SAFE-NET: A Computing Platform for Public Safety Applications

Research Team:

Khaled Abdelghany, Ph.D.
Barbara Minsker , Ph.D.
Michael Hahsler , Ph.D.
May Yuan , Ph.D.

Dallas Fire Rescue Team:

Chief Daniel Salazar
Captain James Thornton

The University of Texas at Dallas

Southern Methodist University

Dallas Fire Rescue Department

Acronym Glossary

- API = Application Program Interface
- AVL = Automatic Vehicle Location
- CAD = Computer Aided Drawing
- CNN = Convolutional Neural Network
- CPR = Cardiopulmonary Resuscitation
- COTS = Commercial Off-the-Shelf
- CUI = Concept Unique Identifier
- EMS = Emergency Medical Service
- ER = Emergency Response
- ESRI = Environmental Systems Research Institute
- FBI = Federal Bureau of Investigations
- GPS = Global Positioning System
- IoT = Internet of Things
- LL = Lincoln Laboratory
- MAE = Mean Absolute Error
- MSE = Mean Square Error
- NPSBN = National Public Safety Broadband Network
- PTZ = Pan Tilt Zoom
- QoS = Quality of Service
- R&D = Research and Development
- REST = Representational State Transfer
- RMSE = Root Mean Square Error
- ROC = Receiver Operating Characteristic
- SQL = Standardized Query Language
- UAS = Unmanned Aerial System
- UMLS = Unified Medical Language System
- WER = Word Error Rate

PSCR

Background

Emergency management is a complex real-time operation that involves several interdependent processes, including:

a) Emergency situation awareness

b) Scheme design for response and rescue

c) Equipment and personnel deployment

d) Start-to-finish mission support

Public Safety Analytics

- There are increasing calls for developing **descriptive**, **predictive**, and **prescriptive** analytical tools using **big data** to enable informed and optimal decision making for public safety applications.

- These tools provide necessary intelligence and decision support capabilities including:
  - Estimation of missing information
  - Incident state prediction
  - Evaluation of response scheme alternatives to determine the optimal strategies

Research Objectives

This research aims at accelerating public safety innovation through the development of **SAFE-NET**.

SAFE-NET is a novel computational platform to support efficient and safe dynamic mobilization of resources and personnel for emergency response.

Presented Problems

Problem 1:
Area-wide Workload Balancing for Robust Response Time

Problem 2:
Spatial risk modeling of traffic accidents for emergency vehicle routing

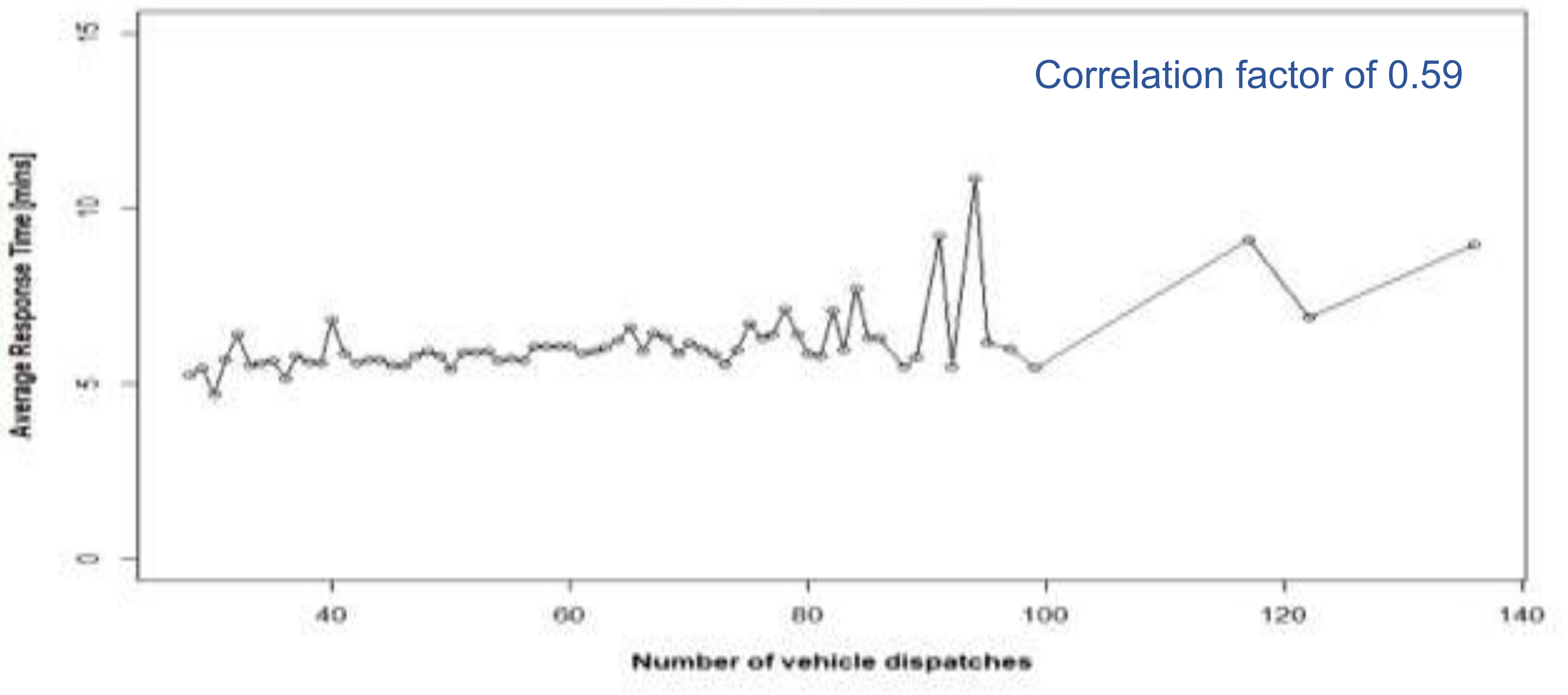
Problem 3:
SAFE-NET Big Data Infrastructure

Part 1:

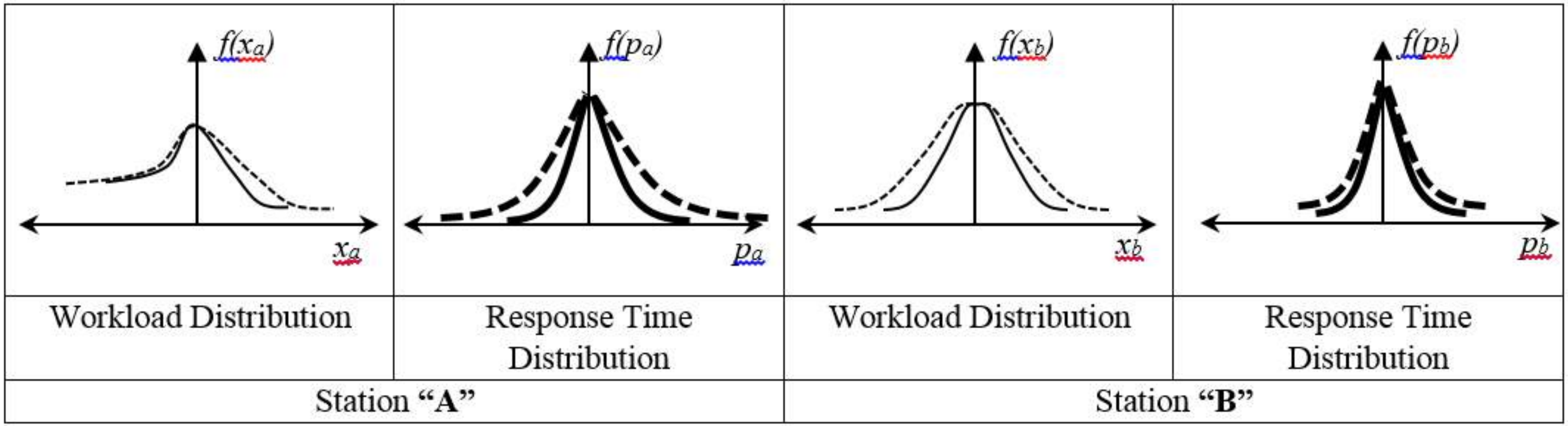
Area-wide Workload Balancing for Robust Response Time

Dr. Khaled Abdelghany
Southern Methodist University

Motivation:
Correlation between Workload and Response Time



Workload and Response Time Distributions



Station B is more capable of "absorbing" uncertainty in the workload.
We observe limited increase in the variability in the response time with the increase in the variability of the workload.

Example of Service Area Overlap for Three Stations in the Dallas Area

Problem Statement

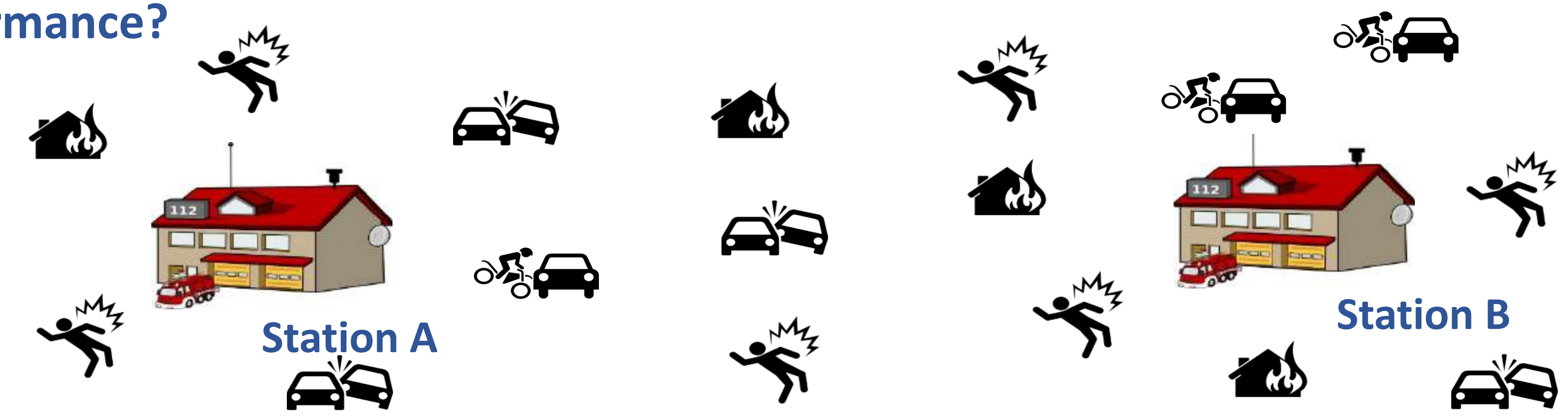
Given:

- The set of stations serving a metropolitan area
- The distribution function of the workload for each station (e.g., no. of emergency dispatches)
- The distribution function of the response time for each station (i.e., system performance)

Required:

The maximum load for each station that maximizes the area-wide response time robustness

Which station should respond to an emergency to achieve a system-wide optimal performance?



Mathematical Formulation

Minimize

$$Z = \sum_a \left(\begin{array}{c} \sum_{s_a} \rho_a(s_a, x_a^c) \cdot g_a(x_{s_a}) + \\ \omega \cdot \frac{1}{|s_a|} \left[\sum_{s_a} \left(g_a(x_{s_a}) - \sum_s \rho_a(s_a, x_a^c) \cdot g_a(x_{s_a}) \right)^2 \right] \end{array} \right) \quad (1)$$

Subject to:

$$\sum_a x_a^c = Q \quad (2)$$

$$x_{s_a} \leq x_a^c \qquad \forall\, a \in A, s_a \in S_a \quad (3)$$

$$x_a^c \leq x_a^{cap} \qquad \forall\, a \in A \quad (4)$$

$$x_a^c \geq 0 \qquad \forall\, a \in A \quad (5)$$

Decision Variables: The workload cutoff for each station x_a^c

The objective function minimizes the total system uncertainty (i.e., maximizes the response time robustness) which is measured as the weighted sum of:

- The expected response time for all stations
- The variance of the response time across all stations

Define μ is the Lagrange multiplier for constraint (2), the formulation above can be written using the Largrangian objective function $L(.)$ in (6) and constraints (3) to (5).

$$L = Z + \mu \cdot (Q - \sum_a x_a^c) \tag{6}$$

The optimality conditions can be derived by differentiating $L(.)$ with respect to the workload cutoff value x_a^c for each subsystem a. Two cases can be encountered:

$$\frac{\partial L(.)}{\partial x_a^c} = 0 \text{ where } x_a^c \geq 0 \tag{7}$$

$$\frac{\partial L(.)}{\partial x_a^c} > 0 \text{ where } x_a^c = 0 \tag{8}$$

The minimum value of $L(.)$ occurs in the positive range of x_a^c.

The minimum value of $L(.)$ occurs in the negative range of x_a^c (x_a^c=0).

Define $\pi_a = \frac{\partial Z(.)}{\partial x_a^c}$, the term $\frac{\partial L(.)}{\partial x_a^c}$ can be written as $(\pi_a - \mu)$.

Thus, the optimality conditions of the problem can be written as follows:

$$x_a^{*c}.(\pi_a^* - \mu) = 0 \qquad \forall\, a \in I \qquad (9)$$

$$\pi_a^* - \mu \geq 0 \qquad \forall\, a \in I \qquad (10)$$

The term π_a represents the marginal cost of uncertainty of station a, which is measured as the increase in the value of the objective function defined in (1) associated with increasing the workload cutoff $x_a^c$of this station by one unit.

System Optimal Equilibrium

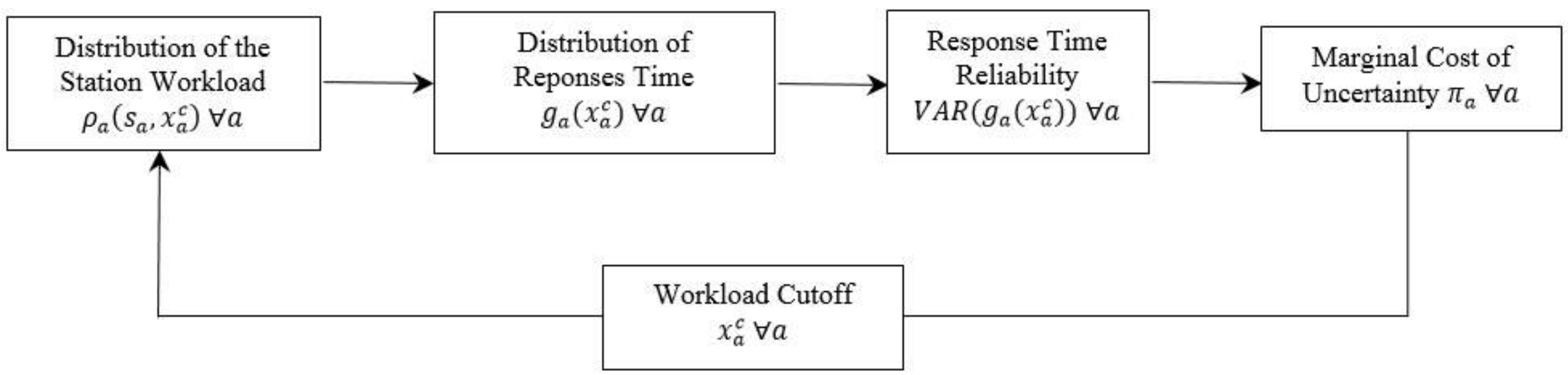
The conditions in (9) and (10) imply that each station a adopts an optimal cutoff workload value x_a^{*c} such that **uncertainty is distributed among the stations resulting in a state of equilibrium**.

At equilibrium, the marginal cost of uncertainty $\pi_a^* \; \forall \; a$ is minimum and equal to μ.

At equilibrium, no improvement can be obtained in the overall response time robustness by modifying the workload cutoff of any of the stations.

Solution Methodology

- An iterative solution methodology is under development.
- The methodology solves for the optimal workload cutoff value for each station.
- The optimal workload cutoff value ensures that all stations are having the same marginal cost of uncertainty.



Part 2:

Spatial risk modeling of traffic accidents for emergency vehicle routing

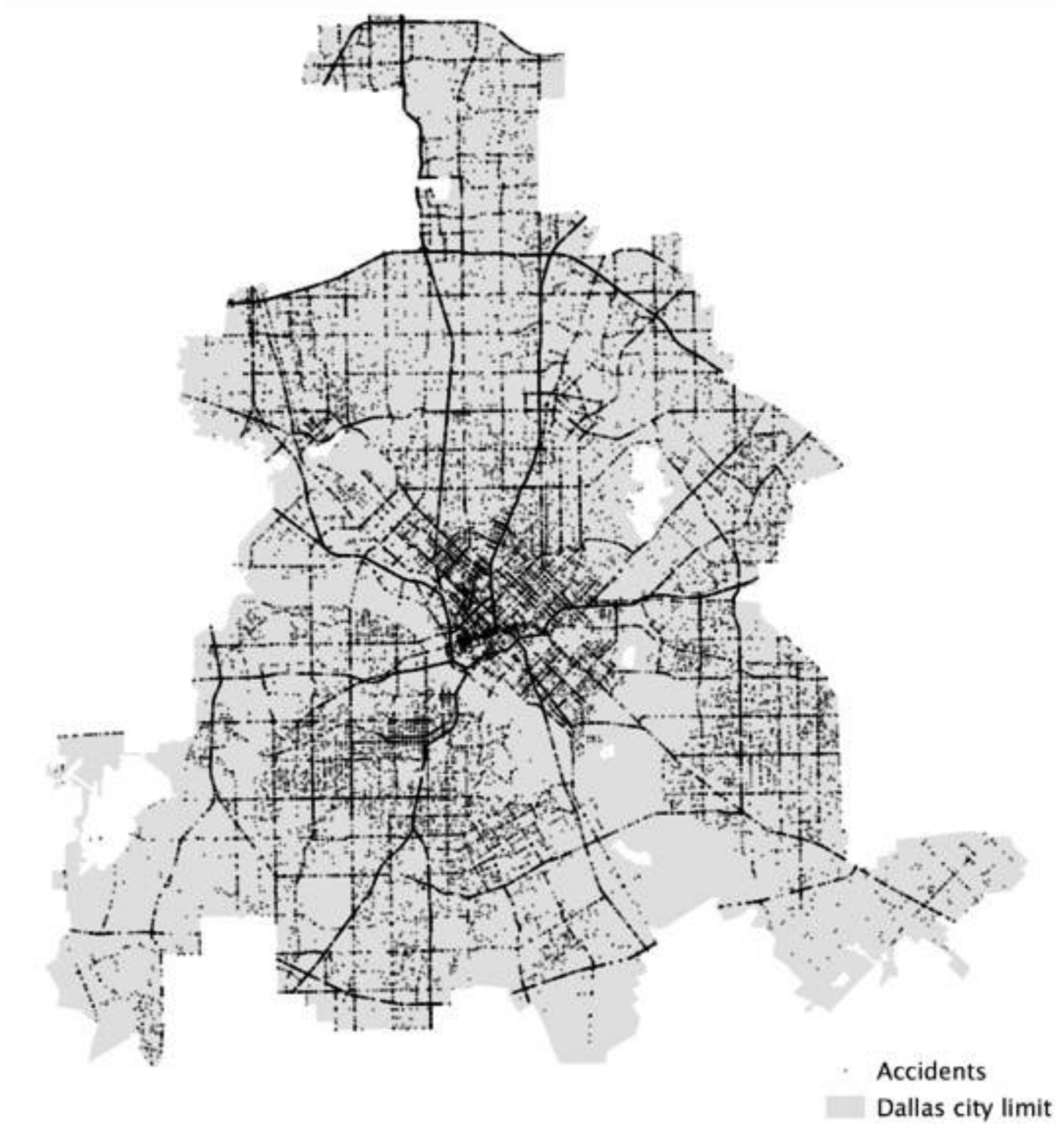
Dr. May Yuan
The University of Texas at Dallas

Responses to emergency calls can present a high risk to the emergency responders. According to the National Highway Traffic Safety Administration (NHTSA), there were approximately 31,600 accidents involving fire trucks from 2000 to 2009 in the nation, and 70% of these fire truck accidents occurred while in emergency use. In the period from 1992 to 2011, there were an estimated 4,500 accidents per year involving ambulances. About 60% of ambulance accidents occurred during emergency response operations. Therefore, it is important to consider spatial risk during dispatch.

We are developing risk analytics with new approaches to model the likelihood of traffic accidents on street segments and over time (hourly). We will then analyze the effects of traffic accidents on emergency vehicle runs in Dallas.

Data used in the spatial risk modeling include:

- TxDOT street centerline networks
- TxDOT traffic accident records
- NOAA national centers for environmental information: Weather daily summaries
- City of Dallas open data portal: city boundary files



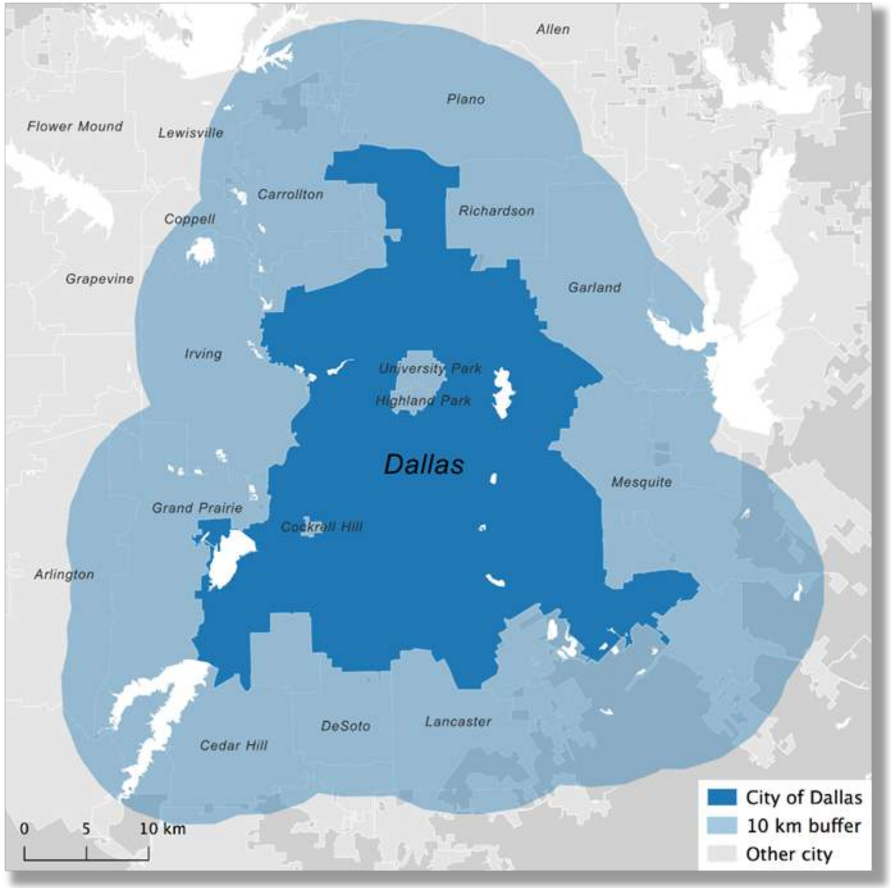
68,480 traffic accidents 2015-2016

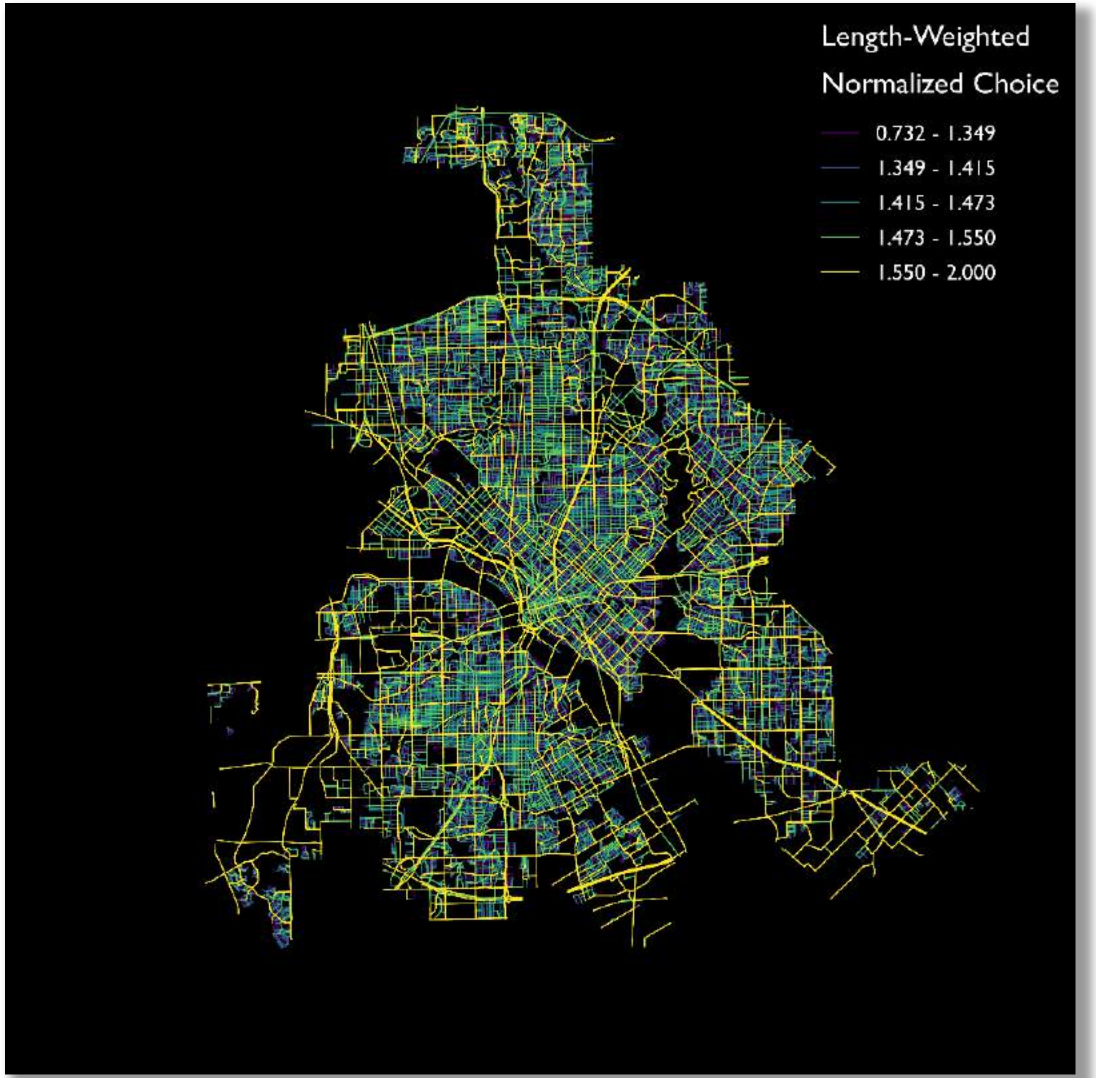
Study area is extended to 10 km around the city boundary to account for spatial effects from surrounding transportation networks.

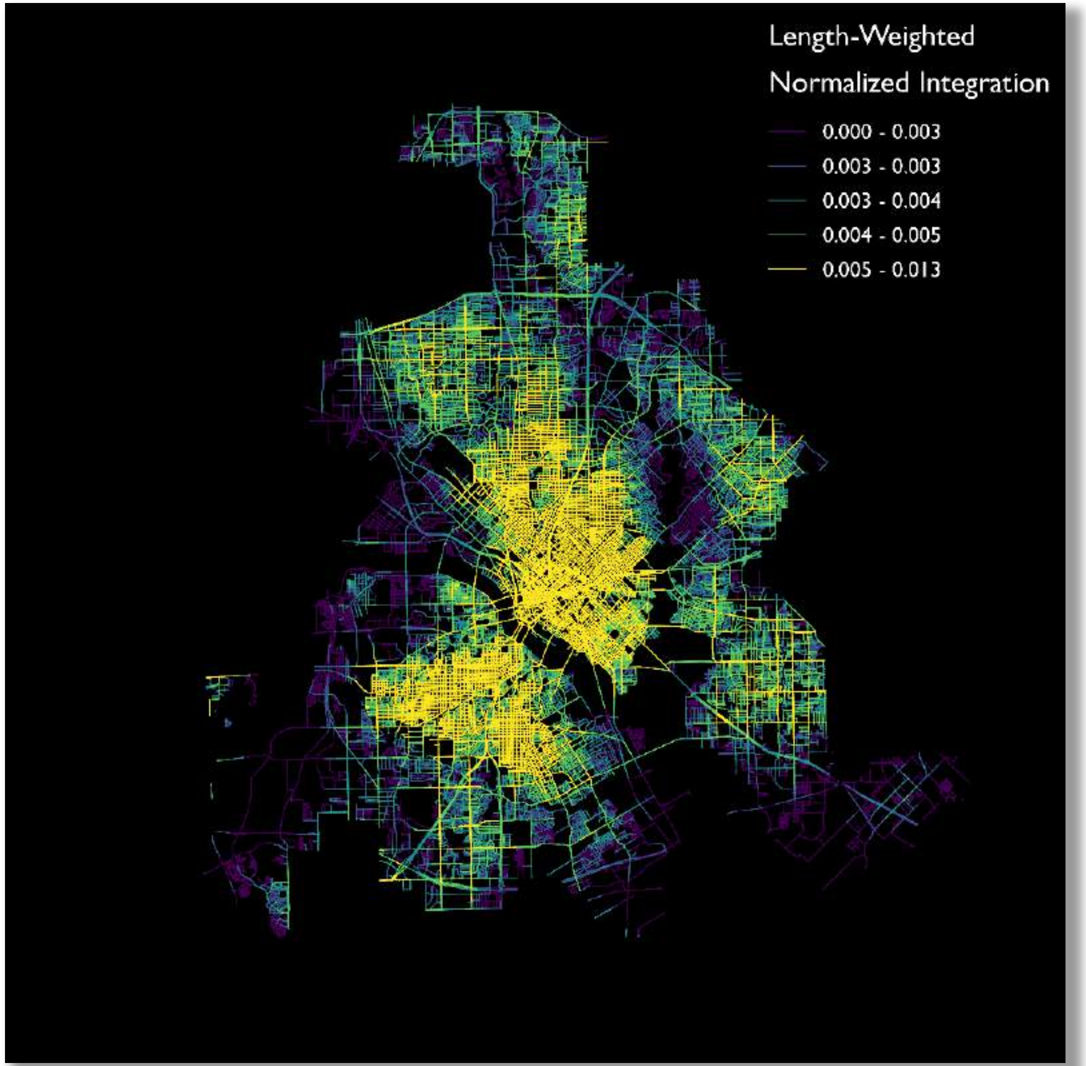
The study assumes that spatial risk is subject to site characteristics of the street networks and time-varying situations.

Site variables: spatial syntax measures, road types, and road widths.

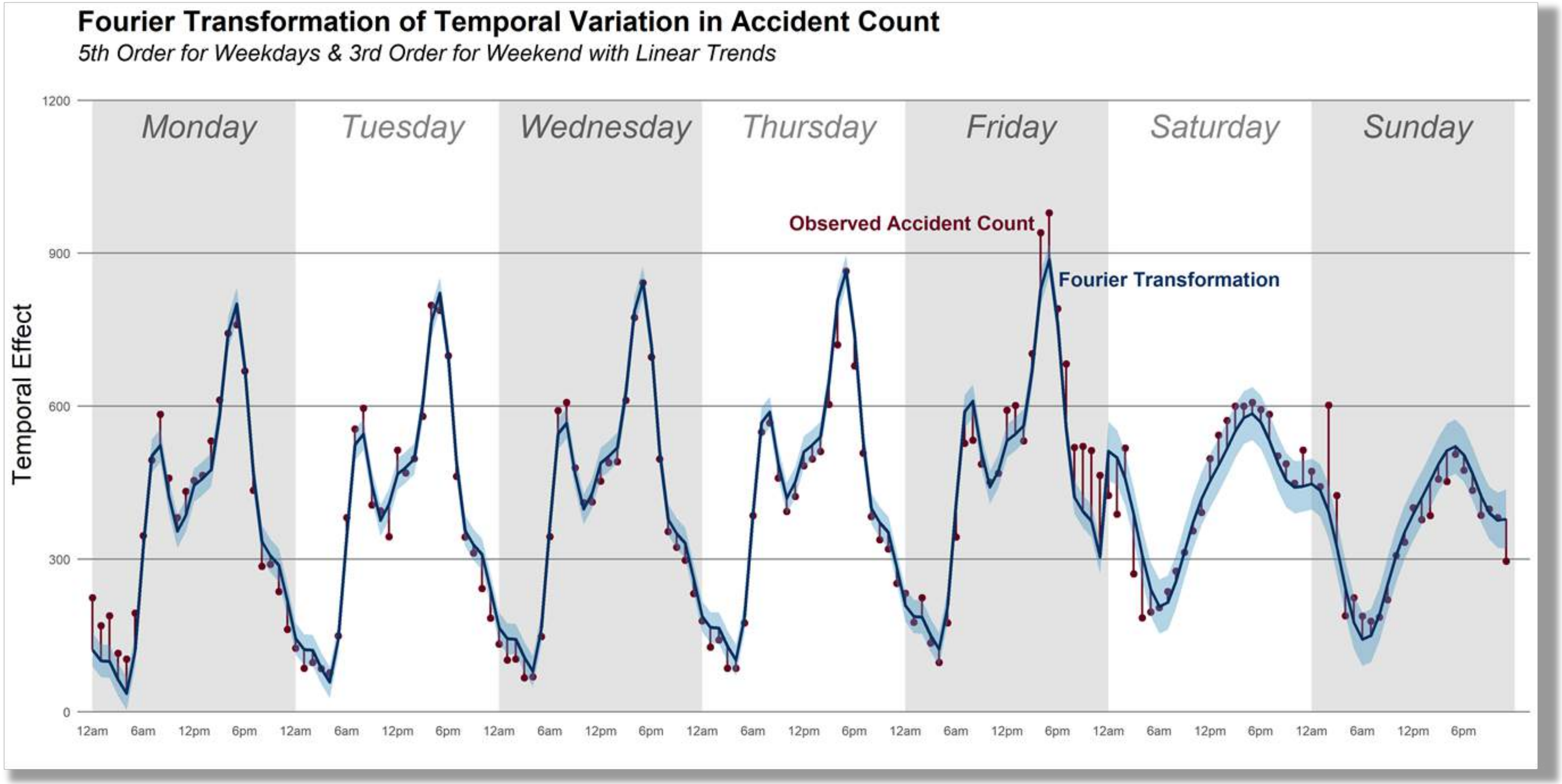
Situational variables: time of day/week, weather parameters, and cascading effects from previous accidents (a.k.a. near repeats).





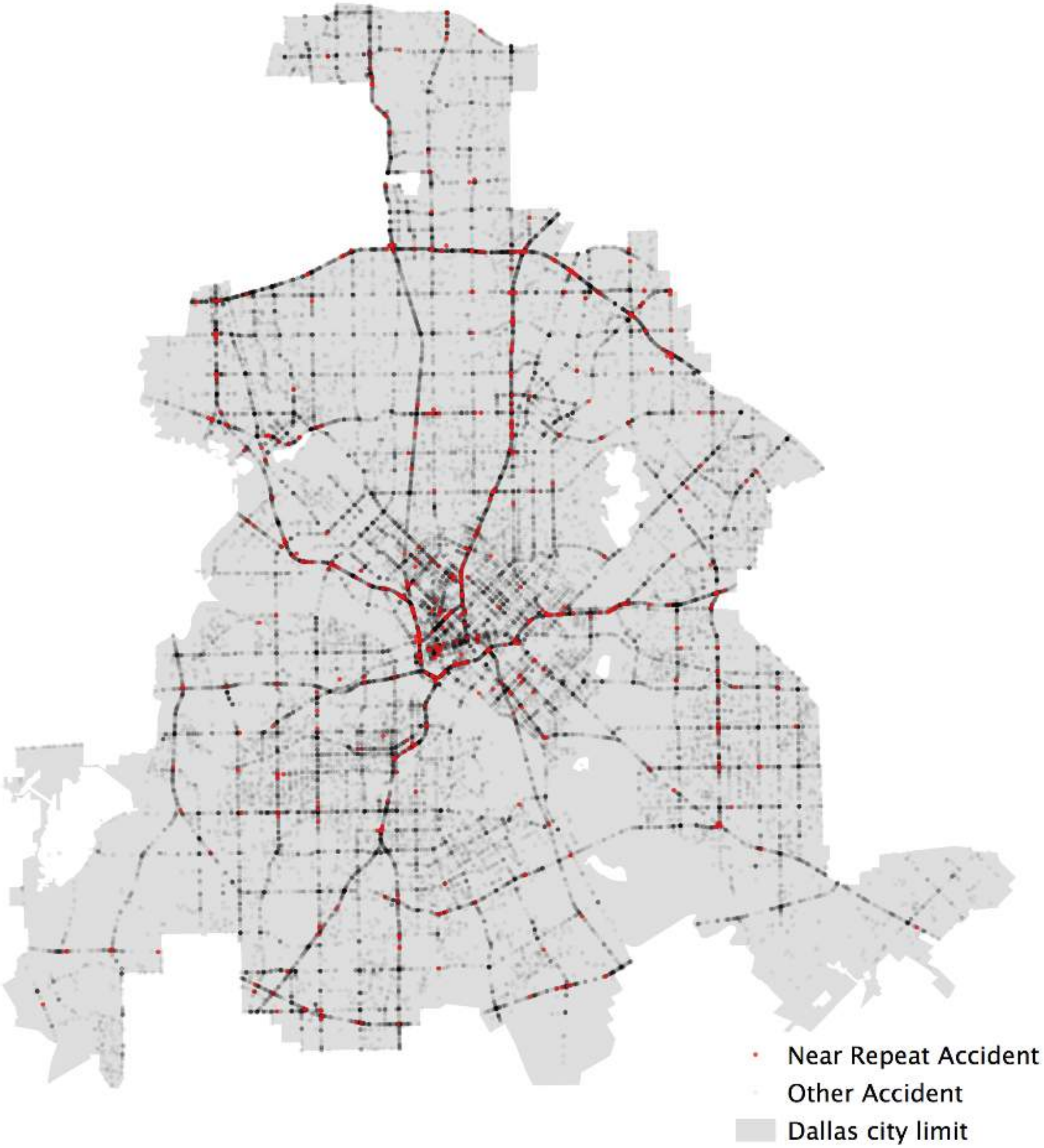


We used two spatial syntax measures. Choice measures the relative flow of a street segment by the frequency of the street segment being part of the shortest paths between any pairs of two points on the network. Integration measures the centrality of a particular street segment using the average distance from the street segment to all other street segments on the network.



Partial F-tests of the Fourier transformation of hourly traffic accident distribution show adjusted R^2 values of 0.9476 for weekdays and 0.7716 for weekends at the 95% confidence level.

Near-repeat traffic accidents are most prominent along primary highways, including President George Bush Turnpike, Central Express Way, I-35 E, and I-30. Major intersections in the downtown and along other major streets also exhibit higher frequencies of near-repeat accidents.



We use logistic regression and random forest algorithm to model the likelihood of traffic accidents on street segments per 100 m per hour. Here are the logistic regression, which significant independent variables include near-repeat, time, major intersections, road types, integration, and choice.

Variable	ΔAUC
Near Repeat	**0.02%**
Frozen Precip.	0.00%
Thunder	0.00%
Fog	0.00%
Below 0°C	0.00%
Precipitation	0.00%

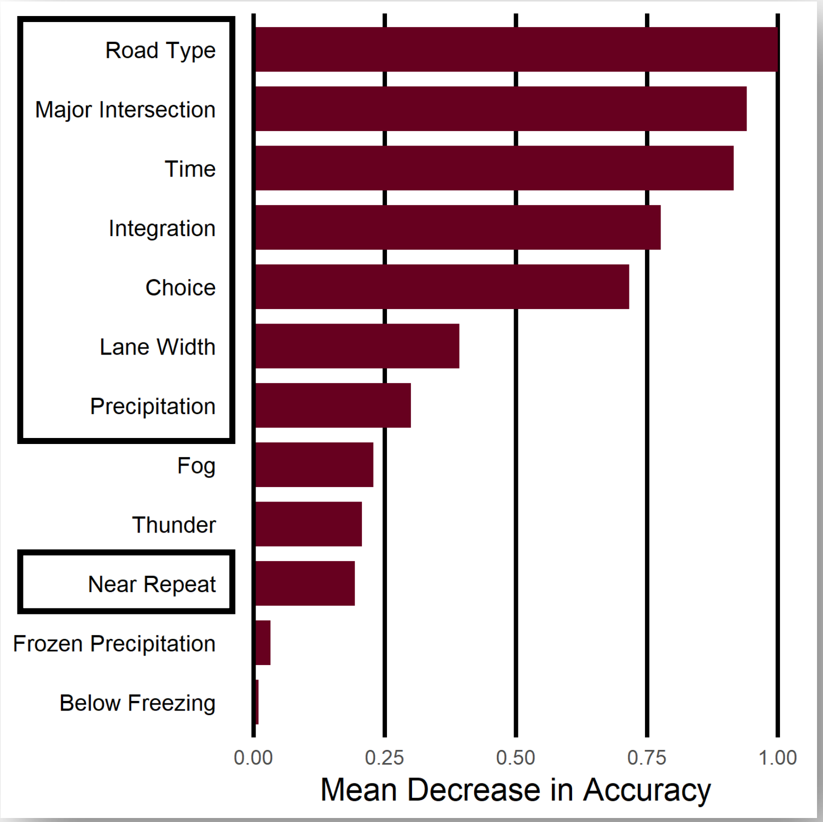
Variable	ΔAUC
Time	**1.18%**
Lane Width	0.00%
Major Inters.	**1.49%**
Road Type	**4.71%**
Integration	**0.33%**
Choice	**0.16%**

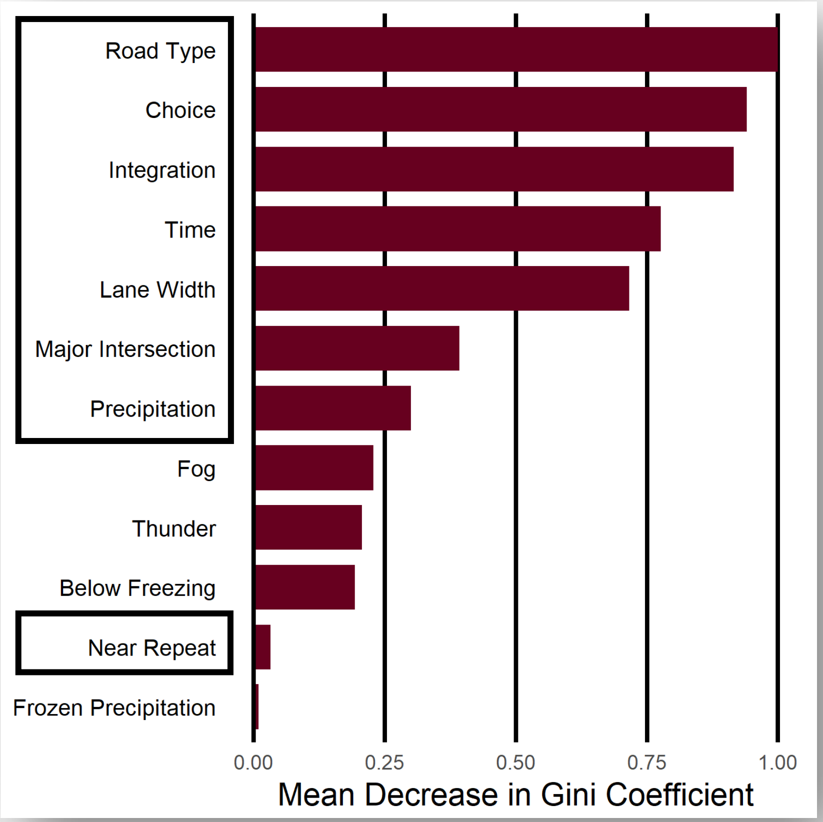
Significant independent variables in logistic regression

Logistic Regression Coefficient Estimates

Variable	Estimate	P-value
Choice	1.356	0.000
Choice x Time	0.001	0.002
Integration	49.04	0.000
Integration x Time	0.122	0.000
Major Intersection (T)	0.918	0.000
Intersection x Time	0.001	0.000

Variable	Estimate	P-value
Highway	2.405	0.000
Other Arterial Road	0.281	0.000
Local Road	-0.694	0.000
Time	0.000	0.997
Near Repeat (T)	1.287	0.000

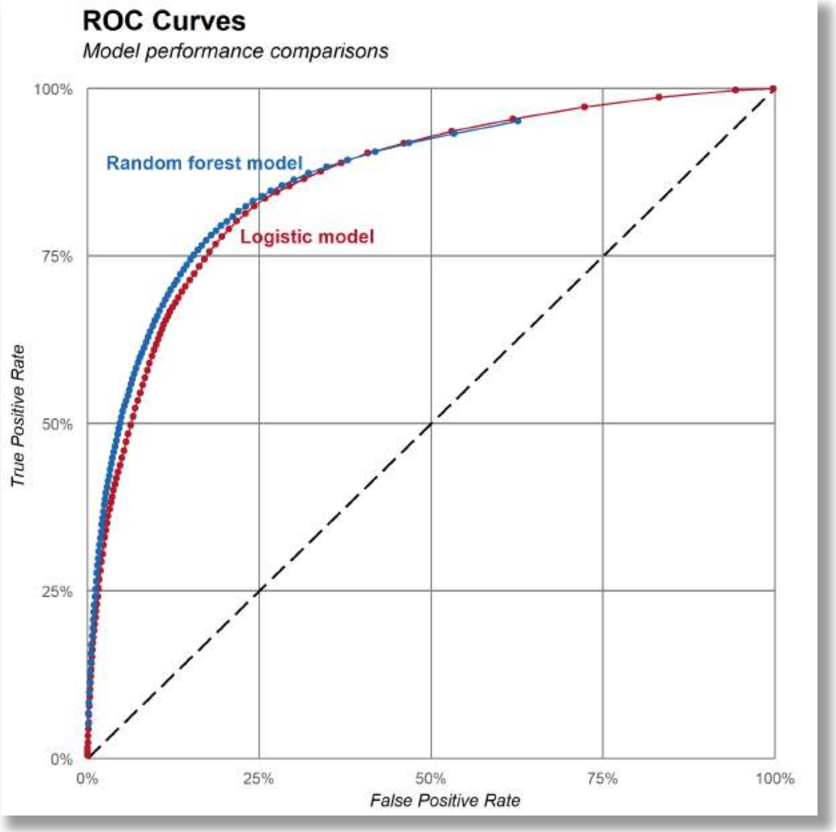




Significant independent variables in the random forest model

The two models show comparable results. The ROC curves suggest the two models perform equally well. The error analysis suggests that the random forest model predicts slightly better than the logistical model.

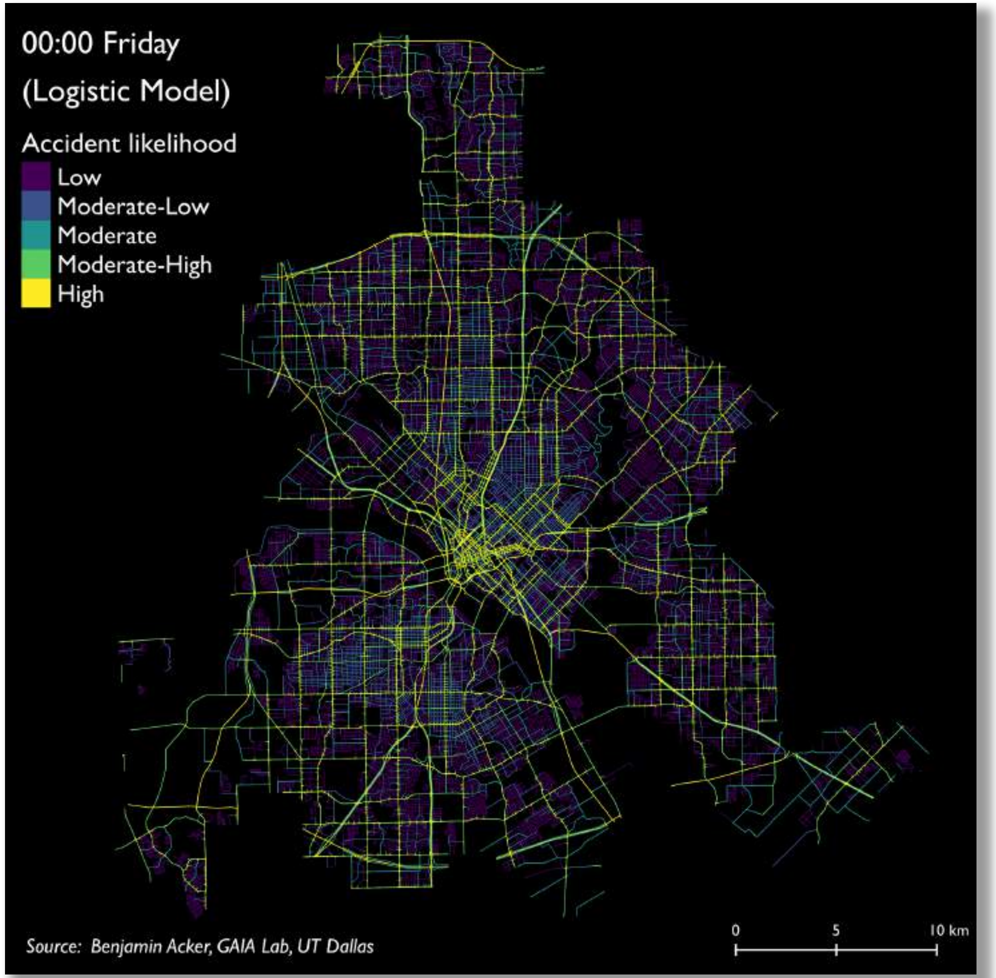
Metric	Logistic Regression	Random Forest
RMSE	0.3350	0.3272
Accuracy	84.11%	85.42%
Sensitivity	52.31%	51.83%
Specificity	93.04%	94.86%

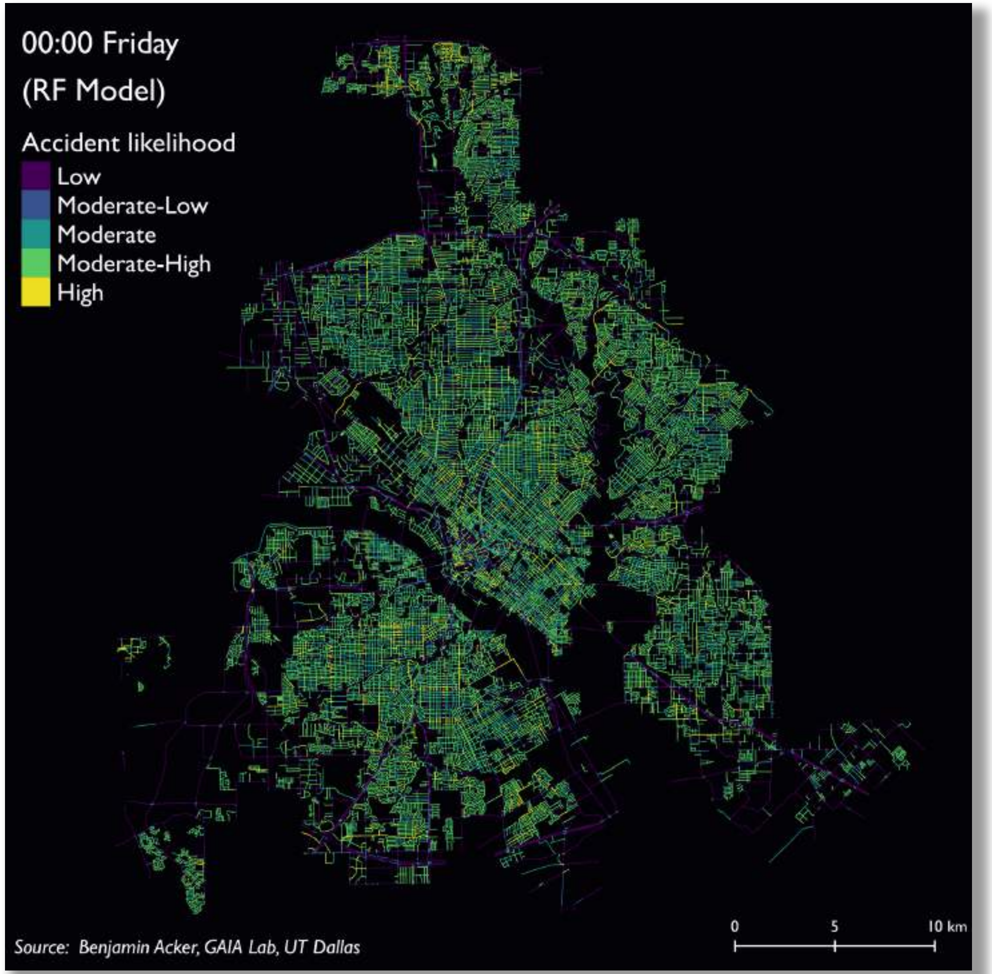


Logistic regression and random forest model predict different ranges of risk likelihoods. We classify their values into five categories for comparison.

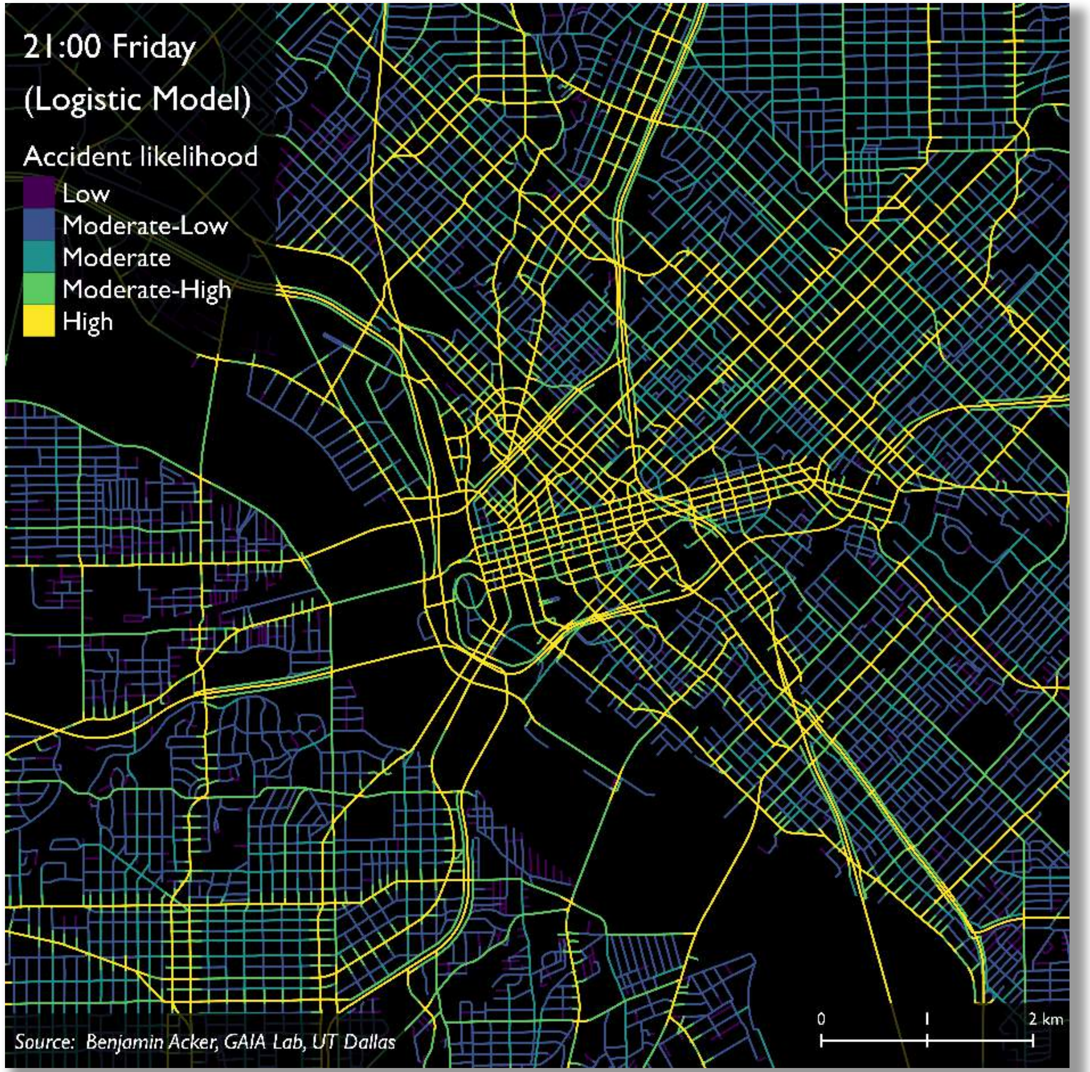
Classification	Logistic (%)	Random Forest (%)
Low	0.0002 - 0.0007	0.0000 – 0.0041
Moderate-Low	0.0007 - 0.0012	0.0041 – 0.0053
Moderate	0.0012 - 0.0018	0.0053 – 0.0068
Moderate-High	0.0018 - 0.0044	0.0068 – 0.0087
High	0.0044 - 2.9527	0.0087 – 0.0192

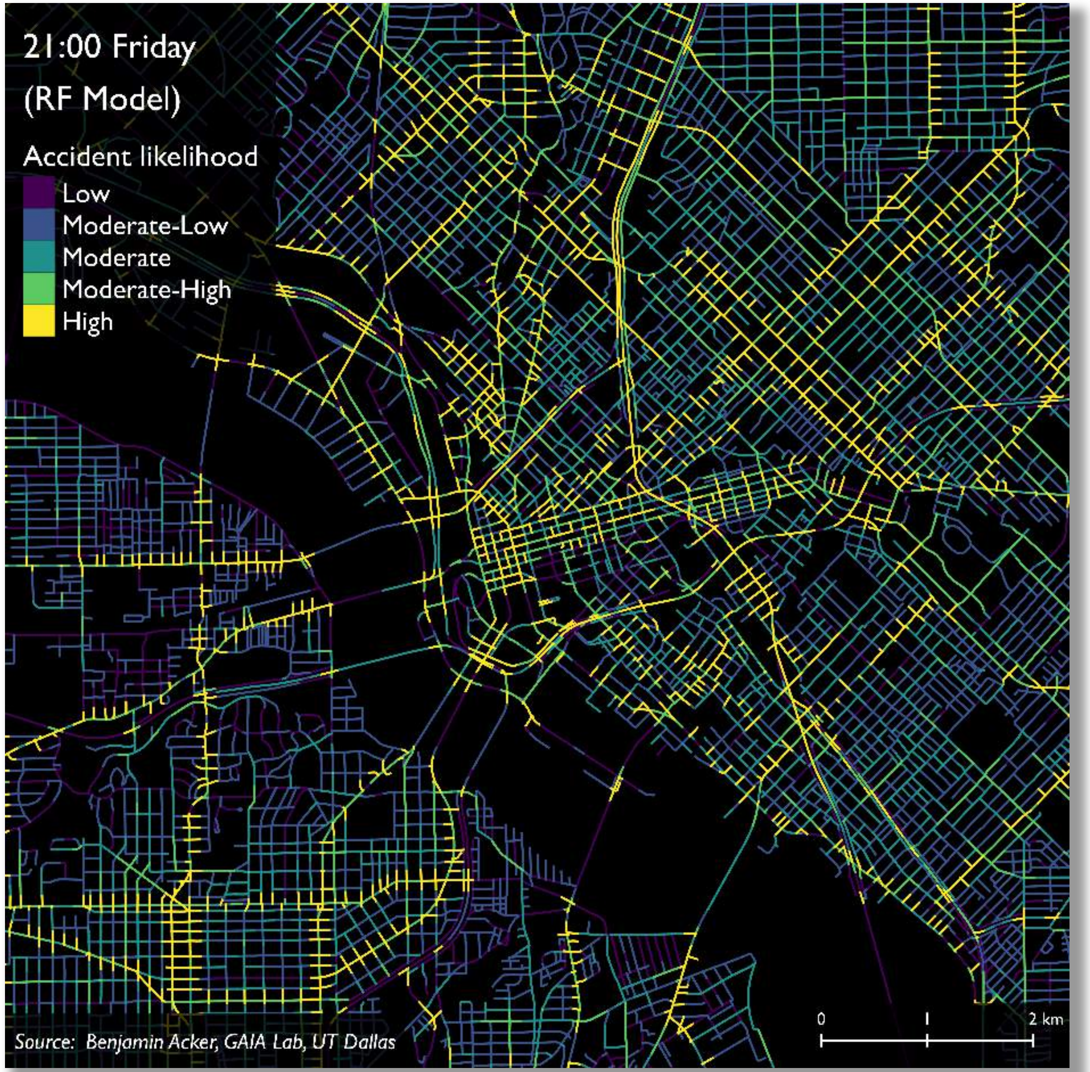
While F-tests showed comparable results at the city level, the two models have distinctive spatial risk predictions. The logistic regression model considers all major streets are of high risk, while the random forest model considers most street segments are of moderate or moderate-low risk and specifies locations of high risk, mostly at street intersections.





A closer look at the model predictions show that the logistic regression tends to attribute high risk to a long stretch of streets, while the random forest model identifies more specific locations of high risk.



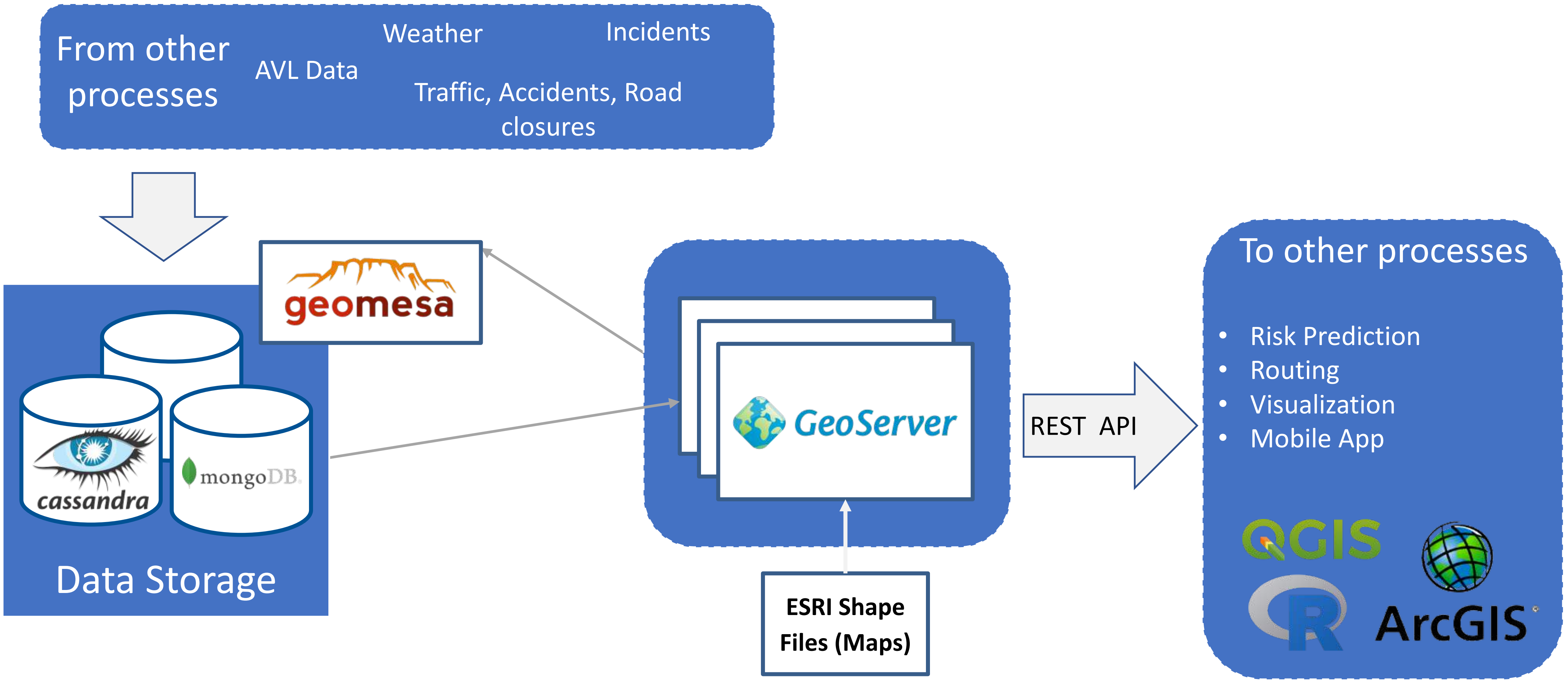


Part 3:

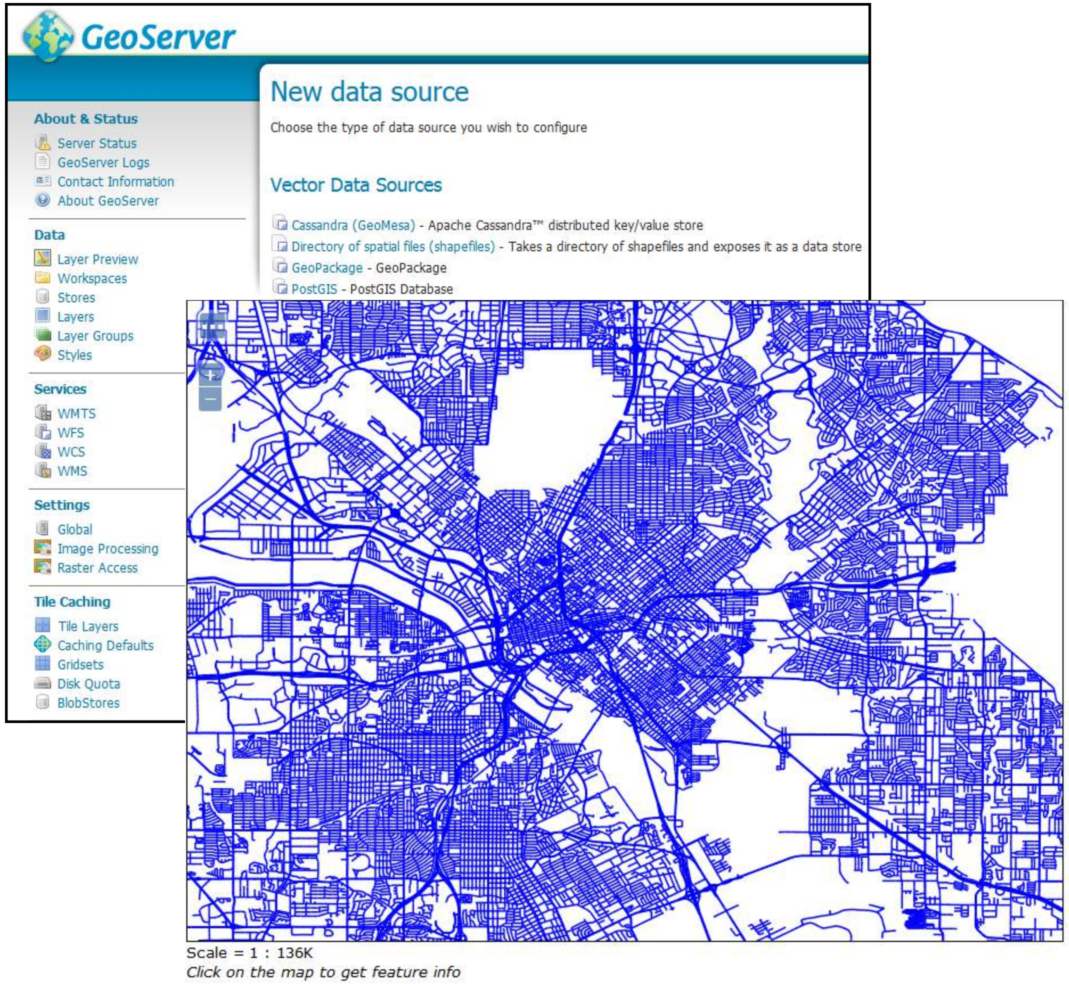
SAFE-NET Big Data Infrastructure

Dr. Michael Hahsler
Southern Methodist University

SAFE-NET Big Data Infrastructure



Various data sources in GeoServer



Dallas Road Network in GeoServer

www.safenet.smu.edu

GeoServer

Open source

Large community

OSGeo
Open Source Geospatial Foundation

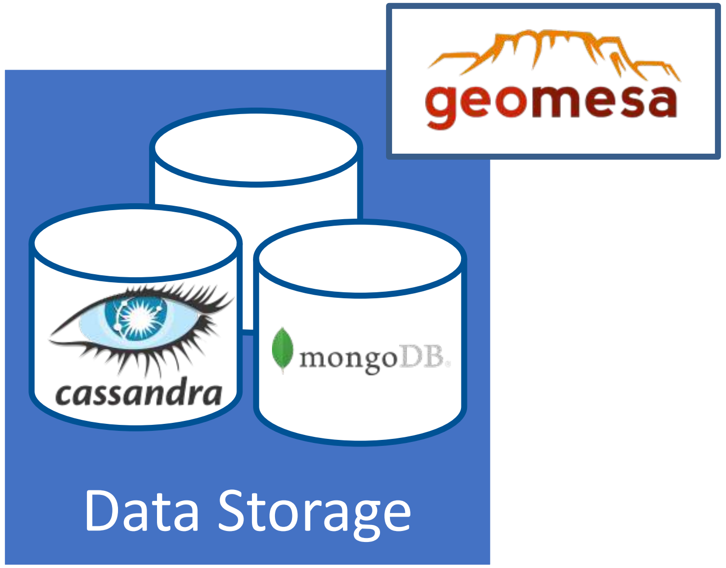
Open standards (OGC compliant)

- Web Feature Service (WFS)
- Web Map Service (WMS)
- Geographic JSON (GeoJSON)
- Geography Markup Language (GML)

Easy integration with GIS tools

QGIS
ArcGIS

Data Storage



Needs

- Scale for large data (historic data)
- Support geospatial data
- Low latency
- Continuous uptime
- Efficient reading and writing buy many processes at the same time

Data Storage

Relational Database Management Systems (RDBMs) is a perfect solution for

- Moderate incoming data velocity
- Size of data is not extremely large
- Data is structured
- Medium number of users of the system
- Data consistency is mandatory

Horizontal Scalability

- Many users
- Many servers distributed over different locations

Data Storage

- **PostGIS**: spatial database extender for PostgreSQL embedded object-relational database.
- **SpatiaLite**: extends the SQLite core to support fully fledged Spatial SQL capabilities.
- **Cassandra + GeoMesa**: high-performance, scalable NoSQL data store.
- **MongoDB**: document-oriented NoSQL database with native GeoJSON support.

Data Storage: Apache Cassandra

- Massively scalable open source solution
- Non-relational database (NoSQL)
- Wide column store (uses key-value pairs)
- No native support for spatial data (GeoMesa)

Properties

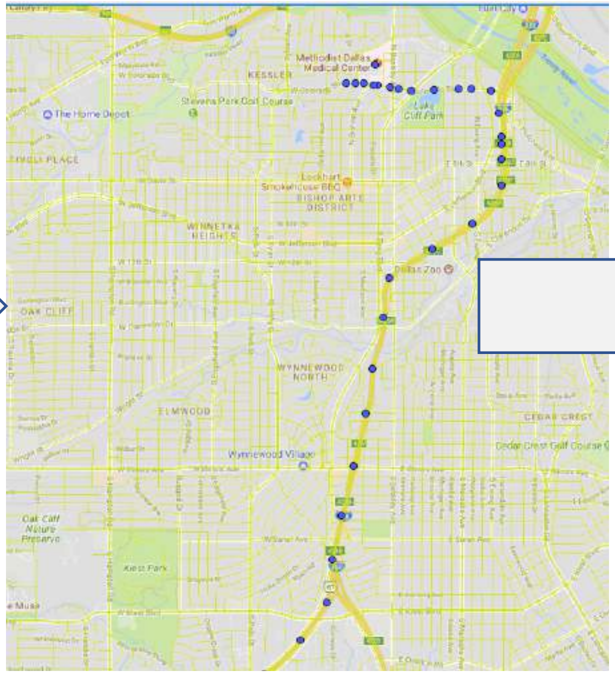
- Decentralized (no single point of failure)
- Supports replication and multi data center replication
- Linear scalability (add more notes)
- Fault-tolerant (replication)
- MapReduce support (Hadoop integration)
- CQL Query language

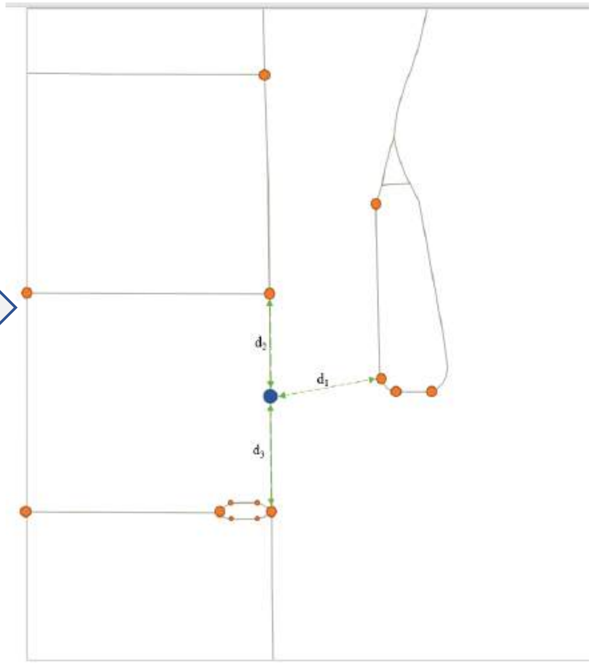
Peer-to-peer network

Automatic Vehicle Location (AVL) Data

- Emergency vehicles are equipped with GPS.
- For many applications, a sequence of used road segments is a better representation.
- Efficiently mapping AVL locations to road segments is difficult.
  - Similarity between points and segments.
  - Missing segments.

1	Master_Incident_Number	Radio_Name	Date_Time	Latitude	Longitude	Heading	Speed
2	2017222902	RE49	10/1/2017 0:05	32759367	96827373	90	35
3	2017222902	RE49	10/1/2017 0:06	32759120	96824710	99	36
4	2017222902	RE49	10/1/2017 0:06	32758931	96823221	NULL	0
5	2017222902	RE49	10/1/2017 0:07	32758764	96822237	98	28
6	2017222902	RE49	10/1/2017 0:07	32758607	96820602	NULL	0
7	2017222902	RE49	10/1/2017 0:08	32758690	96817924	79	40
8	2017222902	RE49	10/1/2017 0:08	32758783	96814980	[illegible]	[illegible]
9	2017222902	RE49	10/1/2017 0:08	32758811	96813415	[illegible]	[illegible]
10	2017222902	RE49	10/1/2017 0:09	32758609	96811016	[illegible]	[illegible]
11	2017222902	RE49	10/1/2017 0:09	32756317	96810117	[illegible]	[illegible]
12	2017222902	RE49	10/1/2017 0:09	32753942	96809830	178	5
13	2017222902	RE49	10/1/2017 0:10	32753140	96809821	181	32
14	2017222902	RE49	10/1/2017 0:10	32751647	96809868	182	11
15	2017222902	RE49	10/1/2017 0:10	32749048	96809876	190	51
16	2017222902	RE49	10/1/2017 0:11	32745090	96813315	238	62
17	2017222902	RE49	10/1/2017 0:11	32742561	96818208	239	64
18	2017222902	RE49	10/1/2017 0:11	32739629	96823323	217	57
19	2017222904	EN49	10/1/2017 0:10	32700973	96835180	NULL	0
20	2017222912	RE15	10/1/2017 0:08	32760128	96824076	NULL	0





Current and Future Work

- Integrate more data sources like
  - traffic, and
  - weather.
- Analyze
  - route choice, and
  - actual travel speed.
- Predictive model for time dependent travel times.
- Adaptive optimal resource choice and support for optimal route choice using (partially observable) Markov decision models.

Questions?

Public Safety Video Communications Demand Model

Andrew Weinert

NIST PSIAP

June 2018

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LINCOLN LABORATORY
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Bottom Line Up Front and Notes

- Analytics and video data scenarios should act as a “second pair of eyes” for the public safety community to enhancement body-worn camera technology

- Wide engagement across Public Safety communication; not just first responders
  - Literature review across national and local levels
  - Face-to-face end user engagement across state of NJ
  - Review and discussion with video and public safety analytic researchers

- Preference to cite national resources with similar anecdotes as New Jersey end-users
  - Enables access to citations that are public and easily accessible
  - Highlights that identified challenges are not unique to New Jersey or law enforcement

- Longer, more comprehensive version of this presentation available as back-up

Lack of Representative Public Safety Video Datasets

- **Video analytics and system development require appropriate training data**

- **Few appropriate public safety datasets exist and most have limited availability due to privacy and security concerns**

- **Video datasets (YouTube-8M[2], YFCC100M[3]) are widely used but are opportunistic, often lacking appropriate safety annotations**
  - ***"Luck of the draw"***
  - **Often single camera perspective**
  - **Lack of scenarios unique to public safety**
  - **Still required to develop "truth" analytics**

"Officers Use Naloxone, CPR To Revive Man[1]"
Example Opportunistic Video

Officers and victim are blocked by black redaction markup of bystanders

Single dashcam video of incident without annotation

[1] https://www.youtube.com/watch?v=2HpWOfcykgY
[2] https://research.google.com/youtube8m/
[3] http://multimediacommons.org/

Objective: Develop Easily-Accessible Video Datasets Representative of Public Safety Operations

> **"One of the most fundamental barriers to seamless data integration is simply a lack of awareness or access to datasets that are accurate, current, and relevant to improving response."**
> ***– NIST Technical Note 1917: Public Safety Analytics R&D Roadmap, April 2016[1]***

- **Video services are increasingly becoming important for public safety operations**
  - **Lack of representative video datasets hinders technical advancement and innovation**
  - **Lack of understanding on how video will operate over and influence the NPSBN**
- **PSIAP effort will accelerate technology innovation for network providers, application providers, and public safety agencies, enabling:**
  - **Calculating network impact of video applications**
  - **Tailoring applications for the unique public safety community**
  - **Informing choices on the applications that will most effectively perform on their network**

NPSBN – NATIONAL PUBLIC SAFETY BROADBAND NETWORK
PSIAP – PUBLIC SAFETY INNOVATION ACCELERATOR PROGRAM
[1] http://nvlpubs.nist.gov/nistpubs/TechnicalNotes/NIST.TN.1917.pdf

Defining a Public Safety Video Communications Demand Model

Objective: Develop a video-based dataset that will be a readily available tool to benchmark communication networks, providing a quantitative understanding of video and video-based analytic demands when selecting a system or service to purchase

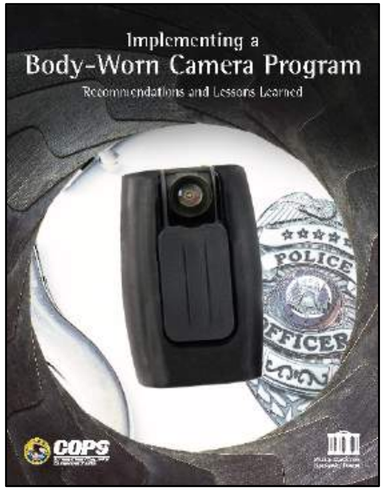
- Research framed by five questions
  1. What information is commonly used and communicated to make decisions?
  2. How should mission-critical and safety-critical information or scenarios be defined?
  3. How are video and video-based analytics currently used? Do they meet expectations?
  4. What are the perception and expectations of future video and video-based analytics?
  5. What incident(s) should the dataset represent?

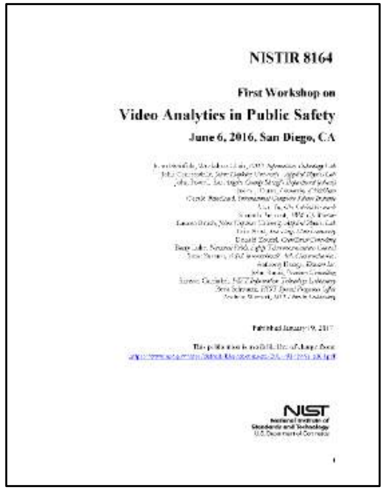
- Wide engagement across Public Safety communication; not just first responders
  - Literature review across national and local levels
  - Face-to-face end user engagement across state of NJ
  - Review and discussion with video and public safety analytic researchers

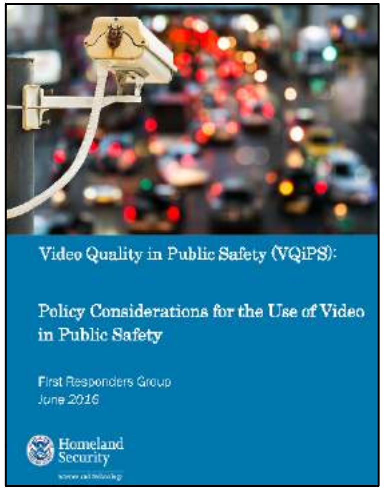
Outline

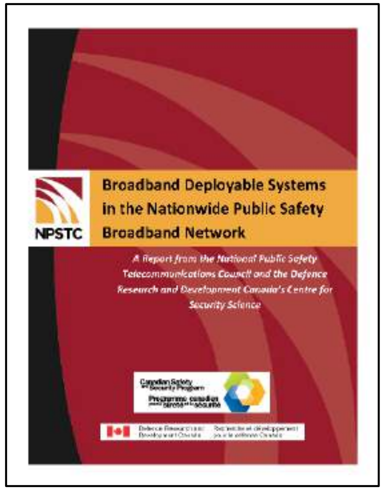
- Overview
- Literature Review
- End-User Outreach
- Dataset Scenarios and Filming
- Video Considerations
- Analytics Considerations
- Analytics “20 Questions” Vision
- Conclusion

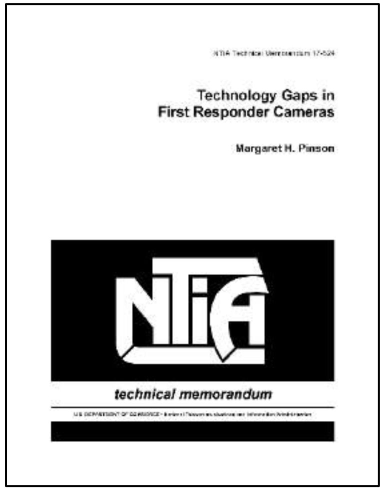
National, State, Local Literature

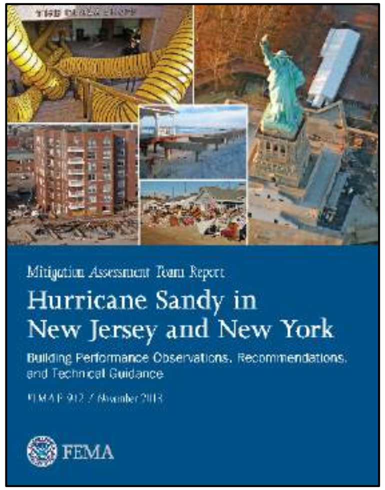


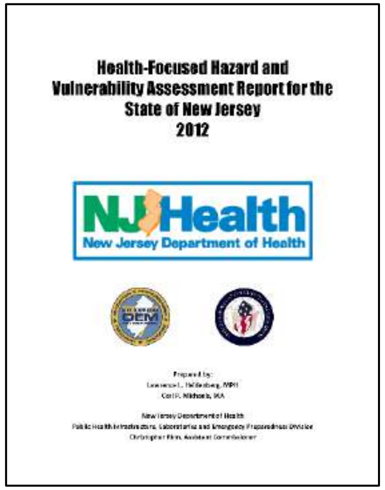


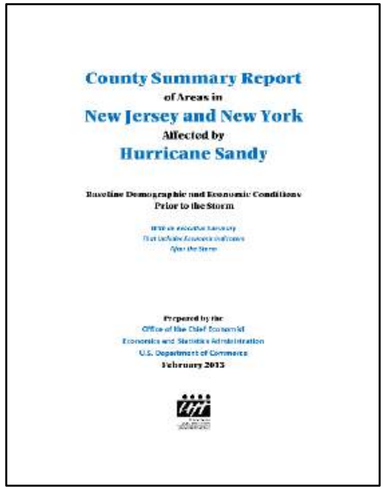


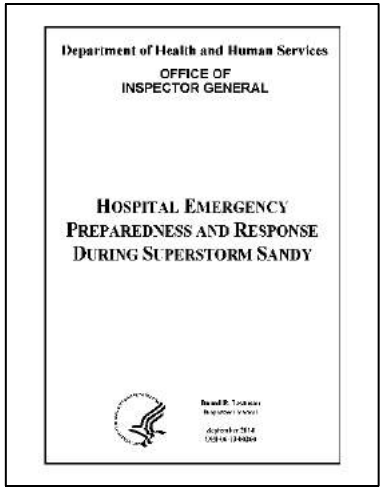












The New York Times

VICE

npr

FBI Uniform Crime Report
Law Enforcement Officers Killed & Assaulted

- **FBI aggregated data from 12K+ law enforcement agencies employing 586K+ officers**
  – **Agencies servicing 268M+ person (83% of nation’s population)**
  – **Statistics available for the last ten years since 2007**
  – **Narrative summaries available for each officer’s felonious death since 2002**

- **Analyzed to identify and characterize dangerous scenarios faced by law enforcement**
  – **Consideration that technology development should help address dangerous scenarios**
  – **57,180 officer assaults in 2016 (8.8 per 100 sworn officers)**
  – **118 officers died in 2016 (66 – felonious incidents, 52 – accidental)**

UCR – UNIFORM CRIME REPORT
[1] Law Enforcement Officers Killed and Assaulted, FBI UCR, https://ucr.fbi.gov/leoka/2016

Trends in Summaries of Law Enforcement Officers Feloniously Killed (2002-2016)[1]

Foot Investigation / Pursuit

- 150+ narrative summaries
- Officers often operate in unfamiliar areas, limiting SA
- Significant risk in rounding corners or hoping fences

Prior Criminal Record

- 300+ narrative summaries
- Officers may not be aware of prior criminal record
- Injuries often occur in known dangerous scenarios

Body Armor

- 400+ narrative summaries
- Often equipped with appropriate PPE when killed
- Victims often shot at close ranges (≤ 10 ft.)

< 40 summary narratives explicitly mention "camera" or "video"

SA – SITUATIONAL AWARENESS
PPE – PERSONAL PROTECTIVE EQUIPMENT

[1] Law Enforcement Officers Killed and Assaulted, FBI UCR, https://ucr.fbi.gov/leoka/2016/ebook-and-pdf-of-narratives/leoka-narratives-feloniously-killed-assaulted-and-injured-2002-2016.pdf

Communications during Incidents and Disasters

- **Smart phones are not the "all in one Swiss Army Knife" capability yet**
  - **Battery life and quality of data (i.e. GPS tracks) may not meet public safety's needs**
  - **Interoperability challenges between systems can put responders in harm's way**

- **1-Officer vehicle assignments are common due to staffing and logistical challenges**

"The trooper retreated to his cruiser and notified his dispatcher that the suspect was armed. However, the victim officer […] did not receive the dispatch that the suspect was armed due to a delay in transmitting information[1]"

"You put me in Puerto Rico, down in Harvey, down in Florida keys where all the cell towers are down and there is nothing...guess what? My GPS unit is working and is doing what I need to do...guess what there are no cell phones and there might not be any satphones[2]"

[1] Law Enforcement Officers Killed and Assaulted, FBI UCR, https://ucr.fbi.gov/leoka/2016/ebook-and-pdf-of-narratives/leoka-narratives-feloniously-killed-assaulted-and-injured-2002-2016.pdf
[2] James Bastan, New Jersey – Task Force 1, Training Manager. October 2017. Interview

Cost and Utility of Communications
The Ability to Communicate Does Not Denote if You Should

- **Most body and dashboard cameras currently locally record and do not stream real-time**
  - General interest in exploring how to support streaming of body camera videos
  - Not every responder has a smartphone: a vehicle could serve as a communication's hub
  - CCTVs often leverage land line or fiber networks, not wireless networks, as backhaul
- **Storage and maintenance costs are significant and relatively new burden on budgets[1]**
  - Archiving just body camera footage could be $500K+ per year[2]
  - Forensic and investigative policies have varying data retention policies…potentially years
- **Streaming all deployed cameras may be fiscally infeasible due to cellular data costs**
  - Streaming body cameras potentially cost tens of thousands a month
- **Agencies may not have infrastructure or policy to monitor influx of new data streams**
  - Many video streams go relatively unmonitored already (i.e. traffic cameras)
  - Analytics to cue human operators are increasingly becoming needed

[1] Rick Callahan. "Some police departments shelve body cameras, cite data costs." September 2016. https://apnews.com/f19d7270535f4202b92de1872278330f
[2] Kate Ryan. "Cost of archiving police body cam footage for year: Over $500K." April 2017 https://wtop.com/montgomery-county/2017/04/archiving-police-body-cam-footage-for-year-500000/

Second Pair of Eyes: Body Worn Cameras
Improve Utility with Emphasis on Situational Awareness

- **Body worn cameras are continually being invested in but have varying buy in / acceptance from the public safety community and public at large**

- **Envision analytics output could be simple status "cues" to minimize communication requirements, respect the privacy of the wearer, and shared autonomously**
  - **Is the officer in a vehicle (yes / no), indoor or outdoor (yes / no)?**
  - **What is the current physical activity (walking, running, prone, etc.)?**
  - **What is the officer facing (a person, a vehicle, a building, etc.)**
  - **Are there any threats the officer needs to be alerted too?**

"While there is a national movement to deploy body worn cameras widely, evidence of their effectiveness is limited […], we conducted a randomized controlled trial involving 2,224 Metropolitan Police Department officers […]. We estimated very small average treatment effects on all measured outcomes, none of which rose to statistical significance[1]"

[1] D. Yokum, et al., "Evaluating the Effects of Police Body-Worn Cameras: A Randomized Controlled Trial," October 2017

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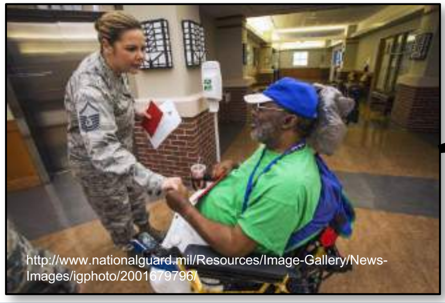
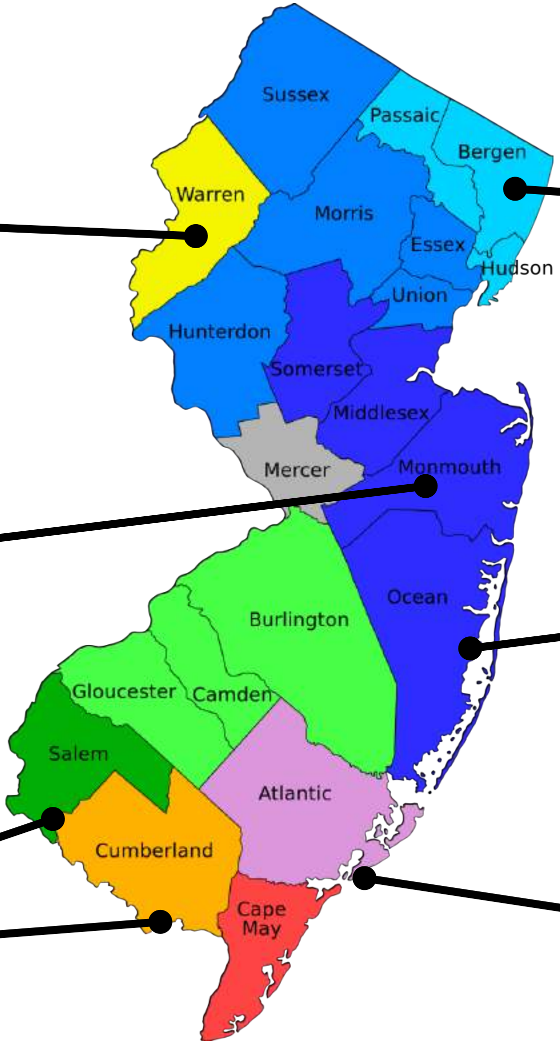
Public Safety Organizations Engaged
Discussed Routine Incidents to Large Disasters

Warren County PSAP

Fire Academy

Southern NJ Long Term Care





State Police

County Animal Response Team

New Jersey Task Force-1 (USAR)

Atlantic City Police Department

PSAP – PUBLIC SAFETY ANSWER POINT
USAR – URBAN SEARCH AND RESCUE
CART – COUNTY ANIMAL RESPONSE TEAM

Request: Scene Description to Improve Situational Awareness

Incomplete Information

"I've gotten calls about car fires than neglected to mention the car was in the garage"

- Enhance existing information
- Provide important contextual information

General Status

"Can the camera tell the OEM my facility has power, so I don't have to call them?

- Detect weather conditions
- Identify if responder is in their vehicle or not

Engaging Experts

"I got a call about a snake, I didn't know it was 12 ft. long…I didn't bring enough people to handle it"

- EMS and telemedicine isn't the only remote expert application

OEM – OFFICE OF EMERGENCY MANAGEMENT

Request: Identifying and Assessing Hazards
Downed Trees to Chemical Spills

- **Analytics can better prepare responders for operations in dangerous or unknown environments**
- **Identification of hazard symbols would have a noticeable change on operations**
- **Better threat identification would improve the initial response and have a positive cascading effect**
- **Urgent need: fire fighters show a higher rates of certain types of cancer[1]**

"Describing the Need to Better Assess Hazards"
Lt Christopher M. DeMaise, Unit Head, NJTF-1

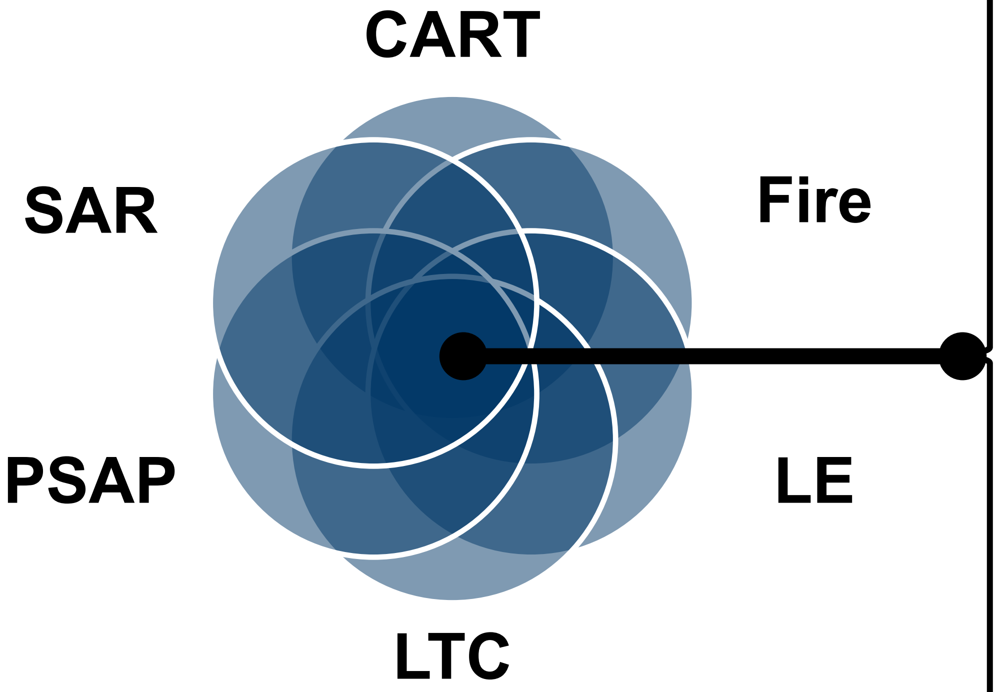
Better situational awareness can influence PPE deployment

Real time tactical intelligence is "invaluable" for maintaining responder safety

PPE – PERSONAL PROTECTION EQUIPMENT

[1] Study of Cancer among U.S. Fire Fighters, https://www.cdc.gov/niosh/firefighters/ffcancerstudy.html

Common Desired Capabilities: Identifying Potential Public Safety Video Services



- **Improve incident or threat description**
  - Improve resource allocation (personnel and gear)
  - Reduce response time with more efficient response
  - Prepare back-up resources better
- **Improve two way situational awareness**
  - “Second pair of eyes” for 1-officer assignments
  - Cue “central” (PSAP, etc.) of responder’s status
  - Respect privacy and limit spying perception
- **Minimize implementing new workload or policies**
  - Reduce amount of data needed by transmit computed edge analytics, not raw video
  - Consider limited budgets and strict governance

CART – COUNTY ANIMAL RESPONSE TEAM
LE – LAW ENFORCEMENT
LTC – LONG TERM CARE
PSAP – PUBLIC SAFETY ANSWERING POINT
SAR – SEARCH AND RESCUE

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Initial Public Safety Broadband Dataset Scenarios
Informed by Public Safety Community

Spring / Summer 2018 Focus

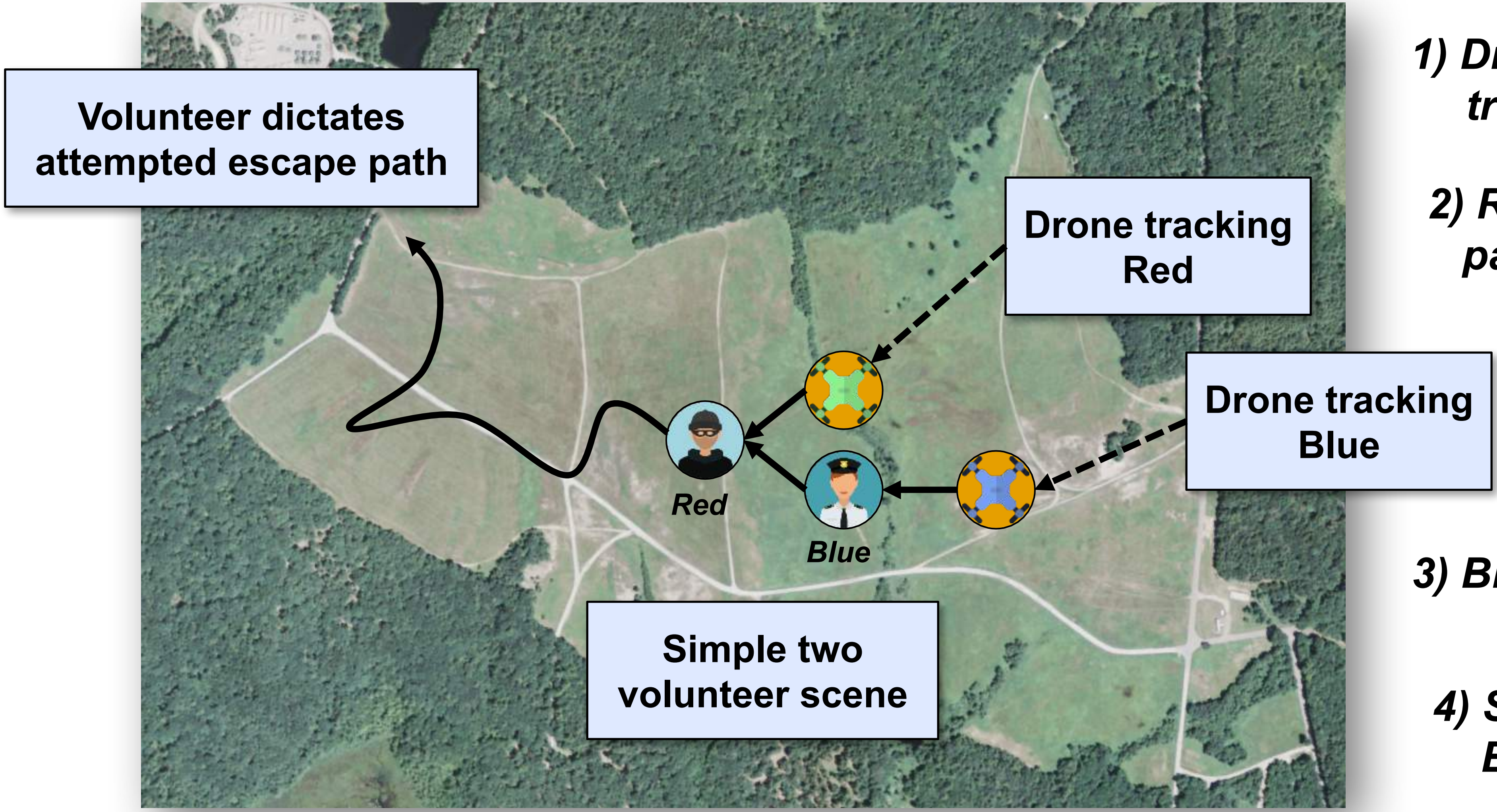
1. **Foot Pursuit**
   - Pursuit can occur in a variety of low and high risk law enforcement scenarios
   - Body-cam footage often an important forensic resource after incident

2. **Approaching an incident**
   - Common occurrence consisting of initial seconds of a traffic stop, approaching a crowd, etc.
   - Rapid escalation to a dangerous scenario possible within seconds

3. **Wide Area Search**
   - Indicated as time and personnel intensive response
   - Encompasses a diverse range of environments and conditions

Scenarios selected based on applicability across jurisdictions to maximize utility: urban / rural, state / local, high / low income

Script: Foot Pursuit



1) Drones configured to track Blue and Red*

2) Red flees from Blue; path determined by volunteer

3) Blue chases after Red

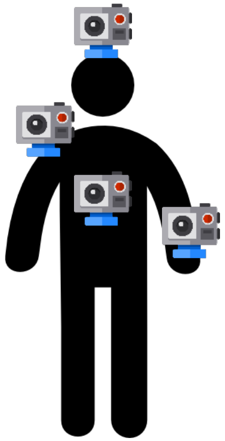
4) Scenario ends once Blue catches Red

***Drones operated if available and permissible**

Potential Mobile Camera Perspectives
Filming Across Environments, Weather, Time of Day, etc.

- Solicit volunteers from employee and s resource groups
  - Rotate volunteers to minimize volunteer commitment and increase on-screen diversity
  - Existing MIT LL UAS testbed leveraged to facilitate overhead imagery collection

- Leverage mobile action cameras and COTS hardware (GoPro / Garmin)
  - Tracking of objects using GPS
  - Minimize concerns of reveling capabilities of public safety systems
  - Easily acquired by other researchers

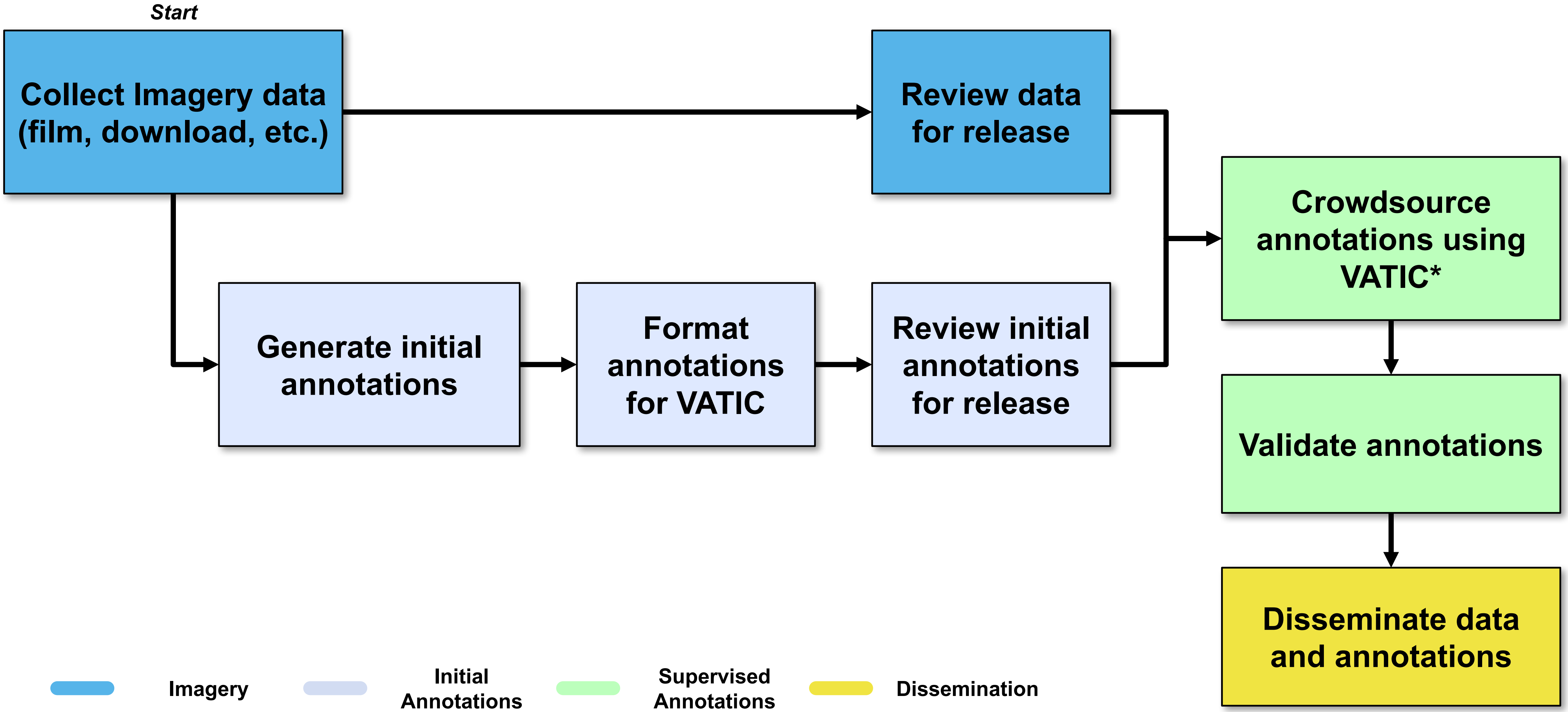


Body-worn
- Wrist
- Chest
- Shoulder
- Head

Drones
- Follow “blue”
- Follow “red”
- Surveil environment

Fixed / Vehicle
- Vehicle dash cam
- Vehicle roof
- Building mounted
- Deployable mast

Proposed Dataset Generation and Annotation Workflow



VATIC – VIDEO ANNOTATION TOOL FROM IRVINE, CALIFORNIA

Recommended Annotations by Public Safety

Recommend	backpack, bicycle, boat, bus, car, dog, fire hydrant, handbag, knife, motorbike, person, suitcase truck
Considered	aeroplane, baseball bat, cell phone, cup, fork, scissors, spoon, stop sign, traffic light, train, wine glass, umbrella
Not Recommended	apple, banana, baseball glove, bear, bed, bench, bird, book, bottle, bowl, broccoli, cake, carrot, cat, chair, clock, cow, dining table, donut, elephant, frisbee, giraffe, hair drier, horse, hot dog, keyboard, kite, laptop, microwave, mouse, orange, oven, parking meter, pizza, potted plant, refrigerator, remote, sandwich, sheep, sink, skateboard, skis, snowboard, sofa, sports ball, surfboard, teddy bear, tennis racket, tie, toaster, toilet, toothbrush, tv monitor, vase, zebra

COUHES Considerations: Outreach Does Not Constitute Human Subject Research

- **MIT COUHES deemed outreach and filming does not constitute human subject research**
  - **Federal Regulations: 45CFR46.102(f)**
  - **DoD: CFR 219.102(f)**

- **COUHES review is not required**

- **Signed form of consent required for focus groups and interviews**

MIT Committee On the Use of Humans as Experimental Subjects

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
77 Massachusetts Avenue
Cambridge, Massachusetts 02139
Building E 25-143B
(617) 253-6787

To: Andrew Weinert
MIT Lincoln Laboratory

From: Leigh Firn, MD
Chairman, COUHES

Date of Determination: July 6, 2017

Determination: Not Human Subject Research

We reviewed your study titled **Fiscal Year 2017 Public Safety Innovation Accelerator Program.**

Since this research does not involve human subjects as defined in the Federal Regulations 45CFR46.102(f), and DoD at 32 CFR 219.102(f). COUHES review is not required.

Please contact me if you have any questions.

COUHES – COMMITTEE ON THE USE OF HUMAN AS EXPERIMENTAL SUBJECTS
https://couhes.mit.edu/

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Reasonable Expectations of Analytics for Public Safety

- Concrete object detection is becoming comparable to human performance
  - Machine learned algorithms are still susceptible to noise and adversary objects
  - Research community focused on tradeoffs between accuracy and computational load

- Semantic techniques are increasingly becoming popular but still challenging for video
  - Semantic analytics more routinely used by natural language processing community
  - Analytics that use the whole image for global context are becoming increasingly capable

- Overhead required to train models have become easier due to open source community

Reasonable Expectations

Accurate detection of common objects (people, cars, etc.)	Larger objects easier to exploit	Raw analytical distributions can be noisy over time	Decent lighting and conditions are key for good accuracy

Video and Analytic Considerations

- **General need for datasets with cluttered urban and rural backgrounds with people, vehicles, and emerging technology (i.e. robots)**

- **Developing a good data set is a combinatorial challenge with various considerations**
  - ***Considerations*: lighting / environmental; audio; timing; and uncertainty**
  - **Public safety is a large community with many stakeholders and needs**

- **Developed data set should address specific video workflow components**
  - **Potential use of data set and targeted analytics need to be stated upfront**
  - **Technology transition of assumed future R&D should be a key consideration**

Major Public Safety Video Workflow Components[1]

[1] J. Garofolo, et al., "First Workshop on Video Analytics in Public Safety," NISTIR 8164, Jan. 2017. https://www.nist.gov/sites/default/files/documents/2017/01/19/ir_8164.pdf

Combinatorial Challenge of Designing A Representative Data Set

Challenge: **Infeasible to film all possible combinations of even a single scenario**

Solution: **Generate short segments of data applicable to multiple scenarios across different conditions**

Police Crash Investigation Report Fields[1]

Field	# Options
Road Divided By	5
Temporary Traffic Control Zone	5
Light Condition	7
Road System	10
Road Character	6
Road Surface Type	5
Road Surface Condition	8
Environmental Condition	9
Crash Type	16
Vehicle Type	30

1,814,400,000 combinations!

[1] State of New Jersey Police Crash Investigation Report NJTR-1, http://www.state.nj.us/transportation/refdata/accident/pdf/NJTR-1.pdf

Lighting and Environmental Considerations

Public Safety often do not operate in clear daylight conditions

- **Lost individuals often call at twilight or night – NJ 911 operator**
- ***"The body cameras showed some limitations in darker environments[1]"***
- ***"During a fight in knee-deep snow, [the suspect …] shot the officer twice[2]"***

Environmental Conditions[3]

Clear

Overcast

Fog

Rain

Snow

Hail

Blowing Sand

Blowing Snow

Severe Crosswinds

Light Conditions[3]

Daylight

Dawn

Dusk

Dark (No Street Lights)

Dark (Street Lights Off)

Dark (Street Lights On Continuous)

Dark (Street Lights Off Spot)

[1] Manuel Gamiz Jr. "Ten limitations of Allentown's body cameras." The Morning Call. October 17, 2017.
[2] Law Enforcement Officers Killed and Assaulted, FBI UCR, https://ucr.fbi.gov/leoka/2016/ebook-and-pdf-of-narratives/leoka-narratives-feloniously-killed-assaulted-and-injured-2002-2016.pdf
[3] State of New Jersey Police Crash Investigation Report NJTR-1, http://www.state.nj.us/transportation/refdata/accident/pdf/NJTR-1.pdf

Timing: Rapid Decisions and Actions are Commonplace

- **Need to represent rapid escalation**
- **Targeted analytics need to be calculated and communicated within seconds**
  - Drives the need for edge computing R&D
  - Alerting is challenging within workflow[2]
  - Scope of analytics constrained by timing

"An officer died from injuries she received during a traffic stop […] The incident, which was captured on the victim officer's in-car video, took less than a minute to unfold[3]"

"2014 Police-Involved Shooting in Atlantic City"
***Atlantic County Prosecutor's Office*[1]**

Sighting of suspect's weapon called out on radio prior to shooting

< 15 seconds from end of vehicle pursuit to weapons fired by police and suspect

[1] Brandon Longo, "Dashcam Video Shows A Barrage of Gunfire During 2014 Police-Involved Shooting," July 2017, http://philadelphia.cbslocal.com/2017/07/24/ac-2014-shooting-dashcam/
[2] J. Garofolo, et al., "First Workshop on Video Analytics in Public Safety," NISTIR 8164, Jan. 2017. https://www.nist.gov/sites/default/files/documents/2017/01/19/ir_8164.pdf
[3] Law Enforcement Officers Killed and Assaulted, FBI UCR, https://ucr.fbi.gov/leoka/2016/ebook-and-pdf-of-narratives/leoka-narratives-feloniously-killed-assaulted-and-injured-2002-2016.pdf

Uncertainty of Public Safety Operations

- Public Safety is not a traditional "9 to 5 job," wide range of reasons to response
  – Datasets and trained analytics need to account for uncertainty and randomness
  – Technology needs to be robust and appropriately react; can't fail due to uncertainty

- Uncertainty can be malicious, accidental, inadvertent, or unavoidable

"The wanted youth opened fire from his hiding place in a closet with a .45-caliber semiautomatic handgun[1]"

"The deputy […] responded to a call about a naked man who was pounding on vehicles in traffic. Seeing the individual trying to forcibly board a bus, the deputy tried to calm the man, but he charged the officer[1]"

[1] Law Enforcement Officers Killed and Assaulted, FBI UCR, https://ucr.fbi.gov/leoka/2016/ebook-and-pdf-of-narratives/leoka-narratives-feloniously-killed-assaulted-and-injured-2002-2016.pdf

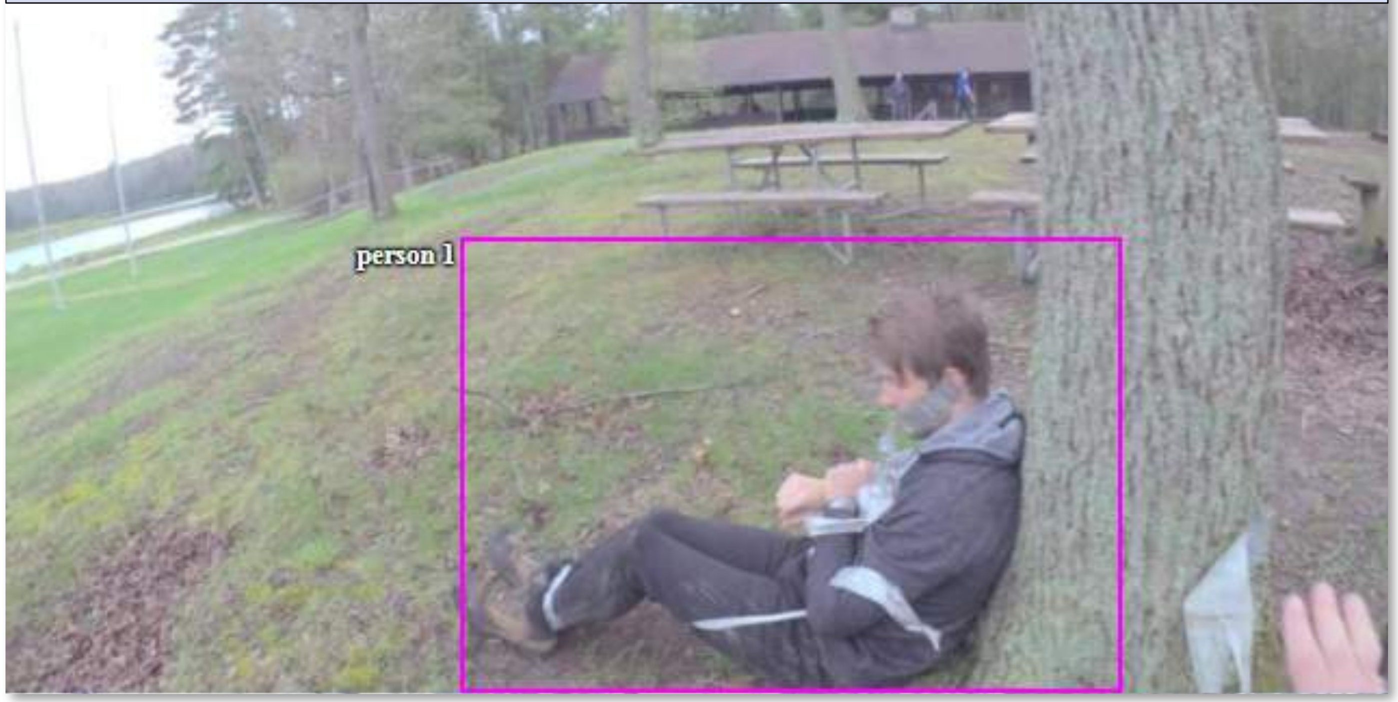
Scenario Diversity, Perspective and Resolution

Inspiration: "Man Bound With Duct Tape Found On Reading Road[1]"

Baseline iPhone

720p with advanced image processing at a standstill

Down-sampled Chest Garmin Virb Ultra 30



Flat color processing with no color correction while moving

Recorded in 4K, processed to 720p to be representative of current body cameras

[1] https://patch.com/massachusetts/reading/man-bound-duct-tape-found-reading-road

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Analytics Vision: “20 Questions” Approach

- **Instead of “one analytic to rule them,” deploy many primitive analytics and heuristically capture “it depends”**

- **Contextual question: Is the officer in danger or in a high risk scenario?**
  - **QoS dependent upon context; can’t and shouldn’t stream all video**
  - **Answering yes / no questions “20 questions” style to characterize context**
    - **Is the officer outside of his car?**
    - **Is it nighttime?**
    - **Is the officer prone on the ground?**
    - **Is someone in view of officer’s**

- **Primitive, lightweight, yes / no analytics can answer these questions**
  - **Enable integration on future body cameras, drones, and vehicles**
  - **Scalable and customizable for different scenarios and justifications**
  - **Minimize potential cellular data costs, a few bytes per analytic**

Potential “20 Questions” Primitive Analytics

“Is it nighttime, yes or no?”

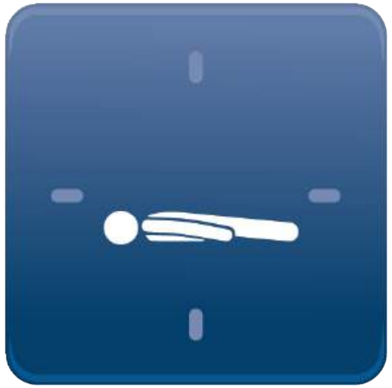
Nighttime

Officer Running

Backpack in View

Multiple People

Officer Out of Vehicle

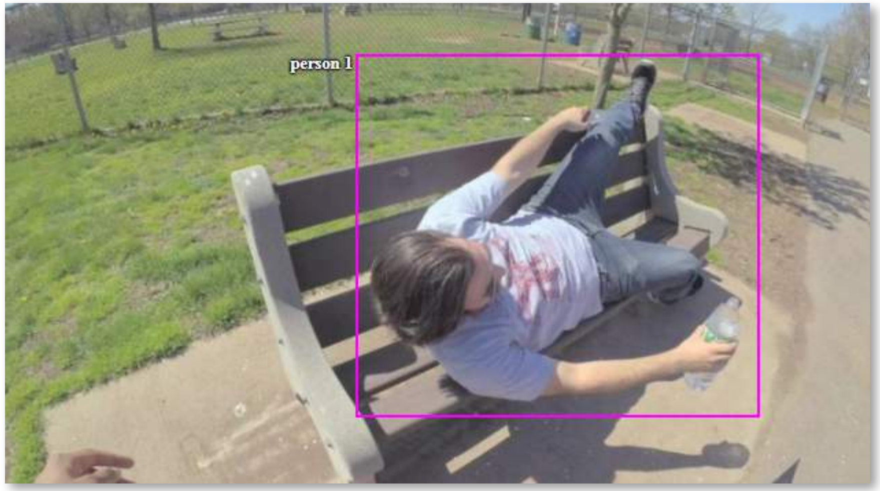


Officer Prone

Vehicle In View

Person in View

Is this a High Risk Scenario?
What Information Does the PSAP Need? Want?



Nighttime

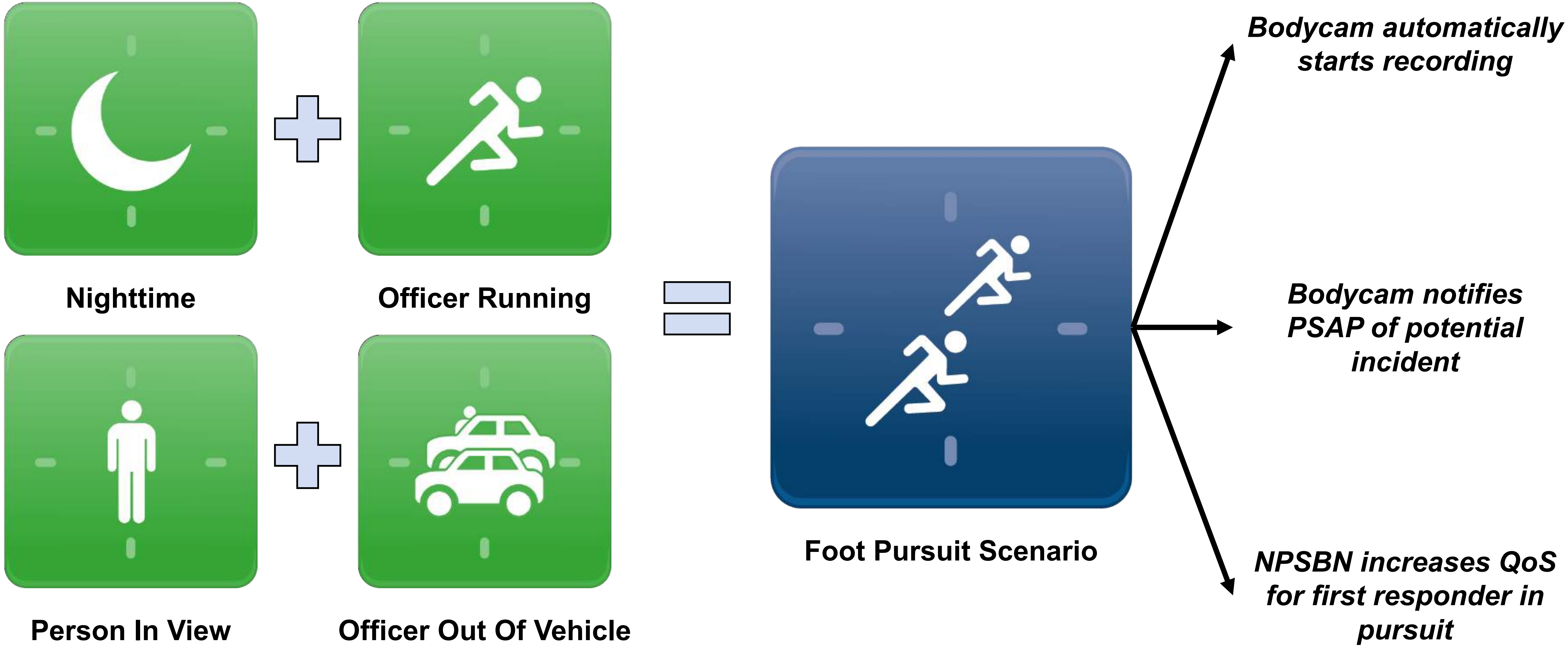
Officer Running

Person In View

Officer Out Of Vehicle

PSAP – PUBLIC SAFETY ANSWER POINT

Envisioned Illustrative Applications
“20 Questions” in Practice



PSAP – PUBLIC SAFETY ANSWER POINT
NPSBN – NATIONWIDE PUBLIC SAFETY BROADBAND NETWORK
QOS – QUALITY OF SERVICE

Next Steps for Analytics

- Develop and release “20 Question” reference analytics architecture
  - Train analytics using collected video and other openly accessible data sources
  - Design analytics using a end-user driven philosophy with end-user feedback
- Explore various analytic development techniques and implementations
  - TensorFlow and convolutional neural networks
  - Google Cloud Vision API service
- Planning to collaborate with FirstNet Innovation and Test Laboratory
  - Deploy reference architecture on representative mobile devices
  - Test across representative communication networks
- Identify technology transition opportunities for dataset and reference architecture

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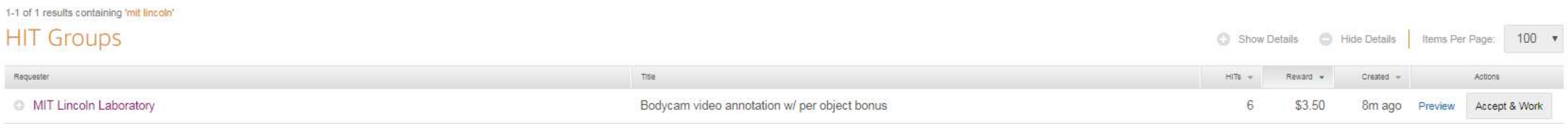
One More Thing…You Can Help and Have the Data!
Addressing the Identified Capability Gap

- **350 Gigabytes approved for public release**
  - **Contact for access and more information**
  - **Public facing website forthcoming to streamline access control**

- **Filming will continue through the summer and fall**
  - **Dataset improves as we add more diverse locales, environments, and scenarios**
  - **Initial continued focus on ground-based foot pursuit scenarios**

- **Video currently being annotated using Amazon Mechanical Turk**
  - **Create a worker account (worker.mturk.com) and search for "MIT Lincoln Laboratory"**



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Thank You!

Questions?

Feedback?

Andrew Weinert
Associate Technical Staff
Humanitarian Assistance and Disaster Relief
Email: andrew.weinert@ll.mit.edu

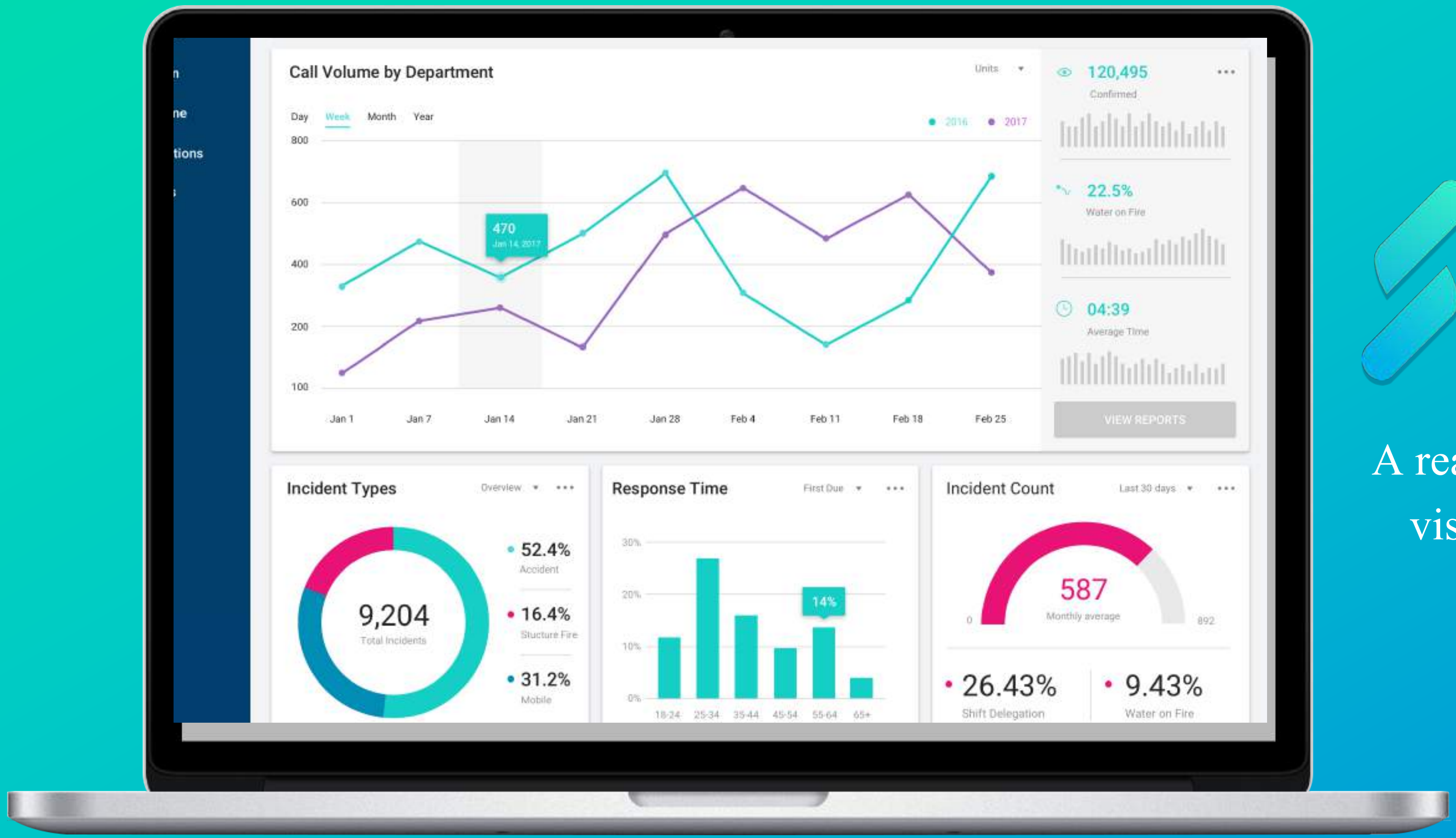

statengine
PSCR Stakeholder Meeting | June 2018
ENG 10 INE
RICHMOND
FIRE

Background

- Volunteer firefighter since 2006
- GIS Technician at Richmond Fire (VA)
- Lead Engineer on multiple grants in the fire service
- NFPA 950 / 951 Standard for Data Exchange for the Fire Service

Challenges

- Technical complexity
- Data is distributed in multiple repositories
- Data optimized for storage, not query
- Lack of infrastructure
- Licensing costs
- Solutions often limited to scripts or applications vs platforms.



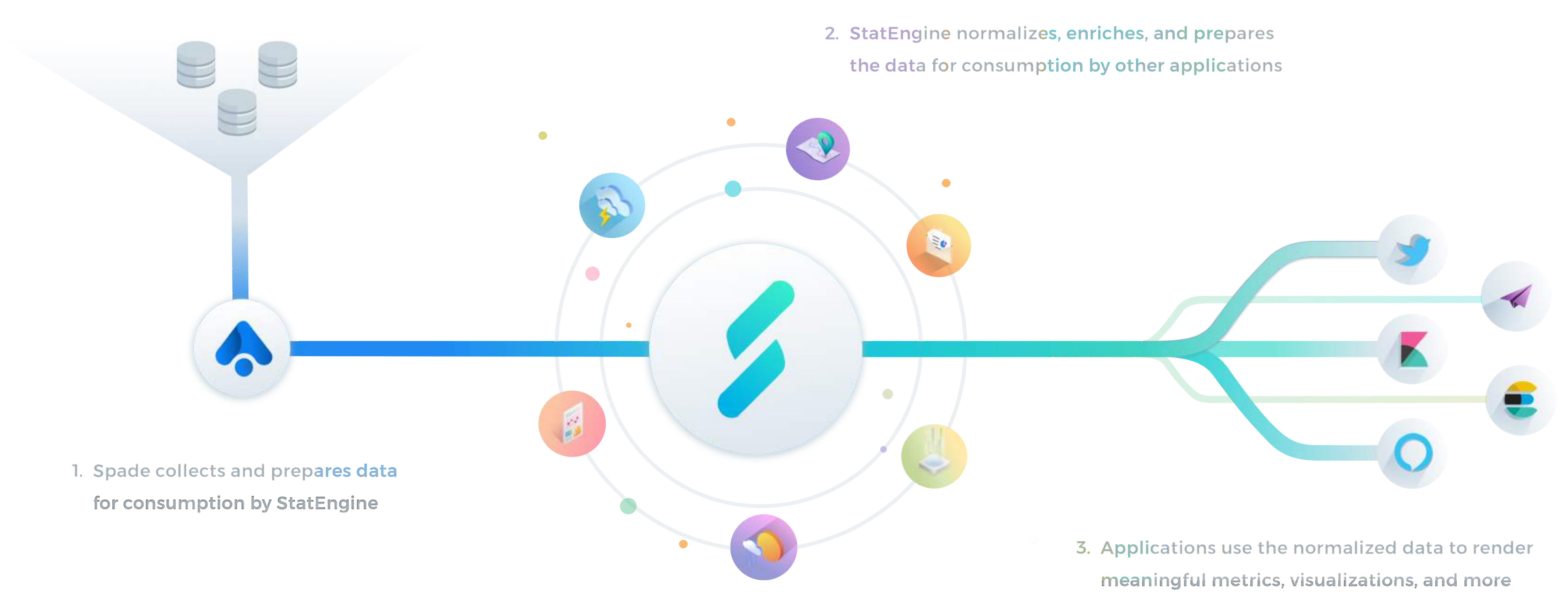
statengine

A real-time, open source, data analytics and visualization platform for public safety organizations.

Project Deliverables

- Data listener
- Data schemas
- Analytics platform
- Visualizations
- On-premises appliance
- Cloud instance
- Documentation

Project Architecture



Project Philosophy

- Maximize ROI
- Transparent
- Flexible
- Multiple paths of dissemination
- Eliminate vendor lock in
- Get in hands of PSOs then iterate

StatEngine Today

525,000

Incidents analyzed

Departments have loaded over half a million incidents in StatEngine in the last 6 months.

3,000

New incidents per day

Real time integrations push thousands of incidents a day to StatEngine.

14

Departments live

Departments across the nation, of all sizes are using StatEngine.

Project Timeline

December 2017

February 2018

May 2018

Release 1 | December 2017

Project Website, basic data schema, automated local install, initial cloud instance, deployment documentation, authentication, data ingest, metrics, devops.

Release 2 | June 2018

Production data schemas, authentication, authorization, basic production cloud instance, automated data ingestion, multi-PSO support, common visualizations.

Release 3 | December 2018

Additional UI customizations, data enrichment, security scans, backup strategies, appliance finalization.

Accelerated Timeline

Original timeline scheduled development from June 2017 to May 2019, with 4 releases. Our development efforts have been accelerated to meet partner demand putting the project significantly ahead of schedule.

June 2018

Release 4

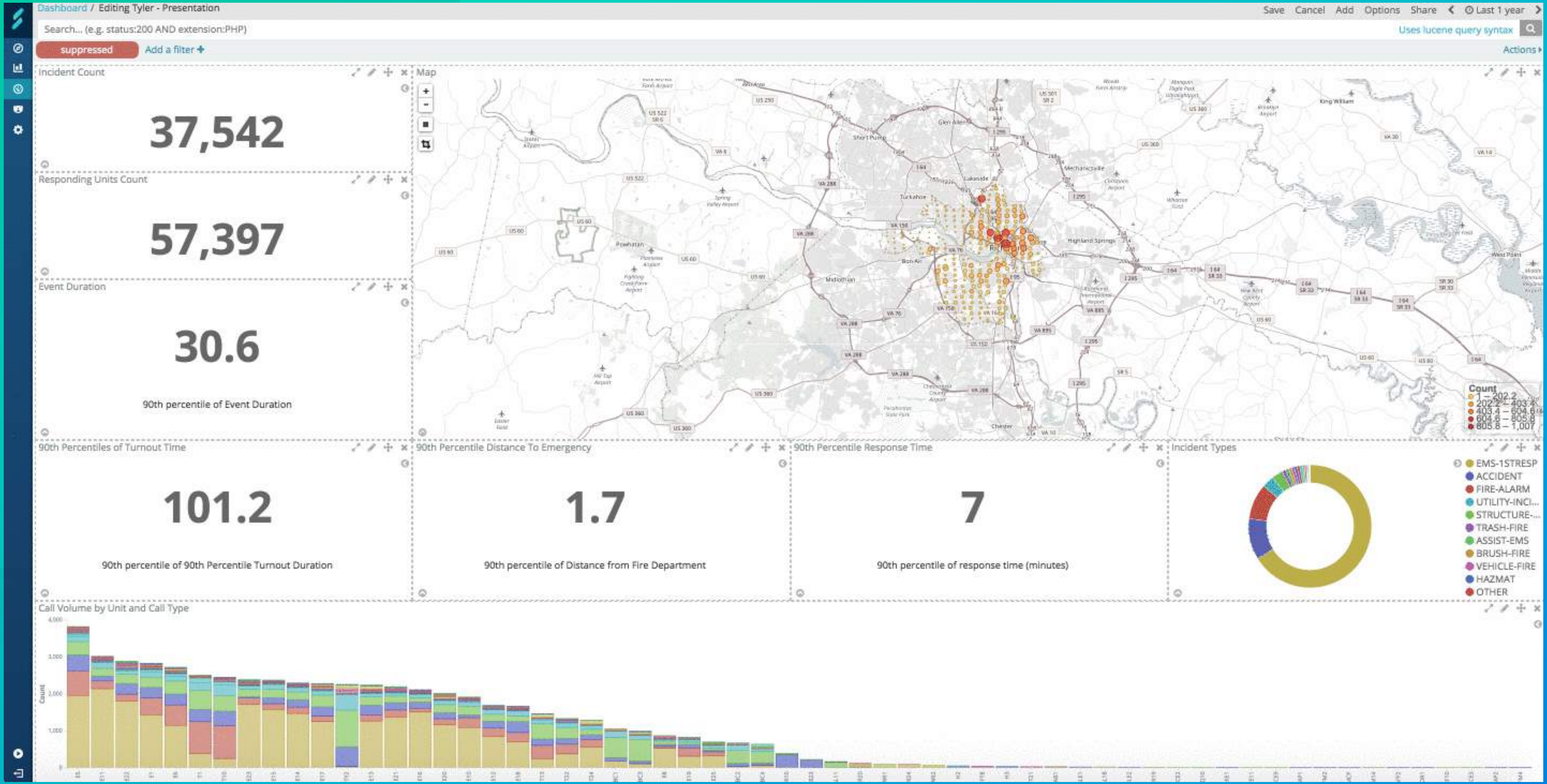
Kibana customizations, reports, fully production cloud instance, training videos and guides, complete documentation, open source all libraries.

July 2018

Project completion!

End of project report, financial close-outs, etc.

What does our service delivery look like over the last year?



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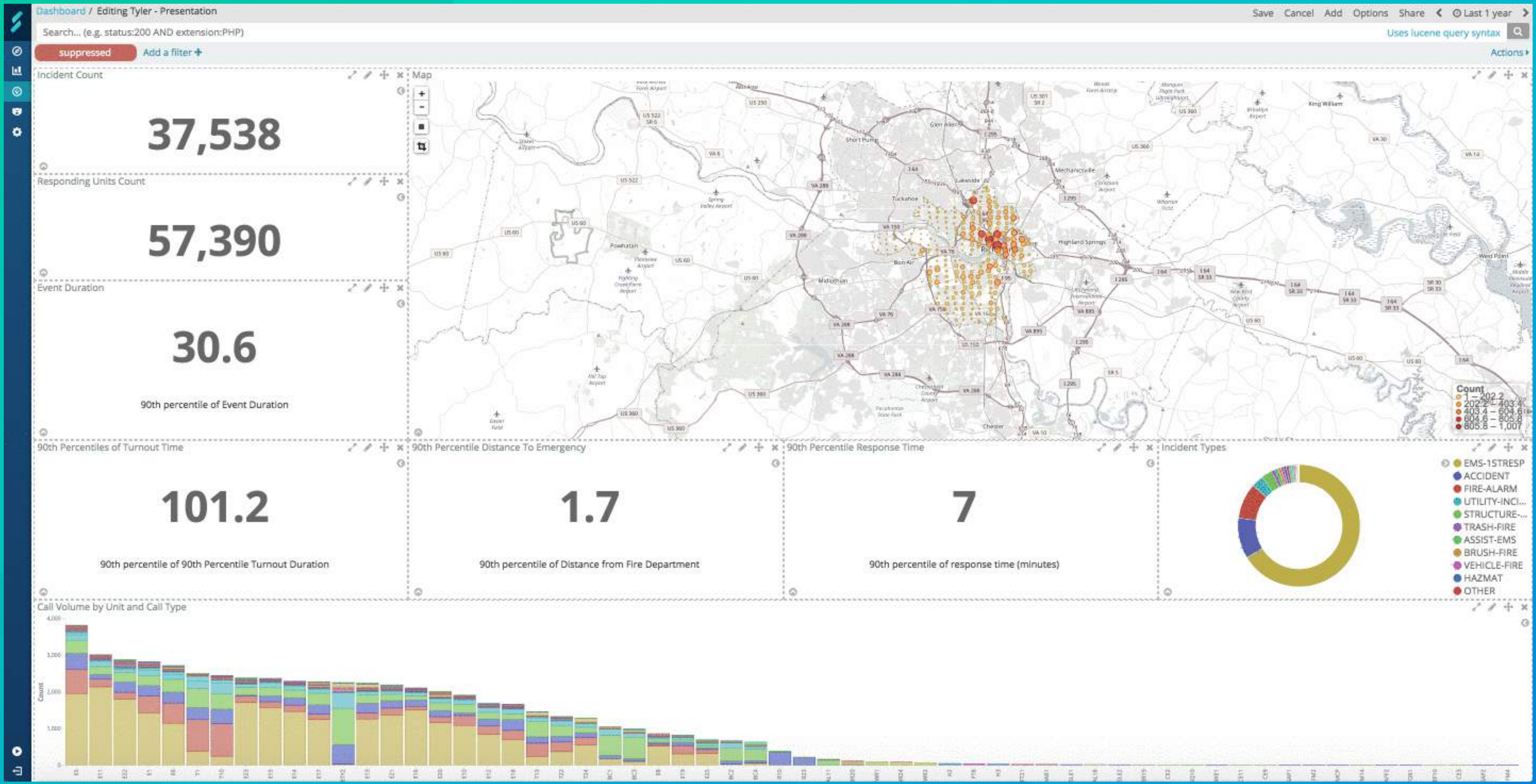
Save Cancel Add Options Share Last 1 year
Search... (e.g. status:200 AND extension:PHP)
Uses lucene query syntax
suppressed
Add a filter
Actions
Incident Count
37,542
Responding Units Count
57,397
Event Duration
30.6
90th percentile of Event Duration
Map
90th Percentiles of Turnout Time
101.2
90th percentile of 90th Percentile Turnout Duration
90th Percentile Distance To Emergency
1.7
90th percentile of Distance from Fire Department
90th Percentile Response Time
7
90th percentile of response time (minutes)
Incident Types
EMS-1STRESP
ACCIDENT
FIRE-ALARM
UTILITY-INCI...
STRUCTURE-...
TRASH-FIRE
ASSIST-EMS
BRUSH-FIRE
VEHICLE-FIRE
HAZMAT
OTHER
Call Volume by Unit and Call Type

What does our service delivery look like over the last year?

...In council district #1?



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suppressed
Add a filter
Actions
Incident Count
37,538
Responding Units Count
57,390
Event Duration
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90th percentile of Event Duration
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90th Percentiles of Turnout Time
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90th percentile of 90th Percentile Turnout Duration
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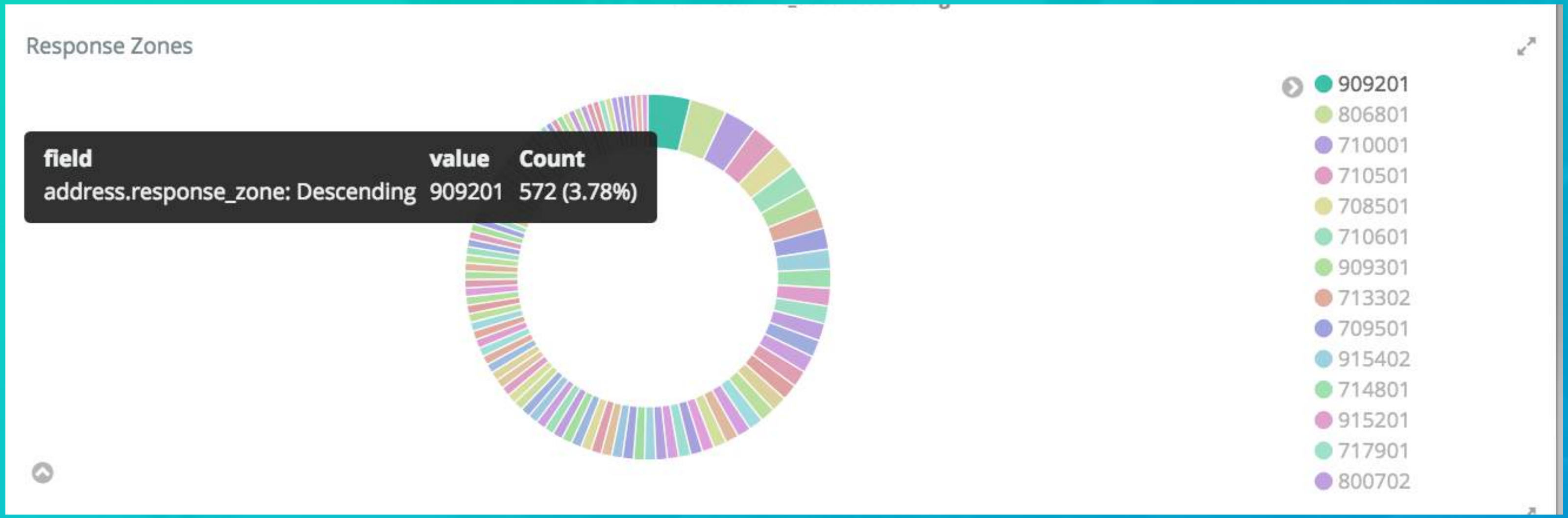
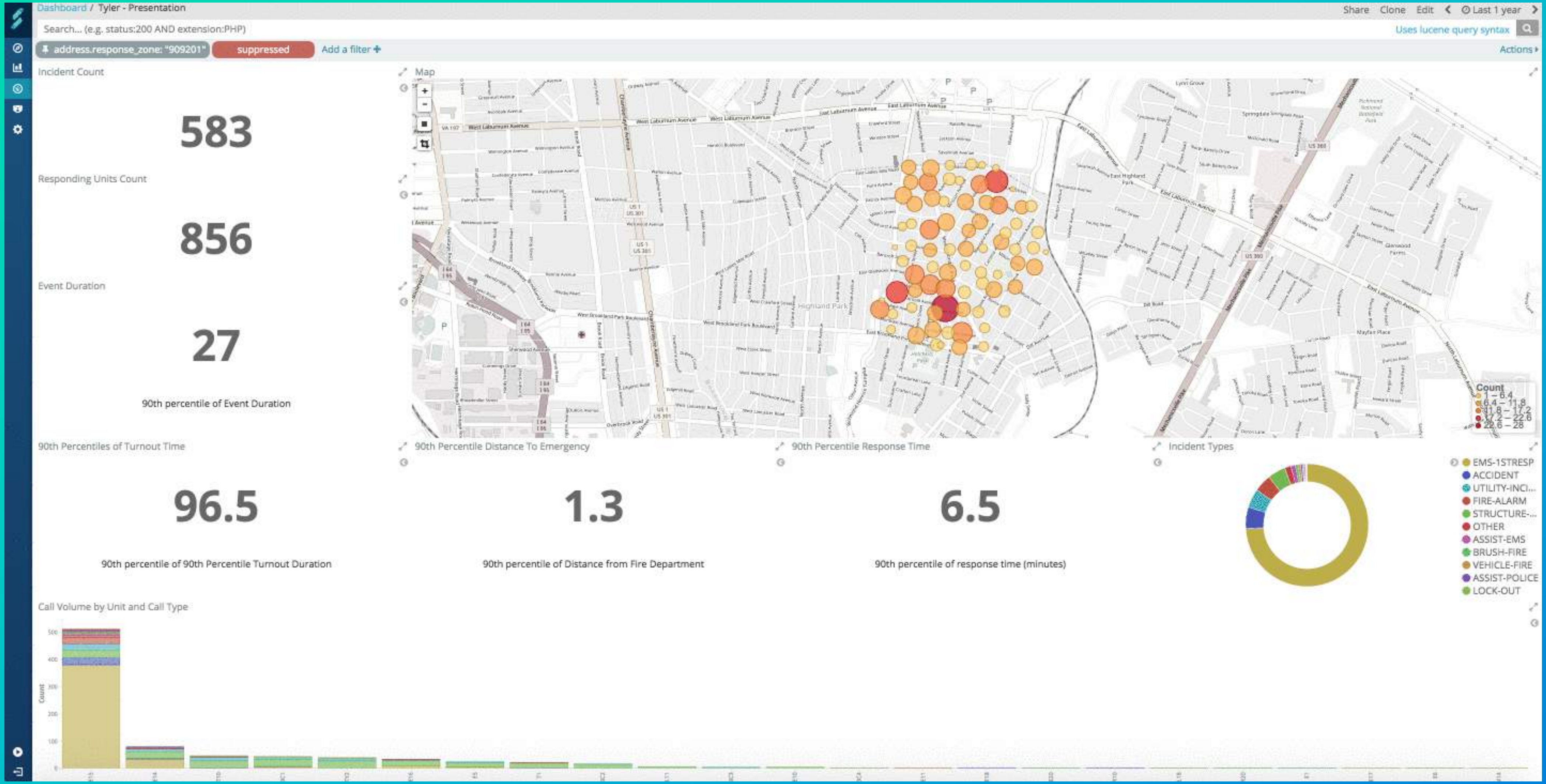
VEHICLE-FIRE
HAZMAT
OTHER
Call Volume by Unit and Call Type

What response zones have highest demand?


Response Zones
field
value
Count
address.response_zone: Descending
909201
572 (3.78%)
909201
806801
710001
710501
708501
710601
909301
713302
709501
915402
714801
915201
717901
800702


Dashboard / Tyler - Presentation
Share Clone Edit Last 1 year
Search... (e.g. status:200 AND extension:PHP)
Uses lucene query syntax
address.response_zone: "909201"
suppressed
Add a filter
Actions
Incident Count
583
Responding Units Count
856
Event Duration
27
90th percentile of Event Duration
Map
90th Percentiles of Turnout Time
96.5
90th percentile of 90th Percentile Turnout Duration
90th Percentile Distance To Emergency
1.3
90th percentile of Distance from Fire Department
90th Percentile Response Time
6.5
90th percentile of response time (minutes)
Incident Types
EMS-1STRESP
ACCIDENT
UTILITY-INCI...
FIRE-ALARM
STRUCTURE-...
OTHER
ASSIST-EMS
BRUSH-FIRE
VEHICLE-FIRE
ASSIST-POLICE
LOCK-OUT
Call Volume by Unit and Call Type

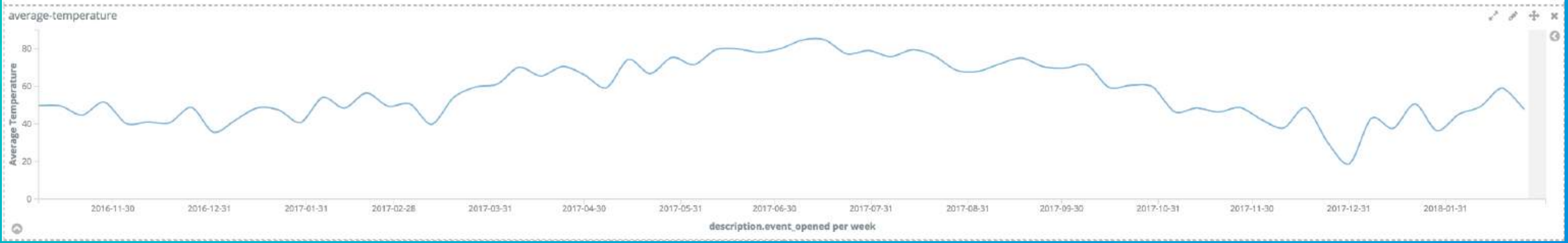
Box 909201 vs Response System

Call Type	Response System	Box 909201	Change
EMS	67%	74%	7%
Accident	10%	5%	5%
Fire Alarms	9%	5%	4%
Utility Incidents	3%	5%	2%

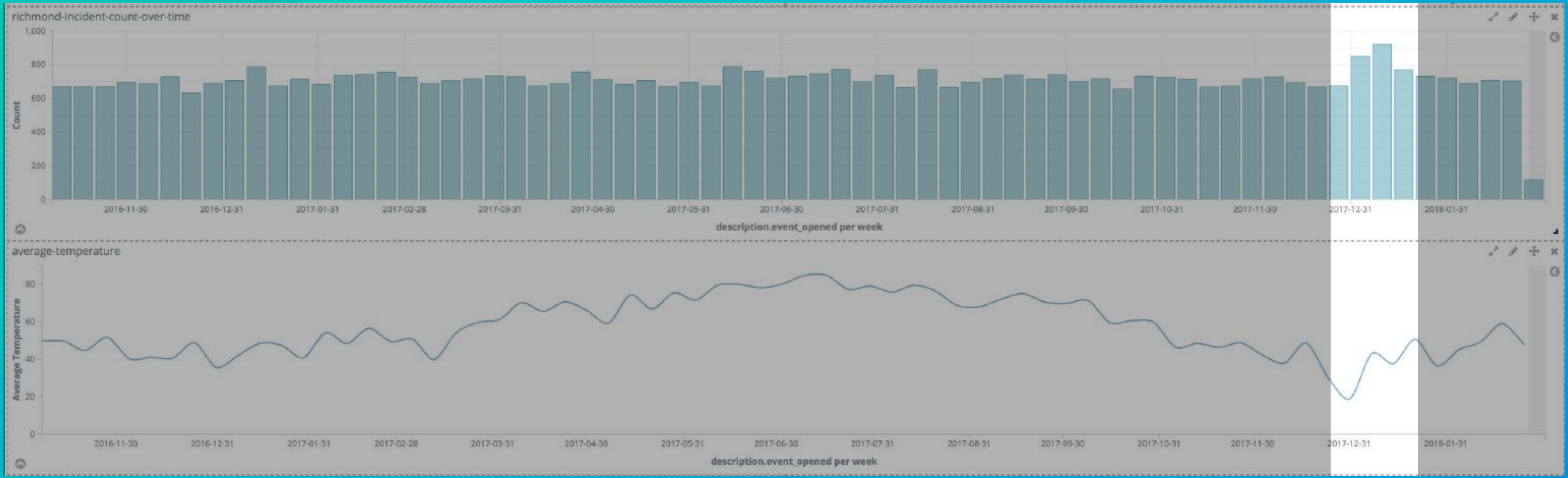
Metric	Response System	Box 909201	Change
Event Duration	30.7 min	27 min	3.7 min
Turn out Time	101.4 sec	96.5 sec	4.9 sec
Distance to Emergency	1.7 mi	1.3 mi	.4 mi
Response Time	7.1 min	6.5 min	0.6 min
Water on Fire	11 min	7.4 min	3.6 min
Command Established	11.8 min	8.4	3.4 min
Primary Search	14.6 minutes	22 min	7.4 min

How does demand for our services change based on weather?

EMS	67%
Accident	10%
Fire Alarms	9%
Utility Incidents	3%

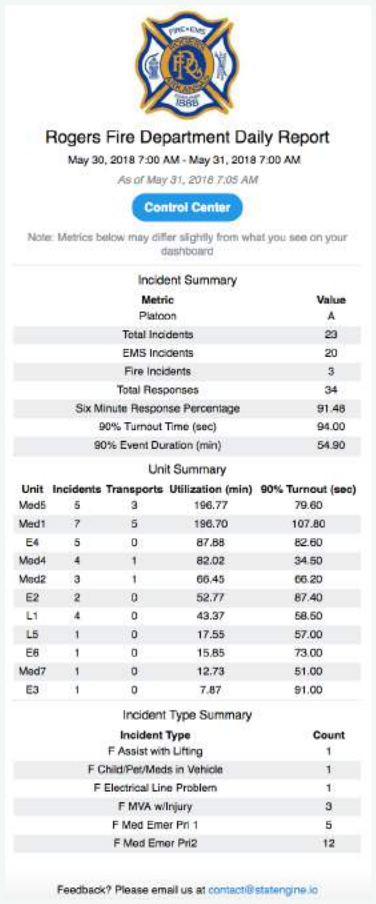


EMS	67%
Accident	10%
Fire Alarms	9%
Utility Incidents	3%



EMS	57%	10%
Fire Alarms	15%	6%
Utility Incidents	11%	8%
Accident	6%	4%

Infinite Possibilities



Rogers Fire Department Daily Report

May 30, 2018 7:00 AM - May 31, 2018 7:00 AM

As of May 31, 2018 7:05 AM

Control Center

Note: Metrics below may differ slightly from what you see on your dashboard

Incident Summary

Metric	Value
Platoon	A
Total Incidents	23
EMS Incidents	20
Fire Incidents	3
Total Responses	34
Six Minute Response Percentage	91.48
90% Turnout Time (sec)	94.00
90% Event Duration (min)	54.90

Unit Summary

Unit	Incidents	Transports	Utilization (min)	90% Turnout (sec)
Med5	5	3	196.77	79.60
Med1	7	5	196.70	107.80
E4	5	0	87.88	82.60
Med4	4	1	82.02	34.50
Med2	3	1	66.45	66.20
E2	2	0	52.77	87.40
L1	4	0	43.37	58.50
L5	1	0	17.55	57.00
E6	1	0	15.85	73.00
Med7	1	0	12.73	51.00
E3	1	0	7.87	91.00

Incident Type Summary

Incident Type	Count
F Assist with Lifting	1
F Child/Pet/Meds in Vehicle	1
F Electrical Line Problem	1
F MVA w/Injury	3
F Med Emer Pri 1	5
F Med Emer Pri2	12

Feedback? Please email us at contact@statengine.io

Tyler Garner

Chief Operating Officer

Prominent Edge

garnertb@prominentedge.com

@garnertb

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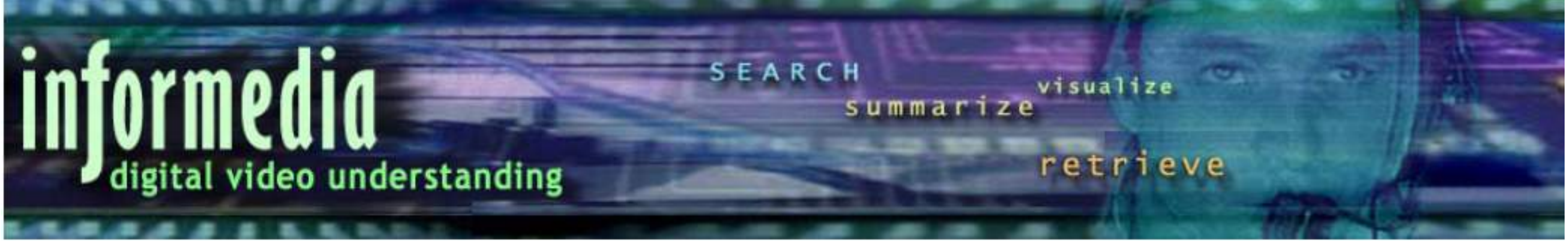


Real-Time Video Analytics for Situation Awareness

Junwei Liang (junweil@cs.cmu.edu)

Alex Hauptmann (alex@cs.cmu.edu)

Introduction

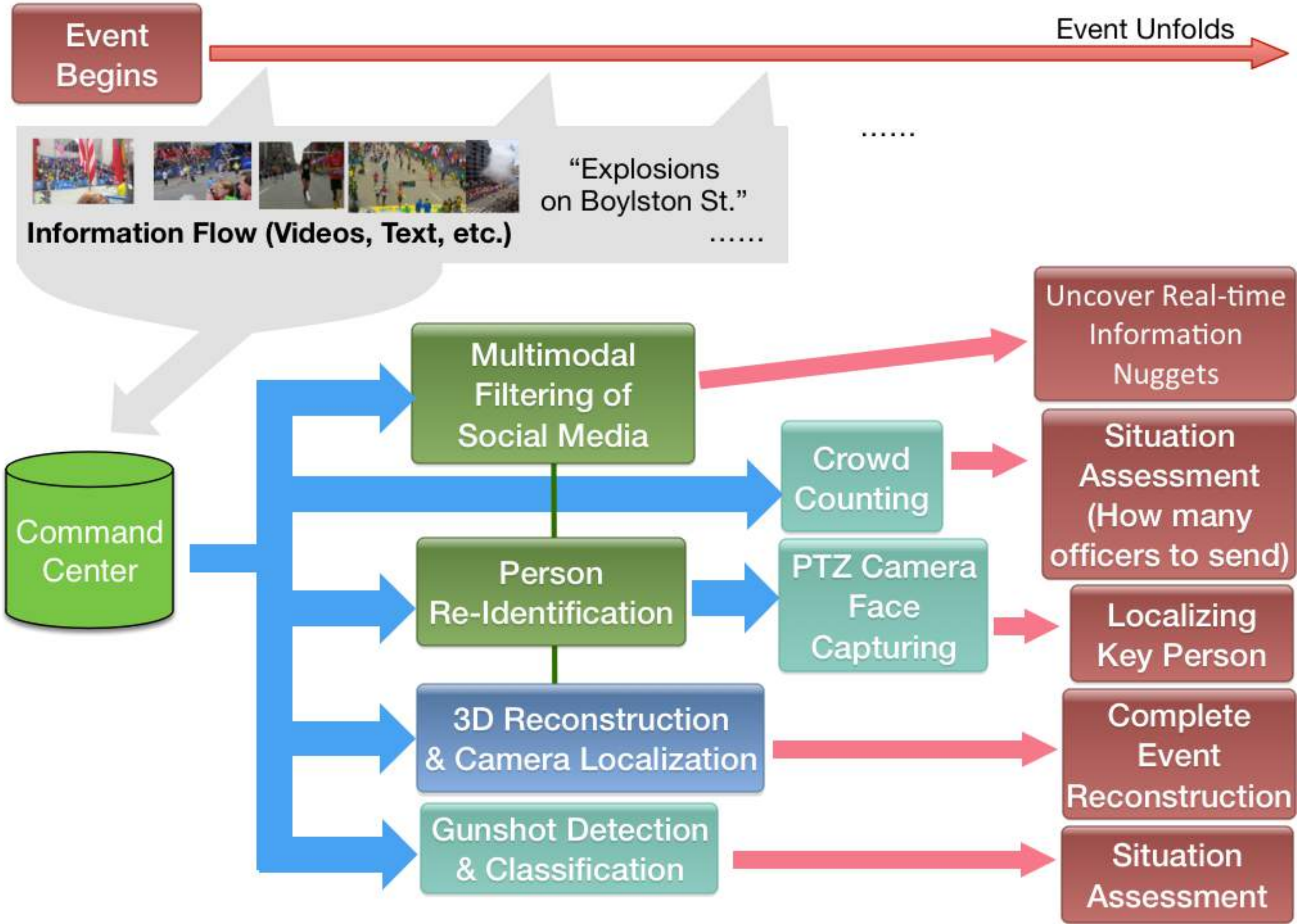
- Ubiquitous camera phones allow public safety events to be captured on video and rapidly shared via social media
- Our project seeks to develop video analytics tools and visualizations based on computer vision and machine learning for public safety events
- The goal is to make public safety analytics less labor-intensive and more manageable at a large scale
  - Augment/enhance the expertise of analysts, not replace decision-making

Introduction

Harness the information potential of event-based video recordings

- Independent tools to be combined into a forensic system
  - Joint analysis of social media videos and texts from an event
  - 3D reconstruction removing the requirement of high resolution images
  - Gunshot and **gun type** classification from cell-phone video
  - Crowd counting for situation assessment
  - Person re-identification
  - Automatic face capturing for Pan-Tilt-Zoom cameras
  - Trainable tools for Google Street View object detection with a first application for detecting fiber optic infrastructure

Integrated Platform Concept



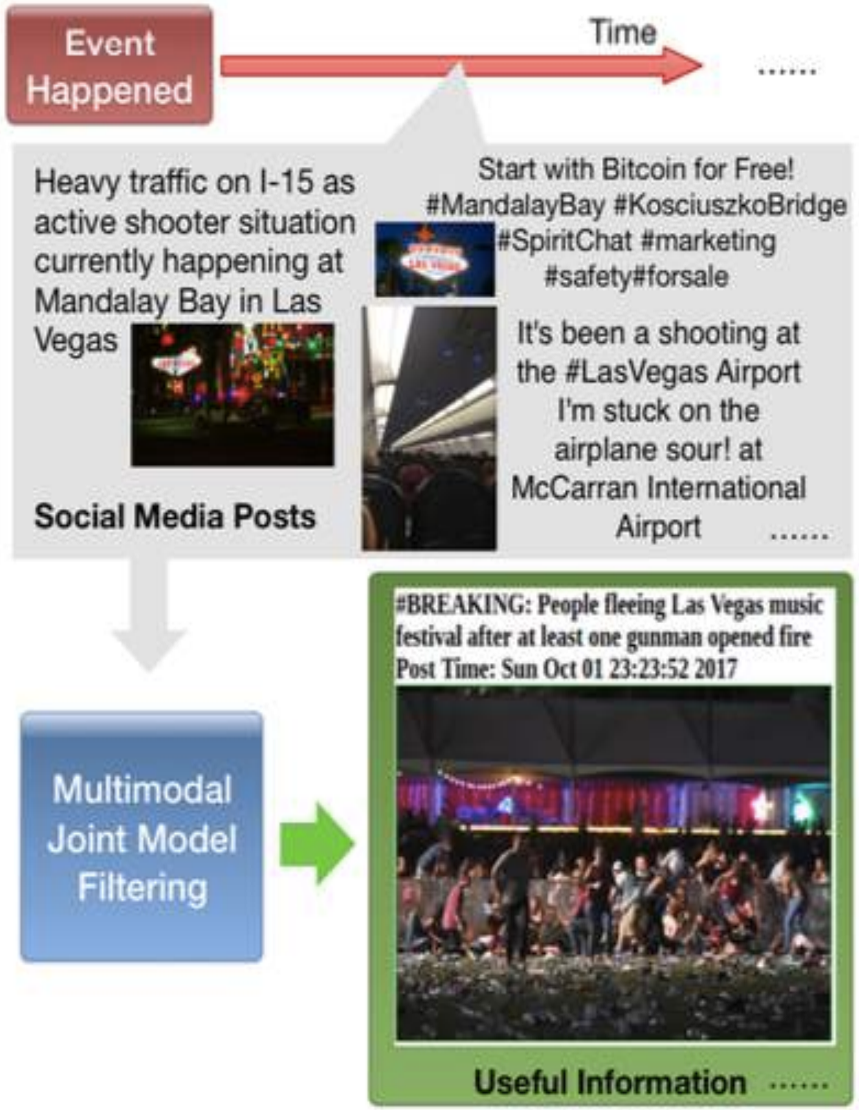
- As event unfolds
  - Information flows into the command center
  - System helps discard useless information
  - Standalone tools for specialized analysis

Current Tools for Video Analytics

- Analytics Tools
  - Multimodal Filtering of Social Media (Demo)
  - Person Re-Identification (Demo)
  - 3D Reconstruction with Camera Localization (Demo)
  - Crowd counting (Demo)
  - Trainable Google Street View Object Detection Tool (Demo)
  - Gunshot Type Detection and Classification (Demo/Download)
  - Automatic Face Capturing for Pan-Tilt-Zoom Camera (Demo/Download)

Multimodal Filtering of Social Media

- As a major public safety event unfolds, social media is an important real-time source of information
- **Goal**
  - **Automatically discover useful information**
- Problem:
  - Too many unrelated or uninformative posts. Distilling useful ones is the first important step towards understanding the event.
- Solution:
  - Model: multimodal joint filtering model to distill "useful" tweets with (text, image, video)
  - (Automatically) identifying useful social media posts in real-time.



How to Define Usefulness

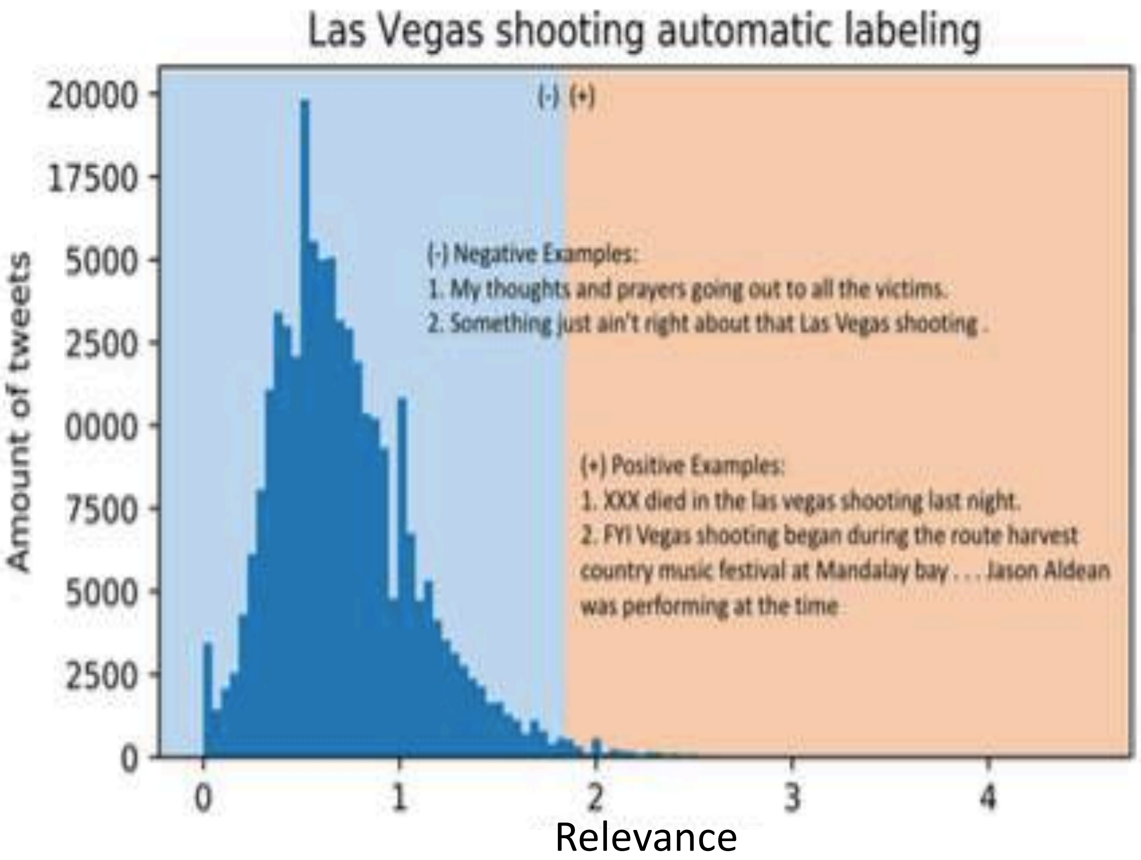
- Data Collection
  - "Usefulness" of a tweet or post is determined by its contribution to the event analysis
  - For research, we treat Wikipedia event descriptions (text/image) as place-holders for actual analytic event reports
  - Links to news reports are generally redundant and thus removed

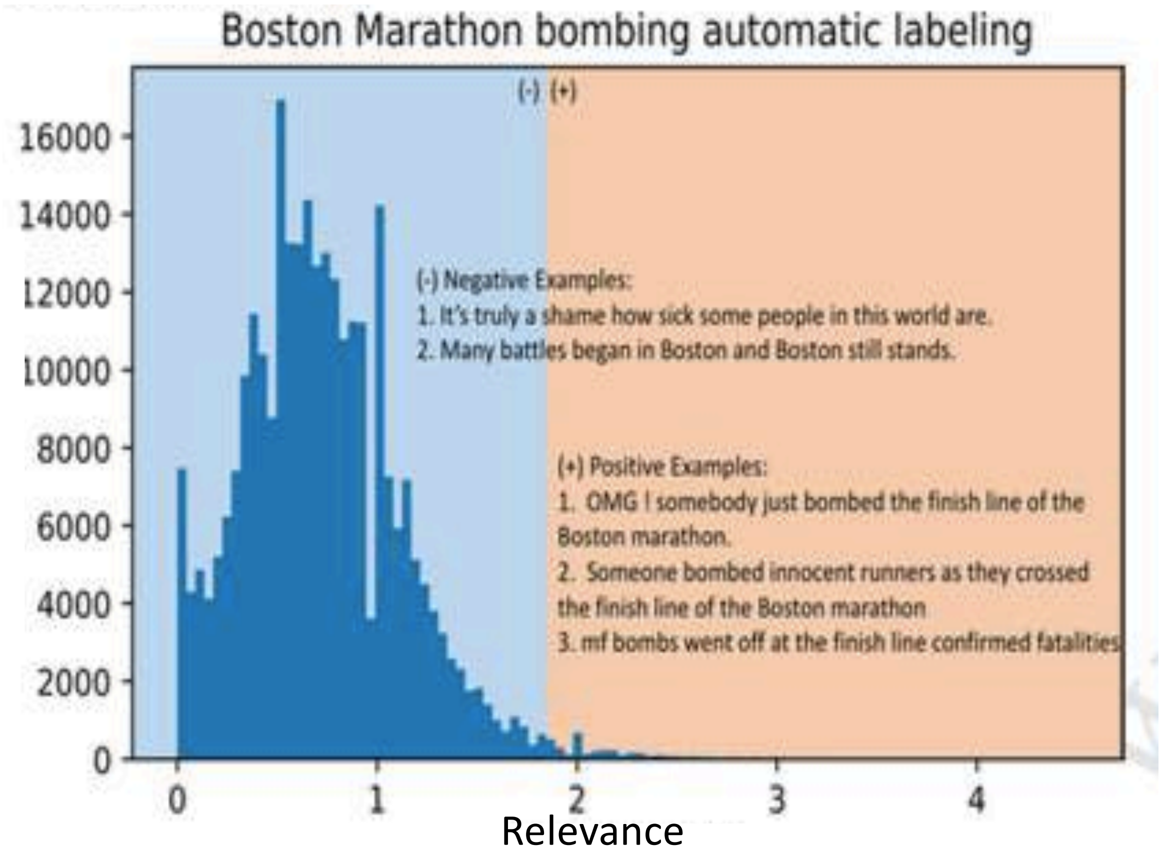
Twitter Data

Example major public safety events between 2013-2017

Year	Event	Tweets	Images	Early Tweets	Useful %
2013	Boston Marathon bombing	1,807,695	70,028 (3.87%)	522,696 (28.92%)	2.0%
2013	Washington Navy Yard shooting	263,621	7,210 (2.74%)	128,069 (48.64%)	2.2%
2015	Charleston massacre	435,051	48,667 (11.19%)	84,992 (19.54%)	2.5%
2015	Paris attacks	400,254	80,976 (20.23%)	47,519 (11.87%)	1.7%
2016	Orlando shooting	191,740	29,314 (15.29%)	76,919 (39.96%)	2.0%
2016	Dallas shooting	291,935	26,340 (9.02%)	48,965 (16.77%)	2.0%
2017	Las Vegas shooting	887,997	123,322 (13.89%)	464,488 (52.31%)	2.1%

Text Examples





- Positive examples: useful tweets
- Negative examples: tweets without useful information

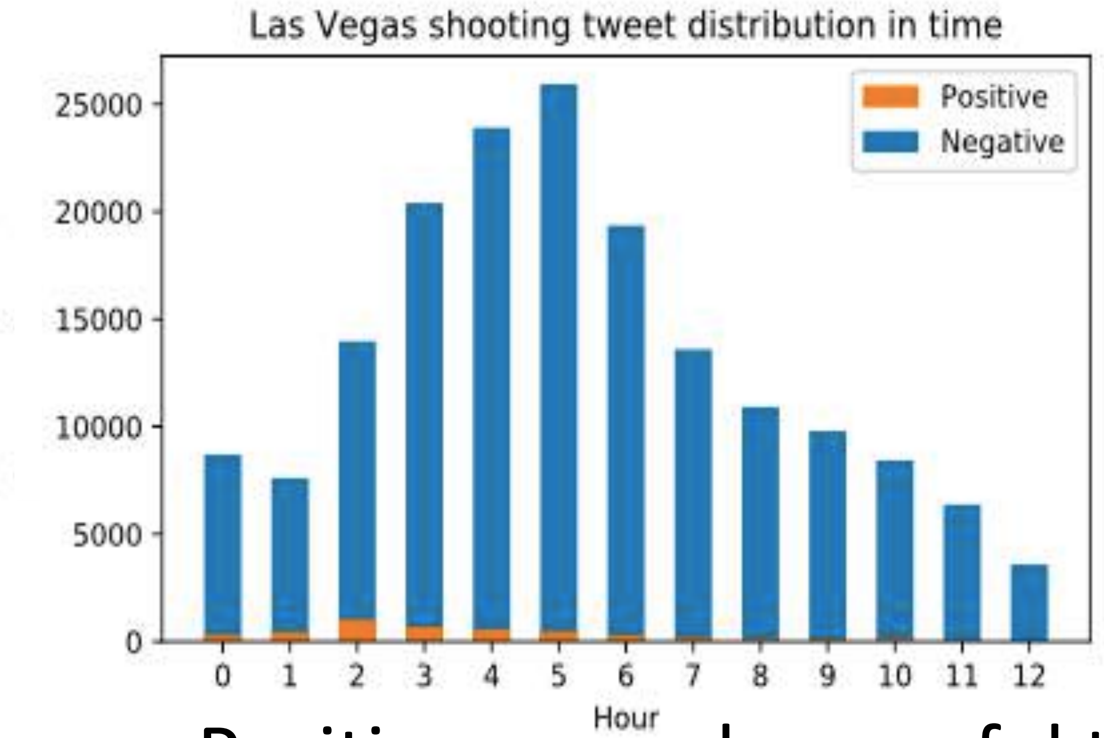
Useful Visual Examples

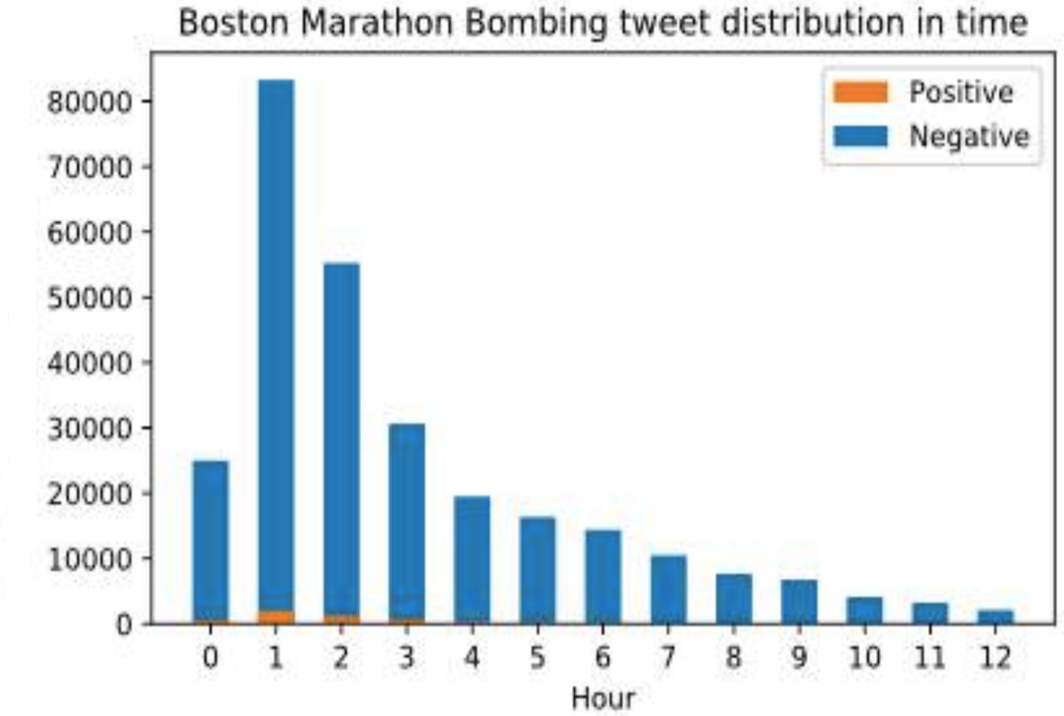
- Left picture: Video footage from the scene
- Right picture: Tweet image

Useful Visual Examples

- Left picture: Video footage from the scene
- Right picture: Tweet image

Hourly Tweet Distribution





- Positive examples: useful tweets
- Negative examples: tweets without useful information

Accuracy

Method	Boston Marathon bombing	Las Vegas shooting
Resnet+SVM (V)	0.5173	0.2282
GloVe+SVM (T)	0.3632	0.3750
LSTM+SVM (T)	0.6487	0.7707
LSTM/Resnet+SVM (T+V)	0.6491	0.7736
ours (T)	0.6683	0.8107
ours (T+V)	**0.6750**	**0.8157**

Demonstration

Las Vegas Shooting

Incoming Tweets as Event Unfolds

dannews at Sun Oct 01 22:23:08 2017:
Witnesses saying ""multiple gunmen"" shooting at people at hotel in Las Vegas

ZDeDeKim at Sun Oct 01 22:28:02 2017:
Active shooter Shots fired at Mandalay Bay Reports one officer has been shot #LasVegas #MandalayBayShooting

Useful Tweets Detected by System

ThonyAvellaneda at Mon Oct 02 00:19:20 2017:
Two killed and 24 injured in the #LasVegas shooting. @eltiempolv @reviewjournal.

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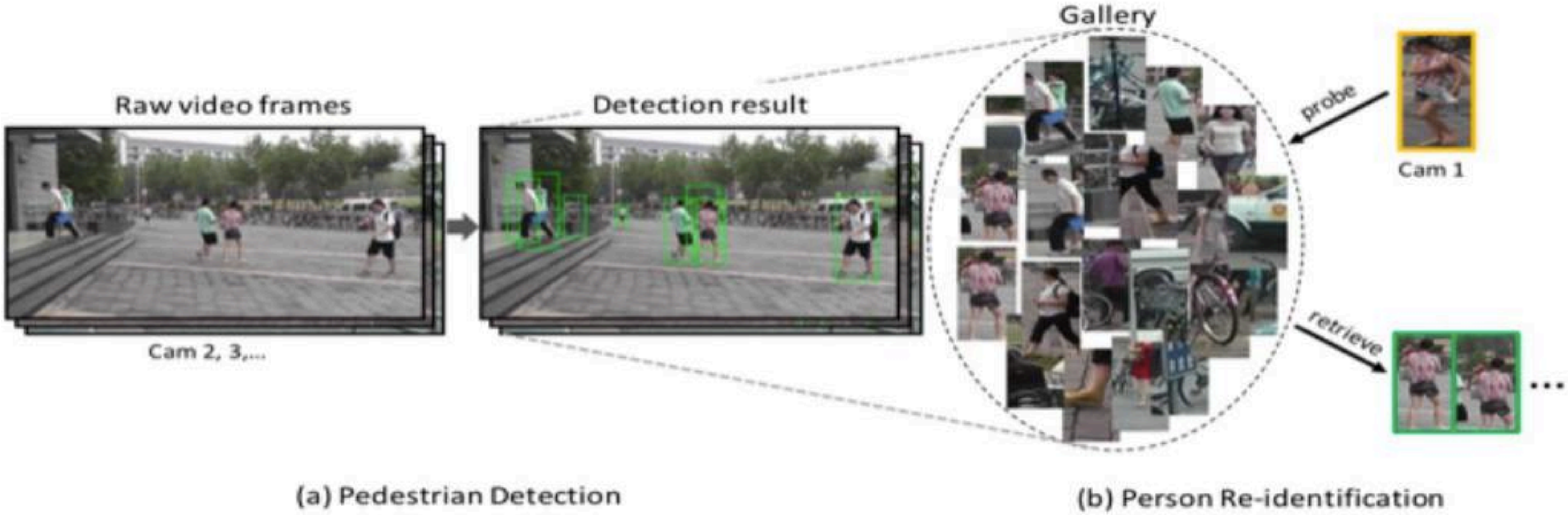
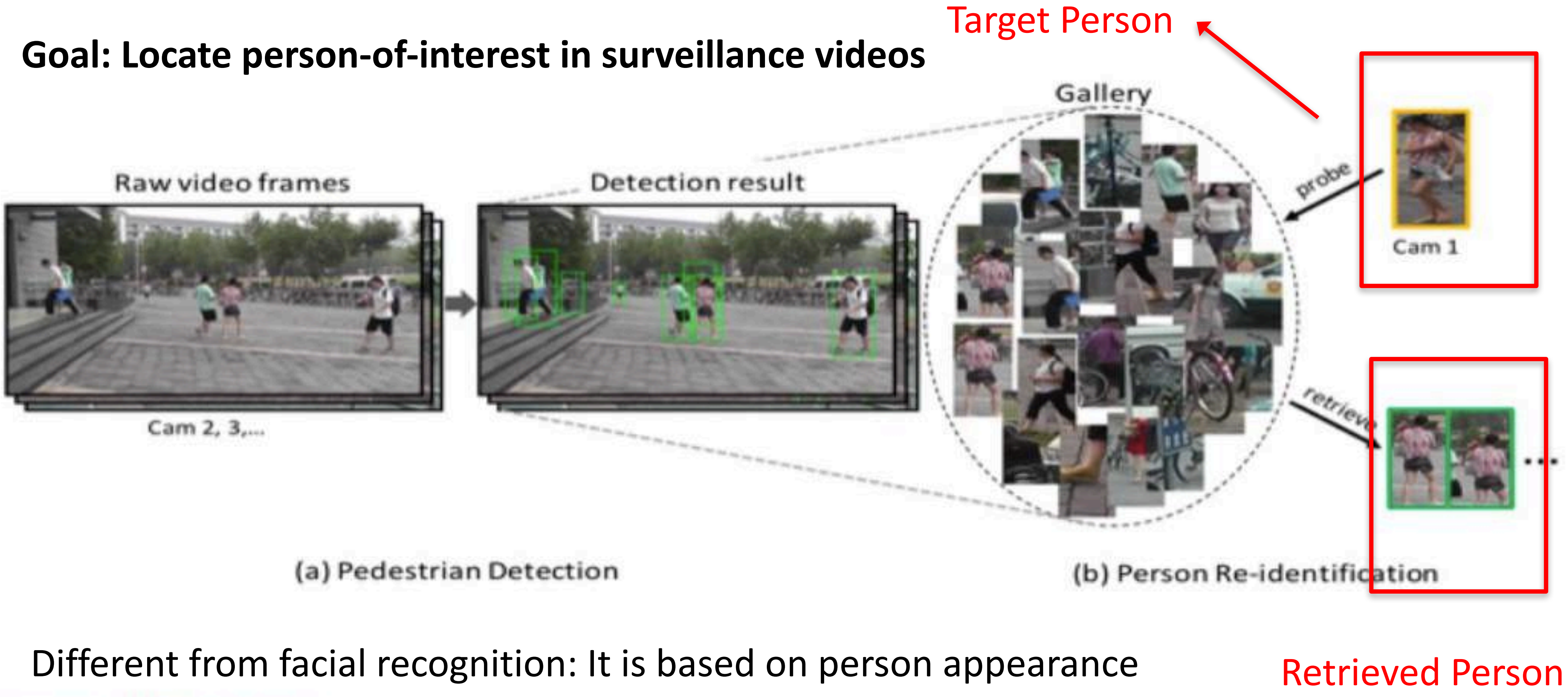
Person Re-Identification



Person Re-Identification

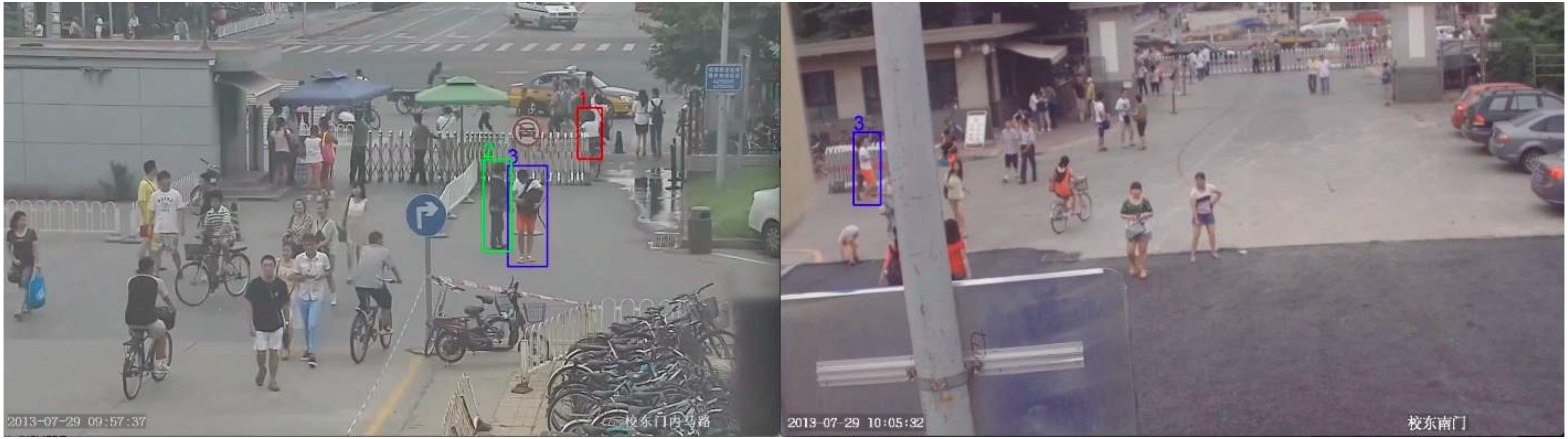
Goal: Locate person-of-interest in surveillance videos



Different from facial recognition: It is based on person appearance

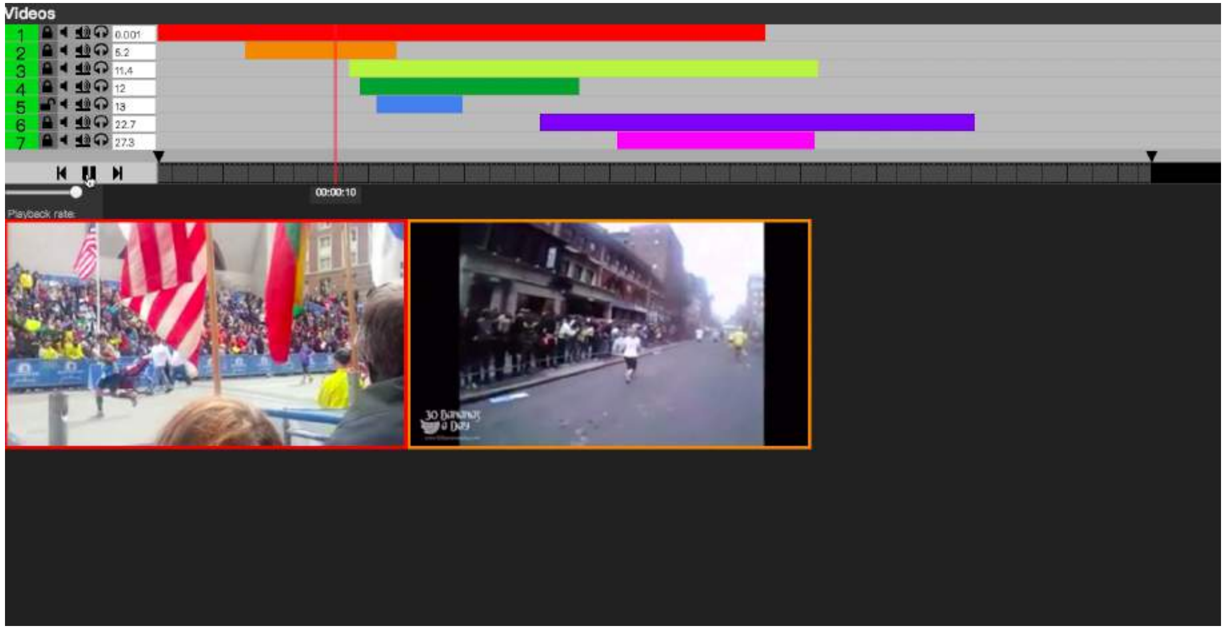
Person Re-Identification

- Demonstration



Recap of Video Synchronization Tool

- Putting videos from social media into a global timeline (Demo/Download)



3D Reconstruction with Camera Localization

- Problem
  - We can synchronize multiple videos but the large number of videos makes it hard to understand the situation
- Goal
  - Reconstruct the scene in 3D and project videos into augmented reality to facilitate better understanding of the event

3D Reconstruction with Camera Localization

- Limitation of existing methods
  - Limited data usually results in poor accuracy
  - Sensitive to environmental changes: lighting condition or blurring
  - Computationally inefficient
- For a real-time system, we need our method to be
  - Efficient
  - Robust to limited data
  - Robust to environment changes

3D Reconstruction with Camera Localization

- Use a deep neural network to learn the 3D model of the environment.
  - Efficiency: The prediction is almost in real time
  - Limited data: No sequence of images is needed
  - Robustness to environment change: Deep learning approach is robust to changes in lighting, motion blur, etc.

3D Reconstruction with Camera Localization

- Training:
  - The network is trained off-line using data from different sources.

Model

- Camera Localization:
  - Given a video frame, the model can determine the location and pose of the camera.

Model

Camera location
Camera pose

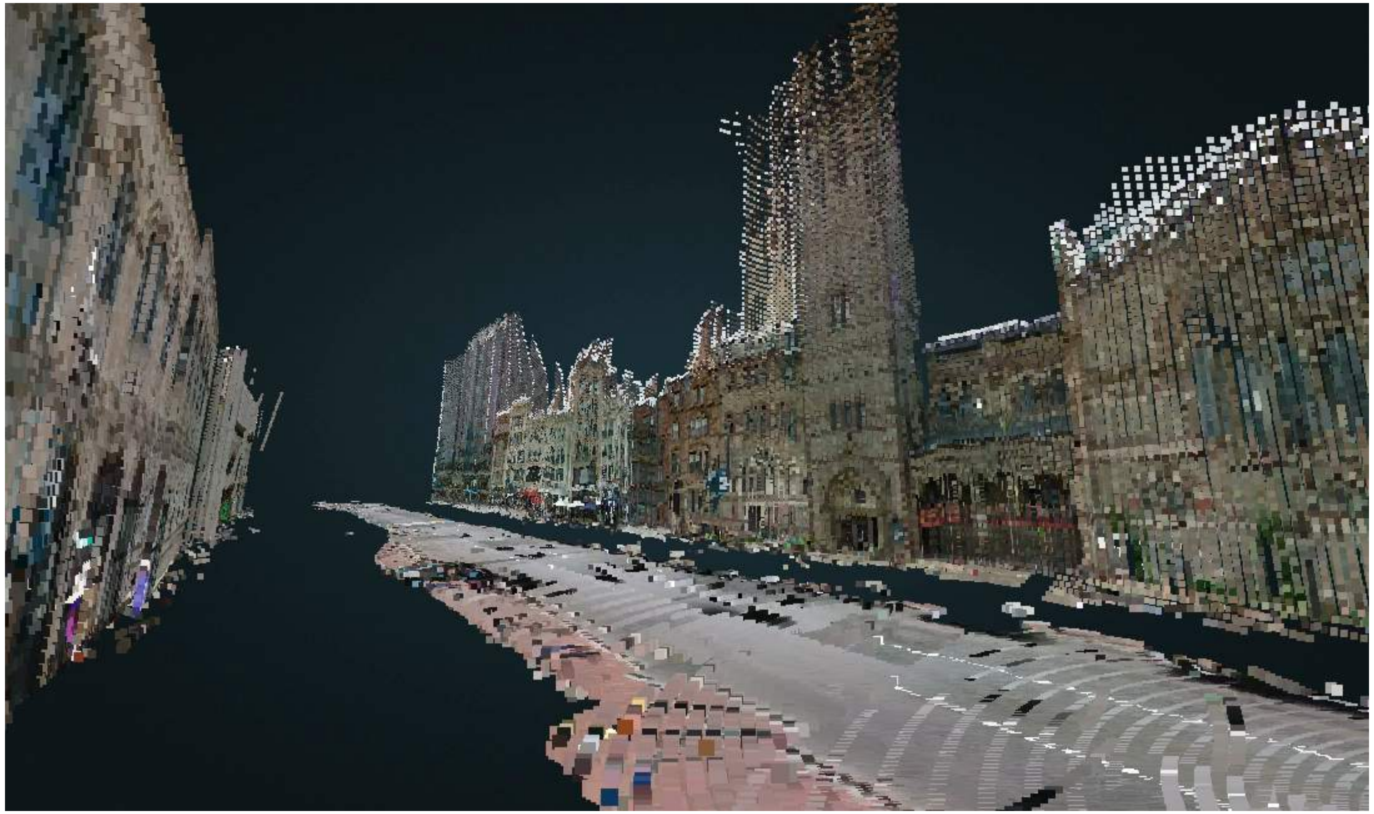
Demonstration – Boston Dataset

- Last year our 3D reconstruction is sparse

Carnegie Mellon University
Language Technologies Institute

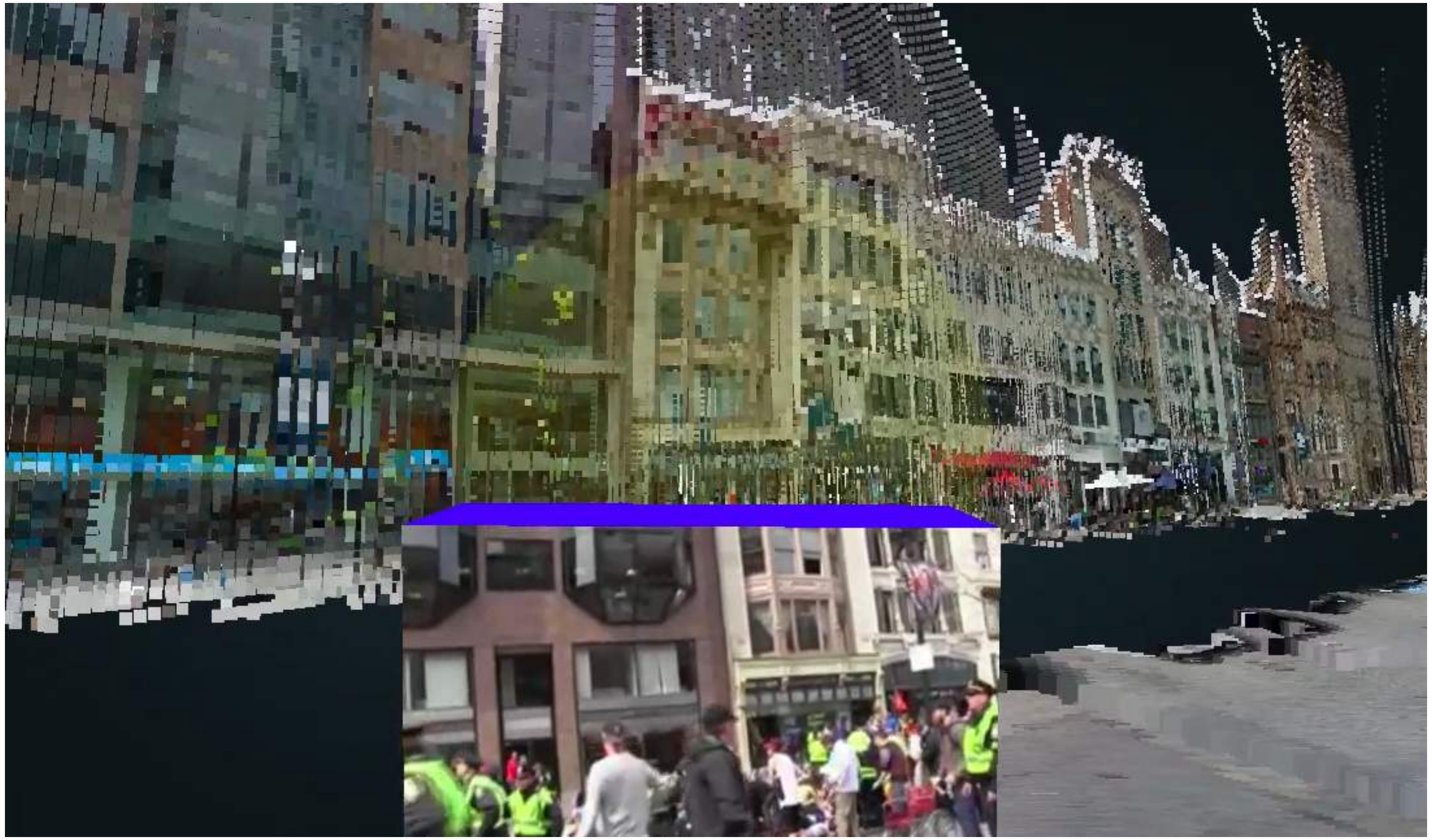
Demonstration – Boston Dataset

- Combining with Dense Point Cloud
  - Reconstructed from Google Street View data



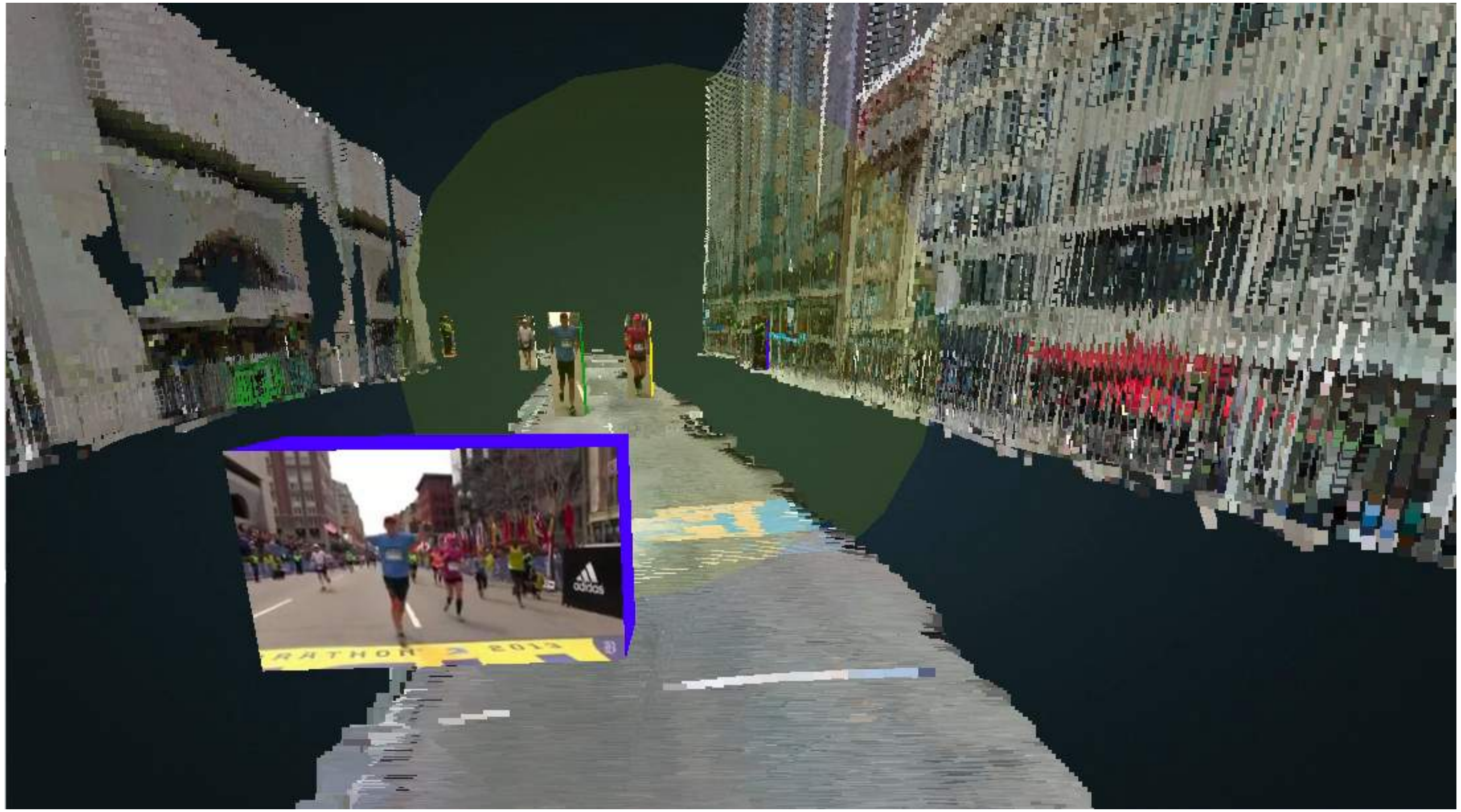
Demonstration – Boston Dataset

- Camera Localization in 3D Space



Demonstration – Boston Dataset

- Person Tracking in 3D Space



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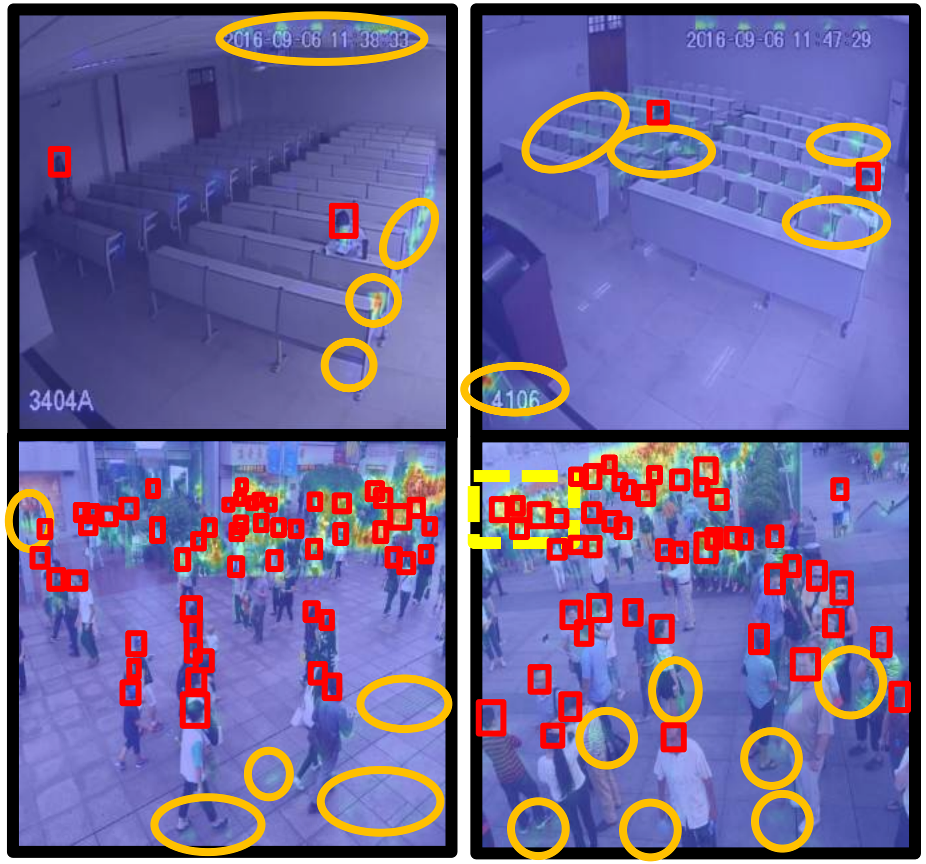
Crowd Counting

- **Goal**
  - **Real-Time detection of the number of people on the scene**
- Application
  - Occupancy monitoring for safety
  - Situation Assessment
  - Crowd management
  - Response coordination

Previous Solution – People Detection

- CNN-based object detectors
  - Detecting person heads: treating the number of head detections as crowd counts
  - Successful for scenes with low person density
  - But difficult for congested areas
    - no clear individual person boundary and detail available
    - highly overlapped people (repetitive textures)
    - **Underestimation**



Overestimated region by regression   Bounding box by detection

CNN: Convolutional Neural Network

Alternative Solution – Estimation

- CNN-based crowd density regression
  - Employing CNN for crowd density heatmap regression
  - Estimating based on the pattern of heads, not counting each every single one of them
  - Overestimation in low crowd density regions

CNN: Convolutional Neural Network

Improved Methodology

- **Problem:** crowd density varies enormously in real-world surveillance application
- **Solution:** DecideNet
  - Counting crowds by combining the two methods

Experimental Results: Mall

Method	MAE	MSE
SquareChn Detector [1]	20.55	439.1
R-FCN [8]	6.02	5.46
Faster R-CNN [25]	5.91	6.60
Count Forest [23]	4.40	2.40
Exemplary Density [36]	1.82	2.74
Boosting CNN [33]	2.01	N/A
MoCNN [17]	2.75	13.40
Weighted VLAD [29]	2.41	9.12
DecideNet	**1.52**	**1.90**

Table 1. Comparison results of different methods on the Mall dataset. The MAE and MSE error of our proposed *DecideNet* is significant lower than other approaches.

Demonstration of Crowd Counting

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Trainable GSV Object Detection Tool

- Goal
  - Utilize Google Street View (GSV) images to detect object-of-interest
  - Trainable to find any permanent object visible from the street

Trainable GSV Object Detection Tool

- Applied the tool for fiber optic infrastructure detection

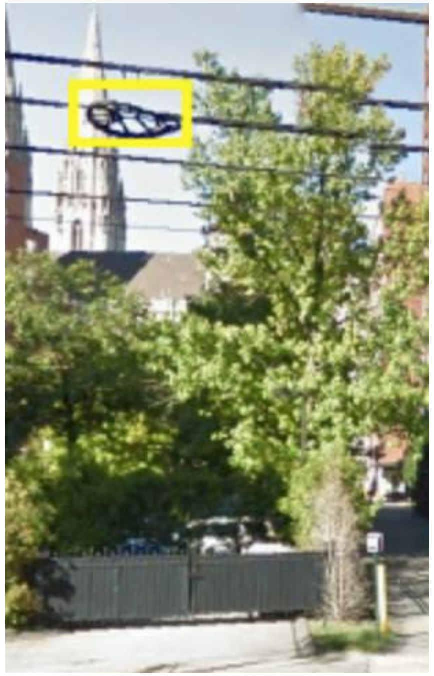
Data Collection for Test Evaluation

GPS	Location	Truth	# full	# of pics to test
40.6466732 -75.4812661	2399 Pine St, PA	Yes	32	2112
42.2092853 -83.7581845	Lohr Textile Greenway, MI	No	20	1320
42.3468485 -71.0894577	Berklee College of Music, MA	No	44	2904
39.7982584 -79.0365287	129 Hunsrick Rd, Meyersdale, PA	Yes	24	1584
41.0642909 -84.9946454	New Haven, IN	No	28	1848
40.448270 -79.947343	Ellsworth Ave, PA	Yes	20	1320
42.352635 -71.110697	InTheRiver, MA	No	20	1320
42.349382 -71.111297	Essex St, MA	No	36	2376
42.338224 -71.0299353	D Street / West Broadway, MA	Yes	24	1584
42.3347537 -71.0237276	Head Island Causeway, MA	No	24	1584
40.576725 -81.583833	Cherry Run, OH	No	16	1056
40.4623975 -79.9444225	Friendship Ave, PA	Yes	60	3960
42.2073349 -83.738078	Lavender, Ann Arbor, MI	No	24	1584
42.349997 -71.105521	Commonwealth Avenue, MA	Yes	60	3960

Evaluation of Fiber Infrastructure Detection

- Indicators
  - Reflector ratio
  - Reflector max confidence
  - Loop ratio
  - Loop max confidence

Reflector



Loop

Mean Accuracy	Mean Recall	Mean F1
0.811	0.833	0.786

Current Tools for Video Analytics

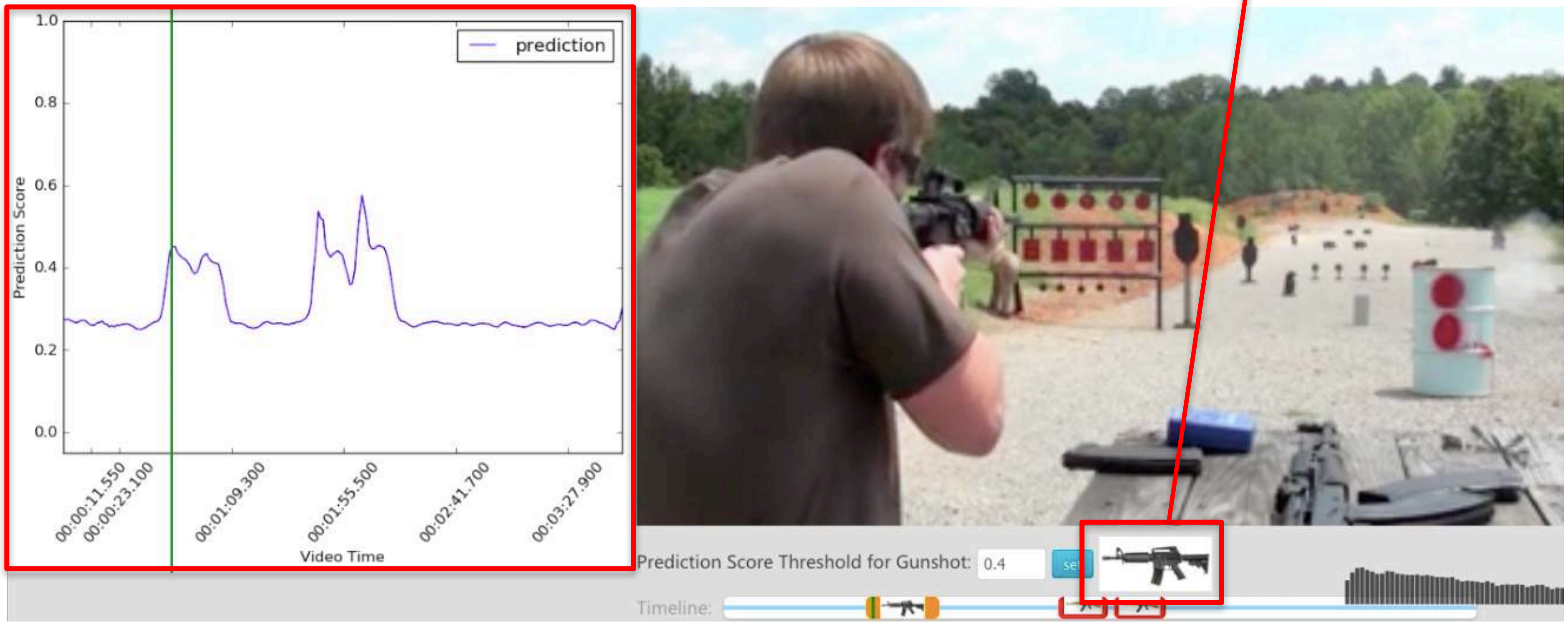
- Analytics Tools
  - Multimodal Filtering of Social Media (Demo)
  - Person Re-Identification (Demo)
  - 3D Reconstruction with Camera Localization (Demo)
  - Crowd counting (Demo)
  - Trainable Google Street View Object Detection Tool (Demo)
  - Gunshot Type Detection and Classification (Demo/Download)
  - Automatic Face Capturing for Pan-Tilt-Zoom Camera (Demo/Download)

Gunshot Detection & Classification

- Goal: Temporally localizing gunshot in videos
  - Classify gunshot type

Current Segment Gunshot Type

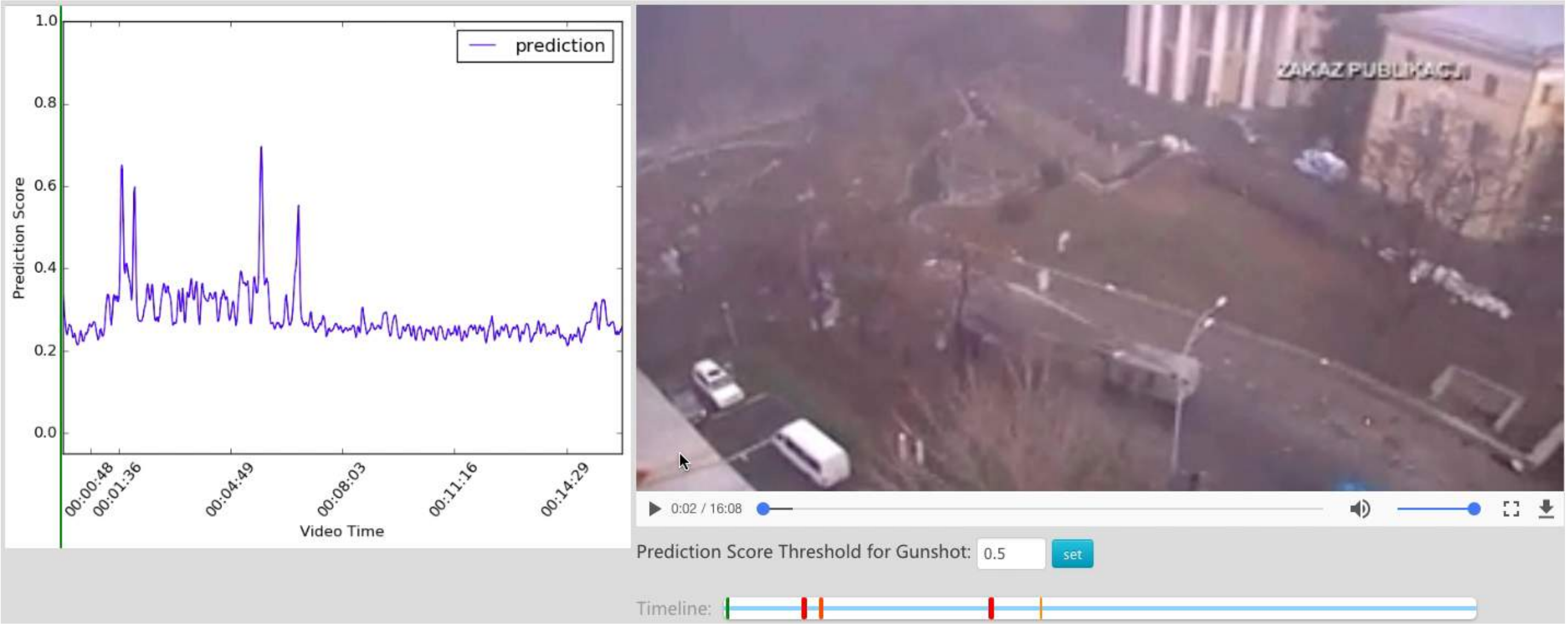
Detected Gunshot Segments



Gunshot Detection & Classification

Carnegie Mellon University
Language Technologies Institute

Gunshot Detection & Classification

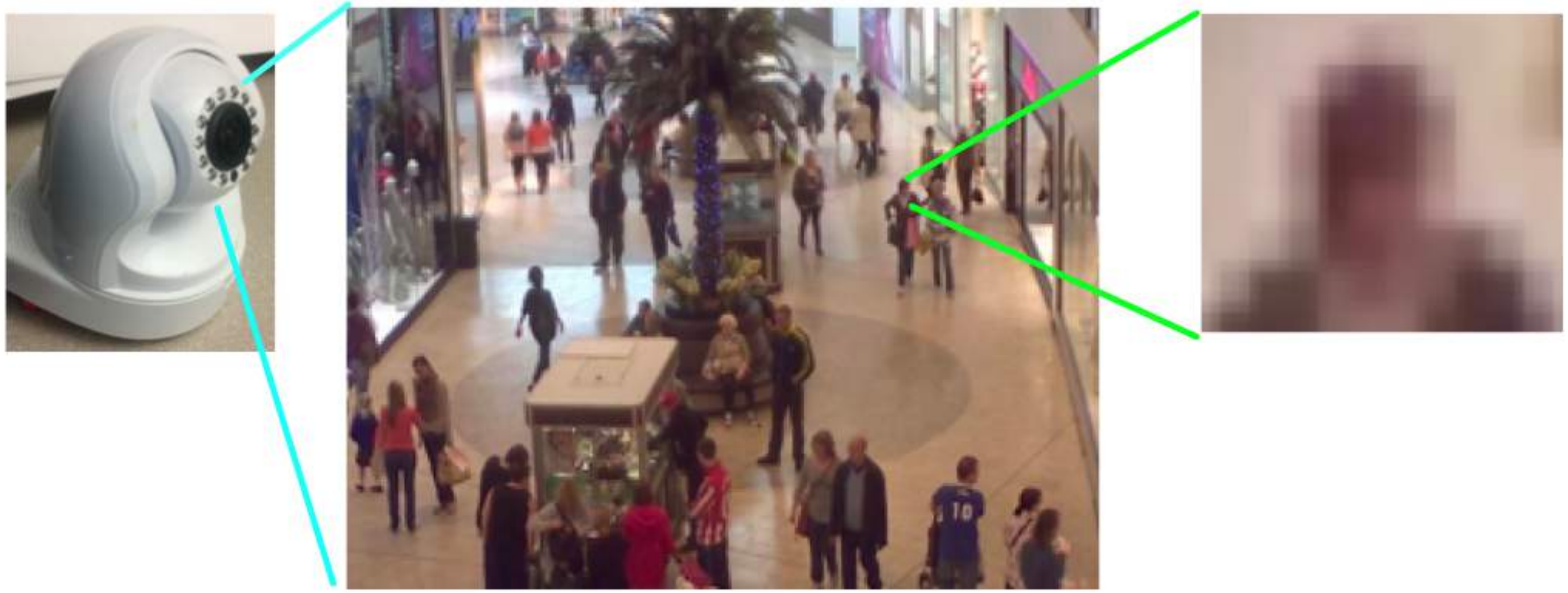


Automatic Face Capturing for Pan-Tilt-Zoom Camera

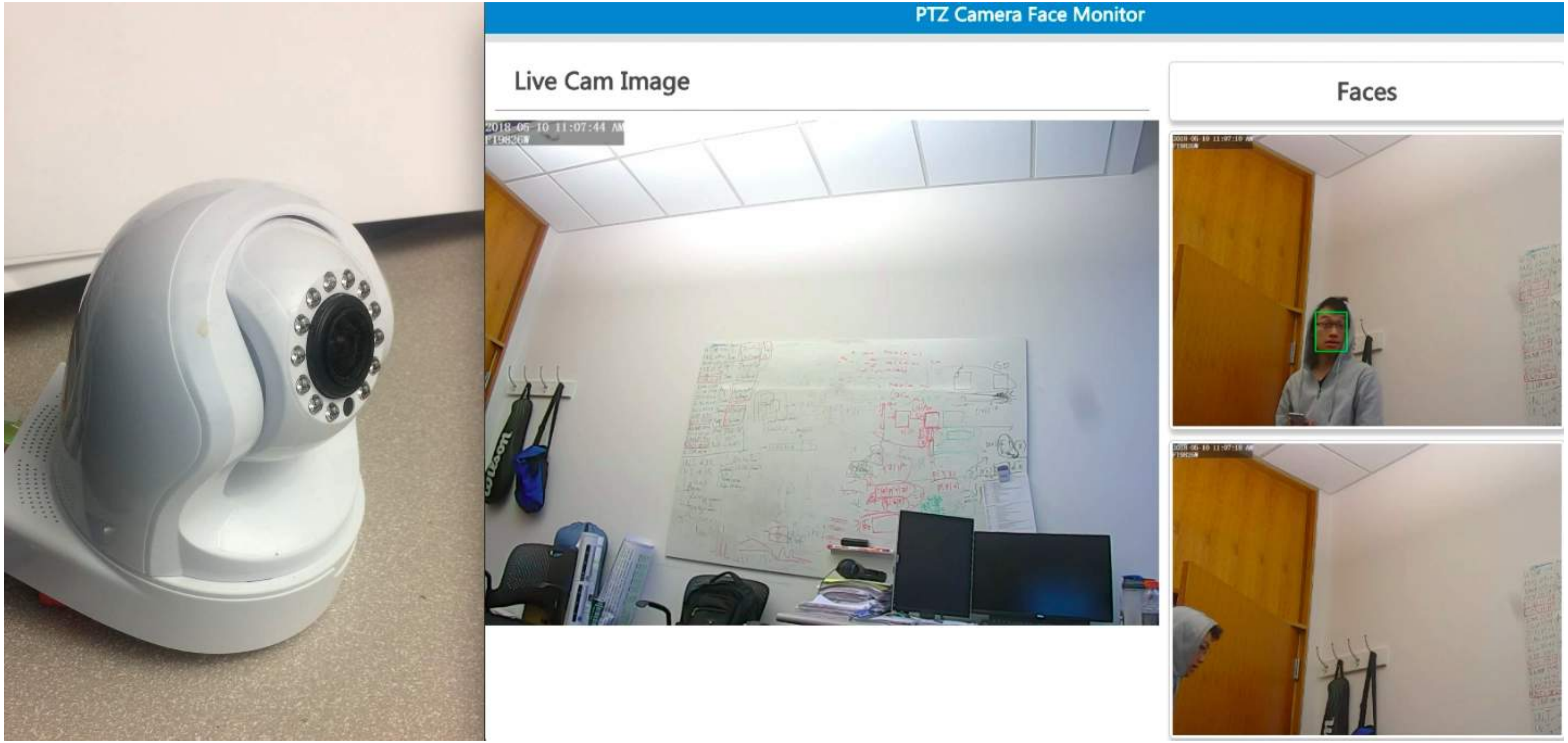
- Problem
  - Standard surveillance footage always misses some faces
    - Especially faces further away

Automatic Face Capturing for Pan-Tilt-Zoom Camera

- Problem
  - Standard surveillance footage always misses some faces
- Goal: Automatically pan-tilt-zoom to capture faces



Automatic Face Capturing for Pan-Tilt-Zoom Camera



Current Tools for Video Analytics

- Analytics Tools
  - Multimodal Filtering of Social Media (Demo)
  - Person Re-Identification (Demo)
  - 3D Reconstruction with Camera Localization (Demo)
  - Crowd counting (Demo)
  - Trainable Google Street View Object Detection Tool (Demo)
  - Gunshot Detection and gun type Classification (Demo/Download)
  - Automatic Face Capturing for Pan-Tilt-Zoom Camera (Demo/Download)

Future Work

- Activity Prediction in Surveillance Videos
  - Predict escape path of a person
- Real-Time Detection in Surveillance Videos
  - Vandalism: graffiti, etc.
  - Person lying on the ground
  - Suspicious behavior, Person carrying weapons, etc.
  - Person physically fighting
  - Flooding/Snow cover alert
  - Infrastructure damage alert: bridges, telephone poles, etc.
- Recognition incorporating Satellite/Drone Footage

- Thank you!
  - Questions?

Backup Slides

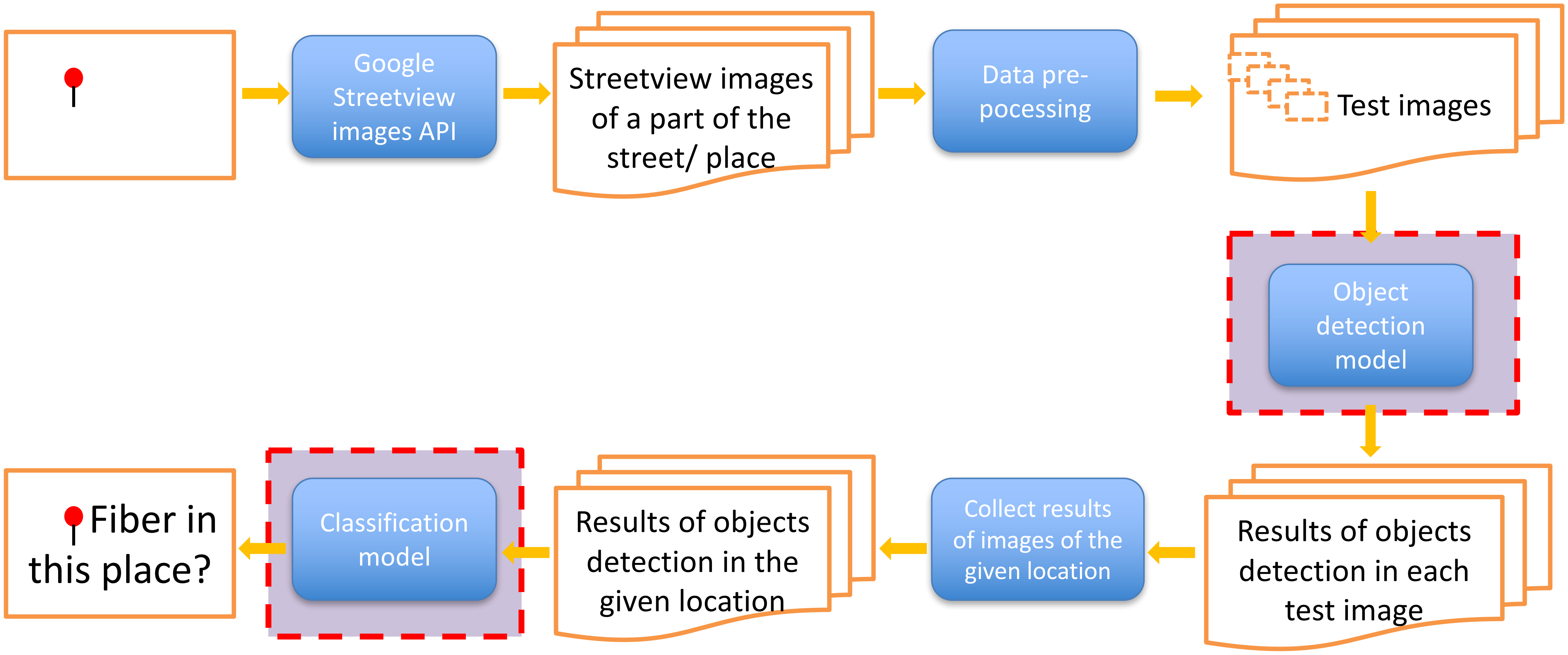
- 2013 Boston Marathon Test Dataset
- Fiber Infrastructure Detection System
- Gunshot classification datasets & models

Urban Event Reconstruction
2013 Boston Marathon Test Dataset

We collected a urban event dataset containing social multimedia data of the Boston Marathon 2013 finish line bombing event, including Google StreetView imagery, map meta data and digital elevation map data. Test video clips are labeled with geolocation and aligned to a global timeline.

- 1,066 relevant video clips
- 22,912 geo-tagged related images
- 1,760 satellite images
- 5h 29m 41s video length
  - 109 event video clips with geo-location
    - precision within 10 meters
  - 44 event videos aligned to global timeline
    - precision within 1s

Fiber Infrastructure Detection System



Gunshot Classification Datasets

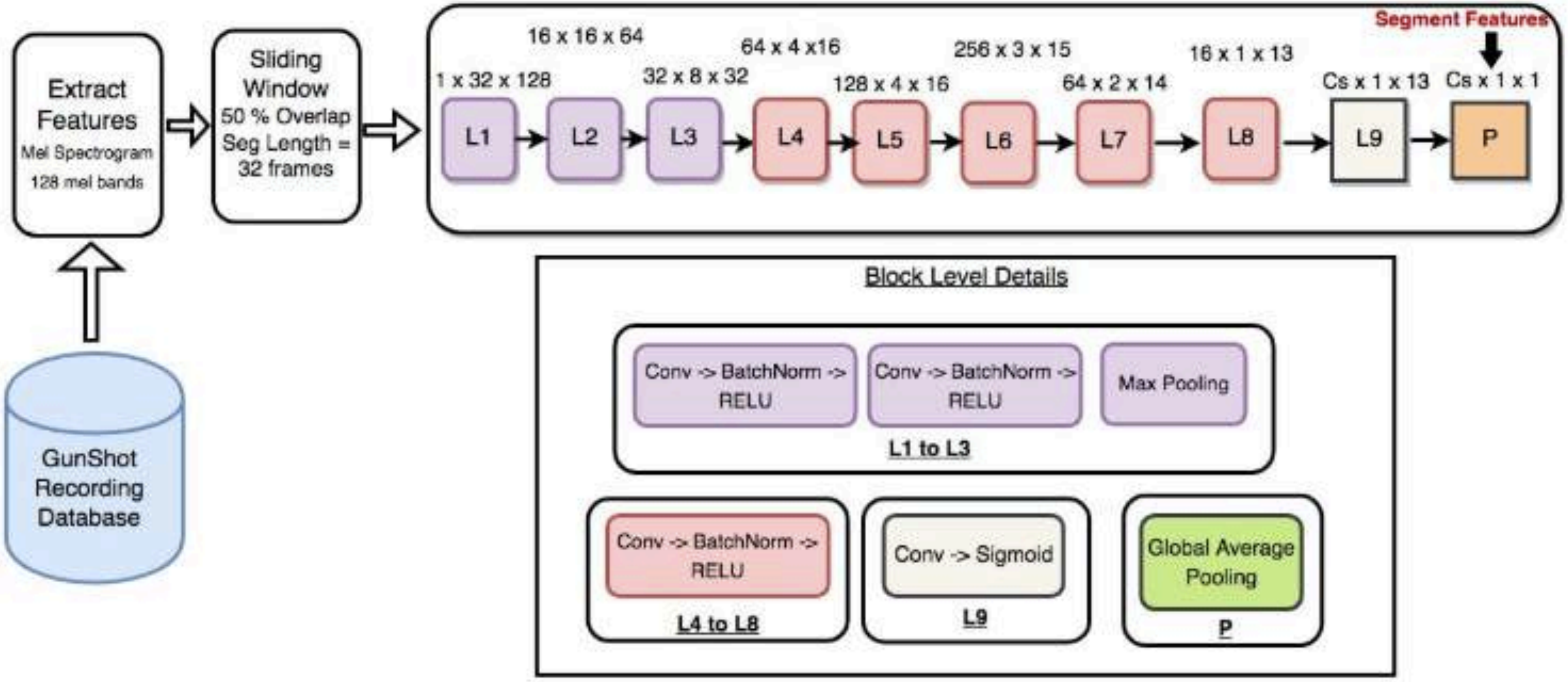
Dataset Source	Annotation Source	Number of Useful Recordings	Number of Gun Types/ Hierarchy
CMU Gunshot recordings	Data available from group annotated by CMU students	417	18 original guntype 15 useful/3 needs more data
Airborne Sound Webpage	Firearm Sound Effects Library	722	8 Gun class with 4 hierarchy of gun type
Spotify Playlists	Rifles and shotguns sound effects Shotgun Sound effects Machine gun sound effects Digieffects Handgun sound effects Handgun Sound effects	100 100 100 100 117	4 Gun type hierarchy
Sounddogs.com	Website provides annotated files	1758	19 guntype/ 17 useful

Carnegie
Languag

Gunshot Classes

GunType Hierarchy	Guns Included
Rifle	AR-15, Sniper rifles, Famas F1, M16, AK 4, 7.65mm Hunting
Submachine	UZI, MP5, MP40, P90, M3, Mac 10, Mini Uzi, 9mm Parabellum, 0.45 ACP
Handgun/Pistol	Revolver, Desert Eagle, Ruger-P95, Magnum gun, Jericho 941, M9 Pistol, Beratta Model, USP, Caliber Pistol,
Machine gun	AK-47, G36C, M249, Gait_AA52_ANF1, M134, M4, Browning M1918, Mg34, 0.223 Remington, Vickers 303
Shotgun	Shotgun, 12 Gauge Shotgun, 12g Pump Action, Benelli M4, Mossberg 500, Mossberg 590, Remington 870

Gunshot Classification Model



Gunshot Classification Experiments

Class	Precision	Recall	F1 - score
Rifle	0.49	0.48	0.51
Submachine	0.62	0.61	0.62
Handgun/Pistol	0.49	0.52	0.47
Machine Gun	0.65	0.62	0.68
Shotgun	0.52	0.56	0.49

Public Safety Analytics

June 6, 2018

FIRE DATA LAB

How it Works

Fire Agency Partnerships

01 CAD/RMS/AVL

02 Data Lake

03 Decision Making

Fire Agencies

Departments & Districts

Fire agency systems continually send real-time data to the Fire Data Lab.

Data Sets

Efficient & Anonymized

The Fire Data Lab creates efficient and anonymized data sets.

Data Science

Industry & Academia

The Fire Data Lab works with fire agencies to develop advanced data analytics.

Fire Data Lab Goals

2018-2019

Provide near real-time analytic tools to 26 departments

Create a "live" dynamic master data set

Provide data tools and frameworks to departments, industry, and academia

Create a community of mentor departments

Provide near real-time analytic tools to 26 departments

Internal Department Performance

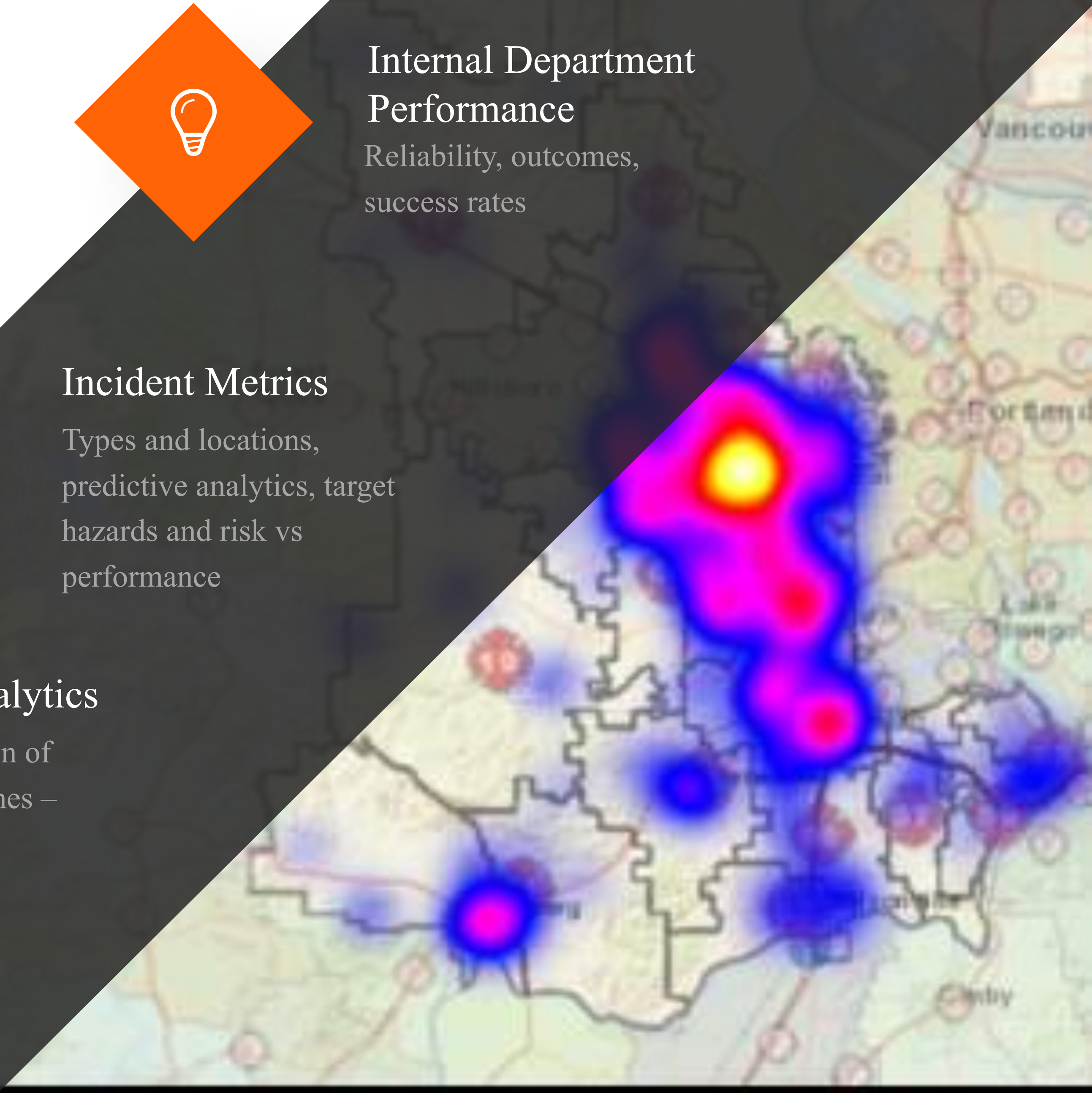
Reliability, outcomes, success rates

Incident Metrics

Types and locations, predictive analytics, target hazards and risk vs performance

Comparative Analytics

Predictive, comparison of approaches vs outcomes – staffing, resources



Create a 'live' dynamic master data set

Data Schema

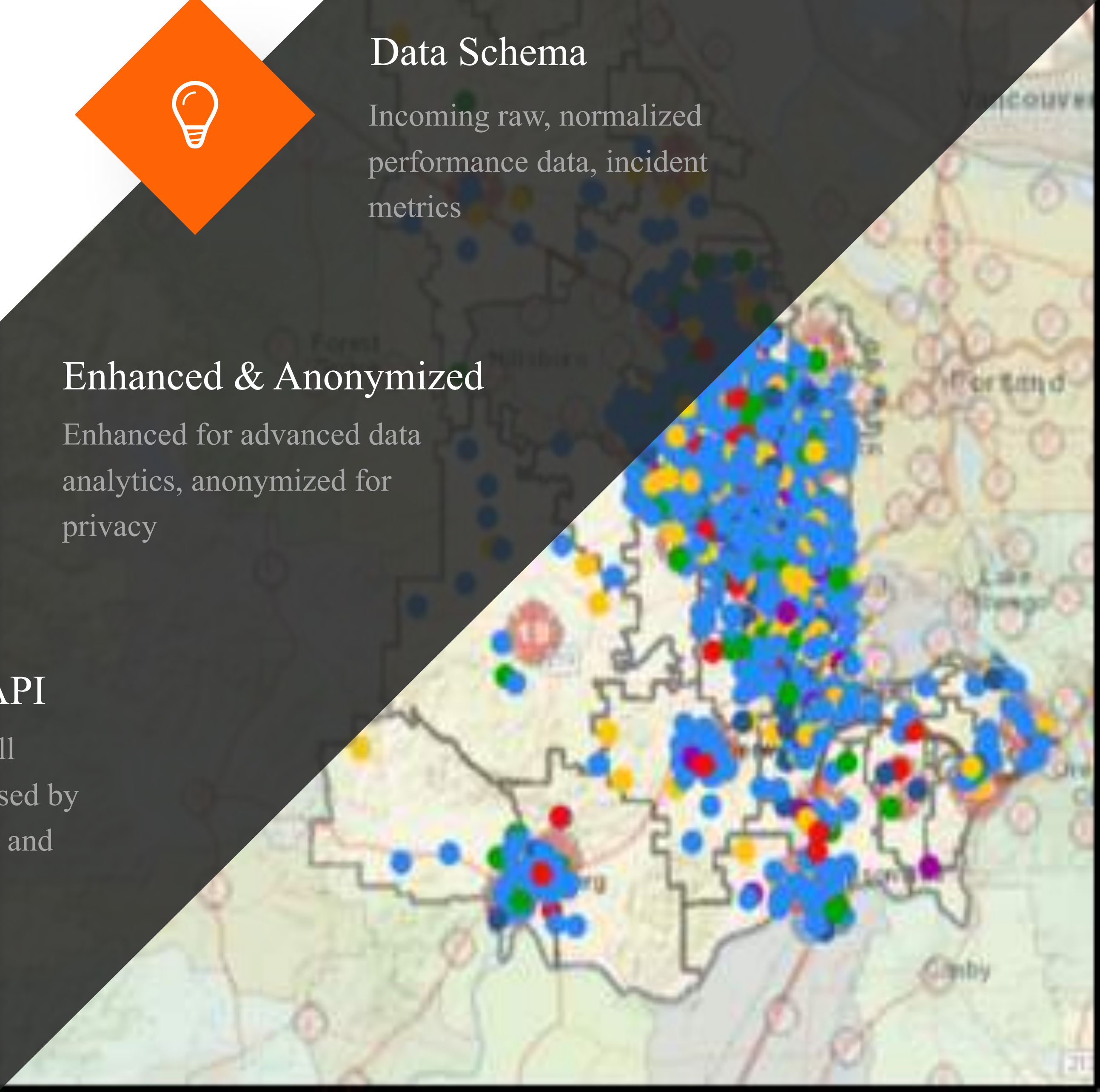
Incoming raw, normalized performance data, incident metrics

Enhanced & Anonymized

Enhanced for advanced data analytics, anonymized for privacy

Data check-out API

Create an API that will allow the data to be used by departments, industry and academia



Provide data tools and frameworks to departments, industry, and academia

Simplified ETL and integration processes

Incoming raw, normalized performance data, incident metrics

Metrics visualization toolkit

Comparative Web Portal

Normalized data reporting, comparison, and query

Create a community of mentor departments

Data Workshops

Working groups led by lead departments in each state.

Data Analytics Summits

Gathering input on desired analytics from participating agencies

Mentor Relationships

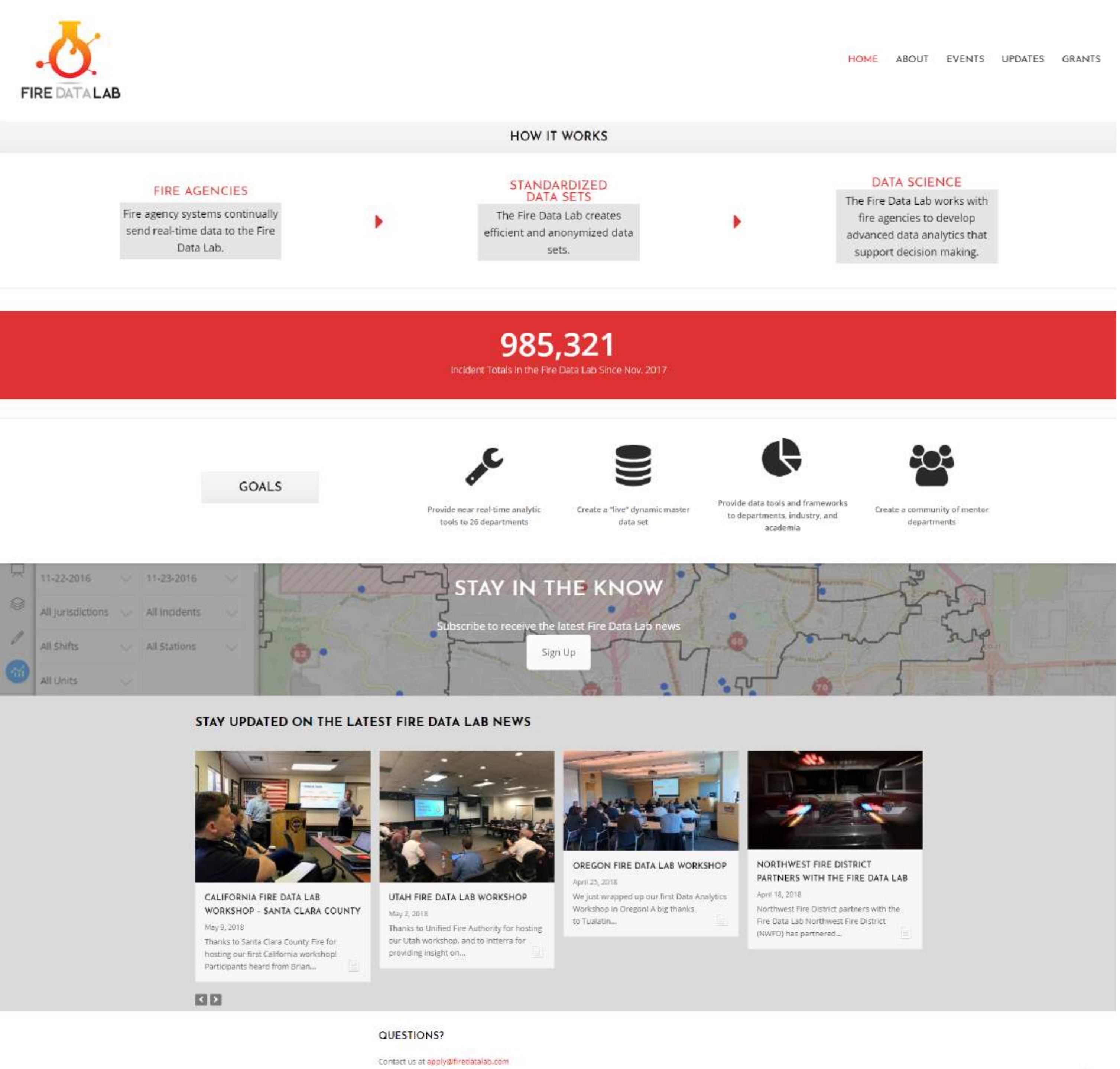
Mentors provide review, advice and next steps

Fire Data Lab Timeline

- **June, 2017** — NIST grant Awarded
- **Aug, 2017** — First Awards Given
- **Dec, 2017** — Data starts flowing
- **April, 2018** — Data Workshops
- **June, 2018** — Data Analytics Summit
- **Aug, 2018** — Second Round of Awards

Progess Report

Program Administration



FIRE DATA LAB

Website

firedatalab.com

Departments 19/26

Unified Fire Authority - UT
Chula Vista Fire - CA
Southern Platte FPD - MO
Eugene-Springfield Fire - OR
Santa Clara County - CA
Santa Clara City- CA
Tualatin Valley Fire & Rescue - OR
Sacramento Metro Fire - CA
Ventura County Fire - CA
Boise Fire - ID
Deschutes County - OR
Sacramento Fire - CA
Cosumnes CSD - CA
Folsom Fire - CA
Sacramento Regional Fire/EMS Comms Center - CA
Southern Marin Fire District - CA
NW Fire Rescue - AZ
Jackson County 3 - OR
Clark County Fire - NV

Event Participation

Presidents’ Forum 2017 – Park City, UT

Fire-Rescue International 2017 – Charlotte, NC

California Fire Chiefs 2017 – Riverside, CA

FORCE Conference 2017 – Boulder, CO

Fall Visioning 2017 – Walla Walla, WA

Presidents’ Forum 2018 – Couer d’Alene, ID

2018 Data Workshops

24th April

26th April

8th May

10th May

24th May

Data Analytics Summit

May 31 – June 1, 2018
San Diego, CA

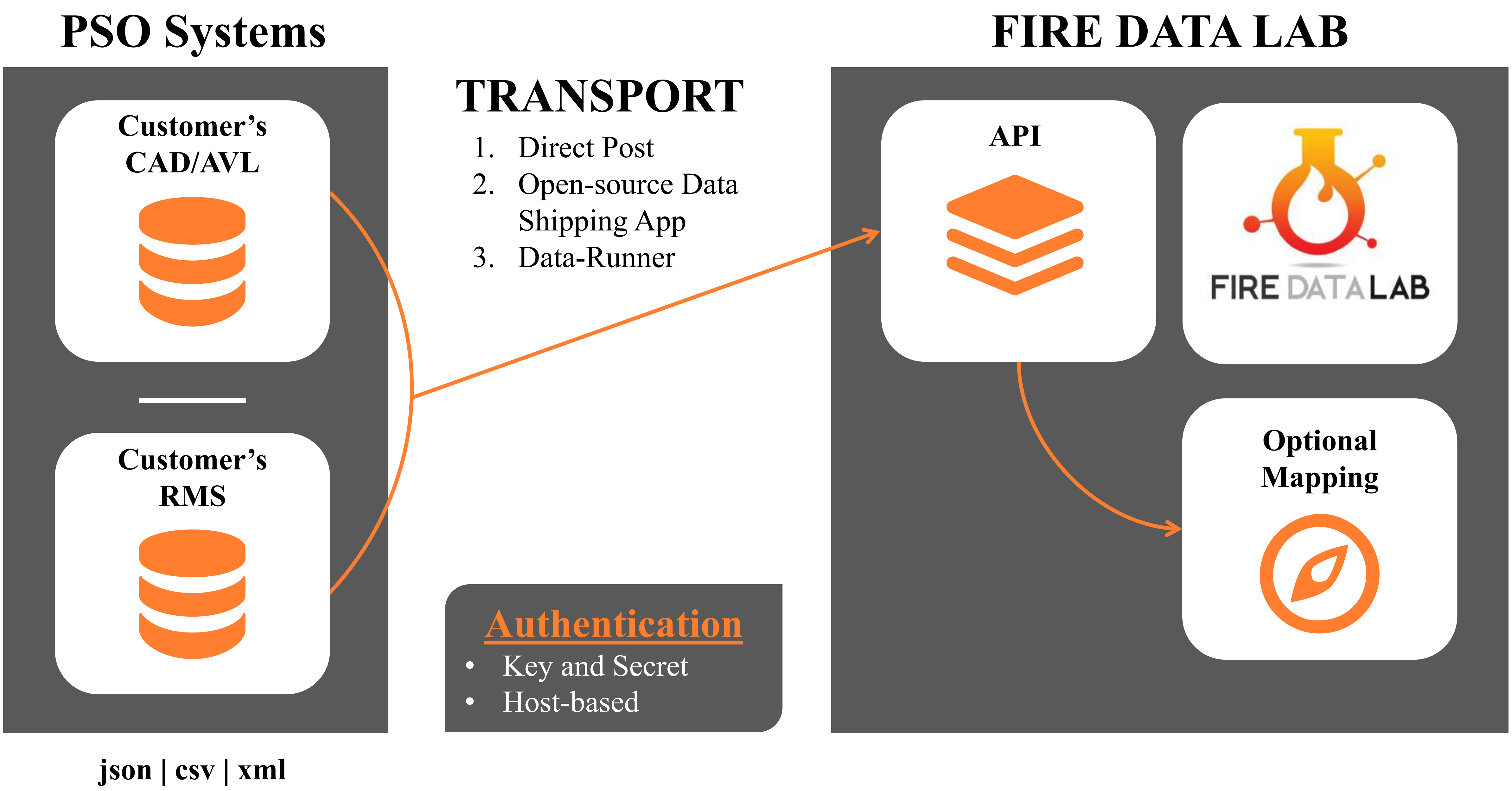
FIRE DATA LAB

Creating a Fire Data Lab Community

Year 1 Lessons Learned

Progess Report

Technical Progress


PSO Systems
Customer's CAD/AVL
Customer's RMS
json | csv | xml
TRANSPORT
1. Direct Post
2. Open-source Data Shipping App
3. Data-Runner
Authentication
• Key and Secret
• Host-based
FIRE DATA LAB
API
FIRE DATA LAB
Optional Mapping

Holding & Enriching Data

FIRE DATA LAB

1. **Data Lake**

RAW

- JSON
- XML
- CSV

2. **Data Warehouse**

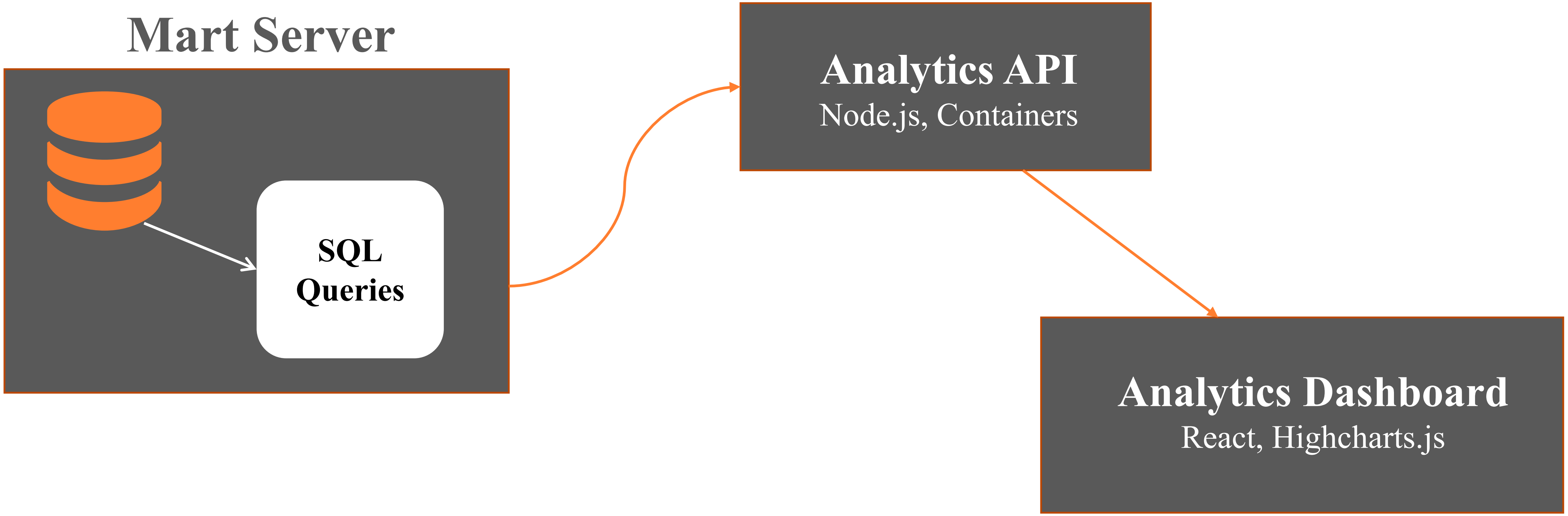
Normalized, semi-structured schema

- Enrich Data

3. **Data Mart**

De-normalized, cached, optimized

Understanding Data



Performance Data

The challenge has shifted from just getting data. Now we focus on how to use it.

Towards Cognitive Assistant Systems for Emergency Response

PIs: Homa Alemzadeh (ECE), John Stankovic (CS), Ronald Williams (ECE)

University of Virginia
ENGINEERING

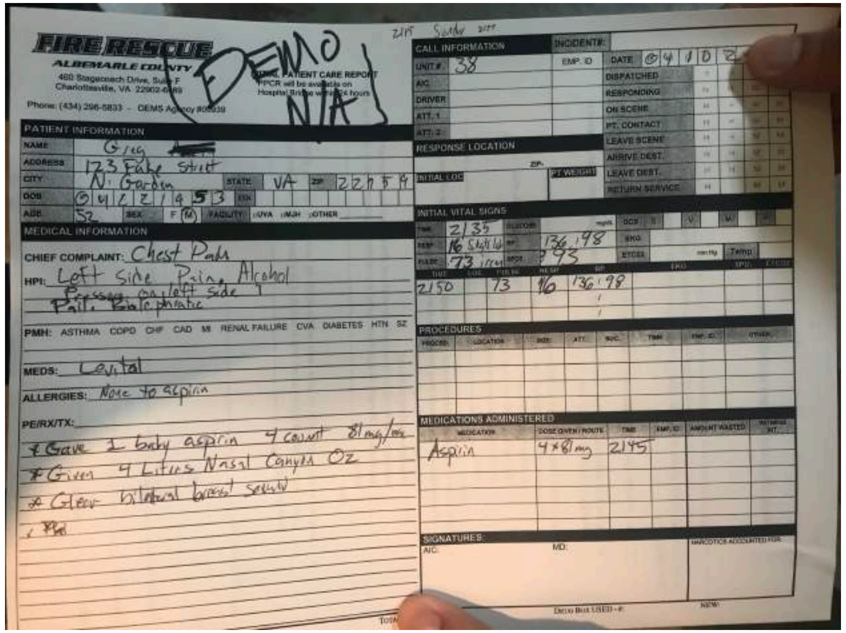
EMS radio call

Conversations with
bystanders and victims

Medical history (EHR)

911 Call record

EMS Protocols

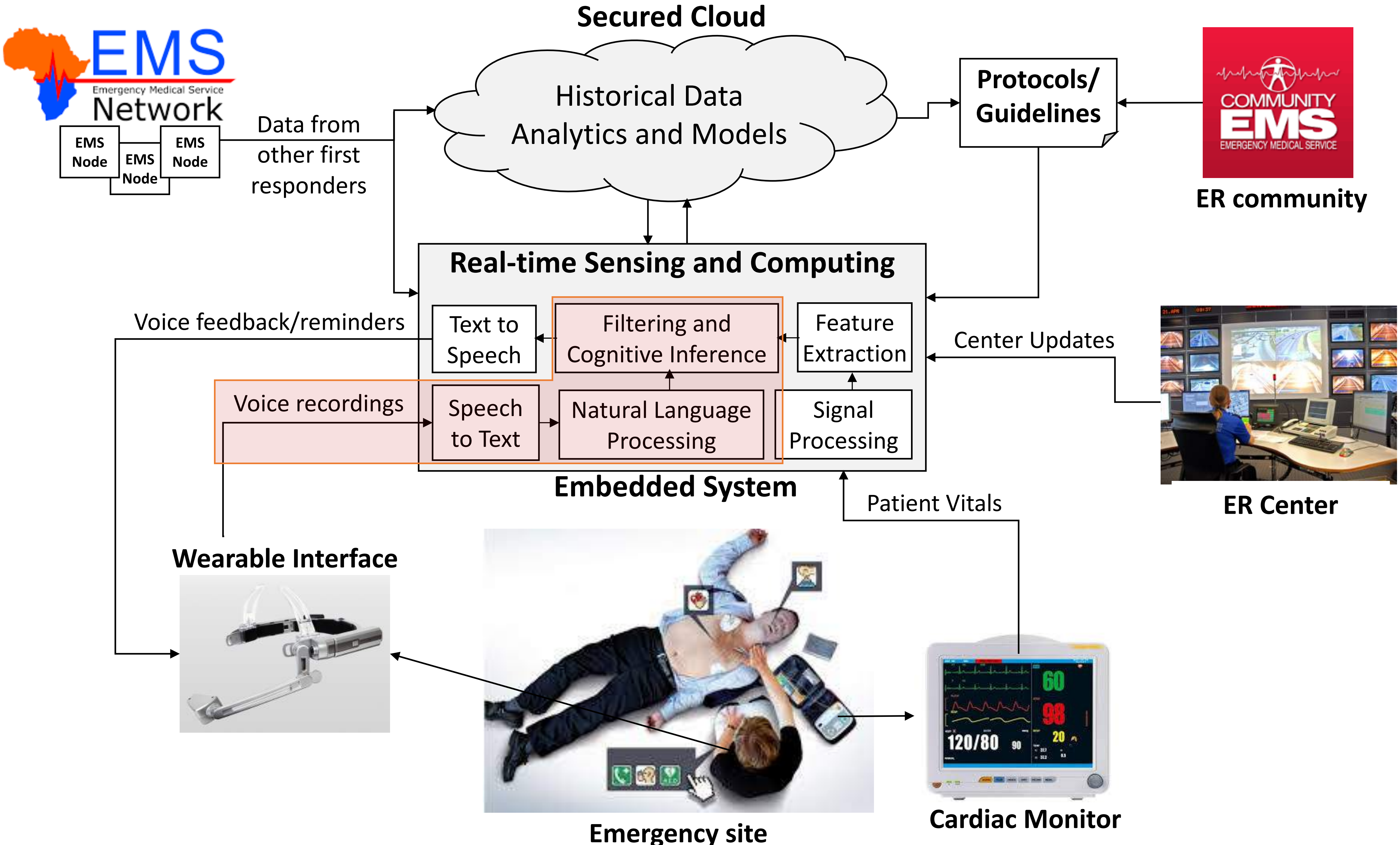


- Information overload
  - Collecting, analyzing, prioritizing
- Recording and summarizing information
- Decision making and execution
  - Iterative / feedback loop based

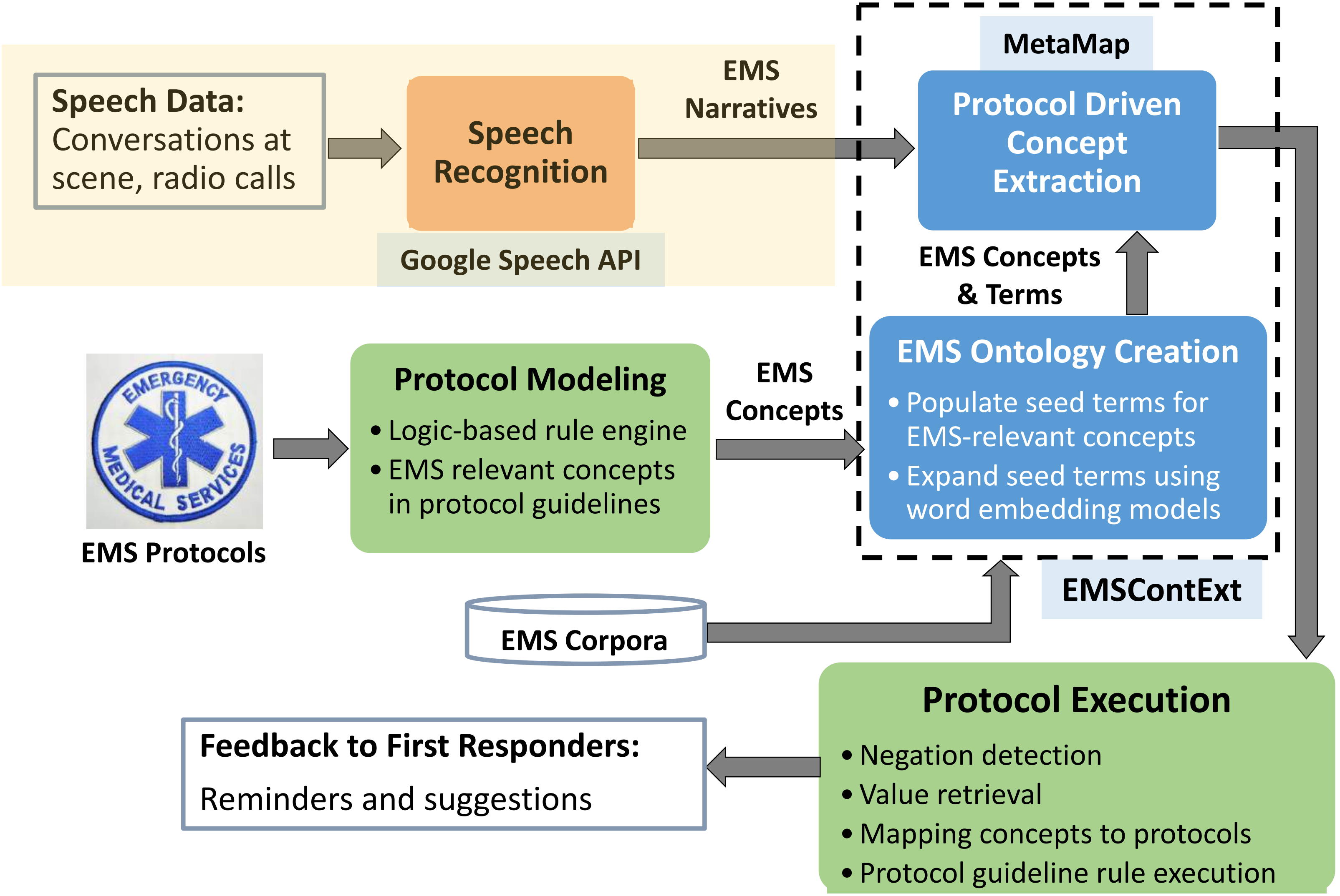
CognitiveEMS:
A Cognitive Assistant System for EMS

- **Resilient data analytics**
- Automated *collection* and *analysis* of data from incident scene
- Filtering and aggregation of in-situ/public data
- Providing dynamic data-driven feedback on effective response actions

- **Anytime real-time sensing and computing**
- Embedded system architecture for real-time data analytics
- Dynamic reconfiguration for resiliency


Secured Cloud
Historical Data Analytics and Models
EMS
Emergency Medical Service
Network
EMS Node
EMS Node
EMS Node
Data from other first responders
Protocols/ Guidelines
COMMUNITY EMS
EMERGENCY MEDICAL SERVICE
ER community
Real-time Sensing and Computing
Voice feedback/reminders
Text to Speech
Filtering and Cognitive Inference
Feature Extraction
Center Updates
Voice recordings
Speech to Text
Natural Language Processing
Signal Processing
Embedded System
ER Center
Patient Vitals
Wearable Interface
60
98
120/80
90
20
Cardiac Monitor
Emergency site

Protocol-Driven EMS Decision Support Pipeline

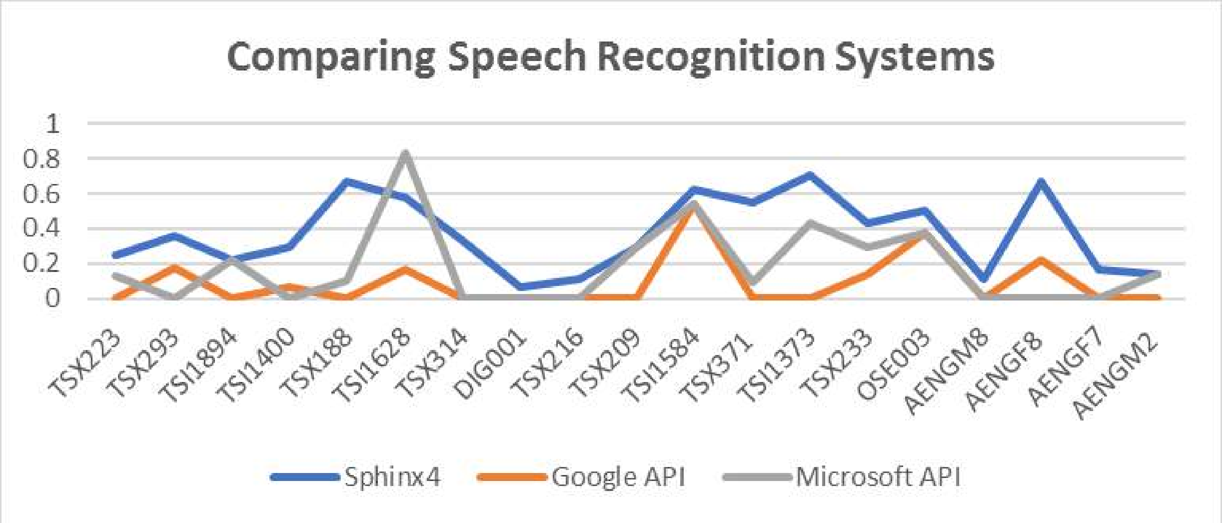


Speech Recognition Tools

Environment		PocketSphinx	Google	Microsoft	IBM
Noise-free	WER	0.80	**0.19**	0.24	0.45
	Runtime (sec)	2.48	**2.72**	3.42	5.34
Noisy	WER	1.05	**0.39**	0.62	0.89
	Runtime (sec)	3.41	**3.00**	3.38	9.84

Table I: Average WER and Runtime for Speech-to-Text tools

$$Accuracy = \frac{N - D - S}{N}$$



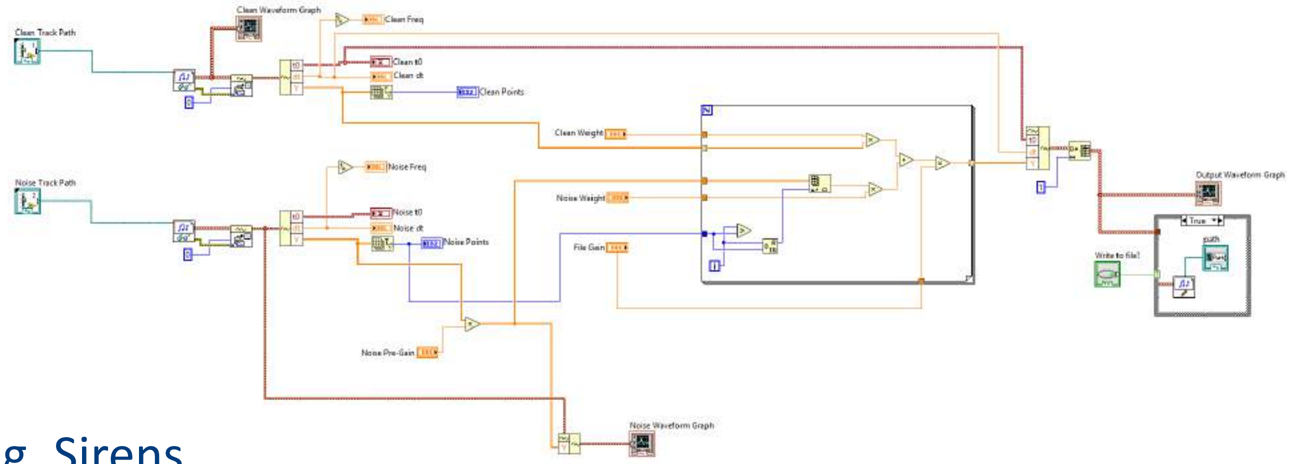
N: total words
I: # of inserted words
D: # of deleted words
S: # of substituted words

$$WER = \frac{I + D + S}{N}$$

- V. Kepuska, G. Bohouta, “Comparing speech recognition systems ¨(microsoft api, google api and cmu sphinx),” *Int. J. Eng. Res. Appl*, vol. 7, pp. 20–24, 2017.

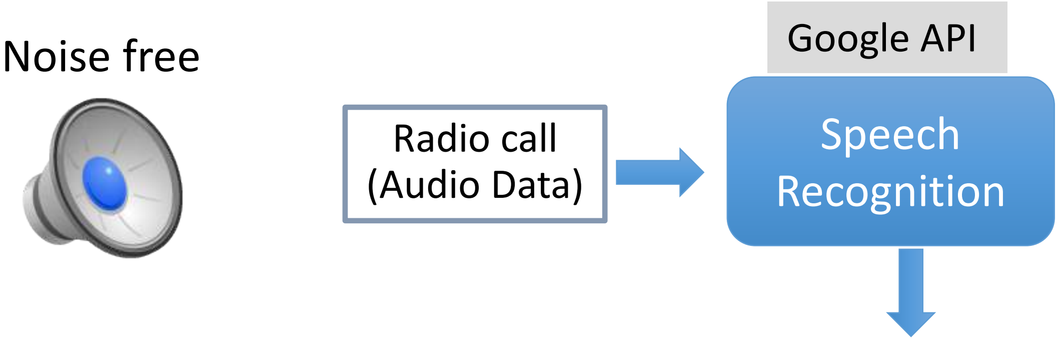
Speech Recognition in presence of Noise

- Assessed the impact of noise on the performance of pipeline
- Model noise and assess accuracy of **Google Speech API** in a controlled way:
    - Simply added up clean and noisy tracks while controlling signal to noise ratio.
    - Assumptions: Sound adds up in air, Not considering reflections



- **Experiments:**
    - 4 short radio calls by paramedics
        - Based on publicly available data
        - About 162 words, 1.5 minutes on avg.
    - Added noise to tracks for
        - Noise profiles: Cafeteria, People Talking, Sirens
        - Noise levels: Low, Medium, High
    - Total of 40 tracks

Noise-Free Speech Recognition

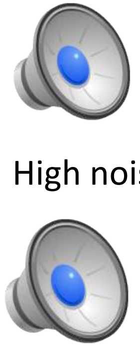


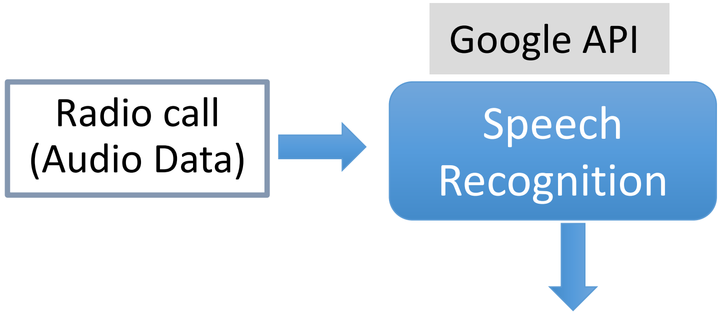
MedStar alpha 1 0 1. McLaren Macomb MedStar Alpha 101. Enroute with a priority two. 33 year old female. Patient was the restrained driver involved in a motor vehicle accident. Stated she was barely moving when she was T-boned by another car traveling approximately 20 to 25 miles per hour. Patient complaining of chest pain. Says she was hit with airbag. Side airbag. No front airbag deployment. She's **awake** and **oriented times three**. Pain reproducible with inspiration of movement. No other. But she's also complaining of some lower back pain, noted when she crawled into the passenger seat. No head or neck pain. No **loc**. Blood pressure is 137 over 83. **Pulse** of 104 regular. **Respiration** is 18. Sinus tach on the monitor. Saline lock established. States 8 out of 10 pain. We're pulling into facility right now. Do you require anything further?

Noisy Speech Recognition

Noise free

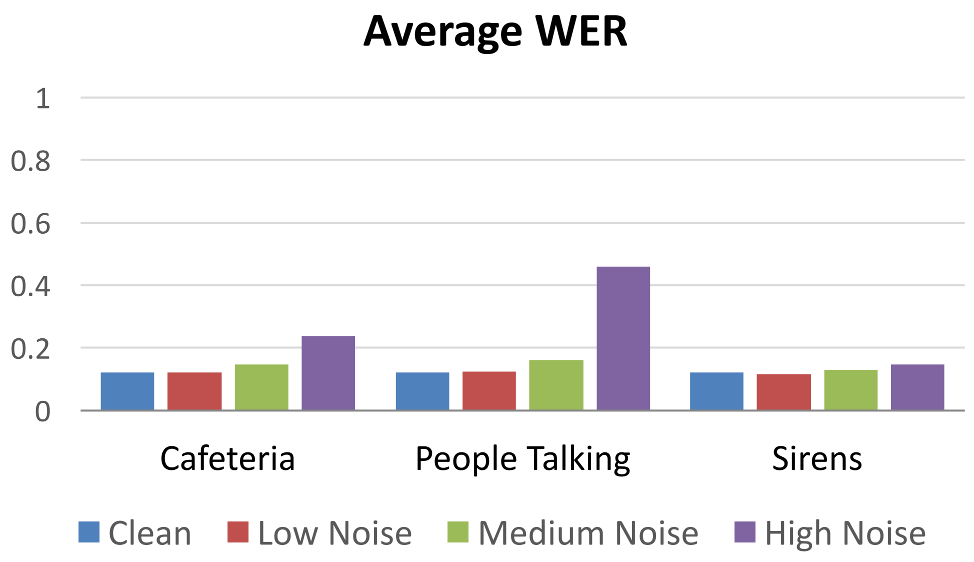
High noise

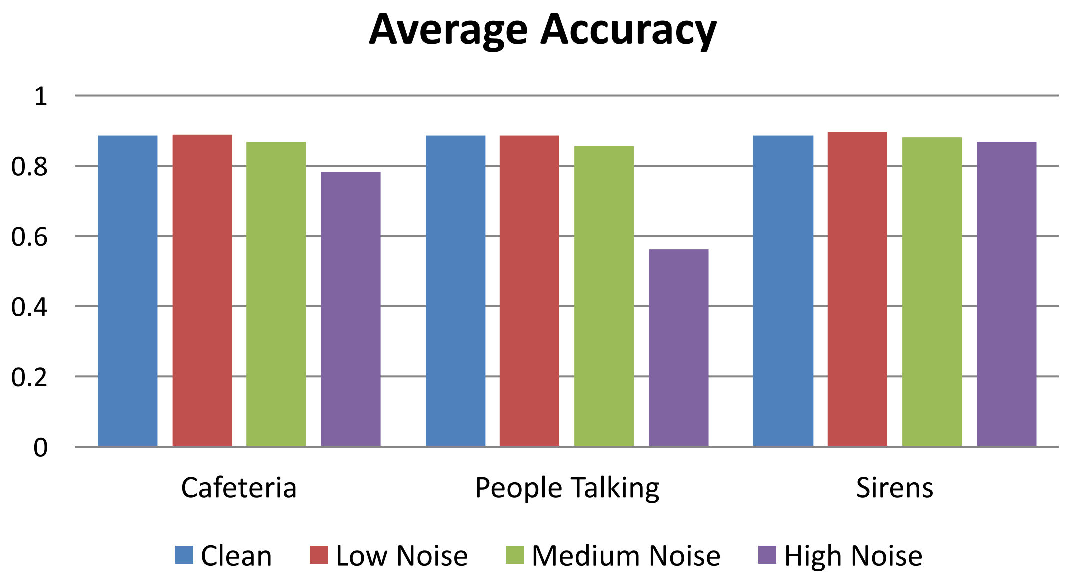




urologist at Star alpha 1 0 1 McLaren Maggie at Star Alpha 101 Amarillo with a priority to 33 year old female patient was the extreme driver involved in a motor vehicle accident states she was barely moving and she was developed by another car traveling approximately 20-25 miles per hour patient complaining of chest pain associated with airbag side airbag no front airbag deployment she is **awake** and **oriented times three** main reproducible Inspirations no other she's also complains of lower back pain noted she crawled into a passport 800 head or neck pain no **loc** blood pressure is 137 over 83 **pulse** of 104 regular **respiration** is 18 sinus tach on a modification Bailey and lock it that way States $8 campaign we're pulling into somebody right now are you require anything further

Noisy Speech Recognition





N: total words
I: # of inserted words
D: # of deleted words
S: # of substituted words

$$WER = \frac{I + D + S}{N}$$

$$Accuracy = \frac{N - D - S}{N}$$

Noise Reduction Techniques

- **Periodic noise reduction using Linear Predictive Filtering (LPF)**
  - Cancel the noise estimated using LPF from the signal containing both speech and noise
  - Example profile: Jet engine noise

Noisy

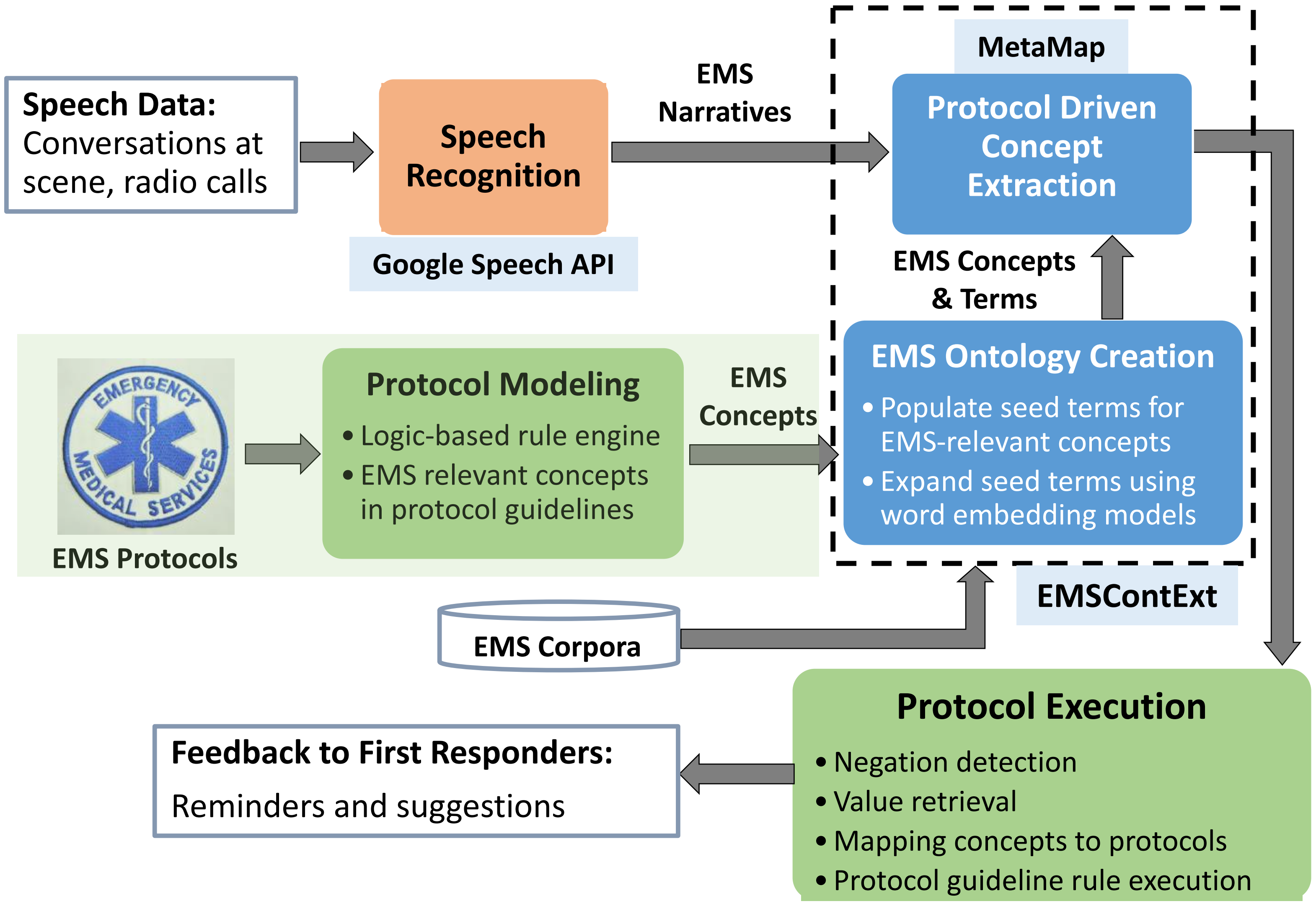
Denoised

- **Non-periodic noise reduction by Independent Component Analysis (ICA)**
  - Two signals with different weights of speech and noise
    - $M_1 = W_{1s}\, S + W_{1n}N$
    - $M_1 = W_{1s}\, S + W_{1n}N$
  - Example profile: Soccer stadium noise

Noisy

Denoised

Protocol Modeling



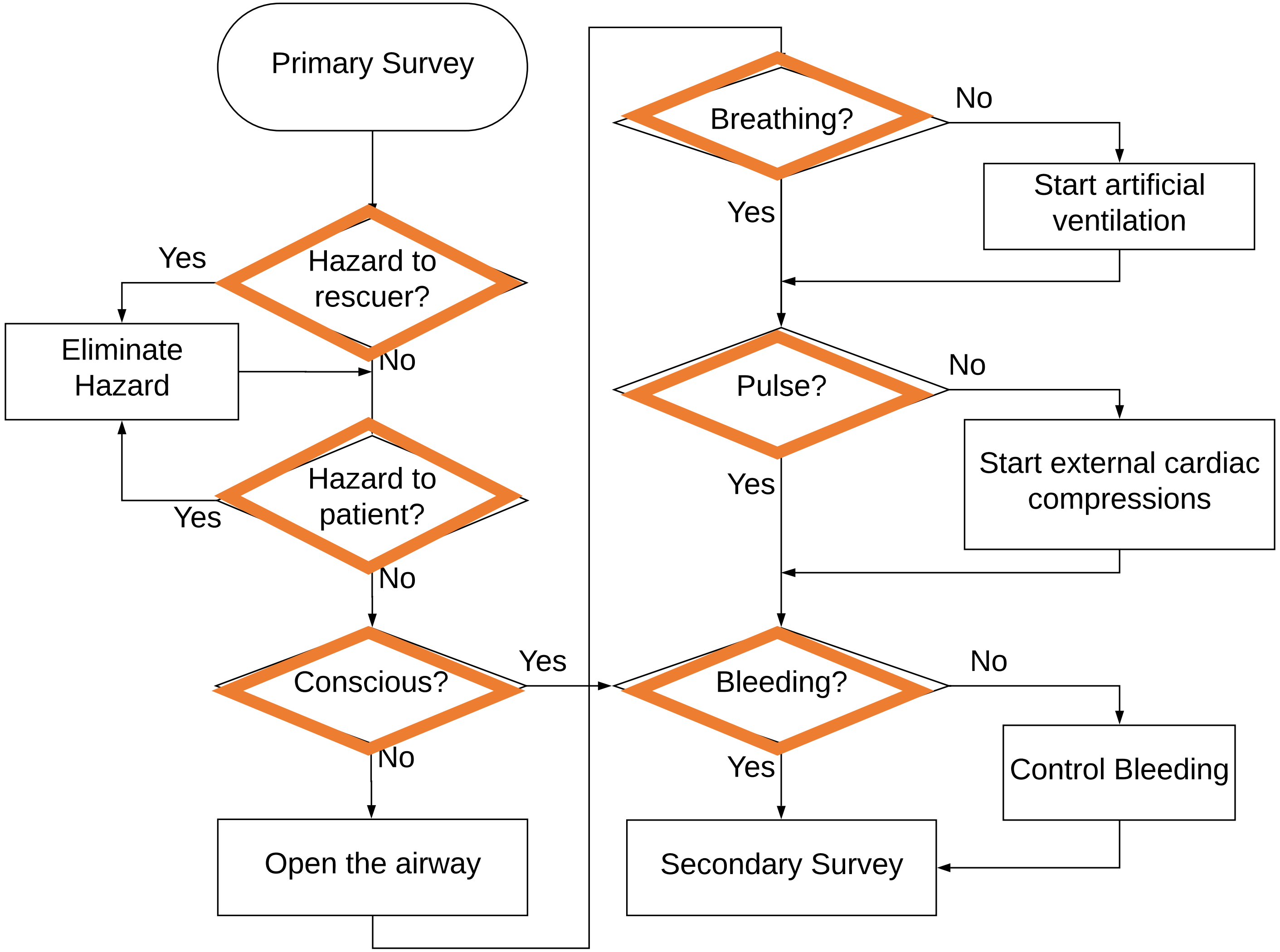
EMS Protocols

- **100+ EMS protocols**
  - General
  - Regional
    - Cardiac, Cardiac Arrest, Environmental, Medical, Neuro, Respiratory, OB/GYN, Injury
  - Protocols vary in structure, complexity, and volume of content

- **66 protocols from TJEMS and West Virginia EMS**
  - 293 concepts identified

- **556 transcribed or paraphrased EMS scenarios**

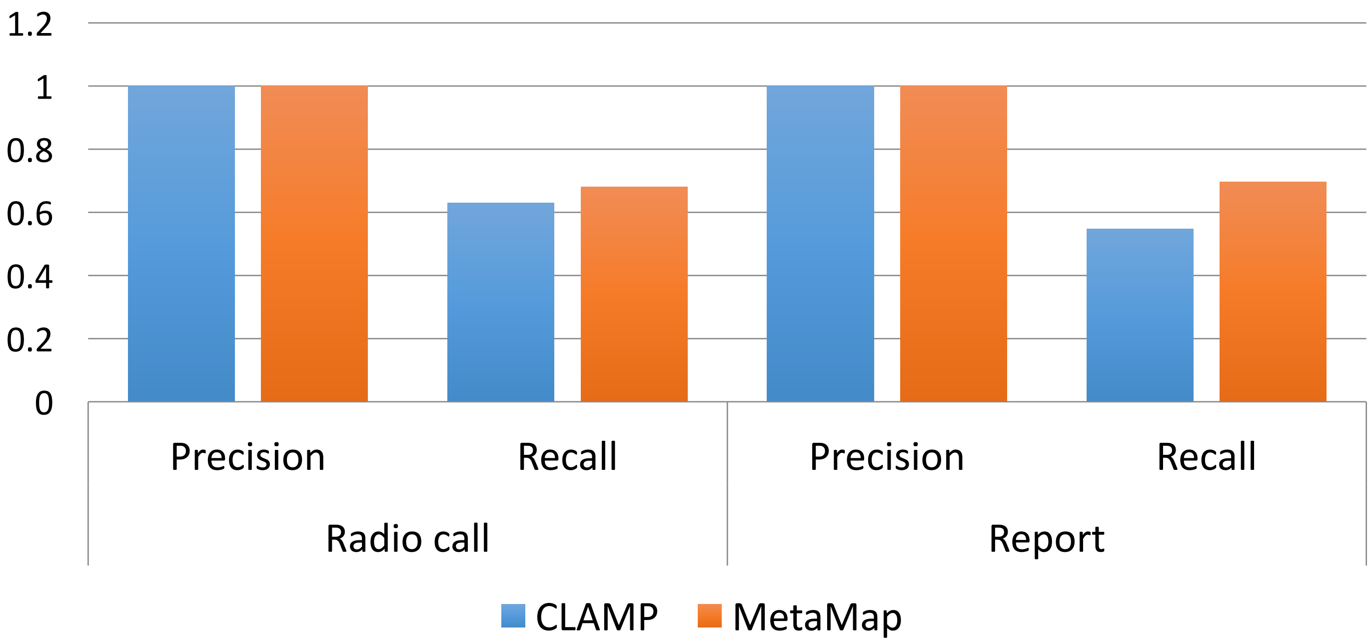
Primary Survey Protocol



EMSContExt: Protocol Driven Concept Extraction

- **Primary survey protocol specific concept list**
  - Hazard to rescuer, hazard to patient, Conscious, breath, pulse, bleed
  - Extended concept list
- **Variation of word**
  - **Lexical:**
    - Breath →breathing
    - Bleed → blood, bleeding
  - **Semantic:**
    - Conscious→ LOC, unconscious, awake and oriented
    - Breath →Respiration/…
- **Severity**
  - No pulse / no breathing: fatal

Preliminary Results on Concept Extraction

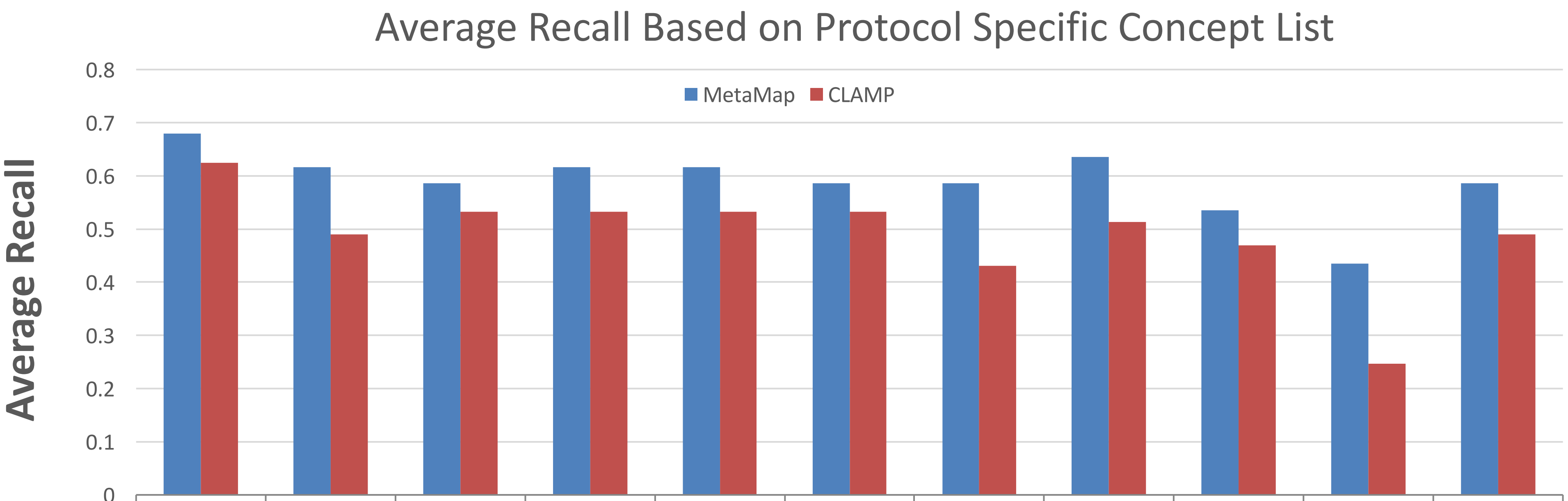


Need more robust techniques for lexicon generation and domain adaptation

Missed concepts might be safety critical

The precision is 1 in all the cases as the tools result in no false positives.

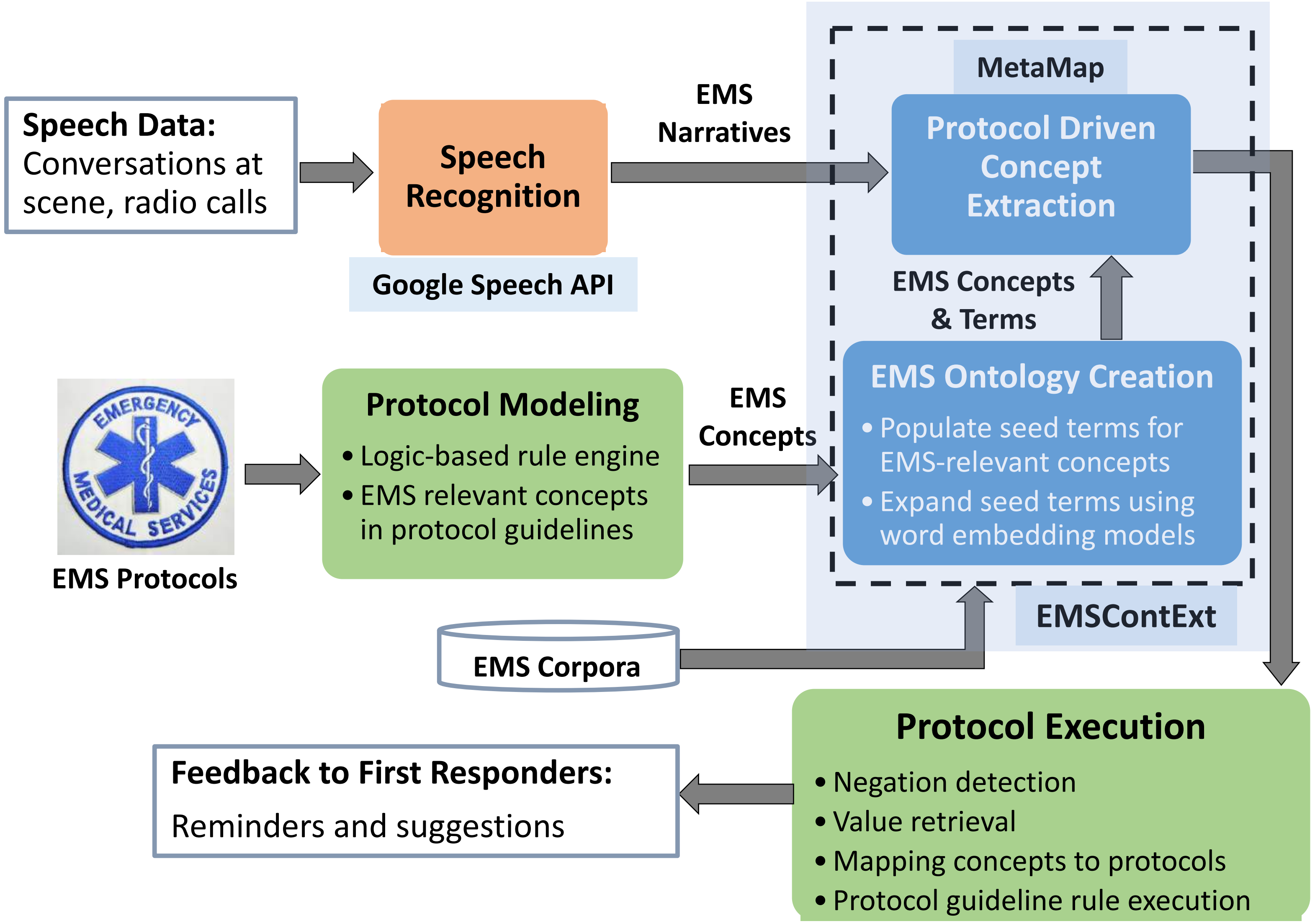
Concept Extraction under Noise



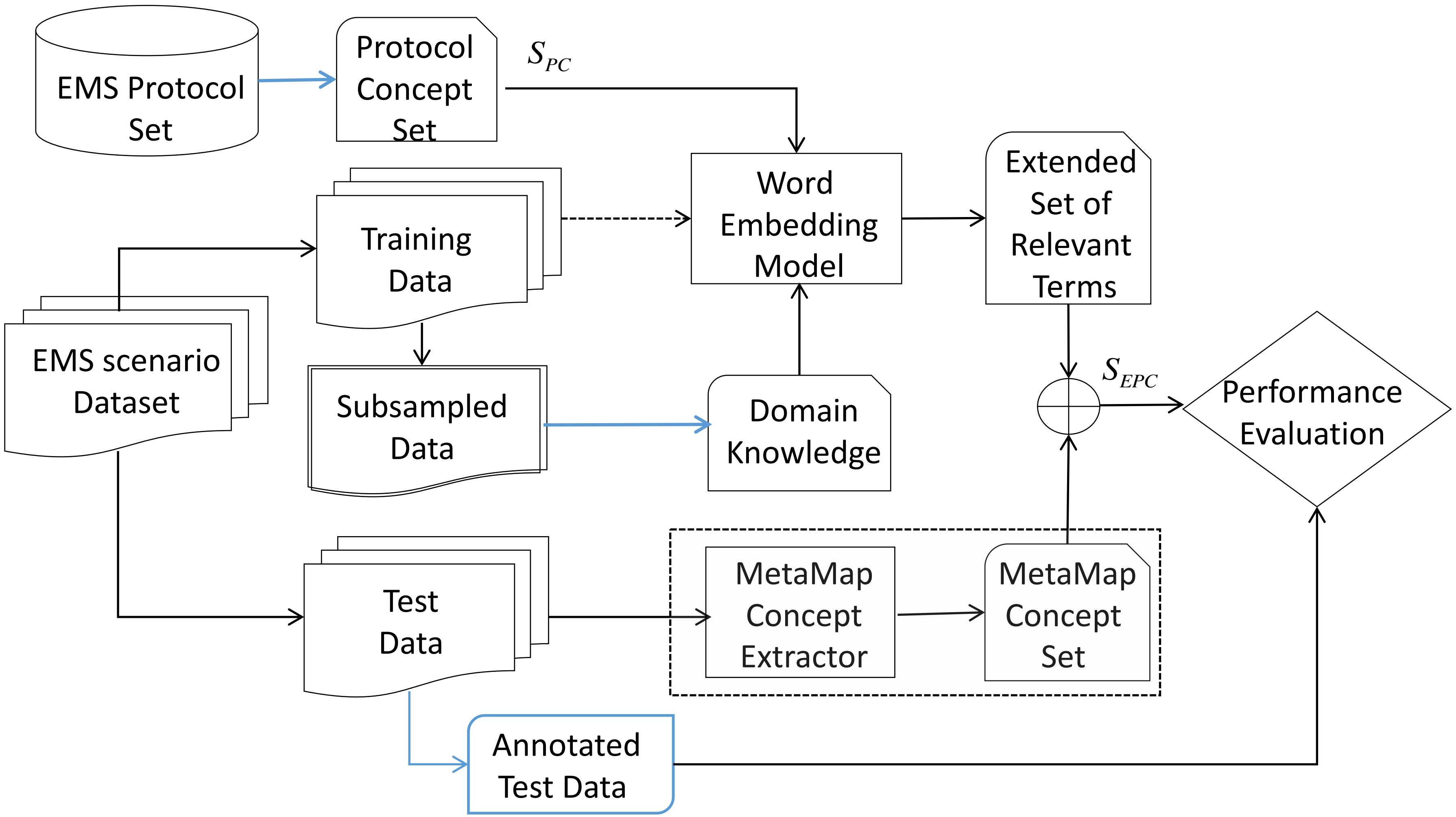
	Original_Transcript	Original_API_Result	Cafeteria_Low	People_Low	Sirens_Low	Cafeteria_Medium	People_Medium	Sirens_Medium	Cafeteria_High	People_High	Sirens_High
MetaMap	0.68	0.62	0.59	0.62	0.62	0.59	0.59	0.64	0.54	0.44	0.59
CLAMP	0.63	0.49	0.53	0.53	0.53	0.53	0.43	0.51	0.47	0.25	0.49

Noise Level

EMSContExt: Protocol Driven Concept Extraction



EMSContExt: Protocol Driven Concept Extraction

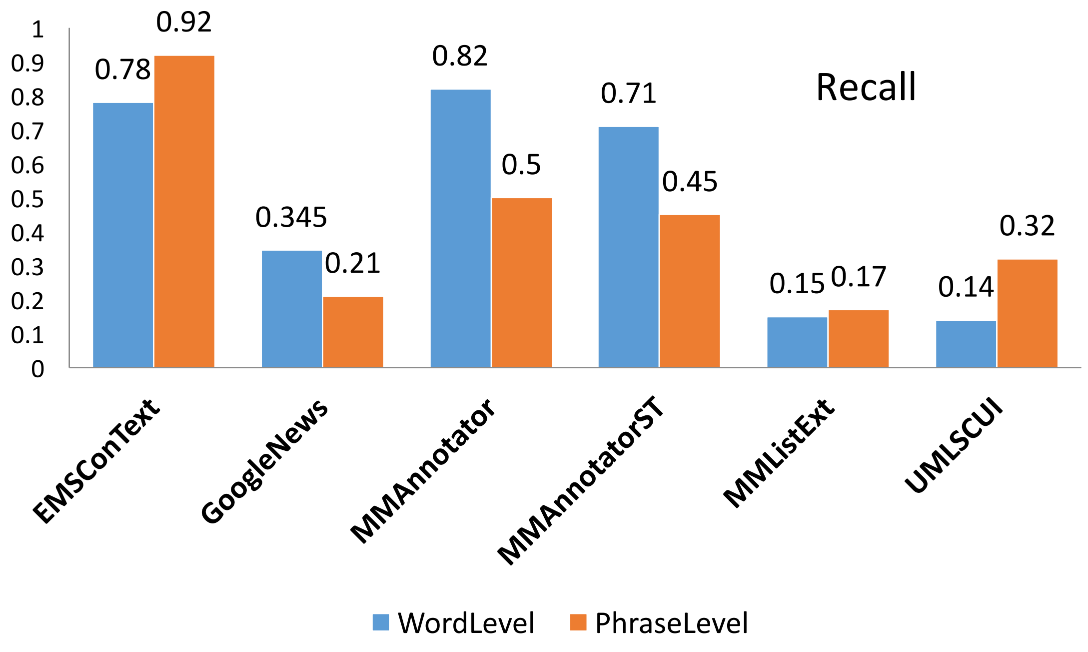


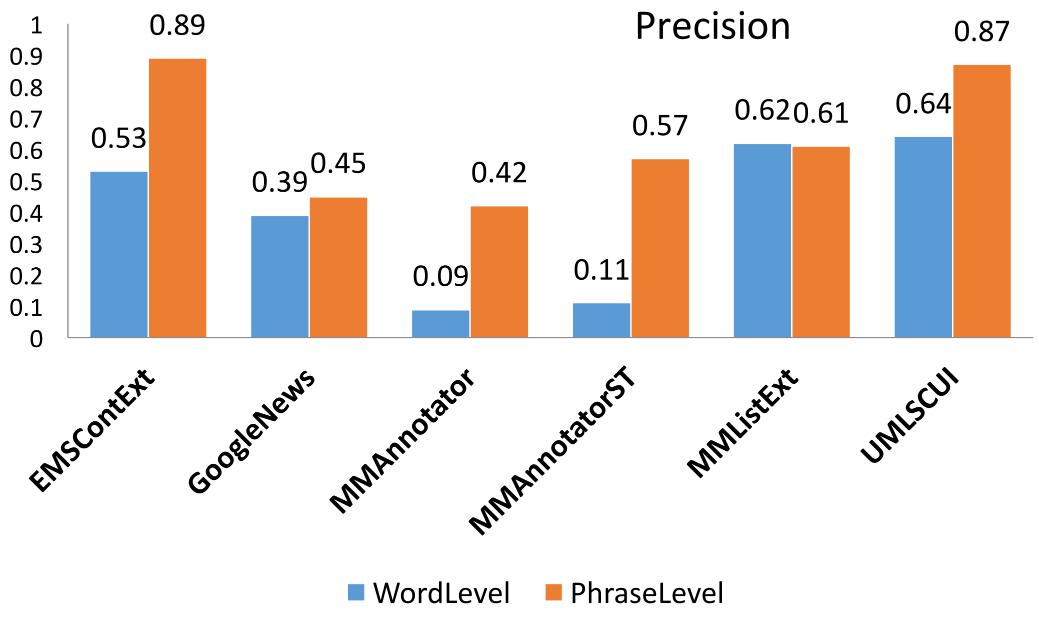
EMSContExt: Protocol Driven Concept Extraction

Data	EMS case Count	Sentence Count	Token count
Training	485	8837	170703
Test	71	823	15740

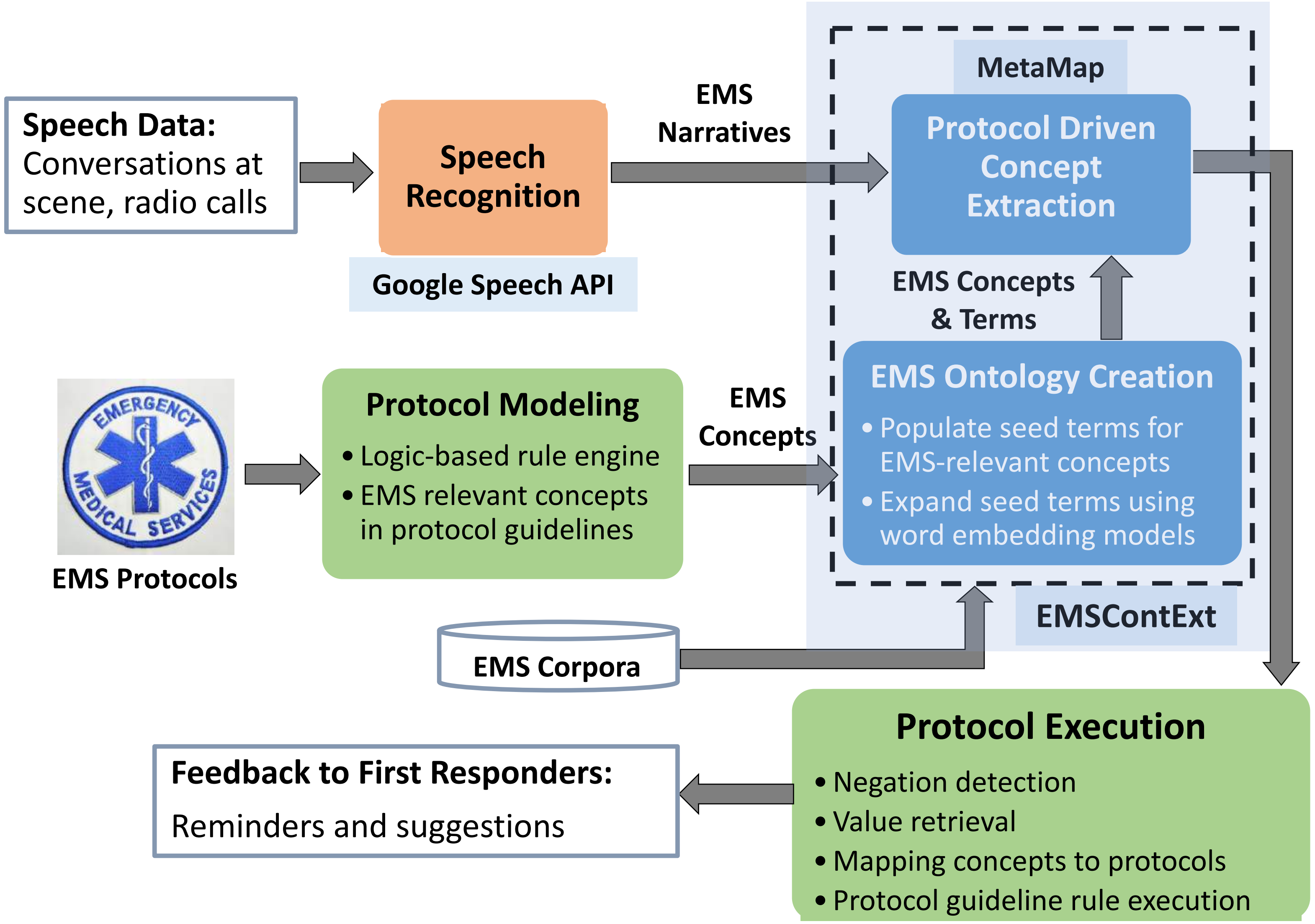
Table 1: EMS Dataset used in the evaluation

- S_{PC}: 293 concepts
- MMListExt: 320
- UMLSCUI: 4111



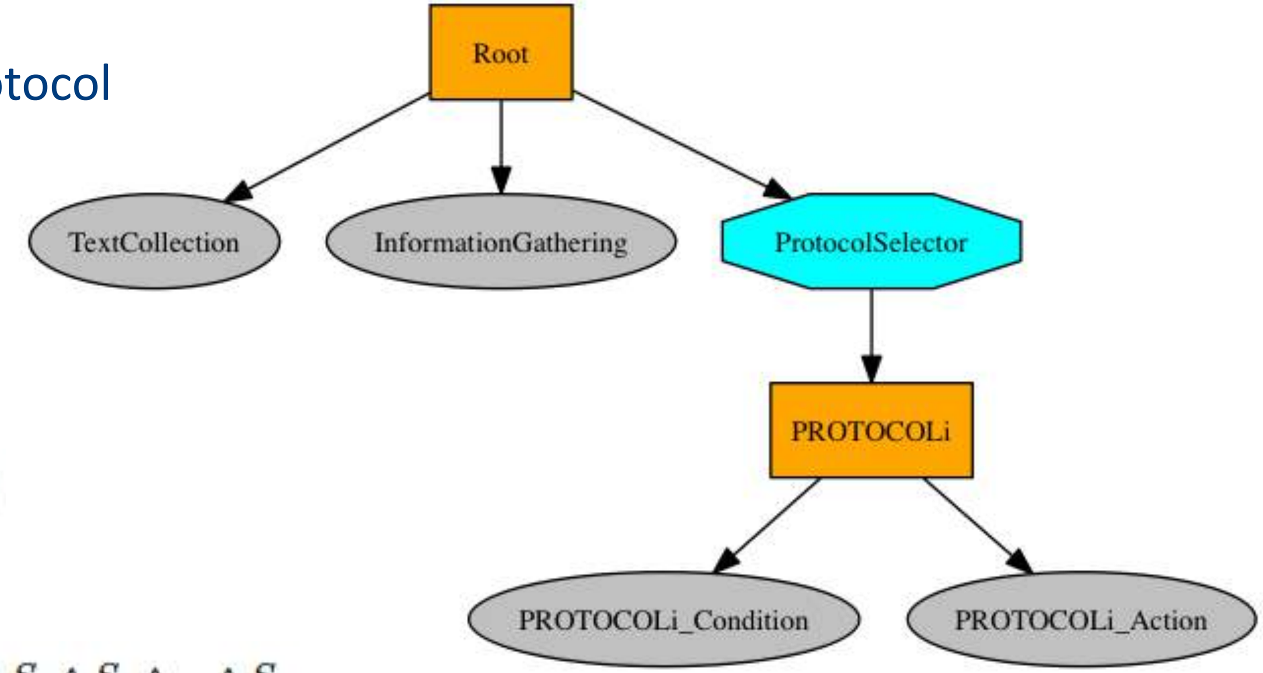


EMSContExt: Protocol Driven Concept Extraction



Protocol Execution

- **EMS protocols modeled using behavior trees and logic rules**
  - Input: current patient status
    - “not breathing”
  - Output: recommended action based on protocol
    - “start artificial ventilation”



- **Information Gathering**
  - UMLS concept extraction
  - Concept filtering
  - Negation detection
  - Value retrieval

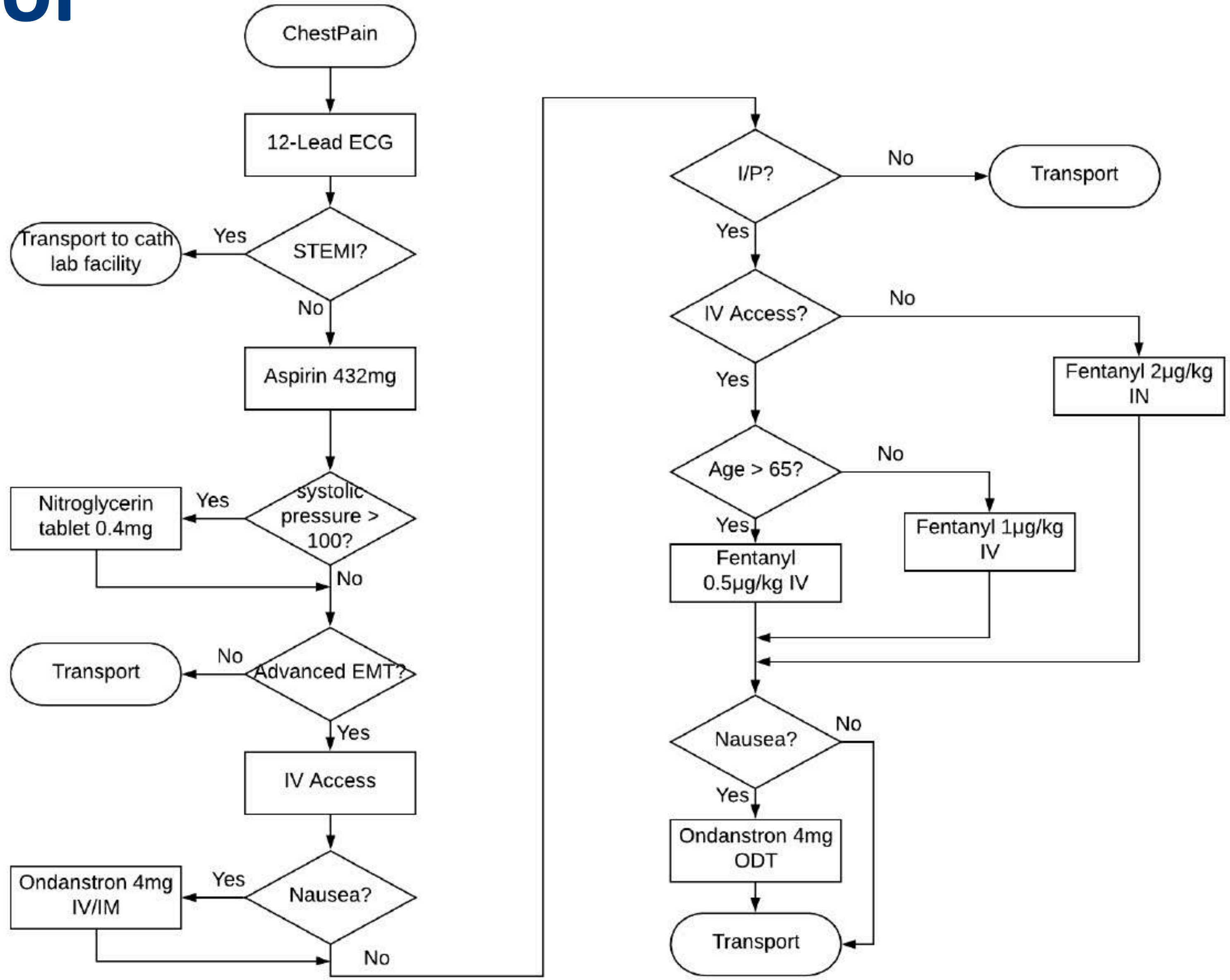
$$(C_i : P_{it}, V_{it}, T_{it})$$

$$PC_i : S_1 \wedge S_2 \wedge \ldots \wedge S_n$$

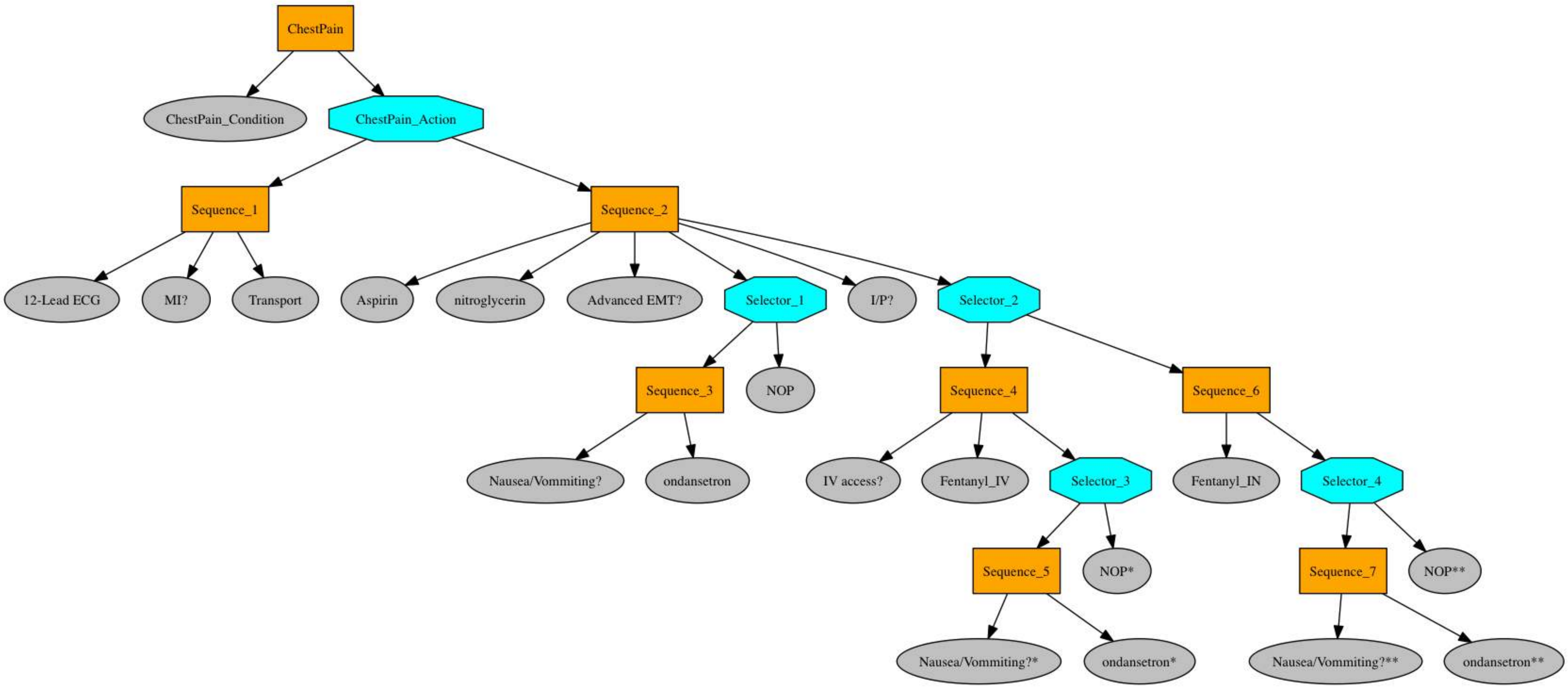
- **Protocol Selection and Execution**
  - Protocol logic rule execution

$$ChestPain : (pain : P_t = True) \wedge ((chest \in pain : T_t) \vee (chest \in pain\ region : V_t) \vee (chest \in pain\ region : T_t))$$

Chest Pain Protocol



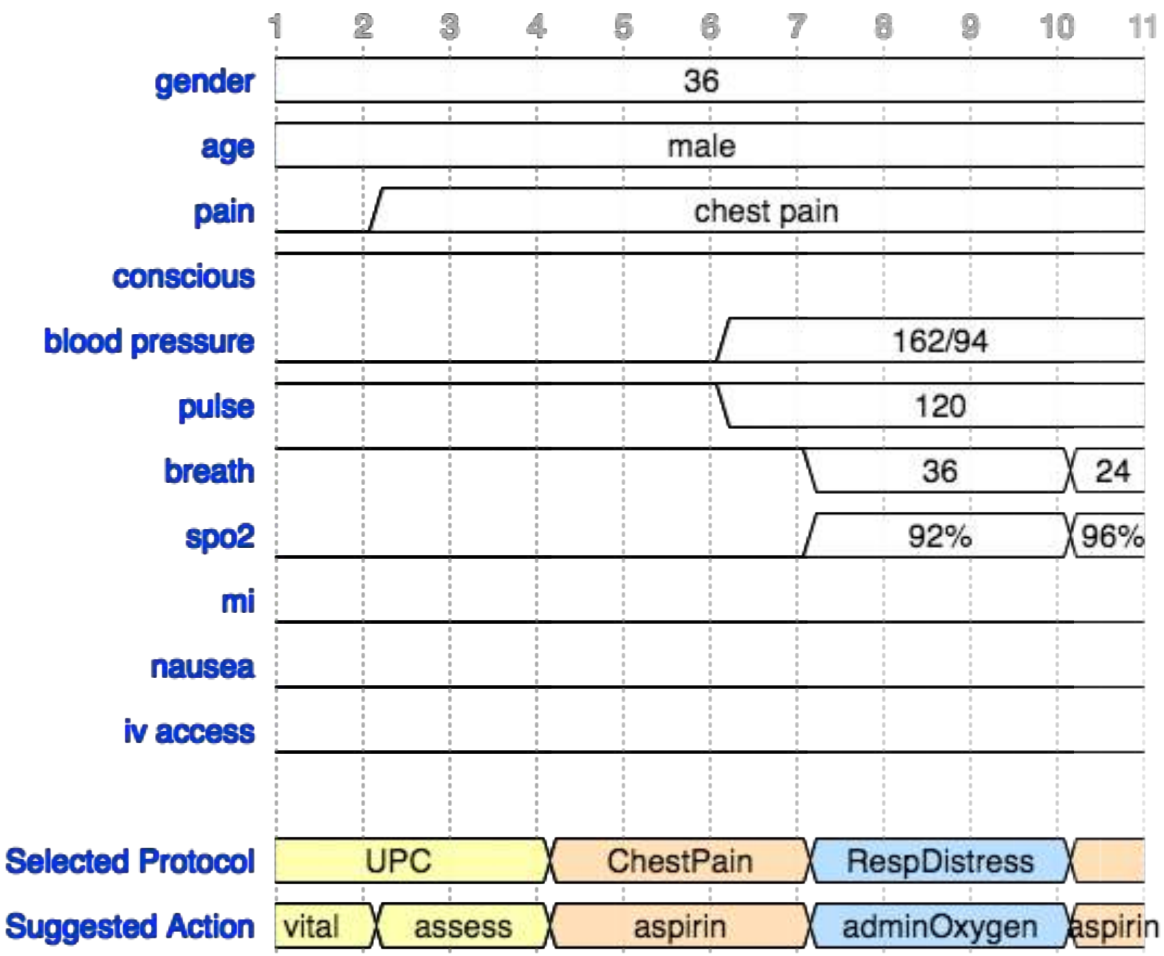
Chest Pain Behavior Tree Model



Protocol Selection and Execution

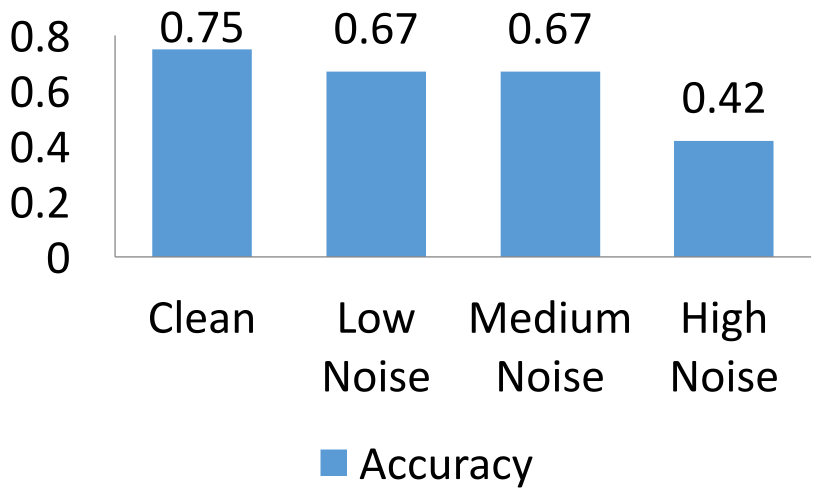
```
1: this is paramedic Smith we are transporting
 a 36 year old male complaining of shortness of
2: breath he also complains of non radiating
 sharp chest pain on expiration symptoms began 1
3: hour ago after exercising he attempted to use
 his inhaler without relief he does have a
4: history of asthma this patient was found with
 obvious respiratory difficulty he is awake
5: and appropriate on exam we find lung sounds
 with wheezes in Upper lobes bilaterally and
6: quiet lower lobes bilaterally initial Vital
 Signs BP 162 over 94 pulse 120 for
7: respirations 36 skin is warm and moistpulse
 oximetry 92% on 15 LPM by non-rebreather ECG
8: sinus tach without a activate we've treated
 with high-flow oxygen followed by one dose of
9: Proventil and atrovent by small volume
 nebulizer the patient has improved and now has
10: respirations of 24 flight wheezes in all
 Fields Pulse oximetry 96% on 6 LPM by nebulizer
```

```
(breath,True,24,wheezes)          ver bp)))
(spo2,True,96%,pulse oximetry)
(breath,True,36,respirations)
(spo2,True,92%,oximetry)
(breath,True,,respiratory difficulty)
```

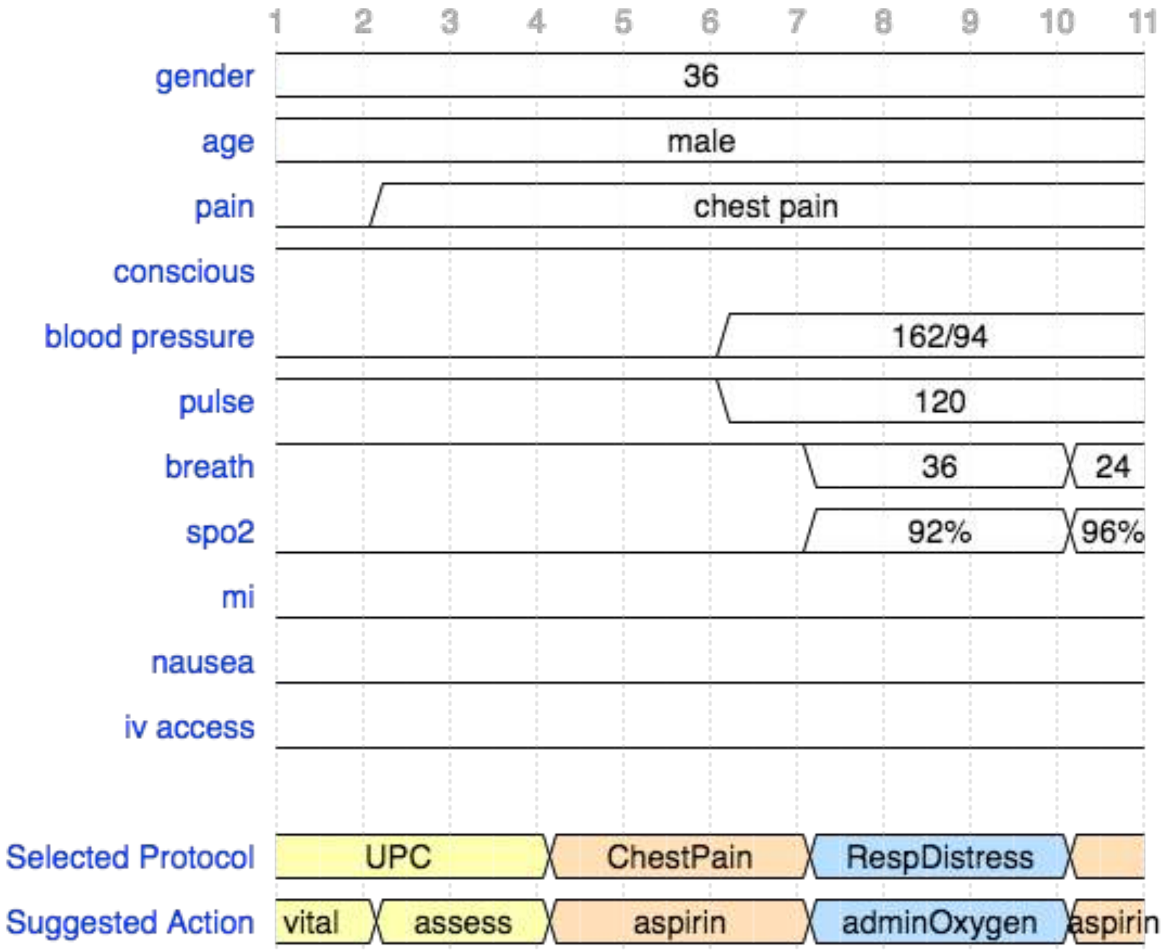


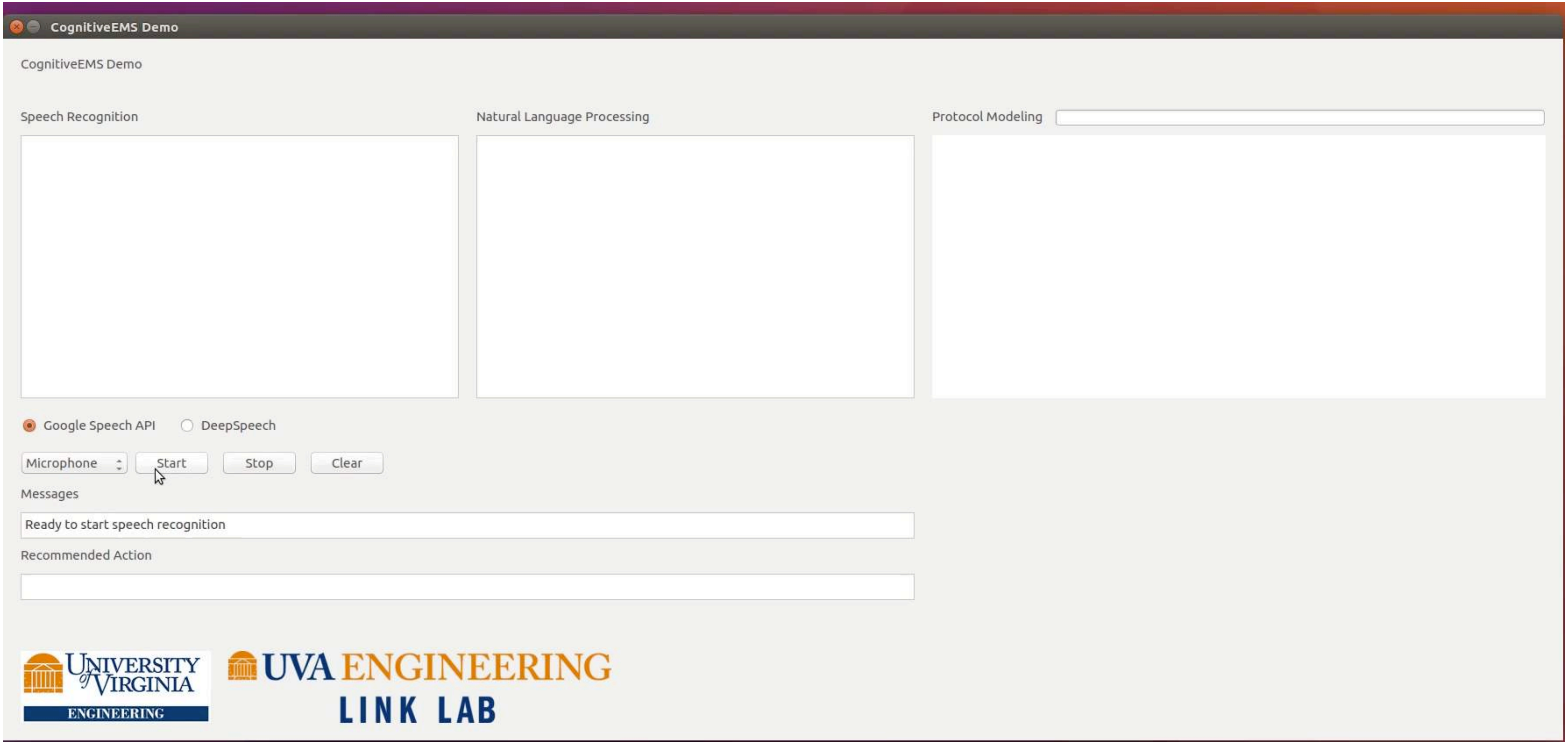
Protocol Selection and Execution

- 8 EMS protocols from 2017 TJEMS guidelines
- 14 example EMS radio calls and reports
- BTs framework identified 9 protocols correctly
- Selection accuracy of **64.3%.**



Percentage of correct suggested actions




CognitiveEMS Demo
CognitiveEMS Demo
Speech Recognition
Natural Language Processing
Protocol Modeling
Google Speech API
DeepSpeech
Microphone
Start
Stop
Clear
Messages
Ready to start speech recognition
Recommended Action
UNIVERSITY of VIRGINIA
ENGINEERING
UVA ENGINEERING
LINK LAB

Ongoing Work

- **Speech Recognition**
  - Noise reduction using ICA with two microphones (directional and omni directional)
  - Offline speech to text conversion (w/o cloud-based Google API)
- **Natural language processing**
  - Extended concept extraction and relation detection (e.g., more concepts, negations, locations)
  - Offline ontology expansion and concept extraction (w/o cloud-based services)
- **Protocol Modeling and Execution**
  - Adaptive rule execution (confidence, history of patient status, previous suggestions)
  - Autonomous learning of protocol models and logic rules (ML-enabled BTs)
- **Real-world testing**
  - More training experiments with North Garden Fire Department
  - Annotation and testing using data collected from Richmond Ambulance Authority

Publications

1. S. Preum, S. Shu, J. Ting, V. Lin, R. Williams, J. Stankovic, H. Alemzadeh, "Towards a cognitive assistant system for emergency response," *Proc. of the 9th ACM/IEEE International Conference on Cyber-Physical Systems (pp. 347-348)*. IEEE Press, April 2018. (Poster)

2. S. Preum, S. Shu, M. Hotaki, R. Williams, J. Stankovic, H. Alemzadeh, "CognitiveEMS: A Cognitive Assistant System for Emergency Medical Services," *Proc. 7th IEEE Workshop on Medical Cyber-Physical Systems*, CPS-Week 2018.

3. S. Preum, S. Shu, R. Williams, J. Stankovic, H. Alemzadeh, "Protocol Driven Concept Extraction for Decision Making in Emergency Response", *Submitted.*

Code and data repository: https://github.com/UVA-DSA/EMS-pipeline

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CS, UVa


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Sile Shu
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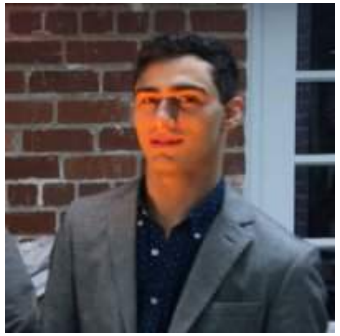
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Richmond
Ambulance Authority

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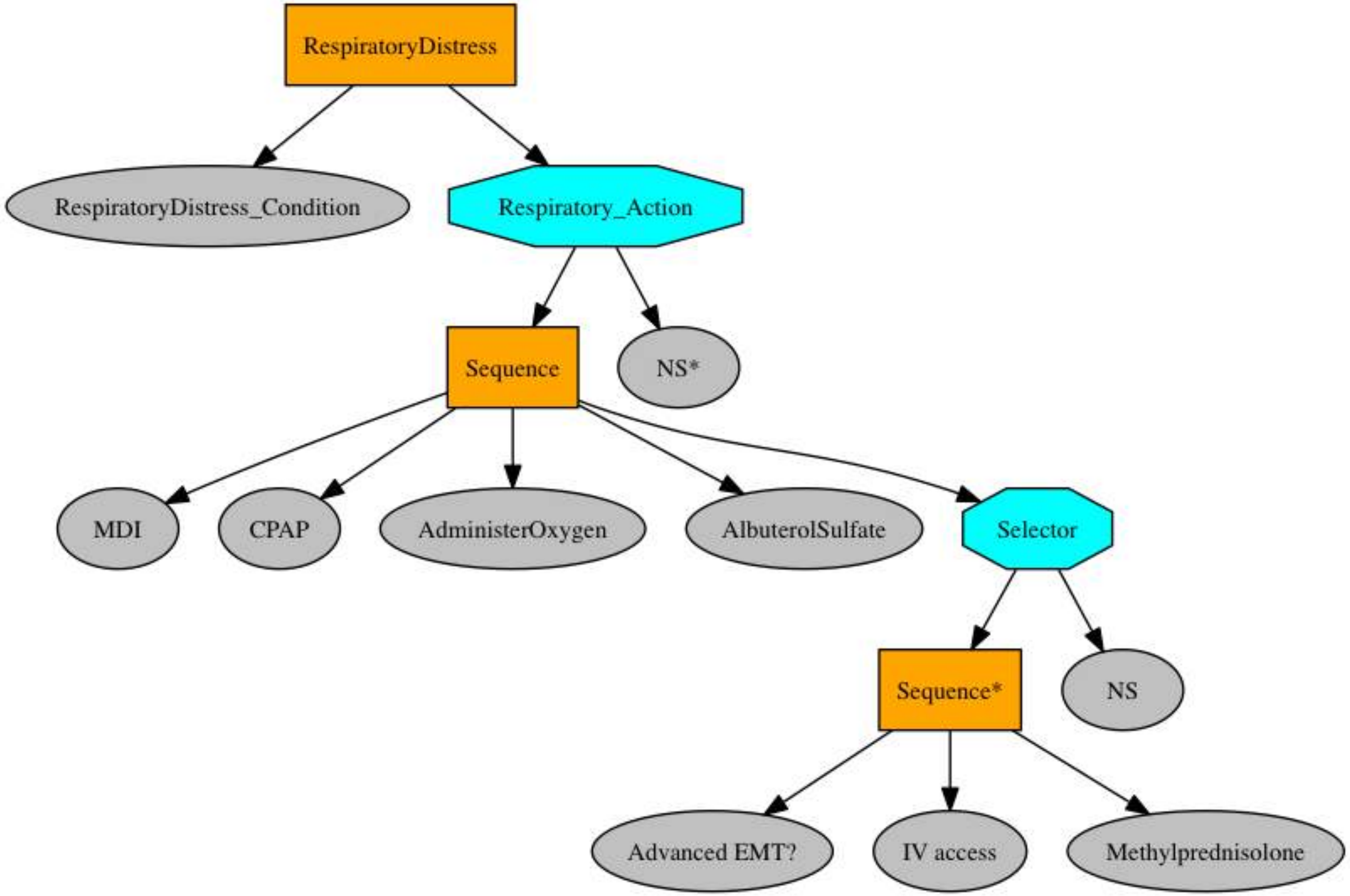
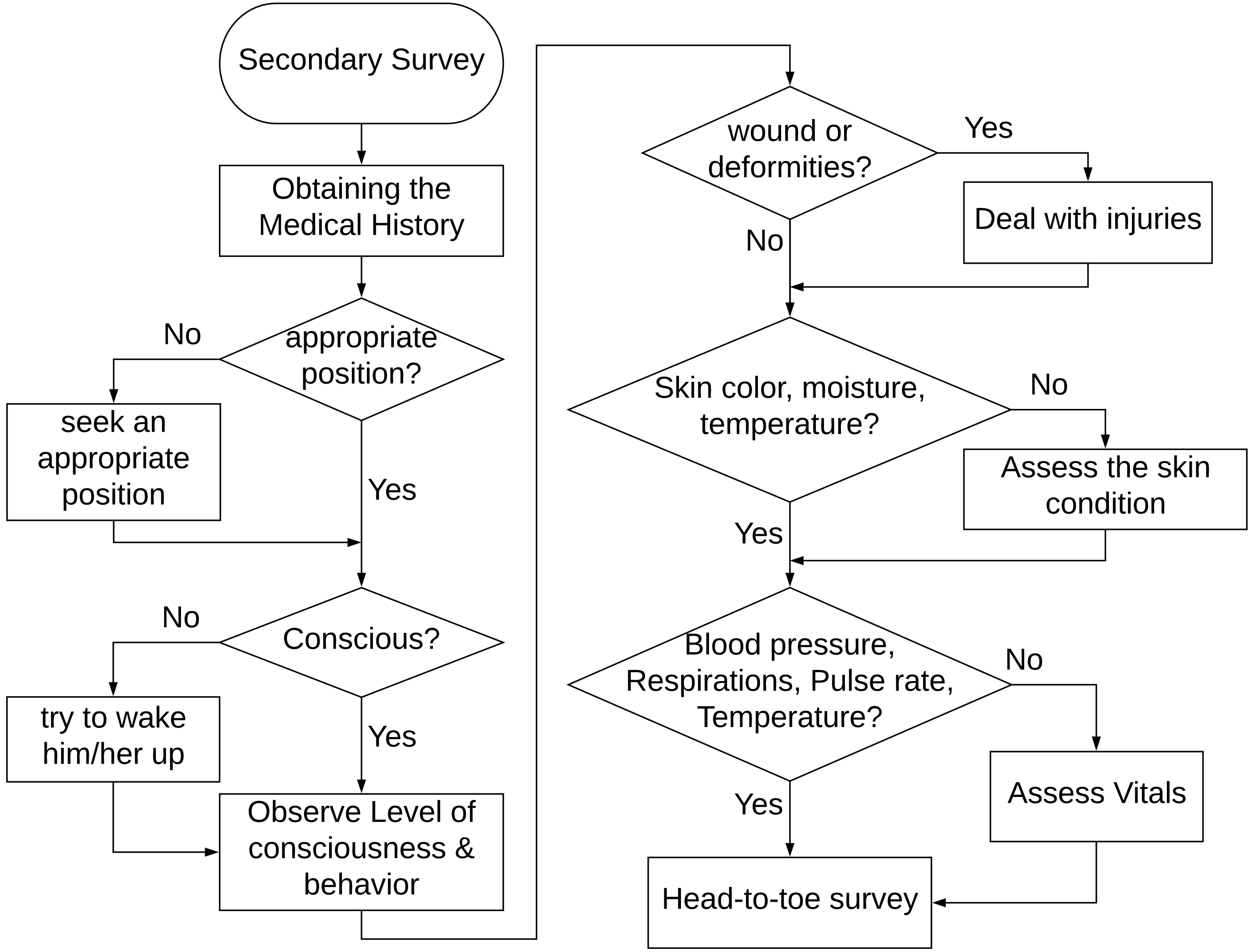
U.S. Department of Commerce

Backup Slides

Respiratory Distress Behavior Tree Model



Secondary Survey Protocol



Big EMS Data

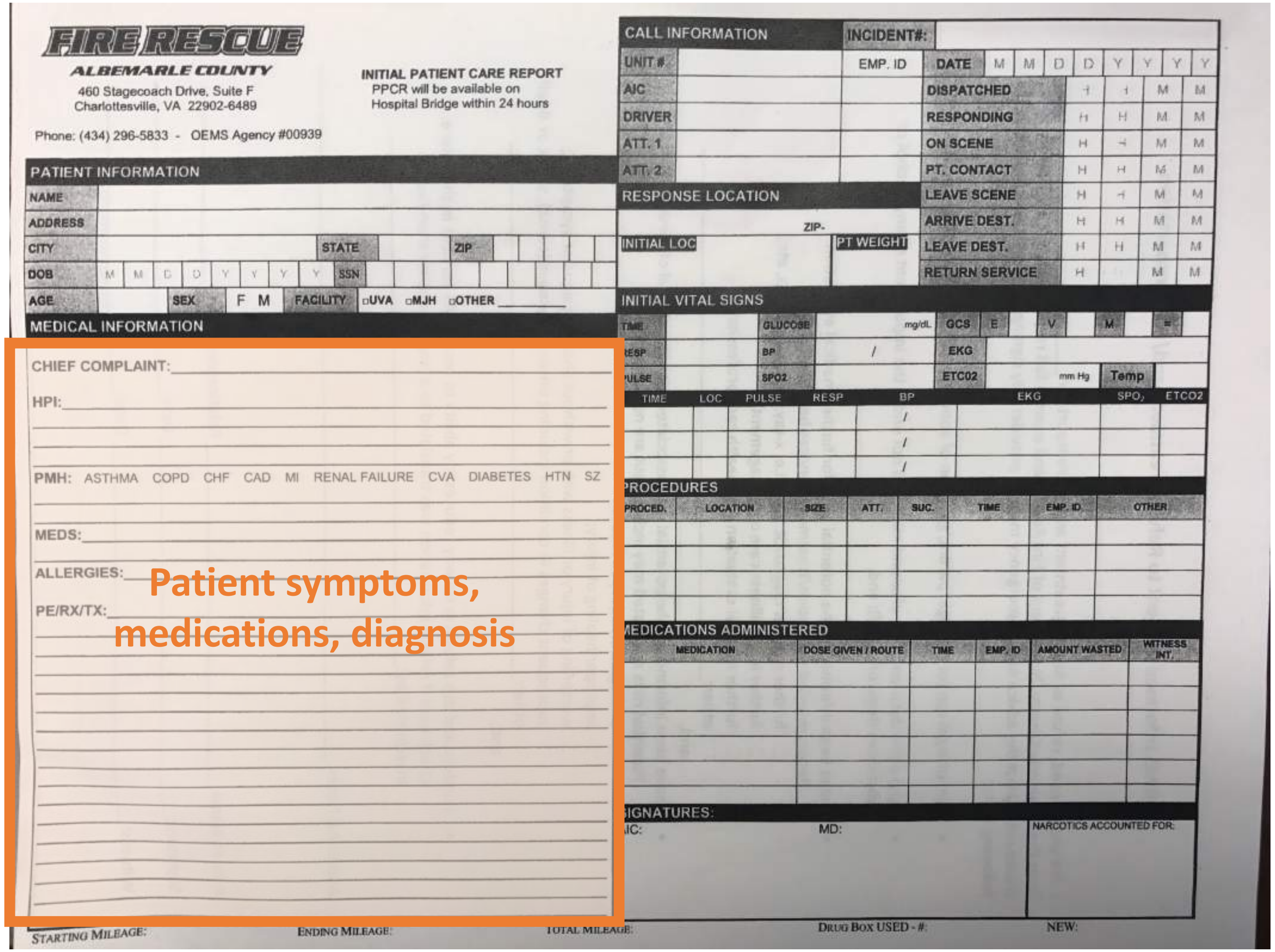
- Over 19,400 credentialed EMS agencies
- 826,000 credentialed EMS professionals
- Over 36,698,000 EMS events were responded to in 2009*

- **Variety of data sources at incident scene:**
    - Observations and communications with center/other responders
    - Sensor data from wearables, mobile, IoT devices
    - Physiological data from patient monitors/medical devices
    - Public data (e.g., protocol guidelines, audio, video, social media)

** G. Mears, et al., "2011 National EMS Assessment (Report No. DOT HS 811 723)," Washington, DC: National Highway Traffic Safety Administration.*

Challenges in Data Analytics

- **Manually reported**
  - Incomplete
  - Inaccurate
- **Unstructured format**
  - Textual reports
  - Voice communications
  - Voice calls
- **Cognitive overload**
- **Resiliency**



Time

EMS Protocol Selection and Execution

Universal Patient Care/Initial Patient Care Protocol

- Scene safety/personal protective equipment
- Primary Assessment with initial interventions ("ABC"s)

Supplemental O2 (Oxygen Administration Guideline)

- 2ndary assessment: vitals, pain, medical history, glucometry

Altered Mental Status Protocol

- IV/IO/Vascular Access
- Glucagon 1 mg IM if no IV access
- Repeat IV Access
- Dextrose 50% 25 grams slow IV push
- Second D50 slow IV push – administered due to glucometer reading and positive response to first dose

Medical: Hypotension/Shock (non-trauma)

- Hypovolemia must be corrected prior to dopamine infusion.
- Identify and manage underlying cause.

Observations/Communications

*EMS Advanced Life Support (ALS) unit dispatched for a **male** patient **unresponsive** in a fast-food restaurant. Patient's estimated to be in his **early twenties**. Patient's **medical history is unknown**.*

*He is seated and slumped with his head resting on his arms on a table. His **LOC is unresponsive** with a **Glasgow Coma Scale (GCS) score of 3**. He is **breathing at a rate of 16 BPM**. His **heart rate is 96 BPM**. His **radial pulse is not palpable**; his pulse is palpated at the left carotid artery. No unusual marks, discoloration, or deformities are noted. Patient noted to be somewhat **diaphoretic**.*

*The glucometer reports a **blood sugar level of 15 mg/dL**. This is a critically low level that requires rapid intervention.*

*The caller reports that the patient purchased a large orange juice and sat down at the table. The orange juice is observed on the table, and it appears that none has been consumed. The manager reports that he noticed the patient with his head on the table and **had not moved for 45 mins** after purchasing the orange juice. The manager was unable to wake the patient at that time, and called 911.*

The patient's LOC starts to improve. He starts to make some sounds and move as he begins to wake.

*A few minutes after **administration of the D50**, the patient appears awake but groggy.*

*Within few moments, patient becomes **completely awake** and oriented but **without memory of the event**. The patient states that he **feels fine**. The patient reports that he is a **type 1 diabetic** and he had **not eaten today**. He had no recollection of buying the orange juice or how he arrived at the restaurant.*

Dynamic Device Reconfiguration