Multimodal Information Recommendation in Open-world Environment

Situational Knowledge on Demand

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- The Acadian flycatcher is a small insect-eating bird of the tyrant flycatcher family.
- Adults have olive upperparts, darker on the wings and tail, with whitish underpants; they have a white eye ring, white wing bars and a wide bill.



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Acadian Flycatcher



• With a wingspan of six feet (2 m), the Laysan albatross is one of the smaller species and is adept at diving for squid, fish and crustaceans.

Laysan albatross





Person Query System (Recommendation)

Datasets



Person Query System (Recommendation)

Datasets

Heer: TMGREEN

WEST LAFAYETTE POLICE DEPARTMENT

04/23/2020 14:07

Incident / Investigation - Case #: 2015-003151 : Off, Narr

On August 21, 2015 1, Officer Jeffery Spicer responded to a report of an attempted strong armed robbery initially put out for the area of 201 S Salisbury (later determined to have occurred near the intersection of State Street and Pierce Street). Dispatch advised that three black males attempted to rob a female of her purse, however they failed and fled southbound in a grey Nissan Pathfinder with an Indiana registration of 42 IMBY. While en route to check south-bound on S River Road, Officer Brewer advised he ran that license plate earlier and it comes back to an older tan (with rust) Pathfinder. As 1 approached the area of US 231 and State Road 25 I did not observe any vehicles matching that description. As 1 varied for the light to turn green to go back to meet with the victim, 1 observed a gold/ran looking Nissan Pathfinder traveling north-bound on US 231 preparing to turn east-bound onto State Road 25. At this time I was able to get behind the vehicle and I noticed that the license plate provided to me by dispatch and Officer Brewer matched that of the one the victim gave to dispatch. I then continued to follow the vehicle east-bound on State Road 25 till we go to the intersection of Old US 231. The vehicle then changed lanes while stopped into the south-bound turn lane for Old US 231 without signaling. Once the vehicle turned south onto Old US 231 it pulled into the CVS parking lot, at which time I activated my emergency lights and stopped the vehicle in the CVS parking lot.

Once the vehicle was stopped I exited my patrol car and held the occupants at gun point until backup units arrived. Once other units arrived on scene we initiated a felony stop on the vehicle and first had the driver exit the vehicle. The driver was later identified as Marquise D LEIGH. And he was detained in handcuffs and placed into a patrol car (LEIGH was wearing a black shirt with long dreadlock style hair). Next we ordered the backscat passenger side occupant out of the vehicle, who was later identified as Kierre D MCCOY was detained in handcuffs the front seat passenger exited the vehicle and was later identified as Derek C SMITH (and he was detained in handcuffs as well (SMITH was wearing a red Adidas track jacket). After the three males were detained and the vehicle cleared of anyone else, Lt. Lord advised that PUPD was going to bring two victims and a witness to my location for an identification show up.

When the three subjects arrived to my location, I had officers bring Kierre MCCOY out of the vehicle and put him up against the wall of the CVS building so that the victims and witness could see him. The male victim, Tyler HO advised that he was not sure on the subject because he was on the ground getting assaulted. The male witness, James ROACH advised that he McCOY looked familiar when I asked him if he did. I then asked if he was sure and he stated that he was about eighty percent sure. I then had the female, Maggie LENGACHER (who was the victim of the attempted robbery) step out of the police car to look at MCCOY. When LENGACHER stepped out and looked at MCCOY she stated, "ya" and that he was the third one to exit the vehicle when the fight broke out. She also stated she observed him in the front passenger seat and that he exited after the driver and backseat passenger did to fight her friends. LENGACHER also advised that all three of them attempted to take her purse during my video recorded interview with her. When I asked her how certain she was on MCCOY being one of the suspects she advised she was eighty-five percent sure and that she really remembers one wearing a white shirt, one wearing a black shirt, and the other wearing a red shirt.

Next I had LEIGH exit the patrol car and lined him up against the CVS wall, at which time I went over to ROACH and HO and they both advised me that they were one-hundred percent sure that LEIGH was one of the suspects that assaulted HO and attempted to rob LENGACHER. HO also advised that LEIGH was the person that instigated the entire incident. When I went and had LENGACHER look at LEIGH she advised me that she was positive on an identification. When I asked her what role he played she advised that LEIGH was the first person to get out of the car, and he tackled her friend, Eric GABBARD. She also advised that he was the first person to push her to the ground and tackle her. I then had SMITH stand up next to the CVS wall to show the two victims and one witness him. When I went and spoke with HO and ROACH, HO advised he was one-hundred percent sure that SMITH was the one that kicked him in the head. ROACH also stated that he was cortain that SMITH was the one who kicked HO in the head. ROACH also advised me that he was cortain he saw SMITH hit LENGACHER. I then had LENGACHER look at SMITH and her initial response was, "yes". I then asked her how certain she was and she advised, 95 % sure and that she was not 100 percent sure only because she thought he was wearing a red t-shirt and not a red track jacket. I asked her what role SMITH played in the altercation and she advised so that he exited from one of the passenger seats when the driver did and that he was one of the subjects who hit HO. She also identified SMITH as being one of the guys on top of her trying to take her purse.

After the two victims and one witness left the area I went up to LEIGH in the back of the squad car and read him his Miranda Rights.





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After the two victims and one witness left the area I went up to LEIGH in the back of the squad car and read him his Miranda Rights.

Suspect was a white male, wearing buttoned-up shirt and blue jeans.









Traffic Cam Snapshot of Silver Sedan







Traffic Cam Snapshot of Silver Sedan



☐ Child left alone on 3rd St in a Silver Sedan







Traffic Cam Snapshot of Silver Sedan



☐ Child left alone on 3rd St in a Silver Sedan



Context:

Earthquake & Rescue Personnel







Traffic Cam Snapshot of Silver Sedan



☐ Child left alone on 3rd St in a Silver Sedan



Mission-relevant info forwarded to Rescue Coordinators!

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Earthquake & Rescue Personnel







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Traffic Cam Snapshot of Silver Sedan



☐ Child left alone on 3rd St in a Silver Sedan

Context:

Normal Day & Regular Petrol









Traffic Cam Snapshot of Silver Sedan



☐ Child left alone on 3rd St in a Silver Sedan



Mission-relevant info forwarded to Police!

Context:

Normal Day & Regular Petrol

Research Questions

- What will be the best method to represent heterogenous knowledge for meaningful retrieval?
- How difficult is it to integrate representations from different modules and identify relevance with user's information need?
- How will the data be delivered to user on-time?
- How can we model the searcher's intent within specific context to deliver more relevant result beyond the specific query?
- Can we identify significant events without explicit inquiry?

Overview



Model the User

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



Data Management

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



Scaling

Techniques to support 1000s of users



Data Relevance

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



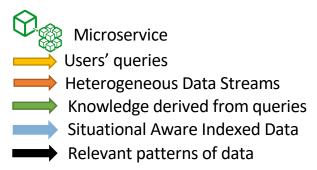
Novelties

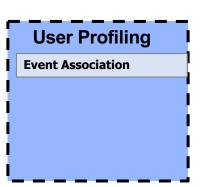
- Detect, and
 Adapt to
 - Novelties
- ModelRobustness





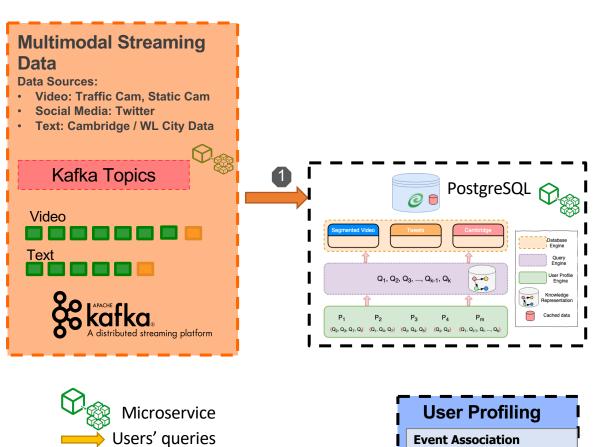


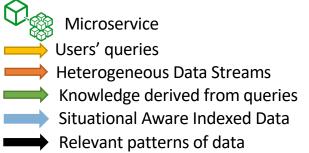








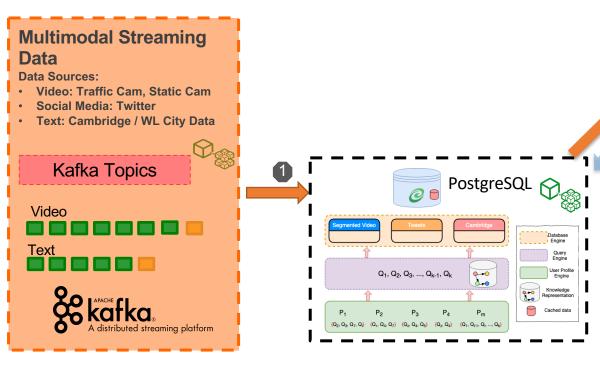


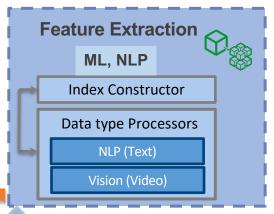


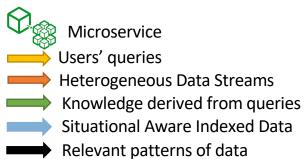








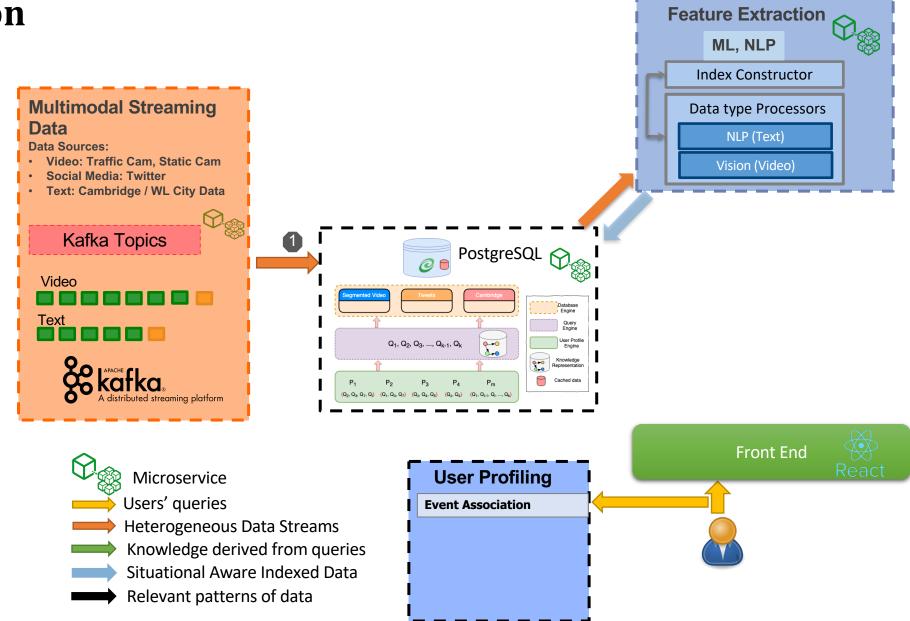


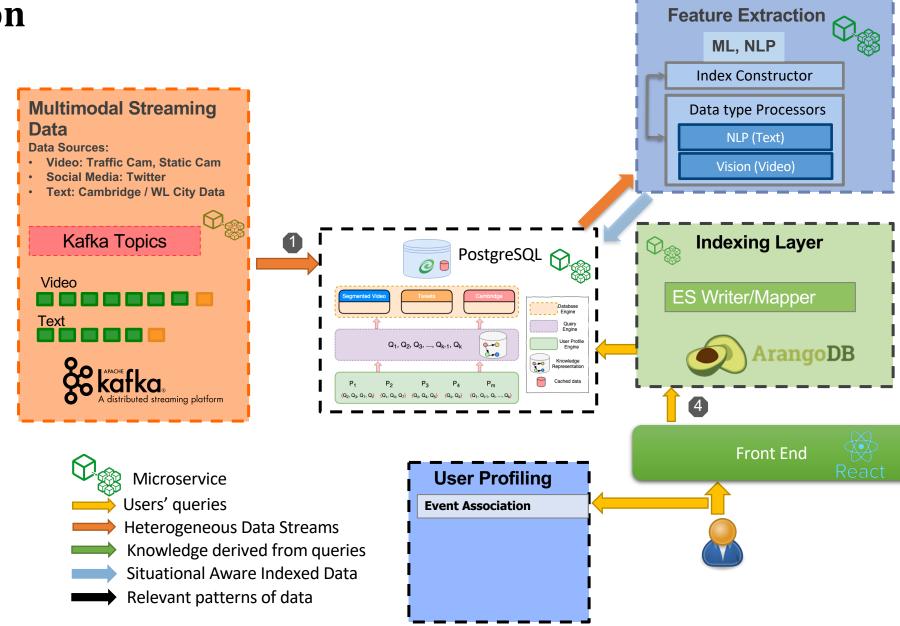


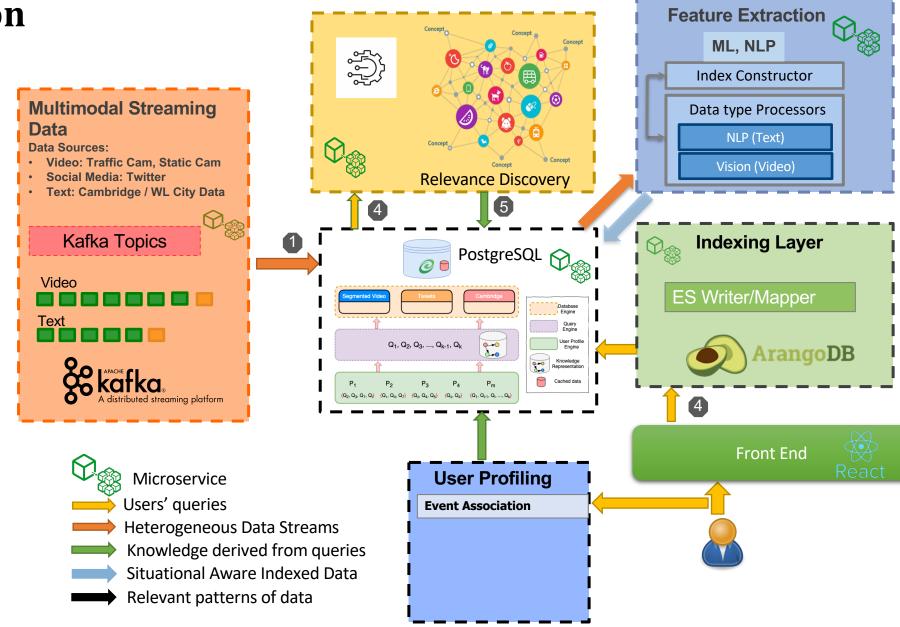


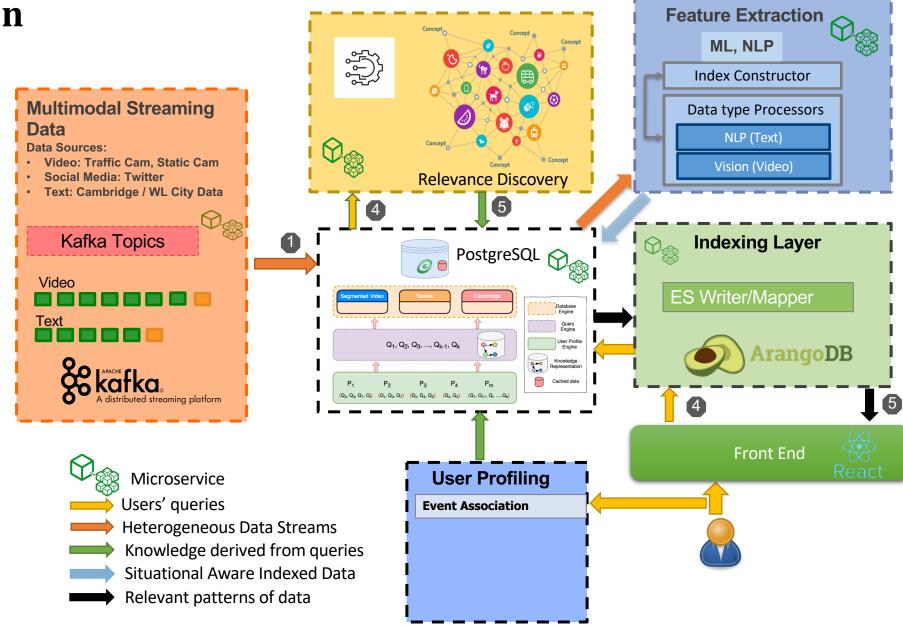


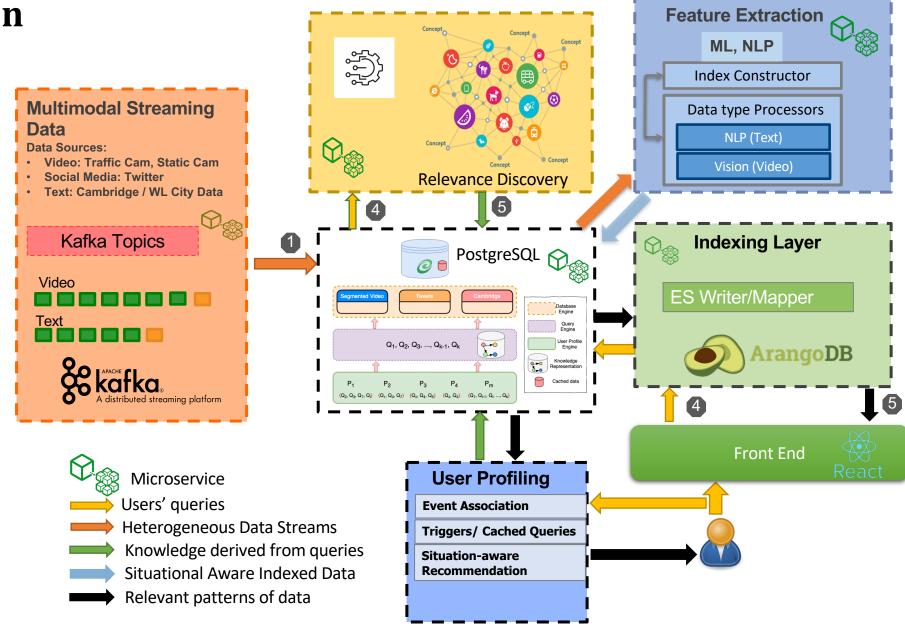


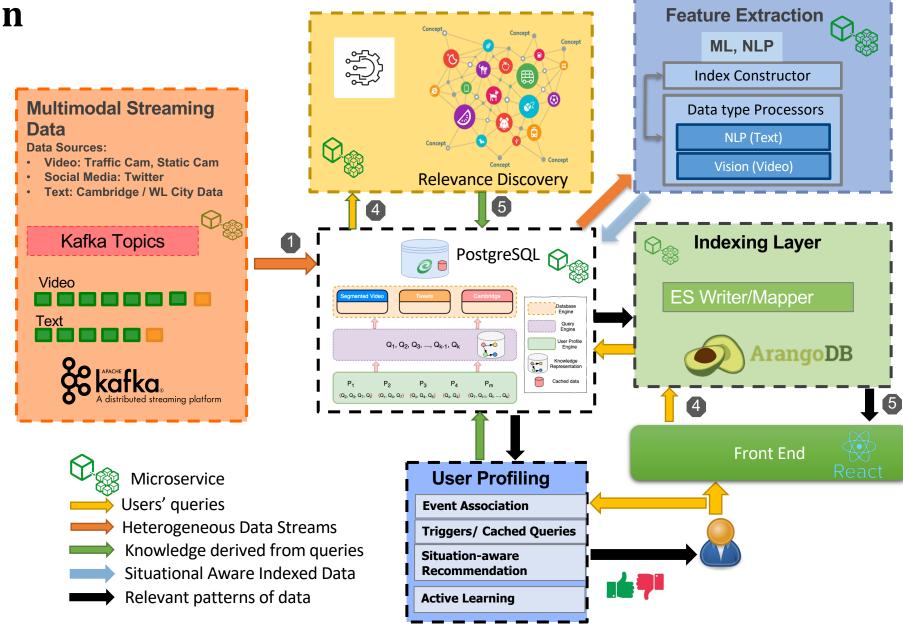




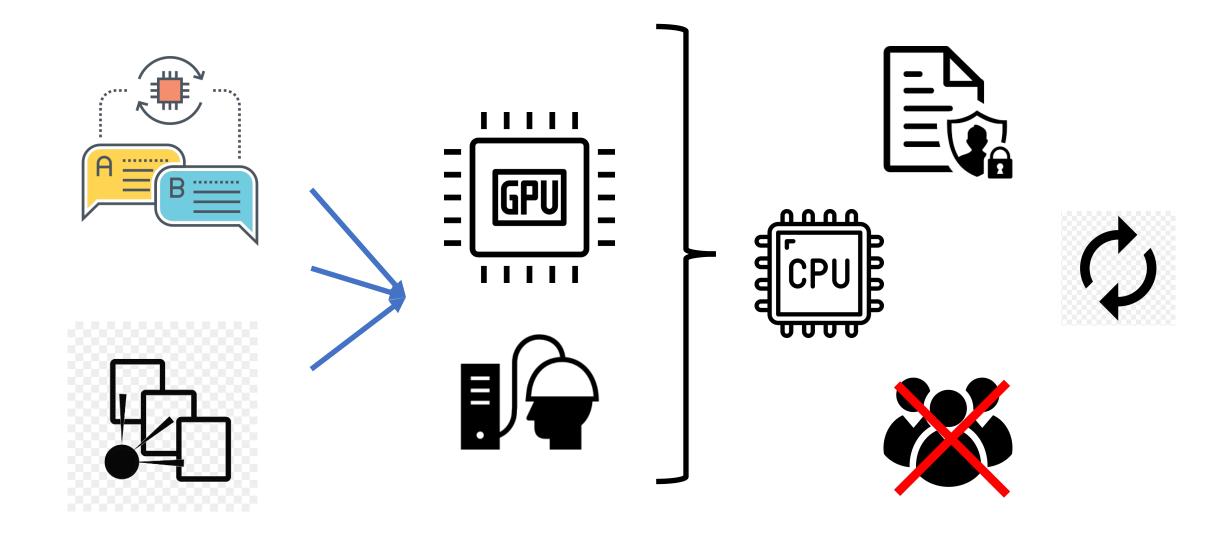




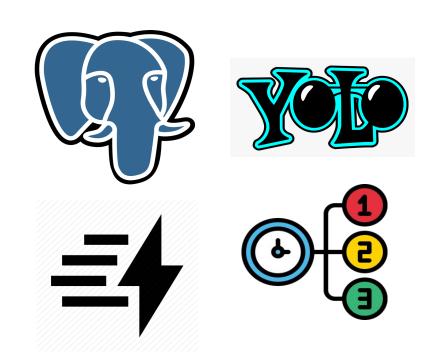




Resource constrained Feature Extraction



Resource Constrained Feature Extraction



Video and Image Feature Extraction

- Priority System
- Object and Attribute Detection
- Heuristic Methods



Text Feature Extraction

- > Regular Expression
- ➤ Language Models
- ➤ PoS-based Classifiers

NORTHROP GRUMMAN

Dataset

Datasets

Features for WLPD:

Constant	Changeable	Other objects	
Attributes	Attributes		
Female	T-shirt	Car	
Male	Shorts	Bicycle	
White	Jeans	Truck	
Black	Pants	Motorcycle	
Hispanic	Jacket	Skateboard	
Asian	Shoes	Backpack	

Activity	Additional
Recognition	attributes
Smoking	Hair color
Running	Tattoo
Walking	Beard
	Bald
	Tall/short
	Headphones



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Data Annotation

- Gender, Race, Age, Hair Color,
 Clothing (jacket/pants/jeans)
 and their descriptions
- Multiple persons are described in same document and annotated separately
- Wearing is evaluated on
 - Clothing Name
 - Clothing Description or Color Value



Table 2: Performance Evaluation of Suspect Attribute Extraction from Incident Reports

				Wearing	Wearing
Attributes	Gender	Race	Height	Attr-only	Attr-value
Precision	0.94	0.94	0.72	0.93	0.92
Recall	0.73	0.73	0.57	0.65	0.87
F1-Score	0.82	0.82	0.63	0.77	0.90



$$C_s = \{ s \in D | sim(q, w) > \theta, w \in s \}$$
 (1)

where u_q and u_w are the embedding vectors for q and w, respectively, and

$$q = \{\text{``clothes''}, \text{``wearing''}, \text{``suspect''}, \text{``shirts''}, \text{``pants''}\}$$
 (2)

$$sim(q, w) = cos(u_q, u_w) = \frac{u_q \cdot u_w}{\|u_q\| \cdot \|u_w\|}$$
 (3)

$$C_s = \{s : s \in D, P(q|s) > \theta\}$$

$$(5)$$



Candidate Sentence Extraction

$$-C_s = \{ s \in D | sim(q, w) > \theta, w \in s \}$$
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Key Phrases describing
Attributes

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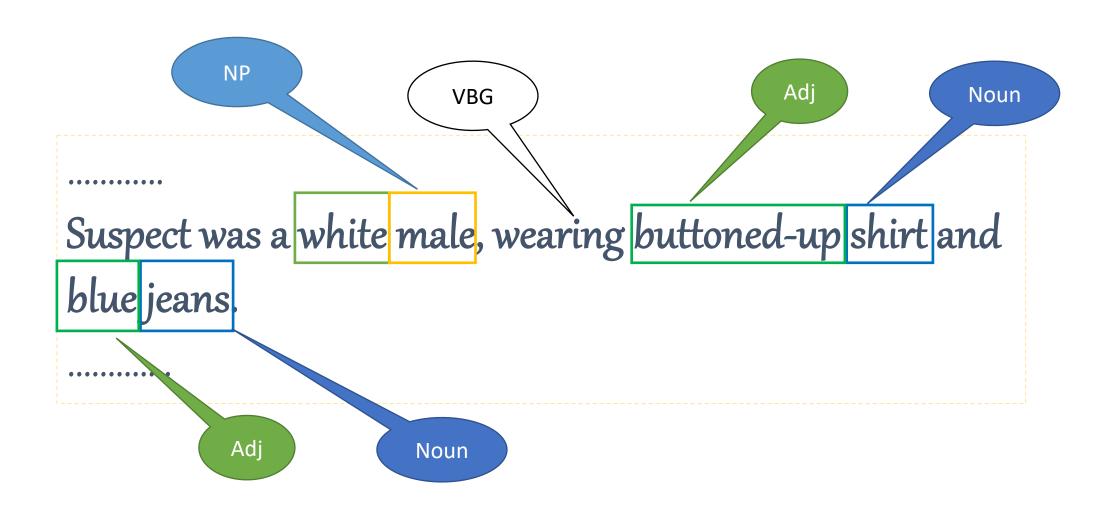


Feature Value Extraction

```
Suspect was a white male, wearing buttoned-up shirt and blue jeans.
```

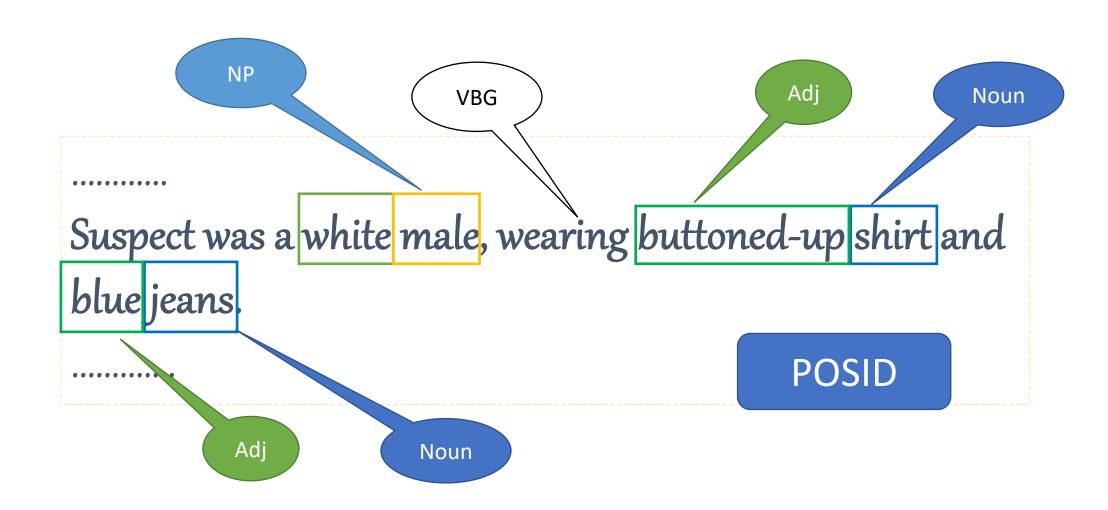


Feature Value Extraction



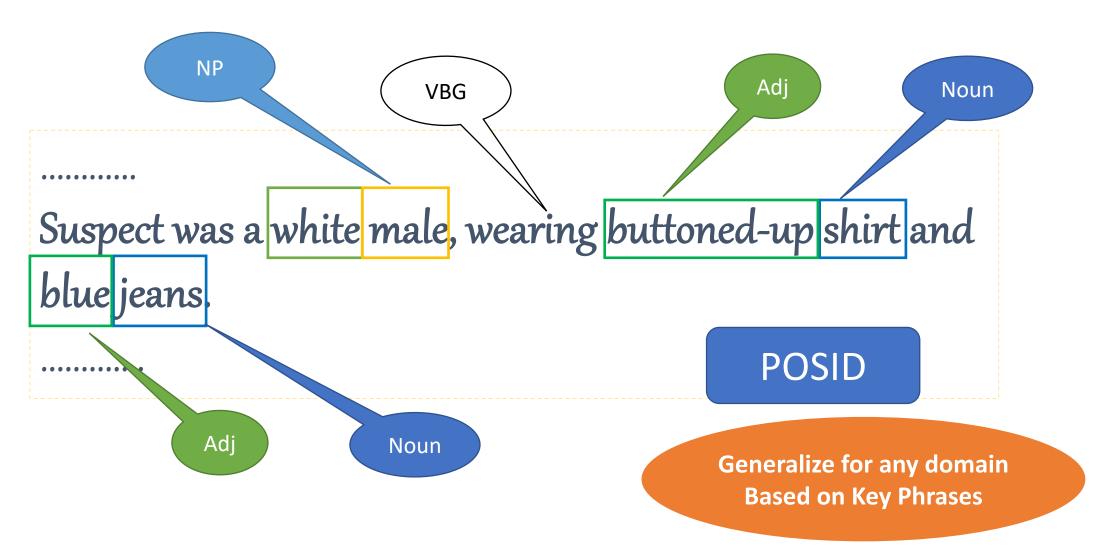


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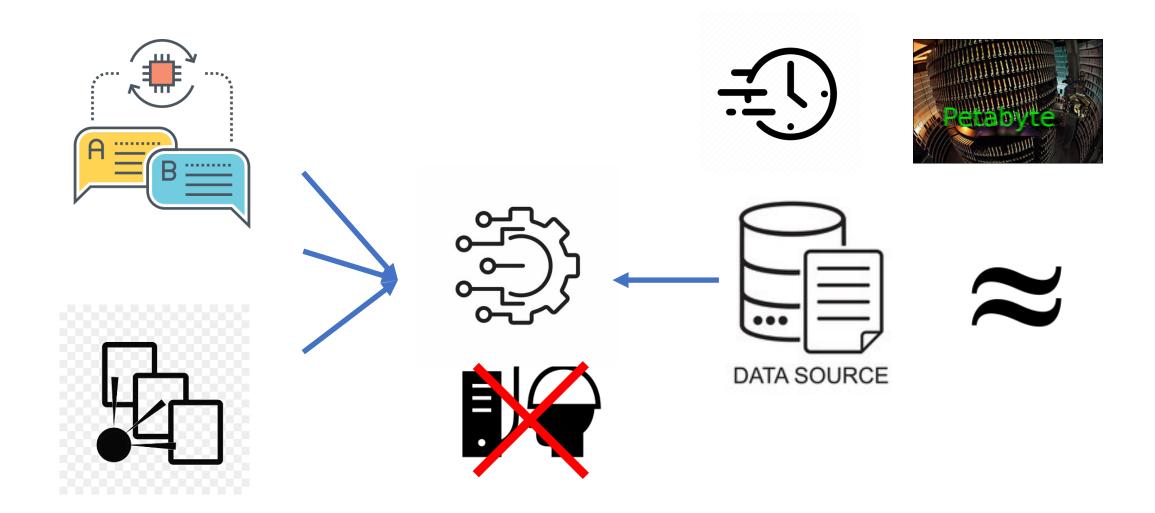




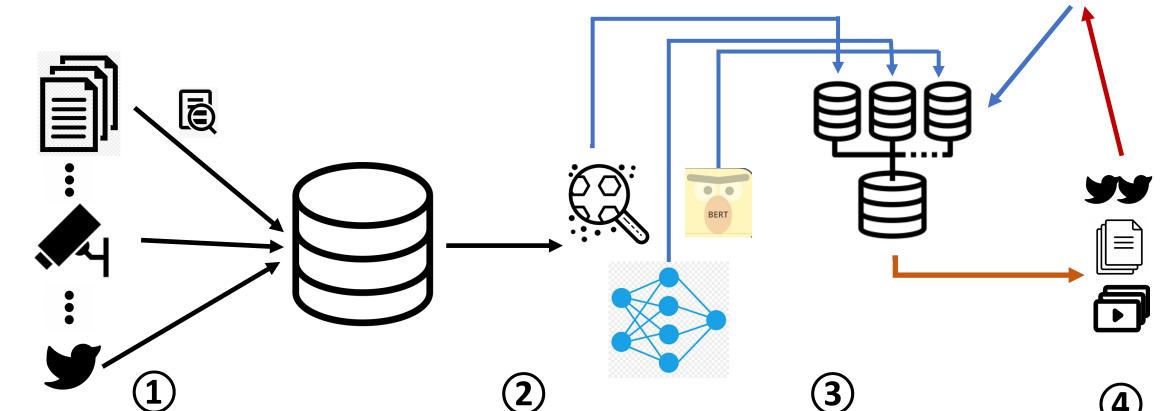
Feature Value Extraction



Challenge 2: Label Independent Data Integration



Knowledge Discovery: EARS-JOIN



Capture Streaming Data; Pre-processing; Convert to MP4, txt; Store in Postgres (Data Capture and Data Storage)

Run ML and heuristic models on video, text and tweets (Feature Identification)

Create Query from
User Requirement with
DDL and return JOIN
results w/ Predicate
Matching

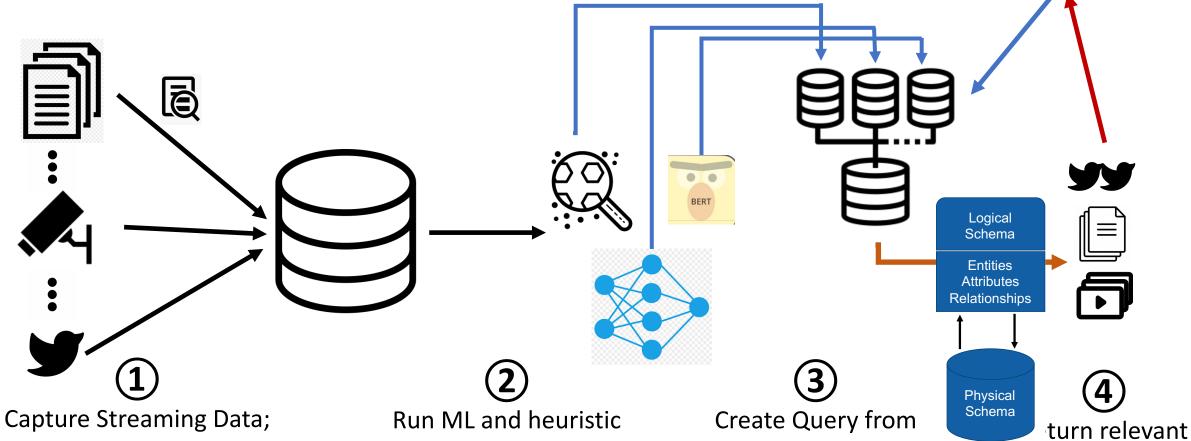
(Data Fusion)

Return relevant results to user's

examples

(Data Retrieval)

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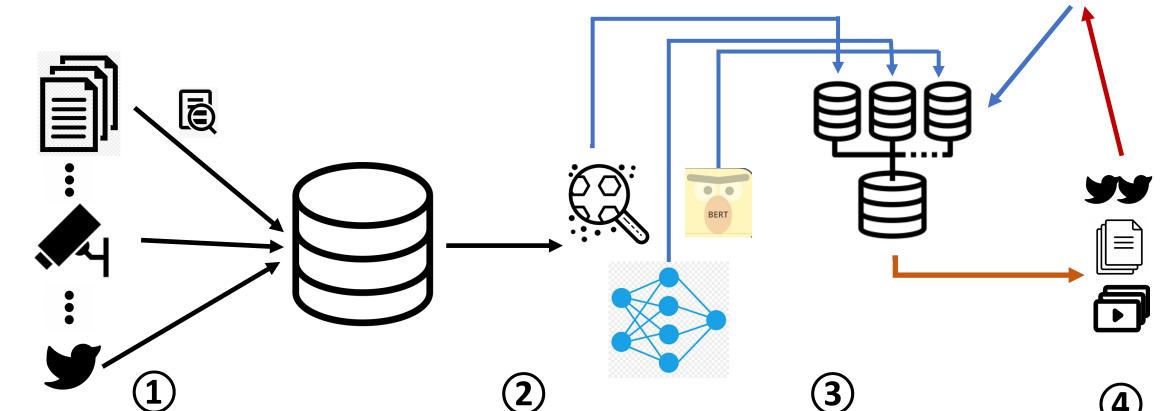
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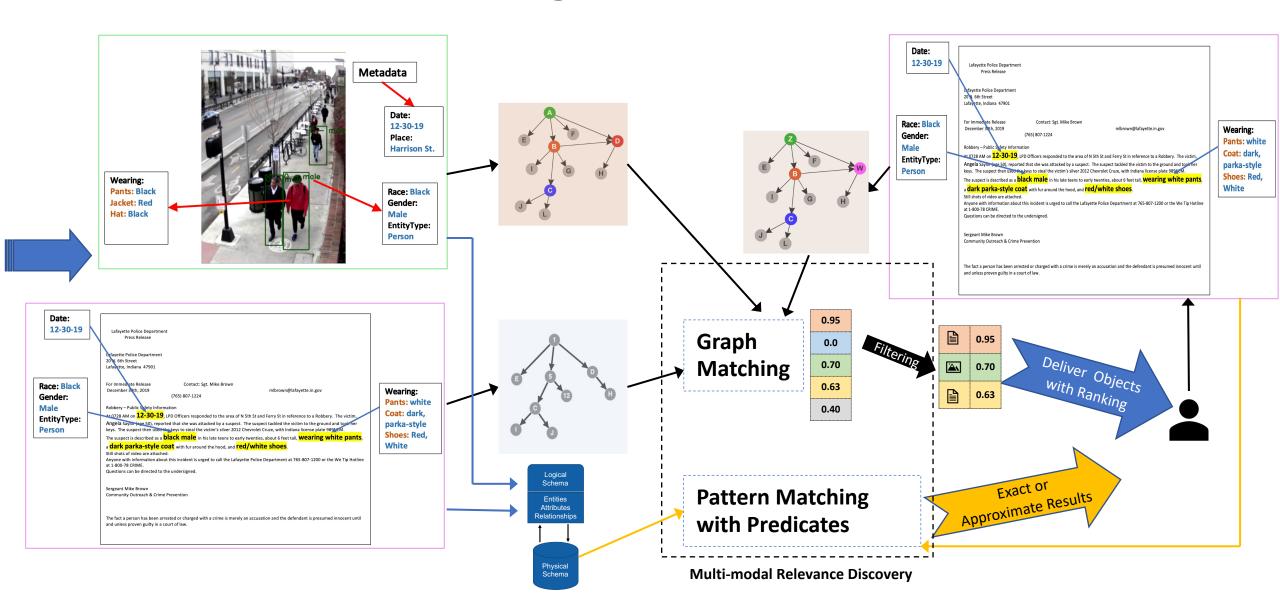
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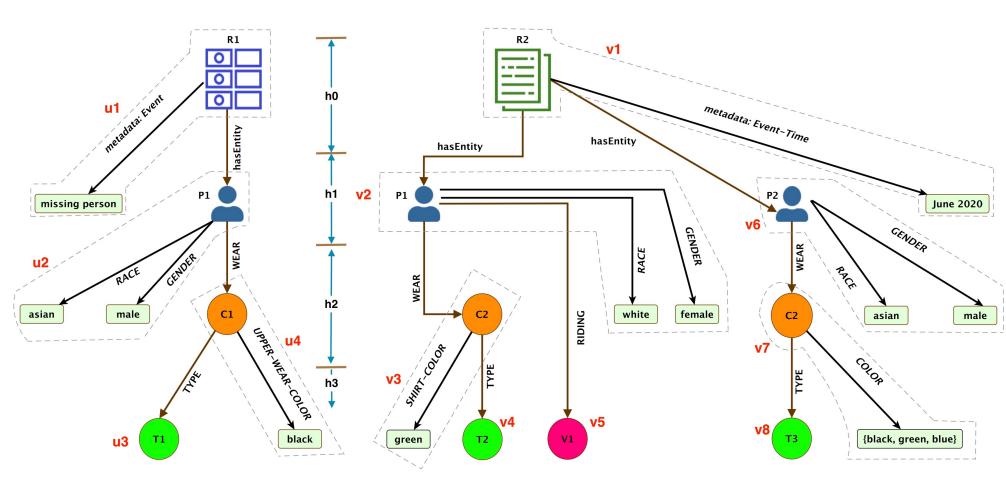
(Data Retrieval)

Relevance Modeling and Data Fusion

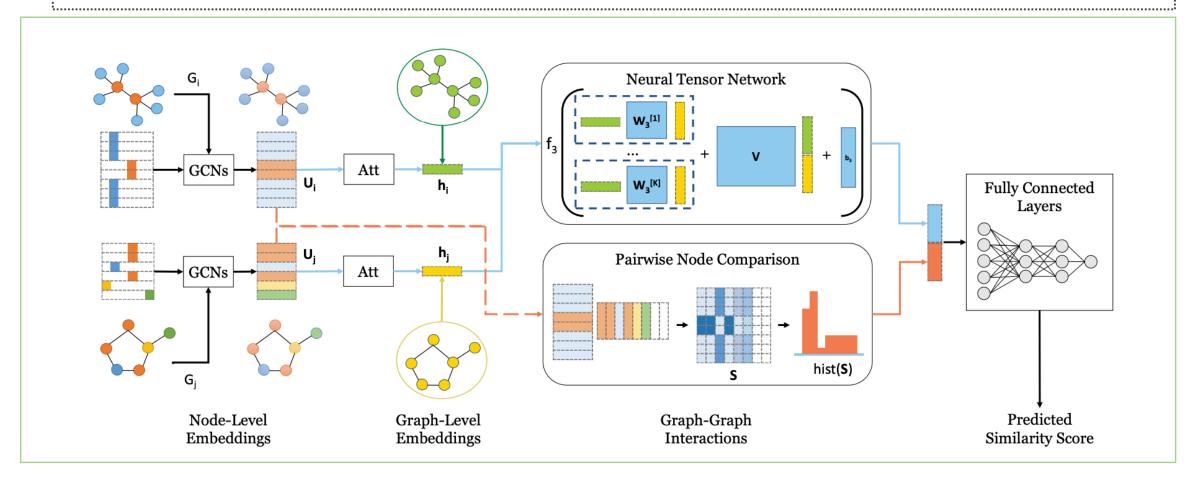


Feature-centric Multimodal Information Retrieval (FemmIR): Graph Matching

- HARG
- Cost Matrix
- Cumulative -Munkres
- Content Edit Distance

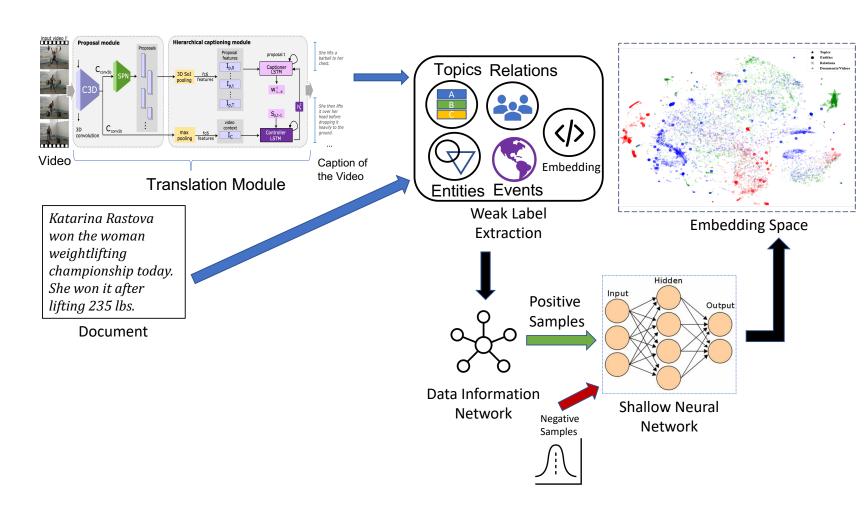


SimGNN: A Neural Network Approach to Fast Graph Similarity Computation [6]

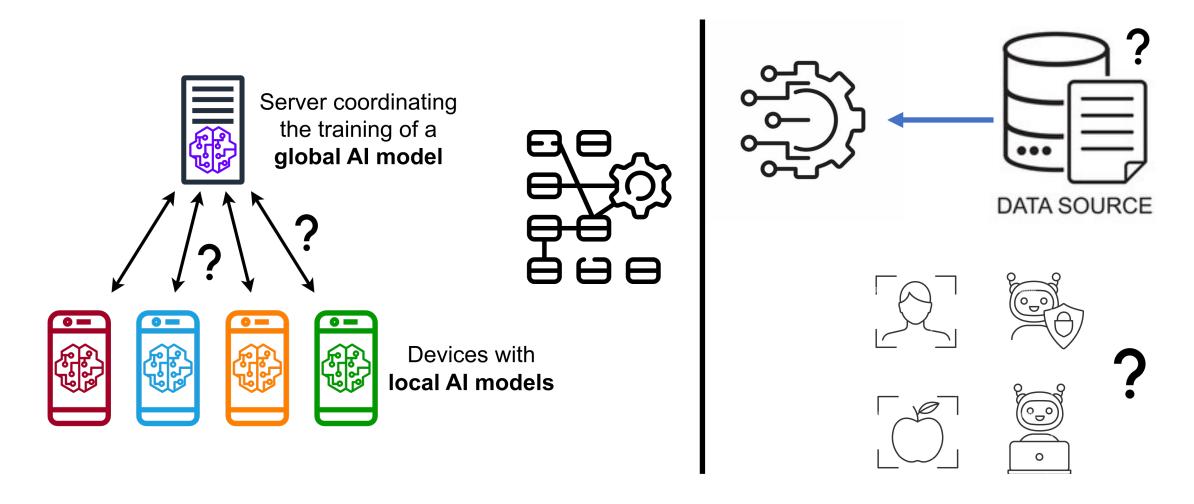


Weakly Supervised Learning (WesJeM)

- translation to a textual representation
- weak feature labels extraction
- Data information network
- Connect data samples to features via interactions
- Contrastive Learning, by jointly embedding in a single space



Challenge 3: Adaption to Open-world Novelties



Novelty Characterization in MMIR

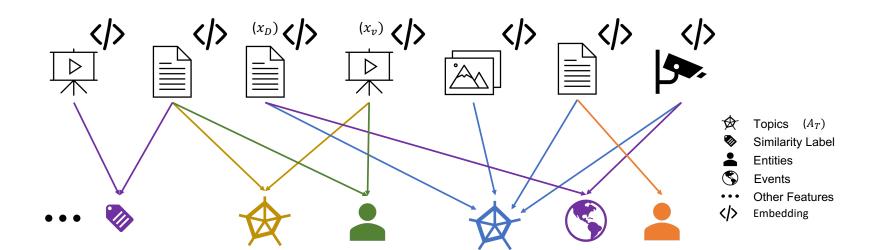
- Covariate shift with change in application domain with the modalities for which translation module is available (covar-1).
- Prior probability shift with novel weak features (prior-1).
- Prior probability shift with no weak features (prior-2).
- Prior probability shift with novel relevance label (prior-3).
- Temporal concept drift with previously relevant data being nonrelevant (concept-1).
- Covariate shift with new modality introduction (covar-2).

Novelty detection in WesJeM

• **Data information network** is used to detect the changes during post-novelty inference.

Novel Instance.

- A test instance x is novel if $G(V_{P_{tr+x}}, E)$ is different from $G(V_{P_{tr}}, E)$.
- Considering a knowledge base for the weak features during training (A_{tr}) , if weak features are absent in A_{tr} during testing, the instance is novel.



Domain Complexity Estimation for Distributed Al Systems in Open-World Perception Domain

- Dimensionality
 - Environment Complexity
 - ID
- Sparsity
- Heterogeneity

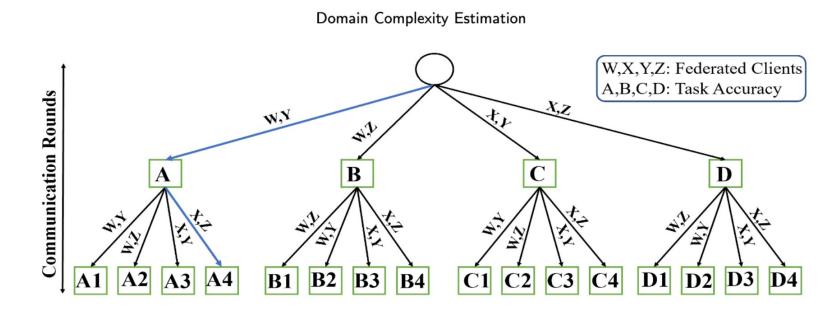
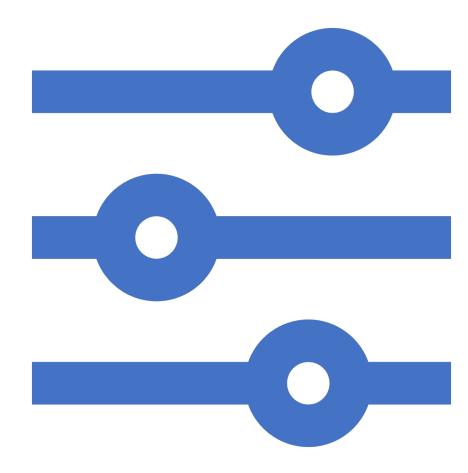


Figure 1: Federated Learning Tree

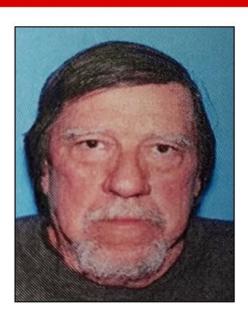
$$F(d,X) = \beta(\sqrt{x_1^2 + x_2^2 + \dots + x_n^2}) + (\frac{1}{m_1} + \frac{1}{m_2} + \dots + \frac{1}{m_d})$$

Applications



Finding a missing person

Missing from: Lehighton, PA • Date Missing: 04/13/2021 • Issue Date: 04/14/2021



Granvil Lang Jr.

Age: 79

Height: 5'5"

Weight: 180 lbs.

Hair: Brown / Gray

Eyes: Brown

- Lang has a gray beard.
- He is believed to be possibly wearing a flannel shirt, blue jeans and sneakers.

MISSING PERSON



Tom Cunningham

13 years old, white, medium build. Last seen on 17th October 2013 wearing blue jeans, a blue hoody and a sleeveless bubble jacket. If you have seen this boy or know of his whereabouts, please contact us. If you have any information whatsoever, please call Dee Valley Police on this number: 08081 57 0243

If you know where Tom is or have any information about him please contact

DEE VALLEY POLICE Dee Valley Incident Room on 08081 57 0243

Difficulty of Investigative Process

Going through countless video feeds









Difficulty of Investigative Process

- Going through countless video feeds
- Human efforts for finding similar M.O.









Difficulty of Investigative Process

- Going through countless video feeds
- Human efforts for finding similar M.O.
- Finding same features throughout heterogenous sources

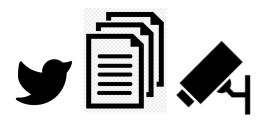








Find-Them's Goals



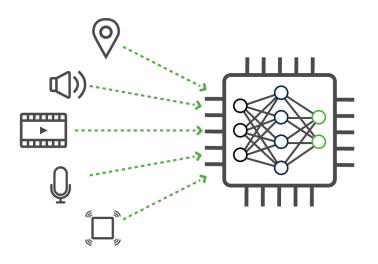
Data Fusion



Automated Investigation



Diffusing Situation (w/ Mental Issues)



Feature Integration from Heterogeneous Sources

EXAMPLE APPLICATION DOMAIN: POLICE INVESTIGATION SYSTEM Similar System in Practice

- https://www.fbi.gov/services/cjis/ndex
- Unclassified national information sharing system that enables criminal justice agencies to search, link, analyze, and share local, state, tribal, and federal records.
- Strategic investigative information sharing system that fills informational gaps and provides situational awareness.
- Analysts: Connecting the Dots
- Detectives: Linking Investigations
- Patrol Officers: Preparing for Encounters
- Regional Dispatchers: Increasing Officer Safety





 incident, arrest, and booking reports; pretrial investigations; supervised released reports; calls for service; photos; and field contact/identification records.

Use cases

- Feature analysis of heterogeneous data for personalized events.
- Fixed queries on data streams.

Event dispatch

- Triggers an event when certain conditions are met.
- Tweet contains certain words and geolocation.
- Alert and dispatch the correspondent procedures/units

Fixed queries

- Fixed queries on top of data streams.
- Cache queries and patterns in Query Engine.
- Aggregated query results from heterogeneous sources.



Accurate data, at the right place, and the right time.

Complete data without noise

Future Research Directions

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

Cars of specific make & model (purple Cadillac) Interested in info. about crimes in a specific district User1 SELECT * FROM video_data WHERE object = 'car' and attribute='purple' SELECT * FROM crash_data WHERE

date_hit = TODAY

Looks for pedestrians in the video data

User2

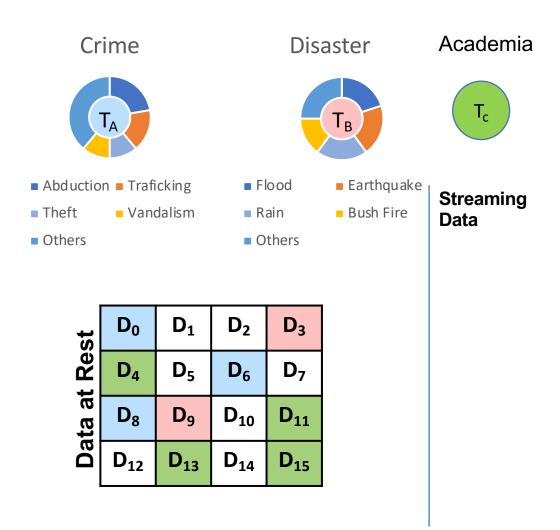
Interested in traffic, accidents, violations

Active Learning to improve intention model with time

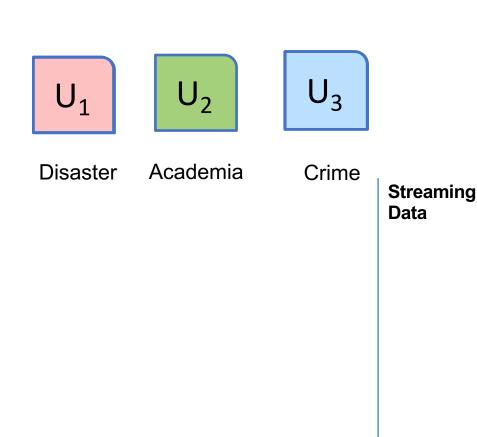
Analyze user queries for user profiling

Expand result of queries with word2vec

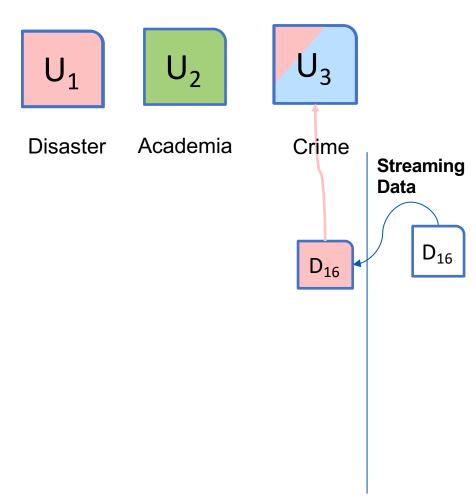
- Extract humaninterpretable topics from a data corpus
- Each topic characterized by features most strongly associated with
- Data as mixtures of topics that spit out features with certain probabilities.
- No need to re-train



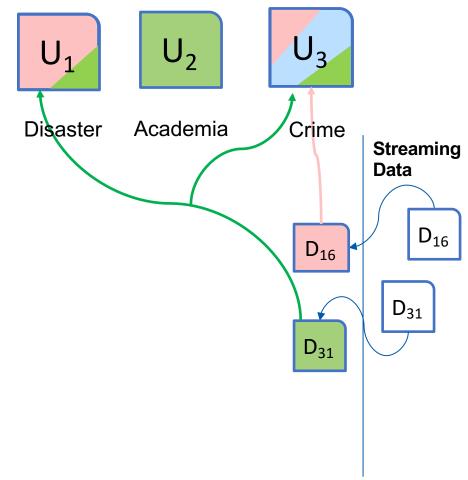
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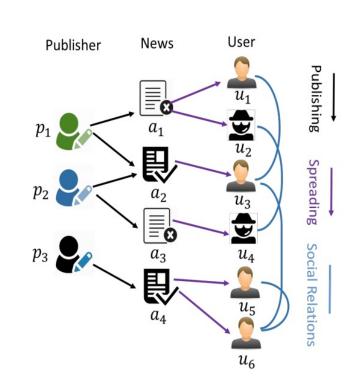
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Cross check integrity and credibility of multimodal data

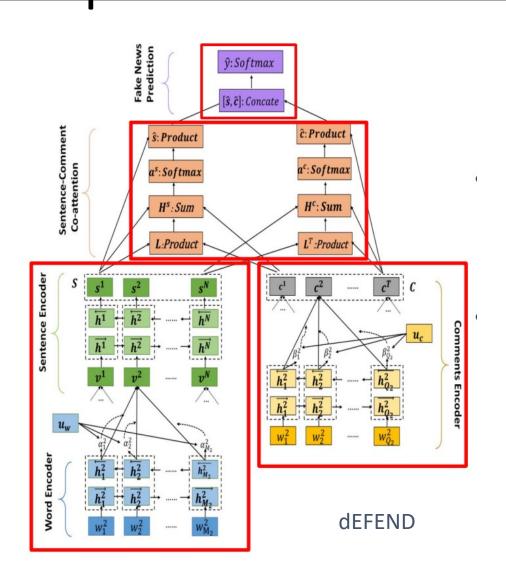


- Detecting fake police leads/ tweets/ [report/ tip news articles] and explaining why it is detected as fake
 - Provide insights and knowledge to domain experts
 - Explainable features from noisy auxiliary information can further help detection performance
- Social context provides rich auxiliary information beyond news content [Tweets and Reports]
 - Goal: learn representations from the heterogeneous network
 - Jointly embedding reports/ news articles and social context
- Information from different modality can help to explain and detect authenticity of another [WeTip News and Tweets]
 - How to model content-content relations?
 - How to leverage authentic knowledge base structured information?



Detection of information credibility with Explanation





- Learn representations for each modality of data
 - Different Attention Networks depending on the data type
- Select top explainable sentences and tweets through a co-attention network
- Detect fake leads with concatenated sentence and tweet representations as Classification task

Kai Shu, Limeng Cui, Suhang Wang, Dongwon Lee, and Huan Liu. ``dEFEND: Explainable Fake News Detection", KDD 2019, August 4-8, 2019. Anchorage, Alaska.

Potential Collaborations

Collaboration	Area
Explanability and Trust	Multimodal information retrieval
Resource Management, Information Completeness	Disaster Resilience
Weak supervision, Credibility, User Modeling	Social media analysis and Big Data
Scalability and Unsupervised, information credibility with explanation	Situational Awareness







Funding

Grants and Proposals

- Vector DBMS proposal for NSF-planning
- DARPA ITM
 - to support building, evaluating, and fielding algorithmic decision-makers that can assume human-off-the-loop decision-making responsibilities in difficult domains, such as medical triage in combat.
 - Difficult domains are those where trusted decision-makers disagree; no right answer exists; and uncertainty, time-pressure, resource limitations, and conflicting values create significant decision-making challenges.
 - Other examples of difficult domains include first response and disaster relief
- DARPA TRIAGE
- Sandia critical mission planning

Past Collaborations

- Various interdisciplinary research centers and initiatives
 - Institute for Defense Analyses (IDA), Information Sciences Institute (ISI)
 - → Novelties in Planning domain
 - MIT (Mike Stonebraker) and University of Michigan (Mike Cafarella)
 - → Situational Knowledge on Demand



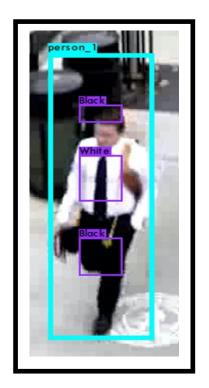


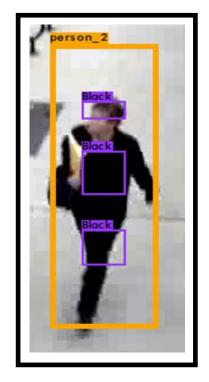
THANK YOU!

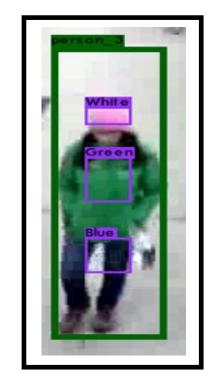
QUESTIONS?

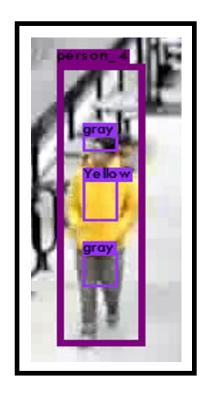


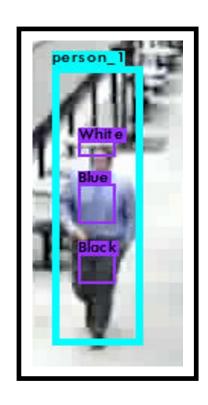
Pedestrian color recognition in a single frame











- Sampling the pedestrian segmented body area
- Extracting the RGB value at every pixel
- > Calculating the color distance to assign the pixel color
- Voting on the majority color of all the pixels to determine the color

Color distance (\triangle C) formula:

$$egin{aligned} ar{r} &= rac{C_{1,R} + C_{2,R}}{2} \ \Delta C &= \sqrt{\left(2 + rac{ar{r}}{256}
ight) imes \Delta R^2 + 4 imes \Delta G^2 + \left(2 + rac{255 - ar{r}}{256}
ight) imes \Delta B^2} \end{aligned}$$



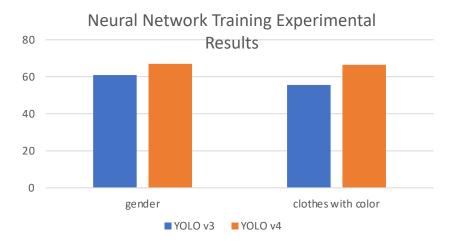
Video Feature Extraction Evaluation

Metrics used:

$$mAP = \frac{1}{|classes|} \sum_{c \in classes} \frac{\#TP(c)}{\#TP(c) + \#FP(c)}$$

Mean Average Precision

 Trained YOLO v3 and YOLO v4 on the 9400+ and 12200+ datasets with 6 classes to detect gender, clothes and color



 YOLO v4 with the largest dataset performed best

Table 2: Performance Evaluation of persons in different colors from web images

Color	Precision	Recall	F1-Score
Black	0.96	0.98	0.97
Purple	0.98	0.88	0.93
Red	0.92	0.92	0.92
Orange	0.96	0.88	0.92
Yellow	0.94	0.98	0.96
Green	1	0.92	0.96
Blue	0.96	0.96	0.96
White	0.91	0.96	0.93

- 8 color classes. Each class with 50 people
- precision and recall stats was calculated as 1 color vs other 7 colors



Network Camera Information Analysis

- Pedestrian Attribute Recognition
 - Frames vs Videos
 - Different Strategies on Convolutional Neural Network

Table 7: Comparisons of recognition accuracy and F1 measure on MARS datasets(%).

Attribute	CNN (Resnet50) ⁶		3D-CNN		CNN-RNN		Temporal Pooling ⁷		Temporal Attention ⁸		Color Sampling	
•	acc	F1	acc	F1	acc	F1	acc	F1	acc	F1	acc	F1
top color	75.22	73.98	67.91	65.19	70.54	67.33	74.98	73.13	76.05	74.64	44.65	38.31
bottom color	73.55	54.09	59.77	36.56	67.71	44.44	71.69	47.84	70.15	46.89	45.26	15.88
gender	90.01	89.71	86.49	76.22	90.07	89.62	91.04	90.63	91.82	91.48	-	-
average	79.59	72.59	67.97	59.18	76.11	67.13	79.24	70.53	79.34	71.01	44.96	27.10

Extracting relations between features, objects and entities Pedestrian tracing in continuous frames



We can trace the walking trajectories of pedestrians by fusion the displacement and clothes color information





We can trace the walking trajectories of pedestrians by fusion the displacement and clothes color information







We can trace the walking trajectories of pedestrians by fusion the displacement and clothes color information







Multi-camera Multi-locations

We can trace the people from multiple cameras located at multiple locations

Camera 1 location A



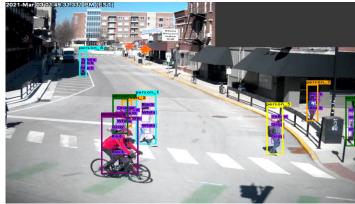
Camera 1 location B



Camera 2 location A

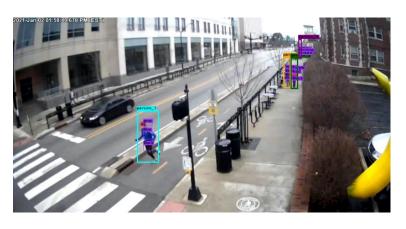


Camera 2 location C



Mark pages according to the proprietary level of information as described in Company Procedure J103 (or remove)

Camera 3 location A



Camera 3 location D





Human pose detection

Pose detection allows the analysis on the people' behaviors across continuous frames

Walking pose tracing



Cycling pose tracing



Weakly Supervised labels

- Representing data in terms of different structural features through which different modalities of data can be similar
- Structural representation of raw unstructured texts (with topics, entities, events, and relationships) allows readers to infer better knowledge
- Feature labels are generated automatically in two steps
 - a textual description of each data sample is generated from any modality;
 - topics, entities, and events are extracted from the textual descriptions and are considered as weak labels for two reasons.
 - quality of the extracted structural units rely on the choice of the extraction models and can be noisy.
 - output generated from the modality specific textual descriptors can be ambiguous and noisy.

Multi-task learning

- For each object, o_i in the graph participating in relation R, s_i^p and s_i^n refers to positive and negative examples. e_{o_i} refers to the vector embedding of the graph object o_i , and y is the label.
- y = 1 for (o_i, s_i^p) pairs and y = 0 for (o_i, s_i^n)

For each individual graph relation, R, we can define the learning objective as follows:

$$L_R = \sum_i L(o_i, s_i^p, s_i^n) \tag{1}$$

$$L(o_i, s_i^p, s_i^n) = y \log sim(o_i, s_i^p)) + (1 - y) \log(1 - sim(o_i, s_i^n)))$$
(2)

where $sim(o_i, s_i^p) = \sigma(e_{o_i} \cdot e_{s_i^p});$ $sim(o_i, s_i^n) = \sigma(e_{o_i} \cdot e_{s_i^n})$

Learning objectives

- Features to Features $(A_T A_T / A_n A_n / A_{event} A_{event})$
 - Similar topics, named entities, or events with embedding value within a certain threshold, are placed together
- Data Sample to Data Sample $(x_D x_V / x_D x_D / x_V x_V)$
 - Positive pairs are selected by
 - Topics, Events and Entities, User Provided similarity labels, and Embedding
- Data Samples to Features $(xA_T/xA_{event}/xA_n)$
- Joint Object Function, $L_{total} = \sum_{i \in O_s, O_s \subset O} \lambda_i L_i$

where O is defined over all the objectives, weight λ_i is set to 1.

$$Rel(a,b) = \frac{\sum_{i \in P(a,b)} w_i}{\sum_{b \in B} \sum_{i \in P(a,b)} w_i}$$

$$Rel(a,b) = sim(e_a,e_b)$$

$$Rel(f, b) = I * N_p(f, b)$$

Reasoning Over the Data Information Network

- Weak Supervised Baseline
 - With the data information graph
 - #paths from one data sample to a given data sample or a given feature
 - counting the paths from one data sample to a given data sample or a given feature.

- Similarity Based Score.
 - Given a data sample, or a feature a and their embedding e_a the relevance score with other data sample b with embedding e_b is:

Novelty Characterization

- Covariate shift with change in application domain with the modalities for which translation module is available (covar-1).
- Prior probability shift with novel weak features (prior-1).
- Prior probability shift with no weak features (prior-2).
- Prior probability shift with novel relevance label (prior-3).
- Temporal concept drift with previously relevant data being non-relevant (concept-1).
- Covariate shift with new modality introduction (covar-2).

Novelty response

- pre-trained retrieval model from WeS-Jem
- three level training strategy
- With new modality introduction novelty, both image and LIDAR modality can be handled with the video translation module. Initial text embedding approaches can generate text embedding for any textual input for prior data shift.
- Linear embedding layers in WeS-JEm maps the OOD inputs into the pre-trained joint embedding space
- For (prior-2) novelty, when system relearns, only the (xx-embedding) objective functions remains active
- For novel modality introduction, a new translation method can be learned.
- User similarity labels provided by Relevance Feedback module have greater weights than old ones