissemination) and on experiences of participants. Finally, the question of whether the peer review methodology is capable of creating a safe learning environment that contributes to organizational learning is addressed.

2. The Peer Review Methodology

The description of the basic peer review evaluation methodology as applied to the policing of major events, is based on Adang & Brown (2008, p. 23-28) and Adang (2013).

At the core of the methodology is its voluntary nature: a peer review will only be carried out after a specific request to a designated coordinator by a commander or organization responsible for the policing of a specific event. The request usually arises because the event or the policing operation is seen to be (by the requester) as with "increased risk", although this is not a requirement.

The main task of the coordinator is to maintain the methodological integrity of the review in all stages of the peer review. The request is preferably made several weeks in advance of the event to be reviewed. Following the request, the coordinator will discuss the specific learning-related questions that the requester/ host would like to see addressed in the peer review. The coordinator checks whether there are not too many questions (a maximum of five), whether the questions can be answered using the peer review methodology, whether the questions relate to matters that fall under the purview of the requester. From a utilization point of view, the coordinator also asks why the requester is interested specifically in these questions. Typical questions include: how does policy or strategy translate into practice? how is (a specific part of) the plan in fact executed? How do different units cooperate or how does the police cooperate with other stakeholders?

Finally, practical details of the review are discussed, this includes organizing for reviewers to have full access to all relevant persons and documents and an agreement that the coordinator can use an anonymized version of the report for analytical and educational purposes. The coordinator also makes clear that a peer review is not a substitute for internal review procedures (debriefings, after action reviews) or accountability mechanisms.

The coordinator then composes a peer review evaluation team consisting of a coordinator, a scientific assistant and four or six police commanders (peers) who, in their own force, fulfil roles similar to that of the requesting host. Prior to the event, practical arrangements and information about the event is shared with peer review team members. Ideally, peer review team members have previously received a training where the methodology is explained to them and they interactively go through the steps of a peer review from planning to data gathering to discussing observations and writing a peer review report. The training also includes a lecture on observation and interpretation and a practical observation exercise. As the issues the peer reviews deal with are different from one peer review to another (dependent on the needs of the requester), no standard checklists or instruments are used in the course of the reviews.

The peer review itself takes three consecutive days. One day before the event is to take place, the peer review team travels to the place of the event. On this first day, the team is briefed on the planned operation by the requesting commander/host, consults any available documentation and acquaints itself with the city and location of the event (especially “hot spots”). Based on this information, the peer review team develops its peer review evaluation plan, identifying what data need to be gathered to answer the questions, in what way and by whom (the tasks are divided over pairs of team members). The peer review team is also briefed by the coordinator about the peer review rules: safety first, confidentiality, informed consent, no interference with the operation and the need for an open, non-judgmental attitude and demeanour. When team members have not previously been trained, more time is taken for the briefing to explain the methodology.

On the second day, the day of the event, data are gathered according to the evaluation plan. Usually, this includes attending briefings, conducting short semi-structured field interviews with police officers from different levels, citizens and other stakeholders (typically between 30 and 100 field interviews are held during a peer review). It always includes observations of police- citizen interactions. Team members would always be free to go where the evaluation plan required them to go. They are instructed to take notes contemporaneously and not to rely on memory.

The third day is devoted fully to sharing of observations and experiences among team members in light of the peer review questions. The coordinator chairs the discussion to ensure an objective approach and making sure that a clear distinction is maintained between observations and opinions. During the discussion, a draft report is prepared on the spot by the scientific assistant and projected on the wall, for team members to check and comment on. Both the discussion and report share a fixed format:

1. Goal of the evaluation: the peer review questions as determined beforehand;
2. Methodology: documents consulted, briefings attended, time and place of observations made, field interviews conducted;
3. Context of the event: a short overview about the event, stakeholders and the police operation;
4. Overview of events: a short overview of events and major decisions made during the policing operation;
5. Observations related to peer review questions: the information gathered linked to the questions;
6. Conclusions, again linked to the questions, including points of attention and good practices.

The third day ends with an evaluation of the peer review process among the team members followed by their departure.

The findings of the peer review team are shared with the host only after the report is finalized. This takes a few weeks. In this period, the coordinator and the scientific assistant complete the draft report and send it out to the team members for comments and a final check. After this process, the final version of the report is sent to the host (and to the host *only*), who is given the opportunity to indicate if the report contains any factual mistakes. The report does not contain names of individuals, but only refers to *functions* (e.g. group commander, member of a riot squad). The report also does not contain specific recommendations. The report becomes the property of the host and it is up to her to decide what to do with it.

For the purpose of this paper, five series of applications of the peer review method were analysed (Table 1, 62 peer reviews in total), based on publicly available documents. The different series of peer review applications were linked to one another by the fact they originated from one another and that the author played a role in all of them as either senior adviser (Europe demonstrations) or project leader (the rest), and participated in 30 of the 62 peer reviews (mostly as coordinator).

Table 1: Overview of peer review applications
N reviews: number of reviews held in each series
N hosts: number of different hosts
N police reviewers: number of reviewers that were police officers
N other reviewers: number of peer reviewers that were not police officers (but students, trainers, academics or municipal officials)
Period: years in which the reviews were conducted

	N reviews	N hosts	N police reviewers	N other reviewers	Period	Source
Europe football	13	13	21	6	2005-2007	Adang & Brown (2008)
Sweden football, demonstrations	16	3	34	26	2008-2009	Adang (2012) Hilton & Wessman (2013)
Netherlands football	6	6	22	6	2009-2010	Adang et al. (2010)
Europe demonstrations	10	10	20	20	2010-2012	Godiac (2013)
Netherlands festivals	17	10	53	19	2011-2013	Adang et al. (2013)

Using the sources mentioned in Table 1, the five series of applications are described below by clarifying who initiated the peer reviews and paid for them and how the basic methodology was implemented. Subsequently, using Doyle's criteria, it is addressed how barriers to learning were overcome and, following Patton, utilisation is explored by indicating how useful the reviews were to the hosts and participants.

3. Five peer review applications

3.1 Peer reviews of international football matches in Europe

Initiation

In 2005, the Dutch delegation to the European Union Police Cooperation Working Party (PCWP) proposed internationally composed police peer review teams to contribute towards successful public order management in the context of international football matches in Europe. The PCWP agreed to the proposal. The peer review teams should involve experienced police officers from several countries, made available by their forces, to observe police operations in real time, providing feedback with a focus on continuous learning and adaptation. The EU handbook on international police cooperation in connection with football matches (EU, 2007) would serve as a benchmark of good practice. A three-year pilot financed by the Dutch Ministry of Internal Affairs (to cover travel and subsistence costs for participants) was started that lasted from September 2005 to September 2008 and was coordinated by the Dutch National Football Information Point and the Police Academy of the Netherlands.

Implementation

Through the network of National Football Information Points, a pool of senior police officers from 13 different European countries was formed. They had to be active commanders with an open mind and an attitude aimed at learning rather than judging; be willing to work with the methodology of observation and evaluation and have a good knowledge of English (both oral and written). Teams were composed of four commanders, a coordinator and a research assistant (a PhD student). Initially, there was some hesitation to host a peer review, but after the first two reviews, requests were received from nine different countries, including from two countries that would be hosting matches during the 2008 European football Championships later.

In the course of the pilot, two interim reports and one final report were made to the PCWP and seven presentations about the pilot were given to international meetings of practitioners. The overall results of the project were published in Adang & Brown (2008), which contained details on the methodology, the text of nine anonymized peer review reports, an overall analysis of the reports identifying good practices and points of attention of general relevance. The book also contained a chapter on theoretical issues related to the policing of football matches.

Overcoming barriers to learning

As far as *system legitimacy* was concerned, police officers from different countries and police researchers participated in the review teams, the series was made possible through the active involvement of international networks (PCWP, NFIPs). The limited need for financial *resources* was provided by the Dutch ministry, reviewers (and their forces) provided their time which was strictly limited. *Liability* was not raised as an issue. Participants agreed to maintain *confidentiality*, reports were provided as internal working documents representing the combined informed but subjective viewpoints from the review team to be used at the discretion of the host, published reports were anonymized. Relevant police *stakeholders* were on board with the reviews, otherwise they would not have taken place. Police forces from different countries acted as hosts, other stakeholders were involved only via field interviews. Especially in the case of the Swiss cities preparing for Euro 2008, the methodology contributed to *risk management* in an innovative way without invoking issues of liability. *Local leadership* proved to be important: without early-adopting individual commanders willing to stick their neck out, asking to be reviewed, the reviews could not have been carried out.

Utilisation and experiences

The PCWP used the outcome of the peer reviews as input for changes in the EU handbook. Especially for the four Swiss Euro 2008 host cities participating in the project, the peer review reports served as an important check on their preparations. Four months before the tournament was to start, this led to a meeting organized by the national Euro 2008 police coordinator, where points of attention were discussed. Subsequently, the host cities concerned held a press conference to communicate to the public how they were going to address the findings of the peer review teams.[2]

The experiences obtained with the peer review methodology in this project directly led to the use of peer reviews in the Denmark (not published), Netherlands and Sweden (see below).

Directly after the pilot, an evaluation meeting was held for peer reviewers and hosts (Adang & Brown, 2008, p. 196-199). Hosts indicated that they were happy and satisfied with the system and that many points were detected that needed correction. They appreciated the exchange of ideas and experiences and the focus on being better in the future. Especially the discrepancies that were noted between what was expected of the operation and actual behaviour was helpful. Several hosts indicated that the report served as a catalyst for change, and that they used it for discussions within their force or with other stakeholders. The following quote is typical:

> *I extracted and also established a set of conclusions, which will be sent to all territorial structures, in order to improve their activities in this field of public order management for sport events, relation with the media, the football clubs and other authorities. I also should mention that the Public Relations Service will set a new more adequate approach with the media for a better response to this hooliganism phenomenon. Therewith, we decided to implement a new pilot system on maintaining public order, during the first two rounds of the National Football Championship. Finally, I would like to say one more time, that I considered this Peer Review very important and useful and I hope that in the future I will have the opportunity to be an evaluation team member for another state that will request this kind of mission*

Interestingly, hosts also indicated that not just the content of the peer reviews was useful, but also the peer review *process* itself: the fact that outside colleagues asked questions and observed operations led to increased reflection.

Reviewers indicated that it was hard work, interviewing people, listening, taking notes, but that it was good to go into the field, that it was important to speak to the people (officers, stewards, fans, citizens) in the street, to see the whole operation: "*This is very difficult in the normal job*". Many reviewers experienced it was difficult to first observe, and then make conclusions: "*You need training in order to do that. You also see your commanders in a different way*". Reviewers also talked about a win-win situation and an excellent opportunity to circulate good practices, as evidenced by these quotes: *"I hope they have learned from me but I also learned from the host city. It is very important." "Every time I go, I learn something new that I can adopt in my system. The reviews enable me to make a network for friends. Breaks barriers down, makes 'daily life' easier".*

According to Adang & Brown, hosts and reviewers agreed that the main success factor of the peer review teams was the peer aspect and the informal, open and utilization-focused way in which the reviews were conducted, aimed at learning from the bottom up and not as an inspection. The element of exchange and the way in which the reviews hold up a mirror, identify good practices and provide encouragement to work with these appeared to be a critical factor of appreciation. The mix between practice and theory was considered to be

[2] https://www.swissinfo.ch/eng/swiss-pass-euro-2008-security-audit/48878. Not being used to the peer review methodology, the words "audit" and "inspection" are used in this journalistic rendering

important as well. Hosts and reviewers identified lack of information as the main barrier to a widespread use of the peer review system.

3.2 Peer reviews of demonstrations and football in Sweden

Initiation
In 2006 the Swedish National Police Board decided to carry out a three-year project to develop a long-term strategy for knowledge development for so-called Special Police Tactics (SPT: tactics that are used to manage public order). The goal of the project was to increase the competency of the police to work knowledge based in public order management and to improve upon the way in which police were upholding the constitutional right of assembly. In the last two years of the project, the peer review methodology became the main method used in the project. Other activities within the project included the development of competency profiles and the organization of workshops and seminars. All project activities were financed by the Swedish National Police Board, participants to the field studies (as the reviews were called in the project) were made available by their police authorities. It was an explicit goal of the project to connect research, education and practice and to this purpose researchers and police trainers were included in the project group that was formed. The project group included members from the Swedish National Police Academy. A steering committee was formed to oversee the project.

Implementation
Participants from the three largest police authorities received a two-day training in the peer review methodology. Eleven demonstrations and five football matches were reviewed. The project group was given the task to choose which events to include in the reviews. The project group then coordinated with the local commander of the police authority concerned on the specific questions to be addressed. For each review a field study group was composed, consisting of six to eight participants including a coordinator and a research assistant. The reviews were coordinated from within the project group and planned well in advance. Before each review a project group member was present at the preparatory meetings in the police authority. In addition to the individual peer review reports, interim reports, a final report and a handbook on the peer review methodology were prepared for the National Police Board. All reports were distributed and discussed at the workshops organized in the course of the project.

In the course of the project, a total of seven workshops were organized to discuss and learn from the results of the field studies. In addition, two international seminars were organized with police officers, researchers and trainers. A final seminar was held at the end of the project to discuss the project results and identify what had been learnt.

Overcoming barriers to learning
As far as *system legitimacy* was concerned, police officers and police trainers from the three main Swedish police authorities and police researchers participated in the review teams. The reviews were coordinated from the national police board and with involvement of local police authorities. Financial *resources* were provided by the Swedish National Police Board, reviewers (from the different police authorities) provided their time which was strictly limited. *Liability* was not raised as an issue. Reports were initially provided as internal working documents representing the combined informed but subjective viewpoints from the review team to be used at the discretion of the host. At a later stage reports were shared among project participants with permission of hosts. Relevant police *stakeholders* were on board with the reviews. Other stakeholders were represented in the project steering committee

and project reference group and were involved via field interviews. However, the Swedish researchers stopped participating in the field studies (but not the workshops and seminars) because they felt the formal requirement of police officers to report crimes they observe could come in conflict with their role as non-intervening observer during the field studies. The methodology explicitly contributed to *risk management* of future events. The project was initiated top-down from the national police board but would not have been possible without the active involvement of individual commanders, asking to be reviewed, confirming the importance of *local leadership*.

Utilisation and experiences
In the course of the project, the results of the field studies were directly used as input for police education. Project group members participated in the development of courses, peer reviewers participated as tutors and the training material was updated to include the latest developments.

Hilton & Wesmann (2013) provide several examples of ways in which reviewers and hosts took advantage of the reviews and concluded that a more open learning climate was developed. At the concluding seminar, the peer reviews were seen as key to the project's success: they had allowed participants to take a step back and reflect on their activities in an uncomplicated way. The strength of the field studies was that they balanced different perspectives. The studies had created a demand for feedback and strengthened the motivation for development. The exchange among practitioners, researchers and trainers was considered crucial.

Hilton & Wesmann also reported on initial difficulties faced by the project: there was no precedent for evaluating police operations in Sweden and the non-judgmental nature of the reviews was at first unclear. The "peer" aspect, the fact that good practices were identified in addition to development needs and the way in which the field studies were discussed at workshops and seminars contributed to a clear change in attitude. This also led to reviewers, who were at first cautious, to give more critical feedback in response to hosts who came to demand this of them.

Some quotes from Hilton & Wessman illustrate how the reviews were experienced:

"For the first time I was able to stand at the side and see how we actually work. [I have] benefited greatly from that experience; [there was] nothing negative at all". "As a result of my participation in the project I have changed my way of briefing the officers and how I discuss different scenarios with my staff before an event." "[It was] extremely useful to participate in a field-study group. One learned so much by watching others command in one's own role. This in turn affected how one worked at home.". "Between the first and last field study, one could see that we got better and better".

3.3 Peer reviews of football matches in the Netherlands

Initiation
The Dutch police chief responsible for coordinating the policing of football in the Netherlands together with the Ministry of Internal Affairs decided to apply the methodology to the policing of football matches in the Netherlands. Coordinated by the Police Academy of the Netherlands and the Dutch National Football Information Point six peer reviews were held in

six different police forces[3]. Through financial support from the Interior Ministry subsistence costs of reviewers as well as the costs of the coordinator were covered. The goal of the peer reviews was similar to that of the European pilot: blamefree learning.

Implementation

This time, the review teams were composed exclusively of Dutch police commanders (four police commanders per review team, with a coordinator and scientific assistant – in this case, a bachelor student). All commanders approached and asked if they would like to act as host, responded positively. In addition to the individual peer review reports, an overall analysis was made that was presented and discussed at a seminar and published together with the six anonymized reports and an evaluation of the peer review process that had taken place.

Overcoming barriers to learning

As far as *system legitimacy* was concerned, police officers from different Dutch police forces and police researchers participated in the review teams, with a coordinating role for the Police Academy. The reviews were initiated with the active encouragement from the Dutch police chief responsible for coordinating the policing of football in the Netherlands and the Ministry of Internal Affairs. The limited need for financial *resources* was provided by Dutch ministry, reviewers (and their forces) provided their time which was strictly limited. *Liability* was not raised as an issue. Participants agreed to maintain *confidentiality*, reports were provided as internal working documents representing the combined informed but subjective viewpoints from the review team to be used at the discretion of the host, published reports were anonymized. Relevant police *stakeholders* were on board with the reviews, as was the Ministry of Internal Affairs, involvement of other stakeholders was via field interviews. The methodology contributed to *risk management* of future events, in one documented case during the course of the project itself. The willingness of individual local commanders to be reviewed was crucial, confirming the importance of *local leadership*.

Utilisation and experiences

The police chief responsible for initiating the reviews accepted the recommendations at the advice of his strategic policy advisory group. In at least three cases, hosts had made changes to their operation at their next match directly as a result of the peer review report.

According to the participants at the final meeting, trust in each other, the creation of a safe learning environment, non-intervention attitude of reviewers, a good introduction of the peer review team in the host organization and an open, learning driven approach of the host force are critical success factors for peer review. Those acting as hosts indicated that initially they felt “exposed” and “watched” but that this was inevitable if you want to learn. Compared with the European peer reviews, a respectful and careful non-judgmental attitude of the peer reviewers was seen to be even more important at the national level: the Netherlands is a small country and a lot of commanders know each other. Management of expectations is crucial in this respect: it must be clear that the peer review report is not an all-encompassing audit, but a reflection of the observations and conclusion of the team members. One of the discussion points was that, even though the likelihood is low, it is possible that team members will witness something during a review that is later subject of an (internal or external) investigation. The common view was that, in that case, there is no problem for individual team members to assist in discovery of the truth.

All hosts agreed on the usefulness and practical relevance of the peer reviews: *“A lot of*

[3] At the time, there were 25 regional police forces in the Netherlands

teachable moments and collegial exchanges" and *"In addition to the report and its benefits for the host, the biggest plus is what you learn from each other during these days"*. *"Initially, I thought I was going to help a colleague with my experience, but I took home some insights that I will surely put to use"*. *"I have never been able to talk with colleagues just about my profession and I am very glad that was possible now, thanks to a few days of peer review*".

3.4 Peer reviews of the policing of demonstrations in Europe: the Godiac project

Initiation
The Swedish National Police Board received EU funding for a project to analyse and disseminate good practices for de-escalation and prevention of public order disturbances at political manifestations in Europe. The peer review methodology was central in this project called Godiac (Good practice in dialogue and communication). The purpose of the project included the promotion of (peer review) evaluation of policing major events at a European level and the development of institutional co-operation and networks at a European level between practitioners, researchers and trainers. Project coordination was provided by the Swedish National Police Board. There were twenty partner organizations in twelve European countries involved in the project: twelve police organizations and eight research/educational organizations.

Implementation
Ten peer reviews were held in nine different European countries. For each review, a team of seven to ten reviewers was composed from a pool of police officers, researchers, trainers and legal referents from the different partner organizations. The reviewers were trained in the peer review method. During the reviewers, pairs of police officers and researchers/ others were formed as much as possible. The methodology used during the Godiac reviews deviated slightly from the standard methodology: more time was devoted in pre-event data collection on the context of the event, and on pre- and post-event exchanges between reviewer, in which the teams spent a substantial amount of time establishing a detailed timeline of the event.

In line with the goal of the project, partner organizations requested reviews for political manifestations/ demonstrations where there was considered to be a potential for conflict. Reviews focused on four questions agreed upon in the project and one question from the host. Following the first field study in Germany, there were some apprehensive reactions from activists and parliamentarians on the false presumption that the project was part of a European wide effort to come up with measures to restrict protest.[4]
The peer review field study reports were discussed during several seminars. Results of the project were laid down in several publications, all made available online: an anthology with research papers, a field study handbook, and a booklet with summaries of the field study reports with recommendations for the policing of demonstrations and political manifestations. The field study handbook, aimed at promoting the use of field studies for evaluation of policing major events, incorporates learning points and developments of the peer review method. It contains detailed checklists and guidelines, including safety and insurance.

Overcoming barriers to learning
With twenty partner organizations (both police organizations and research/educational organizations) in twelve European countries the project had a broad representation and *system*

[4] http://www.heise.de/tp/artikel/34/34000/1.html, https://benjaminlaufer.wordpress.com/2011/02/26/polizei-erforscht-demonstrationstaktiken/

legitimacy and support. However, the project network was temporary and at the end of the project the network ceased to exist. Financial *resources* were provided via the EU and the Swedish National Police Board who funded project coordinators, researchers and travel and subsistence for meetings and reviews (called field studies in the project). Reviewers from the different partner organisations provided their time which was strictly limited. *Liability* was not raised as an issue. As far as *confidentiality* was concerned, reports were provided as internal working documents representing the combined informed but subjective viewpoints from the review team to be used at the discretion of the host. At a later stage, and in line with the project plan agreed upon beforehand, summaries of the reports were published. *Stakeholders* from police and police-related institutions were actively involved with the reviews. Involvement of other stakeholders took place via field interviews. It is unclear if and how the methodology contributed to *risk management* of future events. The project was initiated by the Swedish national police board but depended completely on the voluntary involvement and commitment of the different partner organisations and individuals within those organisations, especially those volunteering to be reviewed, thus confirming the importance of *local leadership*.

Utilisation and experiences
It is difficult to infer from the published sources what the learning effects have been. The project reportedly contributed to the spread of dialogue teams in the UK (especially Liverpool). Regarding Hungary, Hajas (2013) posits that the Godiac project has changed the Hungarian police, in some direct and some indirect ways:

> *As a result, Budapest does not seem like a besieged city during every political protest or other such public demonstration. The commanders and chiefs of police have learned from experience that high-profile crowd management is not the only viable option and instead used crowd management solutions that were flexible and that respected fundamental rights*

3.5 Peer reviews during festival events in the Netherlands

Initiation
After some incidents had occurred, the Board of chiefs of police in the Netherlands felt the need for a long term study into the policing of festival events to develop, identify, validate and exchange good practices. The Dutch police chief responsible for conflict and crisis management in the Netherlands tasked the Police Academy of the Netherlands to execute a project to increase insight in and dissemination of good policing practices that contribute to safe and secure festival events, especially regarding investigative activities, order maintenance and intelligence. The project was financed by the Board of chiefs of police and the Police Academy of the Netherlands. The peer review method was to be an important methodology used in the course of the project, next to dedicated research activities, knowledge exchange seminars and expert meetings. Part of the design of the project centred on peer reviewing a limited number of high-profile festivals across three years, to stimulate organizational learning for each festival and promote exchange of good practices between forces dealing with festivals.

Implementation
Seven different festivals were included in the project, four of which were reviewed in all three years, two in two successive years. In this project, experienced external researchers (rather than students) participated as research assistants. In the third and last year of the project, four

non-police reviewers (municipal officials dealing with festival events) participated in the peer review teams.

The project was characterized by a large amount of exchanges and interaction between researchers, practitioners, teachers and other stakeholders. Once a year a seminar was held for practitioners and researchers, two expert meetings were held with hosts and reviewers, as well as two open conference for festival-related stakeholders. In addition, several informal peer assists (Greenes, 2010) were organized prior to events not subject to peer review, four students wrote their thesis on a topic related to the project. All hosts freely shared the peer review reports they had received with colleagues and welcomed the participation of non-police reviewers in the peer review teams.

The final publication of the project (Adang, 2014) contained an overall analysis of experiences of the peer review teams, the results of the complementary research that formed part of the project and overall conclusions and recommendations. Among the recommendations are more knowledge exchange and education, more involvement of other stakeholders in peer reviews and incorporation of peer review in education and training. In addition to the feedback given in the individual reports, the peer review discussions led to fundamental questions being asked about the role of police at festival events and the coherence between police order maintenance, intelligence and investigative processes.

Overcoming barriers to learning

System legitimacy was assured through participation of police officers and researchers, embedded in hosting police forces, with a coordinating role for the Police Academy and active encouragement from the Dutch police chief responsible for coordinating the policing of football in the Netherlands and the Ministry of Internal Affairs. In terms of *resources*, travel, subsistence and coordination costs for the reviews were financed by the Board of chiefs of police and the Police Academy of the Netherlands. Reviewers (and their forces) provided their time, which was strictly limited. *Liability* was not raised as an issue. Participants agreed to maintain *confidentiality*, reports were provided as internal working documents representing the combined informed but subjective viewpoints from the review team to be used at the discretion of the host, published reports were anonymized. In the course of the project, hosts agreed of their own accord to share reports between them. Relevant police *stakeholders* were on board with the reviews. In the third year of the project, municipal officials were involved in the reviews. Before that time, other stakeholders were already invited to participate in the project seminars. In addition, other stakeholders were included in field interviews. The methodology contributed to *risk management* of future events, in one case during the course of the project itself. The enthusiasm and continually growing interest of individual local commanders to be reviewed confirmed the importance of *local leadership*.

Utilisation and experiences

Hosts and reviewers were unanimous in the value and effectiveness of the peer review methodology as a learning tool. "*The beauty of a peer review is that it makes use of the fact that from the outside, you see other things than from the inside*", as one of the commanders put it. The same commander: "*The beauty is that you enter into a conversation with another professional about how you do things. He asks questions you yourself might not ask. The trick is to jointly look in amazement how things happen and to think about what can be improved. This makes that the peer reviews work better than a regular evaluation*".[5]

[5] https://www.politieacademie.nl/onderwijs/overdescholen/spl/LaboratoriaOpsporing/Paginas/Peer-review-is-samen-leren.aspx (translated from the original Dutch)

The conclusion was also that there is still some way to go: "*There is a great willingness to learn. This also shows in innovations and adaptions based on feedback from the peer reviews. Still, changes are not always implemented. One the one hand, this is partly because other stakeholders are also involved, on the other hand it is sometimes difficult to take leave of old patterns and practices*" (Adang, 2014, p. 198). This last comment confirms once more how, in spite of a willingness to learn, organisational learning and real change can be difficult to achieve.

4. Discussion: Overcoming learning obstacles

The five different applications of the peer review methodology all involved a connected series of between six and seventeen reviews taking place in a one to three year period. In all cases, in addition to individual reports being made, an overall analysis was made of good practices and points of attention that were considered to be of general relevance to the policing of major events. In all applications the peer reviews were the main methodology within a larger knowledge exchange/ knowledge development project, with research activities (very explicit in Sweden, Godiac and Dutch festivals) and a range of dissemination activities such as conferences, seminars and workshops (all applications). The involvement of institutes for police education in all applications made it easier in principle to implement outcomes into police education, although it is not clear in every instance in how far this actually happened. In all but ones of the cases (Godiac), the continuity of the network of institutions/ organisations involved in the peer reviews did not depend on the project.

To summarise: how does the peer review methodology handle the issues identified by Doyle (2014) that need to be addressed to establish a workable approach to learning?

With regard to *system legitimacy*, the peer review methodology as applied now was mainly an internal police affair with involvement from researchers. This was important for creating a learning environment in which participants felt safe. As the example of the Swiss cities shows, the methodology can help "the public to witness the professionalism and commitment of the system's practitioners in action and nourish public trust in the system and its operators" (Doyle, 2014, p. 12) and there clearly seems to be potential for the future here.

With regards to *resources* (issues of time and money*)*, the peer review methodology only required a strictly limited amount of staff time and limited funds: if reviewers are made available by their organizations, basically only travel and subsistence costs need to be covered in addition to the cost of coordinating the review. No blank check is required.

Issues of *liability and confidentiality* could make individuals or organization less likely to participate in a review process. Because the peer review methodology does not focus on errors or near misses, this was much less of an issue and in this respect the peer review methodology clearly differs from the sentinel reviews. Liability was not raised as an issue at all in the course of the reviews. As far as confidentiality was concerned, participants agreed to maintain confidentiality, individual reports were considered to be internal working documents, with the exception of the Godiac project, published reports were anonymized. They were explicitly not presented as a full investigation or evaluation of an event, but as (subjective) viewpoints from the review team. In the Dutch projects, a spontaneous willingness came about amongst commanders to share reports with one another.

Due to its utilization focused approach, the peer review methodology is designed to *get stakeholders on board.* In most applications, this mainly meant stakeholders within police organizations, and mainly police officers as reviewers, but as the example of Netherlands festivals show, there is no reason why other stakeholders cannot be included in review teams, as long as they are credible experts/ professionals in their field and a safe learning environment is ensured[6]. In fact, there is every reason to assume that the inclusion of other stakeholders could benefit the learning effect of the reviews, just as the presence of researchers did. Researchers played specific roles in the peer reviews. The methodology was developed by the author, a researcher, and a main role for researchers was to maintain the integrity of the methodology before, during and after the peer reviews. Researchers also contributed by bringing an outside, non-practitioner perspective to the peer reviews, asking questions on topics practitioners might be taking for granted. During reflections and discussions on good practices, both during the peer reviews themselves as during the seminars linked to the peer reviews, researchers contributed by linking theory and practice. In addition, even though the peer reviews were not designed as data gathering exercises for researchers, the reviews did yield unique field data and, part of the data used for Brown's (2012) thesis on inter-group dynamics in the context of policing foreign nationals were obtained in connection with the peer reviews of international football matches in Europe.

Because the peer review methodology is designed to identify learning needs *before* errors or near misses occur, the methodology actually contributes to *risk management* in an innovative way without invoking issues of liability. Sometimes the main motivation to start with peer reviews is a high profile incident that happened in the past (as was the case in Sweden, where the need for the SPT project was linked to riots during an EU summit in Gothenburg five years previously), sometimes it was an upcoming high profile event (such as the Euro 2008 football championship in Switzerland and Austria). For the implementation of the methodology this makes no difference.

Implementation of the peer review methodology confirmed the importance of *local leadership*. Without early-adopting individual commanders willing to stick their neck out, asking to be reviewed, the methodology cannot establish itself.

Because the focus is not on errors, the *choice of events to be reviewed* becomes much easier with the peer review methodology and can totally depend on the learning needs of the requester. Virtually any event can be a suitable topic for review. Doyle (2014) already mentioned how smaller (rather than notorious or shocking) sentinel events could perhaps yield the most informative accounts. Peer reviews take this thought one step further and all reviews identified numerous learning points, in addition to good practices (this in spite of the fact that in none of the 62 reviews a major incident occurred). Application of the peer reviews to the policing of sporting events, festivals and demonstrations is made easier by the fact that these are discrete events, known in advance, so that the reviews can be planned. Adang (2013) reports that a modified version of the methodology has by now also been applied to review other aspects of police work, such as investigative processes or community policing.

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[6] Moreau et al. (2010) and Abramovic (2011) report on a special application of the peer review methodology in Argentina. In a quite sensitive project financed by the Dutch Embassy in Argentina, members of the federal government, federal police and security forces and prominent human rights organizations cooperated with the goal to stimulate a policing of social protest in line with human rights. "*Despite the difficulties inherent to an initiative of this kind, the challenge was far surpassed. The results speak for themselves*" (Abramovic, 2011: 158, translated from Spanish)

Summing up, the peer review methodology seems to be able to overcome the obstacles to learning identified by Doyle. Still, several obstacles for a successful implementation were identified by participants. One of them was the newness of the methodology for both hosts and reviewers (giving training and becoming familiar with the methodology were helpful in this respect), another that for police officers an observer role could potentially come into conflict with their policing duty (in practice this did not present a problem). Participants reported that implementing changes in police organizations was sometimes difficult. Also, in some cases confusion existed about the nature of the peer reviews. Used as they are to audits and inspections, some police officers initially mistook peer reviews as just another form of audit or inspection. It also had to be made clear that a peer review is not an overall evaluation of (the policing of) a specific event or the making of a factual report of all that happened during the event, but no more and no less than the structured feedback of a couple of experienced professional peers holding up a mirror. This aspect proved to be very important and in all applications participants stressed how different peer reviews felt from audits, inspections or other types of evaluation and how this resulted in more openness. In line with Doyle (2014), in implementing the peer review methodology, it thus proved important to *recognize limitations and manage expectations*.

In addition, next to local leadership, it turned out that institutional “sponsors” are needed to furnish the limited, but necessary funds. To be able to conduct a series of connected peer reviews institutional or collaborative commitment is essential as well, as is leadership in the form of coordination of the different reviews, embedding the reviews in other knowledge exchange practices and analysing the reviews, linking theory and practice. Where these are not available, they become an obstacle.

As far as the *utilisation* of the peer reviews is concerned, in all applications, both hosts and reviewers reported learning outcomes and saw the methodology as a win-win. Especially in Sweden and in the Swiss cities that were going to host matches in the Euro 2008 championship significant transformations occurred of the type that usually only take place after a high profile incident[7]. There was unanimous agreement among participants (both hosts and reviewers) that the reviews constituted a safe learning environment. Both the peer aspect and the utilization focused approach were identified as critical success factors. It created the trust that is so essential in ensuring that a blame free culture is developed (Smith & Elliott, 2000) that does not lead to in-the-job trouble.

It is a limitation of this study that it is based exclusively on the perspectives of those involved in the peer reviews (either as hosts or reviewers), as documented during and after the different applications of the methodology. It would be beneficial for future studies to gather additional data and include the perspectives to include the perspectives of other stakeholders (including citizens) as well. The importance of creating a safe learning environment explains the hesitation to involve non-police stakeholders, as it was felt their involvement could potentially lead to participants feeling less secure and less willing to open up. However, actual experience with the methodology clearly diminished this hesitation. Stakeholders (including citizens) that were interviewed in the course of the peer reviews almost invariably reacted positively to the fact that they were interviewed because the police organisation concerned wanted to learn.

[7] See also previous note regarding application of the methodology in Argentina

5. Conclusion: a workable approach to foster organizational learning?

In conclusion, the peer review methodology seems to be a promising tool to overcome barriers to learning and to foster the type of organizational learning that Geller (1997) advocates and the Task Force on 21st Century Policing (2015) wishes for. Not instead of other tools, such as internal review processes or the sentinel events reviews, but in addition to them. The potential of the peer review methodology is due in large part to the creation of a safe nonadversarial, non-blaming learning environment, real time data collection and stringent avoidance of a one-sided focus on errors.

The overview presented in this paper indicates that the methodology may contribute to learning in three different ways: hosts receive informed and constructive feedback, reviewers gain additional experience and insights and the exchanges taking place in the course of or following the reviews (e.g. in the form of seminars) contribute to the identification of good practices and development of professional norms which in some cases become codified. Experiences show that the interactions taking place between participants also facilitate mutual understanding and cooperation. Interestingly, quite apart from the *products* obtained through the methodology, the peer review *process* itself proved to foster reflection and learning. On numerous occasions, both the pre-review dialogue with the host about the peer review questions and the field interviews with professionals in the course of the reviews led to they themselves becoming aware of potential issues or identifying learning points.

It should be recognised that identifying lessons is not the same as learning: the lessons have to be put into practice as well. Several instances of actual utilisation of the findings have been documented where hosts have actively worked to ensure that evaluation findings are utilized in the spirit of Patton (1979). Several examples mentioned in this paper have shown that peer reviews can be transformative and help mobilize the continuous conversation among practitioners, researchers, policymakers and citizens (cf. Doyle, 2014, p. 15). Having said that, the effects documented so far are in the short term mainly and more research is needed into more lasting long term learning effects of the peer review methodology. It would be interesting in future studies to make comparisons with the safety literature on the one hand, where the failure to successfully learn from incidents is seen as an important issue (e.g. Drupsteen & Guldenmund, 2014) and with the literature on peer (or peer to peer) learning as applied mainly in educational settings (e.g. Topping, 2005), taking into account theories on organizational learning (e.g. Argyris & Schön, 1996).

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PRED POL WEEKLY DOSAGE (HRS)

Div #	Division	Week 1 (12/27/15 01/02/16)	Week 2 (01/03/16 01/09/16)	Week 3 (01/17/16 01/23/16)	Week 4 (01/24/16 01/30/16)	Week 5 (01/31/16 02/06/16)	Week 6 (02/07/16 02/13/16)	Week 7 (02/14/16 02/20/16)	Week 8 (02/21/16 02/27/16)	Week 9 (02/28/16 03/05/16)	Week 10 (03/06/16 03/12/16)	Week 11 (03/13/16 03/19/16)	Week 12 (03/20/16 03/26/16)	Week 13 (03/27/16 04/02/16)	Week 14 (04/03/16 04/09/16)	Week 15 (04/10/16 04/16/16)	Week 16 (04/17/16 04/23/16)	Week 17 (04/24/16 04/30/16)	Week 18 (05/01/16 5/07/16)	Week 19 (05/08/16 05/14/16)	Week 20 (05/15/16 05/21/16)
1	Central	137.58	80.64	38.66	43.06	108.49	39.5	46.98	78.66	86.06	67.73	49.99	36.27	63.24	52.49	83.39	109.38	122.2	108.23	91.29	89.77
2	Rampart	95.68	73.17	68.79	80.42	71.91	76.71	64.7	82.09	107.07	84.7	55.17	22.02	55.33	42.55	42.38	14.96	47.59	54.61	40.33	52.88
3	Southwest																				
4	Hollenbeck	47.31	65.89	54.14	44.88	32.6	26.91	23.57	40.81	29.83	43.23	68.12	53.33	37.91	28.93	23.9	22	26.77	27.55	12.23	19.73
5	Harbor	59.56	52.22	32.32	36.11	29.81	14.72	14.65	2.76												
6	Hollywood	52.54	51.33	60.87	96.68	119.53	100.31	79.03	105.45	56.55	88.01	65.49	64.11	47.47	31.3	52.2	24.03	45.46	70.6	33.96	30.65
7	Wilshire	166.25	87	159.42	157.91	162.33	143.75	128.29	87.72	128.88	57.5	69.03	82.42	98.93	82.27	83.56	83.79	81.91	94.82	84.79	93.7
8	West LA	80.97	43.82	81.6	88.25	162.88	83.94	72.15	109.93	104.17	89.64	50.81	70.92	55.44	38.4	36.41	91.64	62.52	59.11	25.16	77.66
9	Van Nuys	94.49	73.33	60.87	54.84	56.48	46.36	29.2	74.01	77.09	77.42	70.54	70.47	62.26	38.8	43.42	46.7	45.05	69.26	50.48	72.51
10	W. Valley	92.65	43.96	49.17	44.31	69.62	60.84	63.47	122.42	88.13	129.95	61.23	40.7	50.88	42.21	57.98	81.89	73.14	109.46	89.04	89.26
11	Northeast	133.69	77.27	74.56	114.95	101.34	84.11	61.3	119.01	107.16	99.87	78.7	105.83	80.76	119.67	78.7	48.67	84.91	67.82	65.79	59.31
12	77th																				
13	Newton	41.24	36.18	19.84	18.16	10.71	10.54	16.44	8.69	19.55	32.08	17.76	18.33	11.64	14.92	19.7	6.74	6.67	11.27	2.42	8.07
14	Pacific	91.86	96.34	108.82	79.89	105.52	106.7	75.08	77.16	79.15	46.62	53.44	51.62	48.78	22.24	45.44	23.12	34.13	62.54	24.9	38.17
15	N. Hollywood	71.7	45.9	88.41	126.22	150.94	70.51	80.33	84.31	95.46	63.18	69.03	77.89	81.45	43.45	37.72	40.75	49.5	33.06	36.2	66.71
16	Foothill	146.12	180.12	127.8	158.14	170.72	111.01	135.85	116.02	91.95	177.45	173.75	123.76	185.96	108.01	134.43	68.2	81.04	103.51	121.01	166.63
17	Devonshire	73.5	53.45	56.53	65.15	75.79	46.66	38.53	76.05	67.92	57.76	34.49	25.88	49.96	33.45	28.78	35.8	47.7	34.03	31.86	52.67
18	Southeast																				
19	Mission	123.05	137.78	94.13	93.62	122.46	50.54	53.36	70.61	79	87.65	57.09	115.68	90.23	67.84	77.64	85.13	42.93	73.56	50.59	66.18
20	Olympic	158.05	228.44	100.09	150.95	169.01	117.21	107.43	120.51	95.99	84.22	112.57	129.39	127.86	98.41	92.08	103.37	100.78	77.99	81.9	98.16
21	Topanga	99.27	107.95	86.18	49.69	73.59	46.37	93.41	161.86	136.2	151.82	106.47	125.49	111.84	53.06	101.67	113.14	93.57	58.35	55.64	67.19

Div #	Division	Week 21 (05/22/16 05/28/16)	Week 22 (05/29/16 06/04/16)	Week 23 (06/05/16 06/11/16)	Week 24 (06/12/16 06/18/16)	Week 25 (06/19/16 06/25/16)	Week 26 (06/26/16 07/02/16)	Week 27 (07/03/16 07/09/16)	Week 28 (07/10/16 07/16/16)	Week 29 (07/17/16 07/23/16)	Week 30 (07/24/16 07/30/16)	Week 31 (07/31/16 08/06/16)	Week 32 (08/07/16 08/13/16)	Week 33 (08/14/16 08/20/16)	Week 34 (08/21/16 08/27/16)	Week 35 (08/28/16 09/03/16)	Week 36 (09/04/16 09/10/16)	Week 37 (09/11/16 09/17/16)
1	Central	98.73	75.88	72.07	60.54	47.53	99.49	91.59	60.85	101.22	76.64	63.79	56.77	75.16	80.78	71.04	75.56	64.32
2	Rampart	53.91	37.04	40.68	59.28	31.34	49.85	44.57	70.36	38.57	55.35	45.05	52.08	39.62	49.59	57.95	79.42	49.23
3	Southwest																	
4	Hollenbeck	11.55	23.43	12.03	18.43	8.73	20	28.84	14.14	8.89	6.38	7.18	13.17	32.99	65.34	72.16	67.75	33.21
5	Harbor																	
6	Hollywood	23.1	20.94	18.8	37.06	27.27	51.5	23.31	17.29	34.89	35.01	30.51	50.67	38.87	62.58	13.11	20.15	33.31
7	Wilshire	57.05	69.78	70.58	84.32	66.14	89	77.53	85.32	92.36	95.77	109.71	123.73	84.41	86.01	87.99	76.82	90.59
8	West LA	54.4	29.13	22.85	53.73	69.11	66.61	46.59	122.18	56.38	44.04	67.10	46.34	47.84	85.34	54.17	83.97	97.01
9	Van Nuys	54.5	62.42	49.02	50.81	41.85	28.51	33.37	48.03	17.34	22.41	25.34	64.84	55.01	52.05	65.89	78.50	66.21
10	W. Valley	64.91	63.34	66.78	41.97	49.9	63.55	86.03	87.11	55.58	84.06	75.25	73.04	57.95	74.78	52.48	62.53	68.75
11	Northeast	56.74	50.72	45.38	103.49	74.75	66.73	84.84	94.45	52.07	80.97	66.74	72.36	70.82	58.63	55.05	94.30	48.85
12	77th																	
13	Newton	15.64	12.59	8.69	7.25	7.54	2.83	8.84	5.96	17.73	20.55	11.57	22.84	19.56	32.82	16.39	4.60	1.93
14	Pacific	39.49	32.14	25.15	27.78	30.07	31.65	31.9	42.37	31.93	32.46	37.28	30.20	30.78	65.52	55.20	27.75	51.38
15	N. Hollywood	87.84	77.18	85.77	46.74	77.65	62.17	51.89	90.63	44.05	71.47	69.25	101.85	85.08	64.28	86.19	119.05	108.17
16	Foothill	135.66	111.96	145.74	149.18	116.89	89.88	109.92	128.9	86.94	84.59	126.98	111.68	114.12	139.58	94.70	76.50	90.14
17	Devonshire	44.95	31.99	43.16	45.19	38.86	29.47	42.38	52.92	41.66	34.01	37.75	25.83	39.10	31.45	21.60	57.54	28.66
18	Southeast					61.5												
19	Mission	88.88	78.66	55.29	90.62	65.59	36.96	42.38	66.9	60.88	38.56	41.43	40.13	34.80	40.69	23.50	50.38	45.73
20	Olympic	83.45	92.72	105.23	62.94	62.2	75.94	65.67	101.47	70.50	88.17	98.66	93.12	44.38	35.31	57.23	111.00	100.02
21	Topanga	96.44	72.11	65.1	63.06	56.04	51.43	56.48	91.04	77.51	76.84	45.58	99.50	104.87	97.66	111.63	88.43	74.86

PRED POL WEEKLY DOSAGE (HRS)

Div #	Division	Week 1 (12/27/15 01/02/16)	Week 2 (01/03/16 01/09/16)	Week 3 (01/17/16 01/23/16)	Week 4 (01/24/16 01/30/16)	Week 5 (01/31/16 02/06/16)	Week 6 (02/07/16 02/13/16)	Week 7 (02/14/16 02/20/16)	Week 8 (02/21/16 02/27/16)	Week 9 (02/28/16 03/05/16)	Week 10 (03/06/16 03/12/16)	Week 11 (03/13/16 03/19/16)	Week 12 (03/20/16 03/26/16)	Week 13 (03/27/16 04/02/16)	Week 14 (04/03/16 04/09/16)	Week 15 (04/10/16 04/16/16)	Week 16 (04/17/16 04/23/16)	Week 17 (04/24/16 04/30/16)	Week 18 (05/01/16 5/07/16)	Week 19 (05/08/16 05/14/16)	Week 20 (05/15/16 05/21/16)
1	Central	137.58	80.64	38.66	43.06	108.49	39.5	46.98	78.66	86.06	67.73	49.99	36.27	63.24	52.49	83.39	109.38	122.2	108.23	91.29	89.77
2	Rampart	95.68	73.17	68.79	80.42	71.91	76.71	64.7	82.09	107.07	84.7	55.17	22.02	55.33	42.55	42.38	14.96	47.59	54.61	40.33	52.88
3	Southwest																				
4	Hollenbeck	47.31	65.89	54.14	44.88	32.6	26.91	23.57	40.81	29.83	43.23	68.12	53.33	37.91	28.93	23.9	22	26.77	27.55	12.23	19.73
5	Harbor	59.56	52.22	32.32	36.11	29.81	14.72	14.65	2.76												
6	Hollywood	52.54	51.33	60.87	96.68	119.53	100.31	79.03	105.45	56.55	88.01	65.49	64.11	47.47	31.3	52.2	24.03	45.46	70.6	33.96	30.65
7	Wilshire	166.25	87	159.42	157.91	162.33	143.75	128.29	87.72	128.88	57.5	69.03	82.42	98.93	82.27	83.56	83.79	81.91	94.82	84.79	93.7
8	West LA	80.97	43.82	81.6	88.25	162.88	83.94	72.15	109.93	104.17	89.64	50.81	70.92	55.44	38.4	36.41	91.64	62.52	59.11	25.16	77.66
9	Van Nuys	94.49	73.33	60.87	54.84	56.48	46.36	29.2	74.01	77.09	77.42	70.54	70.47	62.26	38.8	43.42	46.7	45.05	69.26	50.48	72.51
10	W. Valley	92.65	43.96	49.17	44.31	69.62	60.84	63.47	122.42	88.13	129.95	61.23	40.7	50.88	42.21	57.98	81.89	73.14	109.46	89.04	89.26
11	Northeast	133.69	77.27	74.56	114.95	101.34	84.11	61.3	119.01	107.16	99.87	78.7	105.83	80.76	119.67	78.7	48.67	84.91	67.82	65.79	59.31
12	77th																				
13	Newton	41.24	36.18	19.84	18.16	10.71	10.54	16.44	8.69	19.55	32.08	17.76	18.33	11.64	14.92	19.7	6.74	6.67	11.27	2.42	8.07
14	Pacific	91.86	96.34	108.82	79.89	105.52	106.7	75.08	77.16	79.15	46.62	53.44	51.62	48.78	22.24	45.44	23.12	34.13	62.54	24.9	38.17
15	N. Hollywood	71.7	45.9	88.41	126.22	150.94	70.51	80.33	84.31	95.46	63.18	69.03	77.89	81.45	43.45	37.72	40.75	49.5	33.06	36.2	66.71
16	Foothill	146.12	180.12	127.8	158.14	170.72	111.01	135.85	116.02	91.95	177.45	173.75	123.76	185.96	108.01	134.43	68.2	81.04	103.51	121.01	166.63
17	Devonshire	73.5	53.45	56.53	65.15	75.79	46.66	38.53	76.05	67.92	57.76	34.49	25.88	49.96	33.45	28.78	35.8	47.7	34.03	31.86	52.67
18	Southeast																				
19	Mission	123.05	137.78	94.13	93.62	122.46	50.54	53.36	70.61	79	87.65	57.09	115.68	90.23	67.84	77.64	85.13	42.93	73.56	50.59	66.18
20	Olympic	158.05	228.44	100.09	150.95	169.01	117.21	107.43	120.51	95.99	84.22	112.57	129.39	127.86	98.41	92.08	103.37	100.78	77.99	81.9	98.16
21	Topanga	99.27	107.95	86.18	49.69	73.59	46.37	93.41	161.86	136.2	151.82	106.47	125.49	111.84	53.06	101.67	113.14	93.57	58.35	55.64	67.19

Div #	Division	Week 21 (05/22/16 05/28/16)	Week 22 (05/29/16 06/04/16)	Week 23 (06/05/16 06/11/16)	Week 24 (06/12/16 06/18/16)	Week 25 (06/19/16 06/25/16)	Week 26 (06/26/16 07/02/16)	Week 27 (07/03/16 07/09/16)	Week 28 (07/10/16 07/16/16)	Week 29 (07/17/16 07/23/16)	Week 30 (07/24/16 07/30/16)	Week 31 (07/31/16 08/06/16)	Week 32 (08/07/16 08/13/16)	Week 33 (08/14/16 08/20/16)	Week 34 (08/21/16 08/27/16)	Week 35 (08/28/16 09/03/16)	Week 36 (09/04/16 09/10/16)	Week 37 (09/11/16 09/17/16)	Week 38 (09/18/16 09/24/16)	Week 39 (09/25/16 10/01/16)	Week 40 (10/02/16 10/08/16)
1	Central	98.73	75.88	72.07	60.54	47.53	99.49	91.59	60.85	101.22	76.64	63.79	56.77	75.16	80.78	71.04	75.56	64.32	67.19	53.59	82.92
2	Rampart	53.91	37.04	40.68	59.28	31.34	49.85	44.57	70.36	38.57	55.35	45.05	52.08	39.62	49.59	57.95	79.42	49.23	39.55	42.40	55.99
3	Southwest																				
4	Hollenbeck	11.55	23.43	12.03	18.43	8.73	20	28.84	14.14	8.89	6.38	7.18	13.17	32.99	65.34	72.16	67.75	33.21	54.63	15.88	67.60
5	Harbor																				
6	Hollywood	23.1	20.94	18.8	37.06	27.27	51.5	23.31	17.29	34.89	35.01	30.51	50.67	38.87	62.58	13.11	20.15	33.31	32.43	34.73	36.98
7	Wilshire	57.05	69.78	70.58	84.32	66.14	89	77.53	85.32	92.36	95.77	109.71	123.73	84.41	86.01	87.99	76.82	90.59	60.35	106.31	81.89
8	West LA	54.4	29.13	22.85	53.73	69.11	66.61	46.59	122.18	56.38	44.04	67.10	46.34	47.84	85.34	54.17	83.97	97.01	60.07	78.49	77.74
9	Van Nuys	54.5	62.42	49.02	50.81	41.85	28.51	33.37	48.03	17.34	22.41	25.34	64.84	55.01	52.05	65.89	78.50	66.21	80.16	50.91	66.06
10	W. Valley	64.91	63.34	66.78	41.97	49.9	63.55	86.03	87.11	55.58	84.06	75.25	73.04	57.95	74.78	52.48	62.53	68.75	39.37	47.49	103.07
11	Northeast	56.74	50.72	45.38	103.49	74.75	66.73	84.84	94.45	52.07	80.97	66.74	72.36	70.82	58.63	55.05	94.30	48.85	53.18	31.84	75.02
12	77th																				
13	Newton	15.64	12.59	8.69	7.25	7.54	2.83	8.84	5.96	17.73	20.55	11.57	22.84	19.56	32.82	16.39	4.60	1.93	1.19	1.42	5.41
14	Pacific	39.49	32.14	25.15	27.78	30.07	31.65	31.9	42.37	31.93	32.46	37.28	30.20	30.78	65.52	55.20	27.75	51.38	29.04	26.40	25.63
15	N. Hollywood	87.84	77.18	85.77	46.74	77.65	62.17	51.89	90.63	44.05	71.47	69.25	101.85	85.08	64.28	86.19	119.05	108.17	87.60	76.54	125.80
16	Foothill	135.66	111.96	145.74	149.18	116.89	89.88	109.92	128.9	86.94	84.59	126.98	111.68	114.12	139.58	94.70	76.50	90.14	96.84	61.89	53.73
17	Devonshire	44.95	31.99	43.16	45.19	38.86	29.47	42.38	52.92	41.66	34.01	37.75	25.83	39.10	31.45	21.60	57.54	28.66	26.69	33.28	24.03
18	Southeast					61.5															
19	Mission	88.88	78.66	55.29	90.62	65.59	36.96	42.38	66.9	60.88	38.56	41.43	40.13	34.80	40.69	23.50	50.38	45.73	61.22	35.24	38.84
20	Olympic	83.45	92.72	105.23	62.94	62.2	75.94	65.67	101.47	70.50	88.17	98.66	93.12	44.38	35.31	57.23	111.00	100.02	74.47	103.94	42.47
21	Topanga	96.44	72.11	65.1	63.06	56.04	51.43	56.48	91.04	77.51	76.84	45.58	99.50	104.87	97.66	111.63	88.43	74.86	84.87	57.07	44.33

Div #	Division	Week 41 (10/9/161 0/15/16)
1	Central	63.50
2	Rampart	34.89
3	Southwest	
4	Hollenbeck	63.30
5	Harbor	
6	Hollywood	23.30
7	Wilshire	64.20
8	West LA	51.09
9	Van Nuys	52.53
10	W. Valley	78.21
11	Northeast	33.24
12	77th	
13	Newton	6.67
14	Pacific	28.34
15	N. Hollywood	103.31
16	Foothill	54.81
17	Devonshire	31.48
18	Southeast	
19	Mission	31.68
20	Olympic	28.75
21	Topanga	57.92

Netherlands Institute for the Study of Crime and Law Enforcement

Dr. George Mohler,
Dr. Martin Short,
Mr. Sean Malinowski,
Mr. Mark Johnson,
Dr. George Tita
Dr. Andrea Bertozzi,
Dr. Jeff Brantingham

[redacted] BH Amsterdam
[redacted] HV Amsterdam
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Subject: Replication of predictive policing study

Date: October 18, 2016

Dear Dr. Mohler, Dr. Short, mr. Malinowski, mr. Johnson, Dr. Tita, Dr. Bertozzi, and Dr. Brantingham,

We would like to ask for your assistance in the organization of a replication of your Predpol evaluation study published in the Journal of the American Statistical Association.

Why do we aim to replicate your work? Although replication lies at the heart of the scientific method, replication research does not always get the funding, exposure, and academic credit it deserves. To stimulate replication research, the Netherlands Organisation for Scientific Research (NWO) has issued a call for proposals, asking researchers to propose replications of cornerstone research. Cornerstone research is research that has proven to be important for science and for society. Your evaluation of predictive policing easily meets that criterion. It is hard to come up with another recent study that has had as many implications for crime prevention and law enforcement.

Our aim is not to implement a predictive policing experiment in The Netherlands but to re-analyze the data you collected in Los Angeles and Kent, and reevaluate the impact and effectiveness of the PredPol trials. As part of the evaluation of proposals, NWO asks us to verify in advance that we can get access to the information (data, study protocols, code) that is needed to conduct the replication study. This is why we are seeking your help.

Specifically, we would like to hear from you under which conditions it would be possible for us to get access to the data, protocols, code and other relevant documentation used in your Predpol evaluation study. In specifying conditions, please include any legal (e.g., contracts), technical (e.g., data encryption), practical and financial requirements. We are prepared to do everything we can to make this replication study possible, and if strictly necessary we are prepared to conduct the study on-site in the USA.

For obvious and understandable reasons, any initiative at replication might be perceived by the original researchers as an expression of doubt, lack of trust in the study's findings, or attempt to discredit the product or intervention being evaluated. We are all only human. We emphasize, however, that we are completely nonpartisan regarding the outcomes of the replication. We have no financial or reputational stakes whatsoever in predictive policing, neither in Predpol nor in any other of the various predictive policing tools that are currently being developed. Our only interest is to learn from replicating an important and impressive study and to be able to publish the results of this replication in a reputable scientific journal. Replication of your findings by independent researchers from another continent will strengthen the evidence base of PredPol implementations in Los Angeles, Kent and elsewhere.

We hope you endorse the importance of an independent replication of your work for science and for law enforcement, and hope that you will do everything you can to help us realize it. We look forward to your reaction.

Sincerely,

Wim Bernasco
Christophe Vandeviver
Catrien Bijleveld

Encls.

- NWO Call for Proposals Replication Studies
- Single-page Vitae of Bernasco, Vandeviver and Bijleveld

RIPS 2016 Industry Sponsors Guide

Thank you for your interest in sponsoring a project in IPAM's Research in Industrial Projects for Students (RIPS) Program this summer! We have developed this short guide for sponsors, so that they know what to expect and understand the commitment they will be making. Please contact us (see page 5) with any questions or concerns about your participation.

Choosing an Industry Mentor

The industry mentor is a mathematician, scientist or engineer at the sponsoring organization who has the most familiarity with the proposed project. This will likely be the same person who writes the project description (below) but may be another researcher in the same area/office with similar expertise. A team of mentors is fine and even desirable, as long as one researcher is assigned to be the main point of contact for the students. The industry mentor must be available throughout the summer (June 20 – Aug. 19, 2016) to meet with the students in person or remotely at least weekly, as well as to respond to their questions by email. He or she must also attend opening day at IPAM (UCLA) on Monday, June 20. When choosing an industry mentor, please confirm that the person has this availability. If the industry mentor will be traveling during the summer, he or she must still be able to communicate with the students by email or phone, or must find a qualified substitute industry mentor for that period of time.

Industry mentors who do not live in LA area should plan to spend a few extra days at UCLA after Opening Day. Face-to-face interaction at the start of the program is important to foster a productive relationship with the students and a good experience overall. We require that the industry mentor resides in the United States if not the Los Angeles area; we have found that a time difference of more than a few hours is impractical, because the students cannot get timely responses to their questions.

Project Description

The project description explains the problem and the reason the outcome is important to the sponsor. The students should be able to appreciate the scope of the project and how mathematics is involved. Based on the project description and their own background research, the students will formulate a statement of work in the first week or two of the program.

The project description should be provisional in nature; that is, not so specific that it proscribes the methodology, but not so general that the students are unable to identify specific objectives. It should list tasks you want the students to undertake, but should not insist on a specific methodology or outcome. A typical project description is 2 or 3 pages long and includes the following components:

- **Title** of project and sponsor, and name of the industry mentor

-Introduction: A brief description of the problem and reasons why a solution to this problem is important to your company or society in general.

-Technical background: A detailed explanation of the problem, including the mathematics involved. This may include graphics and references.

-**Special Requirements**: If a specific programming language, computer hardware, or software packages are required for this project, please state it here. Please also state if any data (or other inputs) will be provided or required.

-Your Expectations: What you expect the students to accomplish during RIPS, including what deliverables you expect at the end of the program. If you have secondary goals for the team that they may not have time to address given the length of the program, you can preface them with the phrase "if time permits…"

-Recommended Reading: Please list two or three articles or chapters that the students may read for background information. You may send one or two of them to your team in advance.

Selection of Students

To help IPAM choose students for your project, please tell us if you have any **prerequisites or desired qualification** for your team along with the project description; for example, do you want students who have taken a particular course in math or science, or have experience with a specific programming language? We will try to accommodate your request. Additionally, please notify us as early as possible if you can only have **U.S. citizens or permanent residents** on your team.

IPAM will receive more than 600 applicants for 36 spots. The directors and a few volunteers from the math community will review the applications. We will make offers to the most qualified students. Once most of the spots are filled, we will begin assigning teams. We will do our best to assign students to your team according to the guidelines you provide us, while also considering the interests of the students. Because we may have cancellations, we typically wait until May 1 to notify the students of their team assignment. We give them the project description about two weeks prior to the start of the program. At that point, we will encourage you to introduce yourself by email to your students, send them an article to read in preparation for opening day, and ask them about specific skills or background.

Technical, Security, and Legal Considerations

IPAM provides its students with dual-boot Windows 7/Ubuntu Linux desktop computers and a variety of software, including a limited number of Matlab licenses and toolboxes, C and C++ compilers, LaTeX, Maple and Mathematica. If your students will need specialized hardware or software that we do not typically provide, please notify IPAM **by May 1, 2016** so that we can discuss the request and, if necessary, make appropriate purchases it in time for the start of RIPS. We welcome offers from the sponsor to provide or purchase these items for the team.

Additionally, if you will be providing propriety data or software to the students and will require them to sign a **nondisclosure agreemen**t, this must be reviewed by IPAM/UCLA prior to the start of RIPS. Please prepare and send us the draft agreement by May 1. As this process involves another UCLA office and may require several iterations, we need to allow sufficient time; we believe a May 1 deadline is early enough to have the document approved by Opening Day.

If your students will need **data** from you, please get permission from your company in advance so the students can proceed with their analysis immediately. If you will need IPAM to provide additional or specific **security** measures to protect your data, please be sure to bring this to our attention by May 1 as well. We may not be able to accommodate late requests. Finally, please notify your students of any rules concerning the use of data.

Finally, RIPS teams may be able to access UCLA's Hoffman Computational Cluster for extra data analysis power; however, as this resource is shared with other researchers there are some limitations on the types and amount of analysis that can be done. If your company has access to high-end computational facilities, please consider providing your students access to your own corporate computing systems. In either case, please let us know if you think you might have needs in this area.

During the Program

All industry mentors will meet with their team for a few hours on Opening Day. Those who are not local will ideally continue the meeting the following day, then continue to discuss the project by conference call or Skype regularly after that. Industry mentor who are local may meet with their students in person at IPAM or at the company's offices throughout the summer.

Your team will have an academic mentor (AM), typically a postdoc or junior faculty member, who will be in residence at IPAM for 20 hours per week. The AM will choose a Project Manager (PM) from among the four students. The industry mentor will communicate primarily with the team's PM throughout the summer. The industry mentor will not give specific instructions to the students or AM; rather, the students will seek to understand the problem and find for themselves a formulation of the problem and path for a solution, with the help of the AM. The PM's role includes leading team meetings, monitoring the team's progress, and delegating tasks as needed. Please remember that the program is an educational experience; in addition to conducting research, the students will also write a Statement of Work and Final Report, and give polished mid-term and final presentations. The standards for these program components are quite high, and will require a significant amount of their time.

The industry mentor will arrange for the students to have a “site visit” towards the end of the summer. (We suggest you schedule it during the seventh or ninth week of the program.) On the site visit, the students will present their research to an audience at the company made up of scientists and others interested in their work. We also recommend that you arrange for a tour and meeting with some or your scientists so the students can learn about other research that your organization sponsors.

We expect that the industry mentor will attend Projects Day if at all possible. If it is not possible, he or she can watch via live-stream video.

A Note on Sponsor Expectations

Please remember that RIPS is primarily an educational experience for undergraduates. For some students, this is their first opportunity to do research. The work statement, which the students prepare and present to the sponsor in the second week, helps to set expectations. If the research objective proves to be impossible, a work statement may be re-negotiated by the team and sponsor. We recommend that you suggest milestones to your team, so that if they do not reach the final goal, you can still walk away with some useful results. Throughout the summer, active dialogue between the industry mentor and the team is critical.

Industry Sponsor Fee and Other Expenses

IPAM will send each sponsor an invoice for the sponsorship fee. UCLA requests payment of the invoice within 45 days of receipt.

IPAM and the sponsor will split the cost of the students’ site visit if it requires air travel and/or a hotel room. This may be negotiated in advance and included in the sponsorship fee, or the sponsor can reimburse the students directly for some of their expenses.

The industry sponsor may incur additional costs associated with the travel, parking, meals, and accommodations of the industry mentor(s) to attend opening day, projects day, and other activities at IPAM.

IPAM has a limited budget for software, hardware, and other expenses that are project-specific. If your team will require purchases, please discuss with IPAM early. We may ask the sponsor to help with the cost if it is significant.

RIPS 2016 TIMELINE

Relevant dates and deadlines for industry sponsors:

February 14, 2016	IPAM's deadline for students to apply. We will begin making offers shortly after this date.
February 14	Provide IPAM with the first draft of your project description and additional information as described under Selection of Students.
April 15-30	IPAM will put you in touch with the academic mentor for your team. The academic mentor may have valuable feedback on the project description that you can incorporate into the final version.
May 1	Notify IPAM of hardware, software and/or security requirements for your project, and present IPAM with a nondisclosure agreement, if it will be required.
June 1	Final version of the project description is due.
June 20	RIPS Opening Day
June 27-July 1	Team will present industry mentor with Work Statement.
July 15	Choose a date for your team's site visit and begin making arrangements.
July 18-22	Midterm presentation take place this week.
August 1-12	Site visits will take place in this two week period (or Aug. 17-18).
August 16	RIPS Projects Day

CONTACT INFORMATION

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Dimi Mavalski, RIPS Program Coordinator
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310-794-7708

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310-267-5247

CURRICULUM VITAE

- **PERSONAL INFORMATION**

Family name, First name: Bijleveld, Catrien
Date of birth: [redacted]
Nationality: The Netherlands

- **EDUCATION**

2002	Master of Law, *cum laude* Faculty of Law, Leiden University, The Netherlands
1989	PhD in Psychology Faculty of Social Sciences, Leiden University, The Netherlands PhD Supervisors: prof. Jan de Leeuw, prof. Willem J. Heiser
1986	Master in Methods and Techniques of Social Science Research, *cum laude* Faculty of Social Sciences, Leiden University, The Netherlands

- **CURRENT POSITION(S)**

2014 –	Director Netherlands Institute for the Study of Crime and Law Enforcement (NSCR), The Netherlands
2003 –	Professor of Research Methods in Criminology, Department of Criminal Law and Criminology, Vrije Universiteit Amsterdam
2010 –	Academy Member Royal Dutch Academy of Science (KNAW), The Netherlands

- **PREVIOUS POSITIONS (LAST THREE)**

2001 – 2014	Senior Researcher Netherlands Institute for the Study of Crime and Law Enforcement (NSCR), The Netherlands
1997 – 2000	Program Coordinator Wetenschappelijk Onderzoek- en Documentatiecentrum (WODC), The Netherlands
1990 – 1997	Assistant Professor (universitair docent) Faculty of Psychology, Leiden University, The Netherlands

- **5 KEY PUBLICATIONS (ALL PEER-REVIEWED)**

1. MESTERS, G., VAN DER GEEST, V., & **BIJLEVELD**, C. (2016). Crime, Employment and Social Welfare: An Individual-Level Study on Disadvantaged Males. [journal article]. Journal of Quantitative Criminology, 32(2), 159–190.
2. VAN DER GEEST, V.R., **BIJLEVELD**, C.C.J.H., & BLOKLAND, A.A.J. (2011). The Effects of Employment on Longitudinal Trajectories of Offending: A Follow-Up of High-Risk Youth From 18 to 32 Years of Age. *CRIMINOLOGY*, 49(4), 1195–1234.
3. BESEMER, S., VAN DER GEEST, V., MURRAY, J., **BIJLEVELD**, C. C. J. H., & FARRINGTON, D. P. (2011). The Relationship Between Parental Imprisonment and Offspring Offending in England and The Netherlands. *BRITISH JOURNAL OF CRIMINOLOGY*, 51(2), 413–437.
4. **BIJLEVELD**, C.C.J.H., & WIJKMAN, M. (2009). Intergenerational continuity in convictions: A five-generation study. *CRIMINAL BEHAVIOUR AND MENTAL HEALTH*, 19(2), 142–155.
5. VAN DER GEEST, V.R., BLOKLAND, A.A.J., & **BIJLEVELD**, C.C.J.H. (2009). Delinquent Development in a Sample of High-Risk Youth: Shape, Content, and Predictors of Delinquent Trajectories from Age 12 to 32. *JOURNAL OF RESEARCH IN CRIME AND DELINQUENCY*, 46(2), 111–143.

CURRICULUM VITAE

- **PERSONAL INFORMATION**

Family name, First name: Vandeviver, Christophe
Researcher unique identifier(s): ORCID iD [redacted]
Date of birth: [redacted]
Nationality: Belgian

- **EDUCATION**

2015	PhD in Criminology (no degrees awarded) Faculty of Law, Ghent University, Belgium PhD Supervisors: prof. dr. Tom Vander Beken & dr. Stijn Van Daele
2015	Doctoral Training (no degrees awarded) Doctoral Schools of Arts, Humanities and Law, Ghent University, Belgium
2011	Master of Science in Quantitative Analysis in the Social Sciences, *with greatest distinction* Faculty of Political and Social Sciences, HUB-KUBrussel, Belgium
2010	Master in Criminology, *with great distinction* Faculty of Law, Ghent University, Belgium
2009	Bachelor in Criminology, *with distinction* Faculty of Law, Ghent University, Belgium

- **CURRENT POSITION(S)**

2015 –	Postdoctoral Research Fellow of the Research Foundation – Flanders (FWO) Faculty of Law, Ghent University, Belgium
2015 –	Visiting Research Fellow Netherlands Institute for the Study of Crime and Law Enforcement (NSCR), the Netherlands

- **PREVIOUS POSITIONS**

2015 – 2015	Postdoctoral Researcher Faculty of Law, Ghent University, Belgium
2011 – 2015	Doctoral Fellow of Ghent University Research Fund (BOF) Faculty of Law, Ghent University, Belgium
2011 – 2011	Junior Researcher Faculty of Law, Ghent University, Belgium

- **5 KEY PUBLICATIONS (ALL PEER-REVIEWED)**

1. **VANDEVIVER, C.**, NEUTENS, T., VAN DAELE, S., GEURTS, D. & VANDER BEKEN, T. (2015). Modeling residential burglars' target selection process at the house-level. *APPLIED GEOGRAPHY, 64,* 24–34
2. **VANDEVIVER, C.**, VAN DAELE, S., & VANDER BEKEN, T. (2015). What makes long crime trips worth undertaking? Balancing costs and benefits in burglars' journey to crime. *BRITISH JOURNAL OF CRIMINOLOGY, 55*(2), 399–420.
3. **VANDEVIVER, C.** (2014). Applying Google Maps and Google Street View in environmental criminological research. *CRIME SCIENCE, 3*(13), 1–16.
4. MISSINNE, S., **VANDEVIVER, C.**, VAN DE VELDE, S., & BRACKE, P. (2014). Measurement equivalence of the CESD-8 depression scale among ageing populations in 11 European countries. *SOCIAL SCIENCE RESEARCH, 46*, 38–47.
5. STAMATAKIS, N., & **VANDEVIVER, C.** (2013). Restorative justice in Belgian prisons: the results of an empirical research. *CRIME LAW AND SOCIAL CHANGE, 59*(1), 79–111.

CURRICULUM VITAE

- **PERSONAL INFORMATION**

Family name, First name: Bernasco, Wim
Researcher unique identifier(s): ORCID iD [redacted]
Date of birth: [redacted]
Nationality: The Netherlands

- **EDUCATION**

1994	PhD in Sociology Utrecht University, The Netherlands PhD Supervisors: prof. dr. Reinhard Wippler, prof. dr. Wout Ultee, prof. dr. Paul de Graaf
1987	MSc Psychology (cum laude) Leiden University, The Netherlands
1983	BSc in Psychology (with honor) Leiden University, The Netherlands

- **CURRENT POSITIONS**

2013 –	Full professor (Chair: Spatial Analysis of Crime) Department of Spatial Economics, Vrije Universiteit Amsterdam , The Netherlands
2005 –	Senior researcher Netherlands Institute for the Study of Crime and Law Enforcement (NSCR), The Netherlands

- **PREVIOUS POSITIONS (LAST THREE)**

2000 – 2005	Researcher Netherlands Institute for the Study of Crime and Law Enforcement (NSCR), The Netherlands
1999 – 2000	Researcher Research and Documentation centre (WODC) Ministry of Justice, The Netherlands
1998 – 1999	Assistant professor Department of Psychology, Leiden University, The Netherlands

- **5 KEY PUBLICATIONS (ALL PEER-REVIEWED)**

1. LAMMERS, M., MENTING, B., RUITER, S. & **BERNASCO**, W. (2015). Biting Once, Twice: The Influence of Prior on Current Crime Location Choice. CRIMINOLOGY, 53, 309–329
2. **BERNASCO**, W., RUITER, S., BRUINSMA, G., PAUWELS, L. & WEERMAN, F. (2013). Situational Causes of Offending: A Fixed Effects Analysis of Space-Time Budget Data. CRIMINOLOGY, 51, 895–926.

3‡. **BERNASCO**, W., BLOCK, R. & RUITER, S. (2013). Go Where the Money is: Modeling Street Robbers' Location Choices. JOURNAL OF ECONOMIC GEOGRAPHY, 13, 119–143.

4. **BERNASCO**, W. & BLOCK, R.. (2009). Where Offenders Choose To Attack ; A Discrete Choice Model of Robberies in Chicago. CRIMINOLOGY, 47, 93–130
5. JOHNSON, S.D. , **BERNASCO**, W., BOWERS, K.J., ELFFERS, H., RATCLIFFE, J., RENGERT, G.F., & TOWNSLEY, M. (2007). Space–Time Patterns of Risk: A Cross National Assessment of Residential Burglary Victimization. JOURNAL OF QUANTITATIVE CRIMINOLOGY, 23, 201–219

DETECTING FOOT-CHASES FROM POLICE BODY-WORN VIDEO*

RAFAEL AGUAYO†, ALEJANDRO CAMACHO‡, PIYALI MUKHERJEE§, QI YANG¶
SPONSORS: HAYDEN SCHAEFFER ‖ AND P. JEFFREY BRANTINGHAM **

Abstract. Existing methods to record interactions between the public and police officers are unable to capture the entirety of police-public interactions. In order to provide a comprehensive understanding of these interactions, the Los Angeles Police Department (LAPD) intends to utilize *Body-Worn Video* (BWV) collected from cameras fastened to their officers. BWV provides a novel means to collect fine-grained information about police-public interactions. The purpose of this project is to identify foot-chases from the videos using machine-learning algorithms. Our proposed algorithm uses the *Bag-of-Intrinsic-Words* algorithm followed by classification via support-vector machines. Our training dataset consists of 100 training videos (20 foot-chase & 80 non-foot-chase), and a test dataset of 60 LAPD videos (4 foot-chase & 56 non-foot-chase). We achieved results of 91.6% testing accuracy.

1. Introduction. Studying the interaction between police and the public is often a difficult task because little information regarding police-public interaction is retained through activity logs and written reports [4]. In 2014, the Los Angeles Police Department (LAPD) implemented the use of chest-mounted *Body-Worn Video* (BWV) in small deployments, as seen in Figure 1.1, with the purpose of collecting more information regarding police-public interactions. BWV provides another line of evidence for outcomes of interactions.

BWV generates massive volumes of data that can be difficult to analyze. Due to the size of the BWV dataset, it is infeasible for police officers to view all the videos in order to find specific interactions, *e.g.* foot-chases. Since many BWV videos are likely to be used as evidence, an automated labeling mechanism can save valuable time and resources while maintaining confidentiality of the data. Our work focuses on devising a learning algorithm that can automatically detect whether a particular video contains a foot-chase or not. From our exploration of the literature, such a project is the first of its kind to have been attempted.

This paper is organized by the following sections. Section 2 discusses previous work done relevant to video and image processing. Section 3 describes the BWV data and preprocessing procedure. Section 4 discusses the mathematical background behind the feature-extraction methodology, and, our proposed Bag-of-Intrinsic-Words method. Section 5 presents our results and analysis on the BWV provided by the LAPD.

2. Previous and Related Work. In recent years, researchers have devised various methods for filtering, parsing, recognizing objects, and classifying video data. Since video data is composed of a sequence of frames, there is significant overlap between video and image processing techniques [3]. In [9], the authors presented a unified view of the different statistical structure of natural images. These models were designed to reflect certain properties of intrinsic systems. The authors in [6]

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*This work was supported by the Institute of Pure and Applied Mathematics, University of California, Los Angeles.

FIG. 1.1. *Sgt. Dan Gomez of the LAPD wearing a BWV camera. BWV provides a first-person perspective of the officer. (Marcus Yam / Los Angeles Times).*

considered an incremental-batch Bayesian probabilistic model in order to learn object categories from still images. Their approach allowed the model to learn the parameters in an incremental fashion. Thus, real-time learning was feasible.

There are several semi-supervised approaches in computer vision and imaging studies [16, 14, 12, 5, 20, 21] that use keypoints to extract information from videos. Keypoints in images can be identified in frames using descriptors such as SIFT (scale-invariant feature transform) and PCA-SIFT [11, 17, 2]. In [1], the authors developed SURF (Speeded-up Robust Features) from SIFT to identify points of interest using existing image edge-detectors and descriptors. Semi-supervised approaches have been used to extract quantitative information from images and videos using SURF [11, 17, 2, 1, 15]. SURF tests to see if distorted images of an original image contain the same points of interest. A qualitative comparison performed by [15] showed that SURF features are robust to noise, displacements, and most geometric and contrast-base transformations.

Bag-of-Visual-Words is a method proposed by [21] for classifying scenes. The idea behind [21] is derived from a text-based classification schema, where weighted terms and frequency are used to classify documents. The visual categories in images and words in documents is analogous, thus creating a tool for retrieving information [22]. In [8], the authors focused classification on a small region of an image showing that discriminatory localization classification works well with weakly-labeled data [8, 18, 13]. In [20], the authors evaluated previously proposed local spatio-temporal features for action recognition using a standard bag-of-features support vector machine (SVM).

The video data used in previous works is collected from stable and stationary cameras (*e.g.* Hollywood datasets). Our dataset is significantly different Existing methods do not appear to work with videos that are as grainy and distorted as videos collected from moving officers. The Hollywood dataset, in particular, contains frames that have clearly defined and well-lit scenes, followed by carefully directed camera and actor movements. There are few occlusions to the camera view, if any. These properties set the Hollywood video dataset at a considerable advantage over our dataset.

The videos in our dataset undergo severe geometric and photometric distortions, and contain many poor-resolution and grainy scenes. Many videos are recorded in low light, which makes analysis of events occurring within the video difficult. Furthermore, the videos are frequently obstructed by multiple objects such as hands, jacket lapels, car bodies, multiple people and other close-focus moving objects. Thus, the BWV dataset requires tailored algorithms.

3. Body-Worn Video Data. The BWV dataset provided by LAPD is composed of 691 videos (500GB) collected from Central SCI officers in the field from a span of two weeks, December 28, 2015 to January 3, 2014 and May 24, 2015 to May 31, 2015. The videos were collected from Skid Row, Los Angeles. Skid Row is a community commonly affected by problems of homelessness, drug-abuse and assault [19, 7].

The video filename contains the time at which the clip was recorded. Some files indicate that the video was recorded at the same situation but from the perspective of another officer. Unlike the Hollywood dataset, the BWV dataset is recorded under less than ideal conditions. The videos are recorded in environments of high contrast changes (such as movement from indoors to outdoors). Videos recorded at night contain events that are difficult to identify to a user. Scenes also change unexpectedly in the videos, which leads to the blurring between frames. Object occlusion is also another problem. Certain videos contain no data at all as they are completely obstructed by a hand or jacket. Under these constraints, we may lose important information from the videos.

The video is recorded at a resolution of 640×480 pixels at 30 frames per seconds and compressed into an MPEG-4 format. For confidentiality purposes, the videos do not contain audio. The statistics regarding the length of the video are summarized in Table 3.1.

Median	9 min
Maximum	30 min
Minimum	12 sec
Total length	130 hr

Table 3.1
Statistics for the length of the BWV videos.

We perform preprocessing procedures to reduce the size of the files in order to prevent overloading memory resources. We reduce the resolution of the video from 640×480 to 320×240. Subsequently, the data is partitioned into training and testing sets. We further splice the training videos into 30 second clips containing specific actions. A '-1' indicates that the video contains a non-foot-chase event, while '1' indicates that the video contains a foot-chase event. Similarly, testing videos are spliced into 30 sec videos and assigned a label. The testing labels are used solely for accuracy measures. Two videos in our given dataset contained foot-chases.

To train our algorithm, we needed a sufficient number of existing foot-chase videos in order to identify future ones. Due to the sparsity of existing foot-chases, we recorded additional videos to simulate a diverse range of running, walking, and, other movements that were observed from the given dataset. We recorded a total of 67 videos out of which 18 simulated a foot-chase.

For training, we combined our simulated data with BWV data for a total of 100 training videos. We tested on 60 LAPD BWV videos. In this subset, four videos were manually labeled as foot-chase. This proportion was selected to provide a consistent basis for measuring training and testing error on our algorithm.

4. Our Algorithm. Our approach is derived from a text-based classification method on documents known as Bag-of-Words. Bag-of-Words is a sparse vector that contains occurrence counts of categories, usually words present in the document to be classified. We develop our own Bag-of-Intrinsic-Words algorithm to classify our dataset as foot-chase videos or non-foot-chase-videos. We consider a set of videos,

$$U_j(x,t) \in \mathbb{R}^{N \times T_j} \tag{4.1}$$

where N is the number of pixels per frame, T_j is the number of frames in a video, and j is the video index. The frame rate for our BWV dataset is 30 frames/sec.

First, we use built-in MATLAB SURF (Speeded Up Robust Features) keypoint detection algorithm to generate the SURF feature vectors. We initially split the data into three sets: input for Bag-of-Intrinsic-Words, training and testing. We implement a clustering algorithm on the first set to generate a set of descriptors, or "intrinsic words". Then, we use our Bag-of-Intrinsic-Words to test for similarities among videos and create a feature histogram for each video. Lastly, we run a feature-based classifier on the feature histograms, which returns the predicted label of the data set. A visual representation of the feature extraction methodology and pseudocode our algorithm are presented in Figure 4.2 and Algorithm 4.3, respectively.

4.1. SURF (Speeded Up Robust Features). SURF is one of many frameworks that detect keypoints within images. SURF provides not only the location of the keypoints detected in the image but also a radius of the scale at which they are detected as well as an orientation vector for every keypoint detected. Figure 4.1 depicts the SURF keypoints and their radii.

We extract a feature vector, also known as descriptor, from the regions identified by SURF. The descriptor is calculated by dividing the neighborhood of a keypoint into sub-regions until the orientation is computed at the smallest scale. These orientations are then pooled towards the higher regions until a resultant orientation of the keypoint is determined. The descriptor saves each sub-region calculation as an entry. To obtain same number of SURF feature vectors from each input, we partition each video to create 30 second clips by collecting every 900 consecutive frames from $U_j(x,t)$. To further reduce the data size and run time, we down sample the video clips by taking every p-th frame from the clip. The downsampled video is represented by $u_i(x,t) \in \mathbb{U}_j(x,t)$.

$$u_i(x,t) \in \mathbb{R}^{N \times P} \tag{4.2}$$

where $P = 900/p$ and i is the video clip index.

We define F as function that maps the clips to the corresponding SURF feature descriptors: $F : \mathbb{R}^{N \times P} \to \mathbb{R}^{S \times Q}$ where in practice $S = 64$ since the SURF feature vectors lie in 64 dimensional space and $Q = 5P$ if we choose five strongest SURF feature points.

Now, let $A_{S\times Q}$ be the matrix which contains all SURF feature descriptors,

$$A_{S\times Q} = [F(u_1), ...F(u_n)]. \tag{4.3}$$

Then we partition the feature matrix, $A_{S\times Q}$, into three sets: input for Bag-of-Intrinsic-Words, training data, and, test data. These sets are $A^1_{S\times Q_1}$, $A^2_{S\times Q_2}$, $A^3_{S\times Q_3}$, respectively. where $S \times Q_i$ is the dimension of matrices after partition.

FIG. 4.1. *The graph presents the surf features extracted from a test video simulating real data conditions. The SURF feature descriptors are extracted from the radial regions identified by the SURF algorithm.*

4.2. Our Bag-of-Intrinsic-Words. Our Bag-of-Intrinsic-Words describes the local patterns of the videos with smaller dimensions. This method allows us to compare all videos with an unvaried Bag-of-Intrinsic-Words and test for the similarities among videos. Ultimately, this helps us to distinguish whether a clip contains a foot-chase or not.

After partitioning the SURF feature vectors into three sets, we cluster the feature vectors from the first set, $A^1_{S\times Q_1}$ (input for Bag-of-Intrinsic-Words) using the k-means clustering algorithm. We apply the k-means algorithm to $A^1_{S\times Q_1}$ to create our intrinsic words. k-means clustering partitions a dataset into k distinct clusters [10], thereby generating our features. To perform k-means clustering, we first determine the specific number of desired clusters. In this study, we varied k from 100 to 1500. k-means assigns each observation to exactly one of the k clusters based on a distance metric. The k-means algorithm used here measures distance using the standard Euclidean metric. To find the optimal number of k clusters, we minimized the *within-cluster variation*Each centroid created by k-means corresponds to an intrinsic word. We represent the visual words in a matrix $W_{S\times M}$ where each column corresponds to a word. By testing on different M, we find that the optimal number of intrinsic-words is 500.

4.3. Feature Histogram. After we obtain our Bag-of-Intrinsic-Words, we use the idea of Approximate Nearest Neighbor to assign each feature vector from the training and test dataset to the nearest intrinsic word measured by a distance function. Each feature vector belongs to one and only one cluster.

Mathematically, for each new video $U_j(x,t)$, we partition it into small video clips $u_i(x,t)$ where j corresponds to the video index and i corresponds to the video clip index. We then calculate $A_{S\times Q}$ and $D_j(Y)$, the Euclidean distance between each SURF feature descriptor and each intrinsic word from $W_{S\times M}$.

For simplicity we use the Euclidean norm. We assign the SURF feature descriptor to the nearest intrinsic-word, denoted by J.

$$D_j(Y) = \quad \mathrm{Dist}(Y, W_j) \quad := \left(\sqrt{\sum_{i=1}^{P} (Y(i) - W(i,j))^2} \right) \tag{4.4}$$

$$J = \quad \mathrm{argmin}_j D_j(Y) \tag{4.5}$$

The frequency of the intrinsic words for each video creates a feature histogram. If another video has a similar histogram, we expect them to have similar video content. In other words, we expect videos that have similar histograms to share comparable features. The feature histograms are then classified using a linear Support Vector Machine.

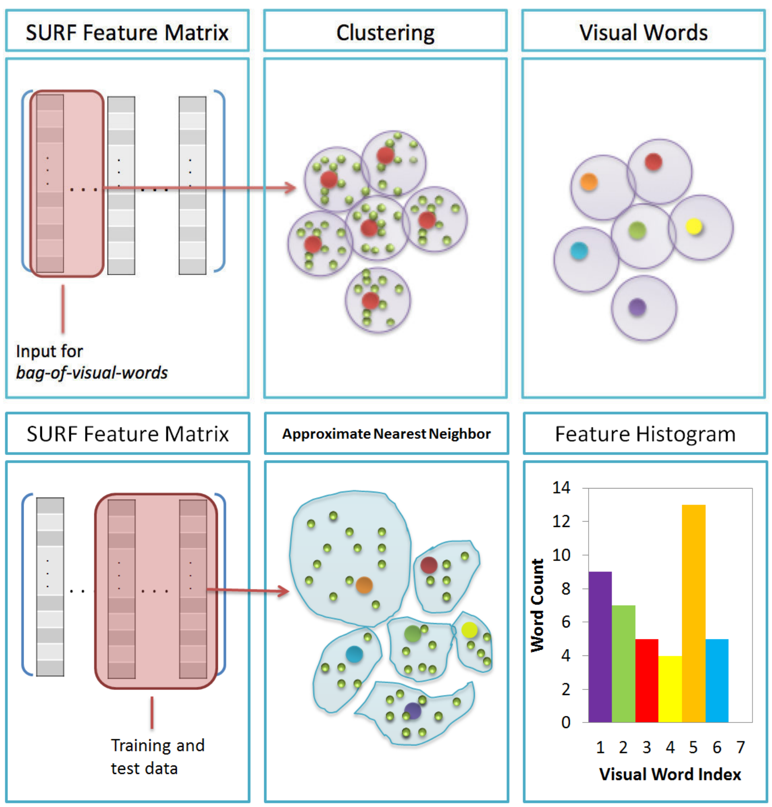

FIG. 4.2. *(From Top-Left to Bottom-Right) This figure contains a visualization of our feature extraction pipeline.*

Algorithm 1 Our Bag-of-intrinsic-Words Algorithm

Step 1: Partition the video data into 30 second clips.

Step 2: Select top five SURF points from each frame and extract the feature vector from those SURF points to form a matrix.

Step 3: Partition the feature matrix into three sets: A^1, input for Bag-of-Intrinsic-Words; A^2, training data; and A^3, test data.

Step 4: Perform k-means on A^1 to create our Bag-of-Intrinsic-Words. The optimal size for our dataset is $k = 500$.

Step 5: Assign each SURF point from A^2 and A^3 to a intrinsic word. Count the frequency of intrinsic words for all SURF points from the same video.

Step 6: Create a histogram of feature occurrence.

5. Results and Analysis. For our algorithm, we partition the BWV dataset into three sets: $A^1_{S\times Q_1}$, input for Bag-of-Intrinsic-Words; $A^2_{S\times Q_2}$, training data; and $A^3_{S\times Q_3}$, test data. After obtaining the intrinsic words from $A^1_{S\times Q_1}$, we apply our algorithm to $A^2_{S\times Q_2}$ and test on $A^3_{S\times Q_3}$ to get the accuracy rate. Each video is also assigned an action label, foot-chase or non-foot-chase.

In Figure 5.1, we see that our testing accuracy starts to increase around 20 videos. As we increase the number of videos, we are better able to classify foot-chase from non-foot-chase videos until our accuracy plateaus around 30 videos. Due to time constraints and computational costs, we retain our testing set at 60 videos. In Figure 5.2, we see that the BWV data is well represented after identifying 500 intrinsic words.

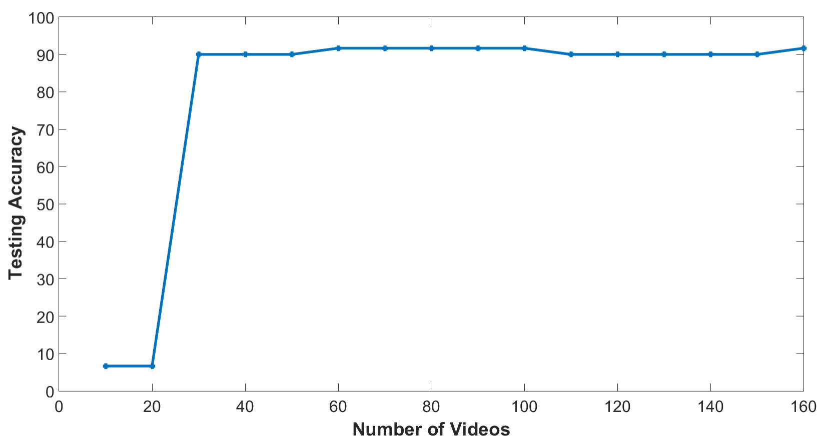

Fig. 5.1. *This plot shows the variability in accuracy when using different training sets.*

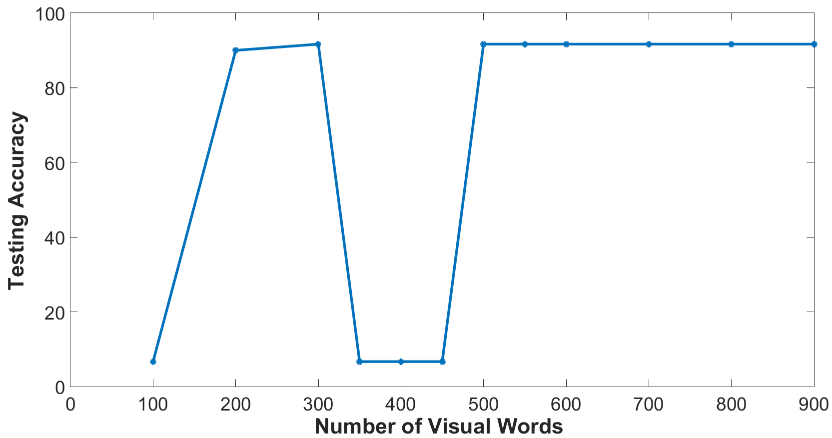

FIG. 5.2. *This plot shows the variability in accuracy when using different number of intrinsic words, or k in k-means clustering algorithm. The optimal number of intrinsic words is 500 since the accuracy plateaus.*

Other metrics we consider for measuring the results of SVM are false negatives and false positives. A false negative prediction means that there was video where a foot-chase instance occurred, but the algorithm mislabeled it as a not-foot-chase. A false positive prediction means that there was a video where a not-foot-chase occurred, but the algorithm mislabeled it as foot-chase. For our project, we are trying to minimize the number of false negatives that occur so that we can detect all of the running videos even at the cost of mislabeling a few of the walking videos as running ones. We reason that the cost of having a user re-verify the running videos over our results is negligible compared to the cost of having a user search through the entire dataset for a single running video that the algorithm potentially failed to detect. Our algorithm generates an accuracy score of 91.6% with 5 false positives and 0 false negatives.

Method	Accuracy	False Negative	False Positive
Bag of Intrinsic Words	91.6%	0	5

TABLE 5.1
This table contains the results for our Bag-of-Intrinsic-Words algorithm.

6. Conclusion. This paper covers a machine learning algorithm for identifying police foot-chase videos. Given the nature of the data and from our exploration of previous research, we posit that our work is the first of its kind to have been attempted in the field. Through our exploratory analysis we also noticed some trends that we will discuss. In Figure 5.1 a possible reason for our accuracy plateauing is due to the extra videos adding no additional value to our model. In Figure **??**, the reason for the accuracy drop in the 300-400 intrinsic word region is due to the SVM failing to converge which will most likely lead to a lack in classification. Going back to our dataset in Table 5.1, we see that we had a very small quantity of true positives. We penalized false negatives (running videos mislabeled as walking) more heavily than false positives (walking videos mislabeled as running). By penalizing false negatives strongly, we ensured that the algorithm does not miss any running videos even at the cost of mislabeling a few walking videos as running ones. Our Bag-of-Intrinsic-

Words algorithm returns results of 91.6% accuracy with 5 false positives and 0 false negatives.

7. Acknowledgements. We would like to thank the Los Angeles Police Department (LAPD) and the Los Angeles Police Foundation (LASF) for sponsoring this project, C.C Sean Malinowski, Sgt. Javier Macias, Sgt. Dan Gomez, and Ofc. Benjamin Hong. Furthermore, we extend our gratitude to the LAPD Air Support Division for the helicopter fly-along. We would like to thank our industrial mentor, Dr. P. Jeffrey Brantingham for his support, and Dr. Hayden Schaeffer for his mentoring and guidance during this project. Lastly, we would also like to thank Dr. Mike Raugh, Dr. Russel Caflisch, Dimi Mavalski, and the IPAM staff. The BWV data was analyzed under UCLA IRB protocol 15-000867. The use of the algorithm and analytics was limited only to the samples and has not be deployed by LAPD.

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June 29th, 2016

LOS ANGELES POLICE DEPARTMENT
Officer Benjamin Hong

Dear Officer Hong:

Enclosed are two copies of the Statement of Work (SOW) and two copies of this cover letter. The SOW outlines our team's current understanding of the problem and addresses our planned approach to a solution.

Please show your approval of the SOW by signing both copies of the cover letter in the space provided on this page, or by indicating your proposed changes, and returning one copy of each (SOW and signed cover letter) to me by Friday, July 8. Otherwise, after that date, we will assume the LAPD's tacit approval.

Sincerely,

Stephanie A Allen

Stephanie Allen
RIPS Project Manager

Institute for Pure and Applied Mathematics (IPAM)
Attn RIPS: Stephanie Allen

Enclosure: Los Angeles Police Department RIPS Work Statement

Cc: Susana Serna, RIPS Program Director
Stacey Beggs, IPAM IPAM Assistant Director

Accepted this 30 day of June 2016

By: ____________________

RIPS 2016 Project Work Statement
Sponsor: Los Angeles Police Department
Change Point Detection Methods Applied to Body-Worn Video

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June 29^{th}, 2016

1 Introduction

Body-worn video (BWV) has come about as another source of information regarding police-public interactions. To produce this video, police officers wear specially designed cameras on their chests to record their interactions with the public. This video then may be utilized when there is public disagreement about police conduct. Furthermore, these cameras have been shown to increase professionalism in the police force [1]. However, the video from the cameras has not been analyzed thoroughly because of the sheer quantity of data produced by them.

The Los Angeles Police Department (LAPD) seeks to protect and to serve the residents and visitors of the city of Los Angeles via patrol, traffic, and specialized divisions. The Department recently undertook a pilot project in its Central Division whereby police officers received body cameras to document their work in the field. The Department gave police officers license to turn the cameras on when they felt their interactions should be recorded. The Research in Industrial Projects for Students (RIPS) LAPD student research group will work with a sample of this data to develop change point detection methods that will help to streamline the video recording and analysis processes.

2 Problem Statement

In this project, we will work to develop change point detection algorithms to apply to video data. A significant change in the content of BWV may occur at the time an officer exits a car and engages in public interactions. However, it is not realistic to require an officer to record the time of exit from a vehicle—for example, in a dangerous situation. The same reasoning applies for other possible change points, such as entering or exiting buildings. Therefore, being able to automatically identify change points in a video stream would both greatly improve the efficiency of BWV analysis and reduce storage requirements. Our immediate goal is to identify the moment of exit from a car because this is a very clear change. We also seek to minimize the false alarm rate as we develop our identification algorithms.

3 Mathematical Background

The mathematical background required for this project is primarily statistical; specifically, it lies in the field of change point detection [3]. Change point detection methods exist to identify critical points in a series where the underlying distribution changes. A wide range of these methods exist. One popular and extensible change point detection method is the cumulative sum algorithm (CUSUM); one variation of this algorithm computes a log-likelihood ratio after each new data point, adds this ratio to the sum of the previous ratios, and tests this aggregate ratio against a chosen threshold [4, 16]. CUSUM is commonly used for change point detection and thus provides a good framework for exploration. The complex spatio-temporal inferential challenges posed by videos may require the use of other change point algorithms drawn from Bayesian methods and kernel methods. Bayesian methods like Gaussian processes are able to deal well with the temporal correlation in videos [5]. Kernel methods can identify interesting features in videos across space and time [6]. Video-specific algorithms also exist for scene labeling and change point detection; these may be applicable as well [7].

4 Computing Background

The bulk of the computing background for this project will involve methods of image and video representation and processing [2, 3]. The machine learning and the computer vision literature provide a variety of methods well-suited to our task. Within machine learning, representation learning algorithms are used to learn low-dimensional feature vectors from high-dimensional input like video. Many of these methods are framed in the theory of artificial neural networks. Specifically, networks such as denoising autoencoders and convolutional nets have seen great success in recent years [8, 9]. These methods work by hierarchically building an increasingly complex sequence of features from video patches. Other machine learning tools from nonlinear dimensionality reduction may be useful as well; for example, kernel principal component analysis finds a nonlinear map from a higher-dimensional set of data to a lower-dimensional one, where inference can be more tractable [10].

From computer vision approaches, we will explore a variety of image processing algorithms. These include methods for image segmentation and boundary detection, as well as local feature detection algorithms such as SIFT (Scale-Invariant Feature Transform) and SURF (Speeded Up Robust Features) [11, 12]. All these methods will provide different ways of describing the relevant features of our images compactly. Once derived from an image, these features can be intelligently consumed by a regularizing classifier like a support vector machines ("SVM") [13, 14]. SVMs work by finding a number of hyperplanes in n-dimensional space that optimally segment data into two or more classes [15].

5 Possible Solutions and Project Objectives

Our first objective is to build a classifier to detect if an image has or has not been taken within a car. We plan to use multiple machine learning algorithms such as convolutional neural networks and support vector machines. During the process, we will also perform data analysis on the body-worn video we receive. After developing this classifier, we plan to develop change point detection algorithms to identify the time at which the sequence of images changes from being inside a car to outside a car, which would indicate that the door has been opened. The method developed is intended to work with already recorded videos in storage (offline data). We hope that it will also work on sequentially received video frames (online data).

If time permits, we will work to generalize our change point detection methods to handle more complicated representations of the images. First, we will explore ways to extract multiple features from images, compute difference images, or use other methods of representing the images through time. Then, we will build upon established change point detection methods to write algorithms which can be applied on the extracted time series to identify the variation in the data that results from the opening of a door. If we are successful, we will then proceed to developing methods to deal with online data. The methods developed during this phase of the project may provide a framework for detecting additional change points beyond just the opening of a car door.

Our implementation will be carried out in *MATLAB* and/or *Python*. As we use and develop image processing and change point detection methods, we will also evaluate the efficacy of these methods.

6 Deliverables

In the following subsections, we will outline the materials we plan to provide to the LAPD and also the assistance from the LAPD required by this student research group.

6.1 RIPS to LAPD

- Thursday, July 21^{st}, 2016: We will give a Midterm Presentation regarding our progress on the proposed project.
- August 15^{th}, 2016 - August 19^{th}, 2016: We will present our final results during RIPS's Projects Day, which will be scheduled sometime between August 15^{th} and August 19^{th}.
- Friday, August 19^{th}, 2016: We will deliver our final project report. We will be sure to include our analysis of the video data and explanations of our change point detection algorithm(s) in this report.
- Friday, August 19^{th}, 2016: We will provide the code for our proposed algorithm(s).

  Any Code sent by the 2016 LAPD RIPS student research group to the LAPD will be in compliance with the Software Disclaimer attached to this Work Statement.

6.2 LAPD to RIPS

- Receipt of body-worn video data by Week 2 (June 27^{th}, 2016 - July 1^{st}, 2016)
- Timely response to RIPS LAPD student research group communications

- Weekly meetings and/or conference calls with a representative from the LAPD if necessary
- Site visit at LAPD

7 Timeline

Weeks 1-2 (6/20 - 6/24 and 6/27 - 7/1)

- Gather and review background reading
- Compose and submit work statement (by the end of Week 2)
- Begin data analysis and development of change point detection methods

Weeks 3-4 (7/5 - 7/8 and 7/11 - 7/15)

- Continue work on change point detection methods
- Visit the LAPD site during Week 3
- During the later half of Week 4, start to prepare for the Midterm presentation

Week 5 (7/18 - 7/22)

- Prepare and give Midterm presentation (date to be determined)

Weeks 6-8 (7/25 - 7/29, 8/1 - 8/5, and 8/8 - 8/12)

- Continue working on research
- During Week 8, work on the final report, code, and presentation

Week 9 (8/15 - 8/19)

- Finish research
- Finalize report and code for change point detection methods (for submission to LAPD)
- Present final presentation on RIPS's Projects Day to LAPD (date to be determined)

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IPAM Software Disclaimer for RIPS Sponsors

July 14, 2009

We want our RIPS sponsors to be aware of the nature of software developed by RIPS project teams. IPAM does not regard RIPS software as anything more than a prototype developed as a proof-of-concept only, and it is never developed for commercial use nor is it warranted by IPAM in any way. Here are some points to remember:

1. Software developed by a RIPS project team that appears to have been created wholly by a project team, may in fact contain proprietary codes borrowed from other sources; the sponsor must assume all risk for using such software.

2. IPAM makes every effort to discourage misuse of proprietary software by RIPS project participants; IPAM cannot be held responsible for such misuse.

3. As participants in an academic program, RIPS students will at times be permitted to use software that cannot be used by sponsors without a license.

4. Any restriction required by the sponsor on the use of special software, or platform needed to run the software, should be declared by the sponsor at the time of negotiating the project Work Statement. Otherwise the project team is free to choose software solutions as they see fit.

CONFIDENTIALITY AND NONDISCLOSURE AGREEMENT

Between

THE LOS ANGELES POLICE DEPARTMENT
And
UCLA
Institute for Pure and Applied Mathematics
Dr. P. Jeffrey Brantingham

(Hereafter "Requestor")

The undersigned hereby agrees to the following as conditions to the receipt and utilization of data from the Los Angeles Police Department ("LAPD"), for the purpose of assisting the LAPD with analyzing video footage. This project is titled, "Analyzing Body-Worn Camera Video in the Los Angeles Police Department". The purpose of this project is to identify specific features from video using machine learning algorithms. Researchers will examine video footage from LAPD to determine specific interactions between the police and the public.

1. Definitions

A. "Protected Confidential Material" includes all written information, whether originals or copies, including but not limited to reports, documents, notes, interviews, electronically stored data, photographs, charts or any other information supplied by the LAPD to Requestor, and that material is to be treated as non-public and protected from disclosure or dissemination, in accordance with the terms of this Agreement.

2. Treatment and Use of Protected Confidential Material. Requestor hereby agrees that all Protected Confidential Materials to which he is given access shall remain the property of the City of Los Angeles. Such materials shall be used only for the Project and shall not be used for any other purpose not described in this Agreement. Requestor agrees not to copy, disseminate, or allow access to any Protected Confidential Material.

Requestor further agrees to secure any Protected Confidential Material received from the LAPD in such a way that unauthorized persons or entities cannot retrieve the information by any means, including but not limited to access via computer, remote terminal, or by any other electronic or non-electronic means.

Requestor acknowledges the confidential nature of the Protected Confidential Material supplied by the LAPD, and agrees that disclosure by the Requestor or any individual or group of individuals at the request or direction of the Requestor to anyone not directly identified in this Agreement is strictly prohibited.

Importantly, the Requestor assures that data identified to a specific individual will not be revealed under any circumstances and that the information is being used for research and statistical purposes only.

Project findings and reports will not contain information about individuals or private persons.

3. Return of Protected Confidential Materials. Upon completion of the Project, Requestor shall immediately return all Protected Confidential Material in their possession or control, including any and all copies (whether electronic or non-electronic), to the Los Angeles Police Department. Requestor shall certify in writing that all originals and copies of the material provided under this Agreement have been returned.

4. Monitoring of Compliance and Demand for Document Return. The LAPD may monitor, audit and review the Requestor' program activities and policies to ensure compliance with the requirements and conditions of this Agreement. If the LAPD determines that the requirements and conditions of this Agreement are not being satisfactorily met, it may require the immediate return of all copies of the Protected Confidential Material obtained under this Agreement, take such action as deemed appropriate to protect the security and privacy of this material, and refuse any future requests for information or records from the Requestor.

5. Protection of Personal Identifying Information. In order to protect the identities of any persons whose records are supplied to the Requestor under this Agreement, Requestor agrees to:

A. Use the Protected Confidential Material furnished under this Agreement only for the purpose described by Requestor.

B. Replace the name and other personal identifiers with an alphanumeric or other appropriate code for purpose of conducting the necessary project analyses;

C. Restrict access of all data supplied by LAPD to those individuals whose responsibilities cannot be accomplished without such access; and

D. Store all Protected Confidential Material received from LAPD in secure locked containers.

6. Project Treatment. Requestor agree to insert into the preface of any report citing data analysis conducted on any of the Protected Confidential Material, a disclaimer that the analysis and report are solely the work product of the Requestor and do not represent the position or conclusions of the Los Angeles Police Department.

At the conclusion of the Project, Requestor will provide the LAPD with a copy of any written report derived from the Project. LAPD shall retain the discretion to use the report for whatever purpose or further analysis it deems appropriate.

Requestor acknowledges that any written or oral report generated pursuant to analysis of any of the Protected Confidential Material is not to be published or circulated in any manner other than as explicitly set forth under this Agreement. The City retains sole authority to approve disseminating to individuals, agencies, organizations or entities not parties to this agreement specific information regarding the services, reports, Deliverables and other materials resulting from this Agreement. "Dissemination" as used in this section includes, but is not limited to printed and online articles, reports or publications, and public relations and advertising materials for Requestor's services or participation under this Agreement.

printed and online articles, reports or publications, and public relations and advertising materials for Requestor's services or participation under this Agreement.

7. **Release from Liability.** Requestor agree that the City of Los Angeles and any of its agents or employees shall not be liable for any acts or omissions arising from the production of the Protected Confidential Material to Requestor, its use by Requestor, or any and all resulting analyses or conclusions derived from the Materials. Requestor shall indemnify and hold the City of Los Angeles and its employees and officers harmless for any and all claims, lawsuits, causes of action, damages or costs incurred in any adjudication or settlement of claims, including attorney's fees and costs, which may arise from any alleged use or misuse of documents provided by the LAPD pursuant to this Agreement, or by any negligent or willful act or omission on the part of Requestor.

This Agreement will become effective upon signature of the parties.

I/We hereby agree to all conditions and requirements set forth in this Agreement:

FOR THE LOS ANGELES POLICE DEPARTMENT	**FOR REQUESTOR**
______________________________	By: ______________________________
MAGGIE GOODRICH, Chief Information Officer Commanding Officer Information Technology Bureau	P. Jeffrey Brantingham, Ph.D. University of California, Los Angeles
Date: ______________________________	Date: 5-9-16

IBM

Security Intelligence.
Think Integrated.

IBM's POV
on
Body Cameras,
Intelligent Content Management
&
Smarter Public Safety

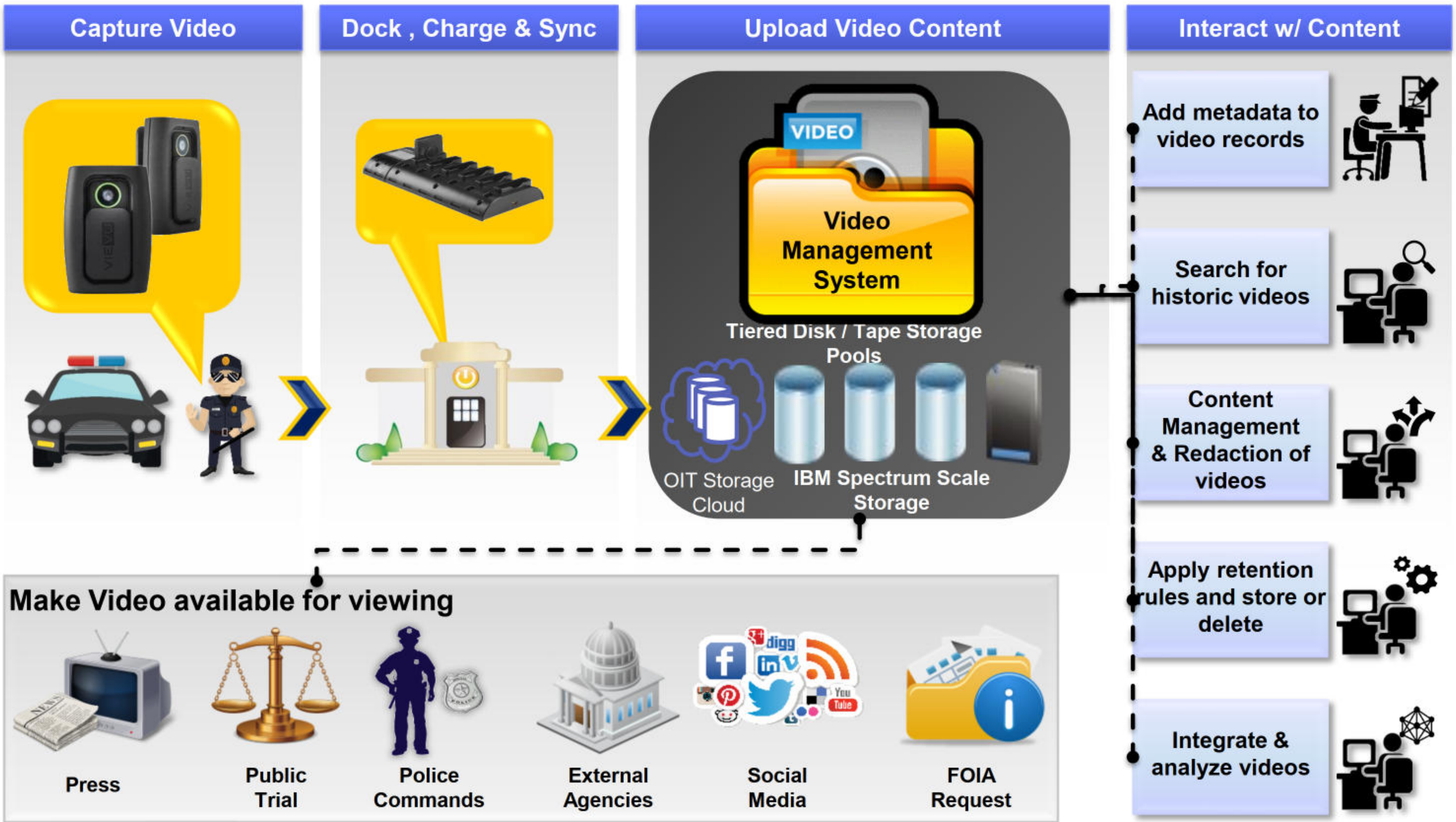
IBM POV of a Holistic Body Camera Program

"The era of ***21st Century Policing*** has seen ***quantum leaps*** in technological capabilities, operational efficiencies (many based on lessons learned and best practices), and the need for greater accountability, the likes of which have not been seen before.

Citizens play a huge role in this equation, as both the sworn "protectees" of law enforcement personnel nationwide, and as critical ***"first communicators"*** at scenes of crime, terroristic acts, and catastrophic natural disasters.

With the ***public's access*** to instantaneous information through ***social media***, both to consume and publish media of all types, along with the pervasiveness of mobile devices capable of ***recording and disseminating incidents in real-time***, the need for a well-managed, flexible, and ***policy-driven Body Camera program*** is of ***critical importance*** to the nation's citizens and law enforcement community."

Body Camera Video Management Process



Hardware – It's not all about the camera…

The Camera device is the "tip of the "iceberg"

- Vendors are proliferating to enter this market
- Proprietary systems which are closed create another silo of information within an agency, limiting access to a "treasure trove" of data

Panasonic

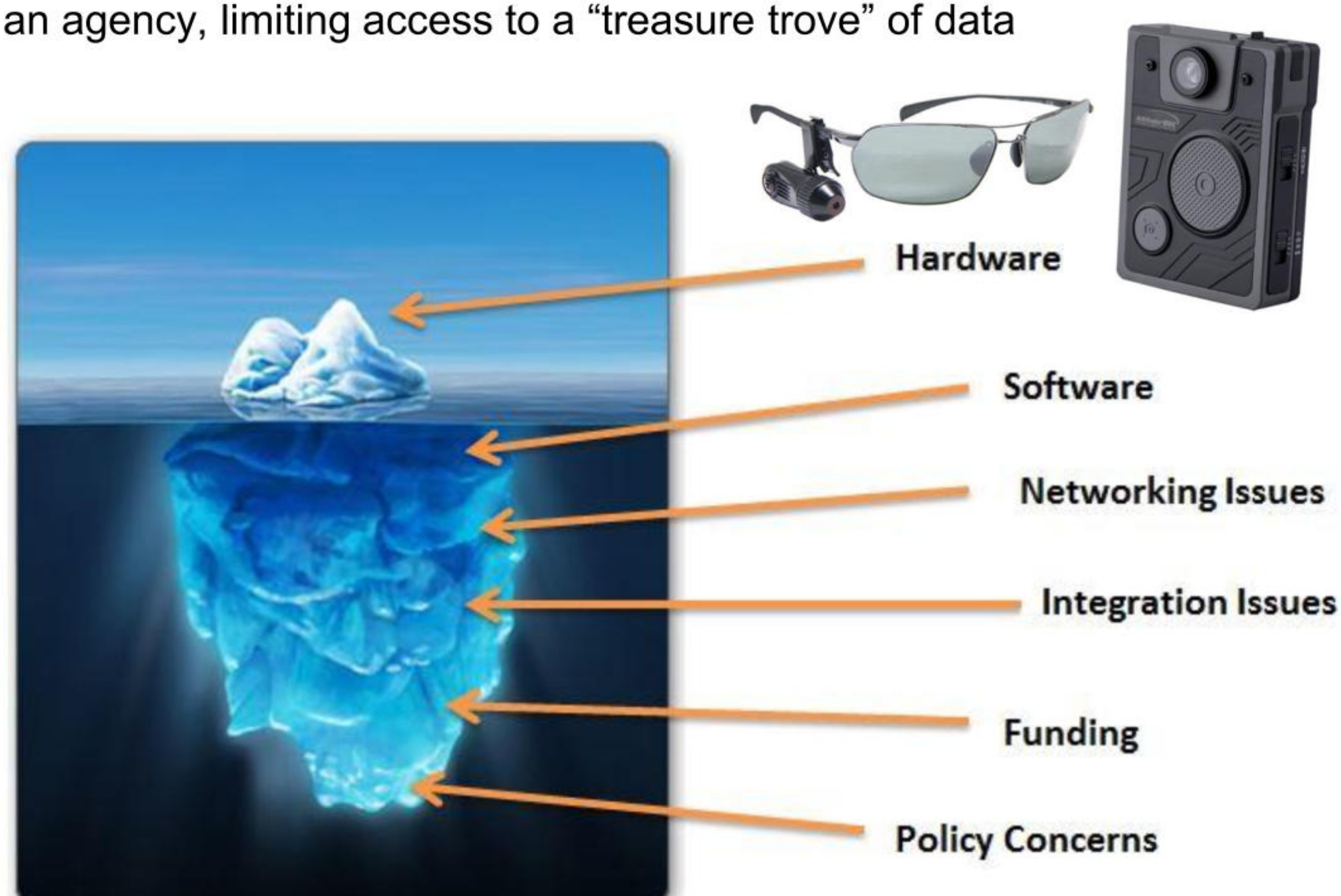
IndigoVision

WOLFCOM.

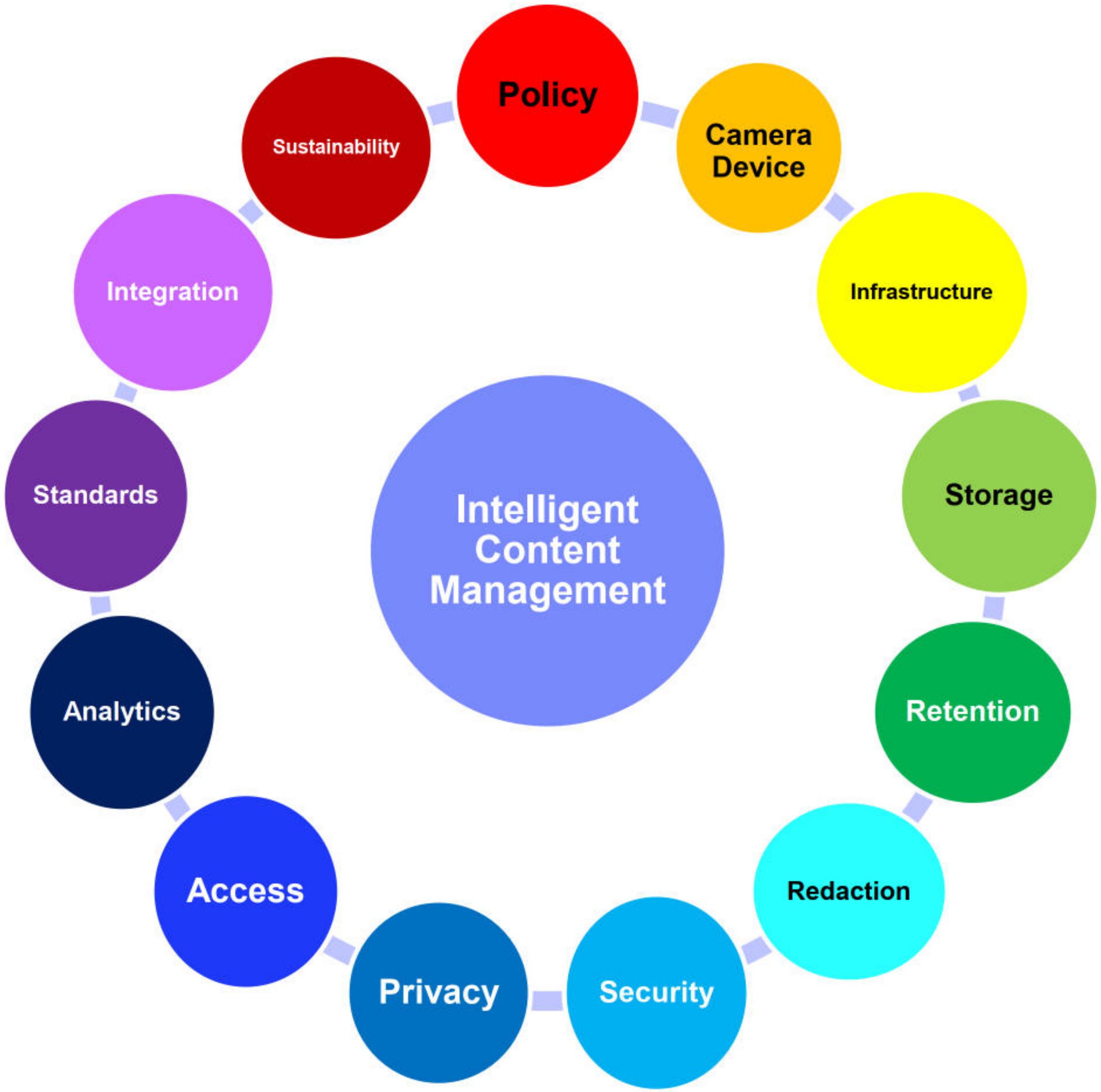
Getac

TASER

VIEVU



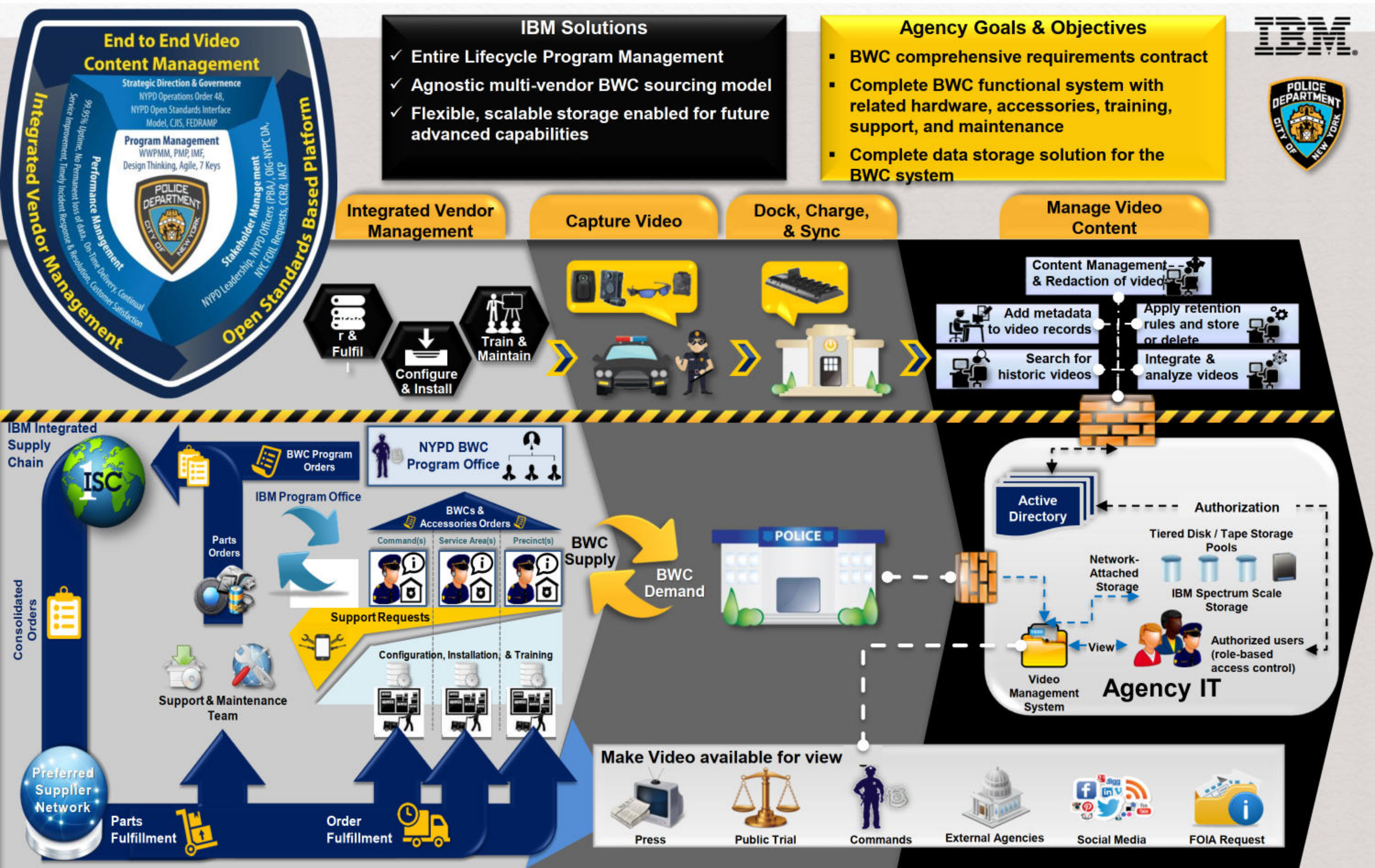
Numerous & Complex Considerations to Manage when Implementing a Body Camera System



Body Camera Challenges and Mitigation

BC Considerations	Challenge	Mitigation
1. **Officer Discretion to Record**	Wearable Camera programs are only as good as the protocols that are defined. Officers not following established protocols need to be identified and retrained – BEFORE issues surfaces.	Baseline(s) developed around protocols and procedures. Baseline is updated based on patrol usage patterns. Outliers identified and followed up on.
2. **Public Notifications**	Ensuring that the general public is aware of the program and their rights.	While outside the scope of IBM's effort, we have deep expertise in communications and change management.
3. **Compliance and QA Reviews**	Patrol command structure should randomly review compliance with protocols and procedures. This can take up valuable time.	Workflows defined with automatic notifications for video segments matching a set criterion such as a specific arrest type or stop.
4. **Mitigating Officer Infractions Recorded on BCs**	Video segments with (alleged) recorded officer infractions - resulting from complaints (versus via a QA review) – must be able to be quickly and effortlessly retrieved by command.	Accurate indexing to enable easy reference to a particular segment.
5. **Access Control**	Video access needs to be limited to specific roles and may need to be assigned dynamically.	Flexible and easy-to-adjust access control and access tracking.
6. **Public Access/FOIA Requests**	Ensuring privacy and safety protections for all populations. Striking a balance between citizen's and officer's rights.	Video redaction capabilities.
7. **Retention and Purging**	18 month retention period requires significant storage volume. Video segments must be carefully tracked to validate evidentiary needs are met, while expired, non-evidentiary segments are purged upon expiration.	An effective, hybrid, data storage scheme coupled with automated retention and purge rules.

A Single View of IBM's Holistic Body Camera Program

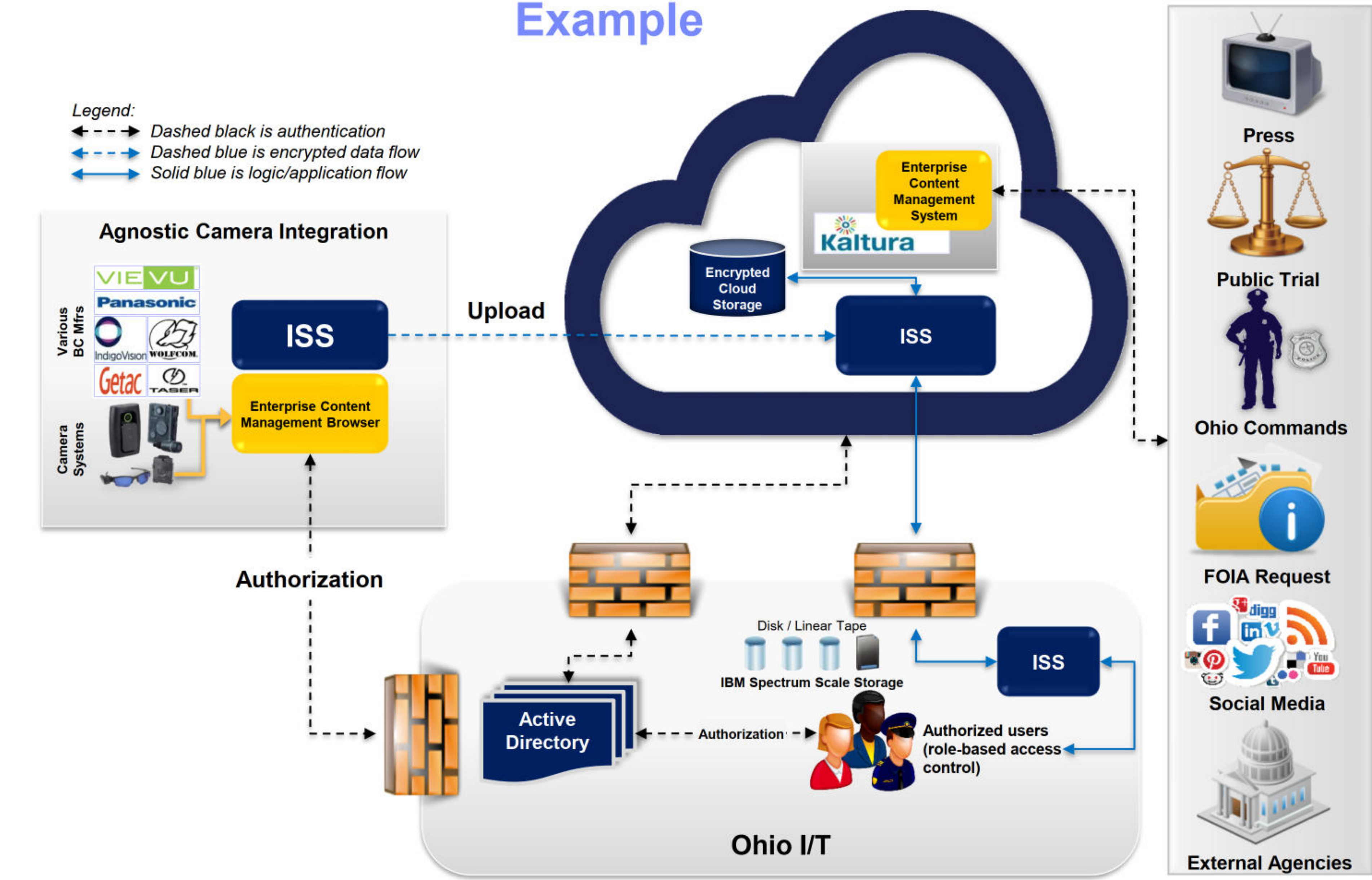


How does IBM view a Body Camera Project Implementation?

IBM Global Business Services (GBS) is well positioned as an End to End program manager of BC programs: PMO, Vendor Management, System Integration, Testing, Support, Maintenance, Systems Management, Analytics, and more…

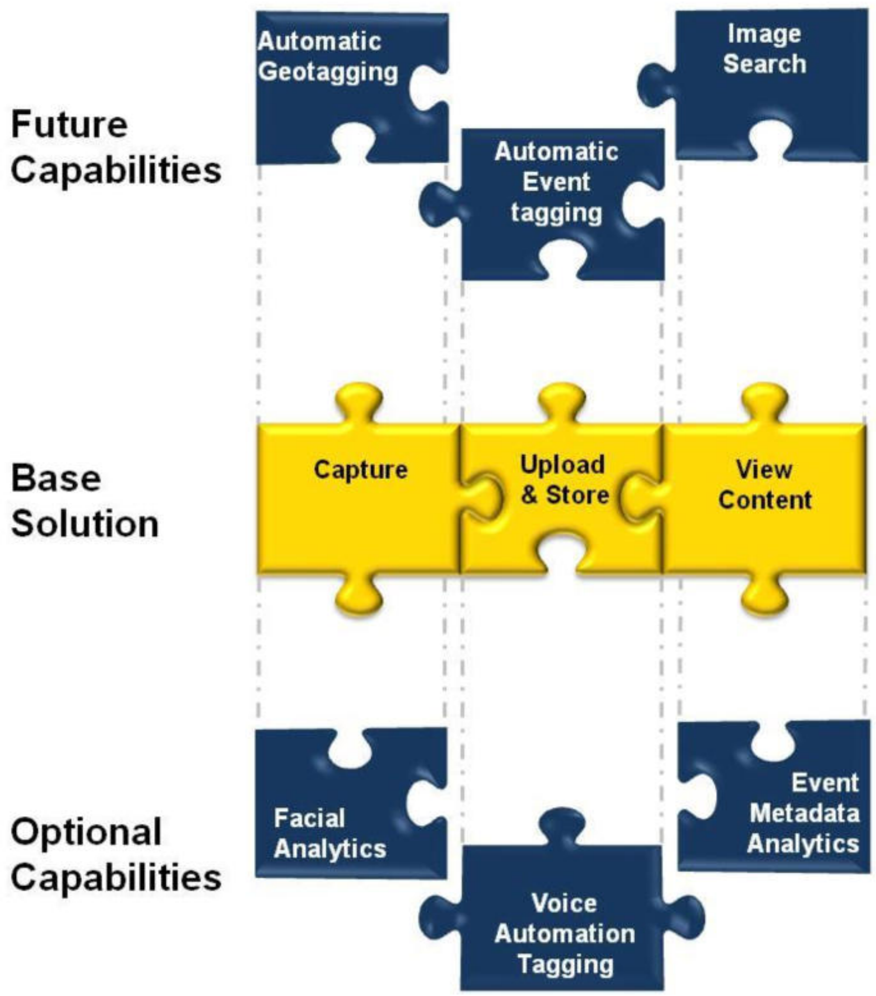
Process	Capture	Collect	Manage	Analyze
Description	• Managing Ordering & Deploying Hardware Devices	• Content Management of data collected from numerous device types	• Data Storage (On-Premise, Hybrid, or Cloud)	• Integration and Video Analytics (FR, 360 Deg. View, Behavioral)
IBM Content	• 3rd Party product to be procured by IBM: • Cameras & Accessories	• MDM & Data Modeling • IBM SW ECM/ Kaltura • Metadata & Tagging • Geo-Location	• Shared Services • IBM Storage: ESS, Spectrum Scale • Cloud: Fed Cloud, Rocket Center, NLETS	• Integration • Analytics Capabilities • Automation and Interoperability (ex Event Triggers and Alerts)
3rd Party Content	• Suppliers: Vievu, Taser, Panasonic, L3, Indigo Vision, Wolfcom, etc.	• BC SW: Taser, Vievu, Indigo Vision, L3, Panasonic, Wolfcom • 3rd Party SW: Other Content Management & VMS Solutions (ex. Genetech)	• Cloud Vendors: Azure, AWS, Others • Storage Solutions: EMC, etc.	• Integration of Cameras, SW, and Data Storage • Additional capability Components (ex Analytics) • Automation and Interoperability

Infrastructure: Hybrid Storage Solution Example



* Minimum BC vendor functionality or possibly

Implementation: A Platform for Future Capabilities, Scalability and Sustainability



IBM Holistic Project Approach

- Device Agnostic
  - Technology Refresh
- Program Management Office (PMO)
- Systems Integration
  - Multi-vendor Complex Integration
- Storage Technology Innovation
- Integrated Supply Chain
- Sustainability

"Future Proof"

The IBM BWC Maturity Model PoV

As an agency journeys up the Maturity Model, IBM's value proposition significantly increases.

The advantage of "traditional" BWC vendors stops somewhere in-between "*Wide Spread Rollout*" and "*Advanced Forensics*"

The client market "first movers" fall somewhere between planning for a pilot and planning for a widespread rollout

Pilot Programs

Limited Rollout to test camera functionality and interaction with Public

Widespread Rollout

- Basic forensic and audit capabilities
- Superior uptime, storage, and operational capabilities required
- Silo'd system

Advanced Access

- Used by multiple agencies and, possibly, the general public
- Increased capabilities for search and retrieval

Deep Analytics

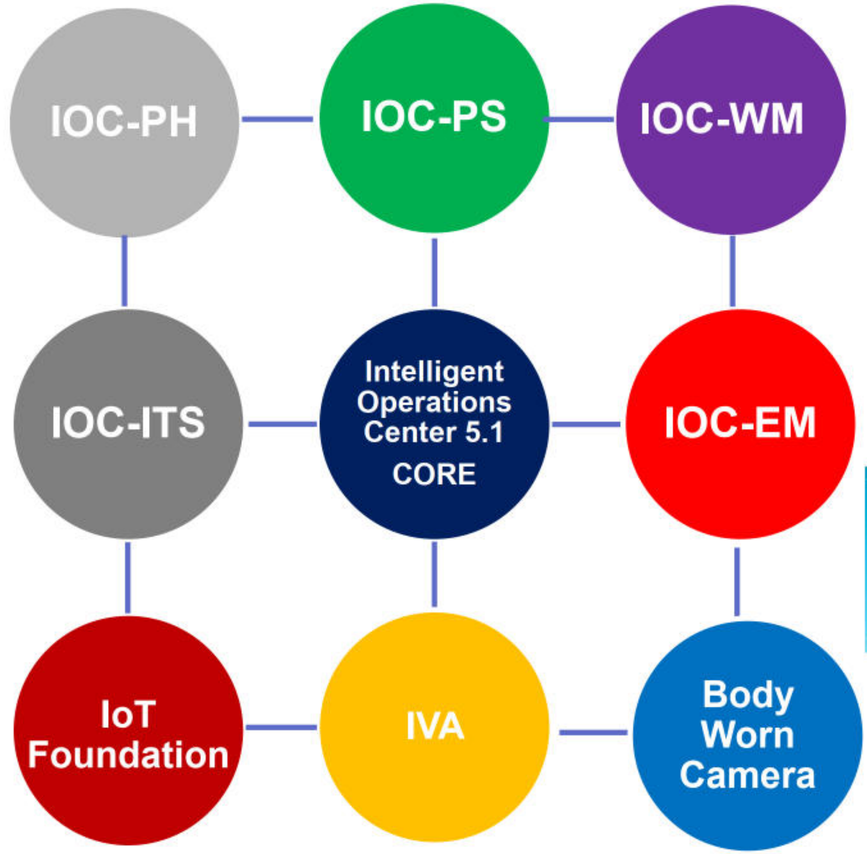
- Gaining insights from MetaData content
- Streaming, real-time analysis, and advanced people/attribute, text, audio, and redaction capabilities.
- Integrate with Static Cameras and bystander video

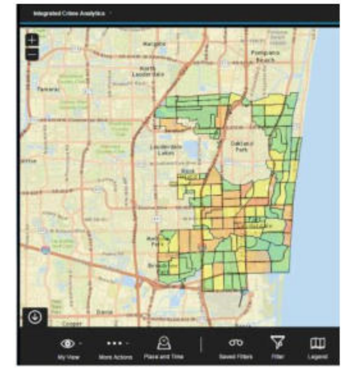
Integrated Situational Awareness

- Leveraging video/image content to improve situational awareness and gain insights
- Integrated with other public safety and image systems.
- Cognitive applied

Our BWC offering aligns with Smarter Cities / IOC investments

Incident Aware





IOC 5.1 can be the integrating hub of all of these technologies, cross domain/industry

Industry Resources & Information Providing Guidance

National Sources: Information, Guidance and Opinion

Industry Organizations:

- DOJ-COPS
- PERF
- ACLU
- Academia
- NACo
- National League of Cities
- National Governors Association
- Major City / County Chiefs & Sheriffs
- IACP
- IAEM
- IJIS
- National Association of Prosecutors & District Attorneys
- National Association of Court Administrators

Industry Publications:

- ✓ National Institute on Justice: Research on Body-Worn Cameras and Law Enforcement
- ✓ Implementing a Body-Worn Camera Program Recommendations and Lessons Learned
- ✓ THE USE OF BODY-WORN CAMERAS BY LAW ENFORCEMENT GUIDELINES FOR USE & BACKGROUND PAPER
- ✓ BODY-WORN CAMERAS MODEL POLICY NOW AVAILABLE

Recent News Articles:

- **SC:** Police came out against a body-camera bill
- **KY:** Bill to Help Cops Develop Body-Worn Camera Programs
- **HI:** Bill would help fund police cameras
- **MI:** Police body cams: Bill would exempt footage from FOIA
- **LAPD:** Lawmakers, police officers disagree on body camera rules
- **TX:** Texas Senate OKs police body camera bill


Thank
You

LAPD Project:

Change-point Detection for Police Body-Worn Video

Industry Sponsor: Commander Sean Malinowski (LAPD Chief of Staff); Ms. Maggie Goodrich (LAPD CIO), Sgt. Javier Macias, Sgt. Dan Gomez, Mr. Arnold Suzukamo (LAPD-IT Bureau).

Academic Mentor:

Academic Supervisors: Jeff Brantingham, UCLA Anthropology; Dr. Craig Uchida, Justice & Security Strategies

Introduction

Body-worn video (BWV) or on-body cameras provide a novel means to collect very fine-information about police-public interactions. The general use model requires officers to initiate recording of video whenever there is an encounter with a member of the public. During such interactions, BWV is recorded in real-time. Recording is terminated at the officer's discretion. BWV is not streamed or reviewed in real-time, but rather is uploaded to a secure cloud storage system at the end of an officer's shift.

BWV is designed to provide another line of evidence for the actions of individuals and the outcomes of interactions between police and members of the public. BWV is therefore evidence relevant to legal proceedings like any other form of evidence collected by police. In a limited number studies, BWV has been shown to reduce the likelihood that situations escalate to a point requiring use of force.

There are considerable challenges facing wide-spread use of BWV. Even small scale deployments are expected to lead to massive volumes of video data that will quickly outstrip the ability of law enforcement agencies to analyze. The resulting fallback position will be to review BWV footage only when it corresponds to adverse outcomes (e.g., use of force). Most video will go unused. Many of the potential benefits of BWV may therefore go unrealized.

The 2016 LAPD-RIPS Project

The 2016 RIPS-LAPD team will work to develop change-point detection methods for use with BWV. Change point detection represents a general class of mathematical problems that seek to identify significant shifts in the behavior of a temporal stochastic process. The process itself is often hidden and therefore changes in process can only be observed indirectly. For example, you might be interested in detecting whether an individual's disposition has changed from friendly (or neutral) to antagonistic given observations of their outward actions such as body position, direction of motion, arm gestures. Detecting changes is a necessary precursor to taking actions. For example, detecting changes in the disposition of an individual captured on video could be used for automated labeling or tagging of the video and, in some cases, automated initiation of some action. A key challenge is to produce change point detection methods that minimize false alarm rates.

The project will rely on a range of data types BWV metadata (e.g., time stamps), BWV audio, and the video images themselves. Computations may be done in Matlab, Mathematica, C, C++, R, Java, or other appropriate computational language.

Key Milestones:

1. Statistical assessment of LAPD BWV and other associated data.
2. Develop change point detection methods.
3. Testing of efficacy of methods.
4. Present to LAPD.

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Program Sean Malinowski and Jeff Brantingham

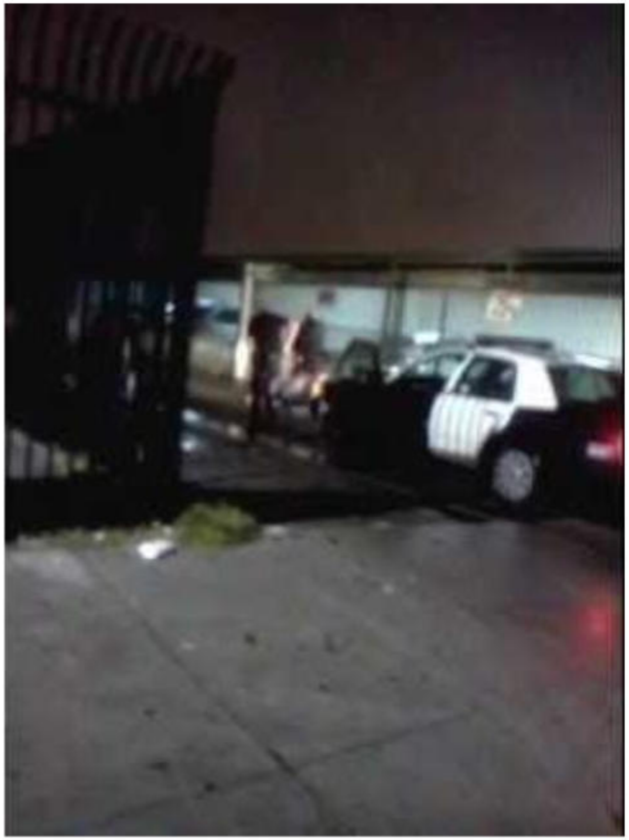
Day	Activity
Sat 23/4	- Arrival at Schiphol, flightno: UA946, arriving at 07:15 - Rodney will be picking you up. - Checking in at www.hoteldenhaag.nl - Visit to The Hague city centre - Dinner at The Pier, Scheveningen
Sun 24/4	- Sightseeing region, guided by Rodney - Dinner at Westbroekpark with other convention members
Mon 25/4	- Convention (morning Sean and Jeff key note speakers, afternoon participating workshop predictive policing)
Tue 26/4	- Morning: convention - Afternoon: visit to ministry of Safety and Justice 3i-session (informative, inter active, inter collegial) about PredPol
Wed 27/4	- Kingsday (national celebration), visit to Zwolle (where the King will be) for a look behind the scene of organizing such a big event and to have a look at the concept of peer review
Thu 28/4	- Jeff flying back to LA at , flightno: UA908, leaving at 11:05 - Rodney (and Sean) will drop Jeff off at the airport - Sean to visit police The Hague
Fri 29/4	- Sean flying back to LA at , flight no: UA947, leaving at 12:00 - Rodney will drop Sean off at the airport

Body-Worn Video Analytics

P. Jeffrey Brantingham – UCLA Anthropology
Andrea L. Bertozzi – UCLA Mathematics

Maggie Goodrich – CIO LAPD
Craig Uchida – JSS

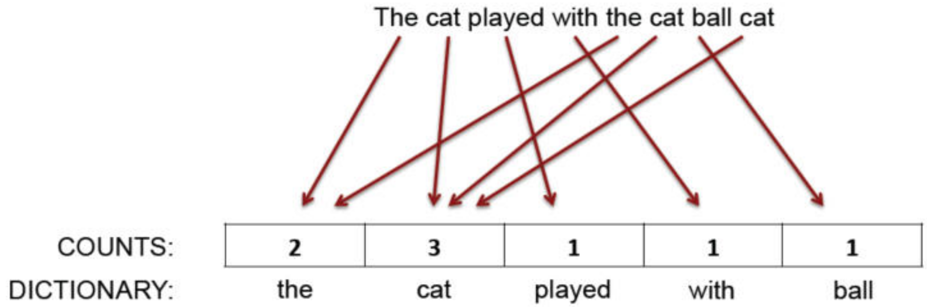
limits of fully-supervised analysis



- >600k hours of video annually
- only video with known content will come to light
- hidden risk/resource
- semi- or fully-unsupervised analysis

Feature Extraction

Bag-of-Visual-Words Representation

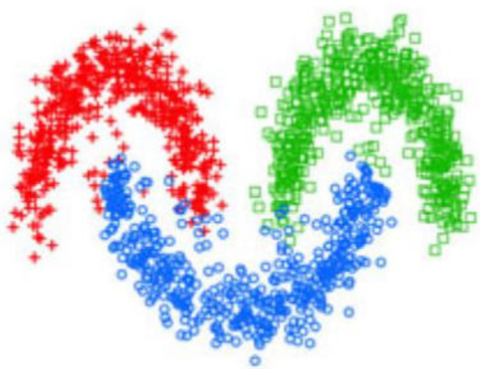


TF-IDF

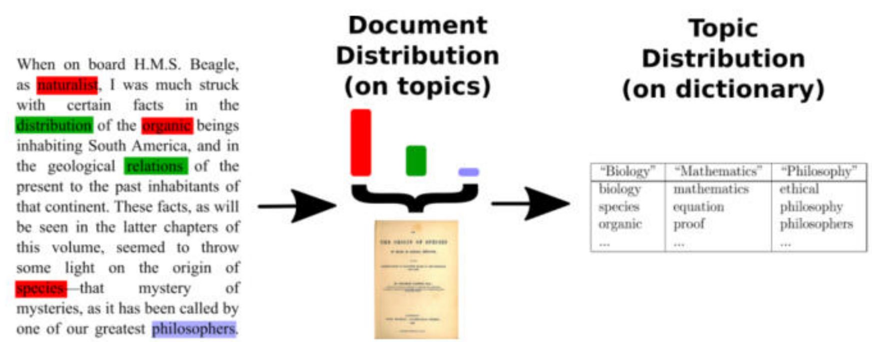
$$f_w = f_{t,d} \log\left(1+\frac{N}{n_t}\right)$$

Clustering

graph Ginzburg Landau



Latent Dirichlet Allocation



Dynamics

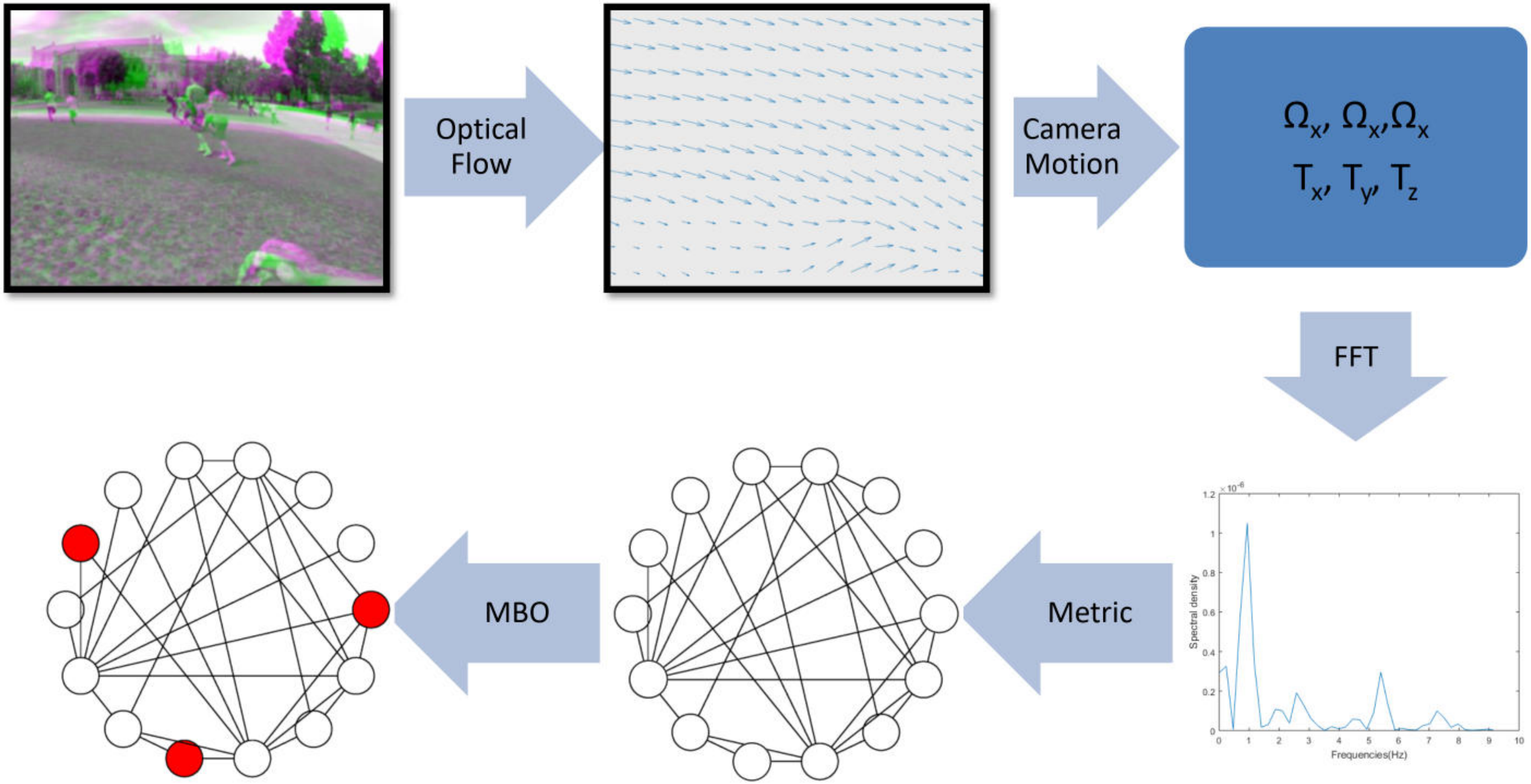
self-exciting topic models

$$\lambda(t) = \mu + \theta \sum_{t_i < t} \omega e^{-\omega(t-t_i)}$$

spatial-density estimation

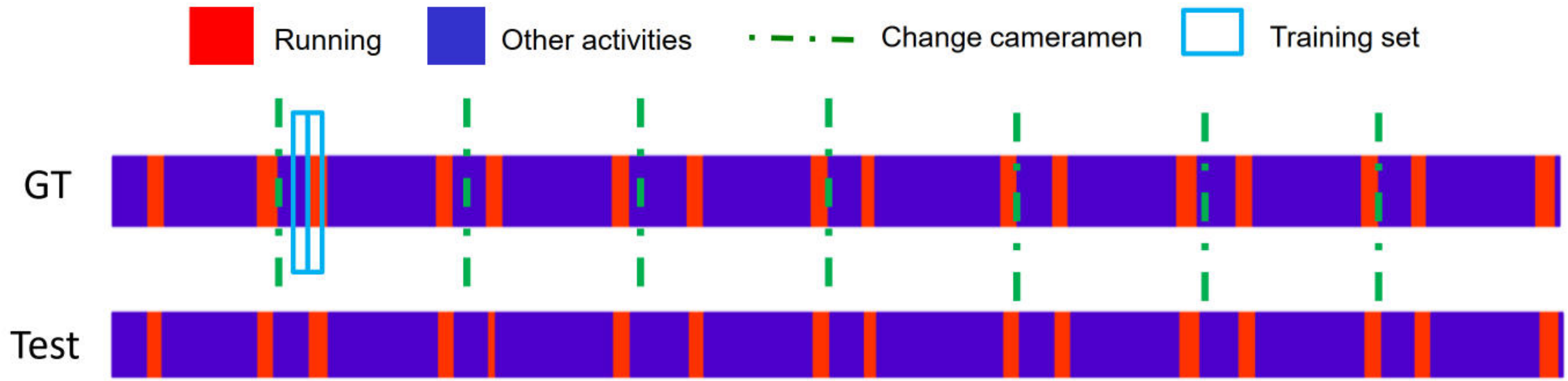
$$\frac{||f_i||_{L_p}}{||f_i||_{L_1}} = \frac{\left(\int f_i^p dx\right)^{1/p}}{\int f_i dx}$$

hard clustering foot chases



Empirical Tests

- 8 subjects + 8 activities for 30 seconds (GoPro)
- 730 LAPD videos with 2 involving foot chases (Axon)



Frame-wise accuracy

FP rate = 0.26%

FN rate = 8.4%

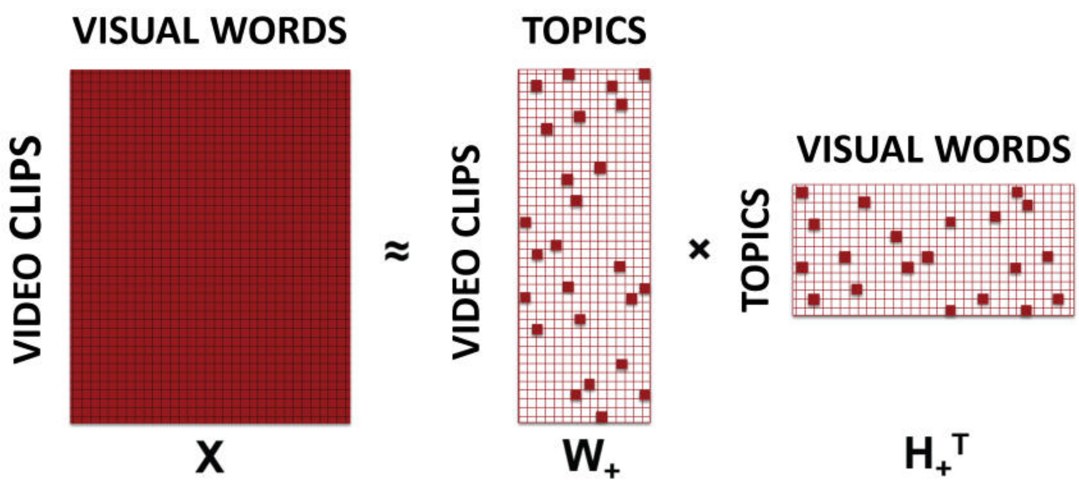
Activity Wise

FN rate = 0.0%

soft-clustering of video topics

visual feature extraction & clustering into a "dictionary"

non-negative matrix factorization



spatial diversity in topics

Most Probable Words

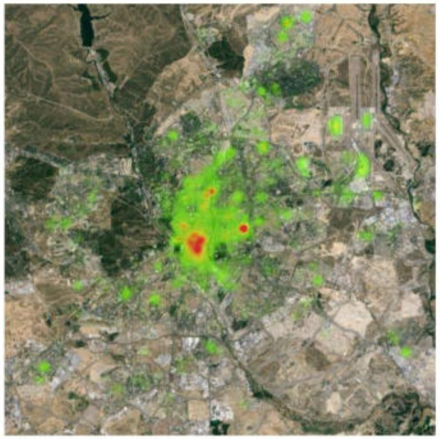
"Traffic"	"English"	"Airport"
km	to	t
trafico	it	barajas
amarillo	the	mad
circulacion	you	aeropuerto
alarcon	that	terminal
pozuelo	be	iberia
verde	all	gate
accidente	like	vip
alcorcon	but	airport
rojo	and	hispanidad

LDA for 3.4m geotagged Tweets & 300 topics

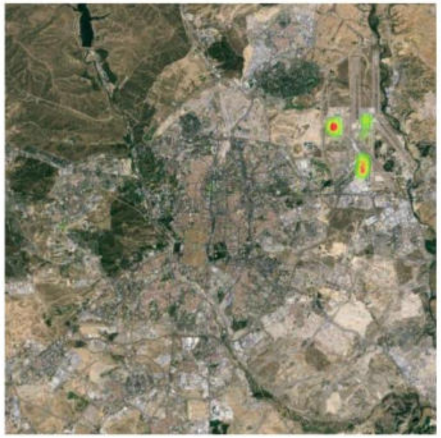
Traffic: Automated traffic reporting
English: Non-dominant languages are a grouped
Airport: Some topics have specific city locations

Distribution (Lp/L1)

Traffic (0.0008)

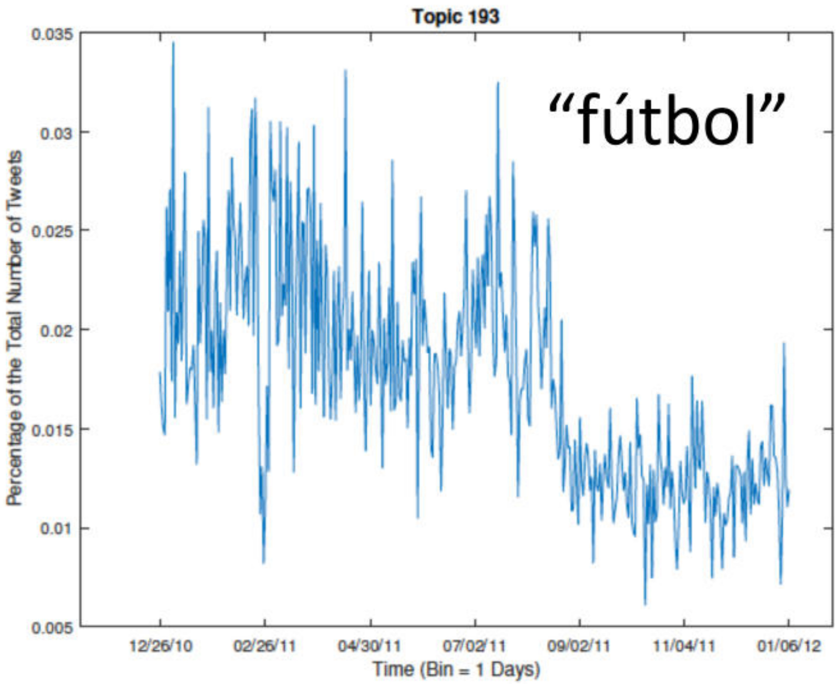


English (0.06)



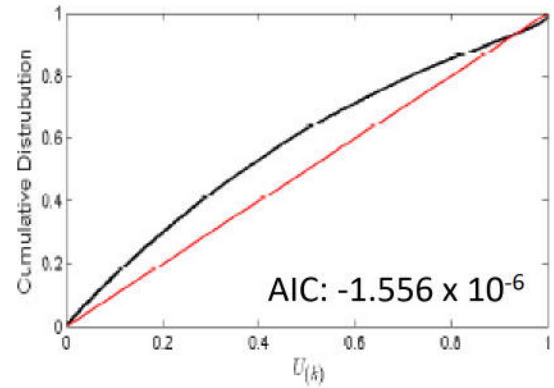
Airport (0.006)

self-exciting topics

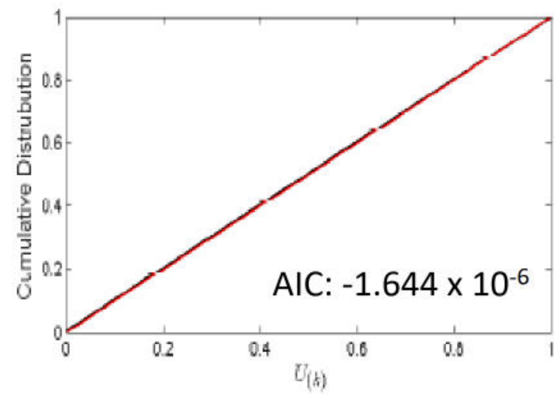


Poisson

$$\lambda(t) = \mu$$



realized residual process fit
Ogata 1988



Hawkes

$$\lambda(t) = \mu + \theta \sum_{t_i < t} \omega e^{-\omega(t-t_i)}$$

a basis for forecasting in space & time

challenges

- BWV presents unique mathematical challenges
  - camera motion
  - image quality (e.g., low light, occlusions)

- algorithms show variable performance across platforms

- making analytics useful for the field

Potential Participants (from the Stanford Symposium)

University-based Technologists

Jeff Brantingham, Professor, UCLA
Greg Hager, Professor, Johns Hopkins
Yaser Sheikh, Associate Professor, Carnegie Mellon University
Vitaly Shmatikov, Professor, Cornell University
Jacob Sniff, MIT Media Lab
Dan Jurafsky, Linguistics and Computer Science, Stanford University

Police Department Representatives

Maggie Goodrich, CIO, LAPD
Sgt. Dan Gomez, LAPD
Assistant Chief Paul Figueroa, Oakland PD
Sgt. Dave Burke, Oakland PD
Commander Robert Moser, SFPD
Chief Scott Thomson, Camden County PD
Chief Laura Wilson, Stanford University PD
Deputy Chief Andrew Acord, Dallas PD
Craig D. Uchida, LAPD Research Partner, Justice & Security Strategies, Inc.

Use Cases

A. Definition:
   - A use case is a methodology used in system analysis to identify, clarify, and organize system requirements to capture the possible ways the user and system can interact that result in the user achieving a goal.
   - They describe the step by step process a user goes through to complete that goal using a software system.
   - They also capture all the things that can go wrong along the way that prevent the user from achieving the goal.
   - A use case can be thought of as a collection of possible scenarios related to a particular goal

B. A use case (or set of use cases) has these characteristics:
   - Organizes functional requirements
   - Models the goals of system/actor (user) interactions
   - Records paths (called scenarios) from trigger events to goals
   - Describes one main flow of events (also called a basic course of action), and possibly other ones, called exceptional flows of events (also called alternate courses of action that an be achieved through textual and visual representations)

C. According to CALEA, the following is a sample list of officer interactions where BWCs could support officers and use cases could be identified:

- Service calls.
- Primary response (patrol in vehicle).
- Self-initiated public contacts/foot patrol.
- Bicycle/motorcycle patrol.
- Emergency response/first responders.
- Searches (vehicle or site).
- SWAT.
- Corrections.

Attachments:

1. Law Enforcement RMS from BJA:
a. This attachment has 'use case' visual charts and representations (including MULIPLE ACTORS) for incident reporting (p.10), investigative case management (p.14), serving warrants, and several additional examples
2. Use Case-template:
a. This is a template and example of how a student would register for classes (and alternative steps to take if there were issues)
3. ATM use case interactive example:
a. http://www.math-cs.gordon.edu/courses/cs211/ATMExample/UseCases.html#Startup
b. http://www.math-cs.gordon.edu/courses/cs211/ATMExample/InitialFunctionalTests.html
c. Examines each part of process (scroll up, click on the goals, page links, explore J)

I think for our situation: it's how the police agencies, through a step by step process, can obtain the info/data/their "goal" from the body worn camera footage- basically, whatever the PDs decide they want/can use out of the footage. (This is what we want to learn from our 'Police experts' in our upcoming discussions.) Our role- we would then work with the tech agencies to come up with the written or chart visual 'use case' (or cases) to achieve these goals (with the software, algorithms etc.)...but translating tech speak to English for the PDs. And within that use case, there would be all different scenarios if something goes wrong with the BWC footage and technology and would address all the what if's the police agencies may encounter in obtaining that goal.

Crime Intel Detail - Minutes in the LASER ZONES

		77th-Minutes in the LASER Zones							
DP	DATE	LASER Zone 1	LASER Zone 2	LASER Zone 3	LASER Zone 4	LASER Zone 5	LASER Zone 6	LASER Zone 7	TOTAL
DP 8	26-Jul-15	32	169	344	0	48	0		**593**
	27-Jul-15	0	73	0	5	2	12		**92**
	28-Jul-15	137	252	230	0	326	3		**948**
	29-Jul-15	318	715	357	4	25	23		**1442**
	30-Jul-15	122	884	78	52	113	0		**1249**
	31-Jul-15	206	742	254	28	39	0		**1269**
	1-Aug-15	83	265	10	0	30	0		**388**
	2-Aug-15	51	0	68	0	0	0		**119**
	3-Aug-15	360	207	68	70	51	4		**760**
	4-Aug-15	98	18	1	9	0	15		**141**
	5-Aug-15	358	288	223	210	39	50		**1168**
	6-Aug-15	320	239	87	0	247	0		**893**
	7-Aug-15	308	138	82	0	90	0		**618**
	8-Aug-15	517	292	66	5	165	0		**1045**
DP 9	9-Aug-15	321	58	263	112	179	25		**958**
	10-Aug-15	141	154	85	69	54	103		**606**
	11-Aug-15	232	451	174	127	187	23		**1194**
	12-Aug-15	224	129	116	89	373	92		**1023**
	13-Aug-15	39	176	493	100	126	81		**1015**
	14-Aug-15	246	189	132	44	183	57		**851**
	15-Aug-15	0	5	132	66	61	15		**279**
	16-Aug-15	297	332	369	212	315	0		**1525**
	17-Aug-15	254	29	26	8	65	910		**1292**
	18-Aug-15	480	235	16	0	185	85		**1001**
	19-Aug-15	122	65	614	67	228	31		**1127**
	20-Aug-15	125	82	87	0	215	42		**551**
	21-Aug-15	536	413	77	160	386	269		**1841**
	22-Aug-15	6	0	170	0	15	0		**191**
	TOTAL	5933	6600	4622	1437	3747	1840	0	24179

Crime Intel Detail - Minutes in the LASER ZONES

	23-Aug-15	1288	405	93	4	76	48		**1914**
	24-Aug-15	122	137	18	45	80	35		**437**
	25-Aug-15	36	227	148	58	73	120		**662**
	26-Aug-15	290	119	15	103	215	120		**862**
	27-Aug-15	204	372	84	126	331	260		**1377**
	28-Aug-15	356	158	110	150	309	148		**1231**
	29-Aug-15	304	25	336	22	387	21		**1095**
	30-Aug-15	195	7	203	104	366	103		**978**
	31-Aug-15	29	155	30	1	237	36		**488**
	1-Sep-15	54	37	0	42	168	0		**301**
	2-Sep-15	265	595	89	16	83	80		**1128**
	3-Sep-15	125	233	155	0	492	8		**1013**
	4-Sep-15	1774	215	333	80	369	24		**2795**
	5-Sep-15	85	1372	495	193	71	118		**2334**
DP 10	6-Sep-15	480	220	116	0	560	0		**1376**
	7-Sep-15	228	168	0	240	411	0		**1047**
	8-Sep-15	40	142	0	0	345	0		**527**
	9-Sep-15	1222	1180	5	0	1167	0		**3574**
	10-Sep-15	720	786	224	38	471	72		**2311**
	11-Sep-15	372	910	420	370	436	4		**2512**
	12-Sep-15	182	816	0	10	241	0		**1249**
	13-Sep-15	262	2168	6	53	250	120		**2859**
	14-Sep-15	262	158	47	87	66	94		**714**
	15-Sep-15	80	1860	436	124	41	56		**2597**
	16-Sep-15	120	128	495	287	322	76		**1428**
	17-Sep-15	258	89	406	324	121	48		**1246**
	18-Sep-15	316	489	343	259	428	156		**1991**
	19-Sep-15	429	527	297	146	563	177		**2139**
	TOTAL	10098	13698	4904	2882	8679	1924	0	42185

Crime Intel Detail - Minutes in the LASER ZONES

	20-Sep-15	395	788	175	180	225	0		**1763**
	21-Sep-15	110	46	85	170	181	9		**601**
	22-Sep-15	330	30	83	150	420	0		**1013**
	23-Sep-15	474	210	97	120	452	0		**1353**
	24-Sep-15	73	8	103	58	423	0		**665**
	25-Sep-15	276	69	97	83	623	45		**1193**
	26-Sep-15	385	65	377	0	481	0		**1308**
	27-Sep-15	348	12	161	8	227	26		**782**
	28-Sep-15	242	582	150	42	44	0		**1060**
	29-Sep-15	465	552	125	20	113	0		**1275**
	30-Sep-15	417	325	23	77	286	0		**1128**
	1-Oct-15	381	460	276	0	284	0		**1401**
	2-Oct-15	161	382	5	20	135	0		**703**
	3-Oct-15	120	46	282	31	241	0		**720**
DP-11	4-Oct-15	251	1135	288	268	156	96		**2194**
	5-Oct-15	208	613	31	0	825	0		**1677**
	6-Oct-15	439	732	93	0	175	0		**1439**
	7-Oct-15	231	108	160	44	359	0		**902**
	8-Oct-15	368	275	394	310	459	410		**2216**
	9-Oct-15	202	237	105	162	85	240		**1031**
	10-Oct-15	220	0	55	30	393	0		**698**
	11-Oct-15	300	86	10	70	241	0		**707**
	12-Oct-15	604	80	10	79	242	0		**1015**
	13-Oct-15	227	145	175	155	310	210		**1222**
	14-Oct-15	395	180	10	20	50	10		**665**
	15-Oct-15	285	45	130	180	110	220		**970**
	16-Oct-15	292	575	65	271	247	309		**1759**
	17-Oct-15	275	30	35	160	213	0		**713**
	18-Oct-15	164	76	20	40	160	50		**510**
	19-Oct-15	100	95	52	25	40	10		**322**
	20-Oct-15	163	80	11	365	5	0		**624**
	TOTAL	8901	8067	3683	3138	8205	1635	0	33629

Crime Intel Detail - Minutes in the LASER ZONES

	21-Oct-15	488	638	45	205	92	56		**1524**
	22-Oct-15	203	180	141	30	322	136		**1012**
	23-Oct-15	230	312	26	5	276	25		**874**
	24-Oct-15	70	330	26	10	330	0		**766**
	25-Oct-15	62	170	20	222	245	0		**719**
	26-Oct-15	20	281	0	10	0	0		**311**
	27-Oct-15	190	366	20	151	339	107		**1173**
	28-Oct-15	69	205	0	199	220	105		**798**
	29-Oct-15	192	377	58	407	217	397		**1648**
	30-Oct-15	0	50	40	50	153	65		**358**
	31-Oct-15	136	159	10	0	113	0		**418**
DP-12	1-Nov-15	244	20	0	0	207	30		**501**
	2-Nov-15	376	0	11	0	342	20		**749**
	3-Nov-15	26	61	10	138	20	0		**255**
	4-Nov-15	628	131	58	207	105	101		**1230**
	5-Nov-15	191	136	185	215	260	60		**1047**
	6-Nov-15	577	73	170	410	89	0		**1319**
	7-Nov-15	70	320	309	420	362	260		**1741**
	8-Nov-15	38	187	96	226	37	140		**724**
	9-Nov-15	111	114	15	50	40	49		**379**
	10-Nov-15	0	125	0	50	25	90		**290**
	11-Nov-15	167	155	230	110	343	72		**1077**
	12-Nov-15	24	260	200	89	104	0		**677**
	13-Nov-15	30	112	210	12	145	0		**509**
	14-Nov-15	40	197	245	87	164	118		**851**
	15-Nov-15	144	111	81	21	224	0		**581**
	16-Nov-15	58	336	0	170	63	330		**957**
	17-Nov-15	54	110	0	67	58	0		**289**
	18-Nov-15	27	30	35	10	171	42		**315**
	19-Nov-15	45	140	61	100	10	135		**491**
	20-Nov-15	231	105	160	0	125	200		**821**
	21-Nov-15	105	100	76	0	231	115		**627**

Crime Intel Detail - Minutes in the LASER ZONES

	22-Nov-15	111	114	16	54	47	49		**391**
	23-Nov-15	77	340	310	425	368	266		**1786**
	24-Nov-15	202	133	185	215	266	71		**1072**
	25-Nov-15	570	80	174	410	87	15		**1336**
	26-Nov-15	86	205	245	80	112	61		**789**
	27-Nov-15	192	377	58	407	217	397		**1648**
	28-Nov-15	0	126	14	80	139	145		**504**
DP-13	29-Nov-15	192	377	58	407	217	397		**1648**
	30-Nov-15	190	366	20	151	339	107		**1173**
	1-Dec-15	220	0	55	30	393	0		**698**
	2-Dec-15	73	8	103	58	423	0		**665**
	3-Dec-15	231	108	160	44	359	0		**902**
	4-Dec-15	26	61	10	138	20	0		**255**
	5-Dec-15	720	786	224	38	471	72		**2311**
	6-Dec-15	480	220	116	0	560	0		**1376**
	7-Dec-15	228	168	0	240	411	0		**1047**
	8-Dec-15	75	151	20	55	80	0		**381**
	9-Dec-15	83	265	30	0	55	0		**433**
	10-Dec-15	579	132	879	244	8	0		**1842**
	11-Dec-15	256	1116	111	315	36	0		**1834**
	12-Dec-15	1053	1325	1062	484	589	0		**4513**
	13-Dec-15	395	180	10	20	50	10		**665**
	14-Dec-15	285	45	130	180	110	220		**970**
	15-Dec-15	292	575	65	271	247	309		**1759**
	16-Dec-15	275	30	35	160	213	0		**713**
	17-Dec-15	368	275	394	310	459	410		**2216**
	18-Dec-15	202	237	105	162	85	240		**1031**
	19-Dec-15	1222	1180	218	175	1167	0		**3962**
	20-Dec-15	465	552	125	118	113	0		**1373**
	21-Dec-15	517	625	156	98	386	0		**1782**
	22-Dec-15	208	613	179	88	825	0		**1913**

Crime Intel Detail - Minutes in the LASER ZONES

23-Dec-15	439	732	207	167	175	0		**1720**
24-Dec-15	86	205	245	80	312	61		**989**
25-Dec-15	0	50	40	50	153	65		**358**
26-Dec-15	488	638	145	205	92	56		**1624**
27-Dec-15	1358	1448	368	886	1212	109		**5381**
28-Dec-15	987	1058	785	1014	1148	0		**4992**
29-Dec-15	1198	1985	288	358	1985	88		**5902**
30-Dec-15	689	852	689	1105	2480	287		**6102**
31-Dec-15	477	1059	1875	869	554	398		**5232**
1-Jan-16	1674	315	433	180	469	124		**3195**
2-Jan-16	2005	1845	1542	869	954	336		**7551**
3-Jan-16	489	173	270	480	189	0		**1601**
4-Jan-16	177	422	249	522	162	260		**1792**
5-Jan-16	289	187	96	226	37	140		**975**
6-Jan-16	311	114	215	50	369	49		**1108**
7-Jan-16	256	379	69	488	545	337		**2074**
8-Jan-16	256	916	311	315	698	129		**2625**
9-Jan-16	1053	1125	1045	587	499	274		**4583**
10-Jan-16	400	186	110	170	341	10		**1217**
11-Jan-16	704	180	254	179	342	89		**1748**
12-Jan-16	327	245	275	255	410	310		**1822**
13-Jan-16	495	280	110	120	150	110		**1265**
14-Jan-16	385	245	230	180	208	328		**1576**
15-Jan-16	692	675	265	371	347	409		**2759**
16-Jan-16	375	130	135	260	313	0		**1213**
17-Jan-16	975	852	1125	569	489	369		**4379**
18-Jan-16	1148	1254	987	756	705	697		**5547**
19-Jan-16	1129	932	520	678	875	885		**5019**
20-Jan-16	1275	1169	902	1185	756	636		**5923**
21-Jan-16	1356	1247	847	1124	769	852		**6195**
22-Jan-16	875	1185	865	357	458	812		**4552**

Crime Intel Detail - Minutes in the LASER ZONES

23-Jan-16	1358	936	874	1087	1269	975		**6499**
24-Jan-16	1685	764	685	622	452	607		**4815**
25-Jan-16	997	251	120	155	280	210		**2013**
26-Jan-16	645	165	87	109	198	366		**1570**
27-Jan-16	1460	480	317	229	88	466		**3040**
28-Jan-16	704	685	275	379	358	759		**3160**
29-Jan-16	472	345	664	355	411	302		**2549**
30-Jan-16	869	678	554	792	344	608		**3845**
31-Jan-16	495	380	210	220	256	208		**1769**
1-Feb-16	386	145	231	287	219	322		**1590**
2-Feb-16	392	562	166	371	348	409		**2248**
3-Feb-16	377	136	132	261	314	88		**1308**
4-Feb-16	318	374	320	287	502	510		**2311**
5-Feb-16	302	337	205	262	185	341		**1632**
6-Feb-16	308	288	158	188	208	498		**1648**
7-Feb-16	358	332	254	170	341	10		**1465**
8-Feb-16	219	288	266	179	342	89		**1383**
9-Feb-16	792	245	157	356	248	159		**1957**
10-Feb-16	665	258	258	89	245	106		**1621**
11-Feb-16	320	365	124	198	141	209		**1357**
12-Feb-16	380	458	187	120	256	206		**1607**
13-Feb-16	671	552	255	287	159	236		**2160**
14-Feb-16	386	246	207	356	180	187		**1562**
15-Feb-16	299	368	168	286	175	105		**1401**
16-Feb-16	303	392	194	341	167	227		**1624**
17-Feb-16	285	408	209	366	222	134		**1624**
18-Feb-16	186	330	224	290	287	300		**1617**
19-Feb-16	168	360	265	580	166	190		**1729**
20-Feb-16	209	302	302	378	208	279		**1678**
21-Feb-16	336	322	420	289	108	307		**1782**
22-Feb-16	378	345	289	198	168	293		**1671**

Crime Intel Detail - Minutes in the LASER ZONES

23-Feb-16	298	454	306	390	234	246		**1928**
24-Feb-16	391	550	346	470	193	318		**2268**
25-Feb-16	246	507	317	267	182	245		**1764**
26-Feb-16	271	460	294	224	302	226		**1777**
27-Feb-16	301	440	250	358	254	185		**1788**
28-Feb-16	439	632	193	124	275	154		**1817**
29-Feb-16	331	208	268	244	359	105		**1515**
1-Mar-16	389	375	494	410	459	457		**2584**
2-Mar-16	302	289	305	262	285	340		**1783**
3-Mar-16	287	110	247	133	493	185		**1455**
4-Mar-16	324	186	256	270	341	214		**1591**
5-Mar-16	504	180	189	179	342	209		**1603**
6-Mar-16	258	13	23	0	10	0		**304**
7-Mar-16	96	271	0	0	10	0		**377**
8-Mar-16	473	1201	110	0	0	0		**1784**
9-Mar-16	90	363	199	0	25	57		**734**
10-Mar-16	375	410	25	0	30	0		**840**
11-Mar-16	325	404	195	0	35	0		**959**
12-Mar-16	358	250	60	0	50	0		**718**
13-Mar-16	377	289	102	0	46	0		**814**
14-Mar-16	287	196	87	0	12	0		**582**
15-Mar-16	245	305	112	0	0	0		**662**
16-Mar-16	402	408	143	0	115	0		**1068**
17-Mar-16	302	387	98	0	33	0		**820**
18-Mar-16	267	309	190	0	0	0		**766**
19-Mar-16	462	459	164	0	22	0		**1107**
20-Mar-16	523	368	141	0	35	0		**1067**
21-Mar-16	574	409	169	0	26	0		**1178**
22-Mar-16	468	436	154	0	0	0		**1058**
23-Mar-16	506	476	186	0	0	0		**1168**
24-Mar-16	465	397	304	0	33	0		**1199**
25-Mar-16	393	506	268	0	0	0		**1167**

Crime Intel Detail - Minutes in the LASER ZONES

26-Mar-16	486	379	207	0	0	0		**1072**
27-Mar-16	65	755	0	0	0	0		**820**
28-Mar-16	422	25	200	0	0	0		**647**
29-Mar-16	335	335	30	0	0	0		**700**
30-Mar-16	255	170	0	0	0	0		**425**
31-Mar-16	205	398	160	0	140	0		**903**
1-Apr-16	428	55	441	0	30	0		**954**
2-Apr-16	200	316	200	120	0	0		**836**
3-Apr-16	370	150	303	0	0	0		**823**
4-Apr-16	326	290	70	0	0	0		**686**
5-Apr-16	340	816	156	0	0	0		**1312**
6-Apr-16	840	755	100	146	0	0		**1841**
7-Apr-16	250	200	270	0	0	0		**720**
8-Apr-16	120	355	0	0	0	0		**475**
9-Apr-16	290	30	180	30	0	0		**530**
10-Apr-16	70	80	33	67	0	0		**250**
11-Apr-16	330	167	90	0	0	0		**587**
12-Apr-16	1734	366	20	0	175	0		**2295**
13-Apr-16	1215	519	0	0	0	0		**1734**
14-Apr-16	1592	383	0	0	0	0		**1975**
15-Apr-16	609	1054	23	190	0	0		**1876**
16-Apr-16	410	132	0	0	0	0		**542**
17-Apr-16	1664	1841	347	0	0	0		**3852**
18-Apr-16	1116	568	257	0	0	0		**1941**
19-Apr-16	190	154	95	0	0	0		**439**
20-Apr-16	1124	259	110	0	0	0		**1493**
21-Apr-16	796	689	324	0	0	0		**1809**
22-Apr-16	1245	169	40	132	178	30		**1794**
23-Apr-16	235	196	0	0	0	0		**431**
24-Apr-16	1404	15	34	0	0	0		**1453**
25-Apr-16	1100	196	51	145	0	0		**1492**
26-Apr-16	1116	113	165	0	0	0		**1394**
27-Apr-16	948	347	291	0	0	0		**1586**

Crime Intel Detail - Minutes in the LASER ZONES

28-Apr-16	1401	0	272	0	0	0		**1673**
29-Apr-16	334	60	48	82	0	147		**671**
30-Apr-16	387	407	331	0	28	0		**1153**
1-May-16	2182	899	668	0	98	0		**3847**
2-May-16	113	247	125	0	0	0		**485**
3-May-16	797	141	402	0	0	0		**1340**
4-May-16	569	1257	34	0	0	0		**1860**
5-May-16	1146	1283	540	104	0	0		**3073**
6-May-16	1474	1343	539	0	0	0		**3356**
7-May-16	1026	331	474	52	0	0		**1883**
8-May-16	401	59	114	0	0	0		**574**
9-May-16	160	591	253	0	0	0		**1004**
10-May-16	893	416	254	0	0	0		**1563**
11-May-16	705	97	175	0	0	0		**977**
12-May-16	787	117	730	0	0	0		**1634**
13-May-16	625	28	64	0	0	0		**717**
14-May-16	103	55	130	10	0	0		**298**
15-May-16	742	689	688	0	0	0		**2119**
16-May-16	625	423	872	0	0	0		**1920**
17-May-16	809	367	721	0	0	0		**1897**
18-May-16	721	664	736	0	0	0		**2121**
19-May-16	669	582	409	0	0	0		**1660**
20-May-16	598	380	522	0	0	0		**1500**
21-May-16	907	322	518	0	0	0		**1747**
22-May-16	622	287	280	0	0	0		**1189**
23-May-16	598	546	249	0	0	0		**1393**
24-May-16	676	598	648	0	0	0		**1922**
25-May-16	502	702	542	0	0	0		**1746**
26-May-16	497	714	726	0	0	0		**1937**
27-May-16	664	631	766	0	0	0		**2061**
28-May-16	603	549	514	0	0	0		**1666**
29-May-16	548	469	522	0	0	0		**1539**
30-May-16	602	579	688	0	0	0		**1869**

Crime Intel Detail - Minutes in the LASER ZONES

		77th-Minutes in the LASER Zones							
DP	DATE	LASER Zone 1	LASER Zone 2	LASER Zone 3					TOTAL
	31-May-16	748	786	692					**2226**
	1-Jun-16	722	532	721					**1975**
	2-Jun-16	809	621	736					**2166**
	3-Jun-16	542	598	809					**1949**
	4-Jun-16	699	669	676					**2044**
	5-Jun-16	746	802	884					**2432**
	6-Jun-16	832	847	721					**2400**
	7-Jun-16	698	822	763					**2283**
	8-Jun-16	878	903	622					**2403**
	9-Jun-16	669	674	759					**2102**
	10-Jun-16	685	654	714					**2053**
	11-Jun-16	856	903	814					**2573**
	12-Jun-16	344	546	256					**1146**
	13-Jun-16	310	269	149					**728**
	14-Jun-16	398	387	403					**1188**
	15-Jun-16	468	482	502					**1452**
	16-Jun-16	409	324	359					**1092**
	17-Jun-16	415	387	363					**1165**
	18-Jun-16	546	402	429					**1377**
	19-Jun-16	562	497	542					**1601**
	20-Jun-16	589	611	636					**1836**
	21-Jun-16	622	647	598					**1867**
	22-Jun-16	522	468	658					**1648**
	23-Jun-16	489	591	682					**1762**
	24-Jun-16	602	644	618					**1864**
	25-Jun-16	563	623	701					**1887**
	26-Jun-16	380	200	430					**1010**
	27-Jun-16	518	260	478					**1256**
	28-Jun-16	690	395	470					**1555**
	29-Jun-16	750	360	433					**1543**

Crime Intel Detail - Minutes in the LASER ZONES

30-Jun-16	490	290	290					**1070**
1-Jul-16	1302	360	370					**2032**
2-Jul-16	1105	310	1072					**2487**
3-Jul-16	742	456	664					**1862**
4-Jul-16	866	489	542					**1897**
5-Jul-16	857	306	512					**1675**
6-Jul-16	907	502	468					**1877**
7-Jul-16	1023	569	517					**2109**
8-Jul-16	1126	487	602					**2215**
9-Jul-16	985	401	719					**2105**
10-Jul-16	762	854	793					**2409**
11-Jul-16	843	954	902					**2699**
12-Jul-16	622	589	871					**2082**
13-Jul-16	708	567	622					**1897**
14-Jul-16	943	824	819					**2586**
15-Jul-16	1016	857	1059					**2932**
16-Jul-16	994	615	1003					**2612**
17-Jul-16	845	742	922					**2509**
18-Jul-16	831	702	978					**2511**
19-Jul-16	769	697	1045					**2511**
20-Jul-16	982	759	1164					**2905**
21-Jul-16	1036	845	1055					**2936**
22-Jul-16	1087	836	918					**2841**
23-Jul-16	1124	904	1077					**3105**
24-Jul-16	877	703	1043					**2623**
25-Jul-16	942	845	967					**2754**
26-Jul-16	902	861	1055					**2818**
27-Jul-16	1066	918	1036					**3020**
28-Jul-16	749	823	922					**2494**
29-Jul-16	1028	788	948					**2764**
30-Jul-16	948	719	802					**2469**
31-Jul-16	1003	863	732					**2598**
1-Aug-16	924	912	941					**2777**

Crime Intel Detail - Minutes in the LASER ZONES

2-Aug-16	967	877	1124					**2968**
3-Aug-16	1036	1012	1016					**3064**
4-Aug-16	1018	919	995					**2932**
5-Aug-16	944	807	1056					**2807**
6-Aug-16	902	712	1102					**2716**
7-Aug-16	1072	808	1148					**3028**
8-Aug-16	827	824	1078					**2729**
9-Aug-16	1164	715	978					**2857**
10-Aug-16	1188	749	1066					**3003**
11-Aug-16	1062	926	1164					**3152**
12-Aug-16	952	922	912					**2786**
13-Aug-16	864	1009	938					**2811**
14-Aug-16	1145	852	1078					**3075**
15-Aug-16	1078	914	987					**2979**
16-Aug-16	1069	876	1146					**3091**
17-Aug-16	958	734	902					**2594**
18-Aug-16	994	1016	1064					**3074**
19-Aug-16	1048	812	1066					**2926**
20-Aug-16	1138	916	939					**2993**
21-Aug-16	745	245	435					**1425**
22-Aug-16	815	630	645					**2090**
23-Aug-16	1095	975	685					**2755**
24-Aug-16	687	480	1145					**2312**
25-Aug-16	915	764	245					**1924**
26-Aug-16	1118	615	149					**1882**
27-Aug-16	885	945	887					**2717**
28-Aug-16	1015	816	873					**2704**
29-Aug-16	781	648	821					**2250**
30-Aug-16	828	419	687					**1934**
31-Aug-16	1071	736	849					**2656**
1-Sep-16	829	841	970					**2640**
2-Sep-16	1035	717	1023					**2775**
3-Sep-16	1093	809	942					**2844**

Crime Intel Detail - Minutes in the LASER ZONES

4-Sep-16	969	629	853					**2451**
5-Sep-16	1028	654	947					**2629**
6-Sep-16	1073	733	849					**2655**
7-Sep-16	887	641	826					**2354**
8-Sep-16	1094	737	892					**2723**
9-Sep-16	1149	745	825					**2719**
10-Sep-16	1175	907	803					**2885**
11-Sep-16	731	385	511					**1627**
12-Sep-16	616	346	432					**1394**
13-Sep-16	687	323	475					**1485**
14-Sep-16	722	357	497					**1576**
15-Sep-16	653	349	486					**1488**
16-Sep-16	602	370	443					**1415**
17-Sep-16	714	394	581					**1689**
18-Sep-16	1090	632	825					**2547**
19-Sep-16	921	527	737					**2185**
20-Sep-16	847	533	744					**2124**
21-Sep-16	884	549	769					**2202**
22-Sep-16	751	516	698					**1965**
23-Sep-16	962	524	775					**2261**
24-Sep-16	1103	604	777					**2484**
25-Sep-16	1008	617	679					**2304**
26-Sep-16	764	522	605					**1891**
27-Sep-16	815	536	631					**1982**
28-Sep-16	843	515	624					**1982**
29-Sep-16	859	539	641					**2039**
30-Sep-16	878	518	653					**2049**
1-Oct-16	921	547	670					**2138**
2-Oct-16	867	526	833					**2226**
3-Oct-16	782	485	751					**2018**
4-Oct-16	775	481	717					**1973**
5-Oct-16	792	477	722					**1991**
6-Oct-16	780	489	708					**1977**

Crime Intel Detail - Minutes in the LASER ZONES

7-Oct-16	796	452	703					**1951**
8-Oct-16	884	486	744					**2114**
9-Oct-16	815	424	655					**1894**
10-Oct-16	731	347	543					**1621**
11-Oct-16	743	362	579					**1684**
12-Oct-16	750	365	586					**1701**
13-Oct-16	718	359	577					**1654**
14-Oct-16	733	351	585					**1669**
15-Oct-16	738	485	615					**1838**
16-Oct-16	512	493	351					**1356**
17-Oct-16	461	466	326					**1253**
18-Oct-16	457	453	317					**1227**
19-Oct-16	464	449	332					**1245**
20-Oct-16	478	442	324					**1244**
21-Oct-16	469	464	331					**1264**
22-Oct-16	615	598	379					**1592**
23-Oct-16	810	715	795					**2320**
24-Oct-16	756	590	652					**1998**
25-Oct-16	739	581	669					**1989**
26-Oct-16	777	563	694					**2034**
27-Oct-16	763	589	688					**2040**
28-Oct-16	742	606	691					**2039**
29-Oct-16	884	625	834					**2343**
30-Oct-16								**0**
31-Oct-16								**0**
1-Nov-16								**0**
2-Nov-16								**0**
3-Nov-16								**0**
4-Nov-16								**0**
5-Nov-16								**0**
6-Nov-16								**0**
7-Nov-16								**0**
8-Nov-16								**0**

Crime Intel Detail - Minutes in the LASER ZONES

9-Nov-16								**0**
10-Nov-16								**0**
11-Nov-16								**0**
12-Nov-16								**0**
13-Nov-16								**0**
14-Nov-16								**0**
15-Nov-16								**0**
16-Nov-16								**0**
17-Nov-16								**0**
18-Nov-16								**0**
19-Nov-16								**0**
20-Nov-16								**0**
21-Nov-16								**0**
22-Nov-16								**0**
23-Nov-16								**0**
24-Nov-16								**0**
25-Nov-16								**0**
26-Nov-16								**0**
27-Nov-16								**0**
28-Nov-16								**0**
29-Nov-16								**0**
30-Nov-16								**0**
1-Dec-16								**0**
2-Dec-16								**0**
3-Dec-16								**0**
4-Dec-16								**0**
5-Dec-16								**0**
6-Dec-16								**0**
7-Dec-16								**0**
8-Dec-16								**0**
9-Dec-16								**0**
10-Dec-16								**0**
11-Dec-16								**0**

Crime Intel Detail - Minutes in the LASER ZONES

12-Dec-16								**0**
13-Dec-16								**0**
14-Dec-16								**0**
15-Dec-16								**0**
16-Dec-16								**0**
17-Dec-16								**0**
18-Dec-16								**0**
19-Dec-16								**0**
20-Dec-16								**0**
21-Dec-16								**0**
22-Dec-16								**0**
23-Dec-16								**0**
24-Dec-16								**0**
25-Dec-16								**0**
26-Dec-16								**0**
27-Dec-16								**0**
28-Dec-16								**0**
29-Dec-16								**0**
30-Dec-16								**0**
31-Dec-16								**0**
1-Jan-17								**0**
2-Jan-17								**0**
3-Jan-17								**0**
4-Jan-17								**0**
5-Jan-17								**0**
6-Jan-17								**0**
7-Jan-17								**0**
8-Jan-17								**0**
9-Jan-17								**0**
10-Jan-17								**0**
11-Jan-17								**0**
12-Jan-17								**0**
13-Jan-17								**0**

Crime Intel Detail - Minutes in the LASER ZONES

14-Jan-17								**0**
15-Jan-17								**0**
16-Jan-17								**0**

Crime Intel Detail - Minutes in the LASER ZONES

		HOLLENBECK-Minutes in the LASER Zones							
DP	DATE	LASER Zone 1	LASER Zone 2	LASER Zone 3	LASER Zone 4	LASER Zone 5	LASER Zone 6	LASER Zone 7	TOTAL
	28-Feb-16	0	0	0					**0**
	29-Feb-16	210	58	233					**501**
	1-Mar-16	112	454	90					**656**
	2-Mar-16	97	380	3701					**4178**
	3-Mar-16	211	447	150					**808**
	4-Mar-16	59	64	29					**152**
	5-Mar-16	16	0	8					**24**
	6-Mar-16	94	52	100					**246**
	7-Mar-16	140	353	490					**983**
	8-Mar-16	155	377	35					**567**
	9-Mar-16	691	163	345					**1199**
	10-Mar-16	427	481	453					**1361**
	11-Mar-16	635	249	330					**1214**
	12-Mar-16	585	58	156					**799**
	13-Mar-16	899	517	978					**2394**
	14-Mar-16	400	441	63					**904**
	15-Mar-16	690	140	265					**1095**
	16-Mar-16	645	360	198					**1203**
	17-Mar-16	134	87	201					**422**
	18-Mar-16	74	186	200					**460**
	19-Mar-16	26	159	50					**235**
	20-Mar-16	944	121	463					**1528**
	21-Mar-16	174	344	383					**901**
	22-Mar-16	284	215	167					**666**
	23-Mar-16	351	116	90					**557**
	24-Mar-16	334	57	198					**589**
	25-Mar-16	1060	254	254					**1568**
	26-Mar-16	504	228	447					**1179**
	TOTAL					0			0

Crime Intel Detail - Minutes in the LASER ZONES

									0
	27-Mar-16	241	142	137					**520**
	28-Mar-16	280	380	100					**760**
	29-Mar-16	423	265	620					**1308**
	30-Mar-16	447	510	516					**1473**
	31-Mar-16	451	490	248					**1189**
	1-Apr-16	985	449	105					**1539**
	2-Apr-16	1344	255	441					**2040**
	3-Apr-16	253	57	510					**820**
	4-Apr-16	200	205	0					**405**
	5-Apr-16	250	206	415					**871**
	6-Apr-16	340	10	260					**610**
	7-Apr-16	545	175	75					**795**
	8-Apr-16	110	265	75					**450**
	9-Apr-16	810	233	30					**1073**
	10-Apr-16	339	319	45					**703**
	11-Apr-16	106	360	470					**936**
	12-Apr-16	315	30	20					**365**
	13-Apr-16	330	20	460					**810**
	14-Apr-16	270	59	45					**374**
	15-Apr-16	61	211	75					**347**
	16-Apr-16	120	105	140					**365**
	17-Apr-16	253	57	510					**820**
	18-Apr-16	200	205	0					**405**
	19-Apr-16	250	206	415					**871**
	20-Apr-16	340	10	260					**610**
	21-Apr-16	545	175	75					**795**
	22-Apr-16	110	265	75					**450**
	TOTAL					0	0	0	21704

Crime Intel Detail - Minutes in the LASER ZONES

23-Apr-16	810	233	30					**1073**
24-Apr-16	339	319	45					**703**
25-Apr-16	106	360	470					**936**
26-Apr-16	315	30	20					**365**
27-Apr-16	330	20	460					**810**
28-Apr-16	270	59	45					**374**
29-Apr-16	61	211	75					**347**
30-Apr-16	120	105	140					**365**
1-May-16	427	787	596					**1810**
2-May-16	298	80	303					**681**
3-May-16	37	90	124					**251**
4-May-16	35	92	328					**455**
5-May-16	30	59	40					**129**
6-May-16	115	487	128					**730**
7-May-16	23	69	92					**184**
8-May-16	324	102	74					**500**
9-May-16	79	180	87					**346**
10-May-16	128	735	12					**875**
11-May-16	285	37	273					**595**
12-May-16	309	25	120					**454**
13-May-16	111	60	31					**202**
14-May-16	71	96	0					**167**
15-May-16	507	457	168					**1132**
16-May-16	147	569	242					**958**
17-May-16	249	276	167					**692**
18-May-16	330	723	706					**1759**
19-May-16	285	1056	121					**1462**
20-May-16	0	175	65					**240**
21-May-16	178	323	612					**1113**
								0
								0
								0
								0

Crime Intel Detail - Minutes in the LASER ZONES

22-May-16	913	223	370					**1506**
23-May-16	166	96	425					**687**
24-May-16	233	378	282					**893**
25-May-16	561	97	28					**686**
26-May-16	130	85	333					**548**
27-May-16	63	86	481					**630**
28-May-16	334	48	95					**477**
29-May-16	394	281	14					**689**
30-May-16	799	403	105					**1307**
31-May-16	1628	224	85					**1937**
1-Jun-16	536	480	643					**1659**
2-Jun-16	1922	590	866					**3378**
3-Jun-16	798	651	500					**1949**
4-Jun-16	588	196	1403					**2187**
5-Jun-16	614	184	686					**1484**
6-Jun-16	1092	279	805					**2176**
7-Jun-16	1833	136	1037					**3006**
8-Jun-16	1228	517	305					**2050**
9-Jun-16	851	403	864					**2118**
10-Jun-16	1473	632	496					**2601**
11-Jun-16	825	577	1229					**2631**
12-Jun-16	842	470	283					**1595**
13-Jun-16	857	11	17					**885**
14-Jun-16	2132	633	996					**3761**
15-Jun-16	868	1036	1107					**3011**
16-Jun-16	439	326	652					**1417**
17-Jun-16	1132	1078	889					**3099**
18-Jun-16	1827	693	675					**3195**
19-Jun-16	1027	151	346					**1524**
20-Jun-16	782	354	730					**1866**
21-Jun-16	634	444	1811					**2889**
22-Jun-16	845	660	603					**2108**
23-Jun-16	684	1249	1067					**3000**

Crime Intel Detail - Minutes in the LASER ZONES

24-Jun-16	283	543	1364					**2190**
25-Jun-16	2257	581	813					**3651**
26-Jun-16	868	83	283					**1234**
27-Jun-16	1156	1292	243					**2691**
28-Jun-16	372	48	418					**838**
29-Jun-16	509	389	616					**1514**
30-Jun-16	1136	628	909					**2673**
1-Jul-16	2606	693	511					**3810**
2-Jul-16	1712	333	477					**2522**
3-Jul-16	**1359**	**471**	**230**					**2060**
4-Jul-16	**1387**	**200**	**559**					**2146**
5-Jul-16	**1026**	**103**	**160**					**1289**
6-Jul-16	**499**	**667**	**473**					**1639**
7-Jul-16	**509**	**493**	**502**					**1504**
8-Jul-16	**1732**	**61**	**707**					**2500**
9-Jul-16	**1556**	**384**	**622**					**2562**
10-Jul-16	**408**	**71**	**1312**					**1791**
11-Jul-16	**633**	**2552**	**36**					**3221**
12-Jul-16	**686**	**584**	**65**					**1335**
13-Jul-16	**3264**	**217**	**1244**					**4725**
14-Jul-16	**5452**	**804**	**1211**					**7467**
15-Jul-16	**1245**	**292**	**598**					**2135**
16-Jul-16	**1019**	**474**	**617**					**2110**
17-Jul-16	**817**	**315**	**88**					**1220**
18-Jul-16	**1129**	**373**	**127**					**1629**
19-Jul-16	**1188**	**1433**	**424**					**3045**
20-Jul-16	**1158**	**1115**	**641**					**2914**
21-Jul-16	**817**	**1164**	**199**					**2180**
22-Jul-16	**1**	**0**	**41**					**42**
23-Jul-16	**192**	**15**	**277**					**484**
24-Jul-16	**460**	**45**	**242**					**747**
25-Jul-16	**547**	**30**	**278**					**855**
26-Jul-16	**569**	**23**	**5**					**597**

Crime Intel Detail - Minutes in the LASER ZONES

27-Jul-16	362	0	596					958
28-Jul-16	7	0	203					210
29-Jul-16	1519	1331	283					3133
30-Jul-16	505	1201	403					2109
31-Jul-16	350	365	0					715
1-Aug-16	351	366	1					718
2-Aug-16	347	202	342					891
3-Aug-16	415	677	352					1444
4-Aug-16	694	284	336					1314
5-Aug-16	720	102	109					931
6-Aug-16	567	56	0					623
7-Aug-16	1879	505	1028					3412
8-Aug-16	1010	1052	139					2201
9-Aug-16	7397	1097	616					9110
10-Aug-16	2740	1216	1075					5031
11-Aug-16	1520	815	841					3176
12-Aug-16	1460	479	440					2379
13-Aug-16	1059	221	157					1437
14-Aug-16	390	658	439					1487
15-Aug-16	467	606	449					1522
16-Aug-16	647	419	605					1671
17-Aug-16	1602	702	619					2923
18-Aug-16	1358	614	478					2450
19-Aug-16	2036	578	262					2876
20-Aug-16	1229	311	888					2428
21-Aug-16	867	398	815					2080
22-Aug-16	563	221	171					955
23-Aug-16	410	1292	1118					2820
24-Aug-16	338	44	168					550
25-Aug-16	1270	167	0					1437
26-Aug-16	1004	45	316					1365
27-Aug-16	1211	407	250					1868
28-Aug-16	880	353	737					1970

Crime Intel Detail - Minutes in the LASER ZONES

29-Aug-16	**664**	**445**	**514**					**1623**
30-Aug-16	**586**	**400**	**353**					**1339**
31-Aug-16	**1018**	**319**	**159**					**1496**
1-Sep-16	**727**	**1019**	**410**					**2156**
2-Sep-16	**746**	**228**	**425**					**1399**
3-Sep-16	**663**	**247**	**504**					**1414**
4-Sep-16	**715**	**186**	**368**					**1269**
5-Sep-16	**476**	**325**	**659**					**1460**
6-Sep-16	**440**	**140**	**555**					**1135**
7-Sep-16	**550**	**567**	**155**					**1272**
8-Sep-16	**1121**	**508**	**92**					**1721**
9-Sep-16	**948**	**650**	**333**					**1931**
10-Sep-16	**591**	**524**	**934**					**2049**
11-Sep-16	**200**	**523**	**712**					**1435**
12-Sep-16	**830**	**181**	**632**					**1643**
13-Sep-16	**410**	**371**	**318**					**1099**
14-Sep-16	**2110**	**454**	**491**					**3055**
15-Sep-16	**1864**	**583**	**712**					**3159**
16-Sep-16	**750**	**194**	**129**					**1073**
17-Sep-16	**332**	**200**	**686**					**1218**
18-Sep-16	**593**	**201**	**355**					**1149**
19-Sep-16	**492**	**73**	**338**					**903**
20-Sep-16	**602**	**210**	**627**					**1439**
21-Sep-16	**1918**	**799**	**378**					**3095**
22-Sep-16	**1034**	**1004**	**1065**					**3103**
23-Sep-16	**829**	**113**	**446**					**1388**
24-Sep-16	**633**	**250**	**325**					**1208**
25-Sep-16	139	416	300					**855**
26-Sep-16	641	79	508					**1228**
27-Sep-16	217	380	308					**905**
28-Sep-16	211	591	448					**1250**
29-Sep-16	401	394	509					**1304**
30-Sep-16	666	958	452					**2076**

Crime Intel Detail - Minutes in the LASER ZONES

1-Oct-16	922	1610	331					**2863**
2-Oct-16	558	295	311					**1164**
3-Oct-16	463	182	262					**907**
4-Oct-16	753	474	590					**1817**
5-Oct-16	764	228	979					**1971**
6-Oct-16	506	359	607					**1472**
7-Oct-16	964	661	440					**2065**
8-Oct-16	474	295	703					**1472**
9-Oct-16	1077	725	491					**2293**
10-Oct-16	620	168	533					**1321**
11-Oct-16	304	665	368					**1337**
12-Oct-16	799	841	497					**2137**
13-Oct-16	666	1042	155					**1863**
14-Oct-16	1276	479	1009					**2764**
15-Oct-16	591	363	579					**1533**
16-Oct-16	1190	297	542					**2029**
17-Oct-16	601	191	776					**1568**
18-Oct-16	664	187	317					**1168**
19-Oct-16	903	361	545					**1809**
20-Oct-16	686	304	61					**1051**
21-Oct-16	1245	490	465					**2200**
22-Oct-16	200	210	310					**720**
23-Oct-16	297	139	136					**572**
24-Oct-16	275	415	465					**1155**
25-Oct-16	416	233	356					**1005**
26-Oct-16	701	599	650					**1950**
27-Oct-16	666	171	586					**1423**
28-Oct-16	655	68	259					**982**
29-Oct-16	710	420	246					**1376**
30-Oct-16								**0**
31-Oct-16								**0**
1-Nov-16								**0**

Crime Intel Detail - Minutes in the LASER ZONES

		HARBOR-Minutes in the LASER Zones							
DP	DATE	LASER Zone 1	LASER Zone 2	LASER Zone 3	LASER Zone 4	LASER Zone 5	LASER Zone 6	LASER Zone 7	TOTAL
	28-Feb-16								**0**
	29-Feb-16								**0**
	1-Mar-16								**0**
	2-Mar-16								**0**
	3-Mar-16								**0**
	4-Mar-16								**0**
	5-Mar-16								**0**
	6-Mar-16								**0**
	7-Mar-16								**0**
	8-Mar-16								**0**
	9-Mar-16								**0**
	10-Mar-16								**0**
	11-Mar-16								**0**
	12-Mar-16								**0**
	13-Mar-16								**0**
	14-Mar-16								**0**
	15-Mar-16								**0**
	16-Mar-16								**0**
	17-Mar-16								**0**
	18-Mar-16								**0**
	19-Mar-16								**0**
	20-Mar-16	17	67	81					**165**
	21-Mar-16	0	307	11					**318**
	22-Mar-16	174	57	139					**370**
	23-Mar-16	24	127	30					**181**
	24-Mar-16	25	100	9					**134**
	25-Mar-16	55	210	85					**350**
	26-Mar-16	74	164	87					**325**
	TOTAL					0			0

Crime Intel Detail - Minutes in the LASER ZONES

									0
	27-Mar-16	117	104	257					**478**
	28-Mar-16	5	41	31					**77**
	29-Mar-16	302	74	369					**745**
	30-Mar-16	14	411	105					**530**
	31-Mar-16	132	173	60					**365**
	1-Apr-16	158	458	267					**883**
	2-Apr-16	274	783	273					**1330**
	3-Apr-16	14	145	140					**299**
	4-Apr-16	131	70	77					**278**
	5-Apr-16	2	85	64					**151**
	6-Apr-16	235	237	139					**611**
	7-Apr-16	13	135	104					**252**
	8-Apr-16	141	43	110					**294**
	9-Apr-16	247	267	142					**656**
	10-Apr-16	278	303	213					**794**
	11-Apr-16	69	464	466					**999**
	12-Apr-16	91	190	69					**350**
	13-Apr-16	43	180	419					**642**
	14-Apr-16	187	83	348					**618**
	15-Apr-16	165	161	253					**579**
	16-Apr-16	15	120	65					**200**
	17-Apr-16	0	261	109					**370**
	18-Apr-16	217	119	235					**571**
	19-Apr-16	171	148	134					**453**
	20-Apr-16	9	312	61					**382**
	21-Apr-16	280	238	210					**728**
	22-Apr-16	209	0	150					**359**
	23-Apr-16	142	162	42					**346**
	TOTAL					0	0	0	13994

Crime Intel Detail - Minutes in the LASER ZONES

24-Apr-16	246	448	557					**1251**
25-Apr-16	104	571	16					**691**
26-Apr-16	24	113	2					**139**
27-Apr-16	87	38	146					**271**
28-Apr-16	351	206	280					**837**
29-Apr-16	278	555	55					**888**
30-Apr-16	13	289	9					**311**
1-May-16	1040	892	171					**2103**
2-May-16	196	312	156					**664**
3-May-16	41	158	103					**302**
4-May-16	76	142	190					**408**
5-May-16	254	96	118					**468**
6-May-16	92	148	52					**292**
7-May-16	178	51	180					**409**
8-May-16	0	46	23					**69**
9-May-16	0	112	141					**253**
10-May-16	370	429	342					**1141**
11-May-16	62	372	50					**484**
12-May-16	116	22	17					**155**
13-May-16	227	438	268					**933**
14-May-16	52	225	165					**442**
15-May-16	0	134	19					**153**
16-May-16	117	197	200					**514**
17-May-16	52	84	0					**136**
18-May-16	60	282	332					**674**
19-May-16	56	208	44					**308**
20-May-16	226	402	218					**846**
21-May-16	120	273	79					**472**
								0
								0
								0
								0
								0

Crime Intel Detail - Minutes in the LASER ZONES

22-May-16	86	203	73					**362**
23-May-16	0	44	53					**97**
24-May-16	0	0	298					**298**
25-May-16	107	168	91					**366**
26-May-16	31	10	22					**63**
27-May-16	128	265	123					**516**
28-May-16	11	95	59					**165**
29-May-16	190	313	810					**1313**
30-May-16	174	364	73					**611**
31-May-16	168	217	14					**399**
1-Jun-16	72	148	16					**236**
2-Jun-16	0	50	0					**50**
3-Jun-16	51	98	62					**211**
4-Jun-16	323	20	118					**461**
5-Jun-16	414	64	65					**543**
6-Jun-16	0	113	79					**192**
7-Jun-16	97	41	81					**219**
8-Jun-16	0	19	67					**86**
9-Jun-16	236	204	22					**462**
10-Jun-16	59	127	49					**235**
11-Jun-16	86	110	392					**588**
12-Jun-16	9	38	25					**72**
13-Jun-16	68	42	41					**151**
14-Jun-16	90	379	248					**717**
15-Jun-16	30	350	237					**617**
16-Jun-16	9	102	242					**353**
17-Jun-16	0	40	5					**45**
18-Jun-16	146	194	11					**351**
19-Jun-16	46	3	39					**88**
20-Jun-16	125	0	11					**136**
21-Jun-16	99	350	327					**776**
22-Jun-16	50	72	212					**334**
23-Jun-16	106	13	19					**138**

Crime Intel Detail - Minutes in the LASER ZONES

24-Jun-16	157	145	109					**411**
25-Jun-16	231	456	203					**890**
26-Jun-16	6	326	182					**514**
27-Jun-16	61	152	5					**218**
28-Jun-16	0	108	107					**215**
29-Jun-16	58	144	258					**460**
30-Jun-16	66	30	0					**96**
1-Jul-16	116	267	145					**528**
2-Jul-16	18	244	191					**453**
3-Jul-16	183	357	255					**795**
4-Jul-16	515	579	575					**1669**
5-Jul-16	102	38	65					**205**
6-Jul-16	54	15	120					**189**
7-Jul-16	84	57	37					**178**
8-Jul-16	47	267	94					**408**
9-Jul-16	2	83	0					**85**
10-Jul-16	50	111	40					**201**
11-Jul-16	0	369	148					**517**
12-Jul-16	124	49	40					**213**
13-Jul-16	0	50	134					**184**
14-Jul-16	42	8	91					**141**
15-Jul-16	44	169	61					**274**
16-Jul-16	10	257	57					**324**
17-Jul-16	59	209	97					**365**
18-Jul-16	8	183	112					**303**
19-Jul-16	50	196	287					**533**
20-Jul-16	62	73						**135**
21-Jul-16	35	81	134					**250**
22-Jul-16	128	23	146					**297**
23-Jul-16	158	58	509					**725**
24-Jul-16	17	306	192					**515**
25-Jul-16	0	30	296					**326**
26-Jul-16	0	22	0					**22**

Crime Intel Detail - Minutes in the LASER ZONES

27-Jul-16	173	361	209					**743**
28-Jul-16	77	260	190					**527**
29-Jul-16	0	32	92					**124**
30-Jul-16	0	119	33					**152**
31-Jul-16	38	55	30					**123**
1-Aug-16	147	105	129					**381**
2-Aug-16	100	134	10					**244**
3-Aug-16	147	116	263					**526**
4-Aug-16	176	438	50					**664**
5-Aug-16	11	75	141					**227**
6-Aug-16	0	0	0					**0**
7-Aug-16	138	358	232					**728**
8-Aug-16	27	573	115					**715**
9-Aug-16	43	66	140					**249**
10-Aug-16	67	163	126					**356**
11-Aug-16	165	707	52					**924**
12-Aug-16	93	380	157					**630**
13-Aug-16	149	429	295					**873**
14-Aug-16	166	210	66					**442**
15-Aug-16	37	174	31					**242**
16-Aug-16	51	3	12					**66**
17-Aug-16	64	104	48					**216**
18-Aug-16	158	217	65					**440**
19-Aug-16	100	207	43					**350**
20-Aug-16	110	119	28					**257**
21-Aug-16	74	261	65					**400**
22-Aug-16	34	124	99					**257**
23-Aug-16	79	4	47					**130**
24-Aug-16	132	568	188					**888**
25-Aug-16	161	99	202					**462**
26-Aug-16	255	415	229					**899**
27-Aug-16	141	379	132					**652**
28-Aug-16	424	365	466					**1255**

Crime Intel Detail - Minutes in the LASER ZONES

29-Aug-16	89	96	30				**215**
30-Aug-16	151	556	76				**783**
31-Aug-16	417	212	166				**795**
1-Sep-16	163	213	145				**521**
2-Sep-16	48	211	240				**499**
3-Sep-16	46	166	41				**253**
4-Sep-16	175	173	91				**439**
5-Sep-16	192	615	658				**1465**
6-Sep-16	60	126	153				**339**
7-Sep-16	115	198	115				**428**
8-Sep-16	133	193	343				**669**
9-Sep-16	254	71	312				**637**
10-Sep-16	410	1	619				**1030**
11-Sep-16	292	342	364				**998**
12-Sep-16	121	36	76				**233**
13-Sep-16	118	136	37				**291**
14-Sep-16	103	357	177				**637**
15-Sep-16	0	207	0				**207**
16-Sep-16	10	0	24				**34**
17-Sep-16	242	130	232				**604**
18-Sep-16	94	91	177				**362**
19-Sep-16	0	59	140				**199**
20-Sep-16	0	0	55				**55**
21-Sep-16	135	21	156				**312**
22-Sep-16	154	131	131				**416**
23-Sep-16	246	61	238				**545**
24-Sep-16	289	351	281				**921**
25-Sep-16	32	303	0				**335**
26-Sep-16	0	67	0				**67**
27-Sep-16	15	69	18				**102**
28-Sep-16	24	146	82				**252**
29-Sep-16	8	36	0				**44**
30-Sep-16	13	239	22				**274**

Crime Intel Detail - Minutes in the LASER ZONES

1-Oct-16	147	367	97					**611**
2-Oct-16	0	26	94					**120**
3-Oct-16	76	58	29					**163**
4-Oct-16	0	67	0					**67**
5-Oct-16	116	100	27					**243**
6-Oct-16	100	10	50					**160**
7-Oct-16	43	43	293					**379**
8-Oct-16	92	0	37					**129**
9-Oct-16	7	33	59					**99**
10-Oct-16	92	19	157					**268**
11-Oct-16	818	126	81					**1025**
12-Oct-16	281	116	0					**397**
13-Oct-16	101	0	234					**335**
14-Oct-16	263	196	59					**518**
15-Oct-16	56	121	77					**254**
16-Oct-16	98	59	189					**346**
17-Oct-16	2	25	0					**27**
18-Oct-16	7	32	58					**97**
19-Oct-16	30	8	122					**160**
20-Oct-16	0	75	0					**75**
21-Oct-16	98	0	25					**123**
22-Oct-16	53	31	66					**150**
23-Oct-16	90	227	0					**317**
24-Oct-16	10	9	3					**22**
25-Oct-16	8	20	0					**28**
26-Oct-16	0	116	0					**116**
27-Oct-16	35	71	24					**130**
28-Oct-16	9	1	0					**10**
29-Oct-16	53	34	9					**96**
30-Oct-16								**0**
31-Oct-16								**0**
1-Nov-16								**0**
2-Nov-16								**0**

Crime Intel Detail - Minutes in the LASER ZONES

3-Nov-16									**0**
4-Nov-16									**0**
5-Nov-16									**0**
6-Nov-16									**0**
7-Nov-16									**0**
8-Nov-16									**0**
9-Nov-16									**0**
10-Nov-16									**0**
11-Nov-16									**0**
12-Nov-16									**0**
13-Nov-16									**0**
14-Nov-16									**0**
15-Nov-16									**0**

Crime Intel Detail - Minutes in the LASER ZONES

		NEWTON-Minutes in the LASER Zones							
DP	**DATE**	**LASER Zone 1**	**LASER Zone 2A**	**LASER Zone 2B**	**LASER Zone 3**	**LASER Zone 4**	**LASER Zone 6**	**LASER Zone 7**	**TOTAL**
DP 8	26-Jul-15	0	0	0	0	0			**0**
	27-Jul-15	250	260	220	340	110			**1180**
	28-Jul-15	190	195	155	60	50			**650**
	29-Jul-15	0	45		30	30			**105**
	30-Jul-15	180	170	55	295	65			**765**
	31-Jul-15	268	310	260	183	375			**1396**
	1-Aug-15	415	420	330	330	525			**2020**
	2-Aug-15	90	220	160	130	0			**600**
	3-Aug-15	0	0	0	0	0			**0**
	4-Aug-15	0	395	305	205	135			**1040**
	5-Aug-15	115	175	30	115	220			**655**
	6-Aug-15	210	530	500	180	140			**1560**
	7-Aug-15	70	440	455	110	60			**1135**
	8-Aug-15	0	95	70	130	105			**400**
DP 9	9-Aug-15	0	0	0	0	0			**0**
	10-Aug-15	45	20	20	0	0			**85**
	11-Aug-15	0	0	0	0	0			**0**
	12-Aug-15	0	0	0	0	0			**0**
	13-Aug-15	40	175	140	255	120			**730**
	14-Aug-15	0	0	0	0	0			**0**
	15-Aug-15	0	0	120	0	0			**120**
	16-Aug-15	0	0	0	0	0			**0**
	17-Aug-15	0	0	0	0	0			**0**
	18-Aug-15	0	30	30	30	0			**90**
	19-Aug-15	0	230	250	40	0			**520**
	20-Aug-15	0	0	240	30	75			**345**
	21-Aug-15	175	97	95	0	75			**442**
	22-Aug-15	0	0	0	0	0			**0**
	TOTAL	2048	3807	3435	2463	2085	0	0	13838

Crime Intel Detail - Minutes in the LASER ZONES

	23-Aug-15	0	0	0	0	0			**0**
	24-Aug-15	0	0	0	0	0			**0**
	25-Aug-15	0	200	0	0	0			**200**
	26-Aug-15	126	24	0	60	30			**240**
	27-Aug-15	0	20	600	0	0			**620**
	28-Aug-15	495	310	185	280	90			**1360**
	29-Aug-15	500	0	0	180	215			**895**
	30-Aug-15	60	82	100	0	0			**242**
	31-Aug-15	180	0	0	0	60			**240**
	1-Sep-15	180	90	0	100	100			**470**
	2-Sep-15	0	180	240	0	0			**420**
	3-Sep-15	120	655	60	90	400			**1325**
	4-Sep-15	285	45	520	45	110			**1005**
	5-Sep-15	0	480	170	0	320			**970**
DP 10	6-Sep-15	90	0	25	30	0			**145**
	7-Sep-15	0	30	30	150	0			**210**
	8-Sep-15	0	0	0	0	0			**0**
	9-Sep-15	338	261	101	392	274			**1366**
	10-Sep-15	220	145	165	265	120			**915**
	11-Sep-15	140	150	140	564	60			**1054**
	12-Sep-15	0	110	15	20	40			**185**
	13-Sep-15	20	60	555	0	35			**670**
	14-Sep-15	285	250	90	0	0			**625**
	15-Sep-15	0	45	235	30	20			**330**
	16-Sep-15	210	115	40	395	430			**1190**
	17-Sep-15	355	90	240	400	280			**1365**
	18-Sep-15	530	210	200	213	180			**1333**
	19-Sep-15	145	0	73	120	44			**382**
	TOTAL	4279	3552	3784	3334	2808	0	0	17757

Crime Intel Detail - Minutes in the LASER ZONES

20-Sep-15	330	440	120	125	150			**1165**
21-Sep-15	0	315	285	80	75			**755**
22-Sep-15	360	385	135	190	90			**1160**
23-Sep-15	276	1269	105	865	293			**2808**
24-Sep-15	780	380	480	310	550			**2500**
25-Sep-15	599	220	435	260	230			**1744**
26-Sep-15	0	0	0	0	0			**0**
27-Sep-15	15	25	30	0	181			**251**
28-Sep-15	370	720	545	385	560			**2580**
29-Sep-15	120	180	120	380	195			**995**
30-Sep-15	390	180	300	350	135			**1355**
1-Oct-15	240	20	0	90	350			**700**
2-Oct-15	480	25	0	90	0			**595**
3-Oct-15	0	0	0	0	0			**0**
4-Oct-15	420	330	330	60	210			**1350**
5-Oct-15	590	490	330	85	210			**1705**
6-Oct-15	420	330	330	60	210			**1350**
7-Oct-15	595	280	170	90	390			**1525**
8-Oct-15	290	125	100	95	195			**805**
9-Oct-15	45	0	0	0	45			**90**
10-Oct-15	55	0	60	0	39			**154**
11-Oct-15	420	330	330	60	210			**1350**
12-Oct-15	340	340	340	340	340			**1700**
13-Oct-15	442	372	372	372	372			**1930**
14-Oct-15	55	0	0	0	90			**145**
15-Oct-15	135	120	0	0	540			**795**
16-Oct-15	0	550	560	0	990			**2100**
17-Oct-15	60	380	400	240	695			**1775**
18-Oct-15	85	0	0	0	0			**85**
19-Oct-15	0	85	0	0	0			**85**
20-Oct-15	90	10	86	15	20			**221**
21-Oct-15	90	160	310	146	420			**1126**
22-Oct-15	20	105	100	120	266			**611**

Crime Intel Detail - Minutes in the LASER ZONES

23-Oct-15	60	290	180	80	355			**965**
24-Oct-15	50	70	30	60	0			**210**
25-Oct-15	90	0	0	0	90			**180**
26-Oct-15		20	0	0	0			**20**
27-Oct-15	100	120	0	100	200			**520**
28-Oct-15	180	0	0	220	100			**500**
29-Oct-15	0	0	0	200	0			**200**
30-Oct-15	300	0	0	0	0			**300**
31-Oct-15	210	60	60	30	30			**390**
1-Nov-15	0	0	0	0	0			**0**
2-Nov-15	0	0	0	0	0			**0**
3-Nov-15	0	0	0	0	0			**0**
4-Nov-15	0	0	0	960	720			**1680**
5-Nov-15	90	145	100	200	210			**745**
6-Nov-15	100	0	0	1320	860			**2280**
7-Nov-15	0	0	0	350	400			**750**
8-Nov-15	60	75	160	290	90			**675**
9-Nov-15	313	30	0	0	60			**403**
10-Nov-15	60	90	25	205	205			**585**
11-Nov-15	325	415	110	790	930			**2570**
12-Nov-15	275	480	0	190	460			**1405**
13-Nov-15	160	455	20	560	695			**1890**
14-Nov-15	325	0	40	645	670			**1680**
15-Nov-15	0	0	0	0	0			**0**
16-Nov-15	0	0	0	0	0			**0**
17-Nov-15	120	60	90	320	330			**920**
18-Nov-15	0	190	100	440	200			**930**
19-Nov-15	265	60	0	120	420			**865**
20-Nov-15	0	60	60	90	80			**290**
21-Nov-15	0	0	0	0	0			**0**
22-Nov-15	0	0	0	400	100			**500**
23-Nov-15	0	0	0	30	360			**390**
24-Nov-15	120	60	30	120	90			**420**

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25-Nov-15	0	0	0	0	0			**0**
26-Nov-15	0	0	0	0	0			**0**
27-Nov-15	0	0	0	0	0			**0**
28-Nov-15	0	0	0	0	0			**0**
29-Nov-15	90	150	80	60	60			**440**
30-Nov-15	0	0	0	35	45			**80**
1-Dec-15	0	0	0	0	0			**0**
2-Dec-15	0	100	0	120	120			**340**
3-Dec-15	60	60	60	240	360			**780**
4-Dec-15	90	210	80	420	360			**1160**
5-Dec-15	45	50	60	290	275			**720**
6-Dec-15	0	0	0	0	0			**0**
7-Dec-15	0	0	0		0			**0**
8-Dec-15	0		0	260	120			**380**
9-Dec-15	180	120	0	120	60			**480**
10-Dec-15	60	0	60	180	180			**480**
11-Dec-15	60	0	0	240	120			**420**
12-Dec-15	120	0	0	240	180			**540**
13-Dec-15	120	60	0	50	30			**260**
14-Dec-15	45	60	0	70	82			**257**
15-Dec-15	60	0	0	60	60			**180**
16-Dec-15	180	60	60	240	285			**825**
17-Dec-15	60	0	0	180	120			**360**
18-Dec-15	120	0	0	120	180			**420**
19-Dec-15	0	0	0	0	0			**0**
20-Dec-15	0	0	0	0	0			**0**
21-Dec-15	0	0	0	0	60			**60**
22-Dec-15	120	0	0	240	180			**540**
23-Dec-15	120	0	60	120	0			**300**
24-Dec-15	0	0	0	120	180			**300**
25-Dec-15	0	60	60	120	60			**300**

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26-Dec-15	30	25	25	0	30			**110**
27-Dec-15	200	0	0	135	165			**500**
28-Dec-15	100	0	0	200	100			**400**
29-Dec-15	325	30	30	210	480			**1075**
30-Dec-15	120	60	0	60	60			**300**
31-Dec-15	0	420	0	0	0			**420**
1-Jan-16	0	0	0	0	0			**0**
2-Jan-16	0	0	0	0	0			**0**
3-Jan-16	0	0	120	240	180			**540**
4-Jan-16	5	60	210	514	60			**849**
5-Jan-16	510	620	120	740	945			**2935**
6-Jan-16	300	510	130	180	660			**1780**
7-Jan-16	290	225	100	85	660			**1360**
8-Jan-16	0	635	0	420	730			**1785**
9-Jan-16	30	30	30	530	60			**680**
10-Jan-16	145	40	140	40	275			**640**
11-Jan-16	210	90	215	70	135			**720**
12-Jan-16	320	105	180	170	120			**895**
13-Jan-16	180	500	60	420	450			**1610**
14-Jan-16	495	130	40	255	30			**950**
15-Jan-16	65	560	395	390	1125			**2535**
16-Jan-16	495	530	250	240	455			**1970**
17-Jan-16	160	195	235	475	60			**1125**
18-Jan-16	0	60	60	0	0			**120**
19-Jan-16	268	245	370	180	365			**1428**
20-Jan-16	320	480	100	160	30			**1090**
21-Jan-16	180	240	60		120			**600**
22-Jan-16	0	410	80	75	180			**745**
23-Jan-16	45	451	0	85	240			**821**
24-Jan-16	0	0	0	0	0			**0**
25-Jan-16	0	0	0	0	0			**0**

Crime Intel Detail - Minutes in the LASER ZONES

26-Jan-16	60	40	205	0	0			**305**
27-Jan-16	120		300	0	0			**420**
28-Jan-16	0	110	0	0	0			**110**
29-Jan-16	310	0	200	740	0			**1250**
30-Jan-16	125	70	365	210	0			**770**
31-Jan-16	275	190	585	120				**1170**
1-Feb-16	625	150	495	250				**1520**
2-Feb-16	45	120	660	80				**905**
3-Feb-16	610	0	320	75				**1005**
4-Feb-16	260	0	240	95				**595**
5-Feb-16	220	0	180	0				**400**
6-Feb-16	235	80	925	520				**1760**
7-Feb-16	210	0	165	0				**375**
8-Feb-16	405	60	305	60				**830**
9-Feb-16	410	85	565	430				**1490**
10-Feb-16	410	0	300	0				**710**
11-Feb-16	0	0	245	0				**245**
12-Feb-16	80	0	0	0				**80**
13-Feb-16	120	0	60	0				**180**
14-Feb-16	60	530	300	290				**1180**
15-Feb-16	70	40	40	30				**180**
16-Feb-16	90	165	90	0				**345**
17-Feb-16	220	280	145	145				**790**
18-Feb-16	0	0	0	0				**0**
19-Feb-16	45	30	45	0				**120**
20-Feb-16	0	0	0	0				**0**
21-Feb-16	1042	587	345	144				**2118**
22-Feb-16	78	50	175	140				**443**
23-Feb-16	93	58	40	70				**261**
24-Feb-16	552	479	130	425				**1586**
25-Feb-16	519	299	365	216				**1399**

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26-Feb-16	404	199	448	268				**1319**
27-Feb-16	772	343	344	430				**1889**
28-Feb-16	257	250	209	130				**846**
29-Feb-16	258	185	330	140				**913**
1-Mar-16	271	373	244	50				**938**
2-Mar-16	1075	971	410	202				**2658**
3-Mar-16	657	999	2112	442				**4210**
4-Mar-16	690	820	85	185				**1780**
5-Mar-16	420	310	95	65				**890**
6-Mar-16	480	547	205	105				**1337**
7-Mar-16	578	500	533	337				**1948**
8-Mar-16	15	487	55	90				**647**
9-Mar-16	500	1808	470	573				**3351**
10-Mar-16	543	484	515	220				**1762**
11-Mar-16	190	205	50	155				**600**
12-Mar-16	388	845	186	90				**1509**
13-Mar-16	450	240	285	205				**1180**
14-Mar-16	301	360	205	185				**1051**
15-Mar-16	255	118	180	40				**593**
16-Mar-16	275	160	815	21				**1271**
17-Mar-16	600	370	210	0				**1180**
18-Mar-16	365	680	750	0				**1795**
19-Mar-16	215	252	373	20				**860**
20-Mar-16	238	37	88	0				**363**
21-Mar-16	630	250	395	0				**1275**
22-Mar-16	98	105	159	0				**362**
23-Mar-16	225	462	466	0				**1153**
24-Mar-16	178	407	430	0				**1015**
25-Mar-16	245	375	155	0				**775**
26-Mar-16	190	280	373	0				**843**
								0

Crime Intel Detail - Minutes in the LASER ZONES

DP	DATE	LASER Zone 1	LASER Zone 2	LASER Zone 3					TOTAL
	27-Mar-16	160	255	168					**583**
	28-Mar-16	782	180	105					**1067**
	29-Mar-16	795	371	834					**2000**
	30-Mar-16	889	454	740					**2083**
	31-Mar-16	955	459	440					**1854**
	1-Apr-16	702	345	289					**1336**
	2-Apr-16	420	45	355					**820**
	3-Apr-16	280	167	1458					**1905**
	4-Apr-16	200	475	199					**874**
	5-Apr-16	187	421	120					**728**
	6-Apr-16	354	797	0					**1151**
	7-Apr-16	424	230	430					**1084**
	8-Apr-16	789	525	813					**2127**
	9-Apr-16	587	652	322					**1561**
	10-Apr-16	328	620	228					**1176**
	11-Apr-16	195	220	285					**700**
	12-Apr-16	59	23	88					**170**
	13-Apr-16	328	240	545					**1113**
	14-Apr-16	380	411	350					**1141**
	15-Apr-16	437	112	810					**1359**
	16-Apr-16	112	805	320					**1237**
	17-Apr-16	35	90	150					**275**
	18-Apr-16	15	60	45					**120**
	19-Apr-16	78	93	50					**221**
	20-Apr-16	590	353	740					**1683**
	21-Apr-16	512	335	2414					**3261**
	22-Apr-16	405	338	615					**1358**
	23-Apr-16	650	479	882					**2011**
	24-Apr-16	170	190	185					**545**
	25-Apr-16	200	490	190					**880**

Crime Intel Detail - Minutes in the LASER ZONES

26-Apr-16	420	260	375					**1055**
27-Apr-16	587	60	800					**1447**
28-Apr-16	140	15	1225					**1380**
29-Apr-16	35	570	20					**625**
30-Apr-16	140	40	270					**450**
1-May-16	200	565	190					**955**
2-May-16	30	30	0					**60**
3-May-16	80	273	1490					**1843**
4-May-16	450	470	1455					**2375**
5-May-16	244	436	1341					**2021**
6-May-16	135	215	1130					**1480**
7-May-16	60	405	260					**725**
8-May-16	0	210	220					**430**
9-May-16	55	139	2110					**2304**
10-May-16	155	155	1870					**2180**
11-May-16	522	510	1694					**2726**
12-May-16	377	245	270					**892**
13-May-16	155	75	335					**565**
14-May-16	90	745	60					**895**
15-May-16	19	136	110					**265**
16-May-16	114	287	1686					**2087**
17-May-16	40	230	185					**455**
18-May-16	170	275	1930					**2375**
19-May-16	415	190	1840					**2445**
20-May-16	450	285	320					**1055**
21-May-16	410	190	1604					**2204**
22-May-16	560	190	185					**935**
23-May-16	355	230	1540					**2125**
24-May-16	165	105	820					**1090**
25-May-16	30	25	90					**145**
26-May-16	795	30	2365					**3190**
27-May-16	315	135	1400					**1850**
28-May-16	160	95	1780					**2035**

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29-May-16	140	160	1160					**1460**
30-May-16	155	160	1873					**2188**
31-May-16	450	270	295					**1015**
1-Jun-16	65	90	960					**1115**
2-Jun-16	120	0	630					**750**
3-Jun-16	265	185	970					**1420**
4-Jun-16	40	85	40					**165**
5-Jun-16	120	85	240					**445**
6-Jun-16	35	120	40					**195**
7-Jun-16	160	340	975					**1475**
8-Jun-16	145	245	663					**1053**
9-Jun-16	350	382	350					**1082**
10-Jun-16	200	60	270					**530**
11-Jun-16	300	455	550					**1305**
12-Jun-16	50	270	1380					**1700**
13-Jun-16	245	245	755					**1245**
14-Jun-16	530	140	905					**1575**
15-Jun-16	655	317	1854					**2826**
16-Jun-16	520	270	1006					**1796**
17-Jun-16	60	299	1390					**1749**
18-Jun-16	0	208	1060					**1268**
19-Jun-16	0	320	900					**1220**
20-Jun-16	20	166	290					**476**
21-Jun-16	60	100	345					**505**
22-Jun-16	60	30	210					**300**
23-Jun-16	280	0	1920					**2200**
24-Jun-16	90	60	220					**370**
25-Jun-16	0	0	0					**0**
26-Jun-16	210	126	135					**471**
27-Jun-16	50	165	285					**500**
28-Jun-16	0	65	1025					**1090**
29-Jun-16	110	20	0					**130**
30-Jun-16	335	210	445					**990**

Crime Intel Detail - Minutes in the LASER ZONES

1-Jul-16	303	60	550					**913**
2-Jul-16	261	60	432					**753**
3-Jul-16	180	1525	250					**1955**
4-Jul-16	102	1020	302					**1424**
5-Jul-16	0	1740	600					**2340**
6-Jul-16	20	1950	15					**1985**
7-Jul-16	30	235	40					**305**
8-Jul-16	875	180	0					**1055**
9-Jul-16	320	240	120					**680**
10-Jul-16	220	200	140					**560**
11-Jul-16	90	290	120					**500**
12-Jul-16	25	160	17					**202**
13-Jul-16	415	440	150					**1005**
14-Jul-16	30	550	10					**590**
15-Jul-16	240	1975	45					**2260**
16-Jul-16	150	625	90					**865**
17-Jul-16	235	200	95					**530**
18-Jul-16	0	120	15					**135**
19-Jul-16	105	110	210					**425**
20-Jul-16	0	0	255					**255**
21-Jul-16	198	0	0					**198**
22-Jul-16	185	90	365					**640**
23-Jul-16	0	90	90					**180**
24-Jul-16	30	55	120					**205**
25-Jul-16	200	120	90					**410**
26-Jul-16	40	1371	25					**1436**
27-Jul-16	0	295	15					**310**
28-Jul-16	50	765	45					**860**
29-Jul-16	72	126	185					**383**
30-Jul-16	130	1880	360					**2370**
31-Jul-16	100	40	0					**140**
1-Aug-16	30	1849	68					**1947**
2-Aug-16	0	1845	84					**1929**

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3-Aug-16	90	1570	45					**1705**
4-Aug-16	60	1810	12					**1882**
5-Aug-16	60	45	10					**115**
6-Aug-16	0	1090	12					**1102**
7-Aug-16	30	1520	120					**1670**
8-Aug-16	60	102	60					**222**
9-Aug-16	125	1974	174					**2273**
10-Aug-16	28	141	116					**285**
11-Aug-16	25	0	90					**115**
12-Aug-16	95	120	135					**350**
13-Aug-16	120	120	95					**335**
14-Aug-16	268	1684	316					**2268**
15-Aug-16	51	1899	276					**2226**
16-Aug-16	154	1643	258					**2055**
17-Aug-16	316	305	0					**621**
18-Aug-16	165	1170	55					**1390**
19-Aug-16	75	1700	280					**2055**
20-Aug-16	680	1820	255					**2755**
21-Aug-16	35	0	0					**35**
22-Aug-16	45	150	125					**320**
23-Aug-16	117	181	407					**705**
24-Aug-16	166	852	75					**1093**
25-Aug-16	209	400	84					**693**
26-Aug-16	315	402	480					**1197**
27-Aug-16	240	60	60					**360**
28-Aug-16	75	1065	60					**1200**
29-Aug-16	70	160	280					**510**
30-Aug-16	10	110	660					**780**
31-Aug-16	120	325	205					**650**
1-Sep-16	15	95	357					**467**
2-Sep-16	30	0	30					**60**
3-Sep-16	180	170	90					**440**

Crime Intel Detail - Minutes in the LASER ZONES

4-Sep-16	180	266	365					**811**
5-Sep-16	30	145	120					**295**
6-Sep-16	228	198	328					**754**
7-Sep-16	0	457	160					**617**
8-Sep-16	60	1770	60					**1890**
9-Sep-16	360	330	60					**750**
10-Sep-16	0	40	0					**40**
11-Sep-16	74	115	215					**404**
12-Sep-16	20	25	150					**195**
13-Sep-16	275	90	150					**515**
14-Sep-16	60	80	150					**290**
15-Sep-16	130	30	70					**230**
16-Sep-16	20	80	100					**200**
17-Sep-16	69	118	0					**187**
18-Sep-16	120	199	143					**462**
19-Sep-16	27	170	60					**257**
20-Sep-16	155	75	70					**300**
21-Sep-16	0	2015	0					**2015**
22-Sep-16	260	0	240					**500**
23-Sep-16	5	1215	0					**1220**
24-Sep-16	120	125	60					**305**
25-Sep-16	60	60	67					**187**
26-Sep-16	60	120	60					**240**
27-Sep-16	261	130	323					**714**
28-Sep-16	55	221	26					**302**
29-Sep-16	0	89	0					**89**
30-Sep-16	38	235	202					**475**
1-Oct-16	92	159	161					**412**
2-Oct-16	30	170	70					**270**
3-Oct-16	75	310	1270					**1655**
4-Oct-16	257	25	1220					**1502**
5-Oct-16	30	42	60					**132**
6-Oct-16	15	80	70					**165**

Crime Intel Detail - Minutes in the LASER ZONES

7-Oct-16	165	274	1440					**1879**
8-Oct-16	0	163	2					**165**
9-Oct-16	158	661	175					**994**
10-Oct-16	115	215	321					**651**
11-Oct-16	130	381	330					**841**
12-Oct-16	190	245	243					**678**
13-Oct-16	110	0	30					**140**
14-Oct-16	400	275	1640					**2315**
15-Oct-16	120	0	1186					**1306**
16-Oct-16								**0**
17-Oct-16								**0**
18-Oct-16								**0**
19-Oct-16								**0**
20-Oct-16								**0**
21-Oct-16								**0**
22-Oct-16								**0**
23-Oct-16								**0**
24-Oct-16								**0**
25-Oct-16								**0**
26-Oct-16								**0**
27-Oct-16								**0**
28-Oct-16								**0**
29-Oct-16								**0**
30-Oct-16								**0**
31-Oct-16								**0**
1-Nov-16								**0**
								0
								0
								0
								0
								0
								0
								0

Crime Intel Detail - Minutes in the LASER ZONES

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Crime Intel Detail - Minutes in the LASER ZONES

		NORTHEAST-Minutes in the LASER Zones							
DP	**DATE**	**LASER Zone 1**	**LASER Zone 2**	**LASER Zone 3**	**LASER Zone 4**	**LASER Zone 5**	**LASER Zone 6**	**LASER Zone 7**	**TOTAL**
DP 8	26-Jul-15								**0**
	27-Jul-15								**0**
	28-Jul-15								**0**
	29-Jul-15								**0**
	30-Jul-15								**0**
	31-Jul-15								**0**
	1-Aug-15								**0**
	2-Aug-15								**0**
	3-Aug-15								**0**
	4-Aug-15								**0**
	5-Aug-15								**0**
	6-Aug-15								**0**
	7-Aug-15								**0**
	8-Aug-15								**0**
DP 9	9-Aug-15								**0**
	10-Aug-15								**0**
	11-Aug-15								**0**
	12-Aug-15								**0**
	13-Aug-15								**0**
	14-Aug-15								**0**
	15-Aug-15								**0**
	16-Aug-15								**0**
	17-Aug-15								**0**
	18-Aug-15								**0**
	19-Aug-15								**0**
	20-Aug-15								**0**
	21-Aug-15								**0**
	22-Aug-15								**0**
	TOTAL								0

Crime Intel Detail - Minutes in the LASER ZONES

	23-Aug-15								**0**
	24-Aug-15								**0**
	25-Aug-15								**0**
	26-Aug-15								**0**
	27-Aug-15								**0**
	28-Aug-15								**0**
	29-Aug-15								**0**
	30-Aug-15								**0**
	31-Aug-15								**0**
	1-Sep-15								**0**
	2-Sep-15								**0**
	3-Sep-15								**0**
	4-Sep-15								**0**
	5-Sep-15								**0**
DP 10	6-Sep-15								**0**
	7-Sep-15								**0**
	8-Sep-15								**0**
	9-Sep-15								**0**
	10-Sep-15								**0**
	11-Sep-15								**0**
	12-Sep-15								**0**
	13-Sep-15								**0**
	14-Sep-15								**0**
	15-Sep-15								**0**
	16-Sep-15								**0**
	17-Sep-15								**0**
	18-Sep-15								**0**
	19-Sep-15								**0**
	TOTAL				0	0	0	0	0

Crime Intel Detail - Minutes in the LASER ZONES

20-Sep-15								**0**
21-Sep-15								**0**
22-Sep-15								**0**
23-Sep-15								**0**
24-Sep-15								**0**
25-Sep-15								**0**
26-Sep-15								**0**
27-Sep-15								**0**
28-Sep-15								**0**
29-Sep-15								**0**
30-Sep-15								**0**
1-Oct-15								**0**
2-Oct-15								**0**
3-Oct-15								**0**
4-Oct-15								**0**
5-Oct-15								**0**
6-Oct-15								**0**
7-Oct-15								**0**
8-Oct-15								**0**
9-Oct-15								**0**
10-Oct-15								**0**
11-Oct-15								**0**
12-Oct-15								**0**
13-Oct-15								**0**
14-Oct-15								**0**
15-Oct-15								**0**
16-Oct-15								**0**
17-Oct-15								**0**
18-Oct-15								**0**
19-Oct-15								**0**
20-Oct-15								**0**
21-Oct-15								**0**
22-Oct-15								**0**

Crime Intel Detail - Minutes in the LASER ZONES

23-Oct-15								0
24-Oct-15								0
25-Oct-15								0
26-Oct-15								0
27-Oct-15								0
28-Oct-15								0
29-Oct-15								0
30-Oct-15								0
31-Oct-15								0
1-Nov-15								0
2-Nov-15								0
3-Nov-15								0
4-Nov-15								0
5-Nov-15								0
6-Nov-15								0
7-Nov-15								0
8-Nov-15								0
9-Nov-15								0
10-Nov-15								0
11-Nov-15								0
12-Nov-15								0
13-Nov-15								0
14-Nov-15								0
15-Nov-15								0
16-Nov-15								0
17-Nov-15								0
18-Nov-15								0
19-Nov-15								0
20-Nov-15								0
21-Nov-15								0
22-Nov-15								0
23-Nov-15								0
24-Nov-15								0

Crime Intel Detail - Minutes in the LASER ZONES

25-Nov-15									**0**
26-Nov-15									**0**
27-Nov-15									**0**
28-Nov-15									**0**
29-Nov-15									**0**
30-Nov-15									**0**
1-Dec-15									**0**
2-Dec-15									**0**
3-Dec-15									**0**
4-Dec-15									**0**
5-Dec-15									**0**
6-Dec-15									**0**
7-Dec-15									**0**
8-Dec-15									**0**
9-Dec-15									**0**
10-Dec-15									**0**
11-Dec-15									**0**
12-Dec-15									**0**
13-Dec-15									**0**
14-Dec-15									**0**
15-Dec-15									**0**
16-Dec-15									**0**
17-Dec-15									**0**
18-Dec-15									**0**
19-Dec-15									**0**
20-Dec-15									**0**
21-Dec-15									**0**
22-Dec-15									**0**
23-Dec-15									**0**
24-Dec-15									**0**
25-Dec-15									**0**

Crime Intel Detail - Minutes in the LASER ZONES

26-Dec-15									**0**
27-Dec-15									**0**
28-Dec-15									**0**
29-Dec-15									**0**
30-Dec-15									**0**
31-Dec-15									**0**
1-Jan-16									**0**
2-Jan-16									**0**
3-Jan-16									**0**
4-Jan-16									**0**
5-Jan-16									**0**
6-Jan-16									**0**
7-Jan-16									**0**
8-Jan-16									**0**
9-Jan-16									**0**
10-Jan-16									**0**
11-Jan-16									**0**
12-Jan-16									**0**
13-Jan-16									**0**
14-Jan-16									**0**
15-Jan-16									**0**
16-Jan-16									**0**
17-Jan-16									**0**
18-Jan-16									**0**
19-Jan-16									**0**
20-Jan-16									**0**
21-Jan-16									**0**
22-Jan-16									**0**
23-Jan-16									**0**
24-Jan-16									**0**
25-Jan-16									**0**

Crime Intel Detail - Minutes in the LASER ZONES

26-Jan-16								**0**
27-Jan-16								**0**
28-Jan-16								**0**
29-Jan-16								**0**
30-Jan-16								**0**
31-Jan-16								**0**
1-Feb-16								**0**
2-Feb-16								**0**
3-Feb-16								**0**
4-Feb-16								**0**
5-Feb-16								**0**
6-Feb-16								**0**
7-Feb-16								**0**
8-Feb-16								**0**
9-Feb-16								**0**
10-Feb-16								**0**
11-Feb-16								**0**
12-Feb-16								**0**
13-Feb-16								**0**
14-Feb-16								**0**
15-Feb-16								**0**
16-Feb-16								**0**
17-Feb-16								**0**
18-Feb-16								**0**
19-Feb-16								**0**
20-Feb-16								**0**
21-Feb-16								**0**
22-Feb-16								**0**
23-Feb-16								**0**
24-Feb-16								**0**
25-Feb-16								**0**

Crime Intel Detail - Minutes in the LASER ZONES

26-Feb-16	**0**
27-Feb-16	**0**
28-Feb-16	**0**
29-Feb-16	**0**
1-Mar-16	**0**
2-Mar-16	**0**
3-Mar-16	**0**
4-Mar-16	**0**
5-Mar-16	**0**
6-Mar-16	**0**
7-Mar-16	**0**
8-Mar-16	**0**
9-Mar-16	**0**
10-Mar-16	**0**
11-Mar-16	**0**
12-Mar-16	**0**
13-Mar-16	**0**
14-Mar-16	**0**
15-Mar-16	**0**
16-Mar-16	**0**
17-Mar-16	**0**
18-Mar-16	**0**
19-Mar-16	**0**
20-Mar-16	**0**
21-Mar-16	**0**
22-Mar-16	**0**
23-Mar-16	**0**
24-Mar-16	**0**
25-Mar-16	**0**
26-Mar-16	**0**
	0

Crime Intel Detail - Minutes in the LASER ZONES

27-Mar-16								**0**
28-Mar-16								**0**
29-Mar-16								**0**
30-Mar-16								**0**
31-Mar-16								**0**
1-Apr-16								**0**
2-Apr-16								**0**
3-Apr-16	0	0	0					**0**
4-Apr-16	0	0	0					**0**
5-Apr-16	0	0	0					**0**
6-Apr-16	219	37	138					**394**
7-Apr-16	41	62	0					**103**
8-Apr-16	99	19	0					**118**
9-Apr-16	0	0	0					**0**
10-Apr-16	0	0	0					**0**
11-Apr-16	7	0	13					**20**
12-Apr-16	155	29	0					**184**
13-Apr-16	138	0	320					**458**
14-Apr-16	8	0	0					**8**
15-Apr-16	0	0	0					**0**
16-Apr-16	34	28	0					**62**
17-Apr-16	10	81	7					**98**
18-Apr-16	74	138	1140					**1352**
19-Apr-16	194	32	409					**635**
20-Apr-16	227	44	18					**289**
21-Apr-16	200	98	723					**1021**
22-Apr-16	332	119	0					**451**
23-Apr-16	86	64	9					**159**
24-Apr-16	24	0	15					**39**
25-Apr-16	22	0	372					**394**
26-Apr-16	94	0	51					**145**
27-Apr-16	283	188	498					**969**
28-Apr-16	0	95	273					**368**

Crime Intel Detail - Minutes in the LASER ZONES

29-Apr-16	198	145	0					**343**
30-Apr-16	19	0	0					**19**
1-May-16	67	0	142					**209**
2-May-16	258	38	971					**1267**
3-May-16	42	46	700					**788**
4-May-16	0	28	0					**28**
5-May-16	158	177	151					**486**
6-May-16	1	180	272					**453**
7-May-16	63	15	32					**110**
8-May-16	0	4	40					**44**
9-May-16	47	10	733					**790**
10-May-16	378	18	927					**1323**
11-May-16	598	52	292					**942**
12-May-16	83	142	528					**753**
13-May-16	449	70	23					**542**
14-May-16	123	188	171					**482**
15-May-16	46	215	100					**361**
16-May-16	40	107	984					**1131**
17-May-16	518	43	526					**1087**
18-May-16	348	45	286					**679**
19-May-16	33	13	165					**211**
20-May-16	200	0	11					**211**
21-May-16	0	36	18					**54**
22-May-16	883	0	91					**974**
23-May-16	883	0	91					**974**
24-May-16	407	26	176					**609**
25-May-16	215	172	353					**740**
26-May-16	70	18	149					**237**
27-May-16	219	39	0					**258**
28-May-16	0	112	2					**114**
29-May-16	48	51	27					**126**
30-May-16	48	39	103					**190**
31-May-16	108	173	462					**743**

Crime Intel Detail - Minutes in the LASER ZONES

1-Jun-16	138	187	325					**650**
2-Jun-16	76	182	111					**369**
3-Jun-16	115	0	0					**115**
4-Jun-16	1	0	0					**1**
5-Jun-16	0	0	69					**69**
6-Jun-16	130	98	259					**487**
7-Jun-16	0	0	461					**461**
8-Jun-16	25	52	20					**97**
9-Jun-16	74	57	0					**131**
10-Jun-16	159	0	0					**159**
11-Jun-16	0	20	32					**52**
12-Jun-16	0	64	0					**64**
13-Jun-16	18	28	748					**794**
14-Jun-16	147	48	366					**561**
15-Jun-16	167	34	250					**451**
16-Jun-16	151	32	427					**610**
17-Jun-16	142	0	6					**148**
18-Jun-16	39	50	40					**129**
19-Jun-16	65	0	16					**81**
20-Jun-16	0	15	156					**171**
21-Jun-16	376	65	260					**701**
22-Jun-16	35	0	357					**392**
23-Jun-16	243	18	3					**264**
24-Jun-16	133	38	0					**171**
25-Jun-16	46	0	100					**146**
26-Jun-16	13	0	0					**13**
27-Jun-16	35	36	167					**238**
28-Jun-16	43	48	84					**175**
29-Jun-16	341	36	141					**518**
30-Jun-16	10	313	405					**728**
1-Jul-16	183	3	33					**219**
2-Jul-16	104	6	255					**365**
3-Jul-16	408	46	172					**626**

Crime Intel Detail - Minutes in the LASER ZONES

4-Jul-16	1	0	5					**6**
5-Jul-16	334	68	2383					**2785**
6-Jul-16	169	163	269					**601**
7-Jul-16	316	85	66					**467**
8-Jul-16	0	0	87					**87**
9-Jul-16	42	75	127					**244**
10-Jul-16	0	21	155					**176**
11-Jul-16	0	0	13					**13**
12-Jul-16	45	212	14					**271**
13-Jul-16	200	12	330					**542**
14-Jul-16	152	133	92					**377**
15-Jul-16	0	0	1					**1**
16-Jul-16	0	3	33					**36**
17-Jul-16	29	36	174					**239**
18-Jul-16	0	0	198					**198**
19-Jul-16	0	13	109					**122**
20-Jul-16	0	39	41					**80**
21-Jul-16	0	0	75					**75**
22-Jul-16	0	27	28					**55**
23-Jul-16	0	88	5					**93**
24-Jul-16	40	8	106					**154**
25-Jul-16	277	244	238					**759**
26-Jul-16	67	297	310					**674**
27-Jul-16	12	22	27					**61**
28-Jul-16	2	99	8					**109**
29-Jul-16	158	120	0					**278**
30-Jul-16	0	250	0					**250**
31-Jul-16	9	53	236					**298**
1-Aug-16	120	285	389					**794**
2-Aug-16	78	11	571					**660**
3-Aug-16	44	162	214					**420**
4-Aug-16	204	113	26					**343**
5-Aug-16	174	10	100					**284**

Crime Intel Detail - Minutes in the LASER ZONES

6-Aug-16	72	0	122					**194**
7-Aug-16	87	41	4					**132**
8-Aug-16	198	11	0					**209**
9-Aug-16	723	40	289					**1052**
10-Aug-16	653	91	31					**775**
11-Aug-16	220	232	64					**516**
12-Aug-16	275	201	108					**584**
13-Aug-16	0	0	0					**0**
14-Aug-16	33	0	85					**118**
15-Aug-16	326	14	17					**357**
16-Aug-16	131	90	334					**555**
17-Aug-16	445	193	7					**645**
18-Aug-16	466	90	113					**669**
19-Aug-16	488	2	8					**498**
20-Aug-16	573	72	0					**645**
21-Aug-16	271	132	30					**433**
22-Aug-16	51	93	309					**453**
23-Aug-16	0	0	333					**333**
24-Aug-16	365	162	227					**754**
25-Aug-16	157	209	45					**411**
26-Aug-16	49	131	115					**295**
27-Aug-16	24	35	45					**104**
28-Aug-16	0	0	87					**87**
29-Aug-16	331	103	118					**552**
30-Aug-16	395	59	189					**643**
31-Aug-16	340	293	254					**887**
1-Sep-16	222	372	187					**781**
2-Sep-16	88	6	54					**148**
3-Sep-16	24	0	98					**122**
4-Sep-16	1	0	64					**65**
5-Sep-16	75	111	86					**272**
6-Sep-16	318	137	1182					**1637**
7-Sep-16	323	30	901					**1254**

Crime Intel Detail - Minutes in the LASER ZONES

8-Sep-16	741	336	25				**1102**
9-Sep-16	433	692	0				**1125**
10-Sep-16	0	0	0				**0**
11-Sep-16	58	99	170				**327**
12-Sep-16	102	228	801				**1131**
13-Sep-16	19	89	294				**402**
14-Sep-16	255	399	60				**714**
15-Sep-16	239	116	0				**355**
16-Sep-16	265	259	225				**749**
17-Sep-16	0	0	6				**6**
18-Sep-16	131	4	310				**445**
19-Sep-16	37	45	267				**349**
20-Sep-16	220	128	101				**449**
21-Sep-16	500	239	194				**933**
22-Sep-16	164	327	245				**736**
23-Sep-16	123	130	340				**593**
24-Sep-16	168	8	27				**203**
25-Sep-16	23	1	47				**71**
26-Sep-16	16	182	241				**439**
27-Sep-16	551	190	635				**1376**
28-Sep-16	189	177	480				**846**
29-Sep-16	186	84	129				**399**
30-Sep-16	40	19	0				**59**
1-Oct-16	21	165	535				**721**
2-Oct-16	74	140	136				**350**
3-Oct-16	144	0	218				**362**
4-Oct-16	335	47	387				**769**
5-Oct-16	349	408	283				**1040**
6-Oct-16	209	321	795				**1325**
7-Oct-16	244	73	940				**1257**
8-Oct-16	91	0	71				**162**
9-Oct-16	15	32	95				**142**
10-Oct-16	14	0	0				**14**

Crime Intel Detail - Minutes in the LASER ZONES

11-Oct-16	163	5	95					**263**
12-Oct-16	373	121	174					**668**
13-Oct-16	234	81	155					**470**
14-Oct-16	55	70	484					**609**
15-Oct-16	131	40	0					**171**
16-Oct-16	24	23	73					**120**
17-Oct-16	416	69	386					**871**
18-Oct-16	345	316	506					**1167**
19-Oct-16	180	136	65					**381**
20-Oct-16	104	0	66					**170**
21-Oct-16	39	25	30					**94**
22-Oct-16	124	126	373					**623**
23-Oct-16	65	0	74					**139**
24-Oct-16	0	0	402					**402**
25-Oct-16	88	57	93					**238**
26-Oct-16	0	9	24					**33**
27-Oct-16	122	57	39					**218**
28-Oct-16	55	25	30					**110**
29-Oct-16	93	353	124					**570**
30-Oct-16								**0**
31-Oct-16								**0**
1-Nov-16								**0**
2-Nov-16								**0**
3-Nov-16								**0**
4-Nov-16								
5-Nov-16								
6-Nov-16								
7-Nov-16								
8-Nov-16								
9-Nov-16								
10-Nov-16								
11-Nov-16								
12-Nov-16								

Crime Intel Detail - Minutes in the LASER ZONES

13-Nov-16								

		MPART-Minutes in the LASER Zo							
DP	DATE	LASER Zone 1	ASER Zone	ASER Zone	ASER Zone	ASER Zone 5			TOTAL
DP 5	17-Apr-16	840							**840**
	18-Apr-16	795							**795**
	19-Apr-16	1235							**1235**
	20-Apr-16	1595							**1595**
	21-Apr-16	925							**925**
	22-Apr-16	1770							**1770**
	23-Apr-16	820							**820**
	24-Apr-16	763							**763**
	25-Apr-16	2115							**2115**
	26-Apr-16	1837							**1837**
	27-Apr-16	1700							**1700**
	28-Apr-16	2118							**2118**
	29-Apr-16	1413							**1413**
	30-Apr-16	1668							**1668**
	1-May-16	1470							**1470**
	2-May-16	790							**790**
	3-May-16	1710							**1710**
	4-May-16	2280							**2280**
	5-May-16	2280							**2280**
	6-May-16	500							**500**
	7-May-16	8664							**8664**
	8-May-16	995							**995**
	9-May-16	1760							**1760**
	10-May-16	2735							**2735**
	11-May-16	1170							**1170**
	12-May-16	2045							**2045**
	13-May-16	1415							**1415**
	14-May-16	585							**585**
DP 6	15-May-16	1035							**1035**
	16-May-16	2035							**2035**
	17-May-16	2360							**2360**
	18-May-16	2480							**2480**
	19-May-16	1600							**1600**
	20-May-16	3300							**3300**
	21-May-16	3051							**3051**
	22-May-16	2980							**2980**
	23-May-16	2090							**2090**
	24-May-16	1985							**1985**
	25-May-16	1655							**1655**
	26-May-16	3470							**3470**
	27-May-16	2195							**2195**
	28-May-16	2570							**2570**
	29-May-16	2260							**2260**

30-May-16	1775							**1775**
31-May-16	872							**872**
1-Jun-16	1611							**1611**
2-Jun-16	2245							**2245**
3-Jun-16	2670							**2670**
4-Jun-16	560							**560**
5-Jun-16	1604							**1604**
6-Jun-16	1800							**1800**
7-Jun-16	1080							**1080**
8-Jun-16	1235							**1235**
9-Jun-16	2445							**2445**
10-Jun-16	1925							**1925**
11-Jun-16	1490							**1490**
12-Jun-16	853							**853**
13-Jun-16	943							**943**
14-Jun-16	1833							**1833**
15-Jun-16	3003							**3003**
16-Jun-16	2913							**2913**
17-Jun-16	1683							**1683**
18-Jun-16	1593							**1593**
19-Jun-16	1180							**1180**
20-Jun-16	1285							**1285**
21-Jun-16	3445							**3445**
22-Jun-16	2605							**2605**
23-Jun-16	2095							**2095**
24-Jun-16	2225							**2225**
25-Jun-16	1340							**1340**
26-Jun-16	976							**976**
27-Jun-16	1840							**1840**
28-Jun-16	3470							**3470**
29-Jun-16	2600							**2600**
30-Jun-16	1380							**1380**
1-Jul-16	1564							**1564**
2-Jul-16	1975							**1975**
3-Jul-16	1738							**1738**
4-Jul-16	3033							**3033**
5-Jul-16	2045							**2045**
6-Jul-16	1765							**1765**
7-Jul-16	3245							**3245**
8-Jul-16	1480							**1480**
9-Jul-16	905							**905**
10-Jul-16	1950							**1950**
11-Jul-16	1000							**1000**
12-Jul-16	1595							**1595**
13-Jul-16	3325							**3325**

14-Jul-16	4825	**4825**
15-Jul-16	5091	**5091**
16-Jul-16	3980	**3980**
17-Jul-16	2349	**2349**
18-Jul-16	2220	**2220**
19-Jul-16	3000	**3000**
20-Jul-16	2800	**2800**
21-Jul-16	3120	**3120**
22-Jul-16	3000	**3000**
23-Jul-16	2537	**2537**
24-Jul-16	800	**800**
25-Jul-16	4280	**4280**
26-Jul-16	2955	**2955**
27-Jul-16	2190	**2190**
28-Jul-16	2000	**2000**
29-Jul-16	1360	**1360**
30-Jul-16	800	**800**
31-Jul-16	2471	**2471**
1-Aug-16	3435	**3435**
2-Aug-16	4033	**4033**
3-Aug-16	4800	**4800**
4-Aug-16	3000	**3000**
5-Aug-16	2810	**2810**
6-Aug-16	1480	**1480**
7-Aug-16	600	**600**
8-Aug-16	1049	**1049**
9-Aug-16	1900	**1900**
10-Aug-16	2362	**2362**
11-Aug-16	3620	**3620**
12-Aug-16	905	**905**
13-Aug-16	1050	**1050**
14-Aug-16	4506	**4506**
15-Aug-16	2030	**2030**
16-Aug-16	1339	**1339**
17-Aug-16	6049	**6049**
18-Aug-16	3185	**3185**
19-Aug-16	1535	**1535**
20-Aug-16	1650	**1650**
21-Aug-16	2685	**2685**
22-Aug-16	2711	**2711**
23-Aug-16	3300	**3300**
24-Aug-16	5497	**5497**
25-Aug-16	2974	**2974**
26-Aug-16	2306	**2306**
27-Aug-16	1420	**1420**

28-Aug-16	6160	**6160**
29-Aug-16	5962	**5962**
30-Aug-16	6977	**6977**
31-Aug-16	6462	**6462**
1-Sep-16	4507	**4507**
2-Sep-16	4292	**4292**
3-Sep-16	3072	**3072**
4-Sep-16	5408	**5408**
5-Sep-16	4513	**4513**
6-Sep-16	4473	**4473**
7-Sep-16	6288	**6288**
8-Sep-16	6123	**6123**
9-Sep-16	5963	**5963**
10-Sep-16	4478	**4478**
11-Sep-16	3300	**3300**
12-Sep-16	4330	**4330**
13-Sep-16	3394	**3394**
14-Sep-16	4450	**4450**
15-Sep-16	2469	**2469**
16-Sep-16	1780	**1780**
17-Sep-16	1570	**1570**
18-Sep-16	910	**910**
19-Sep-16	1190	**1190**
20-Sep-16	1211	**1211**
21-Sep-16	2369	**2369**
22-Sep-16	2335	**2335**
23-Sep-16	1985	**1985**
24-Sep-16	810	**810**
25-Sep-16	1290	**1290**
26-Sep-16	3380	**3380**
27-Sep-16	1390	**1390**
28-Sep-16	4205	**4205**
29-Sep-16	3255	**3255**
30-Sep-16	6405	**6405**
1-Oct-16	2430	**2430**
2-Oct-16	1105	**1105**
3-Oct-16	620	**620**
4-Oct-16	818	**818**
5-Oct-16	3645	**3645**
6-Oct-16	3570	**3570**
7-Oct-16	2515	**2515**
8-Oct-16	3165	**3165**
9-Oct-16	2590	**2590**
10-Oct-16	390	**390**
11-Oct-16	1580	**1580**

12-Oct-16	3005	**3005**
13-Oct-16	2755	**2755**
14-Oct-16	1200	**1200**
15-Oct-16	1850	**1850**
16-Oct-16	1803	**1803**
17-Oct-16	800	**800**
18-Oct-16	1170	**1170**
19-Oct-16	3050	**3050**
20-Oct-16	2670	**2670**
21-Oct-16	3500	**3500**
22-Oct-16	2020	**2020**
23-Oct-16	1020	**1020**
24-Oct-16	620	**620**
25-Oct-16	1530	**1530**
26-Oct-16	2685	**2685**
27-Oct-16	1965	**1965**
28-Oct-16	2845	**2845**
29-Oct-16	1970	**1970**
30-Oct-16		**0**
31-Oct-16		**0**
1-Nov-16		**0**
2-Nov-16		**0**
3-Nov-16		**0**
4-Nov-16		**0**
5-Nov-16		**0**
6-Nov-16		**0**
7-Nov-16		**0**
8-Nov-16		**0**
9-Nov-16		**0**
10-Nov-16		**0**
11-Nov-16		**0**
12-Nov-16		**0**
13-Nov-16		**0**
14-Nov-16		**0**
15-Nov-16		**0**
16-Nov-16		**0**
17-Nov-16		**0**
18-Nov-16		**0**
19-Nov-16		**0**
20-Nov-16		**0**
21-Nov-16		**0**
22-Nov-16		**0**
23-Nov-16		**0**
24-Nov-16		**0**
25-Nov-16		**0**

Crime Intel Detail - Minutes in the LASER ZONES

		SOUTHEAST-Minutes in the LASER Zones							
DP	DATE	LASER Zone 1	LASER Zone 2	LASER Zone 3	LASER Zone 4	LASER Zone 5	LASER Zone 6	LASER Zone 7	TOTAL
DP 8	26-Jul-15	137	103	0	59	0			**299**
	27-Jul-15	58	76	112	18	0			**264**
	28-Jul-15	59	96	41	0	5			**201**
	29-Jul-15	380	823	188	1	18			**1410**
	30-Jul-15	651	261	0	87	0			**999**
	31-Jul-15	304	476	87	47	0			**914**
	1-Aug-15	79	154	0	114	0			**347**
	2-Aug-15	137	43	65	294	9			**548**
	3-Aug-15	64	104	143	35	0			**346**
	4-Aug-15	61	175	12	61	14			**323**
	5-Aug-15	51	289	23	9	0			**372**
	6-Aug-15	214	81	36	39	0			**370**
	7-Aug-15	80	25	83	181	0			**369**
	8-Aug-15	40	199	0	0	29			**268**
DP 9	9-Aug-15	236	41	59	44	86			**466**
	10-Aug-15	316	97	101	24	0			**538**
	11-Aug-15	62	41	388	72	0			**563**
	12-Aug-15	23	285	192	61	79			**640**
	13-Aug-15	0	375	266	0	0			**641**
	14-Aug-15	109	579	91	44	14			**837**
	15-Aug-15	104	409	77	66	40			**696**
	16-Aug-15	43	33	11	15	131			**233**
	17-Aug-15	130	35	151	240	22			**578**
	18-Aug-15	361	121	42	148	43			**715**
	19-Aug-15	157	104	276	55	0			**592**
	20-Aug-15	75	445	80	82	21			**703**
	21-Aug-15	40	171	71	45	47			**374**
	22-Aug-15	34	85	29	22	7			**177**
	TOTAL	4005	5726	2624	1863	565			14783

Crime Intel Detail - Minutes in the LASER ZONES

	23-Aug-15	36	37	42	159	33			**307**
	24-Aug-15	63	61	66	414	0			**604**
	25-Aug-15	178	334	75	93	123			**803**
	26-Aug-15	178	177	26	38	0			**419**
	27-Aug-15	31	53	0	0	0			**84**
	28-Aug-15	135	17	15	62	0			**229**
	29-Aug-15	33	0	0	53	15			**101**
	30-Aug-15	0	129	0	0	84			**213**
	31-Aug-15	116	360	9	188	0			**673**
	1-Sep-15	91	287	0	0	92			**470**
	2-Sep-15	177	301	32	188	4			**702**
	3-Sep-15	197	312	22	120	59			**710**
	4-Sep-15	140	395	104	272	48			**959**
	5-Sep-15	203	486	21	98	165			**973**
DP 10	6-Sep-15	485	716	47	228	71			**1547**
	7-Sep-15	474	458	64	151	188			**1335**
	8-Sep-15	547	1246	217	1592	878			**4480**
	9-Sep-15	895	1061	760	1858	467			**5041**
	10-Sep-15	191	2993	384	1212	179			**4959**
	11-Sep-15	14	14	223	2450	280			**2981**
	12-Sep-15	385	809	302	1096	462			**3054**
	13-Sep-15	284	193	6					**483**
	14-Sep-15	73	623	46					**742**
	15-Sep-15	459	206	502					**1167**
	16-Sep-15	221	325	80					**626**
	17-Sep-15	452	338	391					**1181**
	18-Sep-15	209	499	147					**855**
	19-Sep-15	91	14	88					**193**
	TOTAL	6358	12444	3669	10272	3148	0	0	35891

Crime Intel Detail - Minutes in the LASER ZONES

20-Sep-15	72	64	0					**136**
21-Sep-15	0	72	412					**484**
22-Sep-15	213	326	285					**824**
23-Sep-15	137	190	21					**348**
24-Sep-15	128	40	0					**168**
25-Sep-15	203	163	25					**391**
26-Sep-15	64	115	59					**238**
27-Sep-15	3342	3758	148					**7248**
28-Sep-15	2515	1555	64					**4134**
29-Sep-15	1941	3185	160					**5286**
30-Sep-15	2496	1710	81					**4287**
1-Oct-15	5017	2470	236					**7723**
2-Oct-15	3292	2093	298					**5683**
3-Oct-15	4718	2305	129					**7152**
4-Oct-15	2483	1363	0					**3846**
5-Oct-15	1147	2236	301					**3684**
6-Oct-15	2606	2923	250					**5779**
7-Oct-15	1324	2190	167					**3681**
8-Oct-15	191	460	21					**672**
9-Oct-15	2164	3121	444					**5729**
10-Oct-15	2022	1476	14					**3512**
11-Oct-15	2307	1946	76					**4329**
12-Oct-15	2606	2278	70					**4954**
13-Oct-15	3789	2538	187					**6514**
14-Oct-15	2423	1391	1043					**4857**
15-Oct-15	532	709	27					**1268**
16-Oct-15	2225	1905	136					**4266**
17-Oct-15	1323	1332	786					**3441**
18-Oct-15	1602	1052	36					**2690**
19-Oct-15	1723	708	19					**2450**
20-Oct-15	1711	2060	77					**3848**
21-Oct-15	1126	1694	368					**3188**
22-Oct-15	586	1360	159					**2105**

Crime Intel Detail - Minutes in the LASER ZONES

23-Oct-15	1366	1755	909					**4030**
24-Oct-15	615	488	4					**1107**
25-Oct-15	1210	1619	25					**2854**
26-Oct-15	1592	1181	10					**2783**
27-Oct-15	1706	1207	231					**3144**
28-Oct-15	3699	1999	89					**5787**
29-Oct-15	2093	2785	18					**4896**
30-Oct-15	4270	2666	143					**7079**
31-Oct-15	792	401	316					**1509**
1-Nov-15	5	542	506					**1053**
2-Nov-15	577	478	0					**1055**
3-Nov-15	1383	2674	154					**4211**
4-Nov-15	3923	1801	0					**5724**
5-Nov-15	1467	2552	108					**4127**
6-Nov-15	1214	1329	194					**2737**
7-Nov-15	535	1058	230					**1823**
8-Nov-15	795	601	775					**2171**
9-Nov-15	508	109	128					**745**
10-Nov-15	442	649	531					**1622**
11-Nov-15	1503	898	50					**2451**
12-Nov-15	2666	811	256					**3733**
13-Nov-15	1195	898	321					**2414**
14-Nov-15	244	883	333					**1460**
15-Nov-15	2067	379	366					**2812**
16-Nov-15	1268	1786	388					**3442**
17-Nov-15	813	937	117					**1867**
18-Nov-15	2216	458	288					**2962**
19-Nov-15	1090	1518	652					**3260**
20-Nov-15	922	1690	237					**2849**
21-Nov-15	1125	353	298					**1776**
22-Nov-15	17	490	41					**548**
23-Nov-15	262	183	255					**700**
24-Nov-15	213	450	448					**1111**

Crime Intel Detail - Minutes in the LASER ZONES

25-Nov-15	691	907	646					**2244**
26-Nov-15	483	352	289					**1124**
27-Nov-15	52	1552	71					**1675**
28-Nov-15	525	990	159					**1674**
29-Nov-15	934	276	120					**1330**
30-Nov-15	446	728	152					**1326**
1-Dec-15	1118	968	149					**2235**
2-Dec-15	2253	1355	46					**3654**
3-Dec-15	2494	1676	64					**4234**
4-Dec-15	1126	1778	447					**3351**
5-Dec-15	376	142	129					**647**
6-Dec-15	93	569	19					**681**
7-Dec-15	607	523	276					**1406**
8-Dec-15	913	1809	59					**2781**
9-Dec-15	921	1573	29					**2523**
10-Dec-15	2140	1332	208					**3680**
11-Dec-15	1189	1260	158					**2607**
12-Dec-15	120	769	153					**1042**
13-Dec-15	1474	93	62					**1629**
14-Dec-15	367	553	82					**1002**
15-Dec-15	880	918	173					**1971**
16-Dec-15	947	707	233					**1887**
17-Dec-15	1762	729	116					**2607**
18-Dec-15	1175	357	49					**1581**
19-Dec-15	265	332	43					**640**
20-Dec-15	905	68	143					**1116**
21-Dec-15	108	387	249					**744**
22-Dec-15	901	2581	7					**3489**
23-Dec-15	819	758	113					**1690**
24-Dec-15	399	370	0					**769**
25-Dec-15	754	309	13					**1076**

Crime Intel Detail - Minutes in the LASER ZONES

26-Dec-15	180	189	61					**430**
27-Dec-15	146	635	146					**927**
28-Dec-15	107	495	78					**680**
29-Dec-15	841	1024	125					**1990**
30-Dec-15	954	1933	119					**3006**
31-Dec-15	1064	1766	72					**2902**
1-Jan-16	282	173	21					**476**
2-Jan-16	862	498	136					**1496**
3-Jan-16	208	664	89					**961**
4-Jan-16	1056	589	867					**2512**
5-Jan-16	858	514	225					**1597**
6-Jan-16	678	2109	75					**2862**
7-Jan-16	892	2850	23					**3765**
8-Jan-16	1126	1479	104					**2709**
9-Jan-16	753	1031	192					**1976**
10-Jan-16	107	4	57					**168**
11-Jan-16	847	308	115					**1270**
12-Jan-16	1923	1243	32					**3198**
13-Jan-16	967	2095	363					**3425**
14-Jan-16	1481	2439	354					**4274**
15-Jan-16	1058	1632	112					**2802**
16-Jan-16	244	242	13					**499**
17-Jan-16	97	236	0					**333**
18-Jan-16	743	647	236					**1626**
19-Jan-16	1664	717	757					**3138**
20-Jan-16	1064	552	0					**1616**
21-Jan-16	1651	1608	166					**3425**
22-Jan-16	1830	1098	45					**2973**
23-Jan-16	859	52	564					**1475**
24-Jan-16	286	154	6					**446**
25-Jan-16	759	309	158					**1226**

Crime Intel Detail - Minutes in the LASER ZONES

26-Jan-16	1670	1118	358					**3146**
27-Jan-16	1667	1998	635					**4300**
28-Jan-16	1976	1554	141					**3671**
29-Jan-16	242	518	236					**996**
30-Jan-16	272	867	428					**1567**
31-Jan-16	79	244	423					**746**
1-Feb-16	1192	432	63					**1687**
2-Feb-16	737	714	368					**1819**
3-Feb-16	777	1682	341					**2800**
4-Feb-16	932	1242	328					**2502**
5-Feb-16	296	1242	193					**1731**
6-Feb-16	371	626	163					**1160**
7-Feb-16	105	758	12					**875**
8-Feb-16	428	1307	396					**2131**
9-Feb-16	556	1375	175					**2106**
10-Feb-16	1317	1667	1074					**4058**
11-Feb-16	2522	2841	132					**5495**
12-Feb-16	1141	619	232					**1992**
13-Feb-16	1240	189	0					**1429**
14-Feb-16	164	465	24					**653**
15-Feb-16	768	264	190					**1222**
16-Feb-16	772	1055	27					**1854**
17-Feb-16	559	1157	93					**1809**
18-Feb-16	443	1465	287					**2195**
19-Feb-16	497	2495	95					**3087**
20-Feb-16	451	1471	134					**2056**
21-Feb-16	548	170	110					**828**
22-Feb-16	1448	304	79					**1831**
23-Feb-16	919	1232	365					**2516**
24-Feb-16	1550	1478	145					**3173**
25-Feb-16	2301	1523	52					**3876**

Crime Intel Detail - Minutes in the LASER ZONES

26-Feb-16	698	3143	92					**3933**
27-Feb-16	400	851	37					**1288**
28-Feb-16	673	669	518					**1860**
29-Feb-16	1007	1428	275					**2710**
1-Mar-16	623	2072	201					**2896**
2-Mar-16	1081	1802	29					**2912**
3-Mar-16	362	355	67					**784**
4-Mar-16	2010	1812	31					**3853**
5-Mar-16	388	2226	160					**2774**
6-Mar-16	502	804	481					**1787**
7-Mar-16	581	1938	210					**2729**
8-Mar-16	469	1507	177					**2153**
9-Mar-16	884	1876	286					**3046**
10-Mar-16	261	1778	26					**2065**
11-Mar-16	564	2645	13					**3222**
12-Mar-16	1849	1870	203					**3922**
13-Mar-16	566	1106	82					**1754**
14-Mar-16	581	666	292					**1539**
15-Mar-16	1131	2090	208					**3429**
16-Mar-16	727	1467	86					**2280**
17-Mar-16	1251	2793	199					**4243**
18-Mar-16	1024	2619	14					**3657**
19-Mar-16	400	1752	60					**2212**
20-Mar-16	1463	1306	46					**2815**
21-Mar-16	2860	2156	0					**5016**
22-Mar-16	2054	1687	278					**4019**
23-Mar-16	1442	1881	241					**3564**
24-Mar-16	1344	1574	172					**3090**
25-Mar-16	1971	3022	64					**5057**
26-Mar-16	1903	2116	178					**4197**
								0

Crime Intel Detail - Minutes in the LASER ZONES

27-Mar-16	816	712	123					**1651**
28-Mar-16	253	896	200					**1349**
29-Mar-16	723	2599	501					**3823**
30-Mar-16	1036	1662	12					**2710**
31-Mar-16	806	1701	222					**2729**
1-Apr-16	1180	836	86					**2102**
2-Apr-16	484	1714	254					**2452**
3-Apr-16	215	370	80					**665**
4-Apr-16	839	942	0					**1781**
5-Apr-16	1141	1443	110					**2694**
6-Apr-16	2238	1047	0					**3285**
7-Apr-16	890	1062	39					**1991**
8-Apr-16	144	1485	212					**1841**
9-Apr-16	603	1284	119					**2006**
10-Apr-16	292	1311	201					**1804**
11-Apr-16	634	1366	107					**2107**
12-Apr-16	1448	1260	96					**2804**
13-Apr-16	3644	2438	501					**6583**
14-Apr-16	1987	2739	989					**5715**
15-Apr-16	378	2390	225					**2993**
16-Apr-16	730	1540	1589					**3859**
17-Apr-16	710	1225	17					**1952**
18-Apr-16	1070	1063	101					**2234**
19-Apr-16	1006	1848	14					**2868**
20-Apr-16	1281	967	30					**2278**
21-Apr-16	1053	1335	383					**2771**
22-Apr-16	1352	1838	278					**3468**
23-Apr-16	1469	1862	28					**3359**
24-Apr-16	1198	1146	44					**2388**
25-Apr-16	940	1234	110					**2284**
26-Apr-16	456	576	81					**1113**
27-Apr-16	639	48	167					**854**
28-Apr-16	0	848	199					**1047**

Crime Intel Detail - Minutes in the LASER ZONES

29-Apr-16	0	852	0					**852**
30-Apr-16	737	1912	754					**3403**
1-May-16	2989	2208	38					**5235**
2-May-16	1040	2017	414					**3471**
3-May-16	1488	1098	296					**2882**
4-May-16	1093	1940	32					**3065**
5-May-16	1730	2811	311					**4852**
6-May-16	3091	3004	14					**6109**
7-May-16	918	920	69					**1907**
8-May-16	236	649	382					**1267**
9-May-16	1244	1296	362					**2902**
10-May-16	1578	3072	0					**4650**
11-May-16	1369	2329	590					**4288**
12-May-16	1691	1925	205					**3821**
13-May-16	1714	1612	472					**3798**
14-May-16	954	2194	522					**3670**
15-May-16	1737	819	377					**2933**
16-May-16	1305	829	121					**2255**
17-May-16	2336	1255	0					**3591**
18-May-16	3058	1471	359					**4888**
19-May-16	1184	2389	167					**3740**
20-May-16	1845	1889	48					**3782**
21-May-16	712	1795	130					**2637**
22-May-16	448	1459	233					**2140**
23-May-16	1010	862	183					**2055**
24-May-16	1524	2640	52					**4216**
25-May-16	2477	1934	85					**4496**
26-May-16	1740	2783	0					**4523**
27-May-16	1701	1424	615					**3740**
28-May-16	1788	1852	521					**4161**
29-May-16	1411	1932	175					**3518**
30-May-16	1661	1341	335					**3337**
31-May-16	2095	2138	152					**4385**

Crime Intel Detail - Minutes in the LASER ZONES

1-Jun-16	2489	1816	24					**4329**
2-Jun-16	2156	2037	96					**4289**
3-Jun-16	1043	1432	130					**2605**
4-Jun-16	1485	1697	329					**3511**
5-Jun-16	378	1112	66					**1556**
6-Jun-16	773	569	71					**1413**
7-Jun-16	1017	1435	235					**2687**
8-Jun-16	1972	2296	501					**4769**
9-Jun-16	1899	1257	777					**3933**
10-Jun-16	1131	1793	78					**3002**
11-Jun-16	707	931	28					**1666**
12-Jun-16	655	710	29					**1394**
13-Jun-16	1299	223	25					**1547**
14-Jun-16	1620	325	1					**1946**
15-Jun-16	2208	1376	129					**3713**
16-Jun-16	1975	446	482					**2903**
17-Jun-16	1703	2656	185					**4544**
18-Jun-16	2358	1753	122					**4233**
19-Jun-16	457	81	164					**702**
20-Jun-16	784	599	159					**1542**
21-Jun-16	2780	2653	137					**5570**
22-Jun-16	2656	1461	214					**4331**
23-Jun-16	1706	1287	250					**3243**
24-Jun-16	900	2849	90					**3839**
25-Jun-16	2834	599	73					**3506**
26-Jun-16	404	450	66					**920**
27-Jun-16	454	791	60					**1305**
28-Jun-16	750	530	318					**1598**
29-Jun-16	586	1646	187					**2419**
30-Jun-16	896	393	209					**1498**
1-Jul-16	613	1121	46					**1780**
2-Jul-16	804	279	285					**1368**
3-Jul-16	1743	1466	992					**4201**

Crime Intel Detail - Minutes in the LASER ZONES

4-Jul-16	3337	1285	599					**5221**
5-Jul-16	1060	1069	56					**2185**
6-Jul-16	1258	1222	0					**2480**
7-Jul-16	826	1096	296					**2218**
8-Jul-16	308	1016	107					**1431**
9-Jul-16	799	838	311					**1948**
10-Jul-16	937	577	86					**1600**
11-Jul-16	761	870	143					**1774**
12-Jul-16	839	1403	95					**2337**
13-Jul-16	746	1259	18					**2023**
14-Jul-16	1165	1545	144					**2854**
15-Jul-16	777	2438	202					**3417**
16-Jul-16	2733	2001	179					**4913**
17-Jul-16	1408	1765	102					**3275**
18-Jul-16	2521	2002	88					**4611**
19-Jul-16	1324	2269	128					**3721**
20-Jul-16	888	970	1009					**2867**
21-Jul-16	2046	1590	28					**3664**
22-Jul-16	1440	1164	482					**3086**
23-Jul-16	939	872	233					**2044**
24-Jul-16	375	1782	71					**2228**
25-Jul-16	955	3766	0					**4721**
26-Jul-16	1956	12166	0					**14122**
27-Jul-16	1430	5874	29					**7333**
28-Jul-16	1502	2641	123					**4266**
29-Jul-16	2330	3584	176					**6090**
30-Jul-16	1133	1776	90					**2999**
31-Jul-16	98	2058	1685					**3841**
1-Aug-16	1334	2254	291					**3879**
2-Aug-16	1203	2577	53					**3833**
3-Aug-16	958	2597	2014					**5569**
4-Aug-16	1751	2130	56					**3937**
5-Aug-16	804	1357	61					**2222**

Crime Intel Detail - Minutes in the LASER ZONES

6-Aug-16	296	1003	303				**1602**
7-Aug-16	1447	2031	46				**3524**
8-Aug-16	1924	1982	39				**3945**
9-Aug-16	1888	2644	342				**4874**
10-Aug-16	1723	2858	328				**4909**
11-Aug-16	693	5938	3969				**10600**
12-Aug-16	1210	618	35				**1863**
13-Aug-16	894	803	0				**1697**
14-Aug-16	477	792	348				**1617**
15-Aug-16	1715	1752	280				**3747**
16-Aug-16	1198	1046	195				**2439**
17-Aug-16	760	1905	243				**2908**
18-Aug-16	1447	1254	92				**2793**
19-Aug-16	2123	2098	139				**4360**
20-Aug-16	1404	868	195				**2467**
21-Aug-16	1684	438	191				**2313**
22-Aug-16	790	946	133				**1869**
23-Aug-16	1907	1010	51				**2968**
24-Aug-16	1473	1206	660				**3339**
25-Aug-16	281	1025	1578				**2884**
26-Aug-16	1279	2417	884				**4580**
27-Aug-16	610	805	437				**1852**
28-Aug-16	1058	780	145				**1983**
29-Aug-16	753	1011	527				**2291**
30-Aug-16	832	948	90				**1870**
31-Aug-16	931	1584	1019				**3534**
1-Sep-16	1367	1230	364				**2961**
2-Sep-16	886	943	199				**2028**
3-Sep-16	1366	1184	42				**2592**
4-Sep-16	183	1009	418				**1610**
5-Sep-16	4417	1460	43				**5920**
6-Sep-16	606	1133	525				**2264**
7-Sep-16	832	1486	879				**3197**

Crime Intel Detail - Minutes in the LASER ZONES

8-Sep-16	1835	786	526					**3147**
9-Sep-16	6752	1644	201					**8597**
10-Sep-16	1027	1020	4					**2051**
11-Sep-16	560	539	274					**1373**
12-Sep-16	559	737	256					**1552**
13-Sep-16	830	969	124					**1923**
14-Sep-16	1315	1006	566					**2887**
15-Sep-16	1720	796	281					**2797**
16-Sep-16	781	794	865					**2440**
17-Sep-16	495	234	115					**844**
18-Sep-16	191	590	511					**1292**
19-Sep-16	631	579	92					**1302**
20-Sep-16	1505	715	38					**2258**
21-Sep-16	383	870	8					**1261**
22-Sep-16	1087	1095	269					**2451**
23-Sep-16	604	1027	286					**1917**
24-Sep-16	511	1561	284					**2356**
25-Sep-16	812	681	36					**1529**
26-Sep-16	641	240	115					**996**
27-Sep-16	2190	755	107					**3052**
28-Sep-16	1267	600	404					**2271**
29-Sep-16	505	1657	593					**2755**
30-Sep-16	2377	1000	174					**3551**
1-Oct-16	2073	1236	35					**3344**
2-Oct-16	1133	474	40					**1647**
3-Oct-16	1732	1817	85					**3634**
4-Oct-16	1284	1550	399					**3233**
5-Oct-16	1124	1445	516					**3085**
6-Oct-16	557	2891	834					**4282**
7-Oct-16	1139	232	366					**1737**
8-Oct-16	795	447	298					**1540**
9-Oct-16	161	56	320					**537**
10-Oct-16	1159	566	109					**1834**

Crime Intel Detail - Minutes in the LASER ZONES

11-Oct-16	1724	1320	124					**3168**
12-Oct-16	298	644	10					**952**
13-Oct-16	1285	1230	576					**3091**
14-Oct-16	1208	925	279					**2412**
15-Oct-16	245	638	2002					**2885**
16-Oct-16	665	156	23					**844**
17-Oct-16	762	1118	645					**2525**
18-Oct-16	1798	393	95					**2286**
19-Oct-16	2282	1505	56					**3843**
20-Oct-16	1172	2490	24					**3686**
21-Oct-16	3666	1519	29					**5214**
22-Oct-16	699	511	45					**1255**
23-Oct-16	203	273	7					**483**
24-Oct-16	238	373	23					**634**
25-Oct-16	444	1035	301					**1780**
26-Oct-16	350	1051	68					**1469**
27-Oct-16	1195	1229	50					**2474**
28-Oct-16	292	1184	122					**1598**
29-Oct-16	547	16	140					**703**
30-Oct-16								**0**
31-Oct-16								**0**
1-Nov-16								**0**

Crime Intel Detail - Minutes in the LASER ZONES

		SOUTHWEST-Minutes in the LASER Zones							
DP	**DATE**	**LASER Zone 1**	**LASER Zone 2A**	**LASER Zone 2B**	**LASER Zone 3**	**LASER Zone 4**	**LASER Zone 5**	**LASER Zone 6**	**TOTAL**
DP 8	26-Jul-15	875	80	40	499	857	5		**2356**
	27-Jul-15	687	281	37	183	1573	0		**2761**
	28-Jul-15	737	1351	65	550	581	29		**3313**
	29-Jul-15	861	317	490	562	1031	71		**3332**
	30-Jul-15	287	278	135	214	1502	38		**2454**
	31-Jul-15	808	765	200	109	1973	0		**3855**
	1-Aug-15	746	619	103	417	2715	12		**4612**
	2-Aug-15	925	427	420	578	635	161		**3146**
	3-Aug-15	409	331	230	507	506	30		**2013**
	4-Aug-15	314	231	81	276	614	199		**1715**
	5-Aug-15	303	220	207	483	1188	10		**2411**
	6-Aug-15	156	894	188	100	1042	20		**2400**
	7-Aug-15	369	780	109	109	919	30		**2316**
	8-Aug-15	525	413	111	342	1013	28		**2432**
DP 9	9-Aug-15	481	432	321	382	1111	143		**2870**
	10-Aug-15	899	104	106	200	1226	127		**2662**
	11-Aug-15	423	231	258	296	1117	115		**2440**
	12-Aug-15	419	339	549	178	1624	392		**3501**
	13-Aug-15	1068	408	244	170	667	61		**2618**
	14-Aug-15	1178	696	92	755	1023	141		**3885**
	15-Aug-15	892	687	103	415	1427	146		**3670**
	16-Aug-15	784	141	69	253	842	5		**2094**
	17-Aug-15	827	373	223	436	678	77		**2614**
	18-Aug-15	642	275	79	325	606	165		**2092**
	19-Aug-15	791	598	381	247	898	106		**3021**
	20-Aug-15	1132	177	78	296	1563	56		**3302**
	21-Aug-15	533	540	4	25	1155	685		**2942**
	22-Aug-15	759	206	0	35	1076	0		**2076**
	TOTAL	18830	12194	4923	8942	31162	2852	0	78903

Crime Intel Detail - Minutes in the LASER ZONES

	23-Aug-15	675	246	143	544	977	44		**2629**
	24-Aug-15	471	510	67	217	1446	55		**2766**
	25-Aug-15	1026	203	492	157	257	10		**2145**
	26-Aug-15	669	492	348	124	927	144		**2704**
	27-Aug-15	586	351	94	688	1900	41		**3660**
	28-Aug-15	908	231	138	447	1128	141		**2993**
	29-Aug-15	1031	60	292	51	948	14		**2396**
	30-Aug-15	1169	416	757	370	706	165		**3583**
	31-Aug-15	439	361	420	564	979	137		**2900**
	1-Sep-15	1215	246	301	771	809	12		**3354**
	2-Sep-15	301	821	116	900	1819	325		**4282**
	3-Sep-15	1176	336	403	262	1442	186		**3805**
	4-Sep-15	424	363	109	76	1413	447		**2832**
	5-Sep-15	538	685	516	217	1661	61		**3678**
DP 10	6-Sep-15	479	1088	256	1029	1414	0		**4266**
	7-Sep-15	810	578	221	630	1369	33		**3641**
	8-Sep-15	480	391	445	213	729	171		**2429**
	9-Sep-15	1094	654	301	1063	1043	203		**4358**
	10-Sep-15	903	112	539	1034	1974	227		**4789**
	11-Sep-15	1164	437	341	602	2538	81		**5163**
	12-Sep-15	862	380	277	519	1038	129		**3205**
	13-Sep-15	603	700	197	386	745	158		**2789**
	14-Sep-15	706	822	1158	468	586	33		**3773**
	15-Sep-15	743	277	170	582	884	4		**2660**
	16-Sep-15	259	615	231	367	1807	93		**3372**
	17-Sep-15	1702	240	122	274	1009	0		**3347**
	18-Sep-15	516	946	143	31	1409	55		**3100**
	19-Sep-15	595	294	295	331	488	0		**2003**
	TOTAL	21544	12855	8892	12917	33445	2969	0	92622

Crime Intel Detail - Minutes in the LASER ZONES

20-Sep-15	1156	176	490	641	1357	136		**3956**
21-Sep-15	773	325	233	627	806	710		**3474**
22-Sep-15	305	366	78	746	776	106		**2377**
23-Sep-15	914	483	96	337	716	520		**3066**
24-Sep-15	1273	283	375	299	1170	114		**3514**
25-Sep-15	1557	450	214	375	898	151		**3645**
26-Sep-15	251	163	132	35	606	21		**1208**
27-Sep-15	317	109	80	400	654	120		**1680**
28-Sep-15	106	205	309	89	930	10		**1649**
29-Sep-15	156	85	306	536	306	240		**1629**
30-Sep-15	237	153	303	310	960	120		**2083**
1-Oct-15	452	518	213	77	716	60		**2036**
2-Oct-15	178	131	2130	350	1147	15		**3951**
3-Oct-15	172	203	97	135	929	45		**1581**
4-Oct-15	187	170	70	190	1084	10		**1711**
5-Oct-15	113	423	164	229	422	53		**1404**
6-Oct-15	590	226	0	651	111	158		**1736**
7-Oct-15	431	395	76	410	350	5		**1667**
8-Oct-15	440	183	336	349	402	0		**1710**
9-Oct-15	170	154	100	125	1310	418		**2277**
10-Oct-15	123	183	272	390	679	251		**1898**
11-Oct-15	437	352	129	190	713	10		**1831**
12-Oct-15	686	516	89	167	601	0		**2059**
13-Oct-15	241	363	171	337	817	135		**2064**
14-Oct-15	801	415	212	239	496	46		**2209**
15-Oct-15	417	308	301	363	756	153		**2298**
16-Oct-15	486	263	93	140	734	89		**1805**
17-Oct-15	787	179	149	393	859	32		**2399**
18-Oct-15	397	342	288	247	706	102		**2082**
19-Oct-15	633	438	166	309	772	61		**2379**
20-Oct-15	124	323	514	315	892	0		**2168**
21-Oct-15	176	353	335	464	437	20		**1785**
22-Oct-15	279	22	35	154	559	18		**1067**

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23-Oct-15	494	70	84	193	438	0		**1279**
24-Oct-15	119	322	229	46	430	29		**1175**
25-Oct-15	404	80	40	321	657	5		**1507**
26-Oct-15	306	281	37	183	602	51		**1460**
27-Oct-15	219	433	65	187	381	29		**1314**
28-Oct-15	420	317	140	201	608	62		**1748**
29-Oct-15	196	278	135	214	502	42		**1367**
30-Oct-15	202	126	200	109	673	10		**1320**
31-Oct-15	199	207	103	417	333	22		**1281**
1-Nov-15	286	202	55	400	703	25		**1671**
2-Nov-15	168	144	48	387	688	106		**1541**
3-Nov-15	233	303	67	404	496	99		**1602**
4-Nov-15	240	288	84	333	522	78		**1545**
5-Nov-15	188	245	72	396	384	118		**1403**
6-Nov-15	173	102	104	403	322	88		**1192**
7-Nov-15	164	85	122	422	207	189		**1189**
8-Nov-15	203	150	42	396	509	15		**1315**
9-Nov-15	127	209	102	301	403	74		**1216**
10-Nov-15	307	189	79	460	306	88		**1429**
11-Nov-15	222	208	99	267	486	106		**1388**
12-Nov-15	306	198	83	333	502	112		**1534**
13-Nov-15	156	87	92	378	445	66		**1224**
14-Nov-15	129	228	101	406	308	110		**1282**
15-Nov-15	122	90	106	301	209	28		**856**
16-Nov-15	114	81	222	243	297	43		**1000**
17-Nov-15	257	92	146	349	414	37		**1295**
18-Nov-15	443	156	379	467	434	49		**1928**
19-Nov-15	403	127	187	416	419	42		**1594**
20-Nov-15	479	143	273	342	462	26		**1725**
21-Nov-15	385	83	246	412	348	53		**1527**
22-Nov-15	106	202	85	229	156	46		**824**
23-Nov-15	520	165	49	398	187	55		**1374**
24-Nov-15	505	134	43	402	134	57		**1275**

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25-Nov-15	502	111	28	377	402	69		**1489**
26-Nov-15	497	209	101	507	415	107		**1836**
27-Nov-15	386	307	79	465	432	117		**1786**
28-Nov-15	399	224	57	422	211	97		**1410**
29-Nov-15	243	189	235	264	249	45		**1225**
30-Nov-15	271	123	148	102	210	116		**970**
1-Dec-15	235	390	273	274	446	76		**1694**
2-Dec-15	261	258	379	181	852	175		**2106**
3-Dec-15	293	158	203	157	506	156		**1473**
4-Dec-15	255	199	151	166	613	48		**1432**
5-Dec-15	203	202	255	184	477	68		**1389**
6-Dec-15	384	187	875	223	201	315		**2185**
7-Dec-15	106	74	367	521	302	25		**1395**
8-Dec-15	452	227	298	108	247	218		**1550**
9-Dec-15	471	179	618	543	412	61		**2284**
10-Dec-15	682	288	808	639	561	244		**3222**
11-Dec-15	546	482	216	494	788	362		**2888**
12-Dec-15	568	520	423	656	590	34		**2791**
13-Dec-15	389	267	230	506	337	224		**1953**
14-Dec-15	203	585	478	555	849	78		**2748**
15-Dec-15	665	680	185	780	297	138		**2745**
16-Dec-15	206	561	370	483	845	335		**2800**
17-Dec-15	444	337	487	626	308	203		**2405**
18-Dec-15	207	251	417	403	130	501		**1909**
19-Dec-15	373	206	497	317	380	130		**1903**
20-Dec-15	240	437	353	340	137	246		**1753**
21-Dec-15	654	157	136	608	470	95		**2120**
22-Dec-15	332	360	170	410	684	406		**2362**
23-Dec-15	813	369	285	431	813	46		**2757**
24-Dec-15	193	178	139	1026	580	168		**2284**

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25-Dec-15	194	473	1084	924	487	522		**3684**
26-Dec-15	296	165	610	745	230	98		**2144**
27-Dec-15	72	398	637	1019	255	290		**2671**
28-Dec-15	72	398	637	1019	255	290		**2671**
29-Dec-15	575	262	503	694	628	250		**2912**
30-Dec-15	415	460	751	382	492	109		**2609**
31-Dec-15	318	435	699	571	978	200		**3201**
1-Jan-16	73	417	341	647	395	431		**2304**
2-Jan-16	275	258	284	415	223	104		**1559**
3-Jan-16	199	174	717	841	795	299		**3025**
4-Jan-16	288	200	122	1050	442	125		**2227**
5-Jan-16	209	336	580	440	223	506		**2294**
6-Jan-16	181	631	483	815	417	158		**2685**
7-Jan-16	769	468	749	601	778	12		**3377**
8-Jan-16	499	351	1198	825	715	131		**3719**
9-Jan-16	40	222	135	314	1017	231		**1959**
10-Jan-16	284	192	479	643	238	203		**2039**
11-Jan-16	212	297	244	658	226	162		**1799**
12-Jan-16	158	75	378	329	51	24		**1015**
13-Jan-16	212	145	195	219	130	27		**928**
14-Jan-16	226	333	198	567	589	48		**1961**
15-Jan-16	606	351	226	863	1232	8		**3286**
16-Jan-16	588	132	170	174	933	41		**2038**
17-Jan-16	199	268	117	357	177	192		**1310**
18-Jan-16	178	277	152	298	326	77		**1308**
19-Jan-16	205	446	226	292	187	33		**1389**
20-Jan-16	167	134	170	282	235	114		**1102**
21-Jan-16	194	1159	74	22	2282	40		**3771**
22-Jan-16	354	617	365	854	1967	196		**4353**
23-Jan-16	1377	180	67	36	540	20		**2220**
24-Jan-16	118	667	125	721	558	55		**2244**

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25-Jan-16	173	199	114	269	703	121		**1579**
26-Jan-16	135	208	560	407	636	202		**2148**
27-Jan-16	74	197	196	880	601	183		**2131**
28-Jan-16	245	455	471	500	678	109		**2458**
29-Jan-16	191	317	680	377	555	153		**2273**
30-Jan-16	1002	421	182	671	738	37		**3051**
31-Jan-16	258	223	563	967	532	173		**2716**
1-Feb-16	96	273	235	398	273	107		**1382**
2-Feb-16	77	196	247	444	644	30		**1638**
3-Feb-16	396	703	542	1348	932	183		**4104**
4-Feb-16	389	660	390	1461	421	480		**3801**
5-Feb-16	339	399	413	1021	738	322		**3232**
6-Feb-16	124	130	293	654	161	253		**1615**
7-Feb-16	138	246	303	395	118	25		**1225**
8-Feb-16	155	127	279	236	349	116		**1262**
9-Feb-16	351	64	235	59	238	280		**1227**
10-Feb-16	172	153	616	311	780	321		**2353**
11-Feb-16	261	148	275	342	519	125		**1670**
12-Feb-16	237	396	199	86	868	133		**1919**
13-Feb-16	206	84	253	490	962	188		**2183**
14-Feb-16	332	305	154	602	560	274		**2227**
15-Feb-16	161	217	325	158	219	214		**1294**
16-Feb-16	67	320	164	288	292	219		**1350**
17-Feb-16	207	194	357	451	579	264		**2052**
18-Feb-16	291	637	804	459	848	121		**3160**
19-Feb-16	142	209	305	142	752	58		**1608**
20-Feb-16	223	404	408	476	540	159		**2210**
21-Feb-16	121	214	315	674	151	212		**1687**
22-Feb-16	260	91	82	297	162	398		**1290**
23-Feb-16	352	451	617	736	323	176		**2655**
24-Feb-16	444	465	272	262	518	47		**2008**

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25-Feb-16	585	516	290	350	385	69		**2195**
26-Feb-16	402	360	420	365	716	65		**2328**
27-Feb-16	626	578	455	417	1079	113		**3268**
28-Feb-16	286	500	193	442	854	51		**2326**
29-Feb-16	452	200	82	484	698	121		**2037**
1-Mar-16	115	293	216	293	225	50		**1192**
2-Mar-16	413	272	650	648	525	589		**3097**
3-Mar-16	416	52	426	695	876	106		**2571**
4-Mar-16	256	242	152	432	962	50		**2094**
5-Mar-16	180	208	171	312	624	77		**1572**
6-Mar-16	462	460	305	408	1026	113		**2774**
7-Mar-16	496	87	252	271	595	178		**1879**
8-Mar-16	58	258	772	602	458	9		**2157**
9-Mar-16	204	604	323	720	956	238		**3045**
10-Mar-16	273	489	673	607	247	123		**2412**
11-Mar-16	997	322	155	743	1804	110		**4131**
12-Mar-16	451	453	189	399	1096	204		**2792**
13-Mar-16	620	144	55	659	392	43		**1913**
14-Mar-16	213	184	322	276	256	90		**1341**
15-Mar-16	333	443	425	611	705	65		**2582**
16-Mar-16	193	751	435	839	816	199		**3233**
17-Mar-16	591	699	171	574	1048	315		**3398**
18-Mar-16	198	352	399	435	126	441		**1951**
19-Mar-16	128	259	398	236	421	55		**1497**
20-Mar-16	803	625	277	552	266	18		**2541**
21-Mar-16	323	860	356	955	876	221		**3591**
22-Mar-16	63	429	375	532	336	216		**1951**
23-Mar-16	570	511	154	509	1317	14		**3075**
24-Mar-16	94	125	172	682	1149	78		**2300**
25-Mar-16	248	537	703	1246	595	257		**3586**
26-Mar-16	221	136	443	623	690	135		**2248**

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27-Mar-16	213	295	263	249	386	39		**1445**
28-Mar-16	2383	417	257	368	170	185		**3780**
29-Mar-16	340	387	353	677	834	155		**2746**
30-Mar-16	367	488	649	493	766	156		**2919**
31-Mar-16	401	426	246	487	1332	174		**3066**
1-Apr-16	193	407	896	352	1282	130		**3260**
2-Apr-16	83	158	154	974	1156	109		**2634**
3-Apr-16	351	47	263	802	593	36		**2092**
4-Apr-16	384	130	282	666	361	115		**1938**
5-Apr-16	267	315	153	412	441	21		**1609**
6-Apr-16	354	247	488	827	1220	53		**3189**
7-Apr-16	321	238	573	443	1128	247		**2950**
8-Apr-16	233	396	300	401	563	100		**1993**
9-Apr-16	207	249	224	547	1178	215		**2620**
10-Apr-16	279	138	311	486	308	19		**1541**
11-Apr-16	212	275	388	198	344	203		**1620**
12-Apr-16	398	122	118	366	436	216		**1656**
13-Apr-16	332	628	125	346	788	161		**2380**
14-Apr-16	265	215	520	648	1678	125		**3451**
15-Apr-16	217	629	433	454	752	178		**2663**
16-Apr-16	104	255	371	406	777	223		**2136**
17-Apr-16	104	101	642	474	517	13		**1851**
18-Apr-16	335	354	246	695	185	119		**1934**
19-Apr-16	471	336	424	683	619	126		**2659**
20-Apr-16	229	177	181	361	374	117		**1439**
21-Apr-16	163	427	505	716	1352	306		**3469**
22-Apr-16	130	425	527	348	727	600		**2757**
23-Apr-16	284	174	63	448	279	29		**1277**
24-Apr-16	286	238	356	629	660	249		**2418**
25-Apr-16	338	162	147	284	613	198		**1742**
26-Apr-16	295	324	223	627	295	181		**1945**
27-Apr-16	395	136	454	667	1080	286		**3018**
28-Apr-16	324	646	390	283	273	519		**2435**

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29-Apr-16	144	284	155	260	417	307		**1567**
30-Apr-16	390	315	272	196	552	141		**1866**
1-May-16	752	546	362	720	411	51		**2842**
2-May-16	195	152	289	235	282	186		**1339**
3-May-16	498	356	379	396	368	162		**2159**
4-May-16	553	144	695	369	367	228		**2356**
5-May-16	196	423	655	320	708	157		**2459**
6-May-16	233	575	364	645	250	101		**2168**
7-May-16	208	286	247	315	949	20		**2025**
8-May-16	182	118	570	946	227	98		**2141**
9-May-16	387	269	259	237	393	99		**1644**
10-May-16	346	141	603	226	112	125		**1553**
11-May-16	29	170	439	424	1173	31		**2266**
12-May-16	177	358	422	788	908	35		**2688**
13-May-16	499	264	320	159	1199	29		**2470**
14-May-16	262	574	245	442	652	331		**2506**
15-May-16	472	72	333	461	501	292		**2131**
16-May-16	457	168	561	532	244	5		**1967**
17-May-16	215	533	196	580	336	127		**1987**
18-May-16	113	450	351	287	971	727		**2899**
19-May-16	466	174	451	784	612	7		**2494**
20-May-16	506	738	836	681	1222	163		**4146**
21-May-16	176	123	269	383	910	206		**2067**
22-May-16	525	627	411	576	474	173		**2786**
23-May-16	170	254	203	245	149	402		**1423**
24-May-16	201	133	262	268	409	157		**1430**
25-May-16	428	302	87	768	596	8		**2189**
26-May-16	478	329	485	513	670	124		**2599**
27-May-16	116	129	353	395	367	114		**1474**
28-May-16	262	278	536	636	1141	77		**2930**
29-May-16	185	81	244	330	213	186		**1239**
30-May-16	535	320	528	601	422	45		**2451**
31-May-16	764	368	577	745	187	146		**2787**

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1-Jun-16	680	512	286	473	292	103		**2346**
2-Jun-16	408	425	571	1227	756	258		**3645**
3-Jun-16	386	219	412	709	1319	188		**3233**
4-Jun-16	411	189	196	522	1234	108		**2660**
5-Jun-16	82	191	401	818	719	101		**2312**
6-Jun-16	163	393	287	490	605	211		**2149**
7-Jun-16	406	120	429	845	282	98		**2180**
8-Jun-16	338	485	842	982	353	43		**3043**
9-Jun-16	511	522	379	554	333	63		**2362**
10-Jun-16	231	132	294	450	886	187		**2180**
11-Jun-16	41	156	424	364	531	77		**1593**
12-Jun-16	292	551	383	542	44	83		**1895**
13-Jun-16	98	256	535	382	379	45		**1695**
14-Jun-16	253	352	234	299	257	75		**1470**
15-Jun-16	265	184	350	680	408	20		**1907**
16-Jun-16	138	310	304	478	803	254		**2287**
17-Jun-16	38	284	527	259	410	90		**1608**
18-Jun-16	369	651	422	372	77	29		**1920**
19-Jun-16	383	329	257	503	645	129		**2246**
20-Jun-16	60	145	242	702	208	74		**1431**
21-Jun-16	85	320	299	622	806	38		**2170**
22-Jun-16	75	284	486	466	387	48		**1746**
23-Jun-16	63	188	306	720	367	62		**1706**
24-Jun-16	128	324	487	516	702	82		**2239**
25-Jun-16	98	438	234	412	608	44		**1834**
26-Jun-16	402	414	388	608	555	89		**2456**
27-Jun-16	105	255	466	602	377	46		**1851**
28-Jun-16	206	402	367	559	812	48		**2394**
29-Jun-16	357	385	209	498	327	33		**1809**
30-Jun-16	209	294	348	766	407	43		**2067**
1-Jul-16	199	301	502	648	722	77		**2449**
2-Jul-16	264	488	547	501	589	65		**2454**
3-Jul-16	408	369	498	702	564	56		**2597**

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4-Jul-16	584	361	466	605	365	55		**2436**
5-Jul-16	602	467	367	559	802	44		**2841**
6-Jul-16	621	502	224	564	327	88		**2326**
7-Jul-16	550	302	478	802	502	166		**2800**
8-Jul-16	699	455	623	656	700	125		**3258**
9-Jul-16	547	556	623	625	423	102		**2876**
10-Jul-16	547	556	623	625	423	102		**2876**
11-Jul-16	422	399	486	806	554	104		**2771**
12-Jul-16	607	387	574	622	365	122		**2677**
13-Jul-16	559	562	409	467	645	130		**2772**
14-Jul-16	707	534	288	589	344	66		**2528**
15-Jul-16	788	305	503	822	487	103		**3008**
16-Jul-16	600	488	700	437	605	124		**2954**
17-Jul-16	402	503	576	611	412	122		**2626**
18-Jul-16	386	388	404	454	311	164		**2107**
19-Jul-16	533	396	522	513	461	103		**2528**
20-Jul-16	486	467	378	312	416	145		**2204**
21-Jul-16	622	573	301	341	547	166		**2550**
22-Jul-16	601	422	471	766	423	101		**2784**
23-Jul-16	557	346	602	385	581	116		**2587**
24-Jul-16	243	189	235	264	249	45		**1225**
25-Jul-16	271	123	148	102	210	116		**970**
26-Jul-16	235	390	273	274	446	76		**1694**
27-Jul-16	261	258	379	181	852	175		**2106**
28-Jul-16	293	158	203	157	506	156		**1473**
29-Jul-16	255	199	151	166	613	48		**1432**
30-Jul-16	203	202	255	184	477	68		**1389**
31-Jul-16	336	200	360	571	427	150		**2044**
1-Aug-16	628	282	611	271	101	59		**1952**
2-Aug-16	281	67	408	381	609	149		**1895**
3-Aug-16	463	323	230	339	209	74		**1638**
4-Aug-16	721	330	576	494	363	181		**2665**
5-Aug-16	292	284	347	387	281	28		**1619**

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6-Aug-16	405	70	480	495	270	26		**1746**
7-Aug-16	228	162	230	937	841	205		**2603**
8-Aug-16	229	27	505	336	309	158		**1564**
9-Aug-16	614	372	244	474	338	162		**2204**
10-Aug-16	320	339	504	413	466	116		**2158**
11-Aug-16	332	453	561	423	384	117		**2270**
12-Aug-16	456	511	187	497	270	98		**2019**
13-Aug-16	536	208	498	394	51	99		**1786**
14-Aug-16	430	778	498	592	786	174		**3258**
15-Aug-16	455	358	253	694	467	82		**2309**
16-Aug-16	269	223	140	541	594	33		**1800**
17-Aug-16	418	149	494	1073	510	117		**2761**
18-Aug-16	174	234	361	206	94	362		**1431**
19-Aug-16	209	319	497	549	148	69		**1791**
20-Aug-16	269	225	560	582	139	53		**1828**
21-Aug-16	533	310	424	356	488	226		**2337**
22-Aug-16	419	383	137	932	381	36		**2288**
23-Aug-16	249	347	273	103	312	395		**1679**
24-Aug-16	584	874	485	169	444	321		**2877**
25-Aug-16	98	267	222	362	571	71		**1591**
26-Aug-16	873	566	254	305	272	93		**2363**
27-Aug-16	205	139	320	814	672	31		**2181**
28-Aug-16	271	235	730	338	217	238		**2029**
29-Aug-16	456	578	415	481	719	317		**2966**
30-Aug-16	167	226	554	543	368	64		**1922**
31-Aug-16	169	219	541	643	224	87		**1883**
1-Sep-16	71	259	862	218	57	242		**1709**
2-Sep-16	171	168	293	366	38	113		**1149**
3-Sep-16	43	207	464	368	88	145		**1315**
4-Sep-16	360	448	498	477	154	30		**1967**
5-Sep-16	316	468	467	551	608	37		**2447**
6-Sep-16	174	230	440	916	457	86		**2303**
7-Sep-16	273	426	458	620	273	258		**2308**

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8-Sep-16	736	457	264	475	1003	69		**3004**
9-Sep-16	745	457	192	70	160	15		**1639**
10-Sep-16	469	575	566	396	410	136		**2552**
11-Sep-16	109	224	204	294	274	108		**1213**
12-Sep-16	867	211	162	698	196	38		**2172**
13-Sep-16	228	576	258	197	216	0		**1475**
14-Sep-16	344	467	131	753	345	78		**2118**
15-Sep-16	141	527	475	615	526	156		**2440**
16-Sep-16	222	557	168	144	221	142		**1454**
17-Sep-16	193	14	192	724	184	119		**1426**
18-Sep-16	420	173	434	389	243	42		**1701**
19-Sep-16	411	183	179	475	332	79		**1659**
20-Sep-16	252	60	259	194	136	58		**959**
21-Sep-16	162	104	171	371	78	263		**1149**
22-Sep-16	156	332	539	240	462	32		**1761**
23-Sep-16	345	315	281	157	276	169		**1543**
24-Sep-16	195	271	382	215	414	137		**1614**
25-Sep-16	141	399	83	323	202	5		**1153**
26-Sep-16	113	410	205	269	450	67		**1514**
27-Sep-16	360	208	136	405	119	106		**1334**
28-Sep-16	282	383	331	144	214	25		**1379**
29-Sep-16	61	305	258	409	250	0		**1283**
30-Sep-16	233	176	53	457	242	89		**1250**
1-Oct-16	128	168	220	63	140	45		**764**
2-Oct-16	272	407	183	266	169	70		**1367**
3-Oct-16	408	119	293	89	122	207		**1238**
4-Oct-16	554	140	168	123	182	226		**1393**
5-Oct-16	136	245	94	466	473	38		**1452**
6-Oct-16	177	293	177	174	422	0		**1243**
7-Oct-16	259	139	65	125	89	171		**848**
8-Oct-16	218	55	291	242	366	263		**1435**
9-Oct-16	144	135	316	425	232	30		**1282**
10-Oct-16	203	59	135	335	450	40		**1222**

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11-Oct-16	181	253	188	115	337	109		**1183**
12-Oct-16	81	131	108	281	228	160		**989**
13-Oct-16	173	30	149	179	133	170		**834**
14-Oct-16	95	158	268	212	200	68		**1001**
15-Oct-16	209	67	288	204	145	89		**1002**
16-Oct-16	49	143	180	111	152	95		**730**
17-Oct-16	67	76	417	105	82	41		**788**
18-Oct-16	103	281	201	308	113	104		**1110**
19-Oct-16	127	368	237	450	107	163		**1452**
20-Oct-16	231	195	0	188	251	29		**894**
21-Oct-16	305	410	355	500	255	230		**2055**
22-Oct-16	240	265	640	435	315	140		**2035**
23-Oct-16	238	251	198	122	134	53		**996**
24-Oct-16	98	70	187	287	172	51		**865**
25-Oct-16	253	264	135	94	202	122		**1070**
26-Oct-16	89	159	330	173	214	52		**1017**
27-Oct-16	143	100	108	221	92	63		**727**
28-Oct-16	125	160	259	327	271	31		**1173**
29-Oct-16	205	64	239	80	226	118		**932**
30-Oct-16								**0**
31-Oct-16								**0**
1-Nov-16								**0**
2-Nov-16								**0**
3-Nov-16								**0**
4-Nov-16								**0**
5-Nov-16								**0**
6-Nov-16								**0**
7-Nov-16								**0**
8-Nov-16								**0**
9-Nov-16								**0**
10-Nov-16								**0**
11-Nov-16								**0**
12-Nov-16								**0**

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13-Nov-16								**0**
14-Nov-16								**0**
15-Nov-16								**0**
16-Nov-16								**0**