Adaptive Social Sensor Event Detection

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Physical Event Detection

- Traditionally performed with physical sensors
- Some domains require global tracking, and some can be performed locally
  - **Global** – Weather/climate tracking
    - Dense physical multi-sensor coverage (barometric pressure, cloud coverage, humidity)
  - **Global** – Earthquakes
    - Semi-dense sensor coverage (near fault-lines especially)
  - **Global/Local** – Rainfall
    - Dense global sensor coverage
  - **Local** – Flooding
    - Local coverage near flood-prone regions
  - **Local** – Yield monitoring
    - Local coverage on corresponding farm
  - **Local** – Subsurface soil/groundwater monitoring
    - Local coverage on corresponding farm's water source

Global physical event detection

- Goals of physical event detection
  - Near real-time detection
  - Global detection

- Almost-global detection possible, but slow
- Dense global sensor coverage is difficult or expensive

Dense Global Event Detection

- Waste-water disposal earthquakes
  - require continuous deployment of seismometers near fracking wells
  - As wells move, seismometers also move
  - As wells expand, new seismometers deployed
- Landslides occur under a variety of conditions and sensor coverage is expensive
  - Uneven terrain with loose soil post-rain
  - Earthquakes with loose soil or rain
  - Heavy rain and flooding near mountainous or hilly regions
- Traffic jams
  - Dense camera cover with anomaly and video event recognition
  - Current approach (Google, Bing): aggregate phone data of drivers
- Other city events: protests, marches, accidents, fires
- Other disaster type events: hail, forest fire, disease, infection

Social Sensor

- Limiting factor is dense, global sensors
- Social sensors: social media + web data + blogs
- Advantages
  - Dense, global coverage (4B Internet users, 3B social media users)
  - Near real-time (events reported within 1m – 2hr usually)
  - Increasing ubiquity + rich historical & behavioral data
  - Multi-modal data (text, image, video)
  - Multi-perspective data (multiple users and sources)

Event Detection from Social Streams

- Social streams can be leveraged for various real-world events beyond disasters
  - Earthquake detection[1]
  - Landslide/Flooding detection
  - Traffic jams, riots, social events[2]
- Near real-time coverage
- Variety of physical events can be detected with the same framework

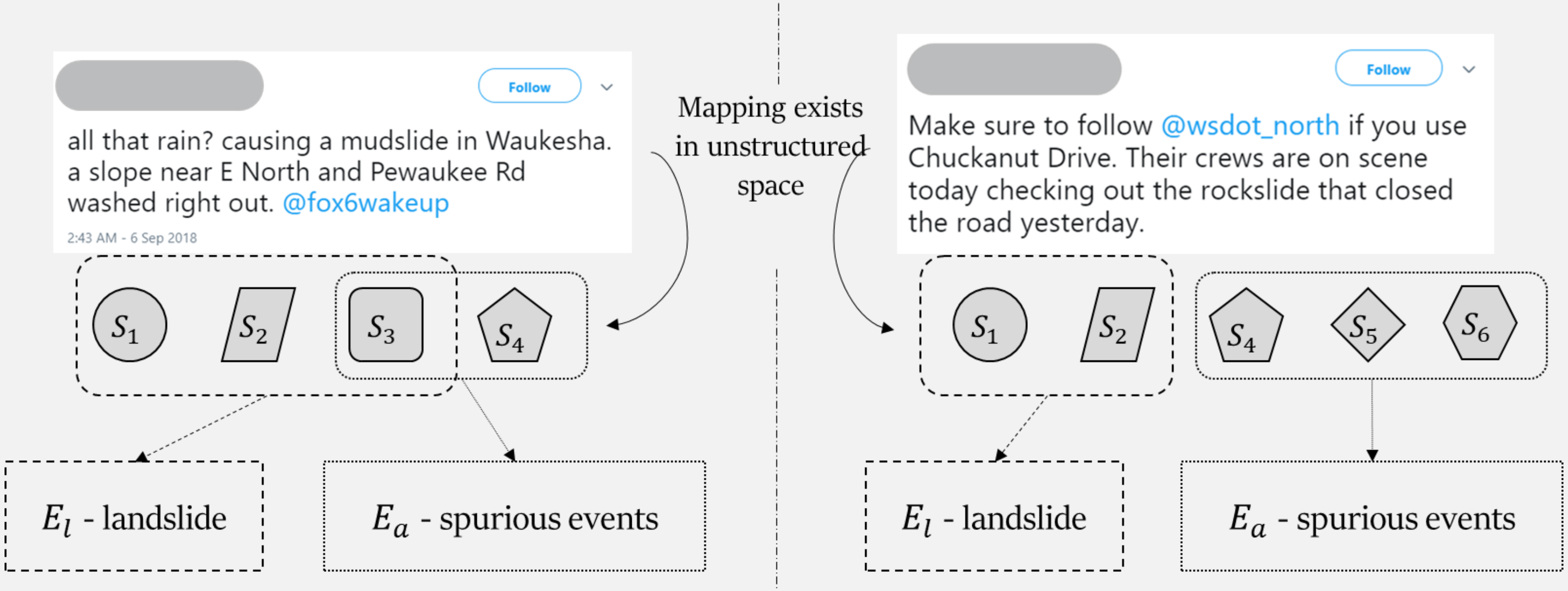
[1]Earthquake Shakes Twitter Users: Real-time Event Detection by Social Sensors, Sakaki et al
[2]Social Sensors and Pervasive Services: Approaches and Perspectives, Rosi et al

Challenges in Social Sensor Event Detection

- NLP on Social Data
  - Social data is noisy + low context
  - NLP is more challenging due to lack of context + noise + short text nature
- Difficult to filter irrelevant topics
  - Text/Image/Video data on large variety of topics (not dedicated sensor)
  - No heuristic or simple filtering rules
- Weak-signal events
  - Millions of events represented in data, with a fraction being relevant
  - Relevant class is the minority class (few training data)
- **Concept Drift**
  - Changes in underlying data distribution exacerbates above problems

Concept Drift in Social Sensors

- A datapoint P_i is a distribution over events $P(E_a|P_i)$
  - $E_a \in \boldsymbol{E}$ (universe of events)
  - $E_{landslide} \in E_a$
- Independently, each point is a generative model over signals $\boldsymbol{S}$
  - $P(P_i|\boldsymbol{S})$
- $E_a = \sum_i^k a_i S_i$



Concept Drift in Social Streams

$$E_a = \sum_{i}^{k} a_i S_i$$

- Concept drift occurs when distribution of a_i changes (usually over time)
- *Real* concept drift
  - Changes in $f(a_i)$ cause changes in true decision boundary
- *Virtual* concept drift
  - Changes in $f(a_i)$ do not cause changes in true decision boundary
- True decision boundary
  - The actual hyperplanes separating classes
  - ML approximates the true hyperplanes

Types of Concept Drift

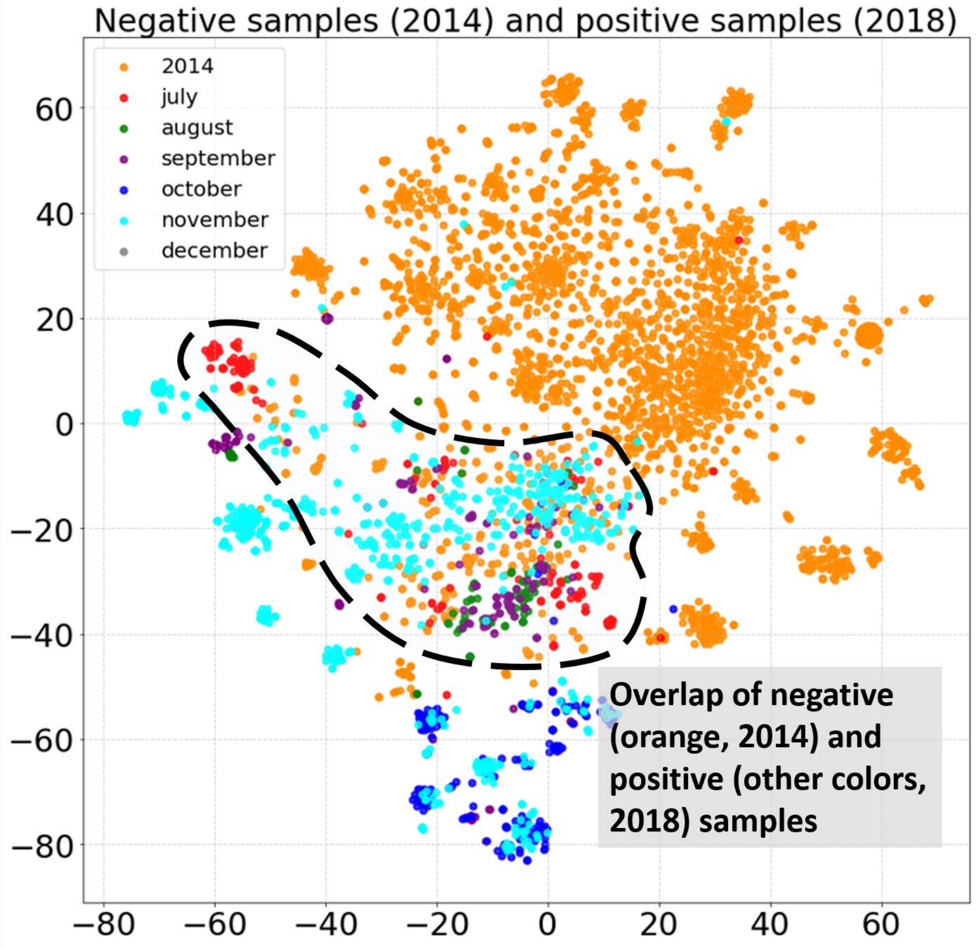
- **Real concept drift**
  - Several approaches to detecting and adapting to real drift
  - get oracle labels, and compare error rate over time of classifier
  - If error rate increases, drift has occurred
  - Use oracle labels to retrain model
- **Virtual concept drift**
  - Virtual drift – new regions of data space discovered over time
  - New data is dissimilar from training data
  - Sometimes difficult to generalize existing machine learning event detection rules

Our Dataset

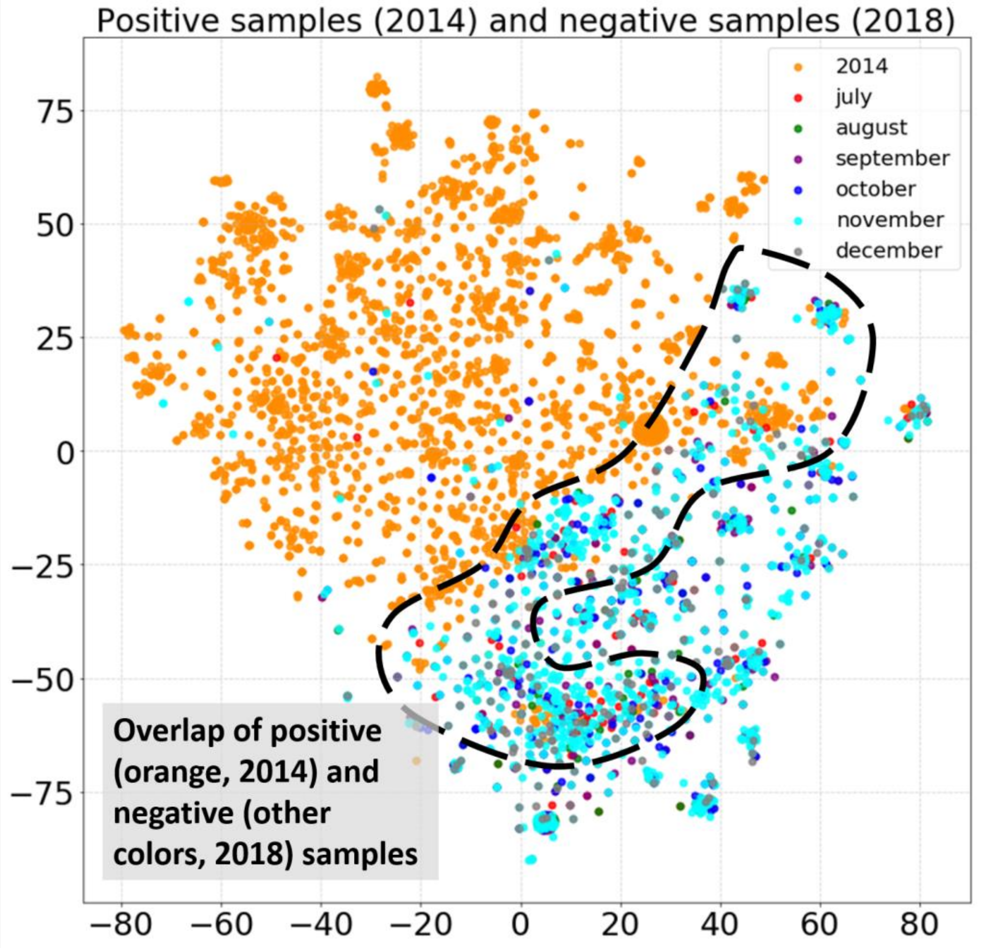
- Physical event detection
- Collected from social sources over several years
- Drift
  - Data ingest techniques change over time
  - Data content changes
  - Increasing noise over time
- Events
  - Landslides
  - Flooding
  - Earthquake

Evidence of Real Drift

False negatives in 2018

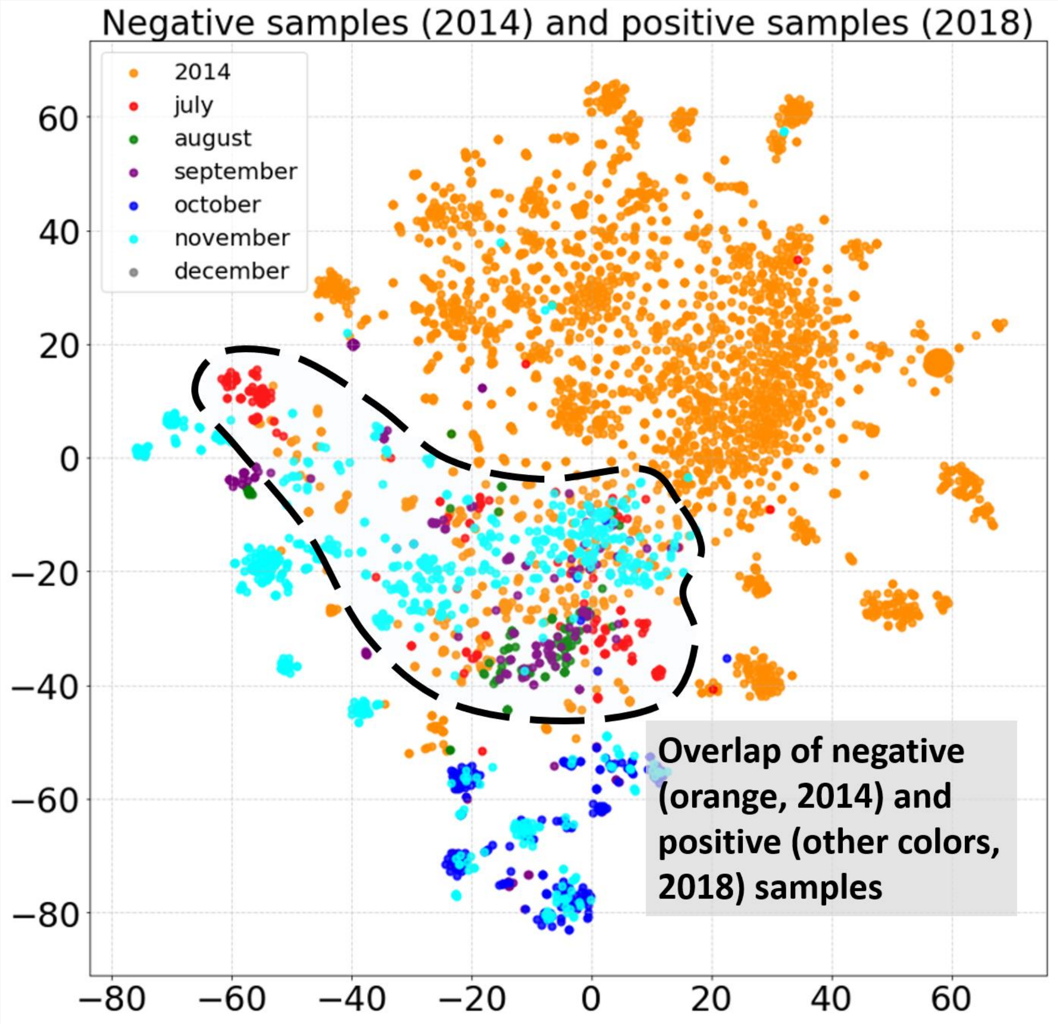


False positives in 2018



Real drift – False negatives

- Each data point from 2014-2018 encoded with *w2v*
- tSNE used for dimensionality reduction on entire dataset (positive + negative)
- For classifier trained on 2014 data only (orange)
- Positive instances of 2018 data indistinguishable from negative samples in 2014
- False negative errors



Real drift – False positives

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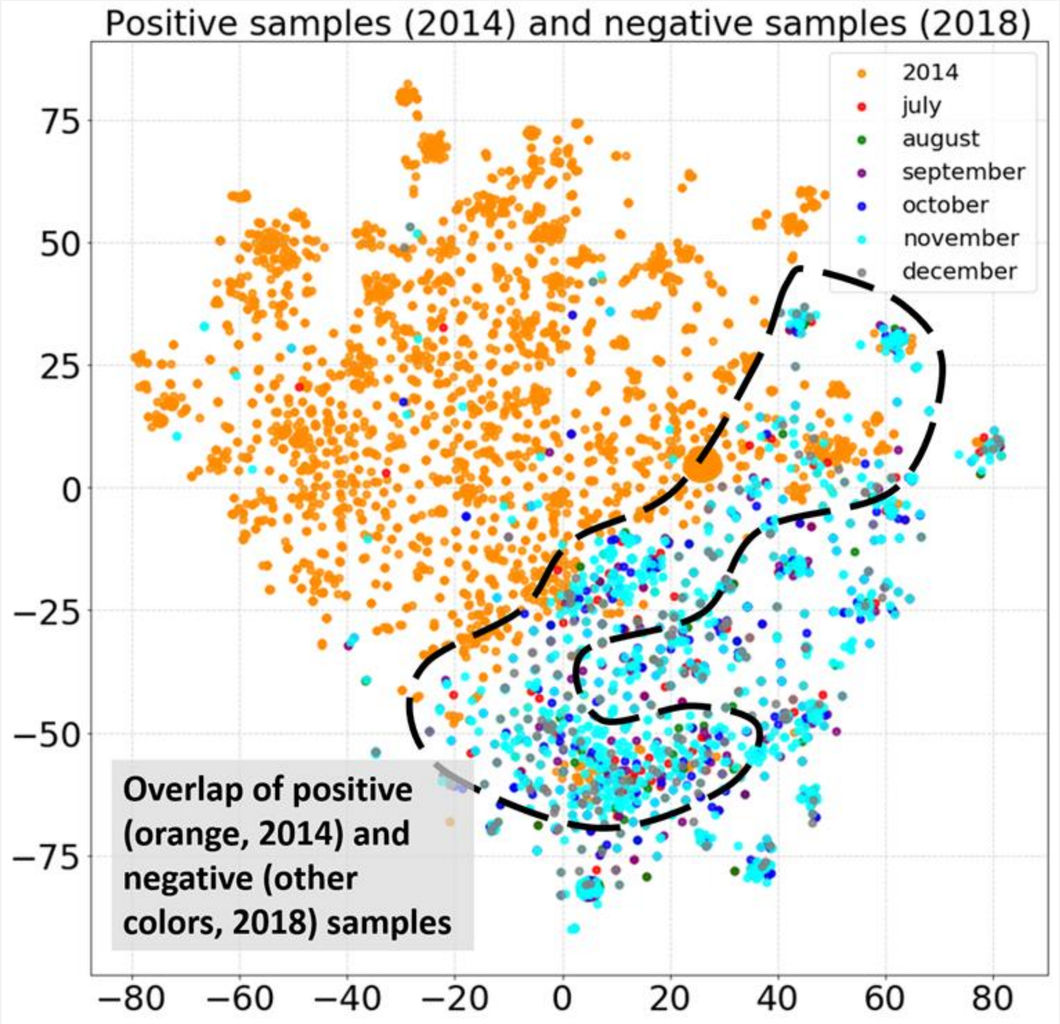
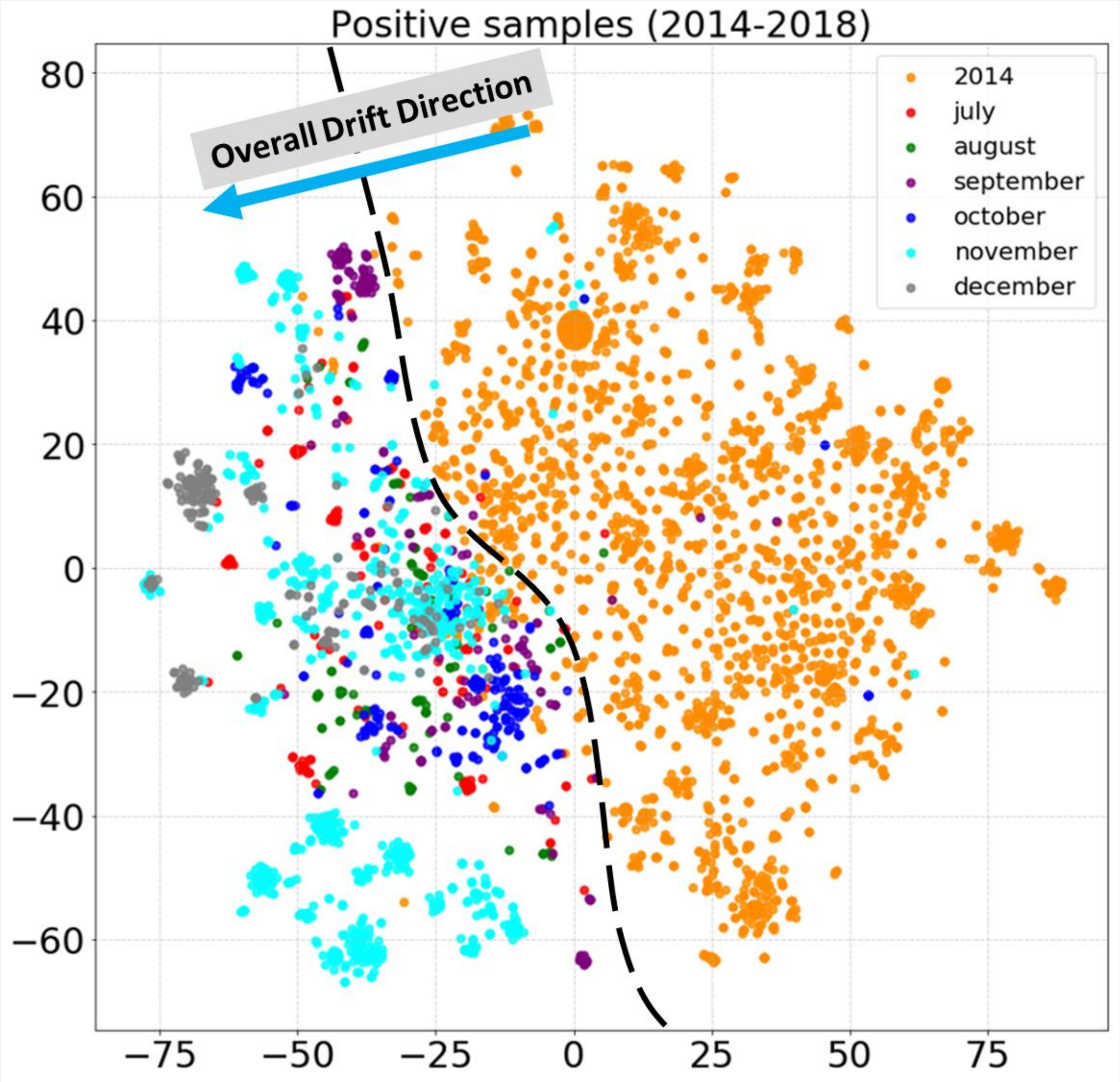


Evidence of Virtual Drift

- Shift in positive samples
- Positive samples in 2018 lie in different region than positive samples in 2014
- Virtual drift can lead to real drift
- ML approximates true decision boundary
- So virtual drift can overstep an incorrectly generalized boundary



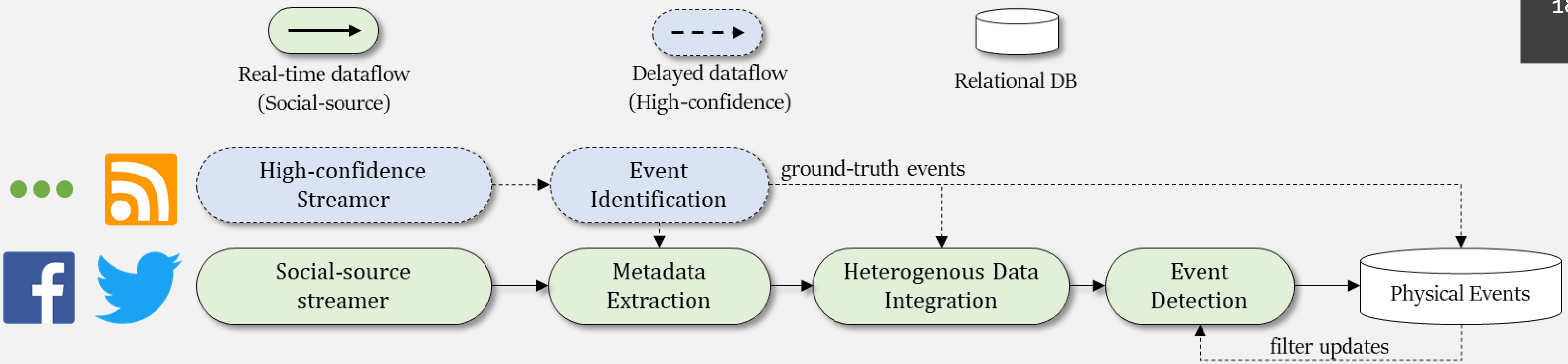
Putting it together

- Our approach addresses two broad challenges
  - ML-based event detection on social streams
  - Drift detection and adaptation for continuous learning
- ML-based Event Detection framework
  - Our framework is designed to be deployable for various event types
  - Real-time streaming from **social** sources,
  - Continuous data collection from **reputable** sources
  - Data processing using pub/sub
  - Event detection with ML classifiers
- Drift detection and adaptation
  - Automated drift detection without oracle labels
  - Drift adaptation without human/oracle labels

Social Stream Event Detection

- Traditional event detection assumptions do not hold

- Event characteristics ~~do not~~ **exhibit changes**
  - Concept drift phenomenon causes changes in underlying data distribution
- Event detection rules ~~do not~~ **fluctuate continuously**
  - Concept drift phenomenon causes changes in decision boundaries
- Raw sensor data are not easily calibrated and ~~do not~~ **have noise**
  - Social sensor data is highly noisy
  - Relevant class is minority class/weak-signal
  - Trend-based methods not feasible for weak-signal events
  - Statistical and deep ML methods useful for social sensor data



Event Detection Framework

High Confidence Dataflow

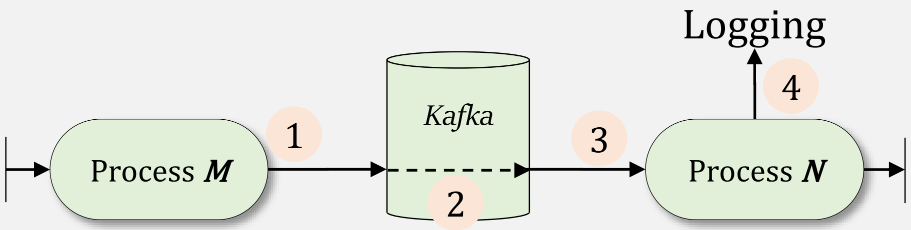
- High latency
- Streamer downloads news articles, government reports
- Event identification to perform event detection
- High confidence sources are stable, with little to no drift

Social Source Dataflow

- Low latency, abundant, noisy, global coverage
- Process datapoint
- Heterogeneous Data Integration for labeling (5%)
- ML-Based Event Detection on the rest (95%)

ASSED Environment Setup

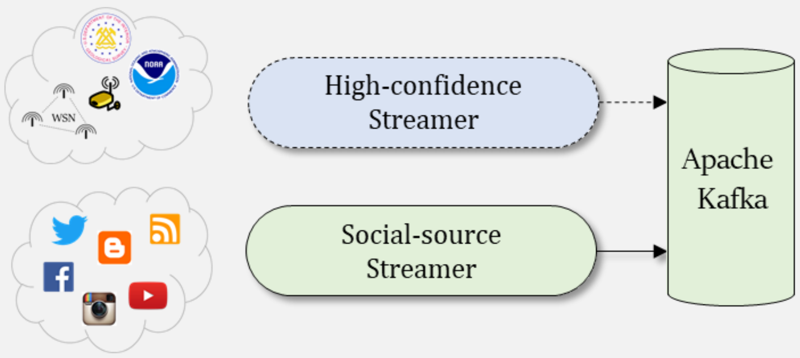
- ASSED framework
- Streamers (**High-confidence** and **Social source**)
  - ASSED supports Twitter API, Google Search API, NewsAPI
- ASSED process
  - Primitives for framework process
  - ASSED processes communicate with each other with Apache Kafka



1. Process ***M*** exports output as <topic-data> pair into *Kafka* with registered *export-key*
2. Kafka keeps output until it is requested or 3 days have passed
3. Process ***N*** continuously reads data from its *import-key* topic
4. Process ***N*** records key offset for recovery

Streamers

- Each data point is saved on disk and sent to Kafka pub/sub
- Each ASSED process is assigned an *import*- and *export*- key
- Buffers between multiple-input processes
  - Kafka does not deal with multiple ingests
  - A topic item can be processed exactly once or continuously until expire
  - With ASSED, we create a buffer process that manages MI dataflow
  - Buffer ingests single-input and pushes copies for each input in MI flow



export-key template

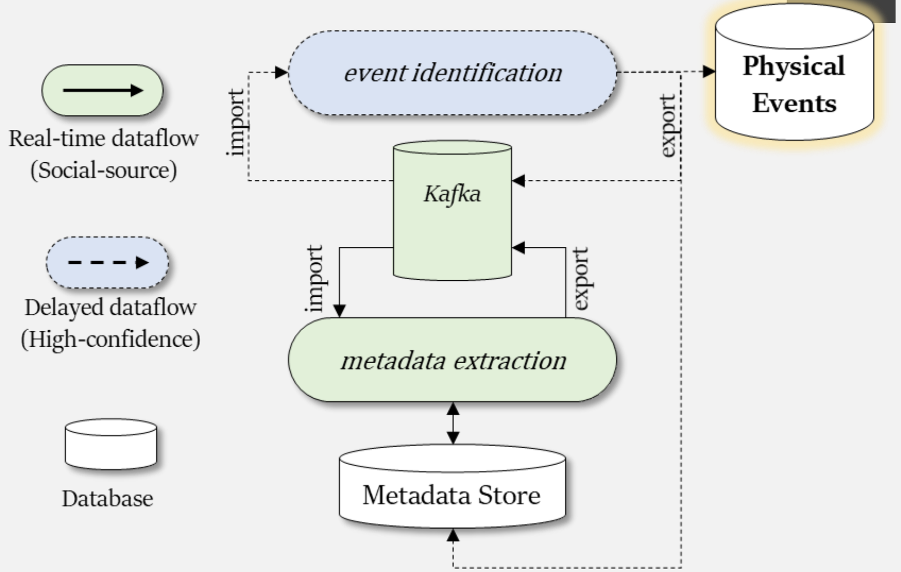
"streamer : lang : key : src : url : id : timestamp"

value format

$P_i = \{p_i, \boldsymbol{l_i}, t_i, \boldsymbol{hl_i}, u_i\}$

export-key attributes	Social-source	Reputable-source
streamer	'ss'	'rs'
lang	Any language supported by ASSED application ('en', 'fr', etc)	'en', 'fr', etc for reputable text sensors (e.g. news articles), or 'num' for numeric data
keyword	Physical event designation of application ('landslides')	Physical event designation of application ('landslides')
source	Name of social network ('Twitter')	Name of reputable source ('NOAA')
url	URL of post "twitter.com/.../1072933351441526784"	URL of source; 'NULL' if source is a physical sensor endpoint
post_id	Local auto-incrementing numeric ID	Local auto-incrementing numeric ID
streamer_timestamp	Local timestamp of commit to *R_Store*	Local timestamp of commit to *R_Store*

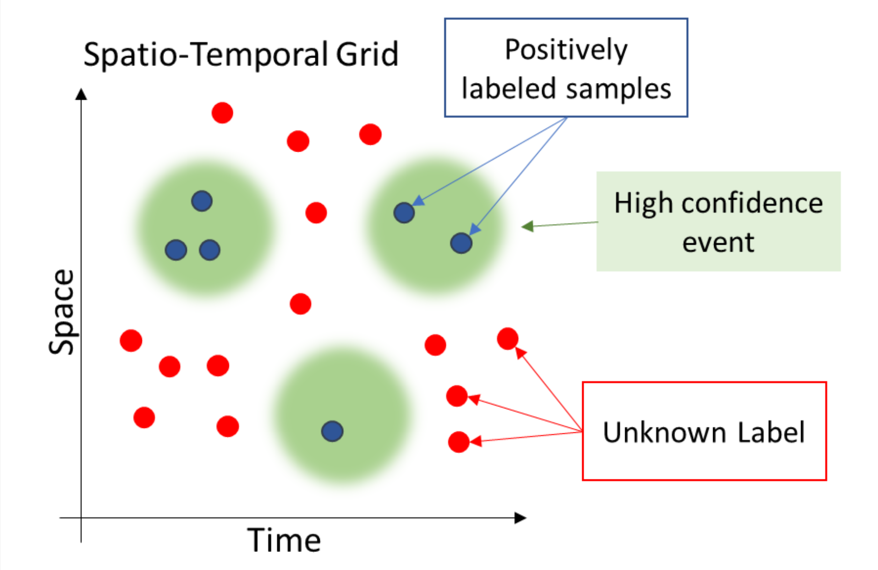
Metadata Extraction



- Event detection requires location
- NER fails on short-text streams (low context)
- We integrate high-confidence dataflow
- High-confidence events' locations stored in Metadata cache (Redis)
- Locations used as substring match for Social Source data

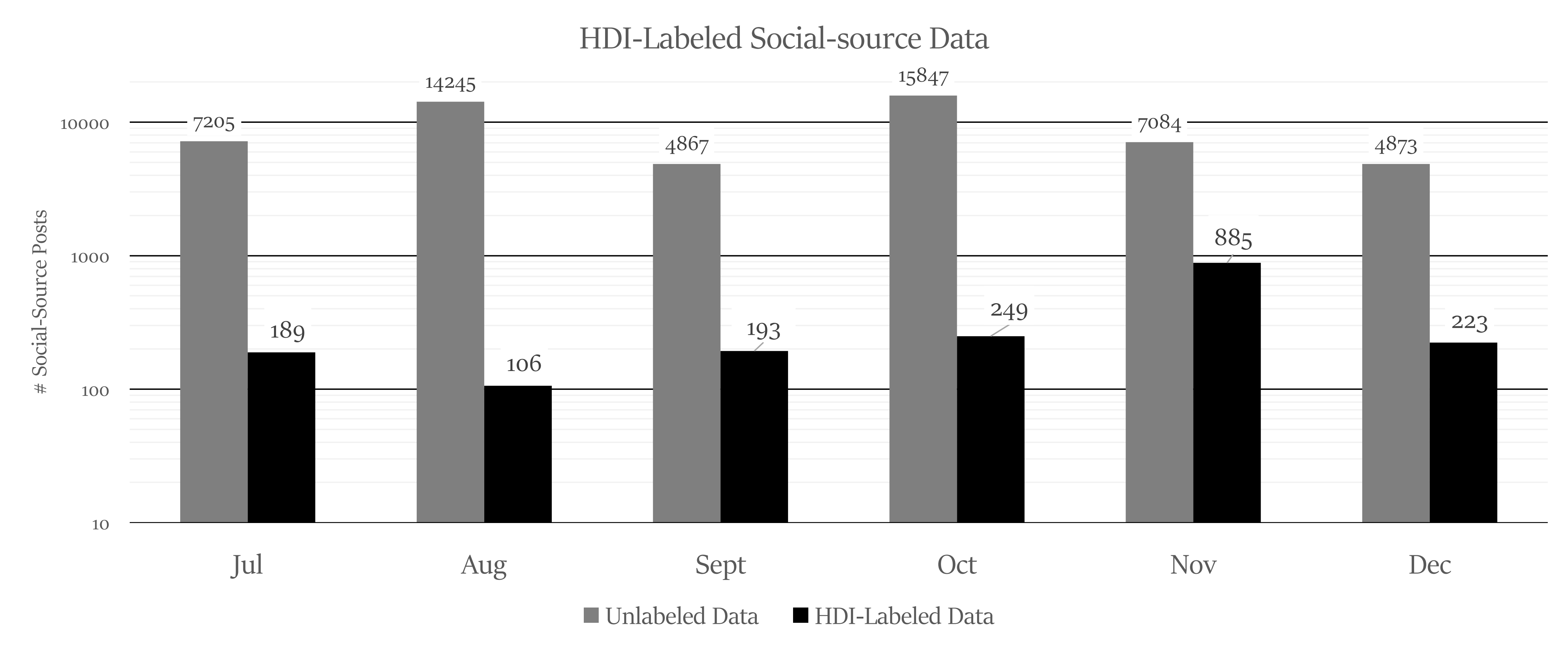
- Additional metadata
  - User information

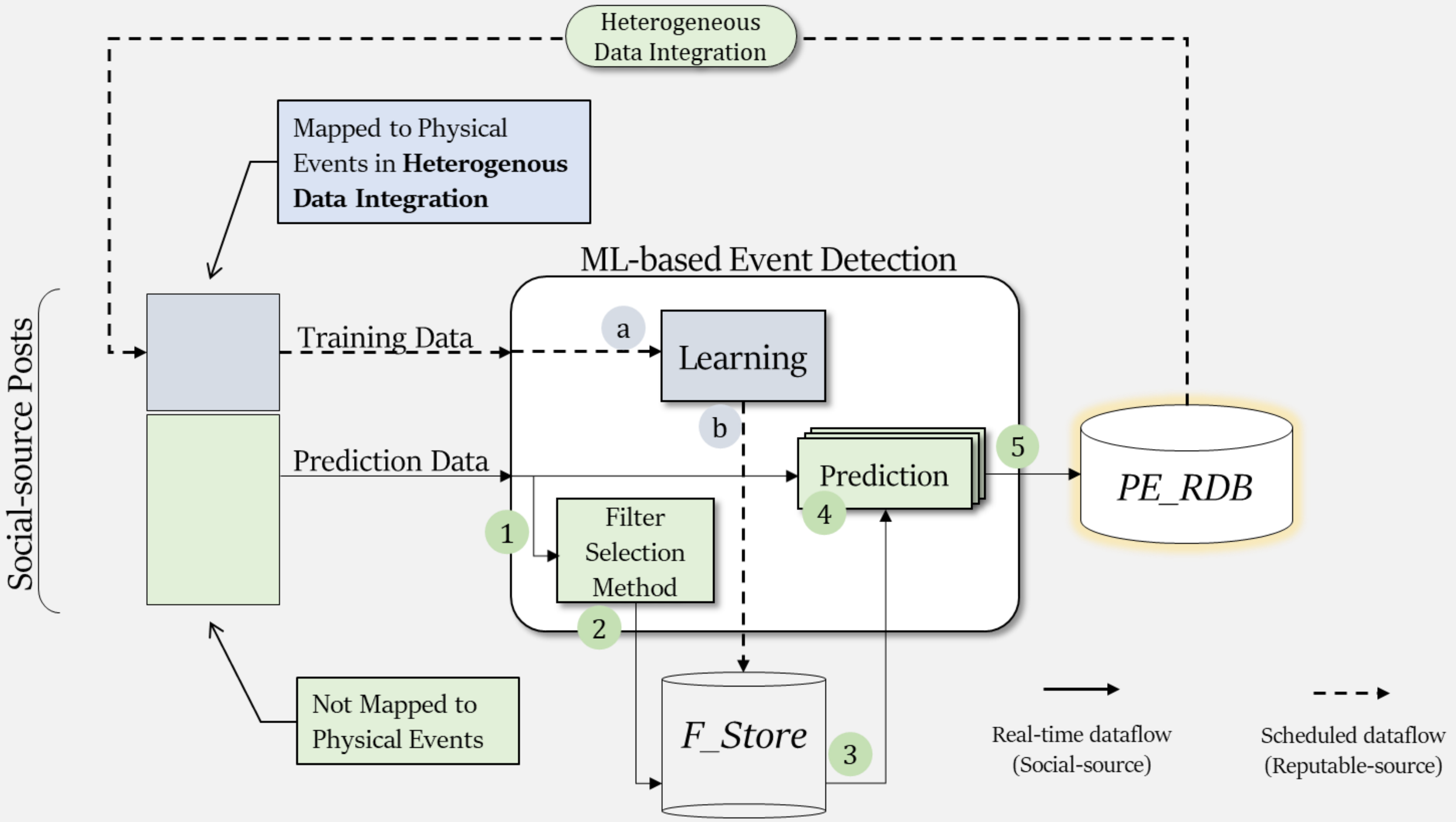
Heterogeneous Data Integration



- Traditional event detection approach
  - Generate model on training data
  - Use initial model for all events
- This fails in drifting environments
  - Virtual drift – generalization failure
  - Real drift – model *must* be updated
- High-confidence sources are ground-truth data
- Social posts in same spatio-temporal region are labeled as relevant events
- Remaining posts are passed through ML-based Event Detection
- On average, 5% of social posts can be so labeled

Heterogeneous Data Integration





Filter Generation/Updates

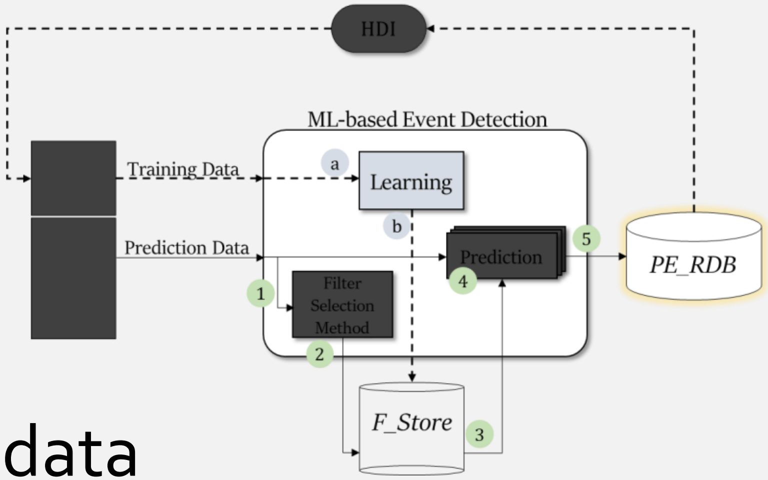
- a ASSED generates new filters + updates existing filters
- b Filters are sent to *F_Store* with training data

Event Detection

1. Data cleaning and encoding
2. Processed data sent to ASSED
3. ASSED matches data to *F_Store* filters (k-NN)
4. Selected filters create an ensemble
5. Detected events are sent to *PE_RDB*

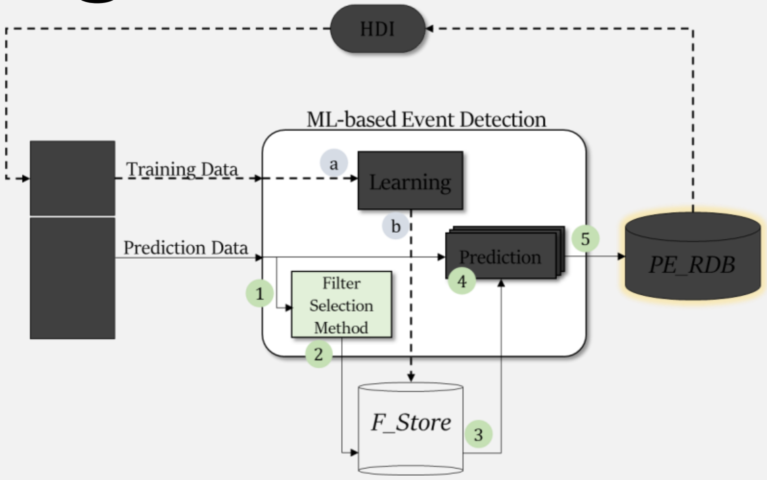
ML-Based Event Detection

Event Detection - Learning



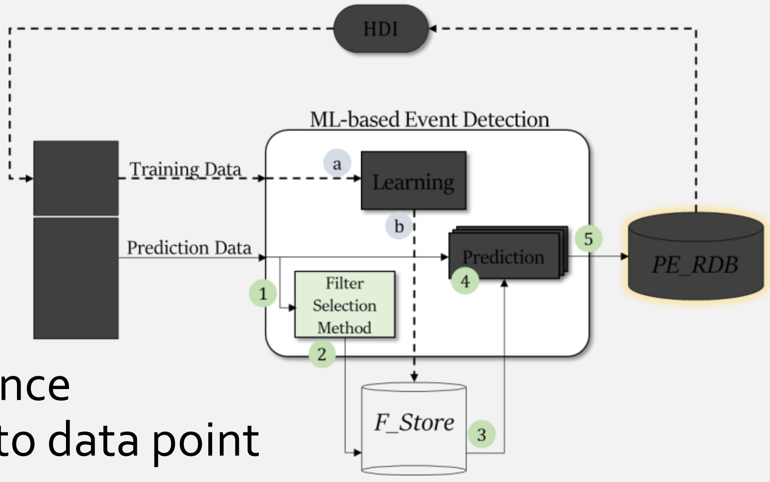
- HDI-Labeled data, where available, is used to generate new classifiers/filters
- Each filter is stored in a *Filter* database (*F_Store*)
- A filter is referred to using its compressed training data
  - Centroid of training data
- **Concept drift adaptivity**
  - Filters continuously and automatically updated using HDI labels
  - HDI labels do not require human intervention, so no latency in labeling
  - No human cost in labeling/updates either

Event Detection – Classifier filtering



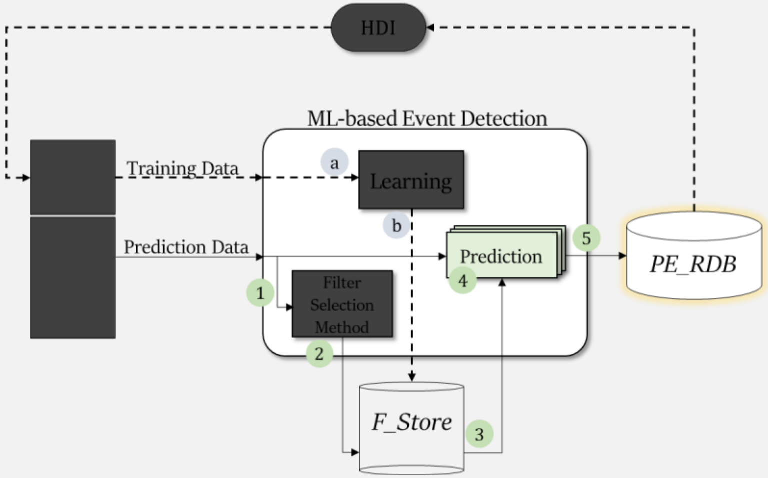
- ASSED allows several modes to filter classifiers for ensemble selection
  - Recent-New
    - Only most recent (prior update/generate window) newly created classifiers
  - Recent-Updates
    - Only most recent updated classifiers
  - Recent
    - All recent classifiers, either new or updated
  - Historical-New
    - All classifiers newly created
  - Historical-Updates
    - All updated classifiers
  - Historical
    - All classifiers created in operational history

Event Detection – Classifier selection



- After classifier filtering, ASSED allows the following selection methods
  - No-further-filtering
    - All filtered classifiers are used to create an ensemble.
    - Ensemble can be unweighted, or weighted on classifier performance
    - Ensemble can also be weighted on distance of classifier centroid to data point
    - Classifiers performance on most recent HDI test-set
  - Top-k Performance
    - Classifiers tested on HDI test-set (stored in *F_Store*)
    - Top-k performant classifiers used in ensemble
    - Weights: unweighted, performance, or distance
  - Top-k Nearest
    - Top-k nearest classifiers to data point
    - Distance measured using training centroid
    - Weights: unweighted, performance, or distance

Event Detection – Prediction

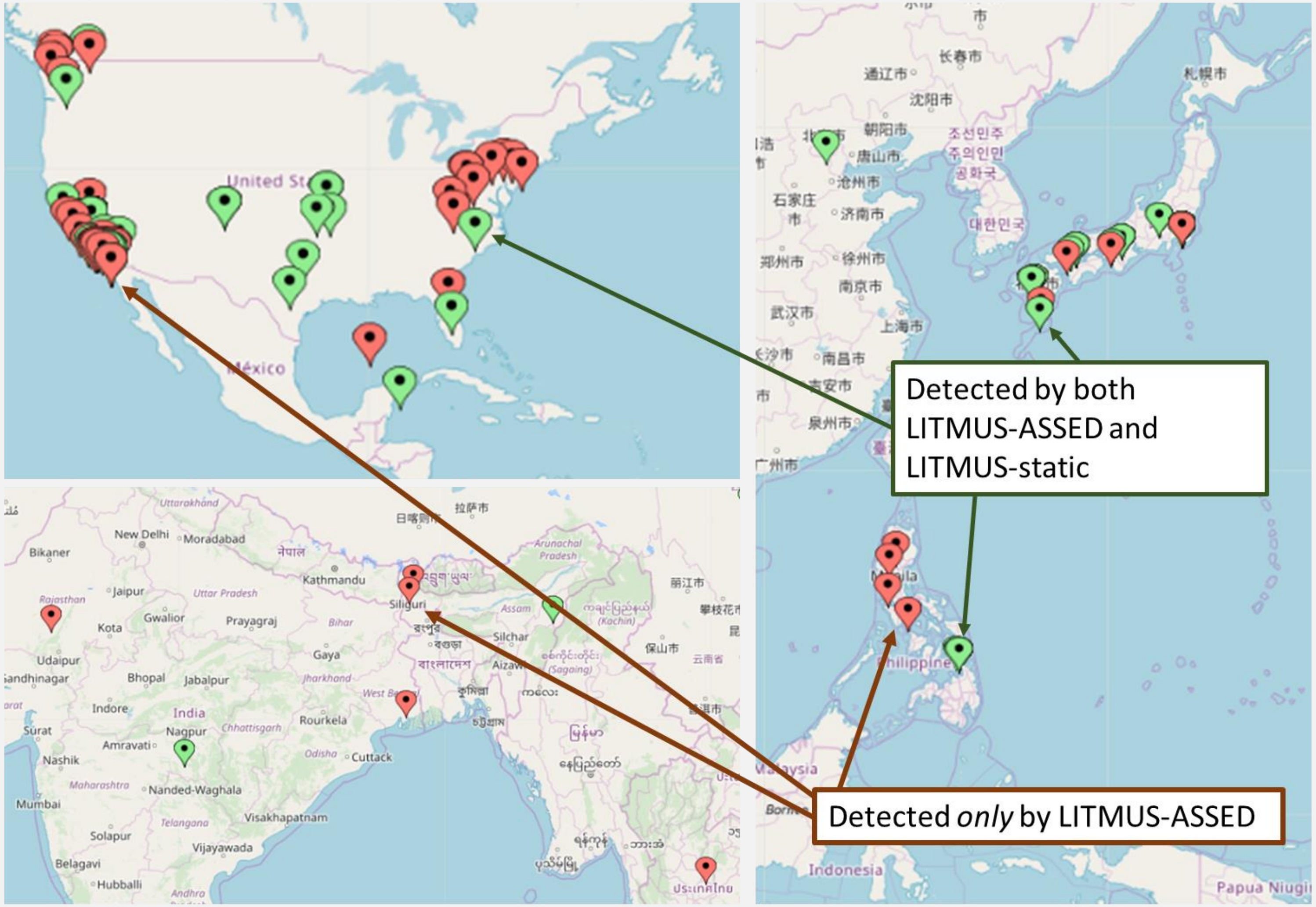


- Generated ensemble used for prediction

- Evaluation
  - Tested static and adaptive approaches
  - Static – learner trained in 2014 and never updated
  - Adaptive – use ASSED framework
  - LITMUS – Landslide Detection System
  - Built with ASSED Framework

  - https://grait-dm.gatech.edu/demo-multi-source-integration/
  - Only ASSED version (does not include static version)

Results Preview



Extraneous information

Extraneous information, Missing context

Extraneous information

Low context, multiple events

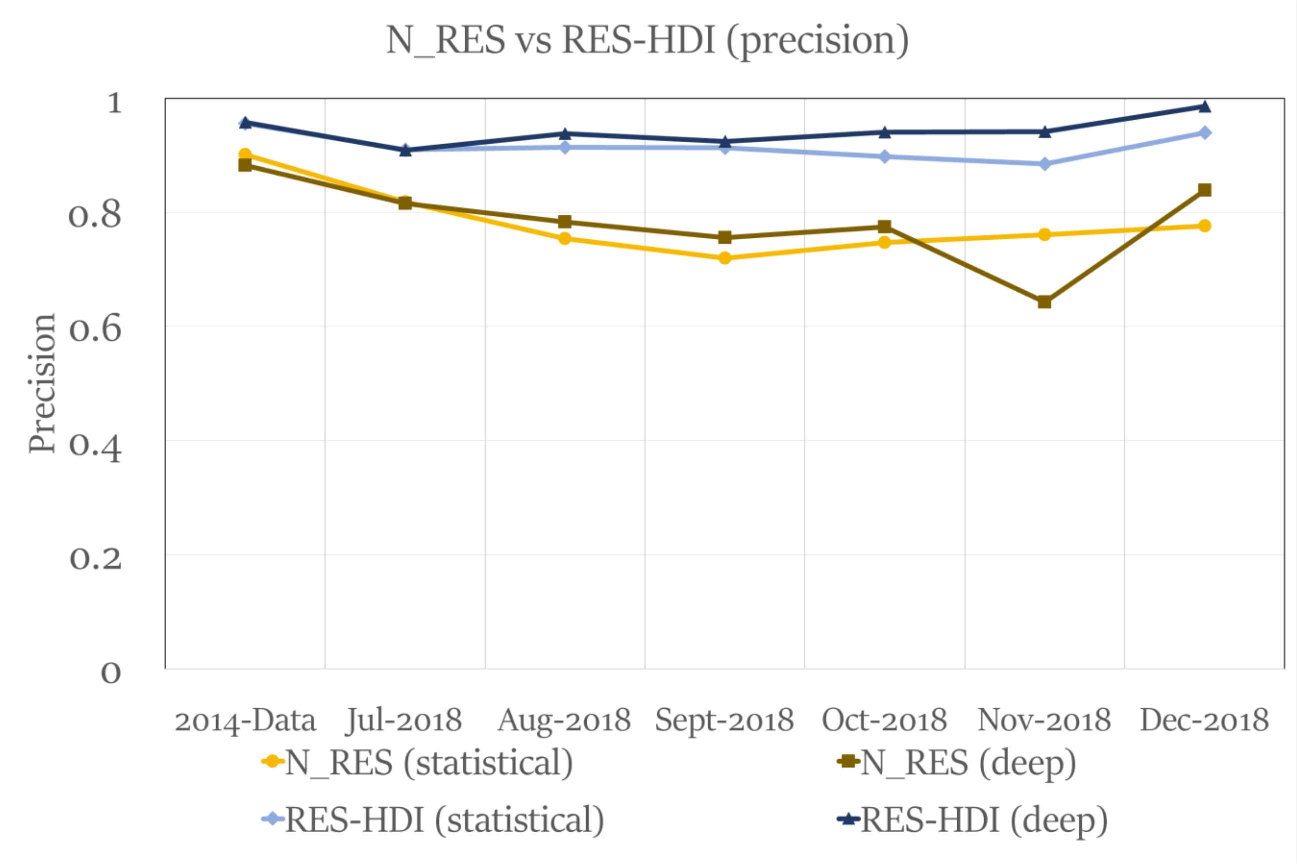
Experimental setup

- We tested four broad approaches (including variations)
- We cover overall results here

Approach	Description	Available Training Data
N_RES	Non-resilient encoding/classifier without HDI	2014 Data
RES	Resilient encoding/classifier without HDI	2014 Data
N_RES-HDI	Non-resilient encoding/classifier with HDI	HDI-Labeled Social data (07/18 - 12/18)
RES-HDI	Resilient encoding/classifier with HDI. (Uses **kNN** scheme)	HDI-Labeled Social data (07/18 - 12/18)

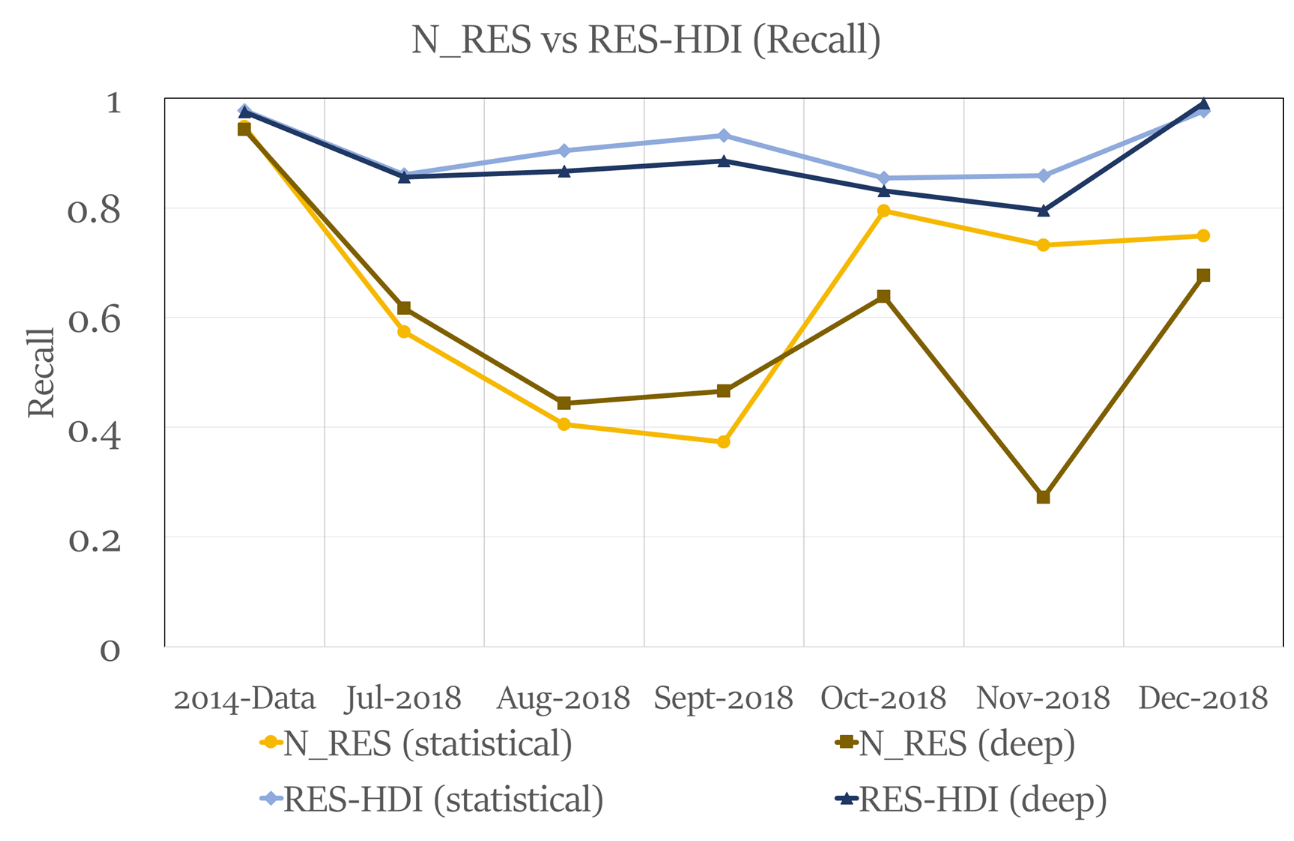
Precision

- **Statistical vs Deep**
  - No significant difference between either in precision
  - N_RES (deep) has slightly more variability in late 2018
- **HDI vs Non-HDI**
  - HDI confers adaptivity from beginning
  - HDI-based updates allow RES-HDI and to outperform N_RES
  - RES-HDI performance begins increasing in late 2018



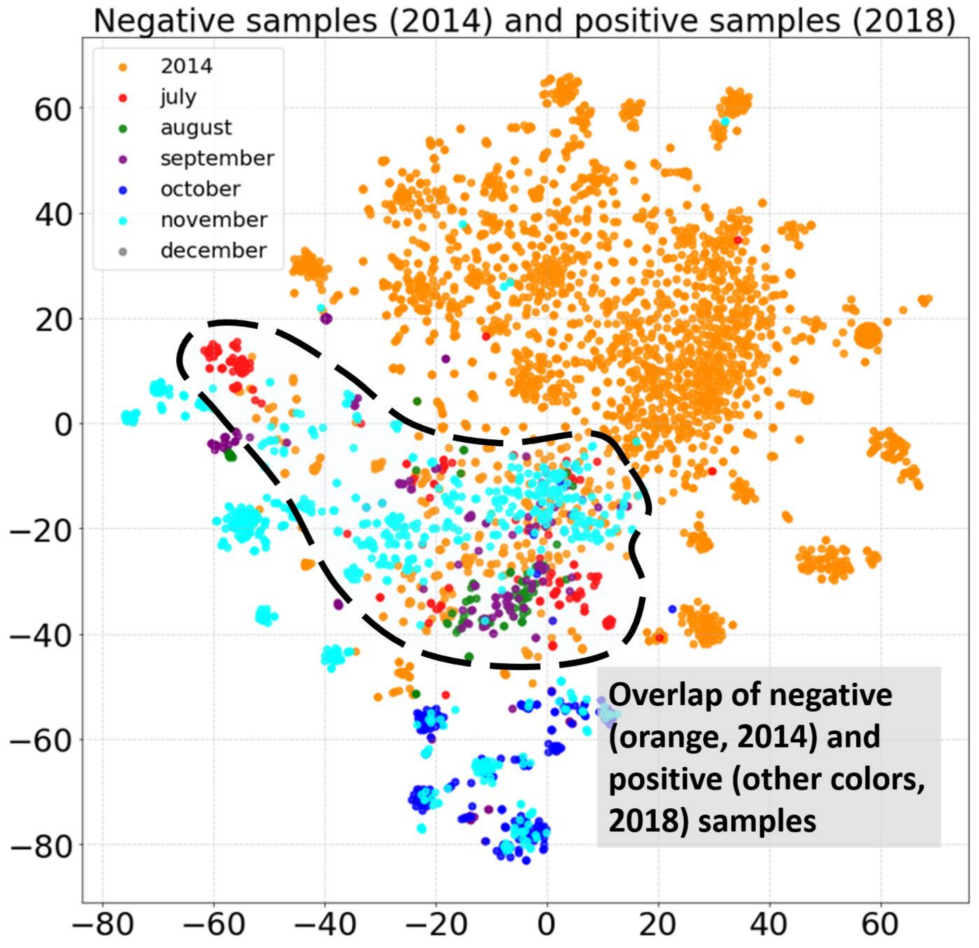
Recall

- **Statistical vs Deep**
  - Significant variability in recall
  - Recall: higher false negatives
- **HDI vs Non-HDI**
  - HDI confers adaptivity from beginning
  - HDI-based updates allow RES-HDI and to outperform N_RES

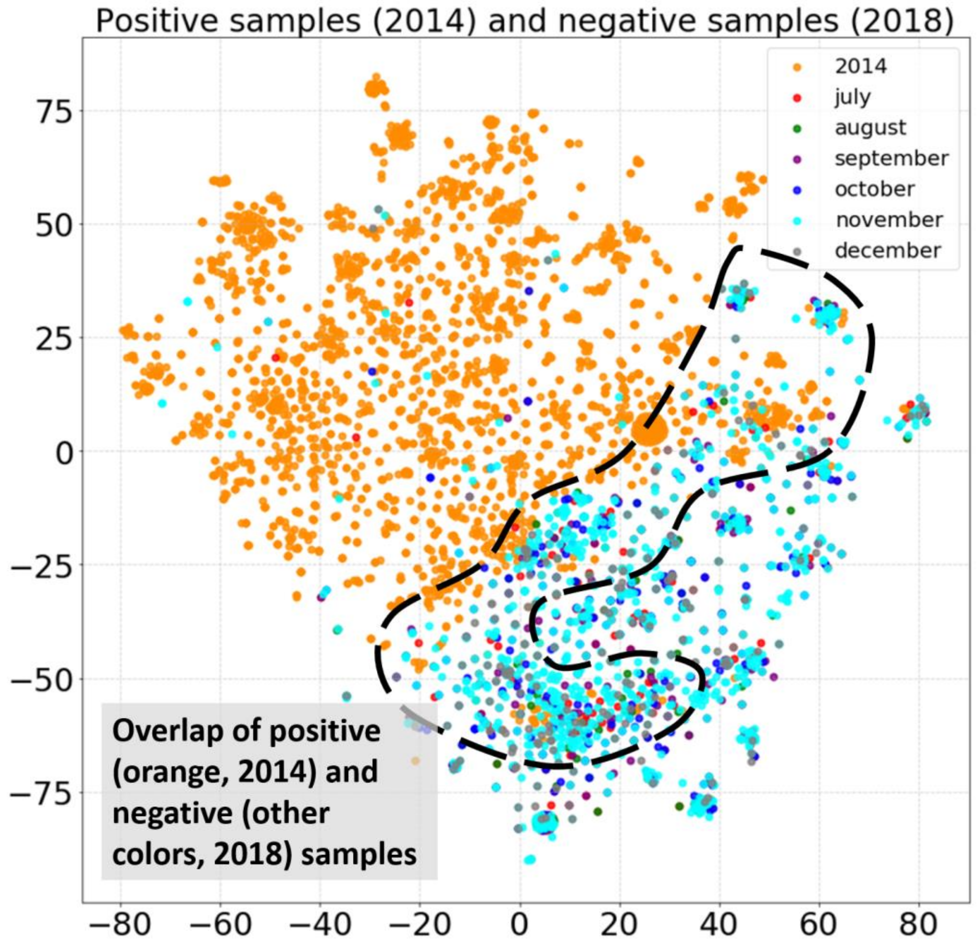


Throwback: Drift

False negatives in 2018

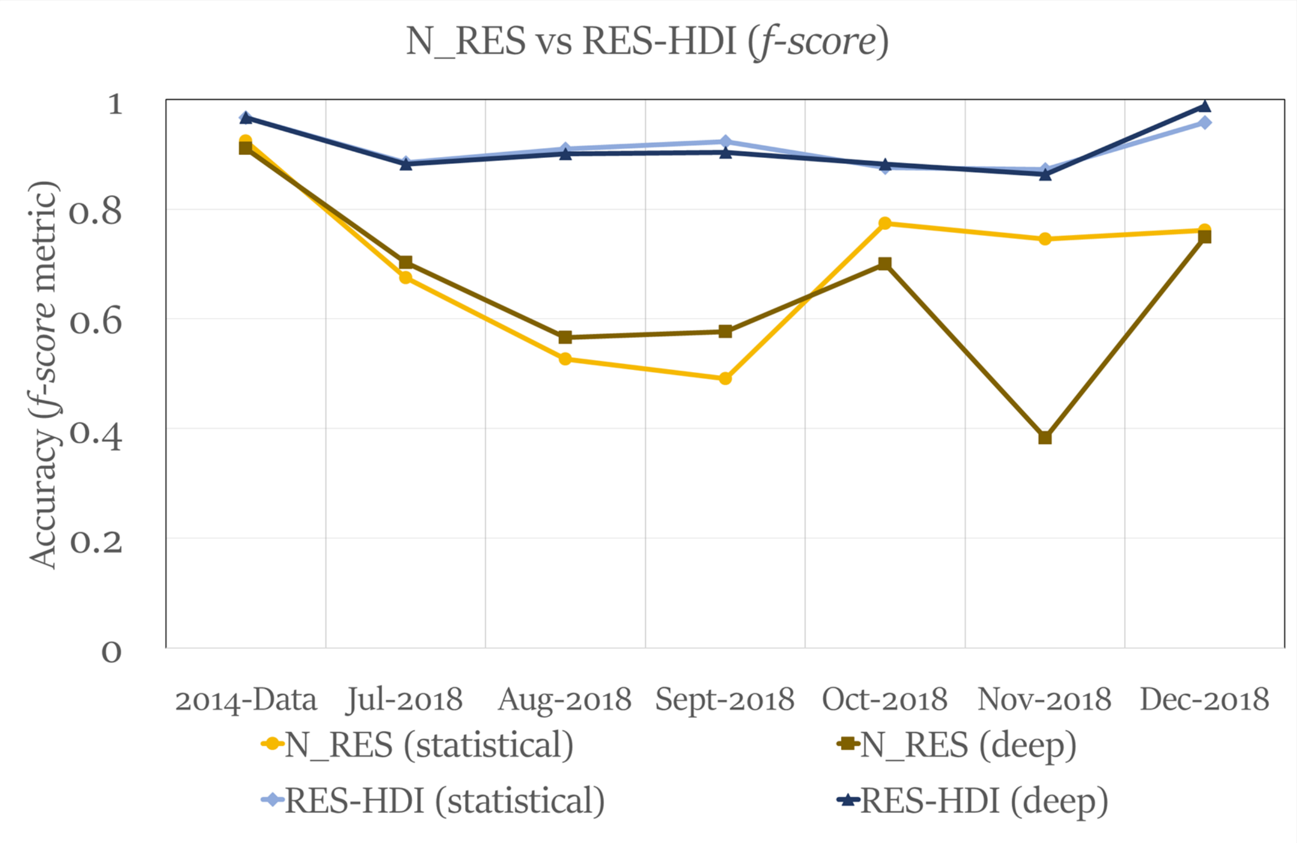


False positives in 2018

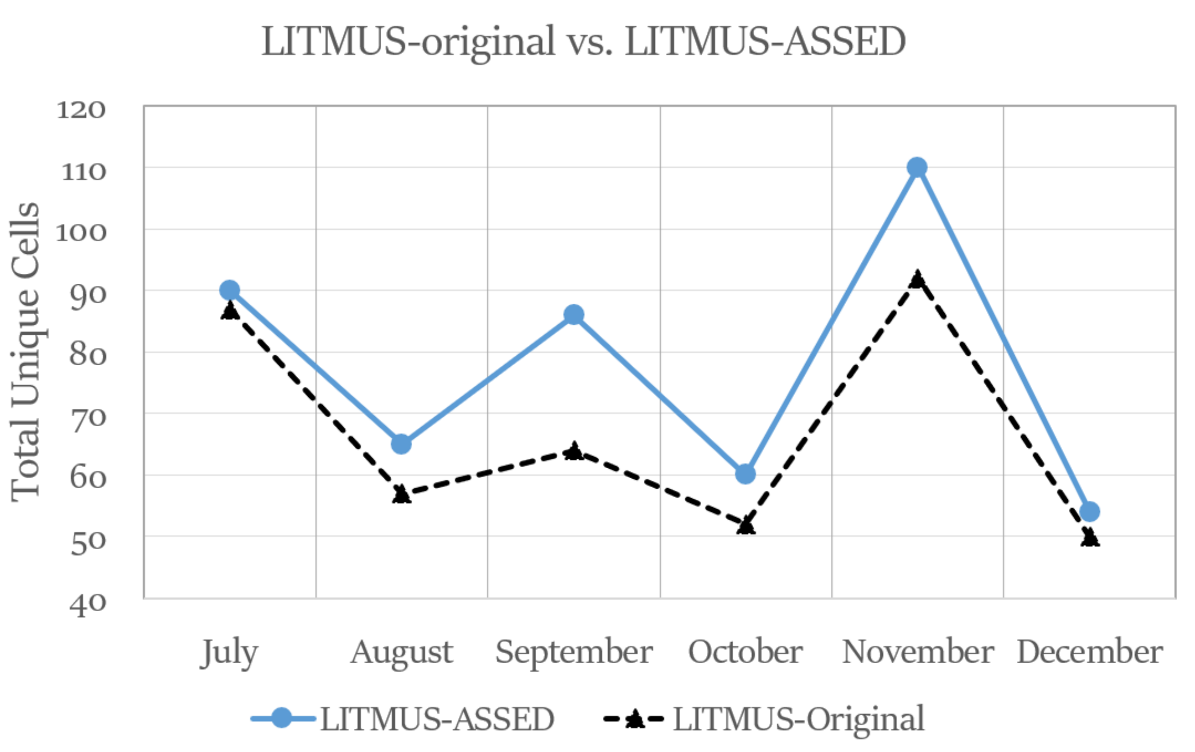


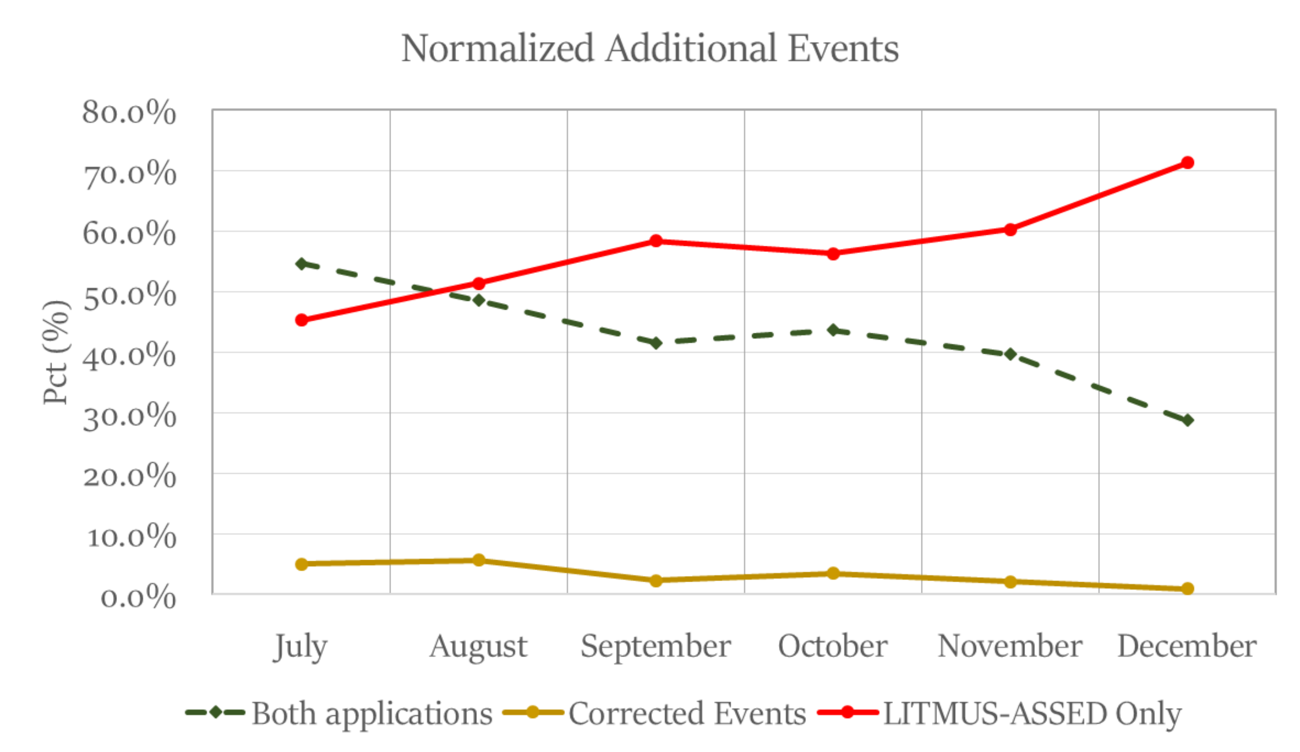
F-Score

- F-score: harmonic combination of precision and recall
- **Statistical vs Deep**
  - Deep learners have variance in performance in drifting conditions without adaptivity
  - Statistical learners deteriorate as well due to low recall
- **HDI vs Non-HDI**
  - HDI confers clear adaptivity
  - HDI-based ensemble (under kNN selection and weighting, with historical filter)
  - F-score: 0.988 for RES-HDI (deep)



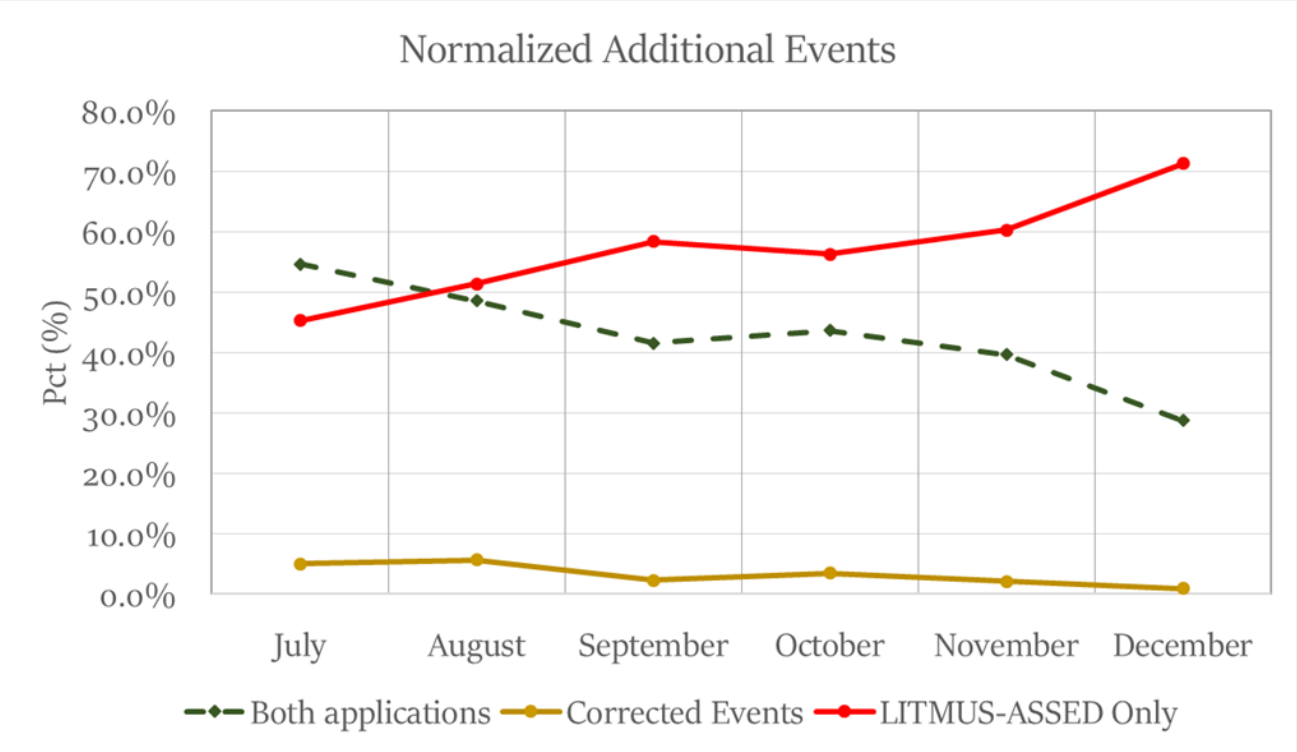
Event detection improvement





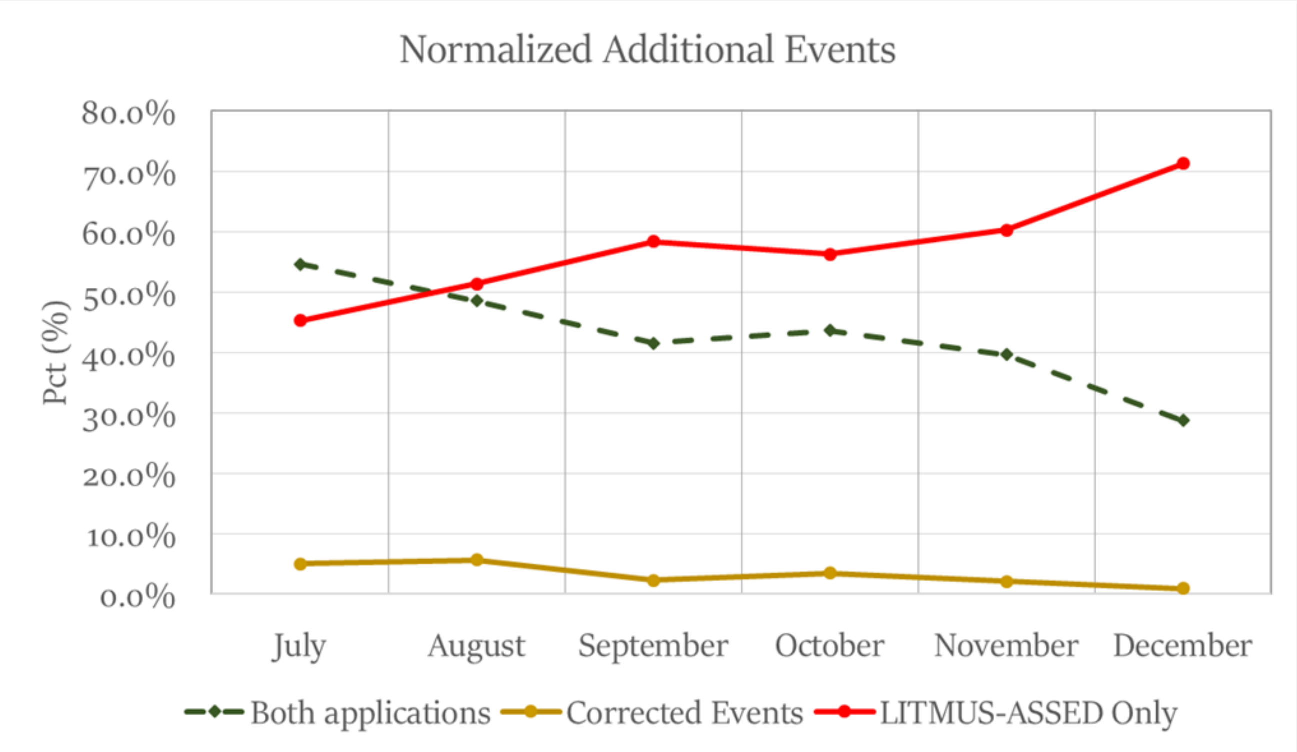
Event detection improvement

- We compare LITMUS-ASSED to LIMUS-static
- Events detected in LITMUS-static were also detected in LITMUS-ASSED
- **Both Events**
  - Events detected in both LITMUS-static and LITMU-adaptive
- **LITMUS-adaptive only**
  - Events in 2018 detected only with ASSED
  - Concept drift adaptivity improves event detection
  - In each case, LITMUS-ASSED detects additional events not detected by LITMUS-static

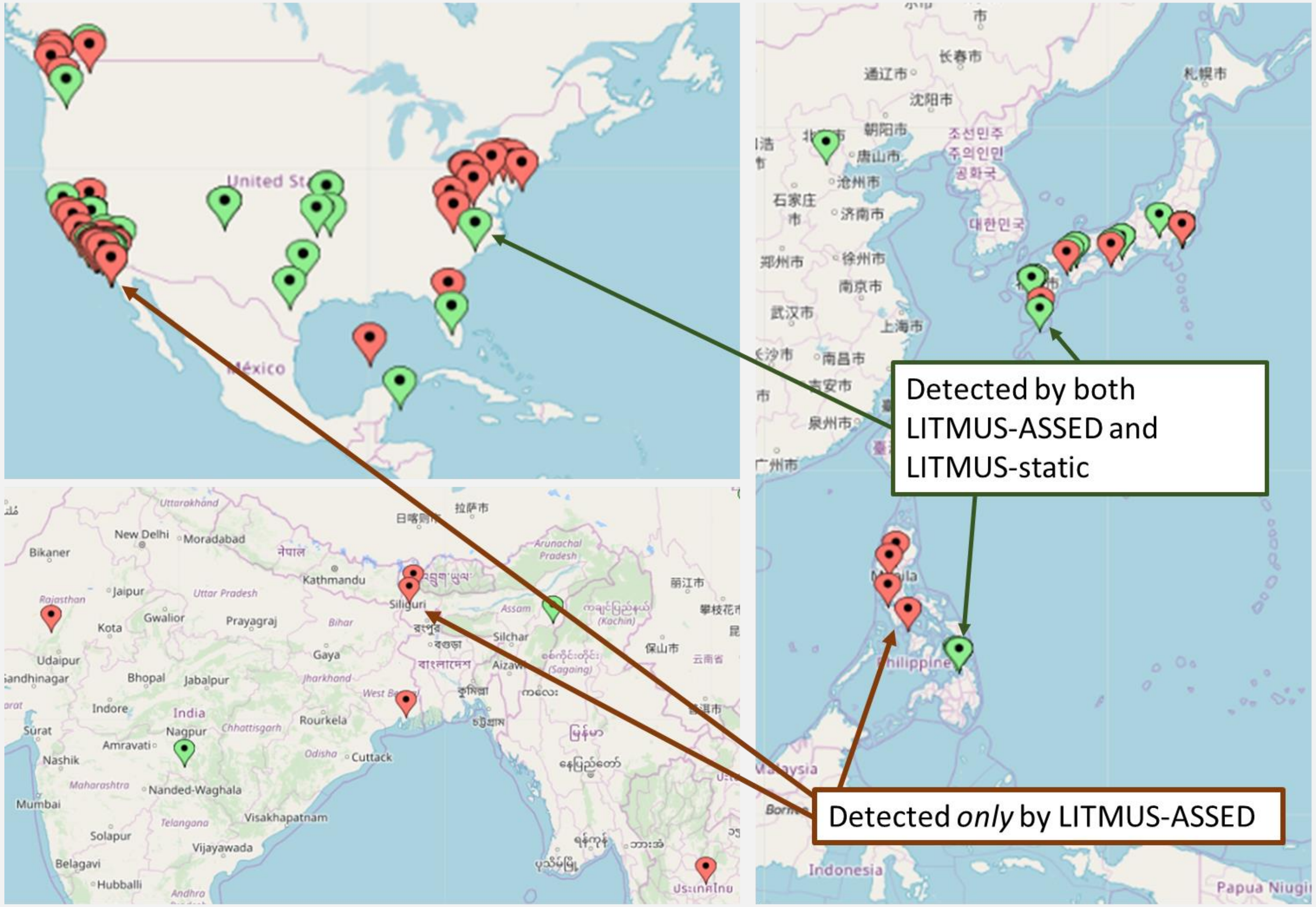


Event detection improvement

- Comparing additional events detections by LITMUS-ASSED only
- Over time, increasing numbers (and fraction) of events are detected by LITMUS-ASSED
- LITMUS-static fails to recognize increasing numbers of true events
- LITMUS-static is more susceptive to the noise



Results – Global LITMUS Coverage



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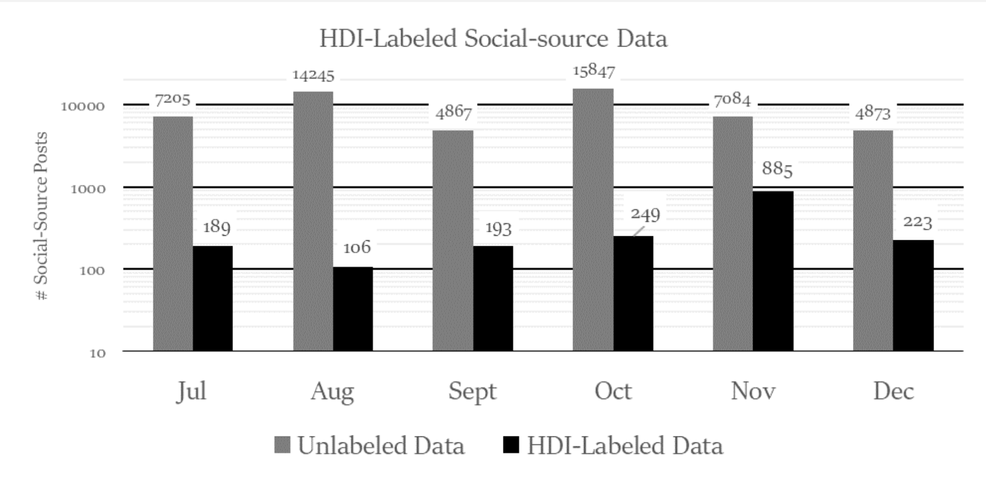
HDI-Based Improvement

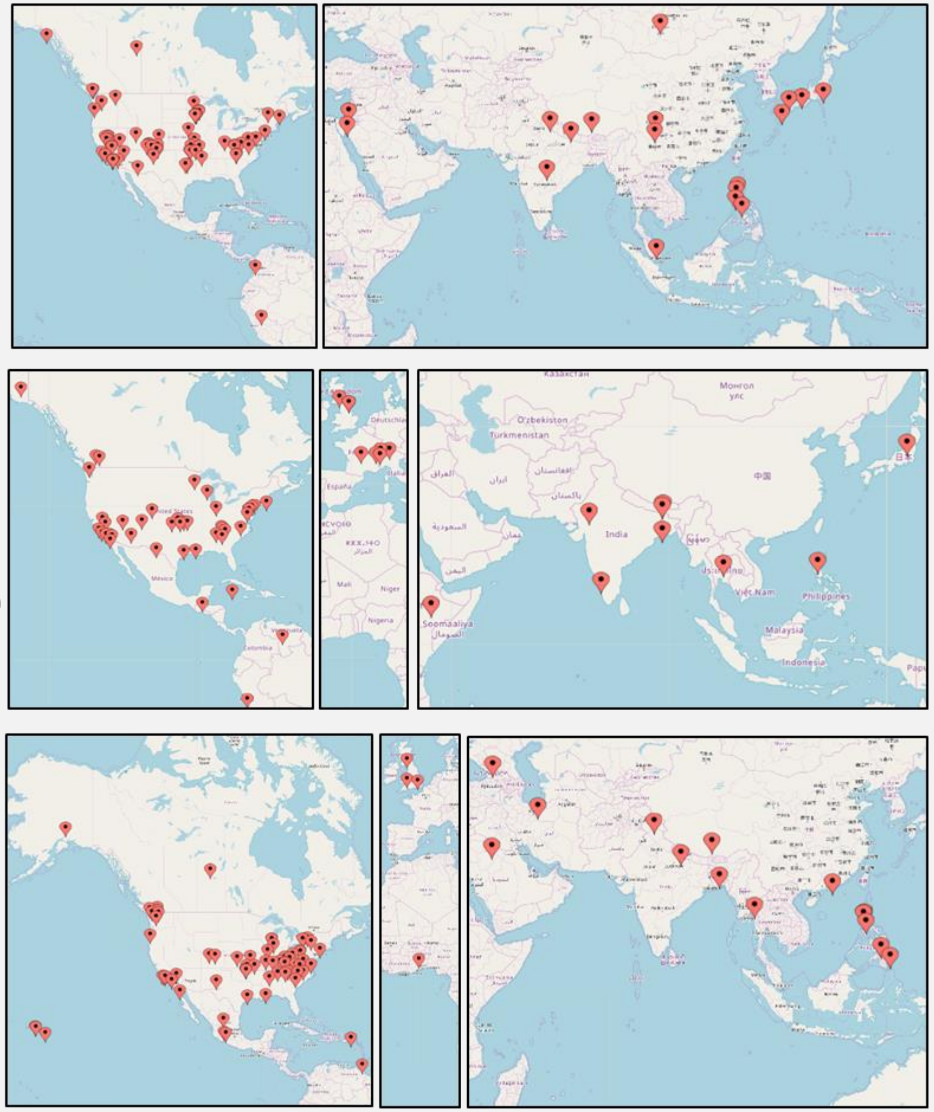


Data Window	Pct of Labeled Data	Improvement	Additional Events
Jul-2018	2.62%	125.5%	183%
Aug-2018	0.74%	159.2%	206%
Sept-2018	3.97%	156.7%	241%
Oct-2018	1.57%	126.1%	229%
Nov-2018	12.49%	225.7%	252%
Dec-2018	4.58%	132.0%	348%

July 2018

August 2018

September 2018



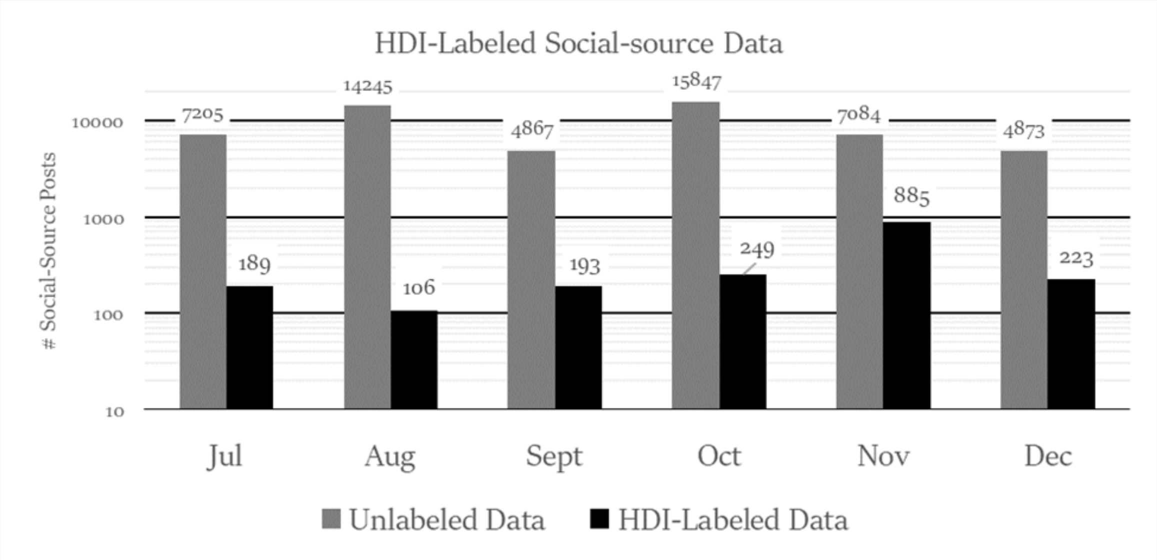
July	
LITMUS & L-ASSED	480
Corrected	44
Additional	398
Both applications	54.7%
Corrected Events	5.0%
L-ASSED Increase	82.9%

August	
LITMUS & L-ASSED	644
Corrected	75
Additional	681
Both applications	48.6%
Corrected Events	5.7%
L-ASSED Increase	105.7%

September	
LITMUS & L-ASSED	365
Corrected	20
Additional	513
Both applications	41.6%
Corrected Events	2.3%
L-ASSED Increase	140.6%

HDI-Based Improvement

- LITMUS-ASSED leverages HDI to significantly improve event detection
- With a fraction of labeled data, LITMUS-ASSED provides classification improvements of > 150% in drifting conditions
    - Compared to typical, static event detection approaches
- LITMUS-ASSED's drift adaptivity is also oracle-independent
    - No human labeler expense
    - No human labeling latency
- Classification improvement leads to detection improvements over time



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Conclusions

- Physical event detection from Social Streams
  - Social Streams are ubiquitous
  - Can operate as a variety of sensors simultaneously
  - Existing dense global coverage and increasing
  - Used for large-scale event detection (earthquakes)
- We develop an approach for general purpose event detection
- Our approach avoids limiting assumptions
  - Handles weak-signals and noisy events
  - Handles changing event characteristics (concept drift)
  - Handles changing decision boundaries and rules (concept drift)

Conclusions

- Our approach does not rely on human labelers
  - Human/oracle labelers are expensive and time consuming
  - We exploit reputable sources to automatically assign labels
- Auto-labeling improves model creation throughput
  - Once auto-label is available, models are immediately tested and updated as and when needed
  - Do not require oracle labelers
- Drift adaptation
  - Deal with real-time, live data
  - Avoid closed data assumptions – not realistic

?

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Raw data - Improvement

Window	Performance		Statistics		HDI-Improvement	
	Static	Augmented	Unlabeled	HDI-Labeled	% Labeled	Improvement
2014-Data	0.911	0.9668	NA	NA	NA	NA
Jul-2018	0.703	0.882	7205	189	2.62%	125.5%
Aug-2018	0.566	0.901	14245	106	0.74%	159.2%
Sept-2018	0.5769	0.904	4867	193	3.97%	156.7%
Oct-2018	0.7	0.8827	15847	249	1.57%	126.1%
Nov-2018	0.3825	0.8634	7084	885	12.49%	225.7%
Dec-2018	0.7493	0.9888	4873	223	4.58%	132.0%