Utility of Social Media in Response to Natural Disasters

Prasenjit Mitra
College of Information Sciences and Technology
The Pennsylvania State University

In Collaboration with: Muhammad Imran, Koustav Rudra, Niloy Ganguly, Pawan Goyal

Aid Needs and Information Needs

Disaster event

Urgent needs of affected people

- Food, water
- Shelter
- Medical emergence
- Donations
- …

Information gathering

Info.

Info.

Info.

Information gathering, especially in real-time, is the most challenging part

Humanitarian organizations and local adminis

RED CROSS

OCHA

Relief operations

Information: A Lifeline During Disasters

The **opaqueness** induced by disasters is **overwhelming**

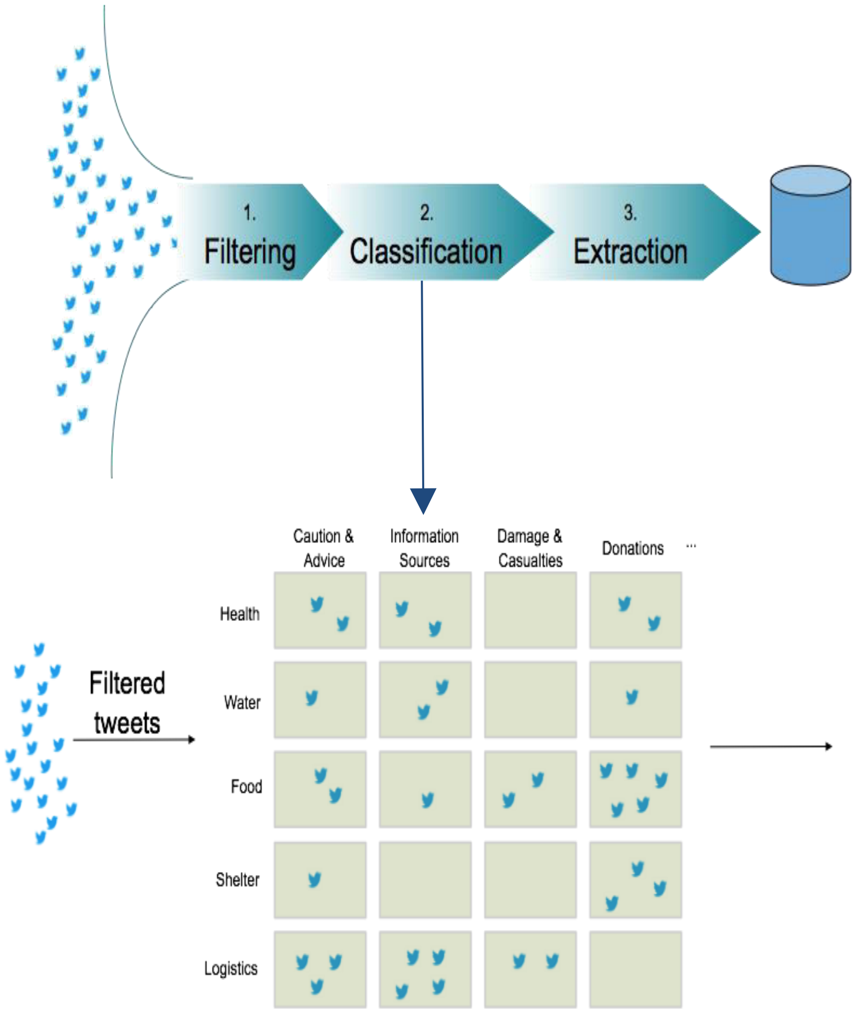
People need information as much as water, food, medicine or shelter

Lack of information can make people **victims of disaster and targets of aid**

Twitter: A Useful Information Source

- Provide **active communication channels** during crises
- **Useful information**: reports of casualties, damages, donation offers and requests
- **Quicker** than traditional channels (e.g. first tweet about Westgate Mall attack reported within a minute)

Information Classification and Extraction from Social Media



"Extracting Information Nuggets from Disaster-Related Messages in Social Media". Imran et al. ISCRAM-2013, Baden-Baden, Germany. -- Best Paper Award

- ~50 million tweets
  - Twitter does not allow sharing of more than 50k tweets
  - Available at: https://github.com/CrisisNLP/lrec16_tools
- 19 different crises from 2013-2015

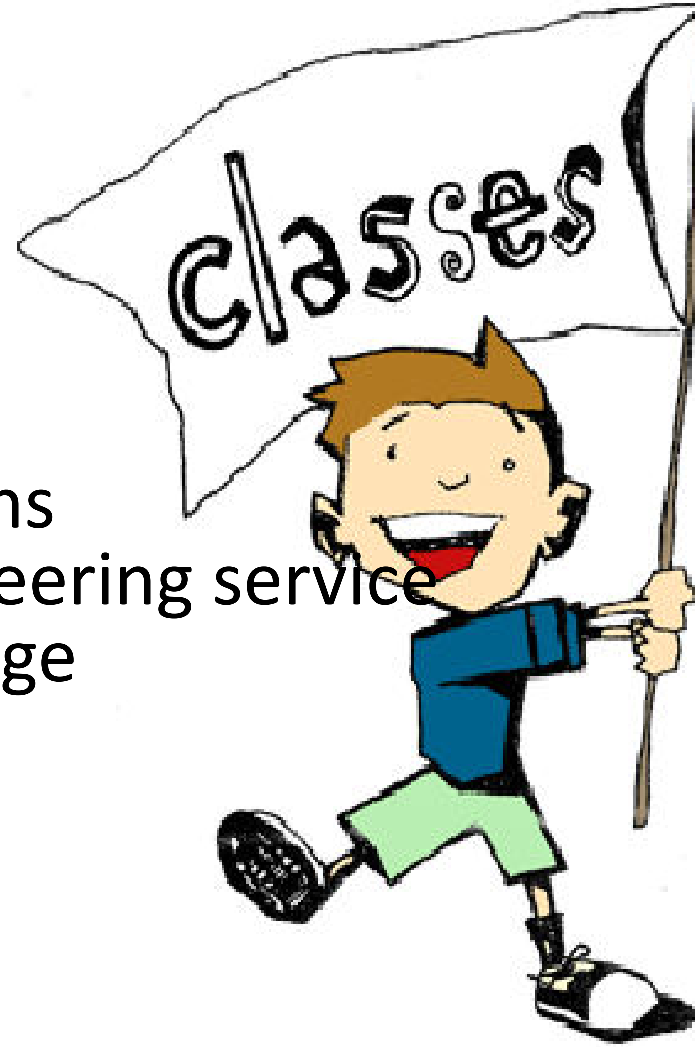
Table 1: Crises datasets details including crisis type, name, year, language of messages, country, # of tweets.

risis type	Crisis name	Country	Language	# of Tweets	Start-date	End-date
arthquake	Nepal Earthquake	Nepal	English	4,223,937	2015-04-25	2015-05-19
arthquake	Terremoto Chile	Chile	Spanish	842,209	2014-04-02	2014-04-10
arthquake	Chile Earthquake	Chile	English	368,630	2014-04-02	2014-04-17
arthquake	California Earthquake	USA	English	254,525	2014-08-24	2014-08-30
arthquake	Pakistan Earthquake	Pakistan	English	156,905	2013-09-25	2013-10-10
yphoon	Cyclone PAM	Vanuatu	English	490,402	2015-03-11	2015-03-29
yphoon	Typhoon Hagupit	Phillippines	English	625,976	2014-12-03	2014-12-16
yphoon	Hurricane Odile	Mexico	English	62,058	2014-09-15	2014-09-28
olcano	Iceland Volcano	Iceland	English	83,470	2014-08-25	2014-09-01
andslide	Landslides worldwide	Worldwide	English	382,626	2014-03-12	2015-05-28
andslide	Landslides worldwide	Worldwide	French	17,329	2015-03-12	2015-06-23
andslide	Landslides worldwide	Worldwide	Spanish	75,244	2015-03-12	2015-06-23
loods	Pakistan Floods	Pakistan	English	1,236,610	2014-09-07	2014-09-22
loods	India Floods	India	English	5,259,681	2014-08-10	2014-09-03
ar & conflict	Palestine Conflict	Palestine	English	27,770,276	2014-07-12	2014-10-02
ar & conflict	Peshawar Attack Pakistan	Pakistan	English	1,135,655	2014-12-16	2014-12-28
iological	Middle East Respiratory Syndrome	Worldwide	English	215,370	2014-04-27	2014-07-14
nfectious disease	Ebola virus outbreak	Worldwide	English	5,107,139	2014-08-02	2014-10-27
irline accident	Malaysia Airlines flight MH370	Malaysia	English	4,507,157	2014-03-11	2014-07-12

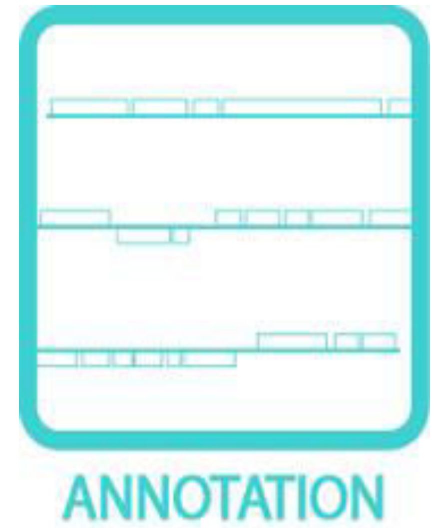
Classes

- Injured/dead
- Missing, trapped, found
- Displaced people & evacuations
- Financial needs, offers, volunteering service
- Infrastructure & utilities damage
- Caution & advice
- Sympathy & emtional support
- Other useful information
- Not related/Irrelevant

- Input from UN OCHA



Annotation



- De-duplicated messages annotated
  - Volunteer
    - SBTF using our Micromappers platform
  - Crowd-sourced

  - Three different annotators have to agree

OOV Terms

- Slangs
- Place Names
- Abbreviations
- Spelling errors

- Annotated to normalized forms

Basis for research

- Text classification
- Normalizing informal language

- Word embeddings from 52 million disaster-related tweets

Pre-processing

- Stop-words, URLs, and user-mentions are removed
- Stemming using the Lovins stemmer
- Unigram and bigram features
- Feature selection using information gain
  - Select top 1k features

- Paid workers via Crowdflower

Word Embeddings

- Trained on tweets to generate word embeddings as in Word2vec
- Pre-processing
  - Replace URLs, digits, usernames with fixed constants
  - Remove special characters
- Continous Bag of Words (CBOW) architecture
  - Negative sampling
  - 300 word representation dimensionality

Classifiers Used

- Naiive Bayes
- Support Vector Machine
- Random Forest

- Logistic Regression
- Recurrent Neural Networks
- Convolution Neural Networks

Evaluation

- 10-fold cross-validation

- Most classes provide acceptable results (>= 0.8)
- Missing, trapped & found people
  - Smallest class
  - Not enough training data

Table 2: Classification results in terms of Area Under ROC Curve for selected datasets across all classes using Support Vector Machines (SVM), Naive Bayes (NB), and Random Forest (RF).

Datasets	Classifier	Caution and advice	Displaced people and evacuations	Donation needs or offers	Infrastructure and utilities damage	Injured or dead people	Missing trapped or found people	Sympathy emotional support	Other useful information	Not related or irrelevant
2014 Chile earthquake	Size(%)	15%	2.80%	0.76%	1.70%	5.60%	0.54%	25%	30%	19%
	SVM	0.87	0.89	0.57	0.90	0.97	0.23	0.93	0.86	0.93
	NB	0.86	0.93	0.78	0.88	0.97	0.64	0.93	0.87	0.95
	RF	0.83	0.86	0.67	0.74	0.96	0.46	0.94	0.86	0.92
2015 Nepal earthquake	Size(%)	2.10%	3.10%	28%	4.50%	11%	5.80%	17%	22%	6.50%
	SVM	0.47	0.80	0.89	0.85	0.95	0.86	0.88	0.76	0.75
	NB	0.68	0.82	0.91	0.90	0.95	0.89	0.91	0.79	0.84
	RF	0.56	0.73	0.89	0.74	0.94	0.87	0.89	0.76	0.75
2013 Pakistan earthquake	Size(%)	6.30%	0.82%	15%	2%	17%	0.49%	5.60%	35%	18%
	SVM	0.77	0.80	0.92	0.76	0.95	0.63	0.82	0.84	0.84
	NB	0.82	0.87	0.94	0.91	0.93	0.74	0.83	0.84	0.84
	RF	0.68	0.70	0.92	0.77	0.95	0.69	0.78	0.88	0.83
2015 Cyclone Pam	Size(%)	7%	3.10%	17%	11%	7.20%	1.30%	5%	25%	24%
	SVM	0.76	0.80	0.92	0.85	0.95	0.39	0.66	0.77	0.90
	NB	0.79	0.82	0.92	0.86	0.97	0.56	0.79	0.80	0.94
	RF	0.68	0.80	0.90	0.80	0.95	0.47	0.71	0.79	0.92
2014 Typhoon Hagupit	Size(%)	20%	6.60%	5.50%	5.10%	3%	0.58%	13%	33%	13%
	SVM	0.74	0.95	0.88	0.76	0.94	0.44	0.92	0.74	0.81
	NB	0.75	0.96	0.89	0.82	0.96	0.57	0.92	0.78	0.81
	RF	0.71	0.97	0.84	0.73	0.94	0.58	0.91	0.75	0.80
2014 India floods	Size(%)	3.60%	1.40%	2.60%	4.30%	47%	0.87%	1.30%	14%	25%
	SVM	0.82	0.80	0.92	0.92	0.97	0.66	0.63	0.87	0.97
	NB	0.89	0.92	0.93	0.90	0.93	0.79	0.83	0.89	0.98
	RF	0.83	0.79	0.86	0.87	0.97	0.66	0.65	0.91	0.96
2014 Pakistan floods	Size(%)	3.90%	6.20%	25%	5.40%	13%	6.40%	6%	32%	2.30%
	SVM	0.71	0.84	0.82	0.77	0.94	0.85	0.88	0.74	0.47
	NB	0.83	0.80	0.85	0.79	0.94	0.85	0.89	0.77	0.65
	RF	0.72	0.80	0.87	0.78	0.95	0.84	0.86	0.79	0.59
2014 California earthquake	Size(%)	6.30%	0.48%	4.30%	18%	10%	0.51%	4.10%	47%	9.40%
	SVM	0.84	0.54	0.93	0.88	0.97	0.62	0.84	0.77	0.72
	NB	0.88	0.57	0.94	0.86	0.97	0.79	0.90	0.78	0.77
	RF	0.81	0.49	0.87	0.89	0.98	0.57	0.88	0.81	0.77

Results: In-domain (earthquakes)

Exp. Type	Source (s): Train set (size)	Target: Test set (size)	Precision	Recall	F-measure	AUC
SS	ITEQ (100%)	CREQ (30%)	0.76	0.56	0.57	0.85
MSWT	ITEQ (100%) + CREQ (70%)	CREQ (30%)	0.85	0.85	0.84	0.95
SS	CREQ (100%)	GUEQ (30%)	0.62	0.55	0.51	0.85
MS	ITEQ (100%) + CREQ (100%)	GUEQ (30%)	0.77	0.66	0.69	0.93
MSWT	ITEQ (100%) + CREQ (100%) + GUEQ (70%)	GUEQ (30%)	0.84	0.85	0.83	0.97
SS	GUEQ (100%)	BOEQ (30%)	0.73	0.42	0.48	0.73
MS	ITEQ (100%) + CREQ (100%) + GUEQ (100%)	BOEQ (30%)	0.76	0.49	0.55	0.68
MSWT	ITEQ (100%) + CREQ (100%) + GUEQ (100%) + BOEQ (70%)	BOEQ (30%)	0.90	0.87	0.87	0.95
SC1	CREQ (100%) + GUEQ (100%)	BOEQ (30%)	0.80	0.43	0.56	0.76
SC2	ITEQ-EN (100%) CREQ (100%) + GUEQ (100%)	BOEQ (30%)	0.77	0.45	0.51	0.77
SC3	ITEQ-EN (100%) + CREQ (100%) + GUEQ (100%) + BOEQ (70%)	BOEQ (30%)	0.88	0.85	0.85	0.97
SS	BOEQ (100%)	NEEQ (30%)	0.48	0.25	0.15	0.64
MS	ITEQ (100%) + CREQ (100%) + GUEQ (100%) + BOEQ (100%)	NEEQ (30%)	0.54	0.25	0.15	0.60
MSWT	ITEQ (100%) + CREQ (100%) + GUEQ (100%) + BOEQ (100%) + NEEQ (70%)	NEEQ (30%)	0.87	0.86	0.86	0.97
SC1	CREQ (100%) + GUEQ (100%) + BOEQ (100%)	NEEQ (30%)	0.53	0.29	0.21	0.63
SC2	ITEQ-EN (100%) + CREQ (100%) + GUEQ (100%) + BOEQ (100%) + NEEQ (70%)	NEEQ (30%)	0.86	0.86	0.86	0.98

Table 2. In-domain single-source (SS), multi-source (MS), multi-source with target crisis (MSWT), and special case (SC) model adaptation results for earthquake datasets

Results: In-domain (floods)

Exp. type	Source (s): Train set (size)	Target: Test set (size)	Precision	Recall	F-measure	AUC
SS	PHFL (100%)	QUFL (30%)	0.60	0.50	0.51	0.82
MSWT	PHFL (100%) + QUFL (70%)	QUFL (30%)	0.86	0.85	0.85	0.97
SS	QUFL (100%)	ABFL (30%)	0.74	0.61	0.61	0.83
MS	PHFL (100%) + QUFL (100%)	ABFL (30%)	0.42	0.43	0.40	0.81
MSWT	PHFL (100%) + QUFL (100%) + ABFL (70%)	ABFL (30%)	0.80	0.80	0.79	0.96
SS	ABFL (100%)	MNFL (30%)	0.61	0.52	0.53	0.77
SC1	PHFL (100%)	MNFL (30%)	0.70	0.61	0.60	0.91
SC2	PHFL (100%) + MNFL (70%)	MNFL (30%)	0.77	0.75	0.75	0.95
MS	PHFL (100%) + QUFL (100%) + ABFL (100%)	MNFL (30%)	0.74	0.69	0.70	0.89
MSWT	PHFL (100%) + QUFL (100%) + ABFL (100%) + MNFL (70%)	MNFL (30%)	0.81	0.80	0.80	0.95
SS	MNFL (100%)	CLFL (30%)	0.65	0.54	0.48	0.85
SC	QUFL (100%) + ABFL (100%)	CLFL (30%)	0.75	0.67	0.70	0.94
MS	PHFL (100%) + QUFL (100%) + ABFL (100%) + MNFL (100%)	CLFL (30%)	0.80	0.76	0.76	0.94
MSWT	PHFL (100%) + QUFL (100%) + ABFL (100%) + MNFL (100%) + CLFL (70%)	CLFL (30%)	0.83	0.83	0.83	0.96
SS	CLFL (100%)	SDFL (30%)	0.55	0.41	0.29	0.78
MS	PHFL (100%) + QUFL (100%) + ABFL (100%) + MNFL (100%) + CLFL (100%)	SDFL (30%)	0.61	0.53	0.54	0.85
MSWT	PHFL (100%) + QUFL (100%) + ABFL (100%) + MNFL (100%) + CLFL (100%) + SDFL (70%)	SDFL (30%)	0.88	0.88	0.88	0.98

Table 3. In-domain single-source (SS), multi-source (MS), multi-source with target crisis (MSWT), and special case (SC) model adaptation results for floods datasets

Text Normalization

- Intentionally shorten words by using abbreviations, acronyms, slangs, words without spaces

Types

- Typos/misspellings
  - earthquak
- Single-word abbreviation/slangs
  - Govt, srsly (seriously), msg (message)
- Multi-word abbreviations/slangs
  - Brb, imo
- Phonetic substitutions
  - 2morrow, 4ever, gr8
- Words without spaces
  - prayfornepal, wehelp

Dictionaries

- Online dictionary to normalize abbreviations, chat shortcuts & slang
  - http://www.innocentenglish.com/news/texting-abbreviations-collection-texting-slang.html
  - SCOWL (Spell Checker Oriented Word Lists)
    - Aspell English Dictionary
      - 350k word list
      - Has place names
        - » But a lot of place names from Nepal, etc. were missing
  - MaxMind world cities database
    - 3million+ cities

Misspellings

- Train a language model
  - Wikitionary
  - British National Corpus
  - Words from the SCOWL dictionary

- Language model predicts the corrections within one edit-distance range and among those the one with the highest probability

- More than one character change
  - Human workers

Normalization

- OOV Tags
  - Slang
  - Abbreviation
  - Acronym
  - Location Name
  - Organization Name
  - Misspelling
  - Person Name

Related Work

- Classification
  - (Imran, et al., 2016, Hughes & Palen, 2009, Imran, et al., 2015)
- Corpora
  - Temnikova et al., 2015
  - CrisisLex (Olteanu, et al., 2015)

Towards Standard Baselines and Datasets

CRISIS NLP
Natural Language Processing

- Access to 52 million tweets
- Around 50k labeled tweets into humanitarian categories
- Largest word2vec embeddings trained on 52m crisis-related tweets
- Out-of-vocabulary dictionaries

CrisisNLP.qcri.org

Concept based Extractive Abstractive Summarization (CONABS)

Enhanced Situational Awareness

Time-critical **situational awareness by generating automatic summaries**

- We use **AIDR (Artificial Intelligence for Disaster Response)** system for:
  - **real-time data processing**
  - **categorizations of tweets**
- We proposed a novel framework for **summarization of informative tweets**

Summarization of Tweets Example

- Dharara Tower built in 1832 collapses in Kathmandu during earthquake

- Historic Dharara Tower Collapses in Kathmandu After 7.9 Earthquake

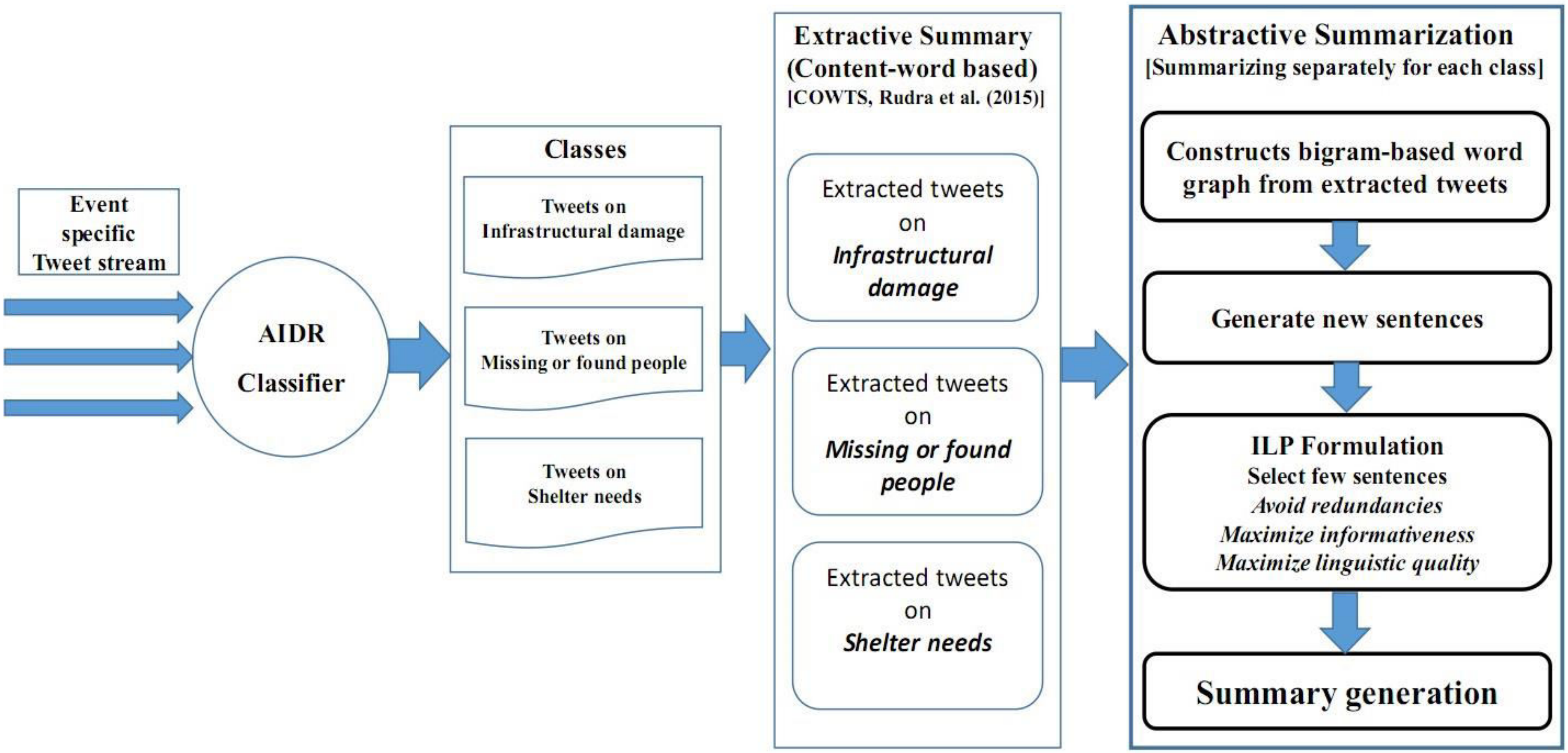
Dharara tower built in 1832 collapses in Kathmandu after 7.9 earthquake.

Key Characteristics and Objectives

- **Information coverage**
  - Capture most situational updates from data. The summary should be rich in terms of information coverage
- **Less redundant information**
  - Messages on Twitter contain duplicate information. We aim for summaries with less redundancy while keeping important updates
- **Readability**
  - Twitter messages are often noisy, informal, and full of grammatical mistakes. We aim to produce more readable summaries
- **Real-time**
  - The system should not be heavily overloaded with computations such that by the time the summary is produced, the utility of that information is marginal

High-level Approach

Automatic Classification and Summarization



Datasets

- **Nepal earthquake** tweets from 25th to 27th April 2015

- AIDR classified tweets to the following categories:
  - **Missing trapped or found people** (10,751 tweets)
  - **Infrastructure and utilities damage** (16,842 tweets)
  - **Shelter and supplies** (19,006 tweets)

Summarizing situational updates

- Some particular types of words play an important role in disaster
- Consider specific types of terms (Content words)
  - Numerals (number of casualties, helpline nos.)
  - Nouns (names of places, important context words like people, hospital)
  - Main Verbs (killed, injured, stranded etc.)

Concept & Event extraction

- Nouns represent concepts and verbs represent events
- Micro level information consists of two core nuggets – a noun part, a verb part
- Develop undirected weighted graph among nouns
- Edge weights represent semantic similarity between two nouns
- Cluster similar nouns like ‘airport’ and ‘flight’
- Each cluster represents one **concept**
- Similarly each verb cluster represents one **event**

Objective

- Reducing redundancies in final summary
- Combining information from similar tweets

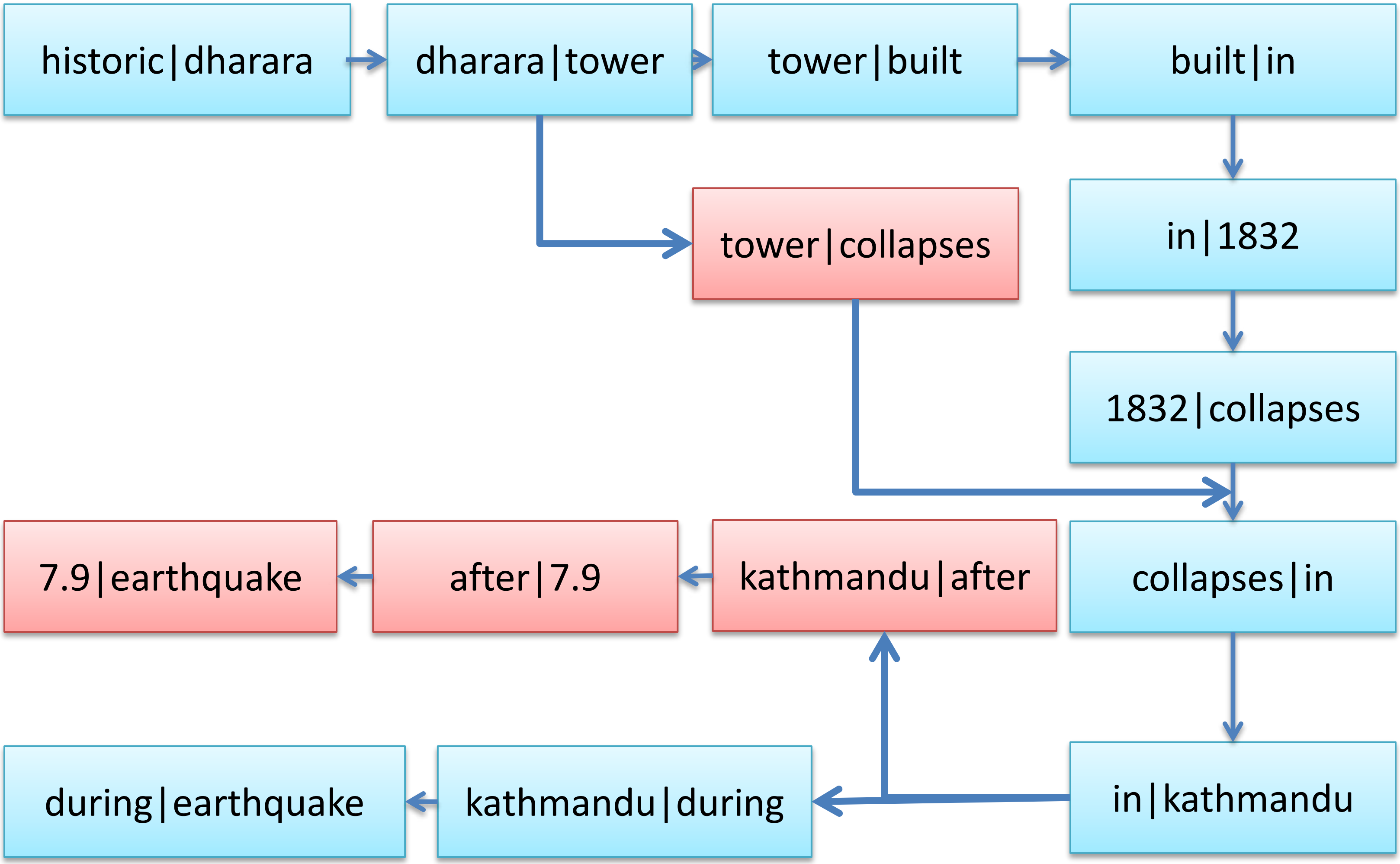
Dharara Tower built in 1832 collapses in Kathmandu during earthquake.
Historic Dharara Tower Collapses in Kathmandu after 7.9 Earthquake.

Dharara tower built in 1832 collapses in Kathmandu after 7.9 earthquake

Approach

- Generate a word graph where nodes are bigrams [deal with informal nature of tweets]
- Generate sentences from the word graph
- **Challenge: Maintaining coherence and readability**
  - Favor sentences generated from a combination of 2-3 tweets
  - Intra-sentence similarity
  - Linguistic quality
  - ILP model combining above factors

- Dharara Tower built in 1832 collapses in Kathmandu during earthquake.
- Historic Dharara Tower Collapses in Kathmandu after 7.9 Earthquake.



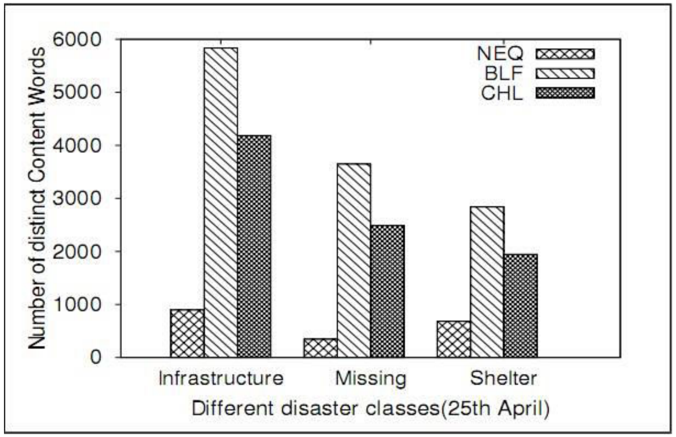
Opportunities

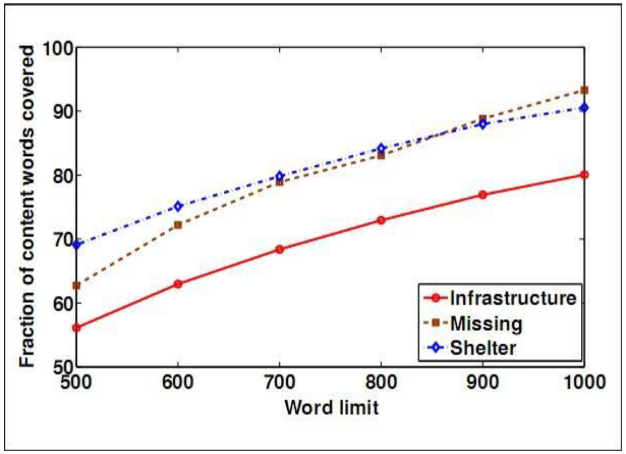
- **Rapid** crisis response
- Time-critical **situational awareness**
- Access to actionable information
- …

- But, it requires **real-time data processing**
- Categorizations of each incoming item should be done **as soon as it arrives**
- **Rapid automatic summaries generation**

The Role of Content Words in Extractive Summarization

- Studies show the significance of content words to capture important events
  - Nouns (e.g. hospitals, buildings, bridges names)
  - Numerals (e.g. number of casualties)
  - Main verbs (e.g. collapsed, destroyed, killed)





Abstractive Summarization

- We generate a word graph where nodes are bigrams
- We generate sentences from the word graph

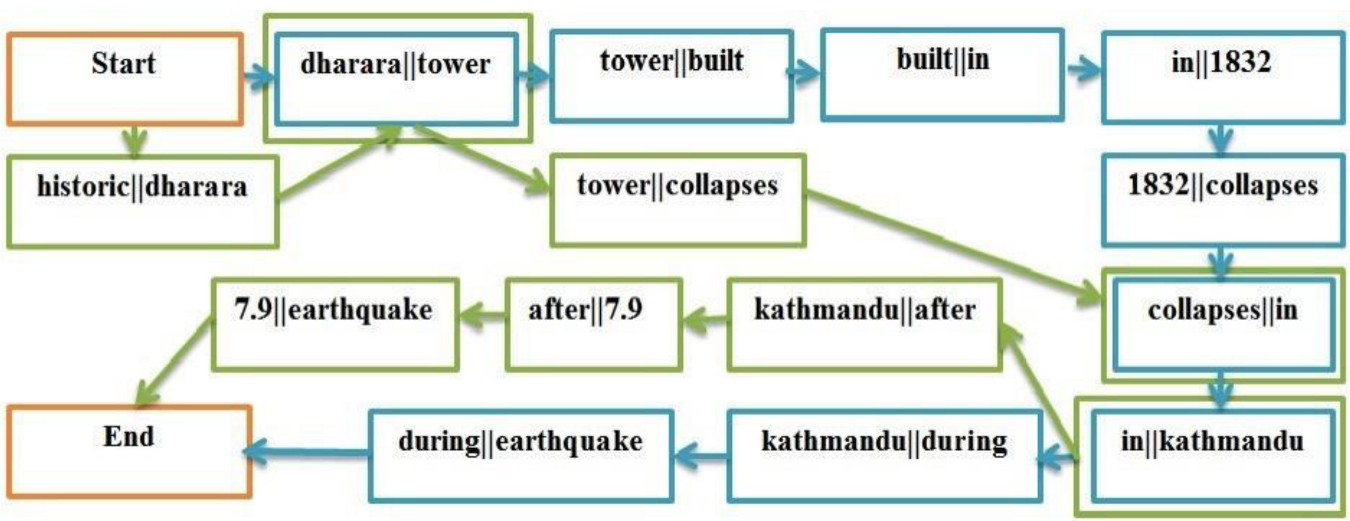
Challenge: **Maintaining informativeness and readability**

- – Covering important content words
- – Favoring more informative paths
- – Maintaining linguistic quality

ILP model combining the above factors

Bi-gram Based Word Graph

- Word graph: nodes represent bi-grams (along with their POS-tags)
- An edge represents consecutive words
- Nodes of two tweets with same bi-gram and POS-tags are merged



ILP Based Formulation

Parameters

- Score of sentences/generated paths (CW(s))
  - Centroid score
- Linguistic quality(LQ(s))
  - Trigram language model
  - $LQ(s) = 1/(1-ll(w_1,w_2,\ldots,w_q))$
  - $ll(w_1,w_2,\ldots,w_q) = 1/L\log_2\prod^{q}_{t=3} P(w_t|w_{t-2}w_{t-1})$

ILP Based Solution

$\max(\sum_{i=1 \ldots n} CW(i) * LQ(i) * x_i + \sum_{j=1 \ldots m} y_j)$	x_i, y_j binary variable x_i tweet indicator, y_j content word indicator CW(i) = tweet i centroid score LQ(i) = Linguistic score of tweet i

Constraints

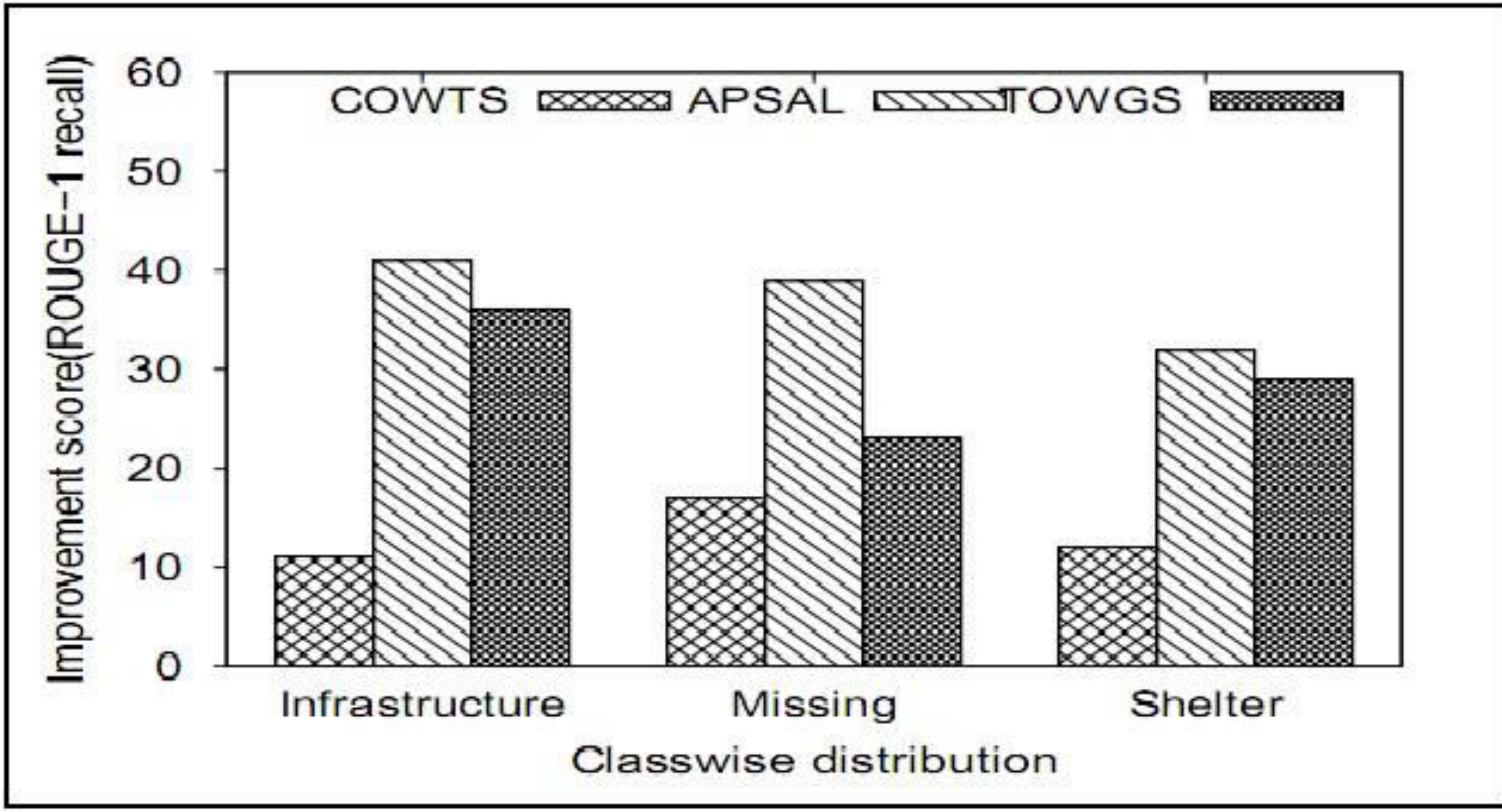
$\sum_{i=1 \ldots n} x_i * \text{Length}(i) \leq L$	Length(i) = number of words in tweet i L = required summary word length
$\sum_{i \in Tj} x_i \geq y_j \quad j = [1 \ldots m]$	Tj = set of tweets where content word j is present If y_j is selected then at least one tweet covering that word is also selected
$\sum_{j \in Ci} y_j \geq \lvert C_i \rvert * x_i \; i = [1 \ldots n]$	C_i = set of content words present in tweet i If tweet i is selected then all the content words of that tweet are also selected

Baselines

- **COWTS:** runtime content-word based tweet stream summarization algorithm [Rudra 2015]
- **APSAL:** affinity clustering based summarization technique [Kedzie 2015]
- **TOWGS:** runtime bigram based abstractive summarization algorithm [Olariu 2014]

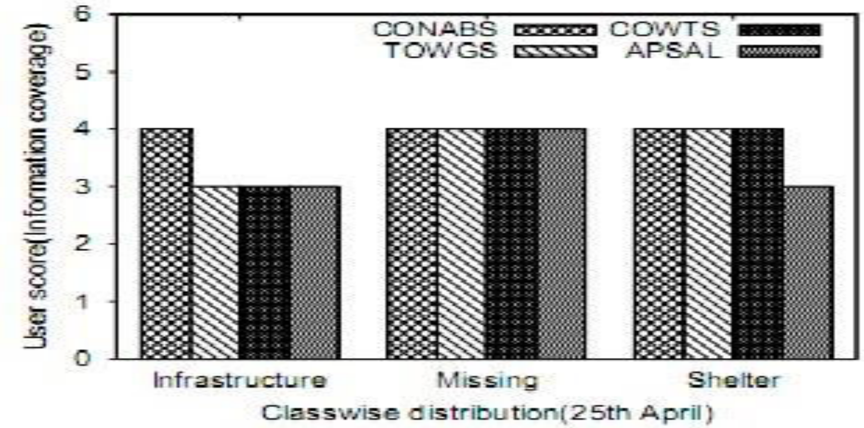
Provide summary for each of the three classes from 25th April to 27th April
Compared against a gold standard summary report generated by experts like **SBTF, UNOCHA**
Generate a system summary of 200 words for each of the three classes across six days

Summarization result

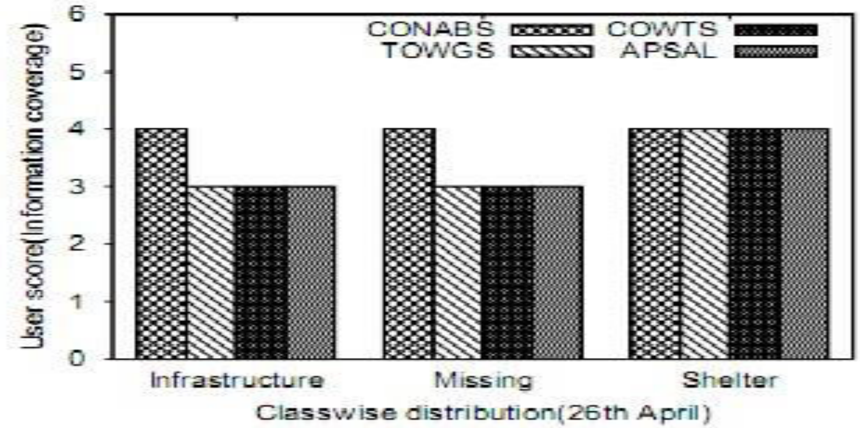


Obtain 20-40% improvement over baselines

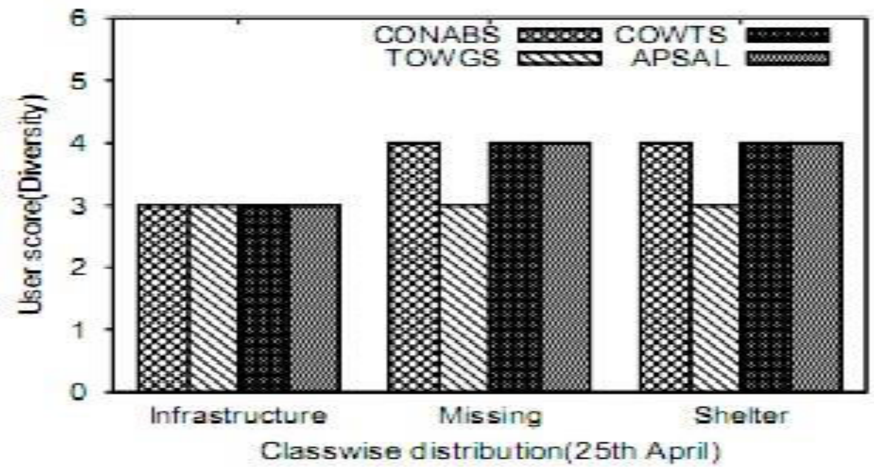
Information coverage and diversity



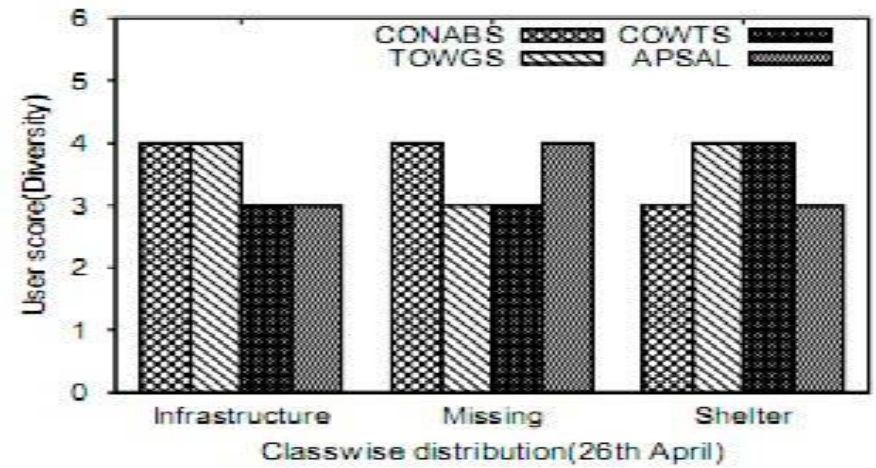
(a) 25th (info. coverage)



(b) 26th (info. coverage)



(a) 25th (info. diversity)



(b) 26th (info. diversity)

Sub-topic identification

- **Objective:** to capture small-scale sub-events such as ‘power outage’, ‘bridge closure’ etc.
- sub-topic as a combination of a noun and a verb where noun represents a concept and verb represents an event

Class	**Topic-phrases**
Infrastructure	‘shut flight’, ‘crack road’
Injured	‘casualty grow’, ‘man trap’
Missing	‘family stuck’, ‘tourist strand’
Shelter	‘water equip’, ‘deploy transport’

Associating nouns with events

- Consider event words like **killed, injured, died** etc. [Ritter 11]
- Identify nouns directly modify the **events**
  - #China media says **buildings toppled** in #Tibet [url]
  - India **sent** 4 Ton **relief** material, Team of doctors to Nepal
- Obtain a high precision of **0.92** compared to three word window based approach

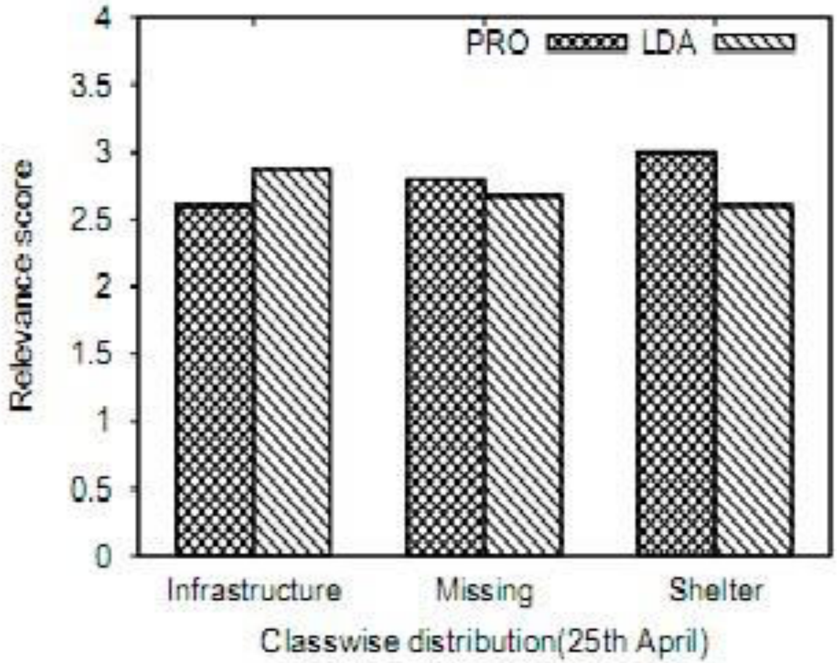
Ranking topic phrases

- Compute Szymkiewicz-Simpson overlap score between noun(N) and verb(E).

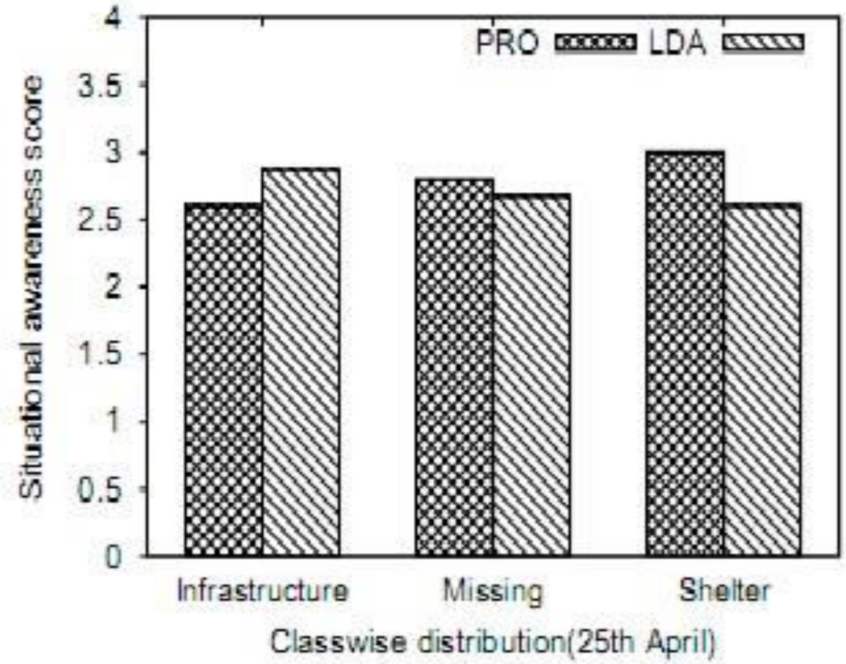
$$Overlap(N, E) = \frac{|X \cap Y|}{min(|X|, |Y|)}$$

- X : set of tweets containing N, Y: set of tweets containing E.

Evaluating topic phrases



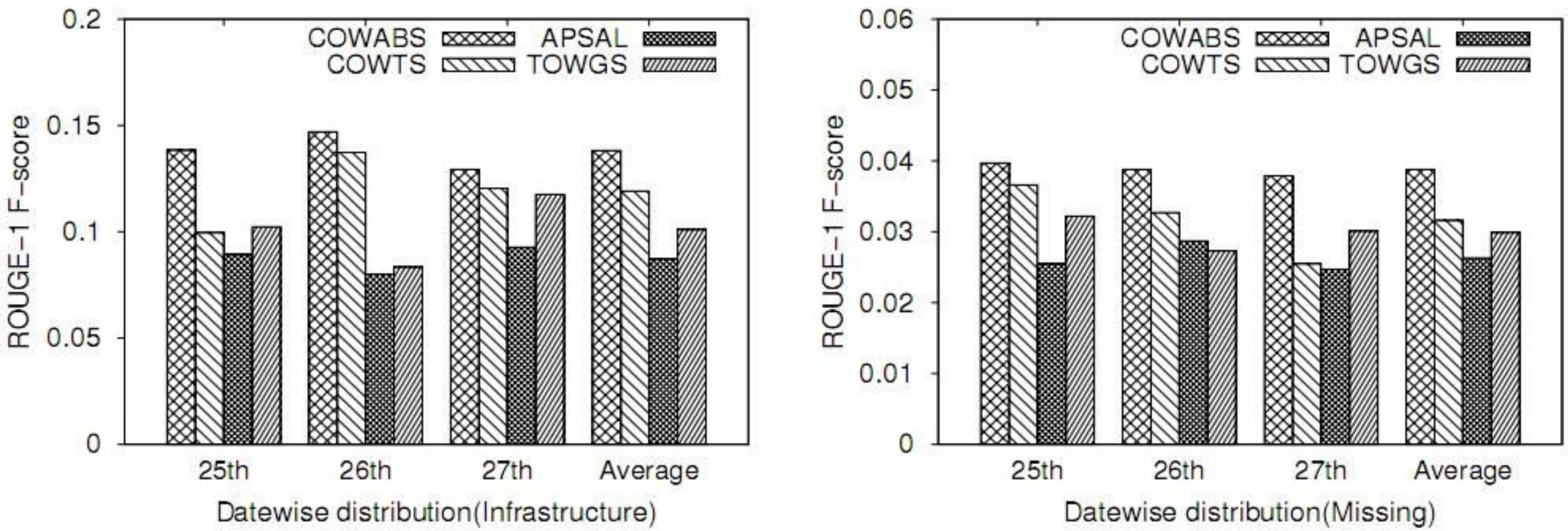
(a) Relevance



(b) Situational awareness

Topic phrases provide relevant as well as important situational information

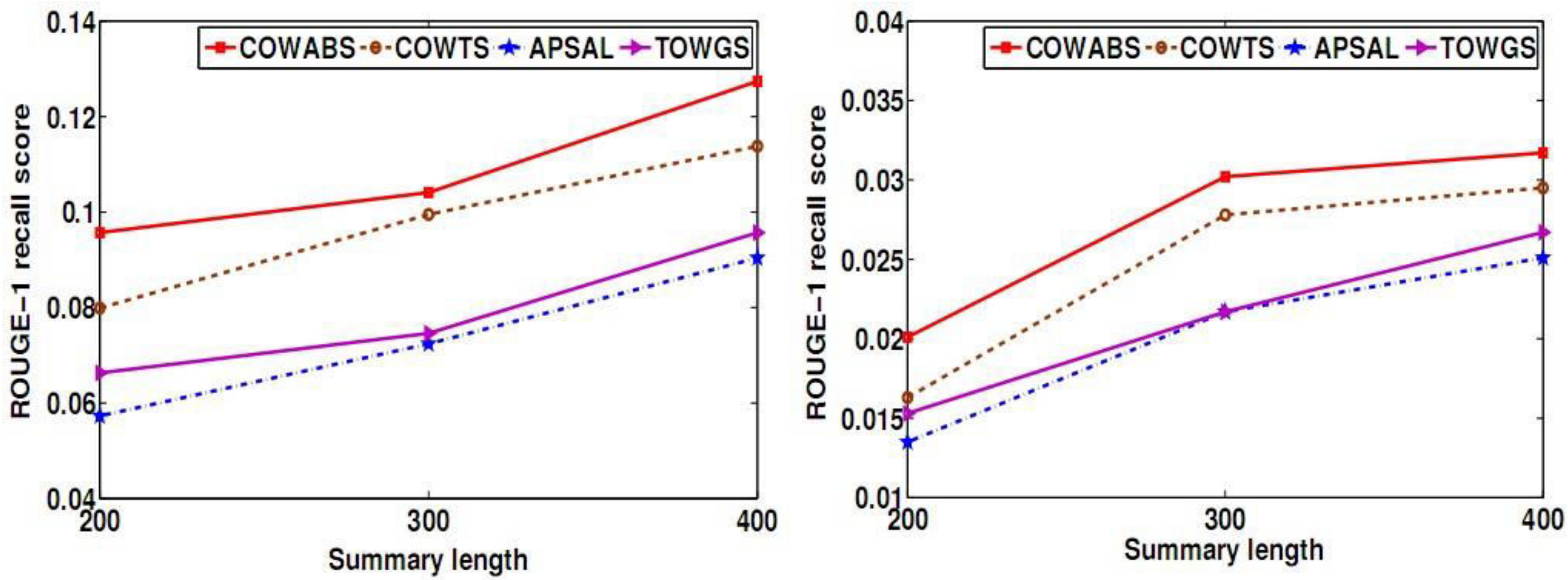
Summarization Results



(a) Infrastructure (b) Missing

- If number of clusters increases, determining importance of different clusters becomes difficult [**APSAL**]
- **COWTS** tries to maximize the coverage of content words but can't combine information from related tweets
- **TOWGS** didn't consider content words into account
- **COWABS** tries to combine similar information from related tweets as well as maximizing coverage of content words

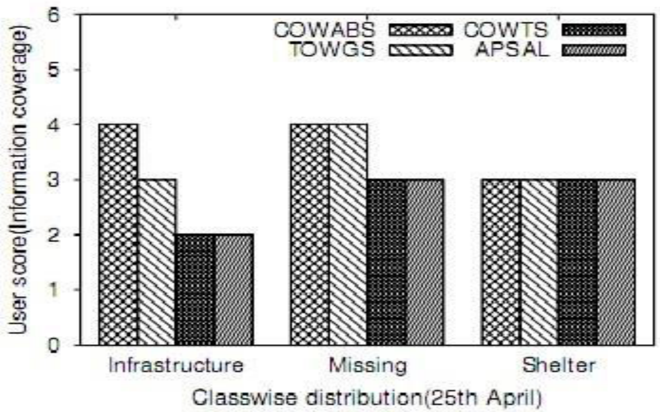
Performance Variation with Summary Length



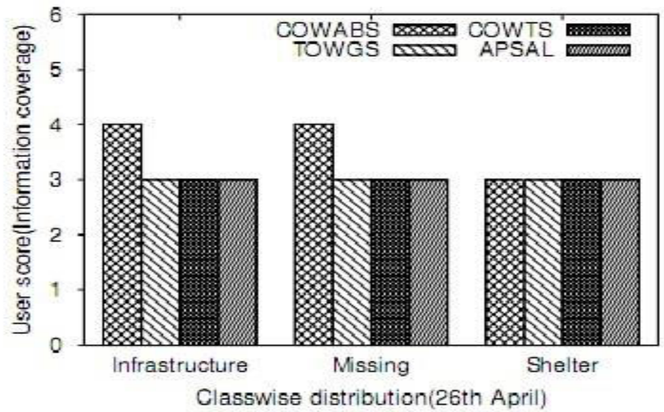
(a) Infrastructure (b) Missing

If summary length increases COWABS still performs better than the baselines

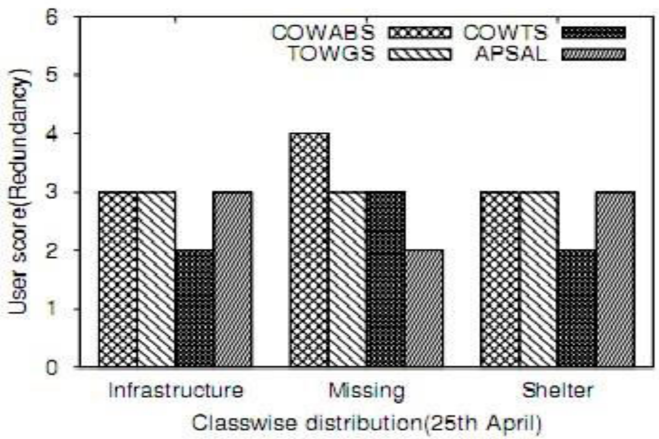
Performance Comparison (User Studies)



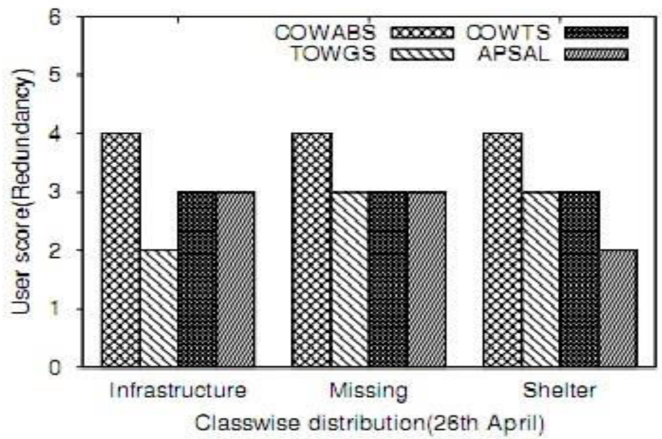
(a) 25th (info. coverage)



(b) 26th (info. coverage)

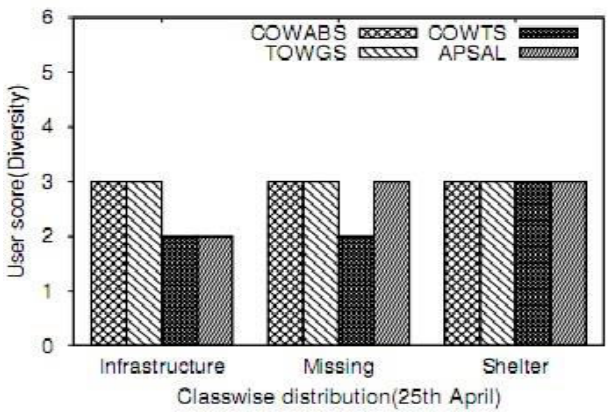


(a) 25th (redundancy)

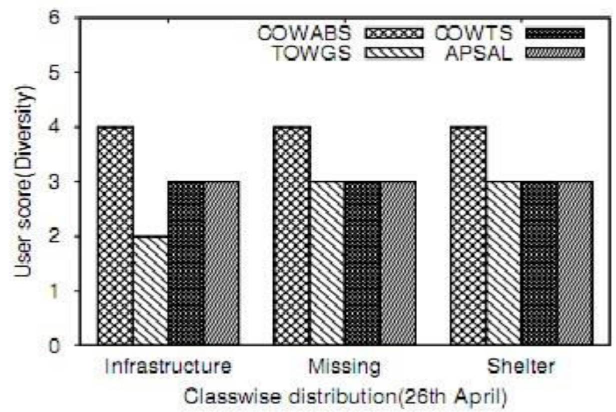


(b) 26th (redundancy)

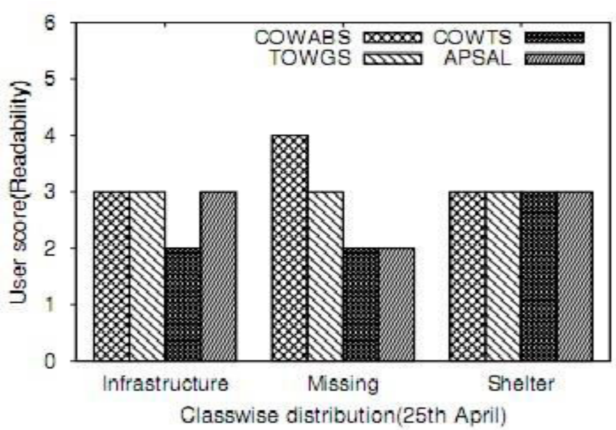
Performance Comparison (User Studies)



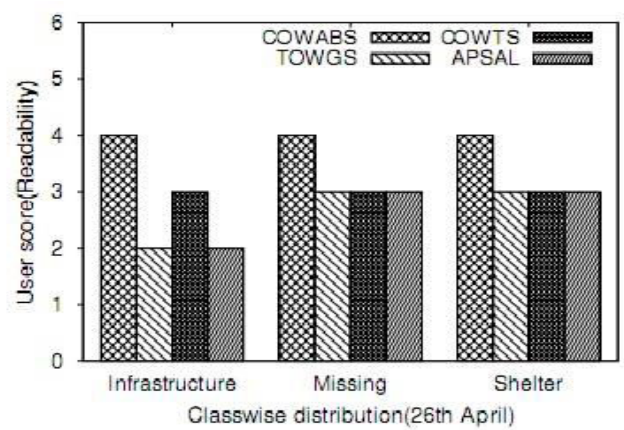
(a) 25th (info. diversity)



(b) 26th (info. diversity)

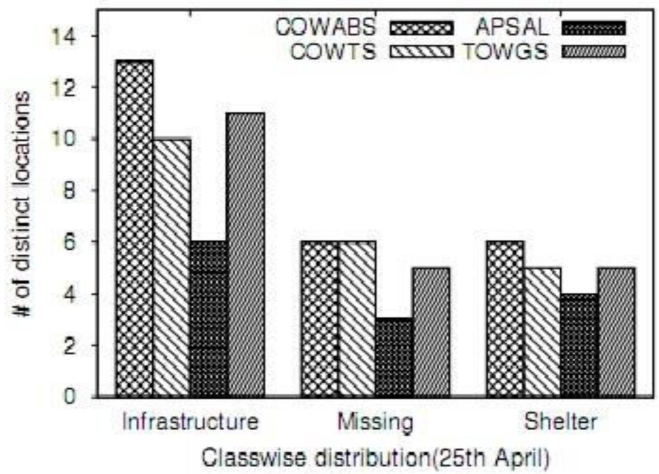


(a) 25th (readability)

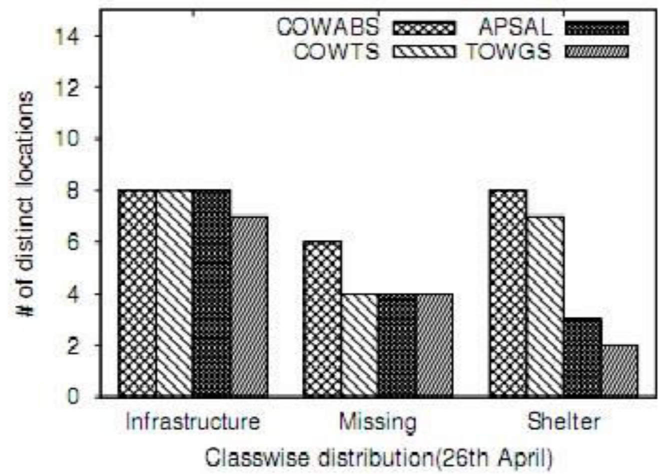


(b) 26th (readability)

Summarization Quality (Location)



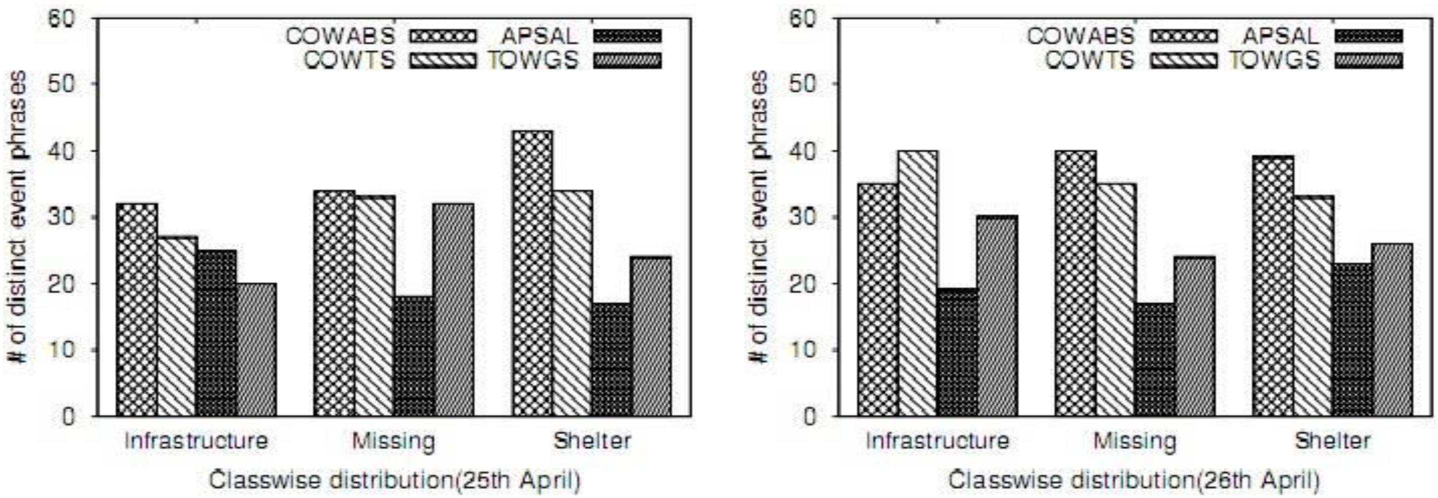
(a) 25th (location coverage)



(b) 26th (location coverage)

COWABS captures information at more granular level with location specific information

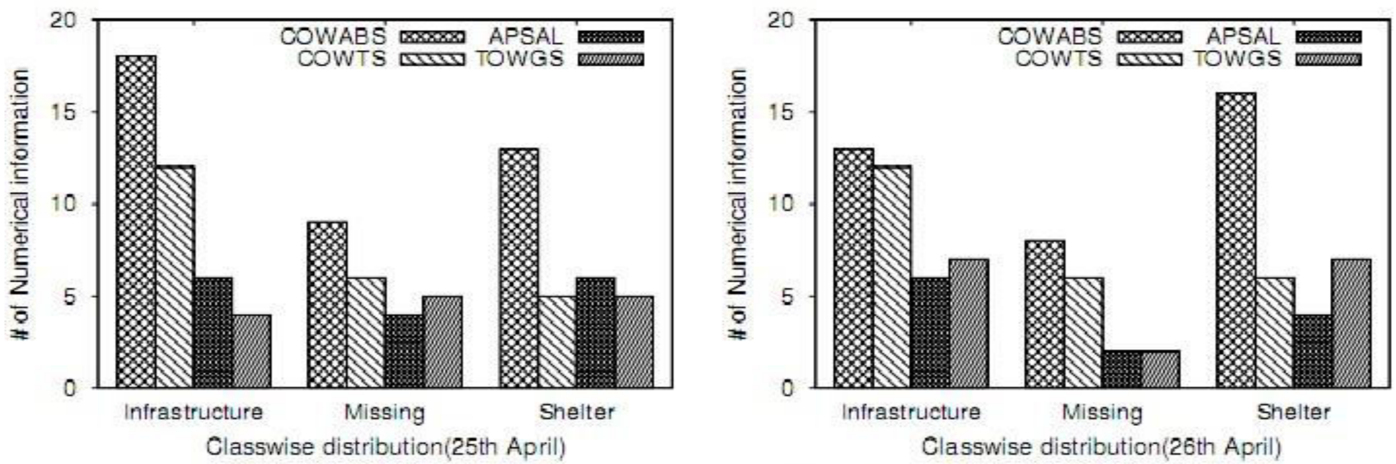
Summarization Quality (Event)



(a) 25th (event coverage) (b) 26th (event coverage)

We extract event phrases using the method proposed by Ritter et al [EMNLP 2011]
COWABS captures more event specific information

Summarization Quality (Numeral)



(a) 25th (numeral coverage) (b) 26th (numeral coverage)

COWABS captures more numerical information which includes information about victims, helpline numbers etc.

Conclusions

- **Rapid situational awareness** is necessary for effective relief operations
- Twitter as **useful information source** during emergencies
- Automatic classification and summarization approach
- Propose approach outperforms all baselines and deemed effective –learned from user studies

Research Vision in Disaster Computing

Beyond bag of tweets

- End-to-end tool
  - Assist in information finding and summarization from among the selected tweets
  - Utility to generate reports or stubs of reports that can then be edited by volunteers
    - Crowdsource? Wikipedia-style report generation?

Refine Pipelines in Crisis Computing

- Make the system more usable (by non-experts), improve accuracy and scalability
- Social Information Analytics: Analyze the data obtained from the crowdsourcing and the collections to model behavior and improved understanding of behaviors of individuals, teams, public, etc.
- Image & Video Processing: Enable categorization of disaster-related images, videos obtained by UAVs, etc.

Information Extraction and Analytics

- Analyze the data obtained from Twitter
  - Do topics drift in a particular way in all disasters of similar nature?
  - How can we build classifiers and adapt them dynamically to make optimal use of old data and the new data to adjust to (and almost predict) the drift of topics?
  - Do people in different regions behave differently in response to different types of crises?
  - …

Social Information Analytics

- Analyze the volunteer interaction via Visual Analytics
- What is the optimal strategy to engage the volunteers to maximize gains?
  - How do we choose the best volunteers?
    - Should we give them the hardest tweets for the system a la active learning?
  - How can we reward the volunteers better?
  - How can we utilize the waning interest of the volunteers and bottle up the energy expressed at the beginning to utilize when the interest tapers down?

…

Multimedia Disaster Data Classification and Analytics

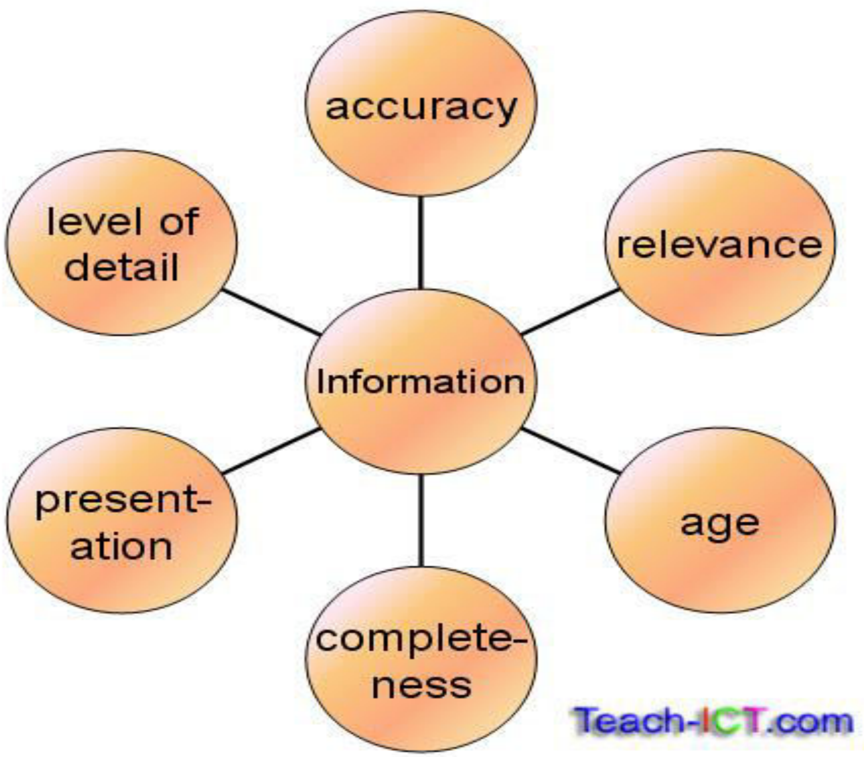
- Images from disasters will be classified into useful/not-useful categories and then sub-categories.
  - Design features/models, etc.
- Images and videos from UAVs
  - Information extraction
  - Damage assessments
  - Needs generation/analysis

Information Integration

- Integrate information from multiple sources
  - Twitter, FB, Instragram, Snapchat, WhatsApp, etc.

Quality of Information

- UNOCHA requires information to be reported from three independent sources



Usability

- Increase usability by non-experts
  - Reduce handholding so that naiive users can set up collection
    - User can choose (a) source of data collection, (b) machine-learning algorithms, (c) which historical data to use for training, and (d) live training text
      - Provide intelligent, optimal defaults by application
  - Research Questions
    - Recommend which datasets are useful for reuse
    - More natural-language interaction
      - Automatic recommendation of model, etc. based on task

Improve Accuracy

- Increase accuracy
  - No tweet left behind
    - Improve accuracy, domain adaptation, transfer learning, semi-supervised learning, etc.
      - Using deep learning
      - Provide user to tune the system to choose whether they want to prioritize recall or precision via sliding scale
  - Use optimal strategy to engage the crowd

Better Utilization

- Co-ordination
- Information organization