Research in Applications for Learning Machines (REALM) Consortium

Situational Knowledge On Demand (SKOD)

- 24 January, 2020
- Bharat Bhargava
- Purdue University

Collaborations

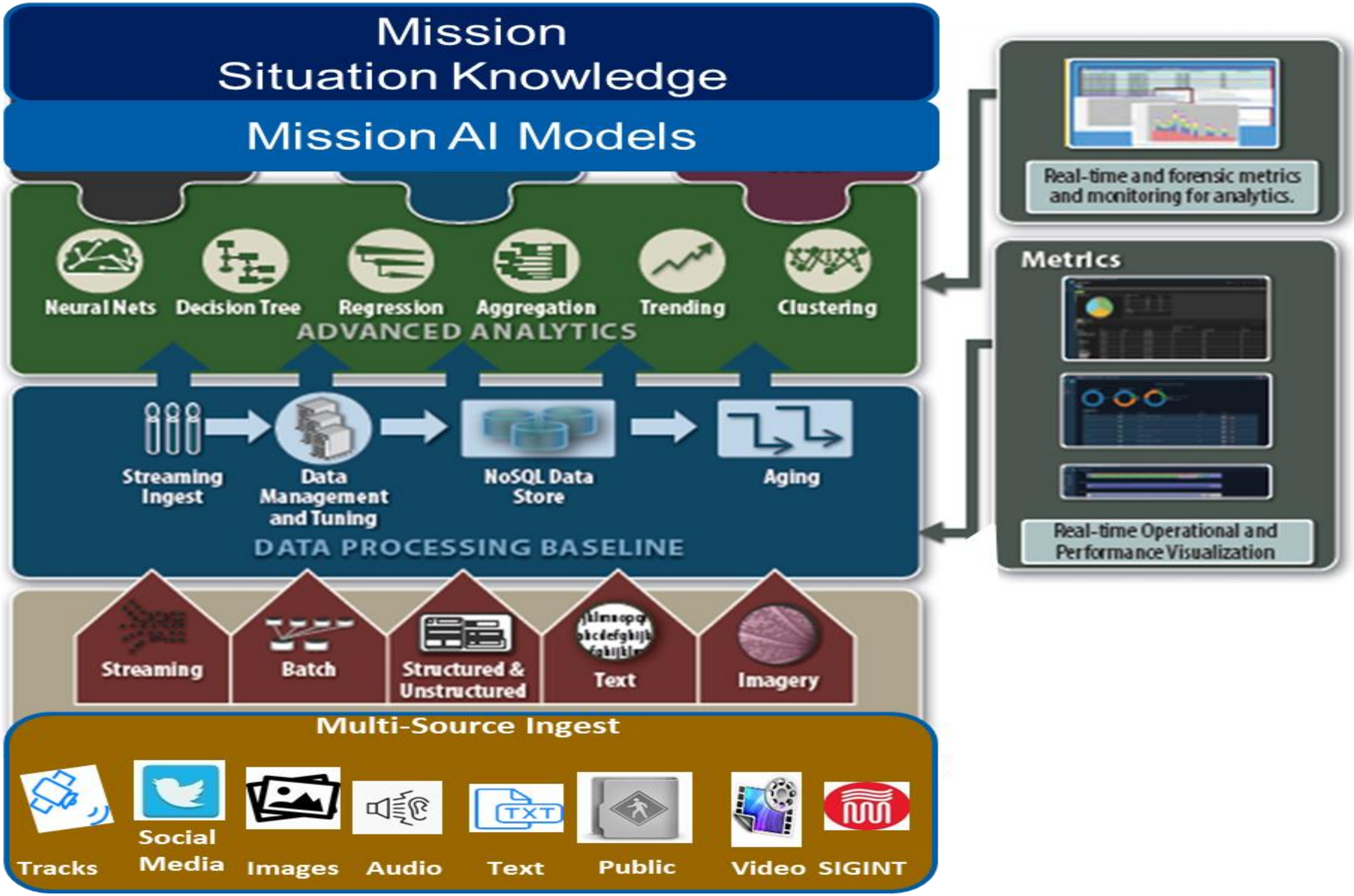
- **Researchers**
  - Bharat Bhargava (Purdue)
  - Michael Stonebraker (MIT)
  - Michael Cafarella (MIT)
  - Aarti Singh (CMU)
  - Peter Bailis (Stanford)

- **Students**
  - KMA Solaiman
  - Alina Nesen
  - Pelin Angin
  - Ganapathy Mani
  - Zachary Collins (MIT)
  - Aaron Sipser (MIT)
  - Tao Sun (MIT)
  - Servio Palacios
  - Miguel Villarreal-Vasquez
  - Denis Ulybyshev
  - Daniel Kang (Stanford)

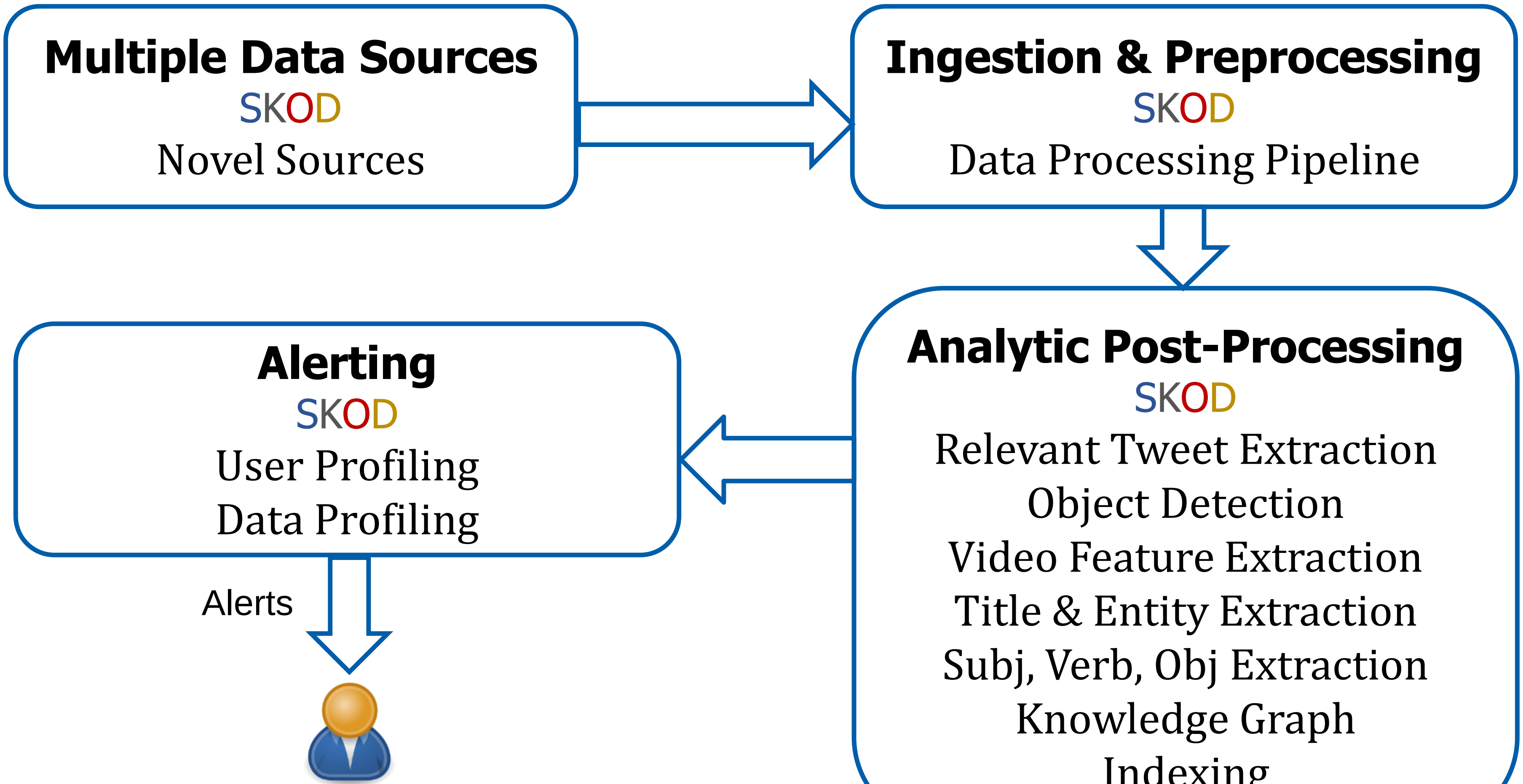
Collaborations

- **NG:** SKOD proposal is developed with the guidance of Dr. Jim MacDonald. His suggestions on situational awareness and real time adaptive ML models with multimodal data helped us formalize the science on this project.
- **Purdue/MIT:** Building a real time Urban Information system for city of Cambridge and to assist West Lafayette Police.
- Joint weekly meeting with **West Lafayette police** Sargent Troy Greene.
- **CMU:** CMU is working with us for building the offline model construction for feature extraction from video dataset, Efficient labeling, transfer learning.
- **Stanford** is working on real-time content reduction and object association.

The project is applicable across a variety of industries, military to commercial to academic. (Jim MacDonald, Northrup Grumman)



Integration with Paradigm (System at NG)



Outline

- Possible Scenarios
- Objectives
- Problem Statement
- Datasets
- **SKOD** Architecture
- Summary
- Deliverables and Demo
- Future Plans

Architecture Modules

- Data Streaming
- **Feature Extraction**
- **Knowledge Graph**
- **User Profiling**
- PostgreSQL Database
- Graph-based Indexing Layer
- Front End

Develop learning algorithms to establish mission based situational awareness

NGC View

Model the User

Techniques to model the user, specifically their mission-needs, preferences, and capabilities

Data Management

- Resource aware management
- Content Reduction to event association
- Metadata Tagging
- Security Policies

Mission Relevance

- Identify the relevance to user's needs
- Assess patterns in data
- Connect disaggregate data sources

Scaling

Techniques to support millions of users

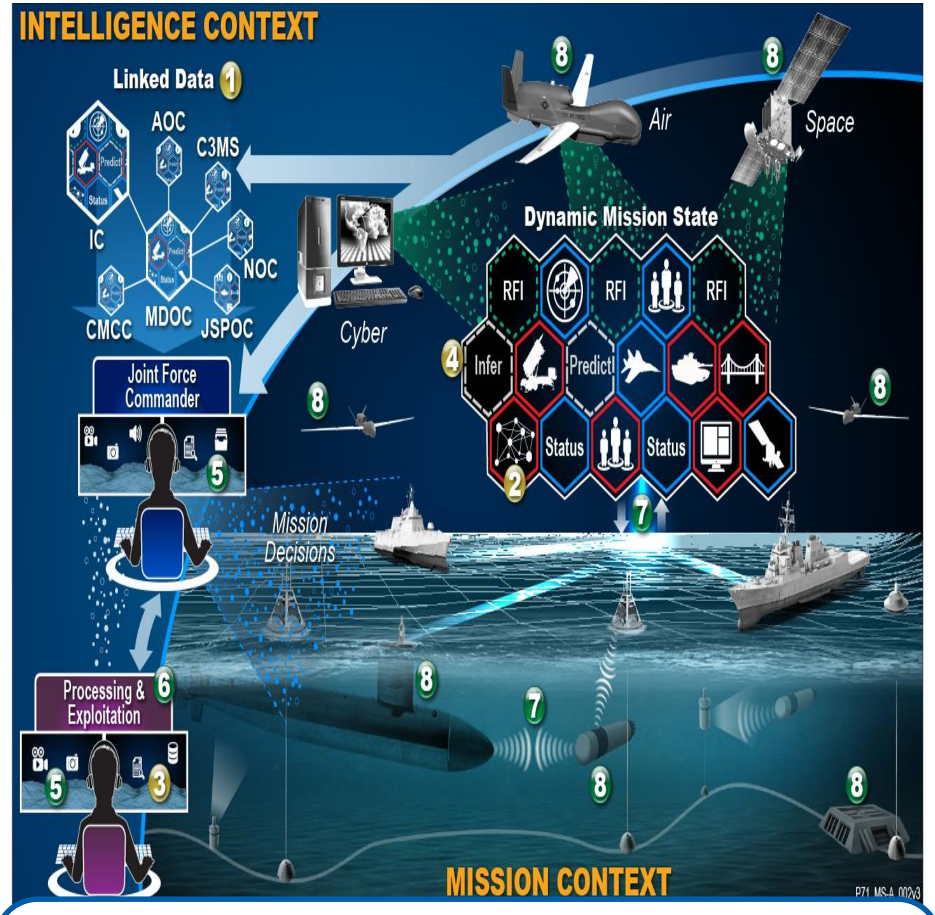
Automatically extract data relevant to significant events, identify patterns related to a mission, and push relevant information efficiently to interested parties

Objective: Automatically extract data relevant to significant events, identify patterns related to a mission, and push relevant information efficiently to interested parties (e.g. analysts, cyber security experts, and decision makers)

- **NGC Guidelines and NEEDS:**
  - **Techniques to model the user, specifically their mission-needs, preferences, and capabilities**
  - **Data management techniques:**
    - **Efficient management, storage, and retrieval of multi-modal data that is aware of infrastructure, storage, bandwidth, and compute resources**
    - **Data mining algorithms to reduce content by association to event attributes**
    - **Novel metadata tagging and indexing of data from heterogeneous sources**
    - **Enforcement of security and data sharing policies**
  - **Determination of Mission Relevance:**
    - **Algorithms that identify the relevance of data to the user's information needs and can process data of varying levels of confidence and provenance**
    - **Means to assess data patterns for rate of occurrence and generalization for predictive value of information to mission**
    - **Collaboration through virtual communities of interest to discover new user-relevant information**
  - **Techniques that support scaling to 1000s of users**

NGC Plans

- Observe and collect user behavior through unobtrusive multi-modal interfaces
- Model the mission interests, preferences, context, priority and capabilities
- Novel streaming metadata tagging and indexing of data from heterogeneous source
- Data mining algorithms that identify mission content by association to event attributes (e.g. by clustering, regression and rules) of streaming sources
- Push context-aware relevant information to the mission user.



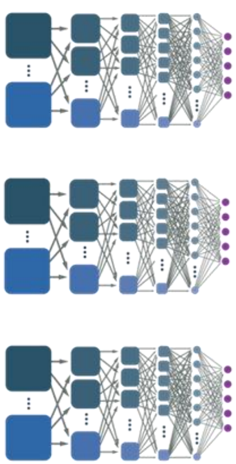
Adapting Mission Information and Processes to Allow Trusted, Collaborative Participation.

Use Cases Northrup Grumman

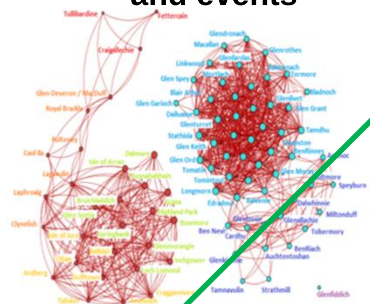
Multi-Intelligence Sources

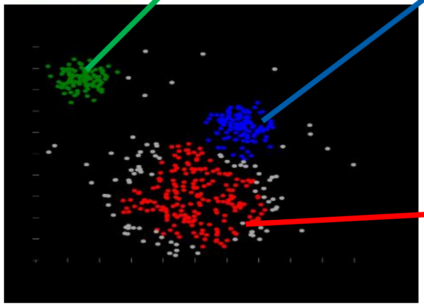
- Text
- Audio
- Video
- Social Media
- News
- SAR
- GMTI
- EO/IR
- Hyperspectral
- RF

Data Correlation

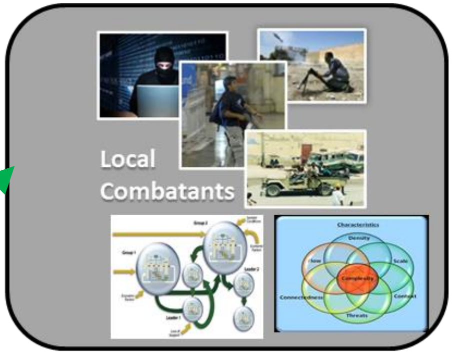


Resolved entities, activities and events

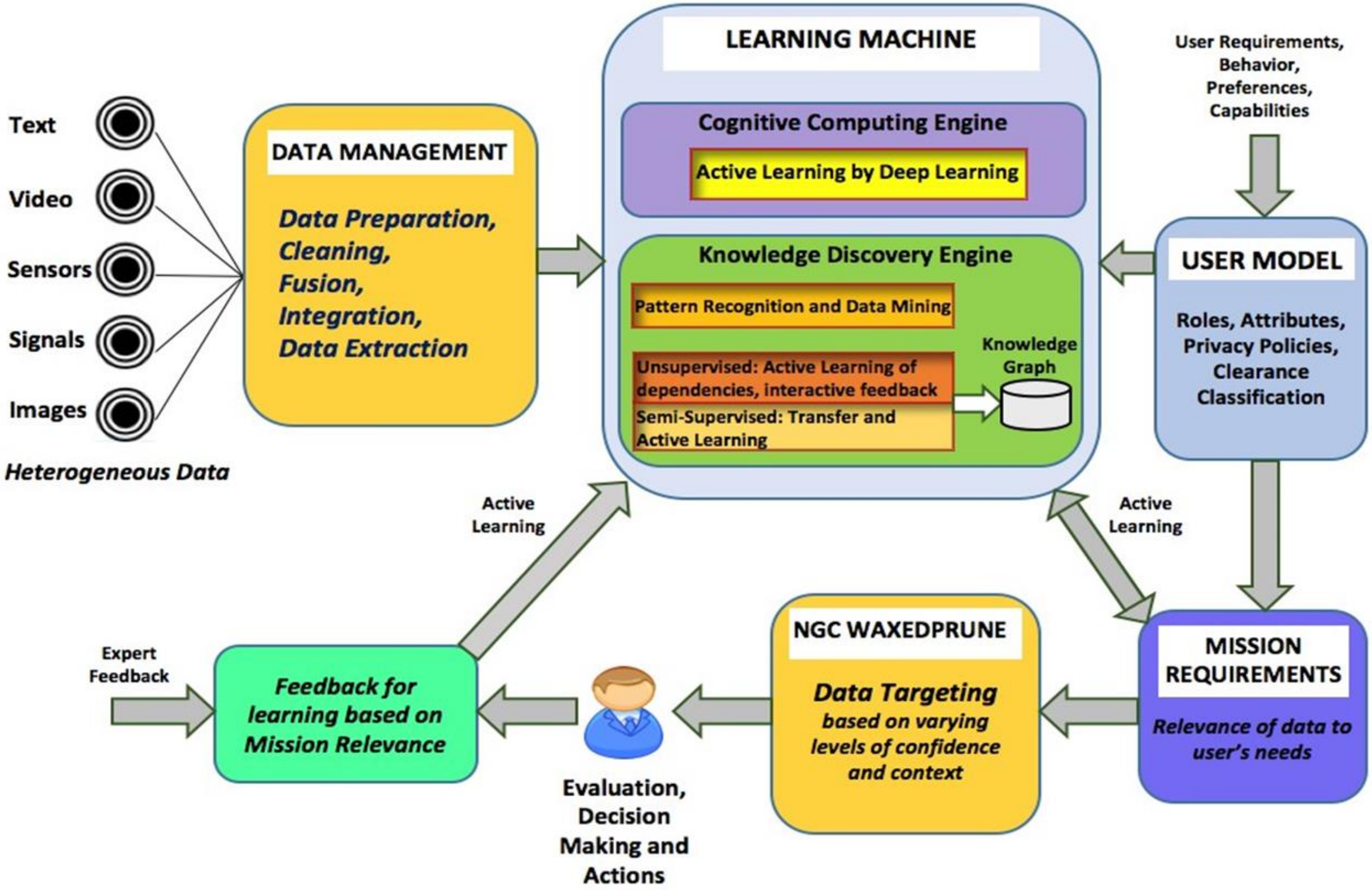




Mission Situational Knowledge



Situational Knowledge on Demand : SKOD Team-Operational Plans



Spectrum of Machine Learning Tasks Applied for SKOD:

- Natural Language Processing for Text Data:
  - LDA (Latent Dirichlet allocation) for topic modeling
  - LSA (Latent semantic analysis) for relationships between documents
- Deep Neural Networks for Video Data:
  - YOLO for object detection and classification
  - Action detection with R-C3D neural network
- Recommendation Engine and Building User Profiles:
  - Variational Bayesian methods for user modeling

https://www.cs.purdue.edu/news/articles/2019/bhargava-realm-ng.html

Research Directions and Algorithms

- CNN based Neural Networks and Transfer Learning for objects from Video.
- Label-efficient learning (Aarti at CMU), Data Completion (Vaneet at Purdue)
- LSA, LDA and Deep Learning (encapsulating Word2Vec) models for topics, ontologies and triplets from Text and to build knowledge base.
- DL model combining attention based Bi-LSTM and CNN [4] to classify tweets for Disaster Resource Management and similar scenarios.
- BlazeIt [5] for complex queries over video related to objects of interest.
- Research DAWN’s End-to-End ML Systems [6] for Recommendation.
- Research reinforcement learning and active learning for User Profiling.
- Apply models to other NG large databases (sensors, signals, text, phone calls, videos, images, voice)

Proposed Solution

- Perform data fusion for heterogeneous data resources
- Clean data from fuzziness and clutter.
- Perform automatic data labeling.
- Identify patterns.
- Push information to the relevant party with or without input from experts in a context-aware, timeless manner.
- Push the relevant information to parties based on their profiles, preferences and context of interactions.

Proposed Solution

Components:

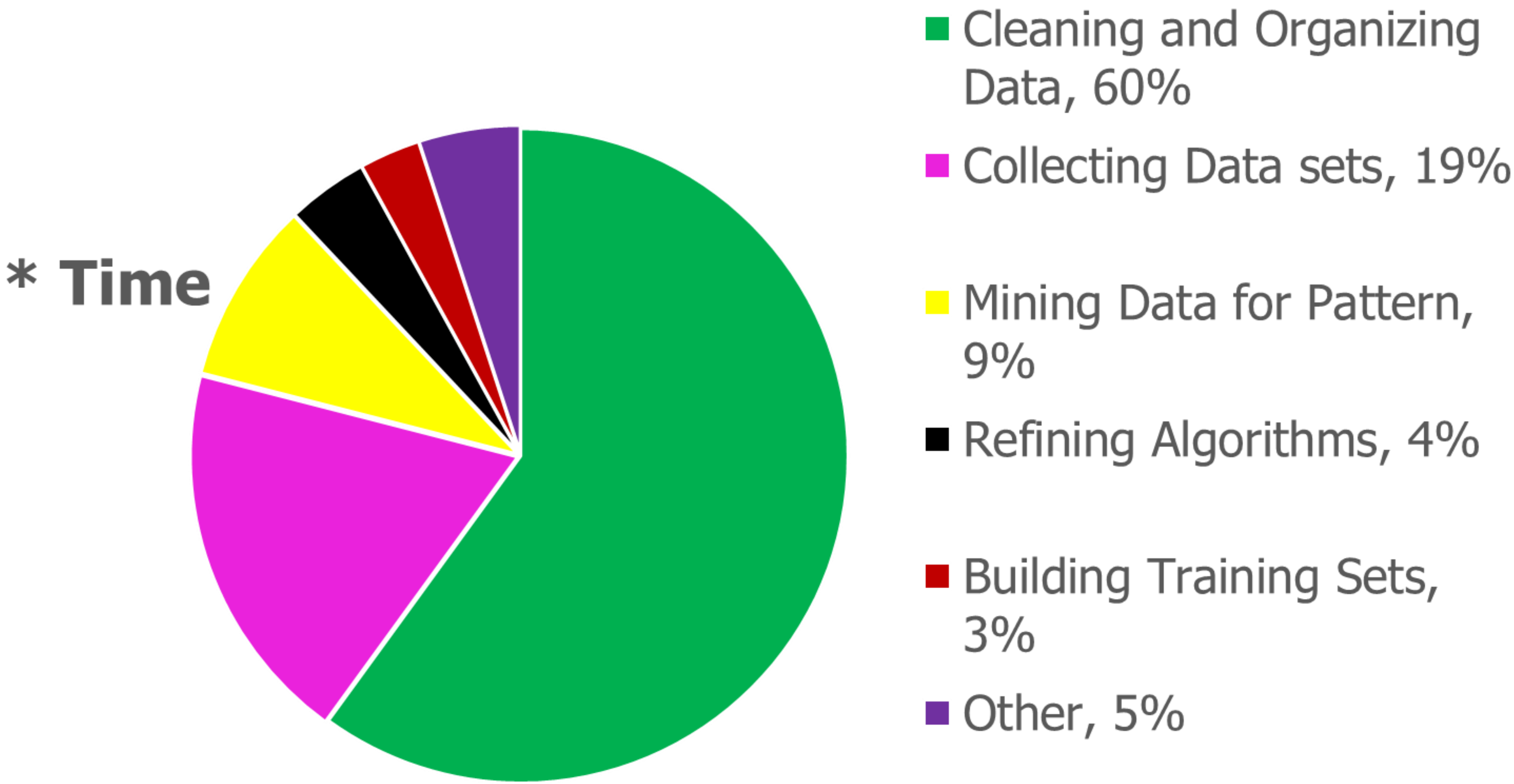
- Data Management
- Data Completion
- Knowledge Graphs
- User Profiles and Target Inform ation Propagation
- Profiling and Data Propagation with WAXEDPRUNE
- Machine Learning Toolkit

Data Management
Vision of Professor Mike Stonebraker at MIT

Problem Statement

- Discover and extract relevant data for a data scientist from multiple sources
- Clean data from fuzziness and clutter
- Perform data fusion for multiple heterogeneous data sources
- Prepare heterogeneous data for Learning Machine Engine

How Data Scientists Spend Their Day



NOBODY REPORTS LESS THAN 80% “MUNG WORK”

* Diagram taken from https://visit.figure-eight.com/rs/416-ZBE-142/images/CrowdFlower_DataScienceReport_2016.pdf

Activities

Relevant Publications:

1. S. Palacios and K. Solaiman, P. Angin, A. Nesen, B. Bhargava, Z. Collins, A. Sipser, M. Stonebraker, J. Macdonald. ***SKOD: A Framework for Situational Knowledge on Demand.*** In *Polystores and other Systems for Heterogeneous Data (**Poly**),* at **VLDB 2019**, LA, California, August 30, 2019.

2. K. Solaiman, B. Bhargava, J. MacDonald. ***Multi-modal Information Retrieval via Joint Embedding.*** In NGC TechFest 2019, October 23 2019.

3. K. Solaiman, B. Bhargava, J. Macdonald. ***DT2Vec:Partial Framework for building a multi-modal knowledge base***, In Submission, 2020.

4. A. Nesen, B. Bhargava, J. MacDonald. ***Explainable Anomaly Detection in Surveillance Video With Deep Learning and Knowledge Graphs.*** (To be submitted)

5. M. Kabir and S. Madria. ***A Deep Learning Approach for Tweet Classification and Rescue Scheduling for Effective Disaster Management.*** In *27th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, Chicago, Illinois, Nov 7, 2019.

6. D. Kang, P. Bailis, and M. Zaharia. ***Blazeit: Fast exploratory video queries using neural networks.*** (2018).

7. Peter Bailis, et al. ***Infrastructure for Usable Machine Learning: The Stanford DAWN Project.*** (2017).

Proposals

- DARPA award on *Science of Artificial Intelligence and Learning for Open-world Novelty (SAIL-ON)* initiative of DoD (JOINT with Information Science Institute)
  - Generating Novelty in Open-world Multi-agent Environments (GNOME)
- Awards from FORD (SDN and Vanets), Sandia Lab (MTD to Harden Space systems), JPL (Security), Northrup Grumman (two projects: ML attacks and Explainable AI and REALM)
- White papers submitted for DoD, ONR, Plans for NSF proposal

AFRL, Rome Request for Information

- The Air Force Research Laboratory, Information Directorate (AFRL/RI) is seeking information to better understand existing vendor offerings within the landscape of research and development (R&D) that could later drive the development of prototypes of Machine Learning (ML) enabled Operational Command & Control (C2) functions and assess their notional value1, 2 to Operational C2.

- The Air Force is investigating the incorporation of Machine Learning capabilities into Air Force C2 applications. As such, it is interested in the identification of C2 applications that can benefit from the incorporation of these capabilities, an understanding of how these applications and operations can notionally benefit, and the algorithms, and necessary data that will be a part of these implementations. This RFI is requesting information to better understand those AF C2 applications that have incorporated ML, those that could incorporate ML in the future and the algorithms which support these advanced capabilities. The C2 applications should fall into one of the following categories: Operational C2 supporting the air tasking process, battle management supporting operations execution, tactical-level C2 supporting the end-user, and Multi Domain C2.

Army Research Lab

- STRONG addresses a critical objective within a broader Army goal to enable effective integration of Artificial Intelligence / Machine Learning (AI/ML) in the battlefield. This program has been developed in coordination with other related ARL-funded collaborative efforts (see descriptions of ARL collaborative alliances at https://www.arl.army.mil/www/default.cfm?page=93) and shares a common vision of highly collaborative academia-industry-government partnerships; however, it will be executed with a program model different than previous ARL Collaborative Research/Technology Alliances.

Long Term Objectives of Research

- Retrieve knowledge for multiple users' changing needs and mission. Relate multi-modal data and dynamically update/build the knowledge base for users. Utilize users' queries to build knowledge on top of a relational database and cache appropriate data and queries to improve performance. Lean about Knowledge graphs from ISI research.

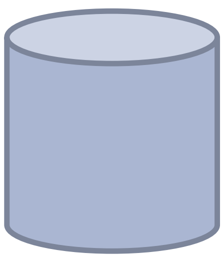
- Integrate new streaming data with knowledge queries already used by mission. Complete the unfulfilled data needs for missions. Discover new knowledge that can benefit mission

- Conduct research in learning machines to make this efficient at large scale

- Research transfer learning, reinforcement learning, active learning and apply to NG large databases (sensors, signals, text, phone calls, videos, images, voice) Some of these are long term objectives. Include efficient labeling, NLP

- Make system practical and responsive and efficient by using systems, ML, and tools already available and used in industry

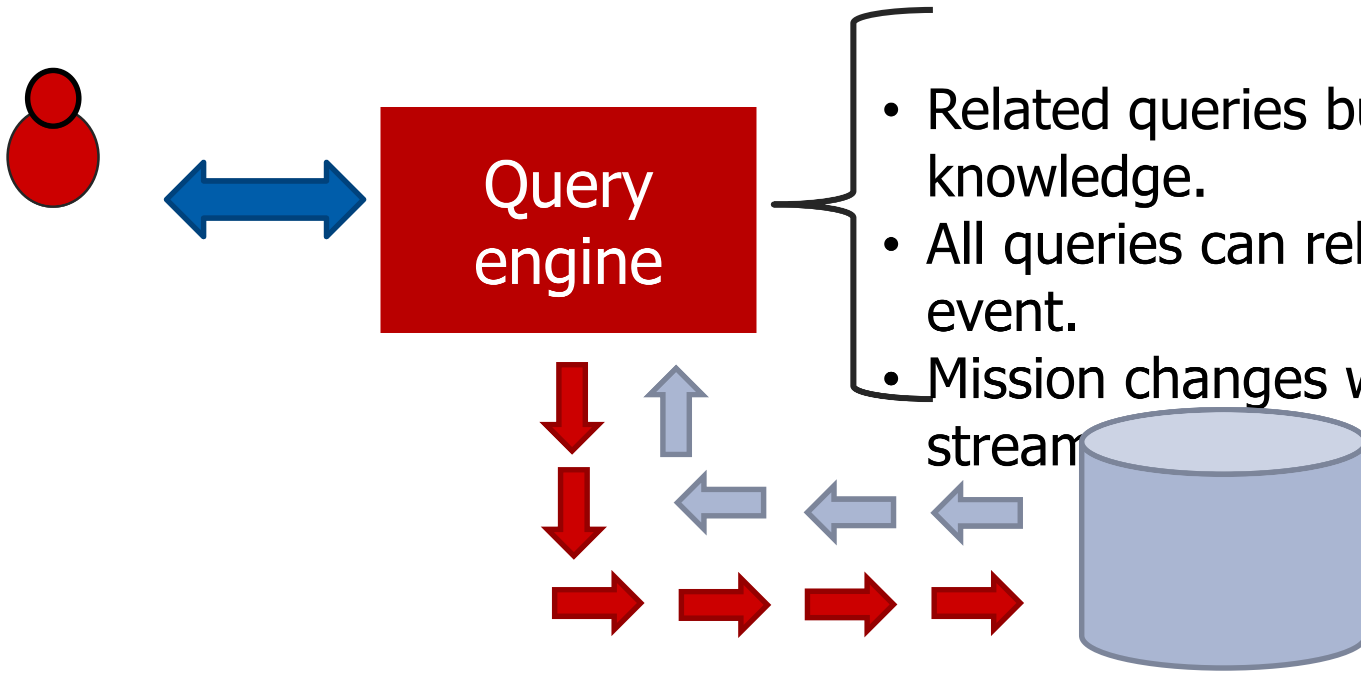
Data Management



Postgres

Data at rest.
Segments of video as tuples in the DB.
Feature analysis.
Queries model the knowledge.

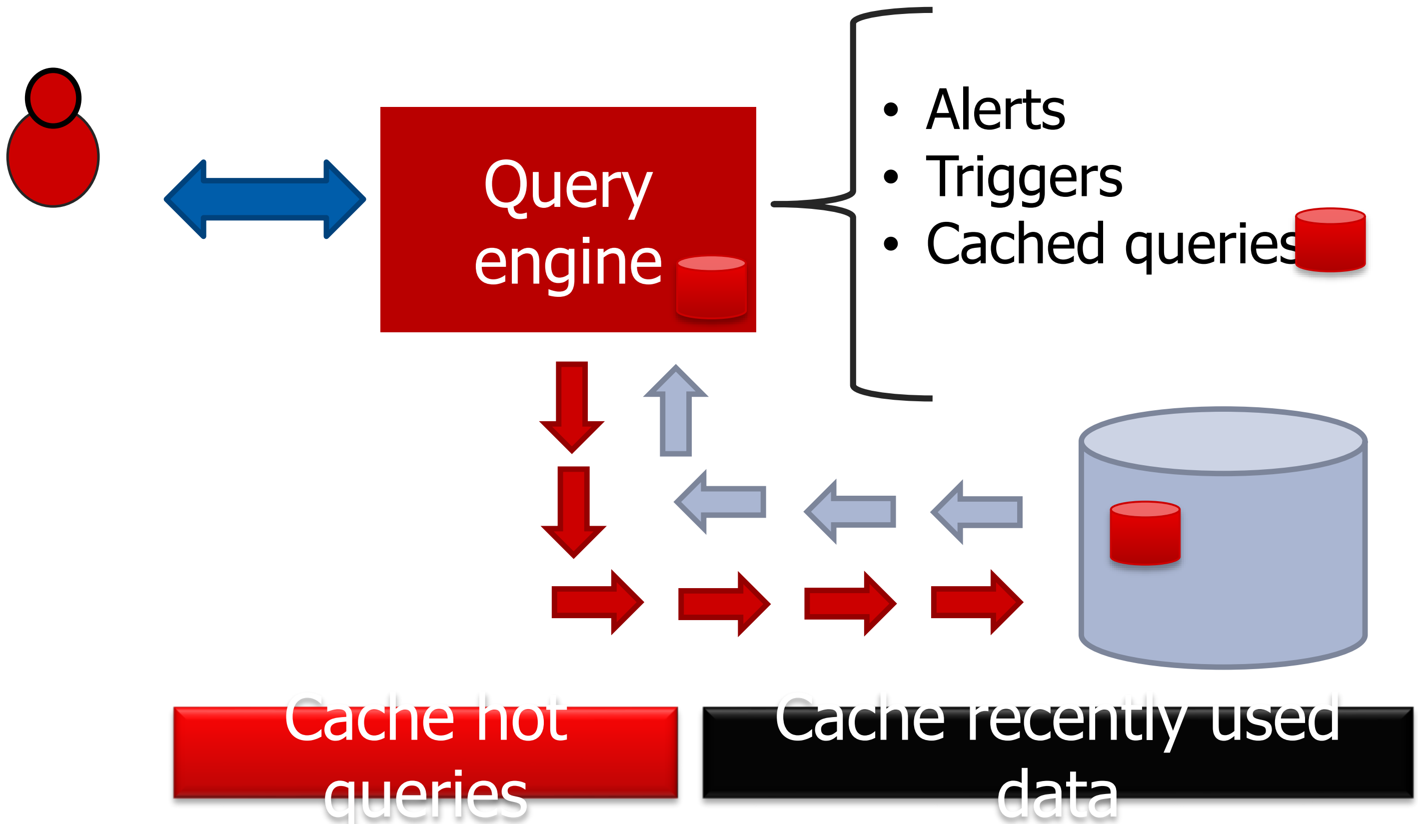
Queries model the knowledge



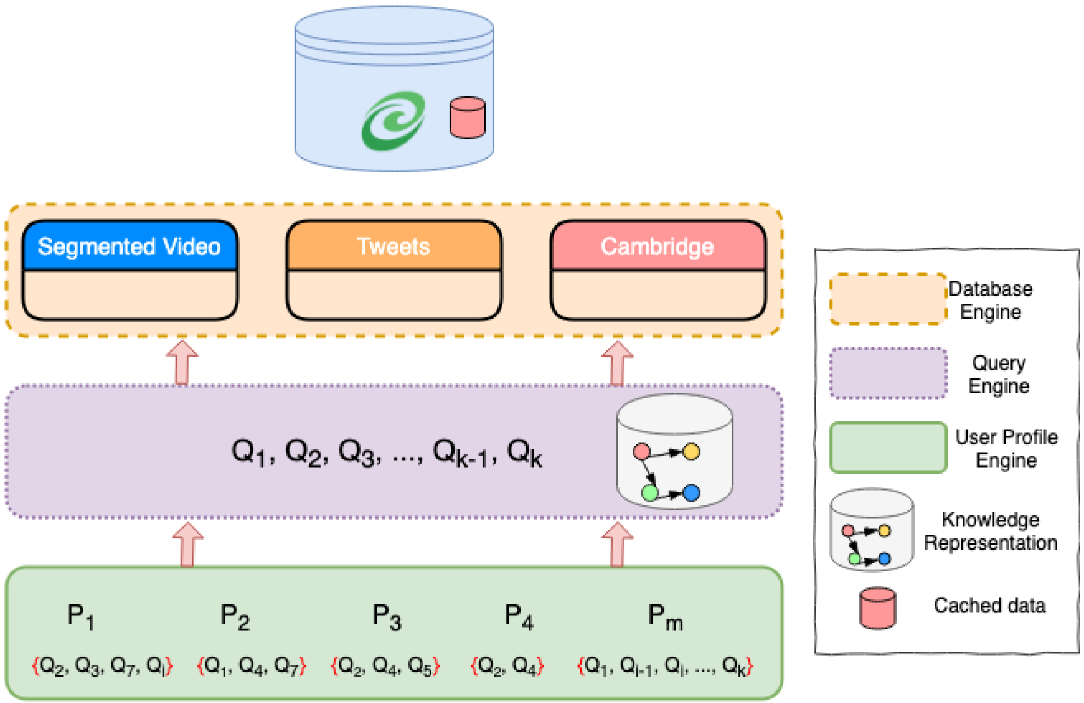
- Related queries build knowledge.
- All queries can relate to one event.
- Mission changes with the data stream

Queries -> Knowledge

Queries model the knowledge



Situational Knowledge Query Engine Architecture



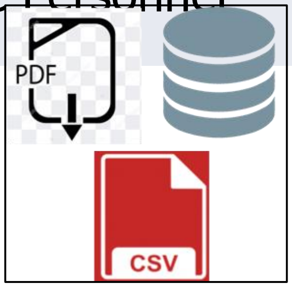
Scenario: Save Child Left Alone in Car in heat or cold

- In 2019, 51 children died from heatstroke after being left in a hot vehicle, 2 in Indiana.*

Context & User	Mission	Contextual Info. Propagation
Normal D… & Regular P…	Finding an Unattended Child in Car	…User
During ar… …uake & Rescue Personnel	Finding an Unattende… Child in Car	…User

SKOD

Situational Information forwarded to Appropriate User



City Data

* https://injuryfacts.nsc.org/motor-vehicle/motor-vehicle-safety-issues/hotcars/

Scenario: Stop Suspected Person from Violence

Context:
New Years Evening

NY Police needs to Know

Suspected Person

GPS tracking
- Headed to NYC times square

Census Records
- No Family Connection to NYC or close by

crimemapping.com
- Is involved in Assault / Disturbing the peace / Homicide / Vandalism

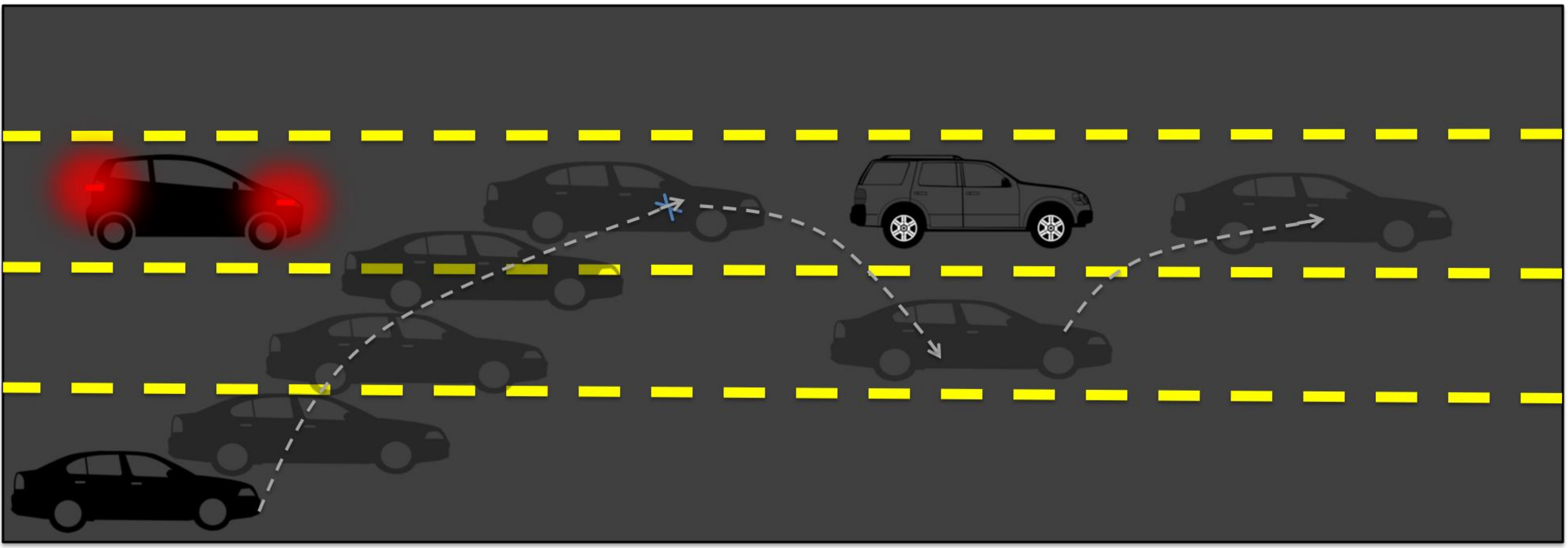
BMV Records
- Record of DUI Convictions

ATF Records
- Record of people buying guns and ammunitions in an area

Urban Information System Scenarios

Identify Unsafe Lane Changes

Identify Jaywalking



City of Cambridge: Agents

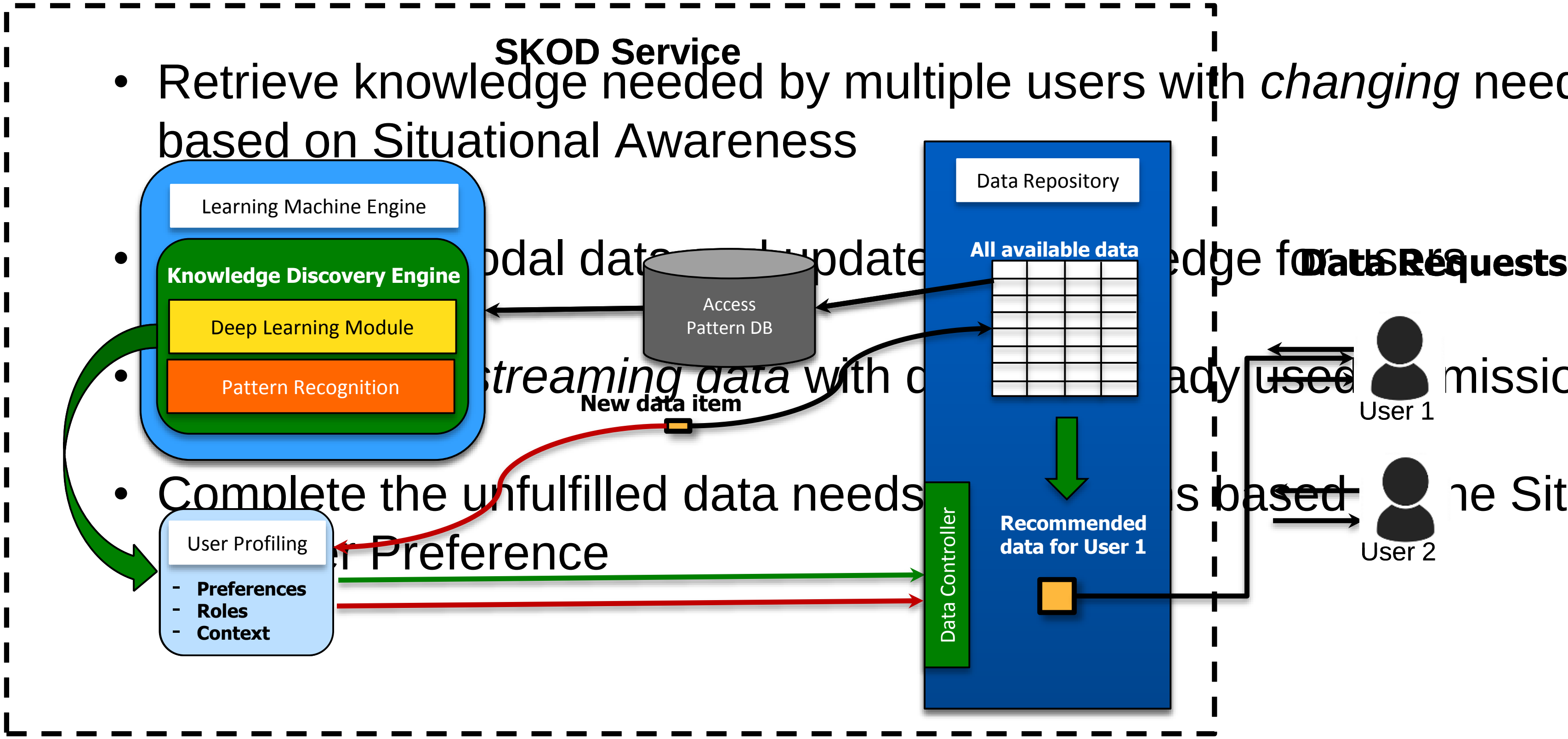
- Numerous agents with different missions in a city (i.e., Cambridge)
  - Cambridge police
  - University (Harvard, MIT) police
  - TRANSIT police
  - Cambridge public works
  - Citizens
  - FEMA (Emergency personnel)
  - Homeland Security

Missions

- Missions with various needs for information
  - MIT police (pedestrians in the middle of the road, unsafe lane changes, ”choke” points, Child left alone in parked car, purple Cadillac used by a bad guy identified …)
  - Cambridge public works (potholes, down or occluded street signs)
  - Citizens (crane or car illegally blocking the sidewalk in front of house)

SKOD Objectives

- Retrieve knowledge needed by multiple users with *changing* needs based on Situational Awareness
- …odal dat… update… edge for users
- …*streaming data* with c… ady used … mission
- Complete the unfulfilled data needs … s based … he Situation …r Preference



Objective 1: New data items are directly pushed to users based on their requests.

Objective 2: Relevant data is efficiently pushed to users based on the User Profiling.

Datasets Collected for City of Cambridge

- **Video**
  - 100+ hours of dashcam video collected at MIT
  - Raw video can be retrieved from MIT database at Cambridge
    - Split into chunks of 30 seconds
    - Metadata collected: geolocation and timestamp for each 30 seconds
- **Unstructured Text** (Twitter data)
  - Collected ~200K tweets (Target ~ 1 million)
  - Automatic tweet parsing and recording system into Postgres in place
- **Structured data**
  - Cambridge public datasets
  - Automatic weekly updates into Postgres in place
- **Data from drones and dashcams**

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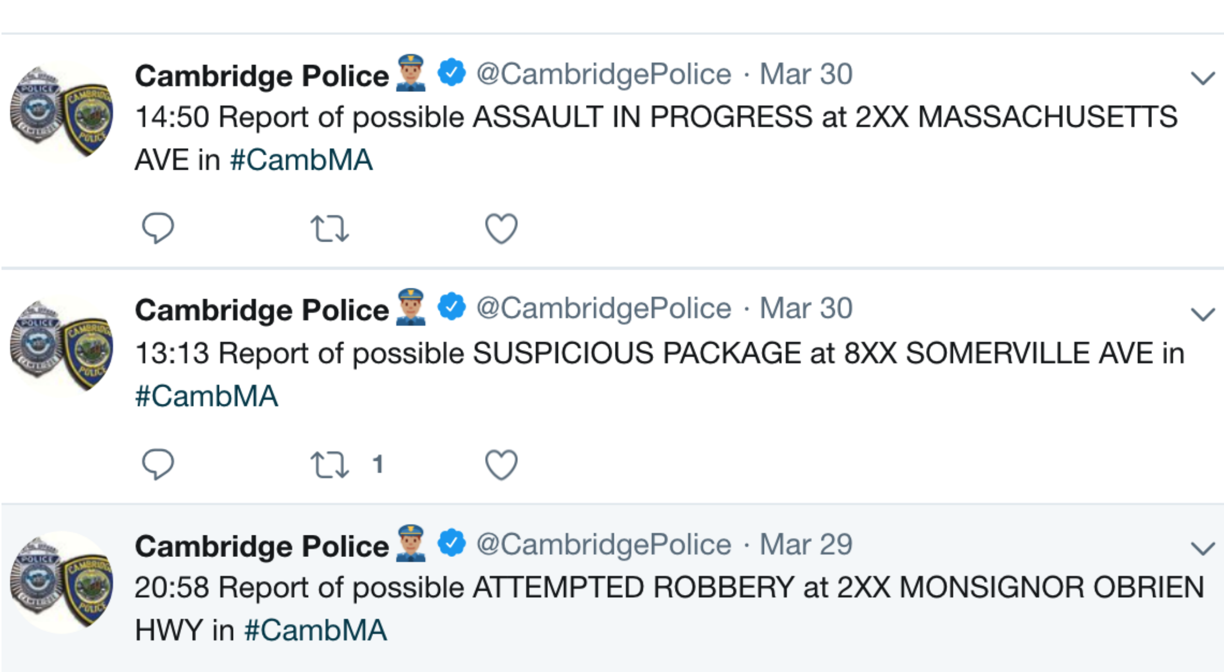
Datasets Example

- Tweets from Cambridge Police
- A video that has a bicyclist without helmet on it 00:01 to 00:27


Cambridge Police @CambridgePolice · Mar 30
14:50 Report of possible ASSAULT IN PROGRESS at 2XX MASSACHUSETTS AVE in #CambMA

Cambridge Police @CambridgePolice · Mar 30
13:13 Report of possible SUSPICIOUS PACKAGE at 8XX SOMERVILLE AVE in #CambMA
1

Cambridge Police @CambridgePolice · Mar 29
20:58 Report of possible ATTEMPTED ROBBERY at 2XX MONSIGNOR OBRIEN HWY in #CambMA

Future Datasets

- Waymo Open Dataset
  - Sensor data
    - Synchronized lidar and camera data from 1,000 segments (20s each)
  - Labeled data
    - Labels for 4 object classes - Vehicles, Pedestrians, Cyclists, Signs

- Yelp Dataset
  - Reviews
  - Businesses
  - Pictures
  - Metropolitan Areas

- News Articles
  - https://www.cambridgema.gov/news?page=2&ResultsPerPage=10
  - Google News

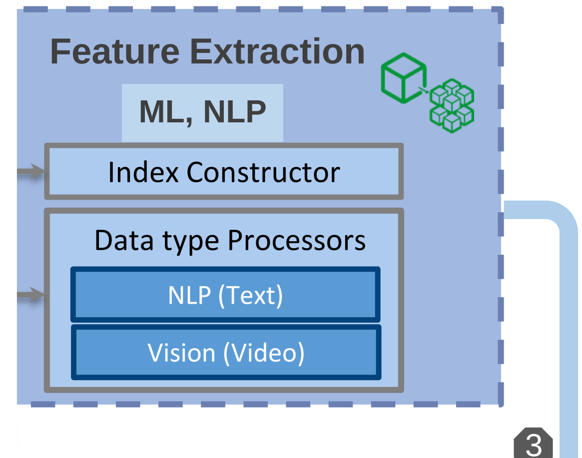
https://waymo.com/open/;
https://www.yelp.com/dataset

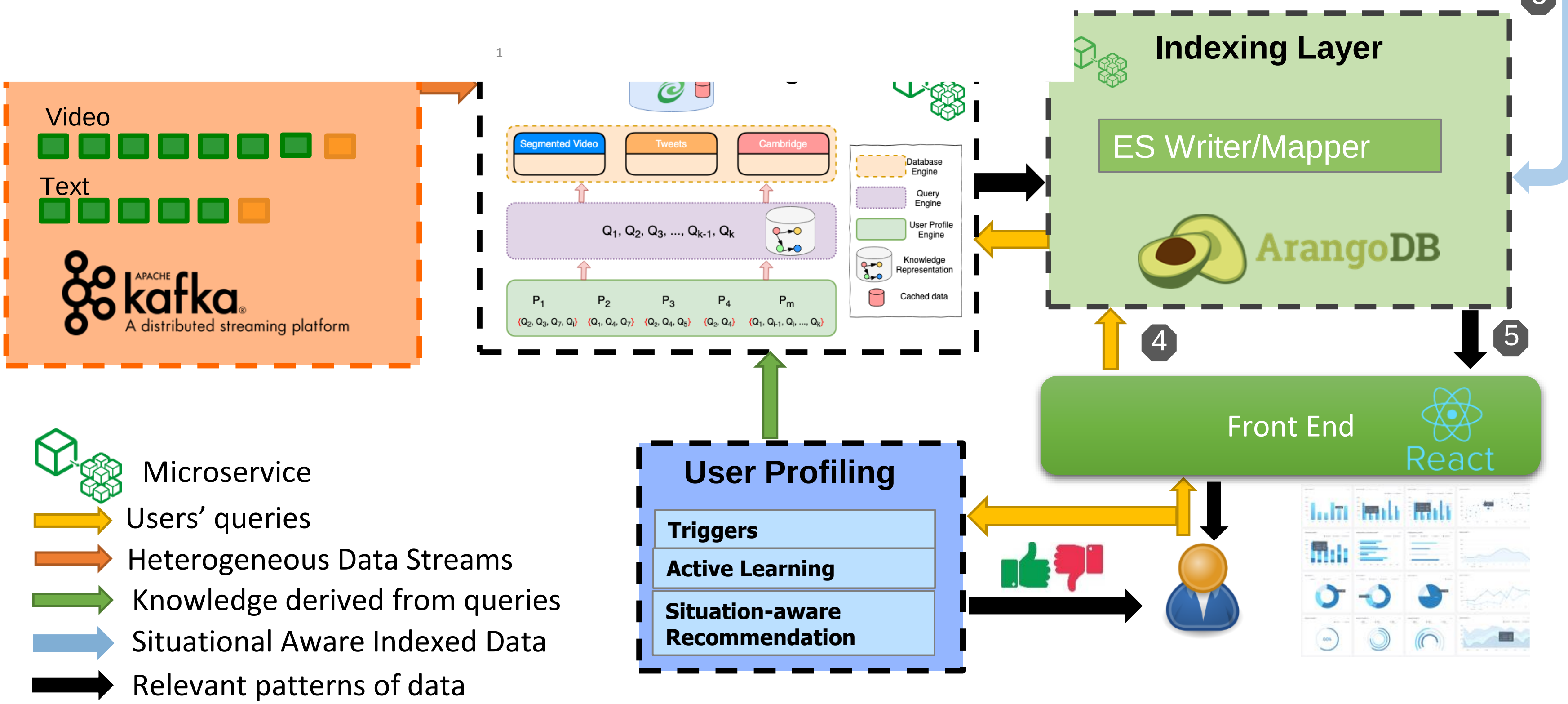
Demo Video

- Simplified Query

  Select * from tweets, videos where tweets.objects_discussed == "car" videos.objects_detected == "car"

- Demo Video URL
  - https://youtu.be/5TqWKzy5SqI





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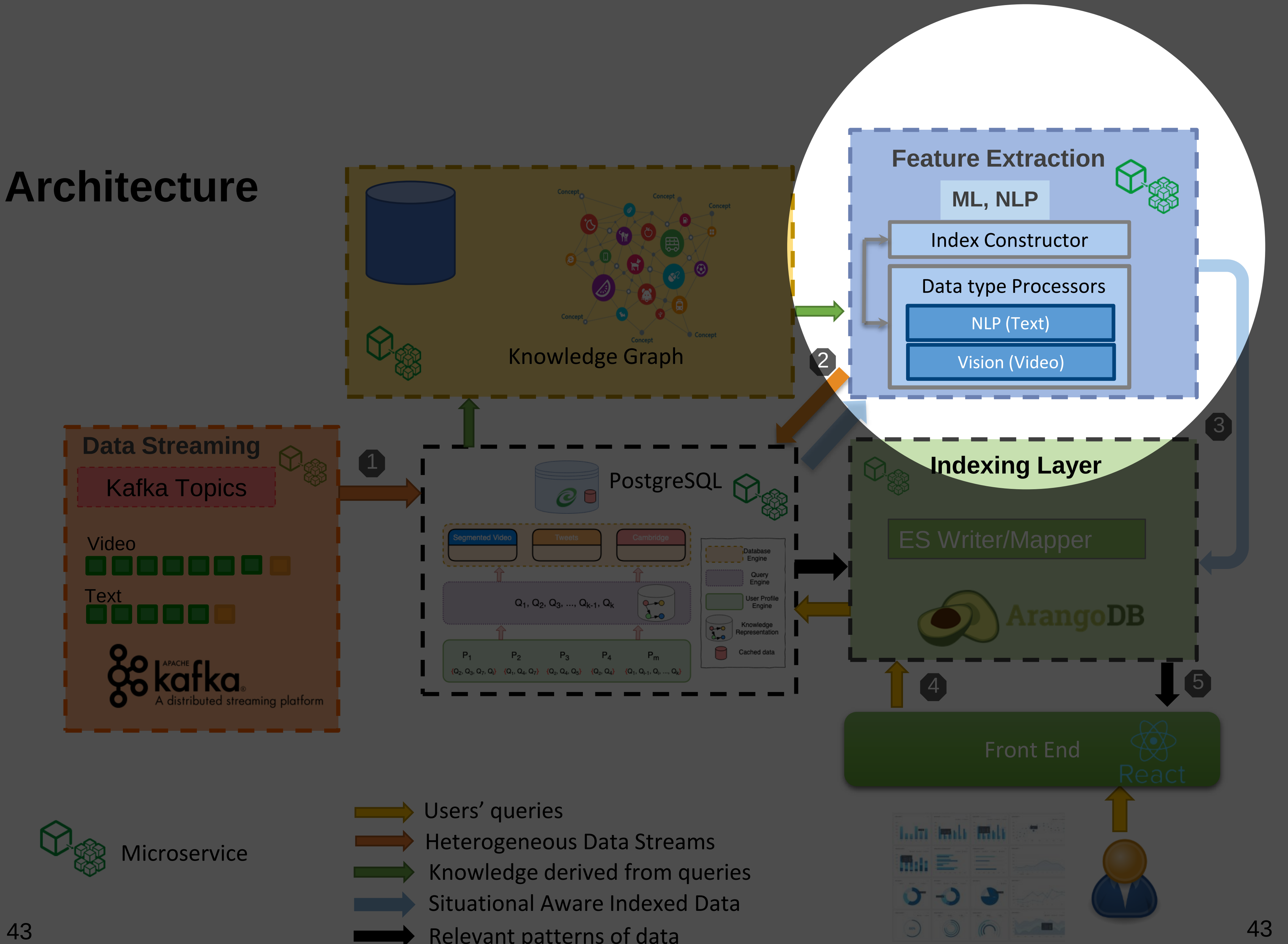
Demo Video

- Simplified Query

  Select * from tweets, videos where tweets.objects_discussed == "car" videos.objects_detected == "car”

- Demo Video URL
  - **https://youtu.be/5TqWKzy5SqI**

Architecture



Extracting Features from Video with Deep Learning

- Object detection and classification: best result achieved with deep learning architectures:
  - Faster RCNN
  - YOLO
  - SSD
- Manual annotation and labeling
  - Time-consuming and expensive for large datasets
  - Outsourced human labor can be employed (MTurk)
- We use *pre-trained* YOLO neural network to extract knowledge, detect and label objects in video
- Retrain YOLO with Transfer Learning for detecting classes outside of pretrained ones

CNN-ROI based Architecture For Object Detection and Classification

- YOLO detects 100+ classes
- Our raw video dataset contains about 15 of the objects from these classes
- YOLOv3 object detection algorithm
  1. Regions of interests (ROI) proposals are generated
  2. For each region, features are extracted and classified with Convolutional Neural Network
  3. Apply non-maximum suppression: all candidate regions where probability of certain object detection is not max are dismissed

YOLO (You Only Look Once) Architecture

1. The image is split into an *SxS* grid of cells.

2. Each grid predicts *B* bounding boxes with *C* class probabilities

- *SxSxBx5* outputs in total

3. Conditional class probabilities are predicted *Pr(Class(i)/Object):*

- *SxSxC* class probabilities
- *SxSx(B*5+C)* output tensor
- *S=7, B=2, C=20 => (7,7,30)*
- Train a CNN to predict (7,7,30) tensor

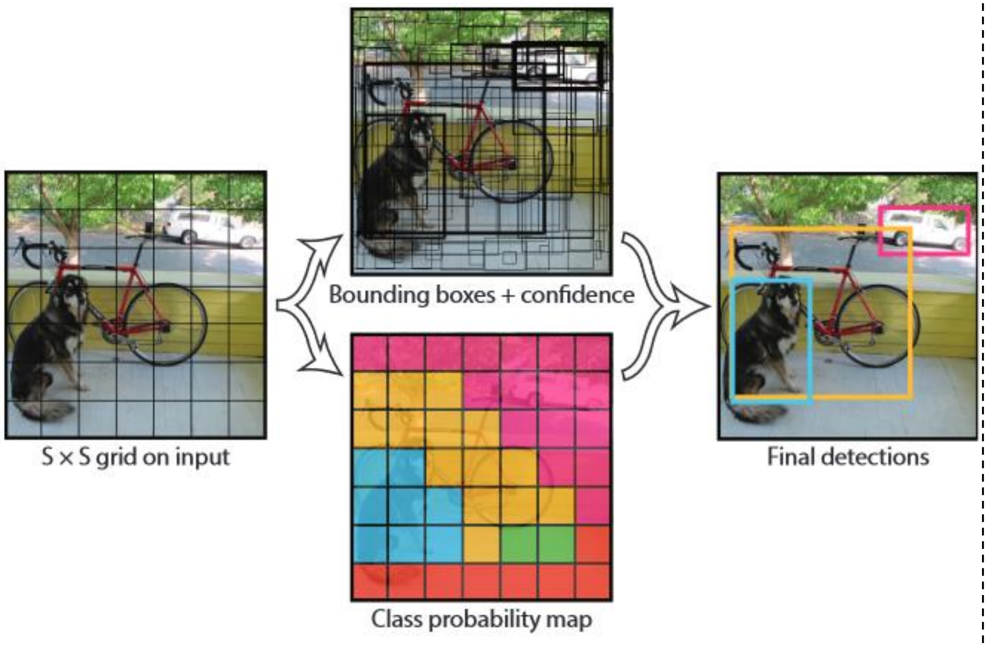


Image source: **You Only Look Once: Unified, Real-Time Object Detection**
Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi
https://arxiv.org/abs/1506.02640

YOLO (You Only Look Once) Architecture

Objective: fast object recognition and detection
Problem: CNN, R-CNN and modifications perform these tasks in multiple steps
Solution: YOLO determines the object location and classifies it in one go

- Optimal for streaming video
- Input image is divided into SxS grid
- Each grid cell predicts bounding boxes (B) and class probabilities (C)
- Bounding box coordinates and class probabilities are encoded in an ouput tensor predicted by YOLO
- Boxes with less than optimal confidence scores are omitted after training

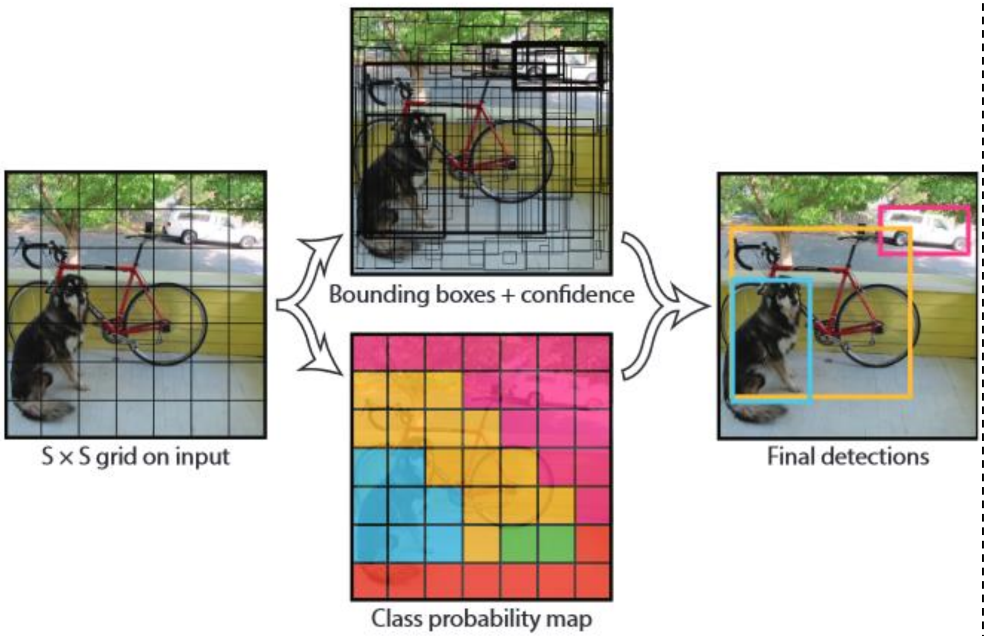


Image source: **You Only Look Once: Unified, Real-Time Object Detection**
Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi
https://arxiv.org/abs/1506.02640

Detected Classes In the MIT Video Dataset

CAR

TRUCK

PERSON

BICYCLE

TRAFFIC LIGHT

STOP SIGN

FIRE HYDRANT

PARKING METER

... AND MORE!

Preprocessing Tweets

- Social media text has jargon, misspellings, special slangs, emojis

15:45 I luv my <3 iphone & you’re awsm apple, love you 3XXX. DisplayIsAwesome, sooo happppppy □ 🙏 http://www.apple.com #apple @sjobs

- Cleaning process –
  - HTML decoding
  - Expanding Contractions
  - Removing URL, Emoji, Reserved words, Smiley, User-mentions (or replace), hashtags
- Preprocessing before tokenization
  - Remove punctuation, space, stop word

Additional tasks for Social Media Texts

- Normalization of Noisy Text
- Awsm ~ awesome, luv ~ love
- **Methodologies**
    1. Lexical normalization
    2. Normalization with edit scripts and recurrent neural embeddings
    3. Find balance between precision and recall

Topic Modeling with Tweets

- Given a **query keyword,** we want to find similar tweets
- We can do that by **finding latent topics** in tweets
- Approach 1:
  - Latent Semantic Analysis, or LSA

Initially, we only have documents with terms

Calculate the document-term Matrix, $tf_{i,j}$
- *Word count for each document*

d1: *Shipment of gold damaged in a fire.*
d2: *Delivery of silver arrived in a silver truck.*
d3: *Shipment of gold arrived in a truck.*

query: *gold silver truck*

Terms	d1	d2	d3	q
a	1	1	1	0
arrived	0	1	1	0
damaged	1	0	0	0
delivery	0	1	0	0
fire	1	0	0	0
gold	1	0	1	1
in	1	1	1	0
of	1	1	1	0
shipment	1	0	1	0
silver	0	2	0	1
truck	0	1	1	1

$tf_{i,j} =$ columns d1, d2, d3; $q =$ column q

Topic Modeling with Tweets

- Raw counts do not work well as they do not account for the *significance* of each word in the document
  - ***'a'*** has little significance in determining topic
- Instead calculates the tf-idf score, $w_{i,j}$
  - Takes the *number of documents the word appears* in into consideration

$$\underbrace{w_{i,j}}_{\text{tf-idf score}} = \overbrace{tf_{i,j}}^{\text{\# occurrences of term in document}} \times \log \frac{\overbrace{N}^{\text{\# total documents}}}{\underbrace{df_j}_{\text{\# documents containing word}}}$$

$$\begin{array}{ll} & \begin{array}{ccc} \text{d1} & \text{d2} & \text{d3} \end{array} \\ \begin{array}{l} \text{Terms} \\ \text{a} \\ \text{arrived} \\ \text{damaged} \end{array} & w_{i,j} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0.022 & 0.025 \\ 0.025 & 0 & 0 \end{bmatrix} \end{array}$$

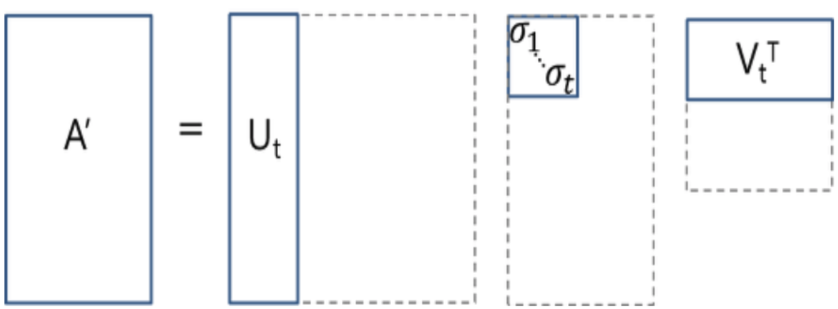
Effect of 'a' is diminished

Topic Modeling with Tweets

- Document-term matrix is very sparse
- So Dimensionality reduction is performed with SVD (Singular Value Decomposition)
- From *Document-term matrix,* A, we retrieve
  - ***Term-topic matrix, V***
  - *Document-topic matrix, U*
- Document is represented with *Term-topic matrix*

$$\mathbf{V} = \begin{bmatrix} -0.4945 & 0.6492 & -0.5780 \\ -0.6458 & -0.7194 & -0.2556 \\ -0.5817 & 0.2469 & 0.7750 \end{bmatrix}$$

$$A \approx U_t S_t V_t^T$$



Dimensionality = 2, instead of 3
Retains top 2 Approximation to represent the document

d1(-0.4945, 0.6492)
d2(-0.6458, -0.7194)
d3(-0.5817, 0.2469)

Topic Modeling with Tweets

- Finally, Apply **cosine similarity, sim(q, d)** to evaluate:
  - the similarity of terms (or "queries") and documents (we want to retrieve passages most relevant to our search query).

d1(-0.4945, 0.6492)
d2(-0.6458, -0.7194)
d3(-0.5817, 0.2469)

$$\mathbf{q} = \begin{bmatrix} -0.2140 & -0.1821 \end{bmatrix}$$

$$\text{sim}\ (q, d) = \frac{q\ .\ d}{|q||d|}$$

$$\text{sim}\ (q, d1) = -\ 0.0541$$

Topic Modeling for Ontologies (Generative Models)

- Even though LSA *finds* similar documents to user query, it has *less efficient* representation for topics.
- Topics are necessary for ontologies while building our knowledge graph
- LDA (Latent Dirichlet Allocation)
  - Generative Model
  - Uses Dirichlet priors for the document-topic and word-topic distributions
  - Results in better generalization for new documents
  - Allows online learning

Results: Similar Documents to Query

U_1 TREE DOWN SCOTT ST

Exact Key (93% Similar)

U_2 PERSON WITH GUN MASSACHUSETTS AVE

```
TREE DOWN SCOTT ST
----------------------------
28:05:55 Report of possible TREE DOWN at 0XX CRAIGIE ST in #CambMA -> 80.33392735150517
51:14:48 Report of possible TREE DOWN at 0XX CRESCENT ST in #CambMA -> 80.43760395651273
53:14:46 Report of possible TREE DOWN at SCOTT ST in #CambMA -> 93.48181521909666
84:18:43 Report of possible TREE DOWN at 0XX LINNAEAN ST in #CambMA -> 81.94027919855219
104:16:09 Report of possible TREE DOWN at KINNAIRD ST &amp; PUTNAM AVE in #CambMA -> 81.26159970959526
174:13:03 Report of possible TREE DOWN at 0XX WENDELL ST in #CambMA -> 79.93348053213126
290:10:39 Report of possible TREE DOWN at 0XX KINNAIRD ST in #CambMA -> 80.9560343546094
293:17:53 Report of possible TREE DOWN at FULKERSON ST &amp; OTIS ST in #CambMA -> 90.27117084780267
398:12:17 Report of possible TREE DOWN at BERKSHIRE ST &amp; MARCELLA ST in #CambMA -> 90.90895098601791
632:14:59 Report of possible TREE DOWN at 0XX HUTCHINSON ST in #CambMA -> 80.16759137585555
688:20:19 Report of possible TREE DOWN at BROOKLINE ST in #CambMA -> 88.74709924118638
760:17:08 Report of possible TREE DOWN at BROOKLINE ST &amp; VALENTINE ST in #CambMA -> 87.41238933159734
874:10:53 Report of possible TREE DOWN at 1XX BERKSHIRE ST in #CambMA -> 73.70560751937646
879:06:09 Report of possible TREE DOWN at 1XX ERIE ST in #CambMA -> 71.49190705032849
880:05:18 Report of possible TREE DOWN at 1XX CHESTNUT ST in #CambMA -> 73.15716612728002
912:15:37 Report of possible TREE DOWN at 0XX HEWS ST in #CambMA -> 80.54769954714662
```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Results: Similar Documents to Query

U_1 TREE DOWN SCOTT ST

Relevant Key (70% Similar)

U_2 PERSON WITH GUN MASSACHUSETTS AVE

```
PERSON WITH GUN MASSACHUSETTS AVE
---------------------------
175:03:07 Report of possible PERSON WITH GUN at 0XX ELIOT ST in #CambMA -> 70.65900536372457
184:Of the two, which is the BB gun? -> 76.7625005125442
224:10:16 Report of possible PERSON WITH GUN at 0XX MAGEE ST in #CambMA -> 71.83745409092073
326:23:04 Report of possible PERSON WITH GUN at 12XX MASSACHUSETTS AVE in #CambMA -> 77.88045951165084
486:@gregkatsoulis With BB guns, you’re right. It can be very difficult to discern in the moment. -> 72.982386068711
620:14:04 Report of possible PERSON WITH GUN at 7XX MASSACHUSETTS AVE in #CambMA -> 83.8386908577769
1073:21:15 Report of possible PERSON WITH GUN at 6XX MASSACHUSETTS AVE in #CambMA -> 85.54233801238702
1105:Note: This was re-classified as a disturbed person report. -> 73.54972555849851
1476:13:25 Report of possible PERSON WITH GUN at 0XX SECKEL ST in #CambMA -> 72.11858946801688
1656:15:16 Report of possible PERSON WITH GUN at 0XX WINTER ST in #CambMA -> 71.14850387777787
2043:17:55 Report of possible PERSON WITH GUN at 2XX WESTERN AVE in #CambMA -> 73.5108387242192
2280:09:08 Report of possible PERSON WITH GUN at RINDGE AVE in #CambMA -> 74.68636367888818
2353:19:00 Report of possible PERSON WITH GUN at 0XX LANCASTER ST in #CambMA -> 71.77698819586664
2451:15:44 Report of possible PERSON WITH GUN at CHAUNCY ST &amp; MASSACHUSETTS AVE in #CambMA -> 92.78417190981489
```


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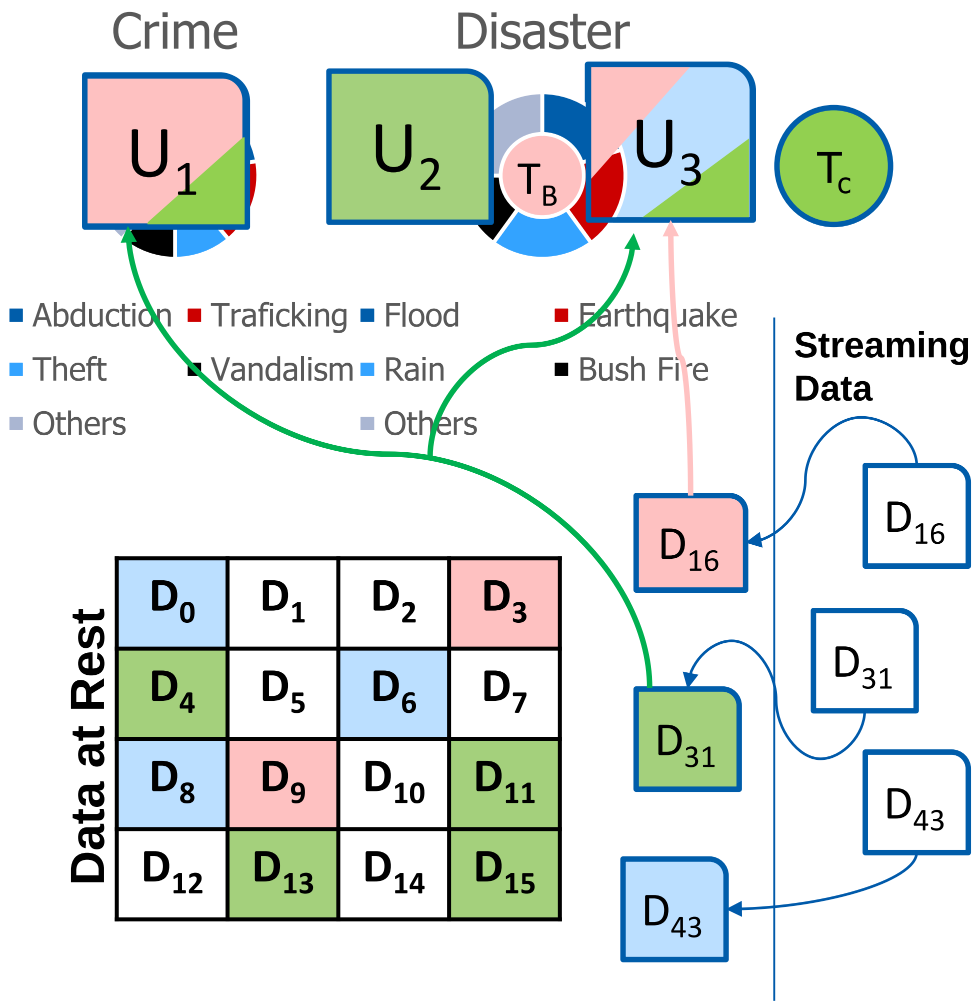
Topic Modeling for Ontologies (Generative Models)

- Even though LSA *finds* similar documents to user query, it has *less efficient* representation for topics.
- Topics are necessary for ontologies while building our knowledge graph
- LDA (Latent Dirichlet Allocation)
  - Generative Model
  - Uses Dirichlet priors for the document-topic and word-topic distributions
  - Results in better generalization for new documents
  - Allows online learning

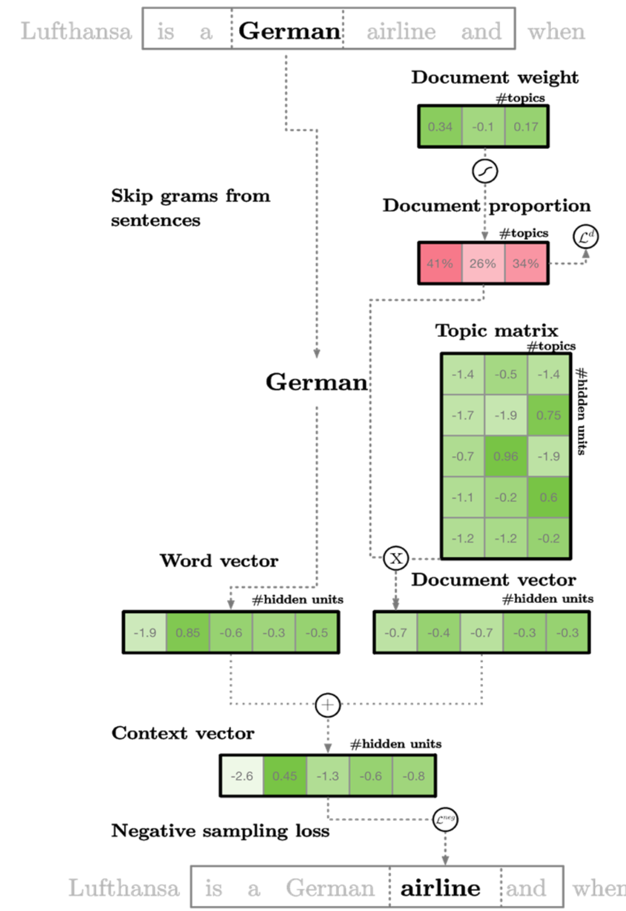
Multiple Data of Interest to Different Users

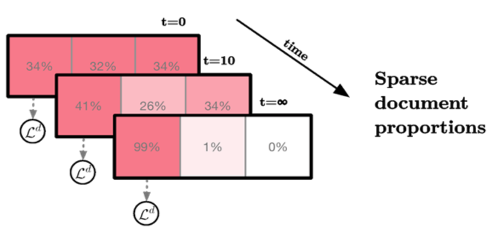
- Extract human-interpretable topics from a document corpus
- Each topic characterized by words most strongly associated with
- Documents as mixtures of topics that spit out words with certain probabilities.
- Uses variational Bayes for inference, no need to re-train



Further Extension

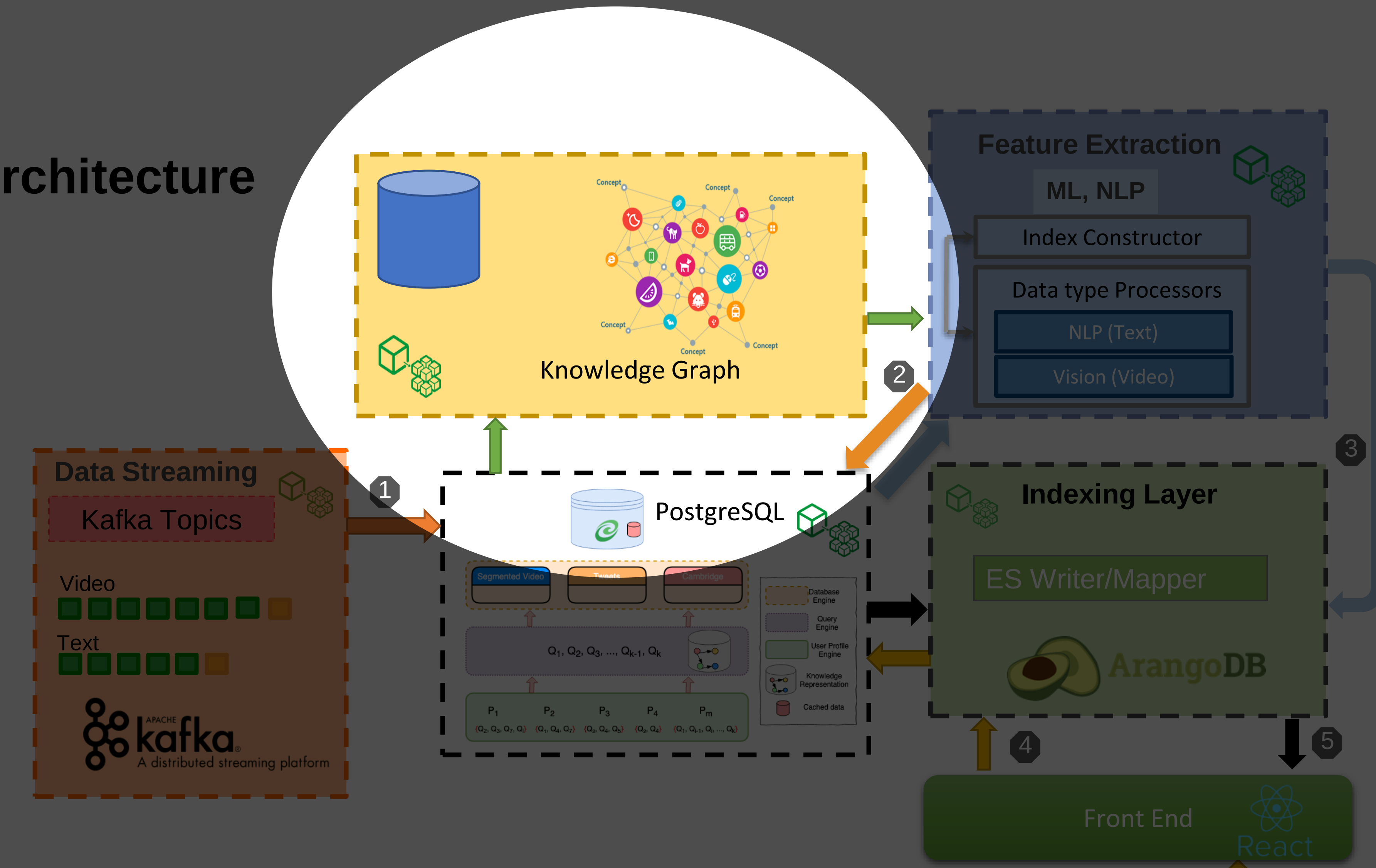
- **Twitter** data has **metadata**
- Metadata bears a lot of information
- **Metadata can be used as context**
- Lda2Vec leverages a context vector to make topic predictions
- We will adapt lda2vec
- Context they used : sum of the word vector and the document vector





https://multithreaded.stitchfix.com/blog/2016/05/27/lda2vec/

Architecture



Microservice

Users' queries
Heterogeneous Data Streams
Knowledge derived from queries
Situational Aware Indexed Data
Relevant patterns of data

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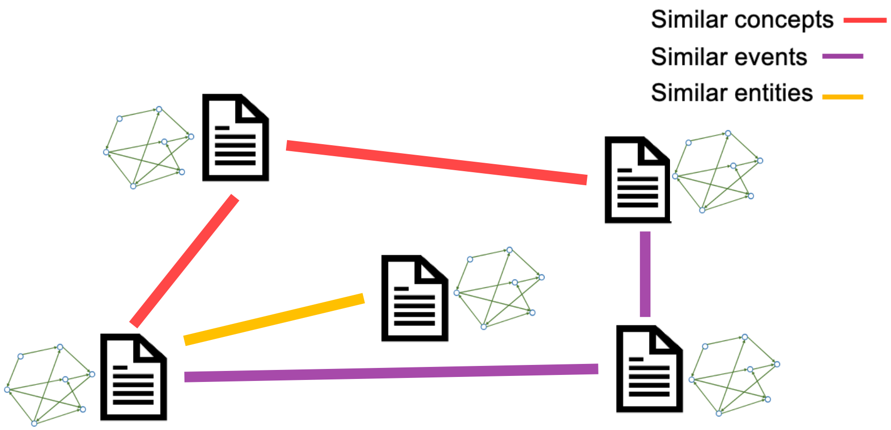
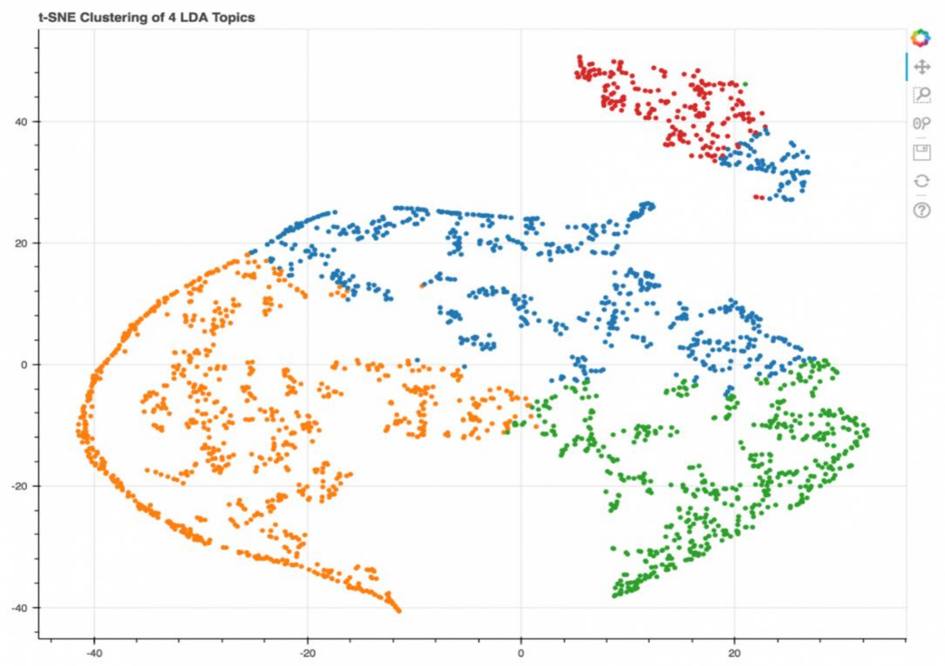
Knowledge Graph (Need to learn from ISI research)

- Ontologies / Concepts are extracted from LDA
- Extract Triplets <Subject, Relation, Object> to represent Events
- Entities are represented by Nodes
- Entities have Attributes (Labels)
- Entities are connected by Relations (Edges)

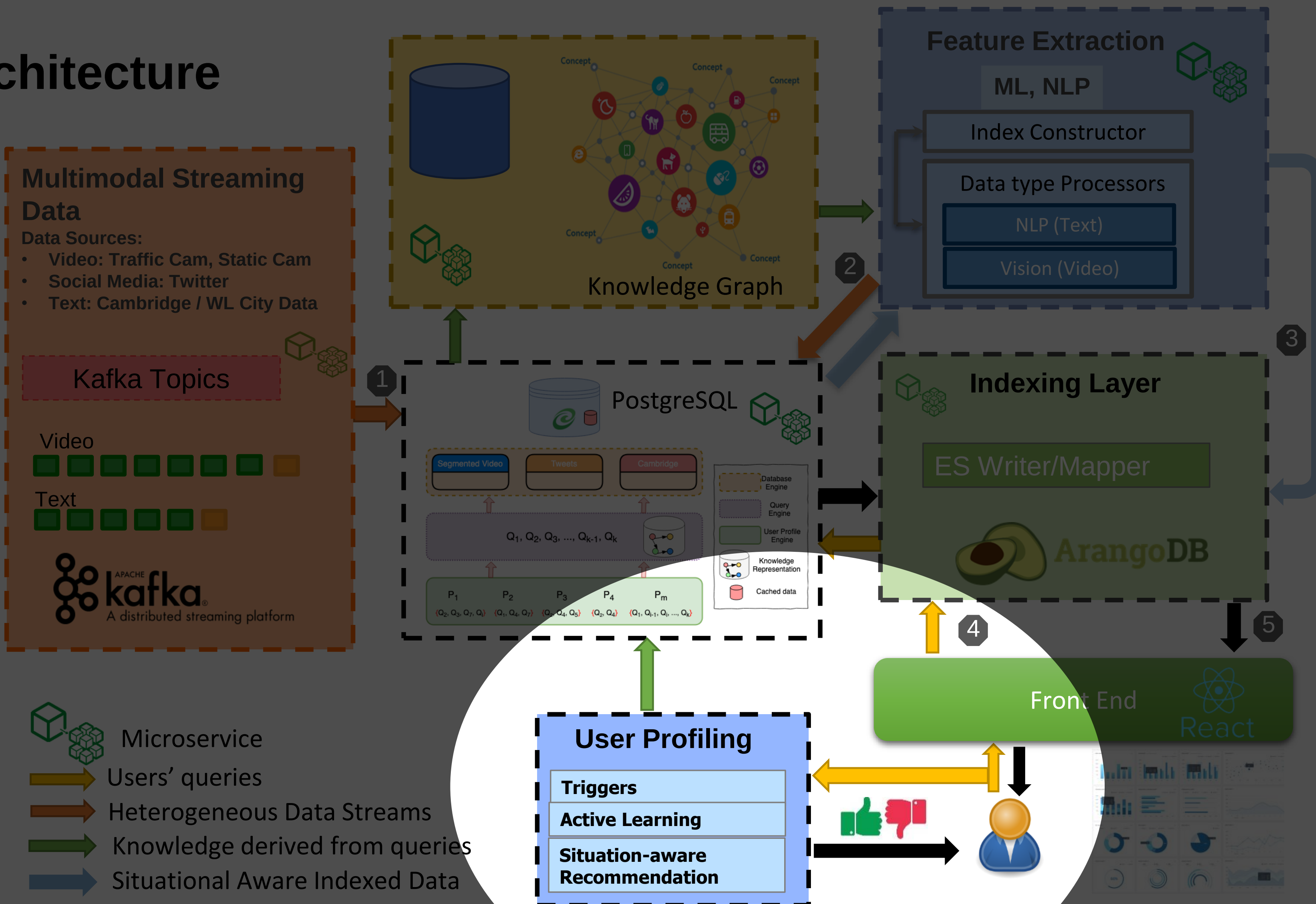
WIP with KG: Multi-modality

- ❖ Multi-modal Information Retrieval
- ❖ Poster represented In Northrop Grumman University Research Student Poster Competition





Architecture



Microservice
Users' queries
Heterogeneous Data Streams
Knowledge derived from queries
Situational Aware Indexed Data
Relevant patterns of data

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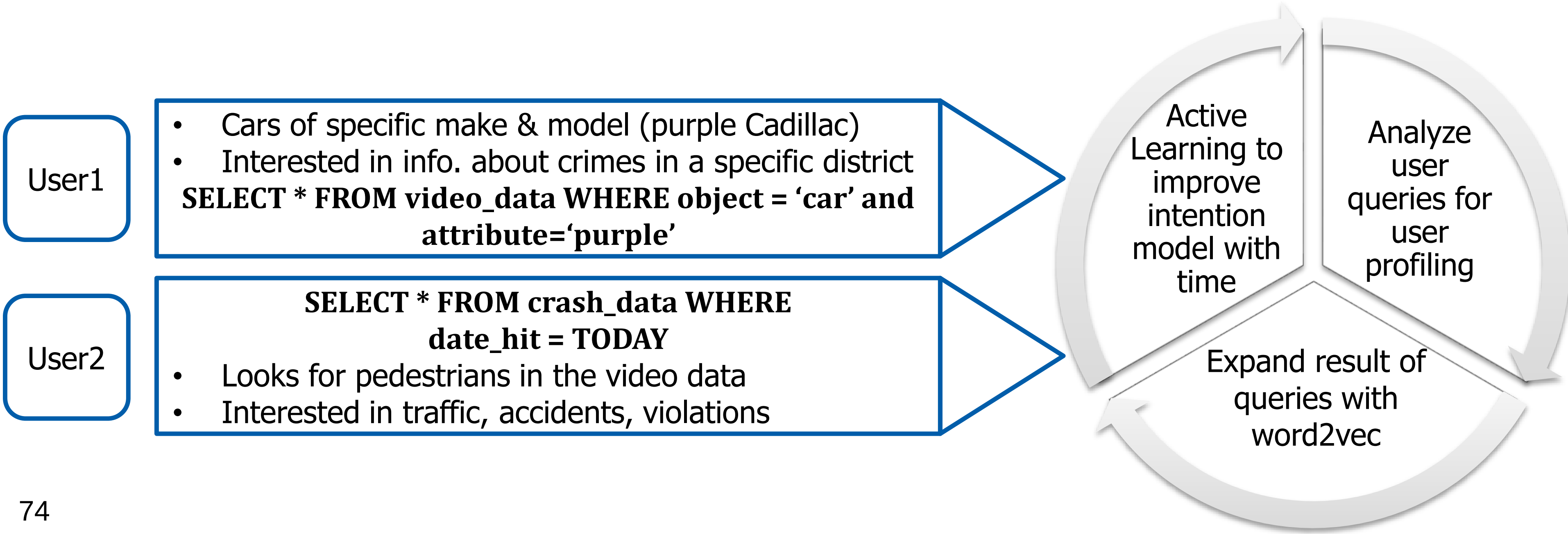
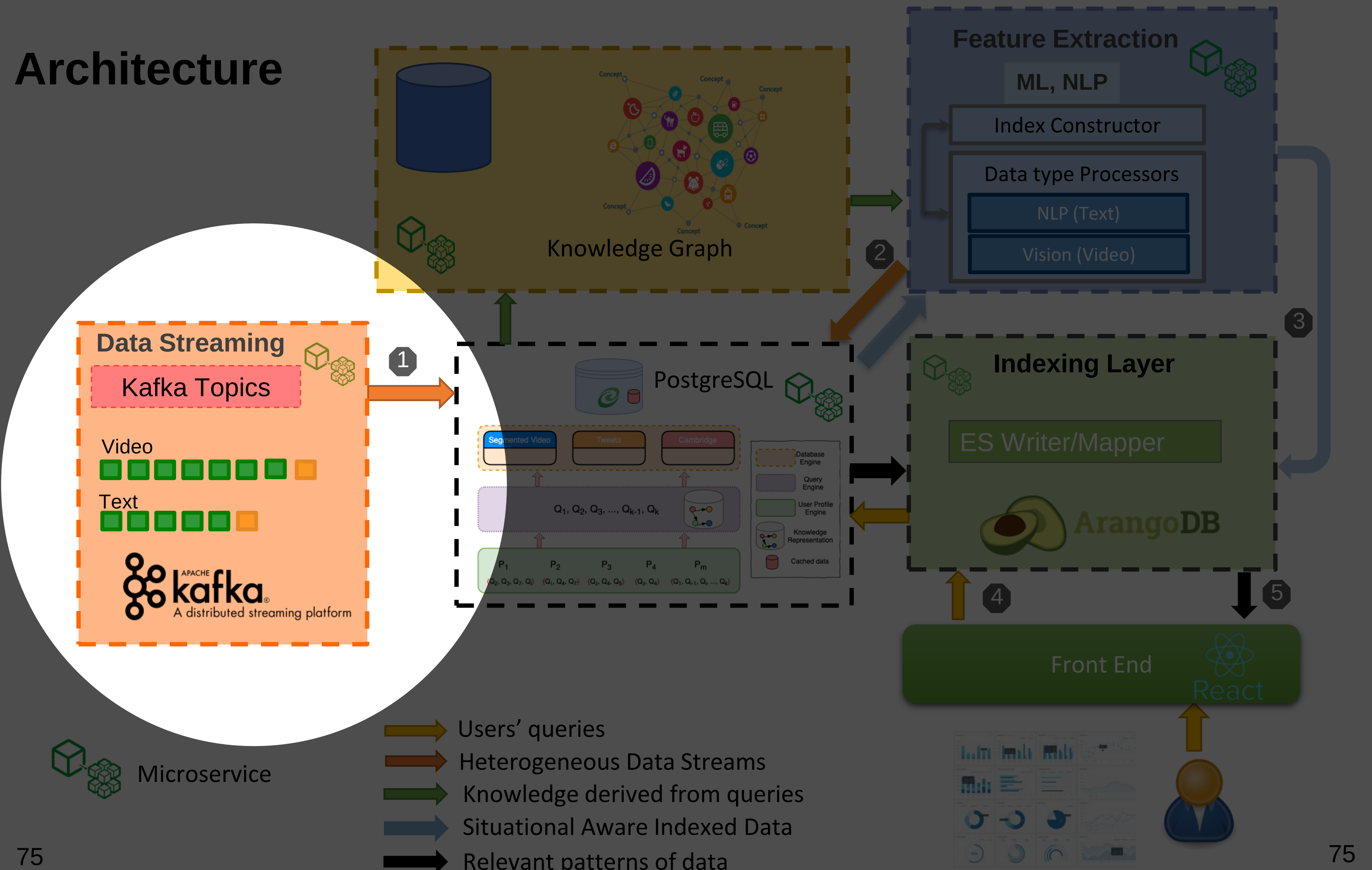
User Modeling: Intention-aware Recommendation Engine

- Sends users streaming data that corresponds to their interests
- Builds User Profiles using the history of user queries
- Active Learning to narrow/expand intention model with more interaction
- Expands user queries with word embedding models to fetch relevant data from the database



Architecture



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Data Streaming Module

- Retrieve RESTFUL and Streaming Tweets
- Populate Postgres with all data
- *Parse collected metadata* to extract targeted information and *store in Postgres*
- Replicable, fault tolerant, scalable and continuous
- Build a Data Processing Pipeline with all features

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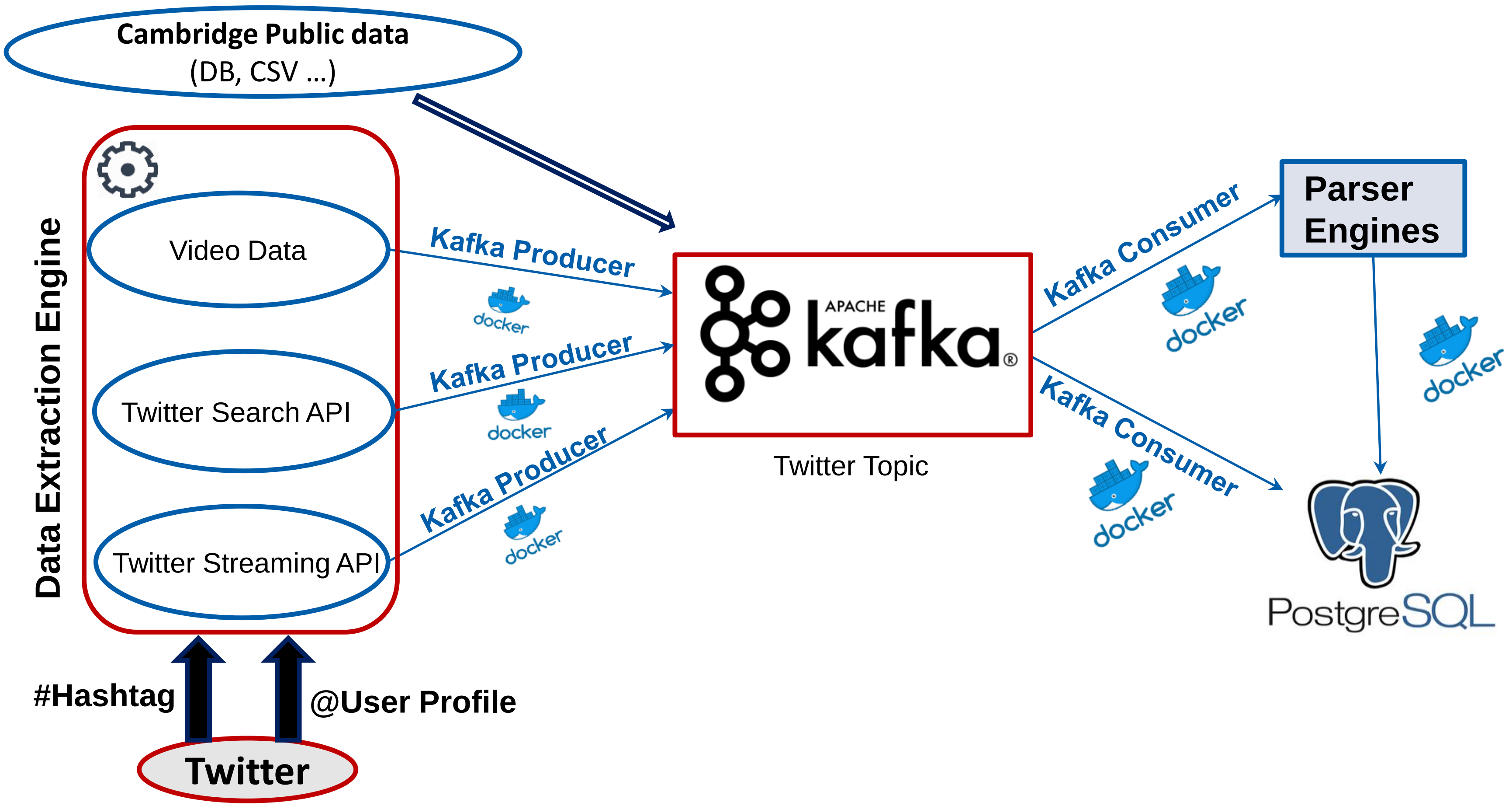
Data Processing Pipeline



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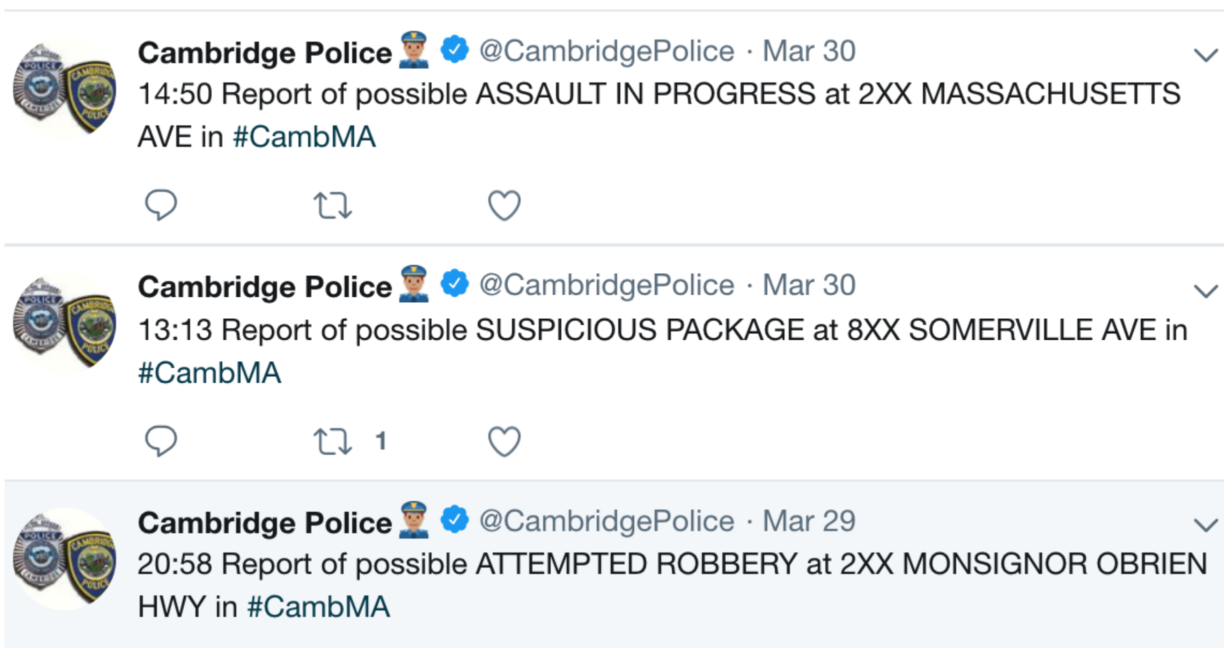
Retrieve Tweets : Implementation Choices

- Search tweets by
  - **Keyword / Hashtag** (i.e, CambMA)
  - **User Timeline** (i.e, CambridgePolice)



Compatibility with other sources of data

- Add new sources
  - JDBC
  - From file
  - Audio
- Kafka Connect provides a framework (extra layer between source and Kafka) to develop connectors importing data from various sources and exporting it to multiple targets
- Kafka Clients allow us to pass and retrieve messages directly to and from Kafka

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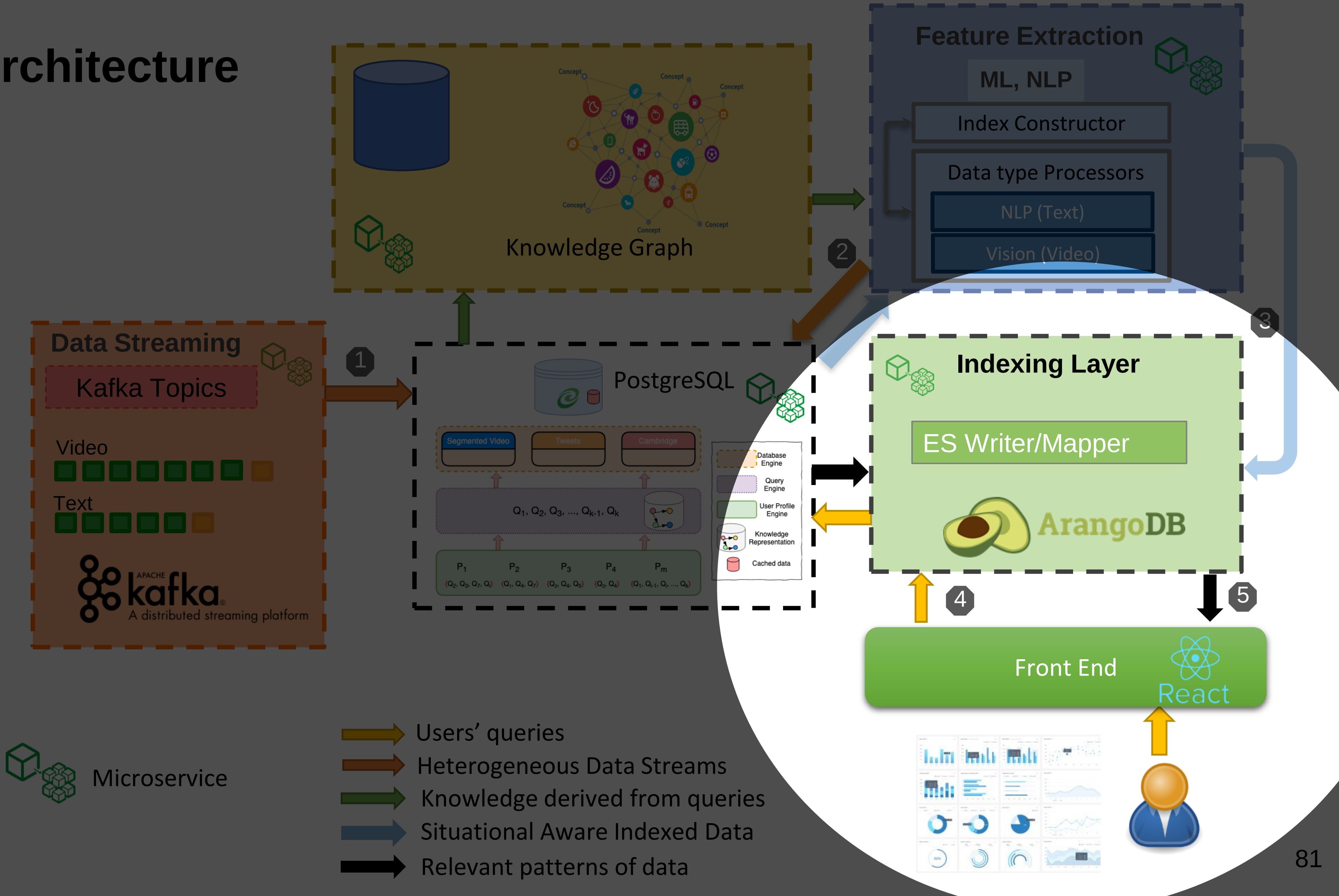
Architecture



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Representing Knowledge

- Build a tree for each index which point to the corresponding frames in Videos
  - Car, Person, Bicycle, Traffic light
- Build a tree for each index which point to the corresponding mentions in Tweets
  - Car, Person, Bicycle, Traffic light
- User Profiling: Built based on similar types of information
- Build triggers in Postgres
  - Data comes in with similar index
  - Deliver to User
- Model all our indices in GraphDB (ArangoDB)

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SKOD Web Framework

- Extract data from Heterogeneous Sources and expose data via Apache Kafka Topics
- Consume data from Kafka Microservice and populate the RDBMS and the Index Layer (Elasticsearch and *Graph Database)*
- Utilizing geolocation to visualize real-time streams on Leaflet map
- Analyze data relationships through graph analytics (clustering)

We utilize the OADA/Trellis framework to build the PoC of the Web App.

SKOD Framework Features

- Open source @
- Distributed Compute Engine (Apache Spark GraphX) and Motif analysis
- ArangoDB Graph Database
- Multiple layers of Cache (PouchDB)@
- Eventual Consistent
- Easy to setup (using Docker containers)
- React based Analytics Web-UI

kafka

Trellis

React

JS

docker

JWT

@ https://github.com/purdue-gask/skod/

@ https://github.com/OADA/oada-cache

Deliverables

- Microservices for all modules
- Source Codes

https://github.com/purdue-gask
https://github.com/OADA

Demo Video

- In the demo video, we demonstrate as follows.
  - How twitter data is consumed and processed via Data Streaming Module
  - Extracting objects from Videos
  - Extracts the tweets that discusses about *Object in Question*
  - Tie features from different modality using the Indexing Layer
    - Build Index on the objects from videos and tweets
  - Functionality of the Front End with Graph Analytics
  - User Profiling extracts other objects that can be of users' interest
  - Allows user to see those objects from all modalities


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OATS
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Demo Video

- Simplified Query

  Select * from tweets, videos where tweets.objects_discussed == "car" videos.objects_detected == "car”

- Demo Video URL
  - **https://youtu.be/5TqWKzy5SqI**

Serving the Community

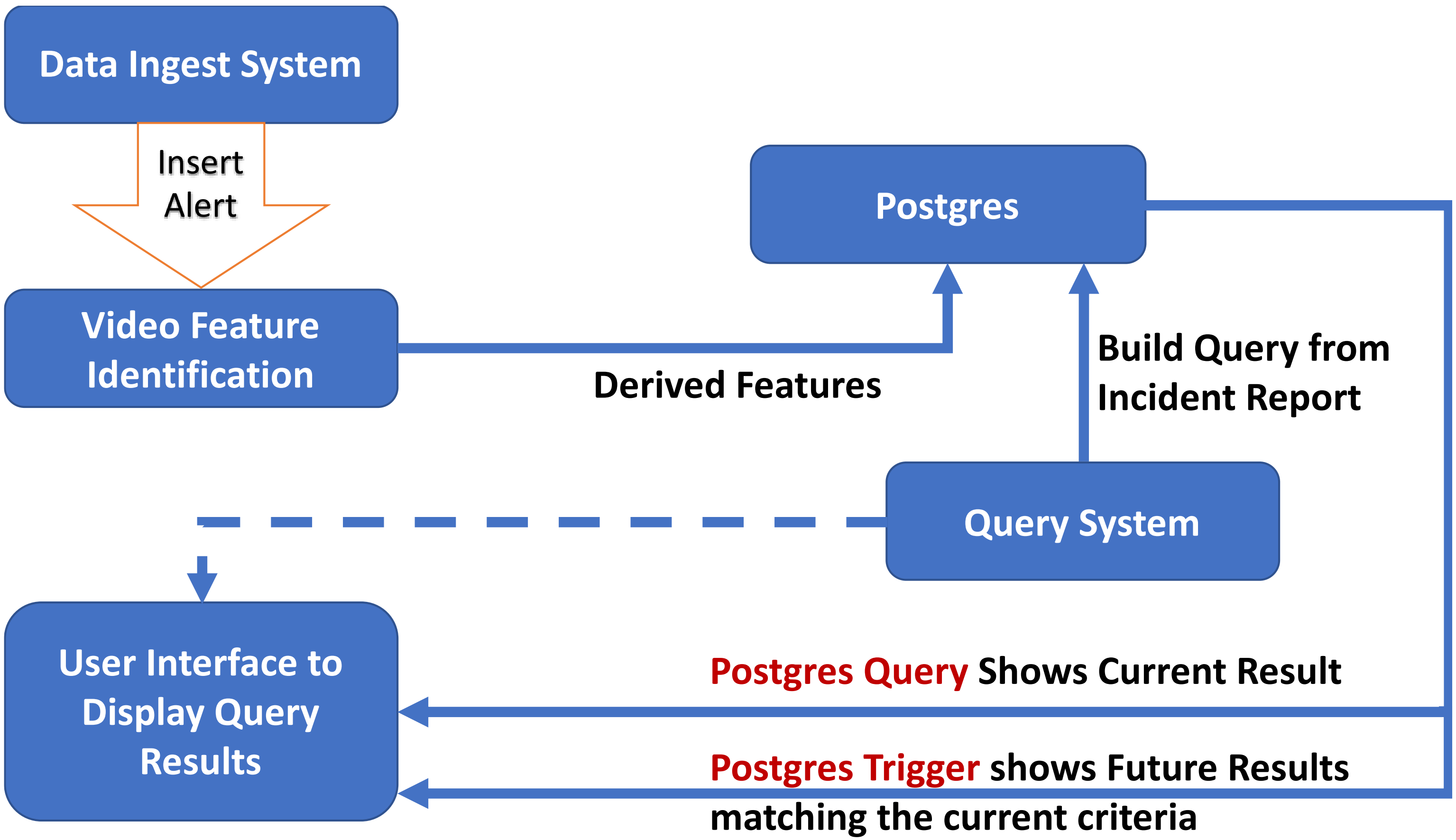
- **Collaboration with West Lafayette Police Department**

- **Another Novel Use-Case**
- **Extending SKOD Framework**
- **Digs Deeper into Features, Knowledge Base and User Profiling**

Problem Definition

Extract targeted search results from heterogeneous data (i.e., video, police dispatch reports, social media) at rest and deliver relevant information from incoming data streams based on context awareness.

Solution Framework



Police Dispatch Report

Communications

Event Report

Event ID: **2019-249942**	Call Ref #: 351	Date/Time Received: 11/02/19 03:13:41
Rpt #: 2019-004262	Prime Unit: 118 GOODMAN, KYLE T	Services Involved
Call Source: W911		LAW
Location: **108 S RIVER RD**		DIST: 175.08 ft
X-ST: *E STATE ST*	Jur: TCPD	Service: LAW Agency: WLPD
E WOOD ST	St/Beat: WLD1	District: RA:
Business: RIVER MARKET APARTMENTS	Phone: (765) 743-9207	GP:
Nature: **ROBBERY**	Alarm Lvl: 0 Priority: P	Medical Priority:
Reclassified Nature:		
Caller: GONG, JIMMY		Alarm:
Addr[redacted]	Phone[redacted]	Alarm Type:
Vehicle #: 595TQF St: IN	Report Only: No	Race: Sex: Age:
Call Taker: BMJENKS	Console: WLPD2CAD	
Geo-Verified Addr.: Yes Nature Summary Code: LAW	Disposition: REPT	Close Comments:
Notes:		

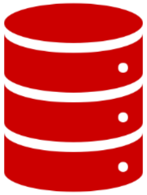
See Event Notes Addendum at end of this report

{106} whte male, dark blue hoodie, glasses, jeans skinny build, possibly 5ft 7in, last seen s/b [11/02/19 03:26:08 PKUMPF]
{11} req ping [11/02/19 03:23:21 BMJENKS]
LPD notified [11/02/19 03:21:42 BMJENKS]
{9} req LPD check cameras for last 10 mins for susp going across pedestrian bridge [11/02/19 03:20:36 BMJENKS
Event spawned for PUPD Event ID:2019249952, CallRef:361 [11/02/19 03:19:32 PKUMPF]
{116} with the victim [11/02/19 03:19:03 PKUMPF]
victim standing by inside building for river market apts [11/02/19 03:17:48 BMJENKS]
took victimes phone, number: [redacted] and wallet and car keys [11/02/19 03:17:16 BMJENKS]
w/m wearing blue/grey hoodie, short hair, with glasses, displayed black handgun [11/02/19 03:16:00 BMJENKS]

Incident Report to Features

Identified 31 Features after interviewing Sargent Green

Describing Suspect Attributes



Incident Querying System

- Includes UI for entering police query for fetching related information
  - [ ] Videos,
  - [ ] Similar Incident Reports, and
  - [ ] Social Information
- Functions as a data collection module

Incident Report to Search Results

- ❑ Inquired features are input into **Incident Report** table in Postgres
- ❑ From these features, system builds
  - **Postgres Query:** For fetching **existing videos and reports** matching the criteria
  - **Postgres Trigger:** Created for fetching **incoming videos and incidents** which will match the criteria

Welcome to the REALM Incident Querying System, Officer!

Please fill in the below form with descriptive attributes of the suspect and click the submit button to retrieve matching results.

Gender:	**Race:**	**Height:**
Female Male Other	White Black Hispanic Asian Other	Tall Medium Short

Wearing	Jeans Color: red Light Dark	Pants Color: red Light Dark	Shorts Color: red Light Dark	T-shirt Color: red Light Dark	Jacket Color: red Light Dark
	Baseball Hat Color: red Light Dark	Sandals Color: red Light Dark	Shoes Color: red Light Dark	Boots Color: red Light Dark	

Hair Color: Black Brown Blonde Ginger	**Tattoos:** Yes No	**Backpack:** Yes No	**Headphones:** Yes No	**Smoking:** Yes No
Posture: Walking Running	**Vehicle:** Bicycle Truck Passenger Car Motorcycle Skateboard	**Facial Hair:** Beard Goatee Mustache	**Hair Length:** Long Short Bald	**Build:** Skinny Fat Medium

Address:

Incident date: (e.g. 12/28/2019)

Incident time: (e.g. 13:10)

Feature Extraction from Incident Report

- Parsing Incident Report for automatic extraction of Features
  - Beneficial for creating Postgres Triggers to identify **similarity of incoming incidents** to previous queries
- **Approach 1:** Build Regular expressions to filter out features and feature values. Assumptions -
  - Reports are highly regular
  - Report follows grammar and is correctly structured

Feature Extraction from Incident Report

Approach 2: Build separate classifiers for each features separately and build an ensemble of classifiers

Find related sentences that mentions selected features

- Latent Semantic Analysis (LSI)

Classifiers based on each features separately

- **SVM**, DTL

Improve upon basic BoW features with

- Embeddings
  - BERT[2], Glove[1]
- PoS, Feature Names

Gender:

- **What is the gender of the suspect?**
- What is the sex of the suspect?
- Is the suspect male or female?

Race:

- What is the race of the suspect?
- What is the ethnic background of the suspect?
- **What is the ethnicity of the suspect?**

A crime **XYZ1 (theft or something)** occured today at time **XYZ2.** Officer **XYZ3** was at the scene of the crime by **XYZ4 (time)** at **ADDRESS.**
Suspect **XYZ5 (name, if known)** is a **XYZ6 (Relative Height) XYZ7(race) XYZ8(Gender)** (example-tall white male). The suspect has **BROWN/BLACK/BLONDE HAIR OR BALD** along with a **FACIAL HAIR (if applicable)** and is in his/her **RELATIVE_AGE** and has a **BUILD (skinny/fat/medium)** build. The suspect roughly weighs **XYZ** lbs/kgs and was last seen wearing a **XYZ9(jeans)/ABC0(pants)/ABC1(shorts)** and a **ABC2(T-SHIRT)/ABC3(JACKET)** with a **ABC4(BASEBALL HAT).** The suspect had **COLOR SANDALS/SHOES/BOOTS** on.

Approach 3: Formulate as **Reading Comprehension** Problem

Feature Extraction from Incident Report

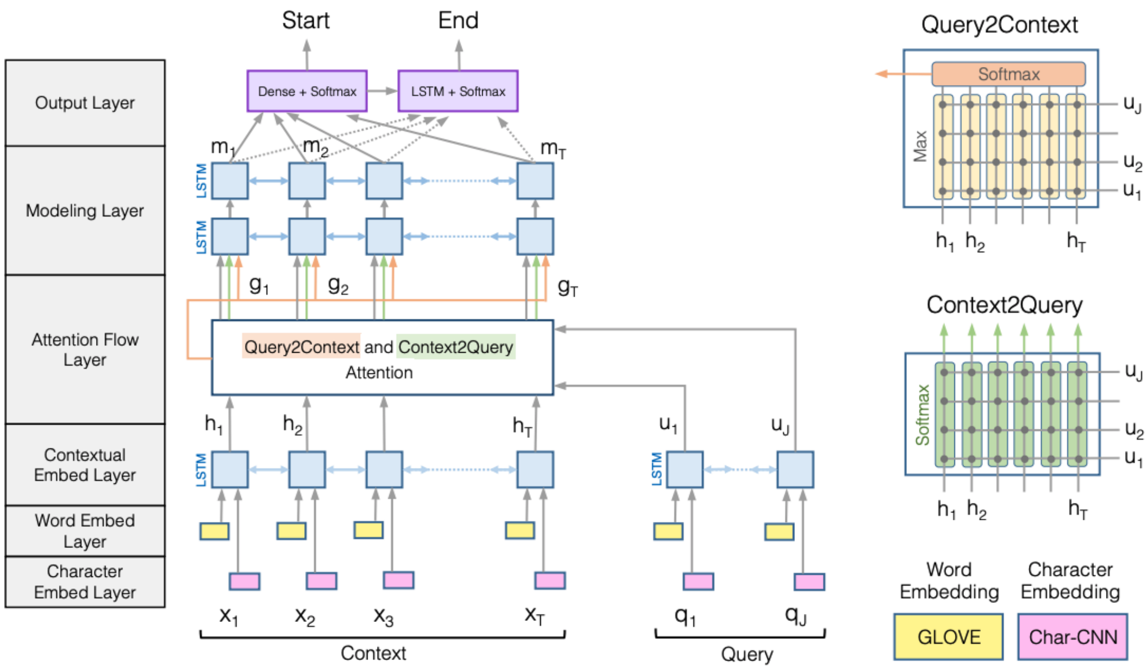
Formulate Questions based on the selected features

Formulate a fixed structure for the incident report

Result: As Machine Comprehension

```
Enter the report: A theft of a sign occurred today. Officer Leuck was dispatched to the scene of the crime at 110 Andrew pl. The suspect is a caucasian male and is in his 20s and has a skinny build. The suspect was seen wearing jeans and also wearing a white T-shirt under a jacket. He had a dark-colored hat on his head turned backward.
```

```
Suspect Attributes

Gender:caucasian male
Race:caucasian male
Height:caucasian male
Wearing:The suspect was seen wearing jeans and also wearing a white T-shirt under a jacket
Hair Color:caucasian male
Vehicle:jeans and also wearing a white T-shirt under a jacket
Build:skinny
```



Bi-Directional Attention Flow Model *

- **SQuAD** : Dataset on a large set of Wikipedia articles
- More than 100,000 questions
- Answer to each question is always a span in the context
- API from AllenNLP [5]
- PyTorch [4]

* Seo M et al (2017) Bidirectional Attention Flow for Machine Comprehension, in ICLR 2017 [3].

Approach 3

Challenges:

- Span as an answer
- Does not recognize multiple feature mentions

Modifications to the model

(To be worked on)

- Binary answer

  Is suspect wearing Jeans?

- Find each iterations of the answer

Feature Identification from Videos

Color Segmentation

Jeans/Pants, Shoe, Hat, Shirt/Jacket, Hair Color

DNN classifier trained for custom classes

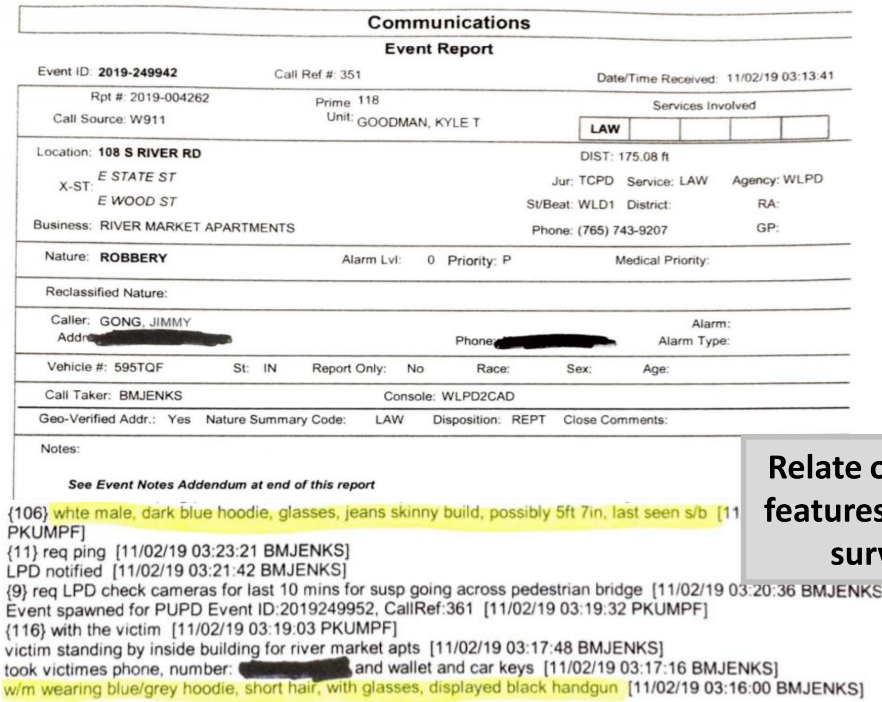
Male/Female

Action Recognition

Walking/
Running/
In Pursuit

Search for Suspect in the Video

- Matching the features extracted from text with features extracted from



Communications

Event Report

Event ID: **2019-249942** Call Ref #: 351 Date/Time Received: 11/02/19 03:13:41

Rpt #: 2019-004262 Prime Unit: 118 GOODMAN, KYLE T Services Involved: LAW

Call Source: W911

Location: **108 S RIVER RD** DIST: 175.08 ft

X-ST: *E STATE ST* / *E WOOD ST* Jur: TCPD Service: LAW Agency: WLPD

St/Beat: WLD1 District: RA:

Business: RIVER MARKET APARTMENTS Phone: (765) 743-9207 GP:

Nature: **ROBBERY** Alarm Lvl: 0 Priority: P Medical Priority:

Reclassified Nature:

Caller: GONG, JIMMY Alarm:

Addr[redacted] Phone[redacted] Alarm Type:

Vehicle #: 595TQF St: IN Report Only: No Race: Sex: Age:

Call Taker: BMJENKS Console: WLPD2CAD

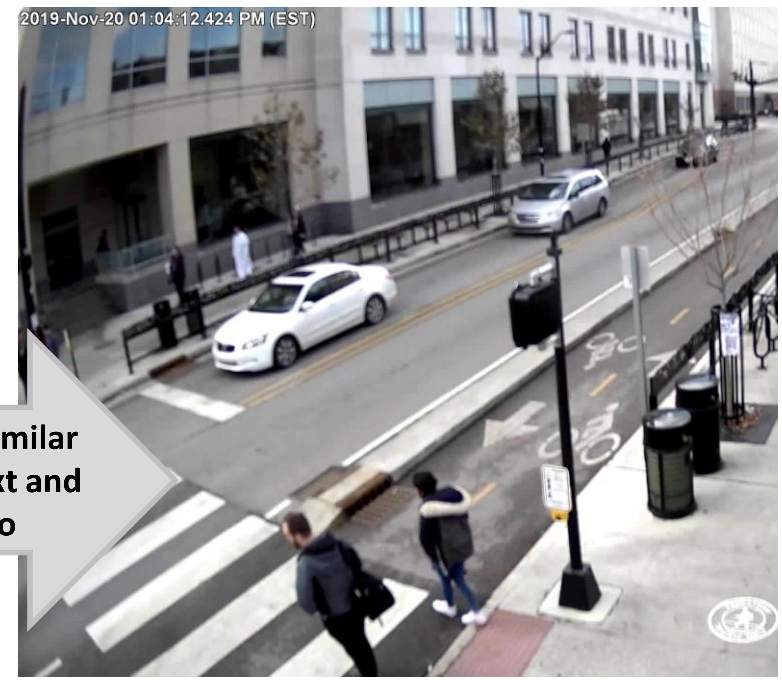
Geo-Verified Addr.: Yes Nature Summary Code: LAW Disposition: REPT Close Comments:

Notes:

See Event Notes Addendum at end of this report

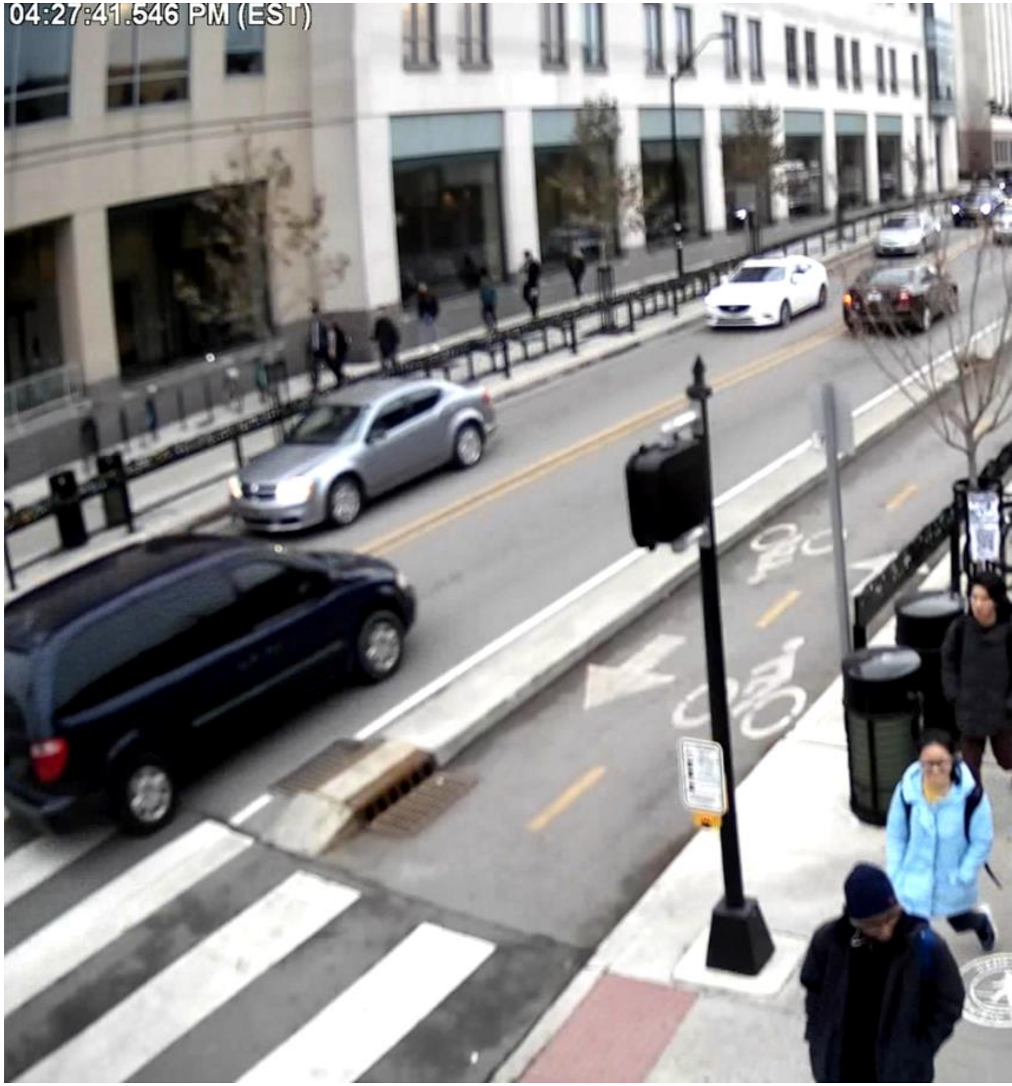
{106} whte male, dark blue hoodie, glasses, jeans skinny build, possibly 5ft 7in, last seen s/b [11 PKUMPF]
{11} req ping [11/02/19 03:23:21 BMJENKS]
LPD notified [11/02/19 03:21:42 BMJENKS]
{9} req LPD check cameras for last 10 mins for susp going across pedestrian bridge [11/02/19 03:20:36 BMJENKS]
Event spawned for PUPD Event ID:2019249952, CallRef:361 [11/02/19 03:19:32 PKUMPF]
{116} with the victim [11/02/19 03:19:03 PKUMPF]
victim standing by inside building for river market apts [11/02/19 03:17:48 BMJENKS]
took victimes phone, number: [redacted] and wallet and car keys [11/02/19 03:17:16 BMJENKS]
w/m wearing blue/grey hoodie, short hair, with glasses, displayed black handgun [11/02/19 03:16:00 BMJENKS]

Relate objects with similar features in Report Text and surveillance video



Surveillance Camera Video Datasets

- Videos from HD surveillance cameras in main streets and high-traffic areas (WL)
- Busy streets close to campus
- Bar district with over 10 cameras down the State street
- **Over a month of archived video** from dozens of cameras



Data Annotation

- Yolo video processing tool — Yolo_mark **
  - Automatically sample the video file into images
  - Manually label the images and output the label in text files
  - Compatible with Darknet framework
- Used Yolo_mark to process video files at 1 frame / sec.
- Manually identify images containing persons first
- Depending on the “person”, label more refined attributes, e.g. male/female, jeans/pant, hat etc.
  - Extensive dataset needed for training (1000+ examples/class)
- For compensation of different locations, angles, distances, time and weather conditions, 1/100 frames are chosen for annotation

** https://github.com/AlexeyAB/Yolo_mark

	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
1×	Convolutional	32	1 × 1	
	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
2×	Convolutional	64	1 × 1	
	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
8×	Convolutional	128	1 × 1	
	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
8×	Convolutional	256	1 × 1	
	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
4×	Convolutional	512	1 × 1	
	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Yolo v3 with 53 layers [6]

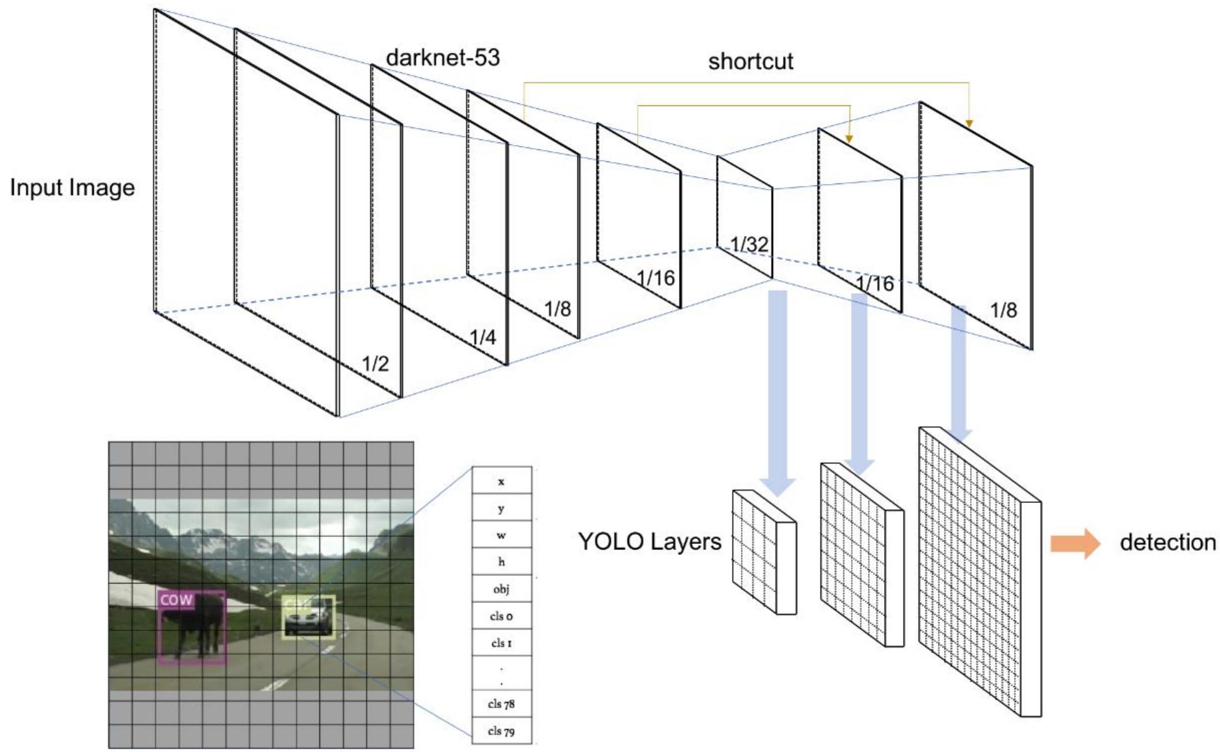
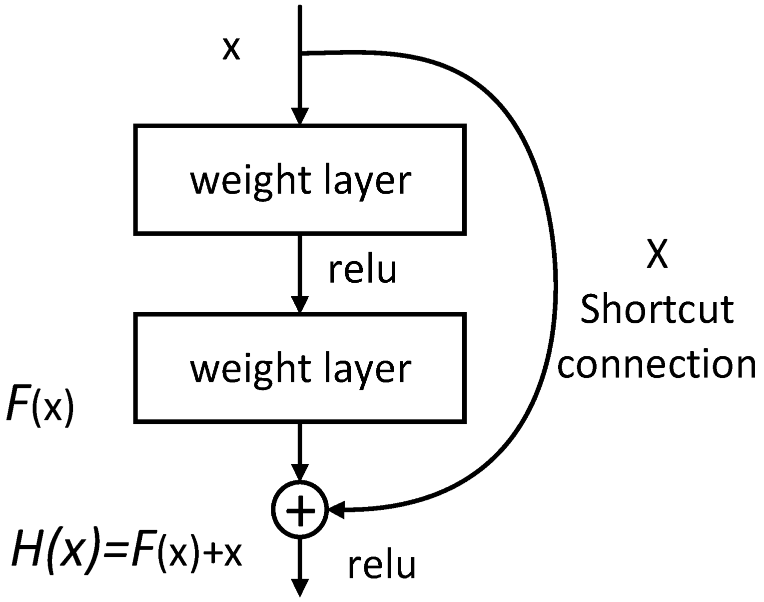


Fig. 1 Schematic of the YOLOv3 network architecture.

https://medium.com/@hirotoschwert/reproducing-training-performance-of-yolov3-in-pytorch-part1-620140ad71d3

Small Objects Detection

- In surveillance video, objects tend to be of small size relative to the captured image
- Short cut connections to skip layers are used for better detection of the small objects
- The output of a shortcut layer is obtained by adding feature maps from the previous layer and 3rd layer backwards
- Shortcut connections strengthen feature propagation, reduce the number of feature maps to increase generalization

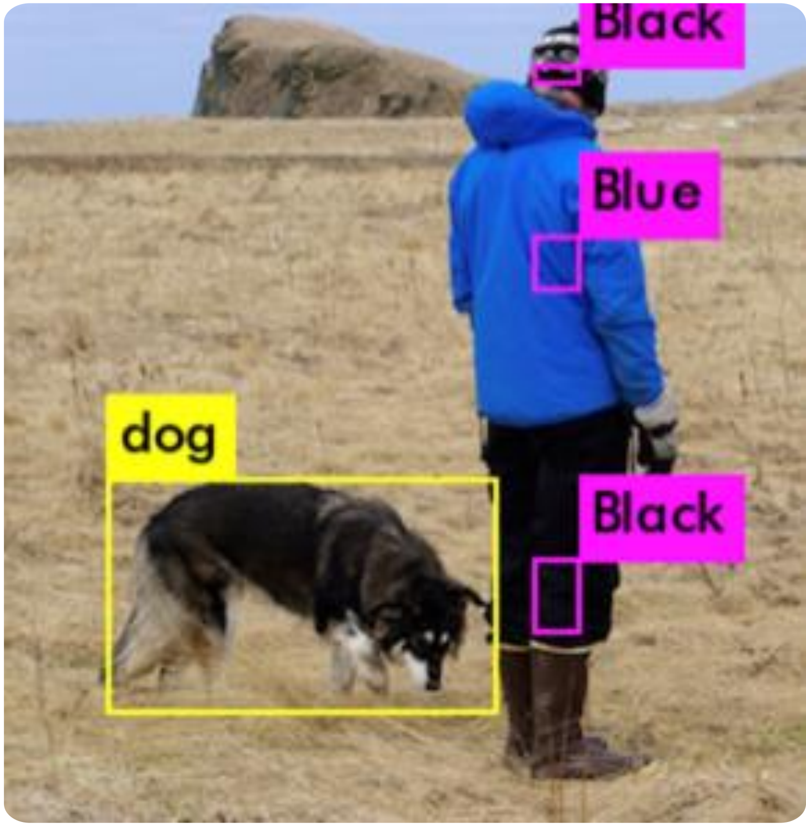


Color Segmentation

- **Goals:**
  - Features: Jeans/ Jacket/ Shirt/ Hat
  - Values: Black Jeans / Blue Shirt
  - **Avoid overhead DNN computation**

- Modified Yolo boxing codes to segment person into
  - head, upper half, bottom half, and foot

- Sampling position is important to not include background colors

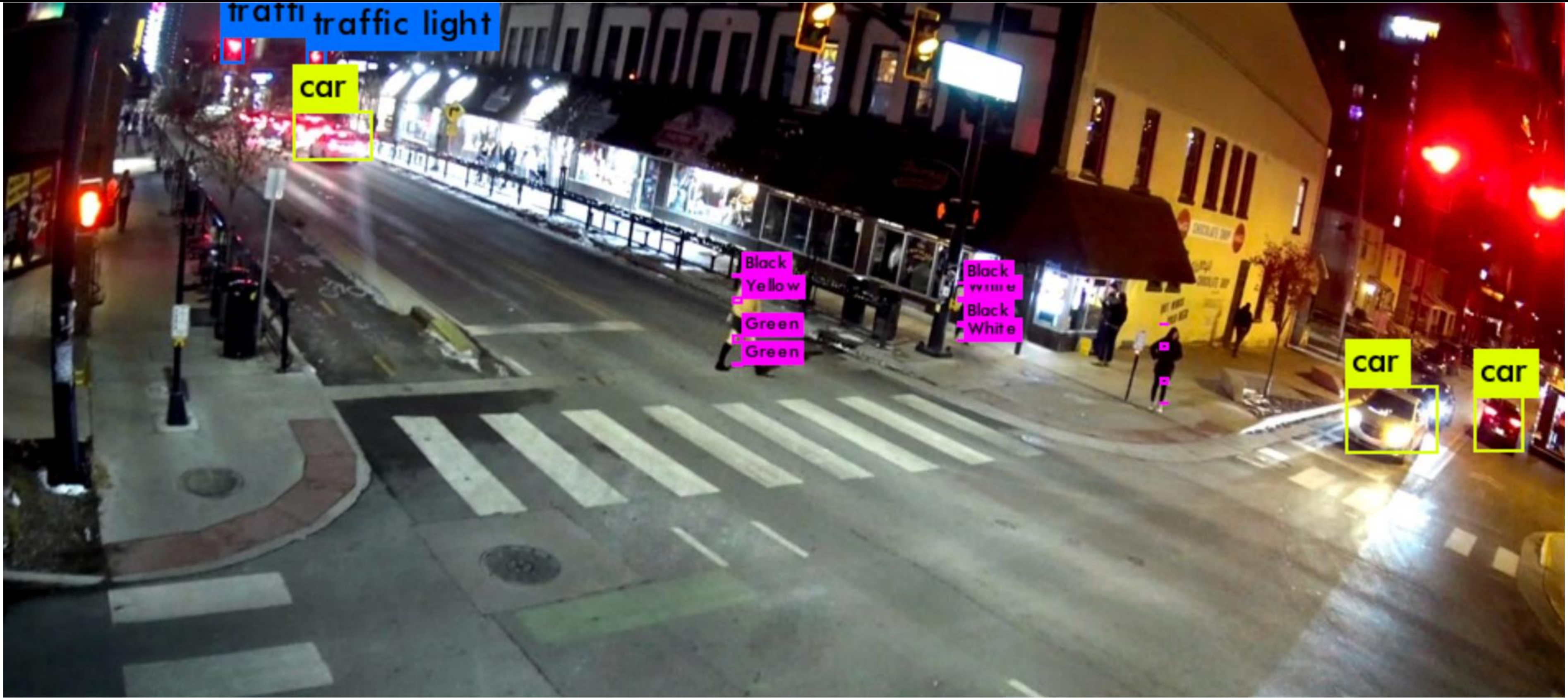


Detecting Clothes Color by Segmentation Analysis

Detecting Clothes Color by Segmentation Analysis

Result Frames

Result Frames



Color Segmentation

- Bottom body is trickier due to different gestures and position
- Run color analysis on different parts to extract color attributes
  - multiple shades of the same color,
  - night-time video colors are different
- **Rule Based** Final Judgement of Color
  - Dark-colored or Light-colored
  - Multiple Shades of same color

Custom Training YOLO

- **Goals:** Gender/ Race/ Wearables
- Training on custom labelled dataset
- Re-train with darknet**
- Results are combined with color-segmented attributes

[* https://pjreddie.com/darknet/yolo/](https://pjreddie.com/darknet/yolo/)

Video Data Processing Module

Raw video data is split in 1-minute segments

Each segment is stored in RDBMS

Each segment is processed by custom-trained DNN and color segmentation module

Extracted features are stored in RDBMS with links to corresponding video segments

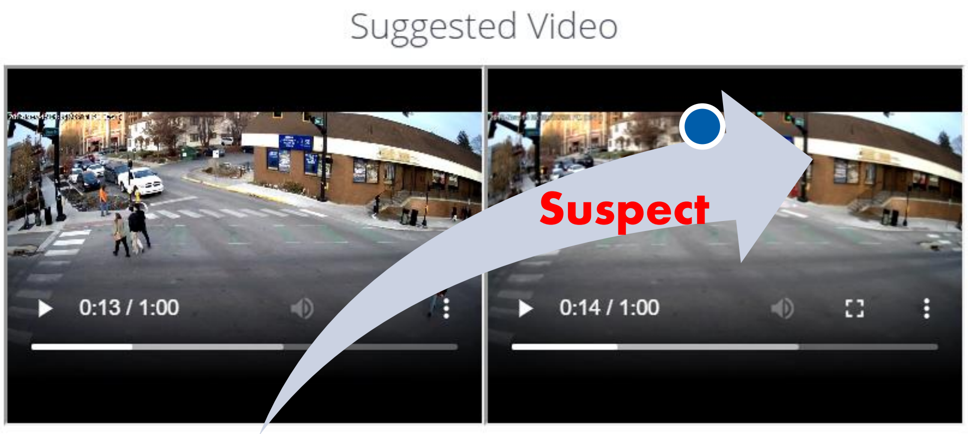
VideoID	Extracted Features/Colors	Location Coordinates	Timestamp
1	'Male', 'Female', 'Red Jacket', 'Green Jacket', 'White Pants'	40.423994, -86.909224	11:35 AM, 15-Nov-2019
2	'Female', 'Red Jacket', 'White Pants'	40.423994, -86.909224	11:36 AM, 15-Nov-2019
3	'Male', 'Female', 'Red Jacket', 'Black Hat'	40.423994, -86.909224	11:35 AM, 15-Nov-2019

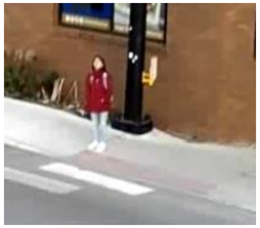
Query Results

Dispatch Report Query searching for features:

```
gender=female,
jacket=true,

jacket color=red,
incident_date=

'2019-11-15'
incident_time=

'20:00:00'
```

Video segments with the requested features are displayed:





Person with the searched attributes:

Action Recognition

- Process Videos instead of frames
- R-C3D [7] predicts activity labels with segment boundaries
- **WIP:** Re-train R-C3D module for surveillance video
- **Future Works:** Adapt YOLO for action recognition to limit computation overhead

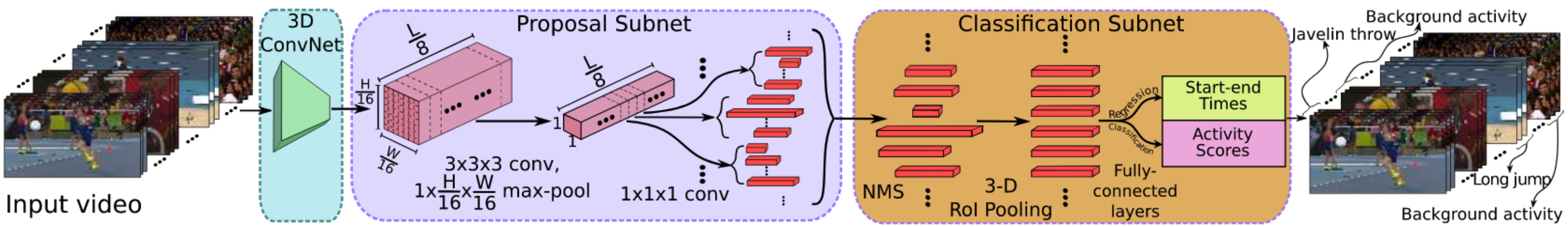


Figure 2. R-C3D model architecture. The 3D ConvNet takes raw video frames as input and computes convolutional features. These are input to the Proposal Subnet that proposes candidate activities of variable length along with confidence scores. The Classification Subnet filters the proposals, pools fixed size features and then predicts activity labels along with refined segment boundaries.

[7] R-C3D: Region Convolutional 3D Network for Temporal Activity Detection - H. Xu et al, arXiv2017.

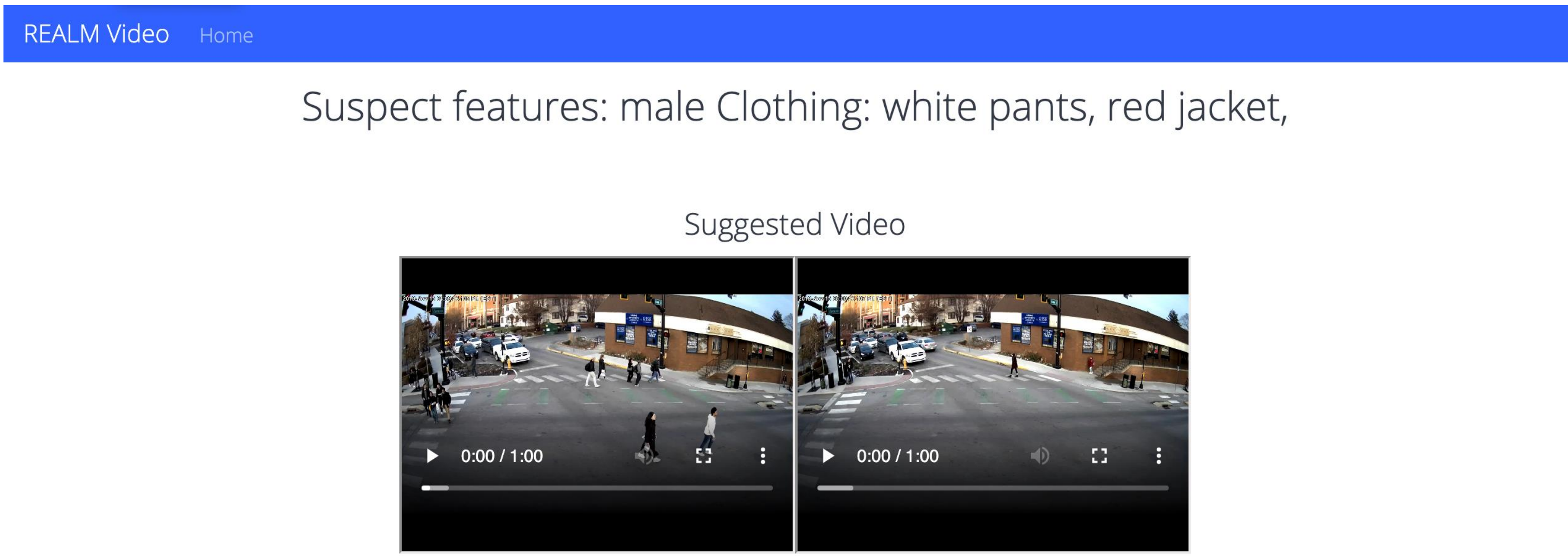
Query Result UI

REALM Video   Home

Incidents

ID	Description	Time of Event
19	Suspect spotted by State St and Chauncy Ave wearing white jeans and a red jacket around 5pm **DEMO MANUAL ENTRY**	2019-11-15 20:01:00
20	Suspect features: Medium White male Clothing: red jeans, red jacket,	
21	Suspect features: Medium White male Clothing: white jeans, red jacket,	
22	Suspect features: Medium White male Clothing: white pants, red jacket,	
23	Suspect features: Medium White male Clothing: white pants, red jacket,	2019-11-15 20:01:00
24	Suspect features: male Clothing: white pants, red jacket,	
25	Suspect features: male Clothing: white pants, red jacket,	2019-11-15 20:01:00
26	Suspect features: male Clothing: white pants, red jacket,	2019-11-15 20:01:00

Query Result UI



Deliverables and Demo

GitHub Repository:

https://github.com/skod-ng

http://18.191.242.90/index.php

http://35.239.251.13:3000/

http://35.239.251.13:3000/

Video samples extracted

REALM Incident Querying System For Policeman

http://18.191.242.90/index.php

Summary

- SKOD aims at delivering right information to the right user at the right time based on situational awareness
- There are numerous users with different missions
- Missions with various needs for information
- SKOD is an end-to-end system to empower such users with relevant knowledge from *streaming* or *stored* data
- SKOD is general purpose and can be specialized to NG use cases

https://www.cs.purdue.edu/news/articles/2019/bhargava-realm-ng.html

Research Tasks

- Processing (Removing irrelevant tweets and noises) large tweets corpus (around 6 million tweets and hundreds or attributes of each tweet).
- Help or Rescue needed Tweets classification. Location extraction of the persons who need help.
- Priority determination based on the tweets text and classification.
- Finding out the most effective rescue scheduling algorithm for various scenarios.

Future Plans for SKOD : Feature Identification

❖ Feature Identification from Video

- Pedestrians, Occluded traffic signs, Crane blocking a sidewalk, Child left in unattended car outside school
- Offline model construction (based on video and open street map)
- On-line execution

❖ Feature Identification from Text

- Interesting subset identification based on keywords
- Parse to an entity-attribute model of interesting info

More SKOD Benefit Scenarios

- Inform Drivers about
  - relevant obstacles and hazards: road closures, potholes, fallen trees and tree branches, ice, dumpster violations, downed road signs, not working traffic lights;
  - routes to avoid obstacles and hazards;
  - relevant POIs;
  - collision probability for a given date, time, weather conditions; recommend the speed.
- Inform blind / differently abled people via a mobile app about:
  - relevant obstacles and hazards;
  - routes to avoid obstacles and hazards;
  - relevant POIs.

More SKOD Benefit Scenarios

- Inform Law Enforcement about
  - suspicious activity (especially in crime-prevalent areas), illegal road constructions, downed road signs, blocked sidewalks, graffiti;
  - relevant obstacles and hazards;
  - routes to avoid obstacles and hazards;
  - collision probability for a given date, time, weather conditions; recommend the speed;
  - detected human faces in crime incidents and car accidents;
  - homeless people detected in certain areas.

References for WLPD

1. Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. GloVe: Global Vectors for Word Representation

2. Devlin, Jacob and Chang, Ming-Wei and Lee, Kenton and Toutanova, Kristina. 2018. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

3. Seo. M et al (2017) Bidirectional Attention Flow for Machine Comprehension, in ICLR 2017

4. Paszke, A.; Gross, S.; Chintala, S.; Chanan, G.; Yang, E.; DeVito, Z.; Lin, Z.; Desmaison, A.; Antiga, L.; and Lerer, A. 2017. Automatic differentiation in pytorch.

5. AllenNLP: A Deep Semantic Natural Language Processing Platform. Matt Gardner, Joel Grus, Mark Neumann, Oyvind Tafjord, Pradeep Dasigi, Nelson Liu, Matthew Peters, Michael Schmitz, Luke Zettlemoyer. 2017

6. **Yolov3**: An **incremental improvement**. J Redmon, A Farhadi

7. R-C3D: Region Convolutional 3D Network for Temporal Activity Detection - H. Xu et al, arXiv2017.

Selected Interesting References

- ReXCam: Resource-Efficient, Cross-Camera Video Analytics at Scale, S. Jain, X. Zhang et al. https://arxiv.org/abs/1811.01268
- You're being watched: there's one cctv camera for every 32 people in uk. https://www.theguardian.com/uk/2011/mar/02/cctv-cameras-watching-surveillance. Accessed:2018-10-27.
- Absolutely everywhere in beijing is now covered by police video surveillance. https://qz.com/518874/. Accessed: 2018-10-27.
- Can 30,000 cameras help solve chicago's crime problem? https://www.nytimes.com/2018/05/26/us/chicago-police-surveillance.html. Accessed: 2018-10-27.
- https://github.com/PurdueCAM2Project (Prof. Yung Hsiang Lu at Purdue)
- https://www.cam2project.net/
- Cross-dataset Training for Class Increasing Object Detection, Y. Yao, Y. Wang et al. https://arxiv.org/abs/2001.04621
- http://usc-isi-i2.github.io/knoblock/,
- https://usc-isi-i2.github.io/kejriwal/
- PROTECTING AMERICA'S SCHOOLS A U.S. SECRET SERVICE ANALYSIS OF TARGETED SCHOOL VIOLENCE, 2019,
- https://www.policyinsider.org/2019/10/protecting-americas-schools-a-us-secret-service-analysis-of-targeted-school-violence.html


NORTHROP GRUMMAN
REALM
Research in Applications for Learning Machines

Data Completion

Professor Vaneet Aggarwal at Purdue

Problem Statement

Data Completion and Classification

- For mission-relevant learning it is important to find structures in the data.
- Use those structures to complete data with reduced number of observations.
- Utilize multidimensional data to complete, classify, and predict data items and further conduct anomaly detection.
- Conducting text classification through deep learning methodologies to determine the mission relevant information.

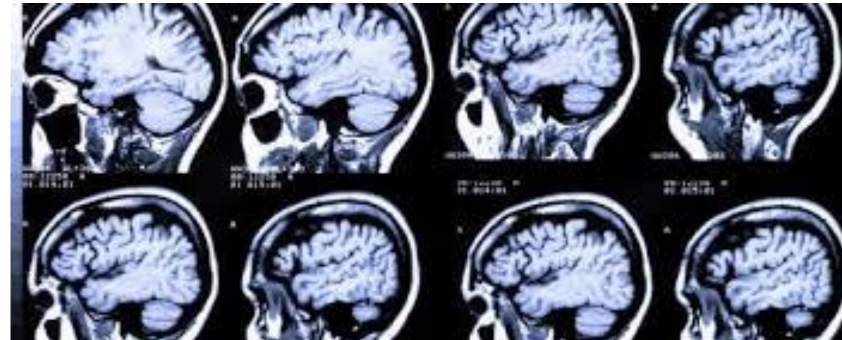
Proposed Solution

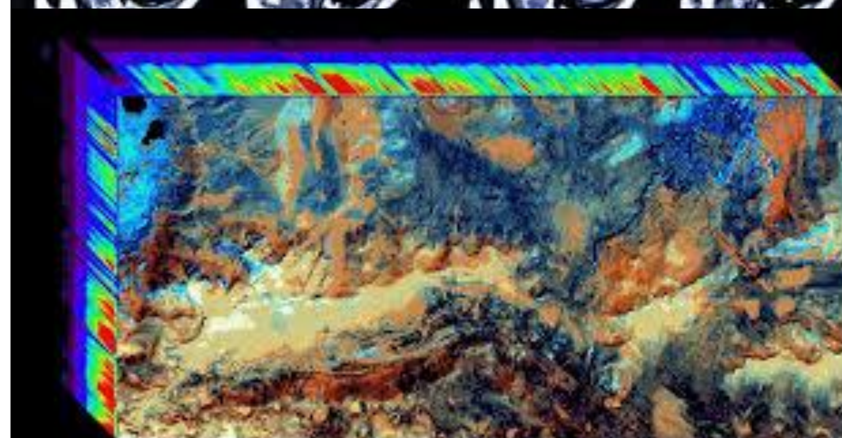
- Finding structures in data and Use the structure for completing data with lower observations Completion.
- In addition, we will introduce multi-dimensional data structures for Completion, Classification, Prediction, Anomaly Detection.
- We will develop an efficient mission (particularly rescue missions during disasters) relevant scheduling algorithm using Twitter data.
- Identify the tweets which are seeking for help or rescue.

Solution Overview

- Finding structures in data
- Use the structure for completing data with lower observations
- Completion, Classification, Prediction, Anomaly Detection
- Multi-tasks Hybrid Scheduling

Utilizing the multi-dimensional Data Structure is important.





Benefits of the Approach

- The number of parameters in neural network (both fully connected and convolution layers) can be compressed by the tensor ring structure.

- The compression leads to faster training and testing times. Further, can improve the error due to less overfitting.

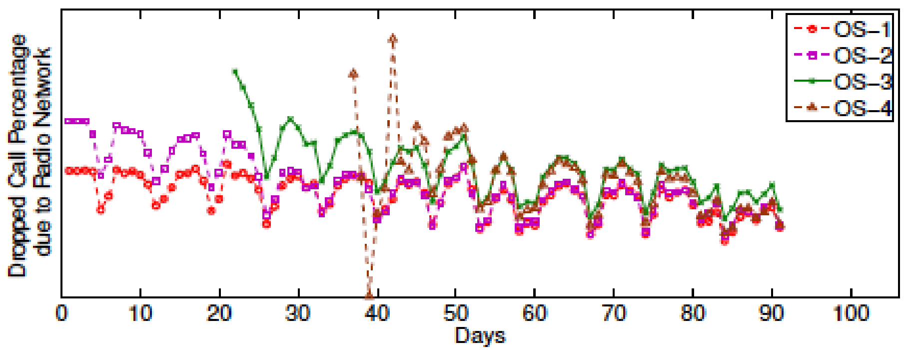
- Improves MNIST error to 0.69% using 11X lower parameters as compares to standard Lenet-5.

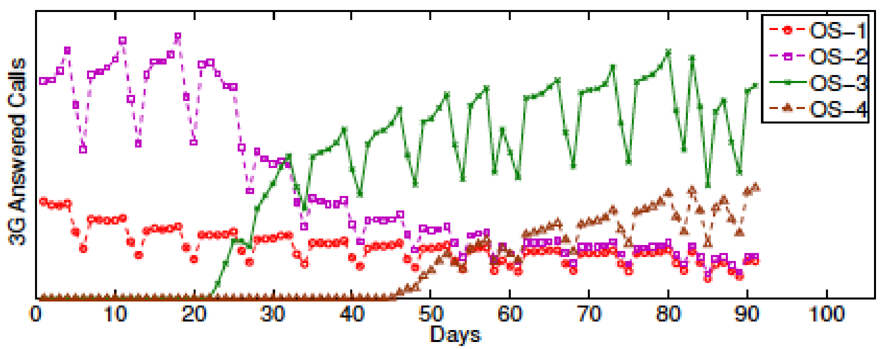
- Multi-tasks Hybrid Scheduling algorithm combines the priority and balances the load. For the same priority and load it acts like FCFS scheduling.

Solution Details

Data Completion (Research of Vaneet Aggarwal at Purdue):

- Multiple features across different OS and times have dependency
- Missing entries due to lower data collection can be interpolated across towers, OS, f





Solution Details

Data Completion:

•Complete Rankings – can be used for recommendations

•Correlation across movie categories, rankings, users

Alice	4			4
Bob		5	4	
Joe		5		
Sam	5			

Solution Details

Tensor Ring Completion:

- Structure in the data leads to recovery of the data from a small number of entries.
- The matrix-based approaches fail to work at these sampling rates.
- Proposed Tensor ring structure based algorithm demonstrates superior performance in missing data completion.

Numerical results: Video Completion

Video

Video with Recovered by Our Approach

Video with 90% missing entries

Solution Details

Application: Scheduling Resources to Flood Victims (Research by Sanjay Madria at MST)

Tweet Classification

- 2500 tweets labeled manually into 6 classes (Rescue needed, DECW, water needed, Injured, Sick, flood) from the 68574 preprocessed tweets.
- A multiclass classifier was developed using Convolutional Neural Network and text embedding to classify every single tweet. A tweet can belong to more than one class at the same time.
- The CNN only trained for hurricane Harvey dataset and tested on both Harvey and Irma data.
- We have compared the accuracy of CNN with Support Vector Machine and Logistic Regression. CNN outperformed the methods with the accuracy of 90.7% on hurricane Harvey and 88.5% on hurricane Irma tweets.

Solution Details

Priority Determination

- We assigned various weights for the above 6 classes to determine the priority score of a tweet.

- Using $f_p = \sum_{j=1}^{n} w_j$, where w_j denotes the weights for different classes we calculate the priorities of each tweet.

- Priority score was used to make the rescue scheduling algorithm fair and efficient.

Datasets

MNIST and Twitter

- LeNet-300-100: Two FCLs with 300 and 100 hidden neurons
- LeNet-5: Two ConvLs followed by two FCLs

Method	Params	CR	Err %
LeNet-300-100 [36]	266K	$1\times$	2.50
M-FC[18, 28]($r = 10$)	16.4K	$16.3\times$	3.91
M-FC ($r = 20$)	31.2K	$5.3\times$	3.0
M-FC ($r = 50$)	75.7K	$3.5\times$	2.62
TRN ($r = 3$)	0.8K	$325.5\times$	8.53
TRN ($r = 5$)	2.3K	$117.2\times$	3.75
TRN ($r = 15$)	20.5K	$13.0\times$	2.64
TRN ($r = 50$)	227.5K	$1.2\times$	**2.31**

Method	Params	CR	Err %
LeNet-5 [36]	429K	$1\times$	0.79
Tucker [28]	189K	$2\times$	0.85
TRN ($r = 3$)	1.5K	$286\times$	2.24
TRN ($r = 5$)	3.6K	$120\times$	1.64
TRN ($r = 10$)	11.0K	$39\times$	1.39
TRN ($r = 15$)	23.4K	$18\times$	0.81
TRN ($r = 20$)	40.7K	$11\times$	**0.69**

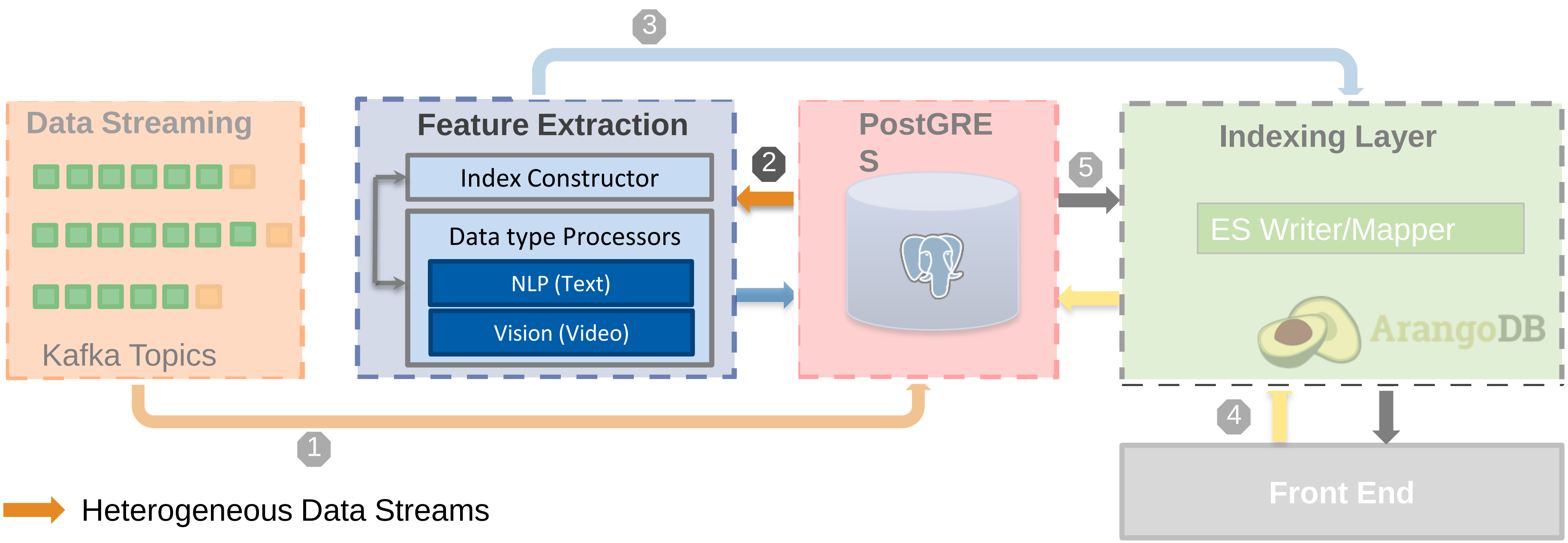
- Sentiment140 dataset with 1.6 million tweets: https://www.kaggle.com/kazanova/sentiment140

Backup Slides

Tweets-Parser-Engine

- Parses metadata to extract
  - Full tweet text
  - User Information
  - Hashtags, URLs, User mentions
  - Geolocation (latitude, longitude)
- Separates and processes
  - Original tweets
  - Retweets
  - Quoted tweets

Feature Extraction Module



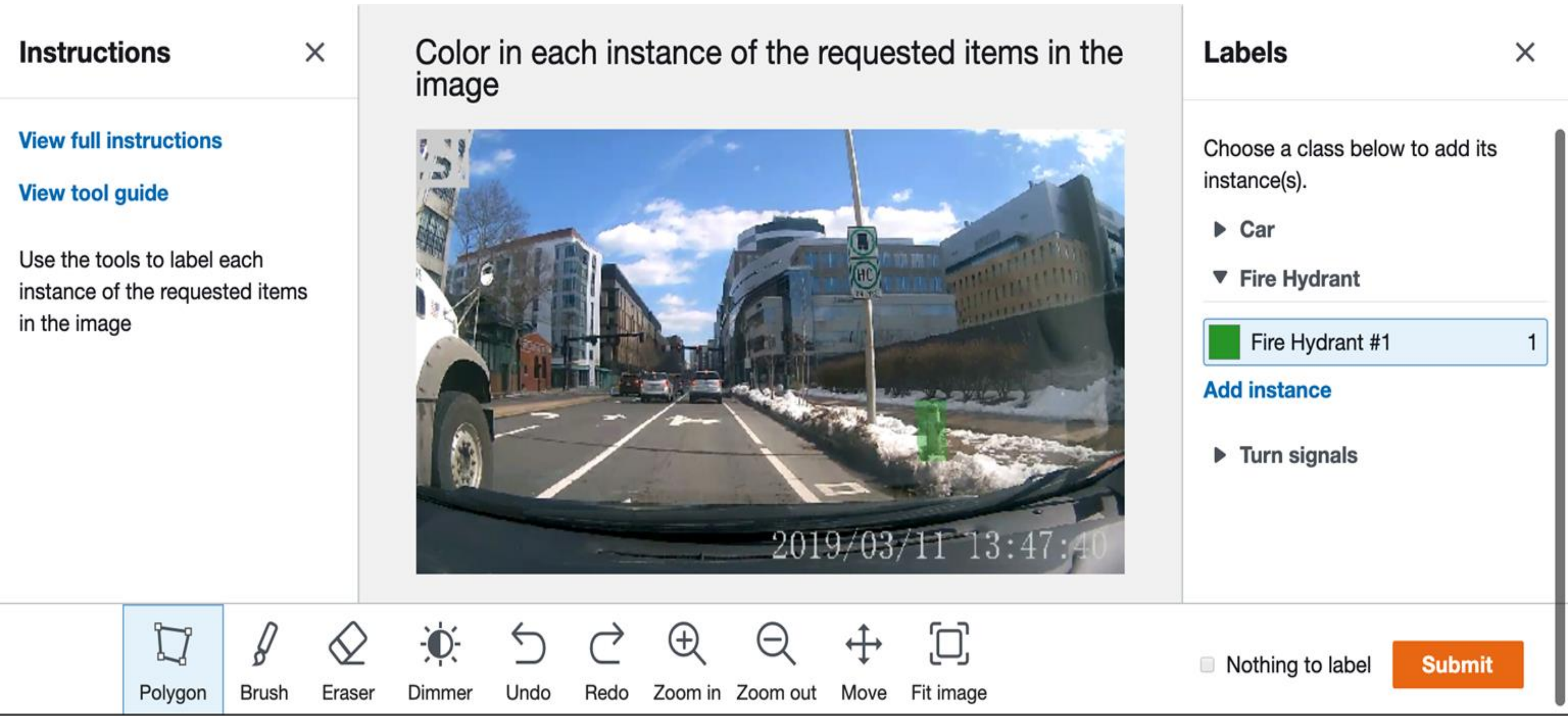
Heterogeneous Data Streams
Situational Aware Indexed Data
Users' queries
Relevant patterns of data

Feature extraction from videos using manual tagging for features

Manual Feature Extraction from Videos

- Features targeted
  - Objects in Video
  - Attributes of the objects
- Amazon Mechanical Turk (Mturk)
  - For task design
  - For annotation collection
  - For task distribution
- Steps
  - Run Object detection algorithms
  - Segment video into frames
  - Modify the existing annotations

Task Design Sample: Instance Segmentation



Task Design Sample: Attribute Tagging

Instructions: Given a frame, describe the attributes of the marked object in the bounding box.

Attributes can include number plate, color of car, street name that can be used to describe the object.

Word/phrase 1

Number plate/SWW-14W

Word/phrase 2

ksolaima@purdue.edu