Resilient Disaster Communications in the Social-Media Era

JUNO-2 Meeting

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NICT National Institute of Information and Communications Technology

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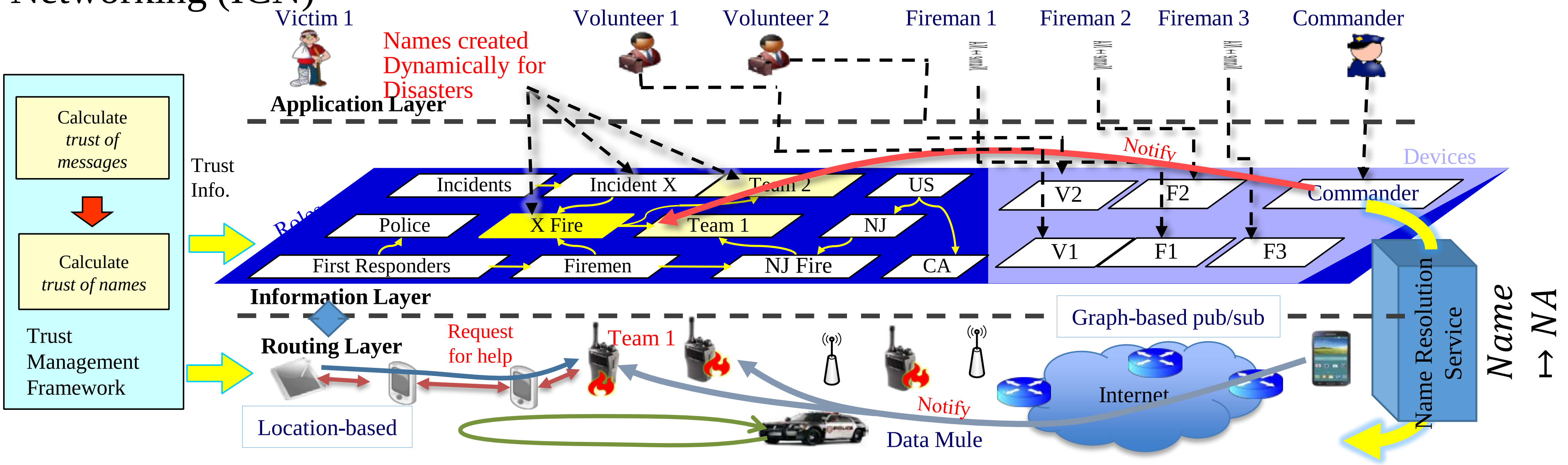
Importance of Communication for Disaster Management

- Communication is key to improving outcomes in the aftermath of a disaster
- Keys to an effective response to a catastrophic incident:
  - Effective communication within and among dynamically formed first responder teams
    - Public safety teams comprising: law enforcement, health, emergency, transport and other special services, depending on the nature and scale of the emergency
- First responders are not the only ones that can help. Increasingly, volunteers are playing a significant part in disaster management
- In the aftermath of a disaster, likely to face communication challenges
  - Infrastructure may be impacted
  - Lack of personnel to support emergency communications
- Complement with social media
- Security and Resiliency are major concerns
- **Project Objective: A network architecture for information and communication resilience in disaster management, that is also secure, integrates volunteers and social media seamlessly in disaster response**

Proposed System Architecture

- **Information Layer -** (Role-Based) Communication
  - Facilitate communication: dynamically formed first-responder teams
    - Communication based on dynamically created roles, rather than locations
    - Include citizens (victims and volunteers) willing to help
- Secure and resilient: incorporate social media communications, based on Information Centric Networking (ICN)



Objectives and achievements

- Task 1: Naming and Publish/Subscribe framework
  - We developed a dynamic graph-based namespace (initially defined by templates) to more appropriately reflect the organization of personnel involved in emergency response
  - Exploit recipient hierarchies for information dissemination, including social media posts
- Task 2: Trust Management
  - Developed the 2-level crowd sourcing system to which verifies credibility of SMPs by leveraging remote/on-site volunteers
- Task 3: Mapping free-form text (social media posts) to namespace
  - Social Media Engine performs online classification and inference using Natural Language Processing (NLP): exploit specialized knowledge of individual public-safety departments with active learning for accurate delivery of social media posts
- Task 4: Secure location-based forwarding
  - Developed the failure-resilient pub/sub protocol and the emergency service based on the protocol
- Task 5: Integration, Experimentation and Evaluation
  - Performed experiments for SMPs posted at large scale disasters and verified the trust management system is able to verify credibility of SMPs

Dissemination of Project Achievements: Summary

- We designed the architecture and published a joint paper
  - UC Riverside: used natural language processing pipelines/ML to map social media info' to map to the naming framework developed; analyzed data from 2 disasters in CA.
  - Osaka University designed/implemented the Pub/Sub protocol and the emergency service, and implemented and evaluated the rescue classifier, a part of SME
  - Shizuoka University designed a biometric authentication of volunteers; did a questionnaire survey
  - Aichi Institute of Technology designed a trust model for volunteers
  - Mohammad Jahanian, Toru Hasegawa, Yoshinobu Kawabe, Yuki Koizumi, Amr Magdy, Masakatsu Nishigaki,Tetsushi Ohki and K. K. Ramakrishnan, "DiReCT: Disaster Response Coordination with Trusted Volunteers," in Proceedings of ICT-DM 2019, Dec. 2019. **(Best paper award)**
- Publications (Japan)
  - Kazuhiko Ohkubo, Tetsuhisa Oda, Yuki Koizumi, Tetsushi Ohki, Masakatsu Nishigaki, Toru Hasegawa, Yoshinobu Kawabe, "Trust representation under confusion and ignorance," in Proceedings of International Workshop on Informatics (IWIN) 2018, pp.195-202, Sept. 2018.
  - Sugimoto Genki , Fujita Masahiro , Mano Yuto , Ohki Tetsushi , Nishigaki Masakatsu, "Micro Disposable Biometric Authentication - An Application Using Fingernail 15 Minute Textures for Nonsensitive Services -," in Proceedings of Proceedings of the 2018 3rd International Conference on Biomedical Imaging, Signal Processing, pp. 68-73, Aug. 2018.
  - Yoshinobu Kawabe, Yuki Koizumi, Tetsushi Ohki, Masakatsu Nishigaki, Toru Hasegawa and Tetsuhisa Oda, "On Trust Confusional, Trust Ignorant, and Trust Transitions," in Proceedings of 13th IFIP WG 11.11 International Conference on Trust Management (IFIPTM) 2019, July 2019.
  - Yuki Koizumi, Yoji Yamamoto and Toru Hasegawa, "Emergency Message Delivery in NDN Networks with Source Location Verification," in Globecom 2019 Workshop, Dec. 2019.
  - Yoshinobu Kawabe, Yuki Koizumi, Tetsushi Ohki, Masakatsu Nishigaki and Toru Hasegawa, "Toward Mathematical Analysis for Quantity of Trusts," in Proceedings of ITC-CSCC 2020, pp. 111-115, July 2020.
  - Yuki Koizumi, Yoji Yamamoto, Toru Hasegawa, "NDN-based Publish/Subscribe Communication in Disasters," in Proceedings of International Conference on Emerging Technologies for Communications, pp.1-4, Dec. 2020.
  - Takumi Kitagawa, Tetsushi Ohki, Yuki Koizumi, Yoshinobu Kawabe, Toru Hasegawa and Masakatsu Nishigaki "Deterrence-Based Trust: A Study on Improving the Credibility of Social Media Messages in Disaster Using Registered Volunteers," in Proceedings of International Conference on Network-Based Information Systems, pp. 188-201, Sept. 2021.

Dissemination of Project Achievements: Summary (cont'd)

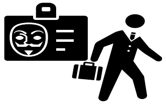
- Publications (US)
  - Mohammad Jahanian, K. K. Ramakrishnan, "Name Space Analysis: Verification of Named Data Network Data Planes", The 6th ACM conference on Information Centric Networking (ICN), September 2019. (Best Student Paper Award)
  - Mohammad Jahanian, Jiachen Chen, K. K. Ramakrishnan, "Graph-based Namespaces and Load Sharing for Efficient Information Dissemination in Disasters", The 27th IEEE International Conference on Network Protocols (ICNP), October 2019.
  - Mohammad Jahanian, Jiachen Chen, K. K. Ramakrishnan, "Formal Verification of Interoperability Between Future Network Architectures Using Alloy", The 7th International Conference on Rigorous State-Based Methods (ABZ), May 2020.
  - Mohammad Jahanian, Jiachen Chen, K. K. Ramakrishnan, "Managing the Evolution to Future Internet Architectures and Seamless Interoperation", The 29th International Conference on Computer Communications and Networks (ICCCN), August 2020.
  - Mohammad Jahanian, K. K. Ramakrishnan, "CoNICE: Consensus in Intermittently-Connected Environments by Exploiting Naming with Application to Emergency Response", The 28th IEEE International Conference on Network Protocols (ICNP), October 2020.
  - Viyom Mittal, Mohammad Jahanian, K. K. Ramakrishnan, "Online Delivery of Social Media Posts to Appropriate First Responders for Disaster Response", The 3rd International Workshop on Emergency Response Technologies and Services (EmeRTeS @ ICDCN'21), January 2021.
  - Mohammad Jahanian, K. K. Ramakrishnan, "Name Space Analysis: Verification of Named Data Network Data Planes", The IEEE/ACM Transactions on Networking, Volume 29, Issue 2, April 2021.
  - Mohammad Jahanian, Jiachen Chen, K. K. Ramakrishnan, "Graph-based Namespaces and Load Sharing for Efficient Information Dissemination" The IEEE/ACM Transactions on Networking, 2021 (Early Access).
  - Viyom Mittal, Mohammad Jahanian, K. K. Ramakrishnan, "FLARE: Federated Active Learning Assisted by Naming for Responding to Emergencies", The 8th ACM conference on Information Centric Networking (ICN), September 2021. (Accepted)

System Model

- Objective
  - Timely delivery of the right information to the right recipients in disasters
  - Disaster response coordination including trusted volunteers
- Players

First responder (FR)
- Perform tasks for disaster management

On-site volunteer
- Perform tasks to verify credibility social media posts according to requests by the volunteer authorities
- Support tasks of first responders



Remote volunteer
- Perform tasks to verify social media posts according to requests by the volunteer authorities

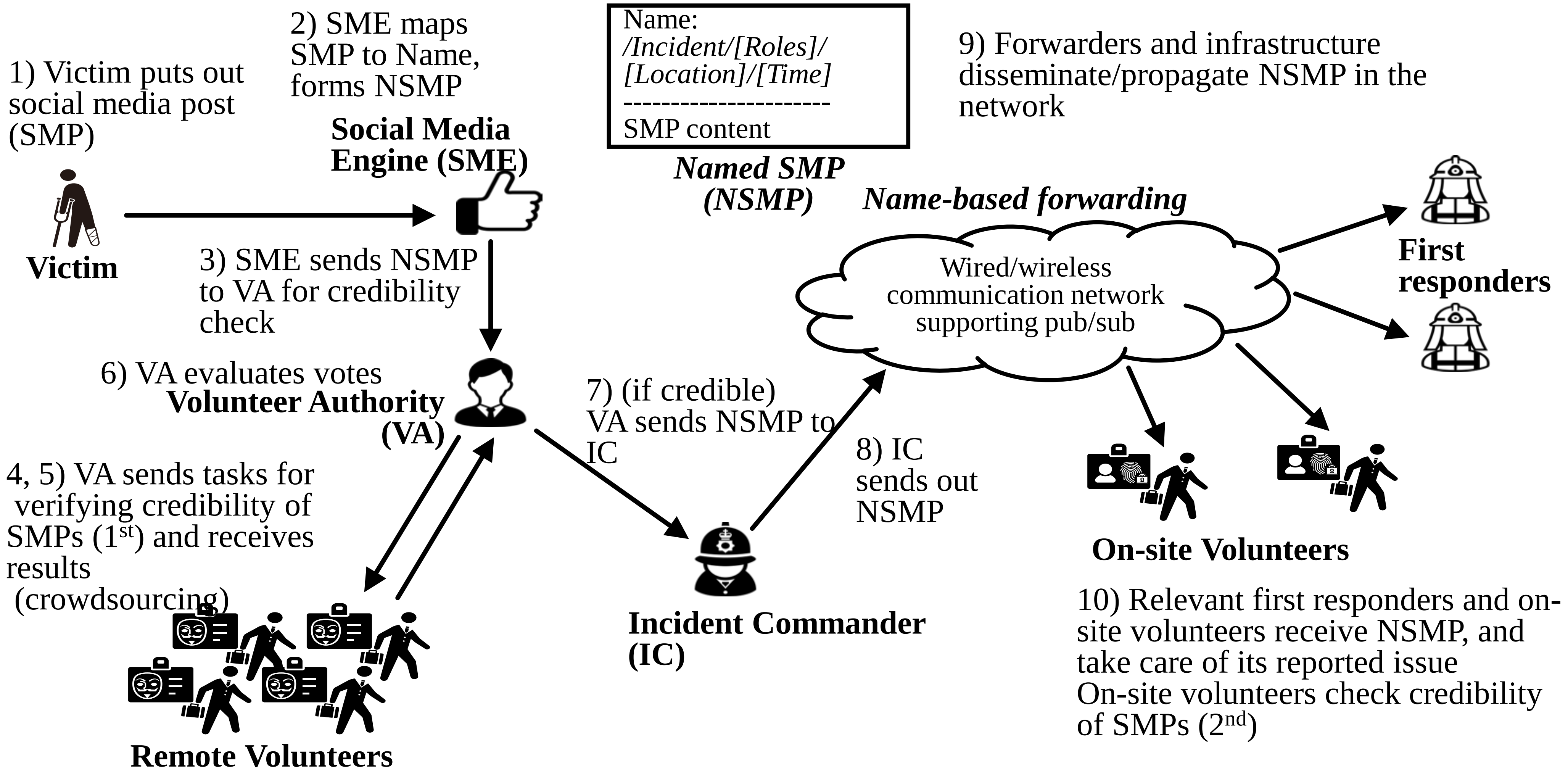
Incident commander (IC)
- Send commands to FRs according to event reports from the VA

Volunteer authority (VA)
- Ask remote/on-site volunteers to check the credibility of social media posts
- Only send credible social media posts to the IC

Social media engine (SME)
- Analyze social media posts to the social media and map them to the name space (named social media posts)

Victim
- Post messages to the social media

Scenario Walkthrough



Architectural Components

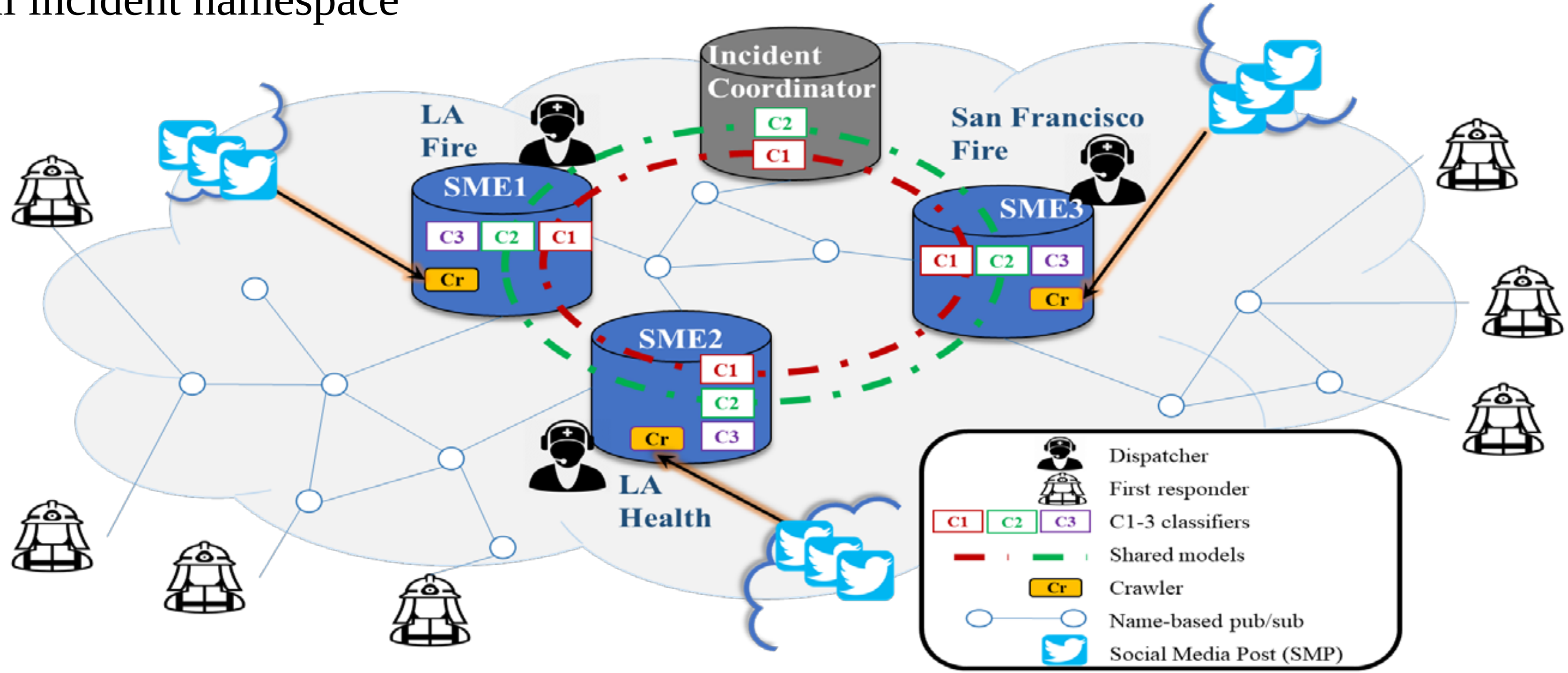
- Naming Schema
  - Unifies the interactions between all different actors (civilians, first responders, etc.) and guides the subscription and publication paths
  - Namespace represents entities related to and critical in incident management, and captures complex relations among them.
- Social Media Engine (SME)
  - Incoming social media posts (SMP), possibly including latitude/longitude, and timestamp, in addition to text, goes through a sequence of stages to be mapped to a (set of) name(s) of the namespace structure
  - Machine-learning based classification procedure maps the textual part of the SMP to the right roles, depending on what tasks and/or issues the SMP is referring to
- Verification Service
  - 2-layer crowd sourcing verifies credibility of SMPs extracted by SME, wherein remote and on-site volunteers work for checking the credibility
  - Trust management system identifies trustworthy volunteers/verifiers based on biometric signature and a trust model

Federated Active Learning Assisted by Naming for Responding to Emergencies

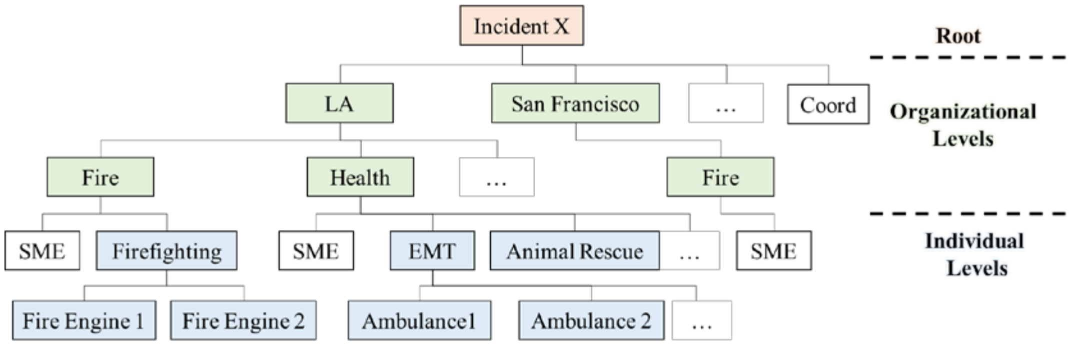
- First responders and other users (victims seeking help) would prefer using free-form text for communication during disasters
  - Social media is being increasingly used for communicating urgent information
- Our name-based pub/sub dissemination can be very helpful to deliver relevant information to the right first responder in a timely manner
- Each publication: Guided by namespace to the most appropriate first responder(s)
  - Challenge: How to assign names to free-form text in **real-time**? (e.g., senders without access to namespace)
- FLARE: Framework to provide efficient, timely dissemination of relevant content to first responder teams assigned to different incident response roles using the specialized knowledge of different first responder departments in a real-time online manner in disasters
  - Classification and learning procedures to map textual social media posts (SMPs) to the right name
  - Multi-level classification - provides increasing level of detail for mapping to namespace
  - Active Learning (reduce labeling effort) and Federated Learning (cooperation of specializations)
    - Better overall delivery accuracy respecting flexibility in managing AL and FL for each classifier

Overview of FLARE

- **Goal:** Provide efficient, timely dissemination of relevant content to first responder teams assigned to different incident response roles using specialized knowledge of first responder (and assisting) departments
- SMEs associated with departments, equipped with multiple classifiers (C1-C3), dispatchers, and the full incident namespace



Mapping Content to Names - Integrated with Learning



- **Map SMP to Names**
  - Map text messages and social media posts
  - Deliver to the correct individuals
  - Information-centric pub/sub (and request/response)
- **Participants**
  - Victims: Request for help using free-form text (tweets, etc.)
  - Incident Commander(s), Dispatchers: manage namespace
  - First responders: Subscribe to the appropriate level of the namespace - respond to messages
- **Social Media Engine (SME)**: Maps free-form text (e.g., social media posts) to the right name components, assigns names, e.g., *"/IncidentX/LA/Fire/Firefighting/FireEngine1/LARegionA"*, and publishes to correct first responder
- SME performs online classification and inference using Natural Language Processing (NLP)
  - Using a trained model to facilitate accurate inference

Mapping Content to Names - Components of SMEs

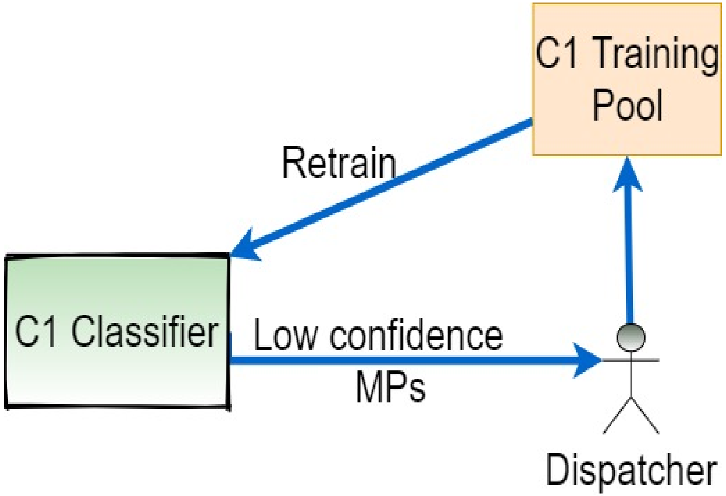
- Each Social Media Engine (SME) has its own (decentralized) **“Crawler”**:
  - Collects text-based content and/or crawls texts in real-time during or in the aftermath of disaster
  - Collects data with specific keywords based on the department’s specialization
- Multiple classifiers
  - **C1 (incident relevance predictor):** Determines if a an SMP is **relevant** to the incident
  - **C2 (organization predictor):** Provides classification corresponding to a coarse organizational-level granularity in the incident namespace
  - **C3 (fine-grained role predictor):** Provides classification corresponding to the finer granularity of individual roles in the incident namespace
- Each SME has a **“Named SMP Generator”:** takes the output of C3 as input and forms and publishes the SMP with full hierarchical name, e.g.,: *“/IncidentX/LA/Fire/Firefighting/FireEngine1”*

Social Media Engine Features

- **DNN Classifier with Universal Sentence Encoder (USE):**
  - Supports incremental learning allowing model to train on new dataset as it is made available
  - USE is pre-trained for sentence embedding over huge data corpus allowing it to capture rich semantic information
- **Active Learning:**
  - Reduces the manual labeling effort of the dispatcher by selecting only crucial messages required for training of the classifier
- **Federated Learning:**
  - Enables learning across various public-safety departments with specialized knowledge to handle notifications related to their roles, in a cooperative manner
- **Message Passing:** A technique to pass SMPs across different SMEs for their finer-grained classification by specialized knowledge of the dispatcher
  - Leverages organizational expertise in labeling more efficiently to eventually achieve better performance

Active Learning

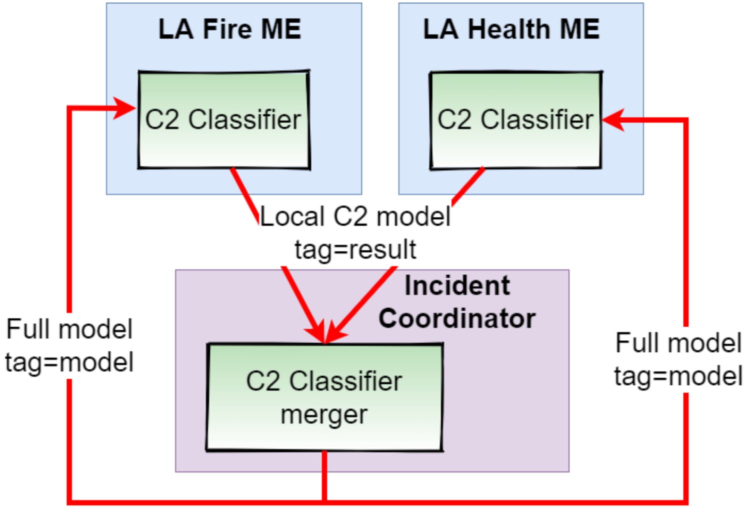
- Each classifier in the Media Engine is assisted by a dispatcher to label a small set of incoming SMPs
- **Specifications:**
  - Determine per-class prediction probability for each incoming SMP
  - Only label low confidence SMPs: Maximum prediction probability below a certain threshold
  - Configurable parameters:
    - Threshold: 0.8 for C1 and 0.7 for C2 (tunable)
    - Batch size: 50 (tunable)



- **Advantages:**
  - Reduced labeling effort for the dispatcher with no loss in accuracy
    - Labelling selective “informative” SMPs rather than all
  - Stream-based active learning enables FLARE to perform real time processing
    - Labelling as data comes in, rather than rely on an offline a priori trained data set

Federated Learning

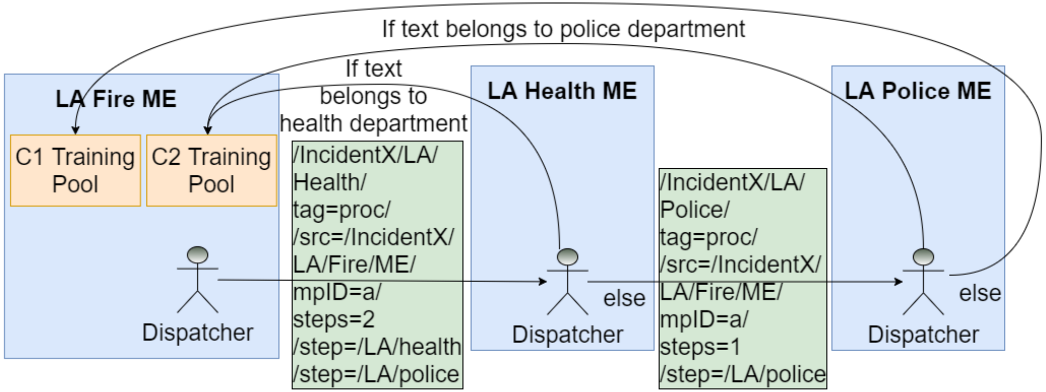
- Allows learning of model across multiple “workers” (SMEs), to assimilate and use the specialized knowledge of different entities (e.g., department-specific knowhow in disaster management) and collectively train the classifiers



- **Specifications:**
  - Algorithm: Vanilla Federated Learning
  - Iterations: Number of times models are aggregated across clients (tunable: based on stopping criteria)
  - Framework: **Flower**
  - Communications based on name-based pub/sub, with special “tags” (hierarchical name components)
    - SME-to-Coordinator, to pass local models “/…/tag=result/…”
    - Coordinator-to-SMEs, to pass aggregated models “/…/tag=model/…”
- **Advantage:** Since each SME works on a different set of data based on the keywords it uses for obtaining its dataset, its classifier is trained uniquely. FL (e.g., at incident coordinator) assimilates knowledge of the individual classifiers to create an aggregate model.

Message Passing

- Even with keyword-based crawling, it's possible that a message may not belong to the SME (department) that first receives it. FLARE uses message passing among SMEs for specialized labeling of text messages.
- If a dispatcher of a particular SME (e.g., Fire ME) is unable to classify the message, it is forwarded to the dispatcher for the SME that has the highest prediction probability predicted by the classifier.
- The process continues until the message is classified by one of the dispatchers - then it is added to the C2 training pool of the origin SME. If none of the dispatchers are able to classify it, the message is marked as irrelevant and added to the origin SME's C1 training pool.
- For message passing, we use the "proc" tag in the messages with required parameters (e.g., message ID, text, list of SMEs sorted by most to least likelihood of affinity to message).

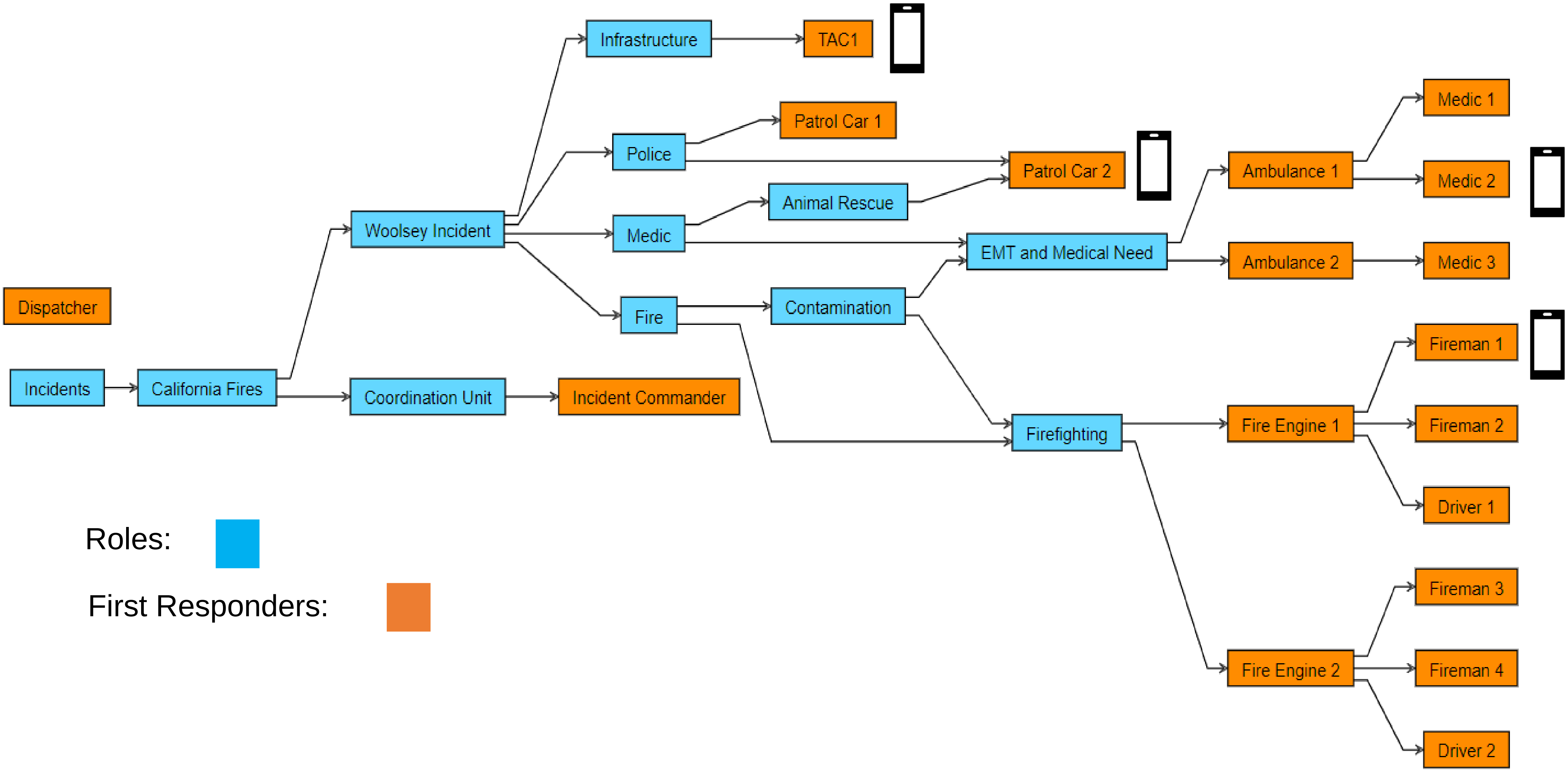


Results

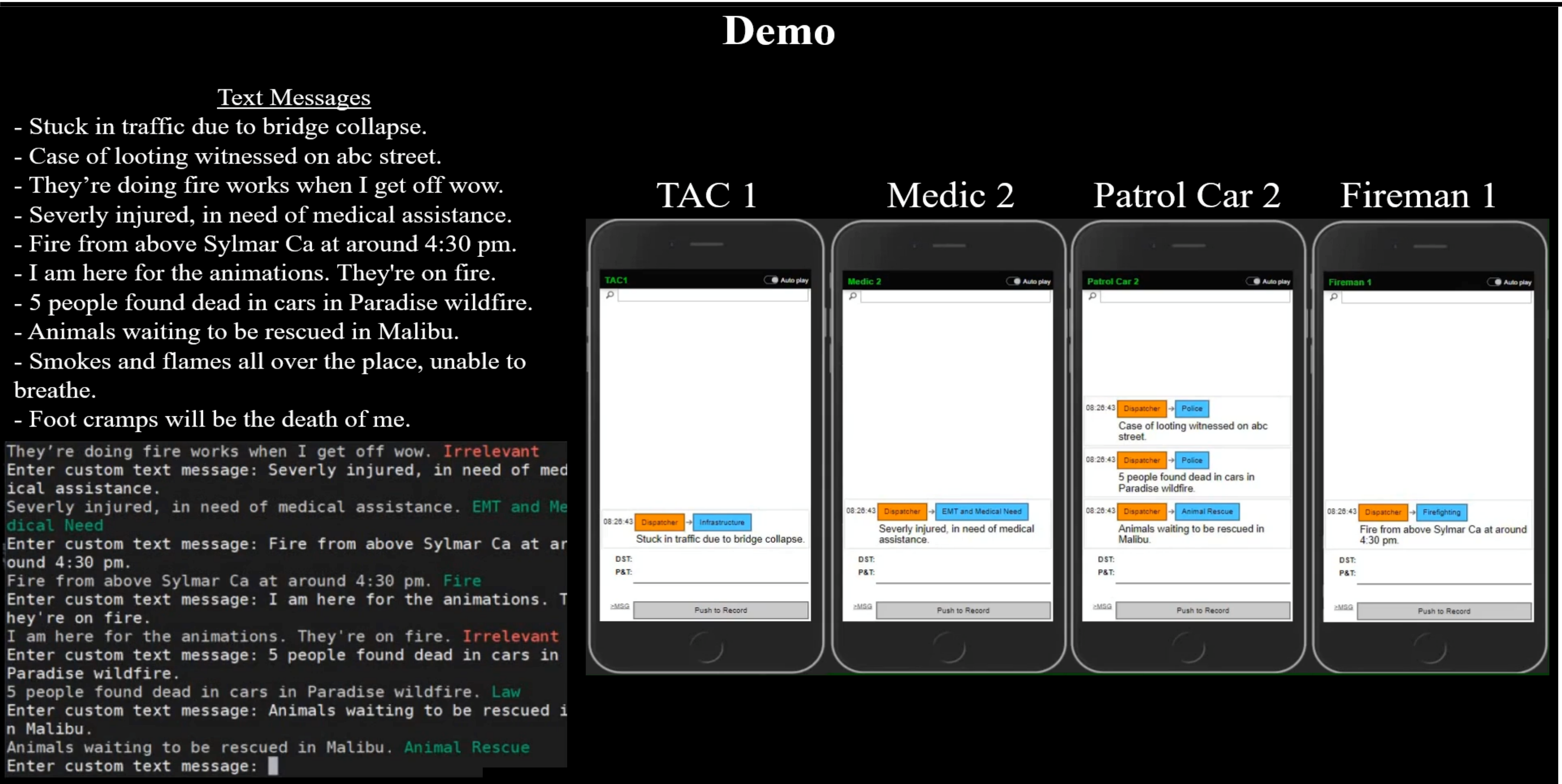
- **Overall results with streaming twitter data collected in California Wildfires**
  - **98.38%** of all disaster-relevant tweets get published and delivered to "some" first responder(s), some may be to the incorrect organization/role
  - **1.62%** of tweets classified "irrelevant" by C1
    - Not examined further
    - But, these tweets appear to be borderline & non-actionable, e.g., opinion
  - **88.18%** of all disaster-relevant tweets get published to first responder(s) in the right organization, whether or not it is to the right fine-grained role
    - Remaining **10.2%** delivered to incorrect organization - but can be delivered correctly based on the feedback from first-responders
  - Overall, **81.93%** of all disaster-relevant tweets get published to the first responder with correct role in right organization, at the finest granularity possible

	C1	**C2**	**C3 (avg)**
Accuracy (initial)	0.8262	0.6847	0.8553
Accuracy (dispatcher-assisted)	0.9091	0.8963	0.9291
Recall/F1 (initial)	0.9462	0.6183	0.8238
Recall/F1 (dispatcher-assisted)	0.9838	0.8589	0.9034
# of input tweets	3521 (of 3521)	2613 (of 2656)	2342 (of 2656)
# of correctly classified tweets	3201	2342	2176
# of tweets labelled	908	1223	441
Overall accuracy	0.9091	0.8818	0.8193

Implementation Example: Incident Name Space

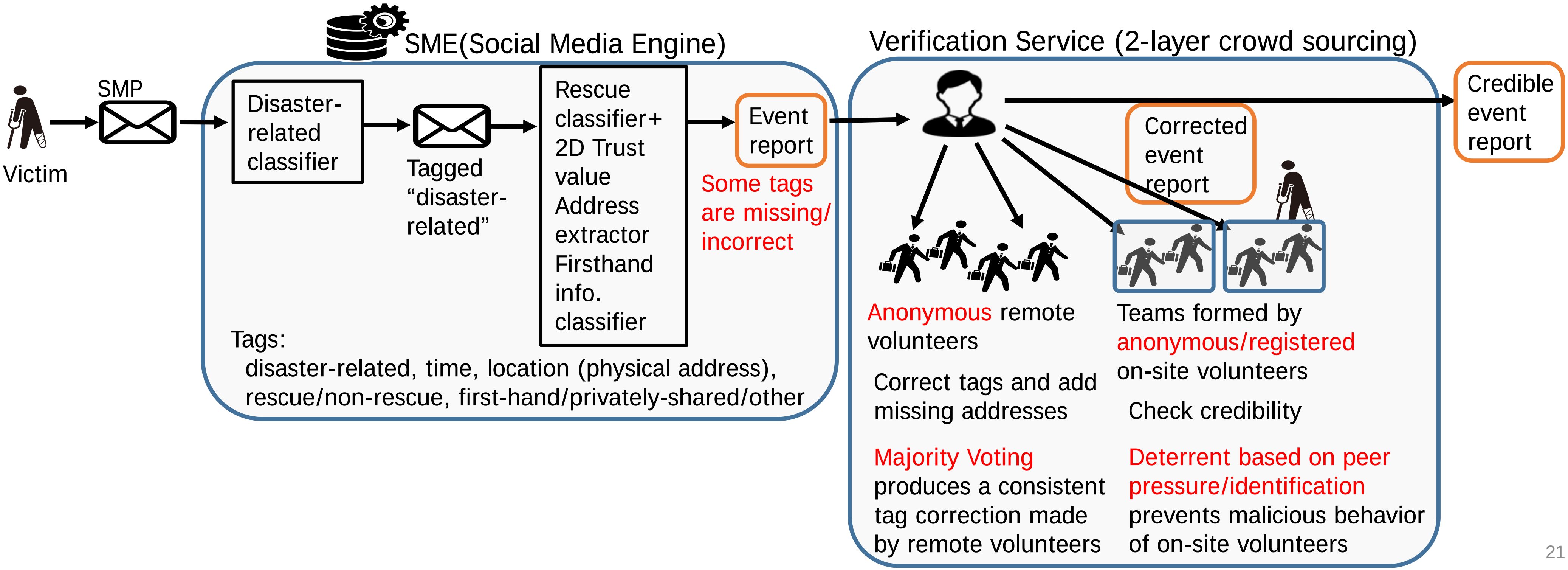


Implementation Example: Processing Tweets



Experimentation of SME and verification service

- Data Set: $7*10^7$ SMPs (tweets) at Western Japan Heavy Rain, July 2018
- SME successfully extracts rescue SMPs from the data set
- 2-layer crowd sourcing successfully verifies credibility of event reports (NSMPs) extracted by SME: Emulation and Agent-based simulation



Implementation of SME and Collaboration Tool

- SME (classifiers)
  - Implement the three classifiers using BERT fine-tuned with tweets of Western Japan Heavy Rain
    1. Disaster related
    2. First-hand information
    3. Rescue request
- Collaboration tools for remote, on-site volunteers and first responders
  - Remote volunteers correct classification results
  - On-site volunteers verify tweets and input the verification results
  - First responders only see tweets verified by on-site volunteers and tweets of high-confident classification to rescue requests

(a) On-site volunteers' view

(b) First responders' view

Screenshots of the collaboration tool

Extracting Rescue SMPs

- Two classifiers for disaster-related (UCR) and rescue (Osaka) are used
- Leaning-based classifier and correction based on 2D trust model
- Evaluation summary:
  - Extraction results of learning-based filter
    - Accuracy 0.96, Precision 0.84, Recall 0.70
  - Correction based on 2D trust model improves precision to 0.90 (explained by next 2 slides)

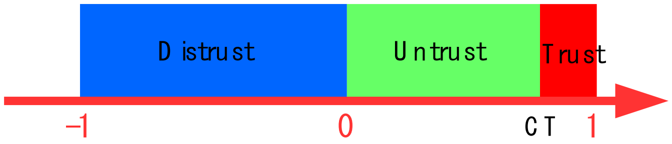
Label / Prediction	Rescue	Others
Rescue	42	8
Others	18	605

- Analysis based on attention values
  - Attention: How much a particular word will contribute to classification results
  - Words representing location names, flooding situations, and victims have a high impact on the rescue request classification

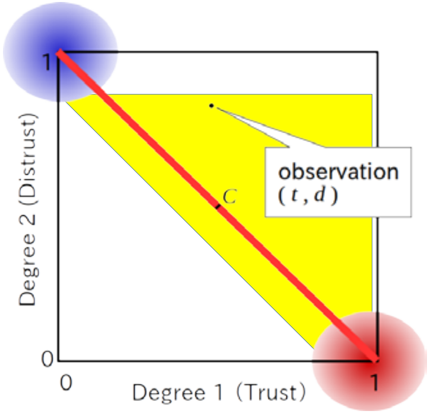
Classification Results	Words of higher attention values
Rescue request (True Positive)	town, - (hyphen), floor, people, left behind, flood, water, city, isolated, Chome (Town number in Japanese)
Rescue request (False Positive)	town, #, floor, city, San (title in Japanese), Chome
Non Rescue Request (True Negative)	#, @, town, http, please, city, people, dissemination
Non Rescue Request (False Negative)	#, evacuation, number, help, city

Correction by 2D Trust values

- Conventional (1D) trust model assumes that a human evaluator can calculate the degree (d) of distrust if the degree (t) of trust is given. (i.e. d=1-t)
  - Marsh, S., Dibben, M.R.: Trust, untrust, distrust and mistrust – an exploration of the dark(er) side. In: Proceedings of the Third International Conference on Trust Management. iTrust'05 (2005)



- However, such an assumption is sometimes too strong (e.g., a FR may judge that a message is basically credible while also having some doubtful aspects), and we introduced a 2D trust model where trust and distrust degrees are independent.
  - Fuzzy logic proves our model's correctness, and we found that our model is more powerful than subjective logic (SL), since only our model can deal with **contradictory situations** (top right region filled yellow).



- To exclude non-rescue requests, we assign 2D trust values to messages in disasters.
  - A high trust degree is assigned if a unique postal code can be derived from a message (i.e., a complete address is provided in the message).
  - A high distrust degree is assigned if there are "non-matching" words (Notice that words and phrases such as "Dear all," "your concern," and "Thank you" are unlikely to be used in an urgent call for help).

Correction by 2D Trust values (Cont'd)

- Example 1:
  (Trust: high, Distrust: low)
  A unique postal code (710-1304) is derived and it does not contain "non-matching" words.
- Example 2:
  (Trust: low, Distrust: not calculated)
  63 postal codes are derived.
  - 716-0009, 716-0039, 716-0018, 716-0015, ...
- Example 3:
  (Trust: high, Distrust: high)
  A unique code (709-0631) is derived, but it contains a non-matching word (物資, **goods**). In this case, a net trust value (t-d) is low.

拡散希望 友人のお母さんを救助ねがいます。倉敷市 真備町 尾崎[redacted]-[redacted] 女性 1 名と犬 1 匹 2 階まで浸水 脚立にのり、水から逃れています。どうか拡散をお願いします。 #倉敷市 #真備 #高梁川 #豪雨 #救助要請 # SOS #自衛隊 #救助

To everyone: My friend's mother needs help. One woman and one dog are flooded up to the 2nd floor at [redacted]-[redacted] Osaki, Mabi-cho, Kurashiki-shi They're having to use a stepladder to escape from the water. Please spread the word. #Kurashiki-shi #Mabi #Koryo river #flooding #rescue request #SOS #Self-Defense Forces #rescue

倉敷真備町は無人家屋で田畑は放置地だったが、総社の秦がまずい。葡萄畑の水をポンプでぬいてるが水浸し。高梁市の叔母が床上浸水。倉敷の叔母以外はみんな避難所。ハトコは総社アルミ工場爆発の消火中。実家借主の息子さんが、コンビニで玄関ごと吹き飛ばされるも無事

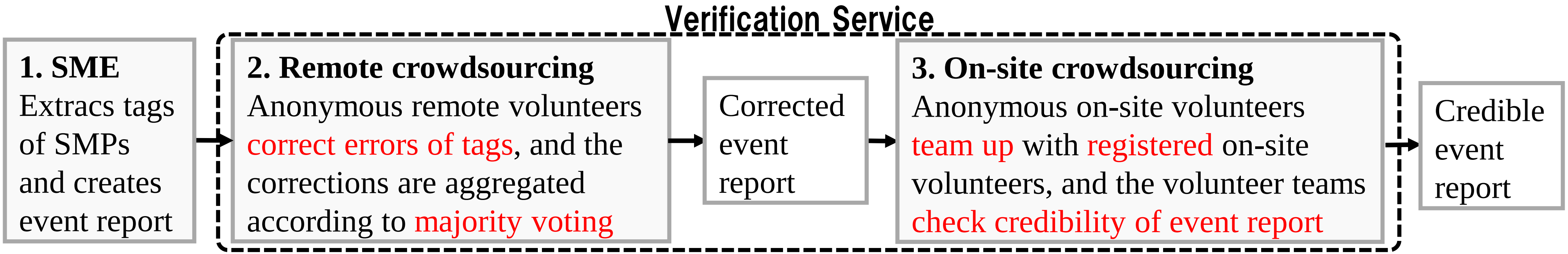
Kurashiki Mabi-cho was uninhabited and the fields were abandoned, but Hata in Soja-shi was in bad shape. They are pumping water out of the vineyard, but it is flooded. My aunt in Takahashi-shi was flooded above floor level. Everyone except my aunt in Kurashiki-shi is in a shelter …. <snip>

岡山市東区東平島の避難場所が小学校らしいんだけど、そこ昨日の夜まで浸水してたから別の場所に避難してるのかな？避難場所へ物資届けたくても遠すぎるしな。。他県からだと何ができるのか。

I heard that the evacuation site for Higashi-hirajima, Higashi-ku, Okayama-shi is the elementary school, but it was flooded until last night, so are they perhaps evacuating to someplace else? Maybe it's too far to deliver goods to the evacuation site? What can you do if you're from another prefecture?

Effectiveness of Verification Service

- **Mechanism :** Verification Service is composed of 2-layer crowd sourcing



- **Goal of evaluation:** The effectiveness of Verification Service is confirmed by
  - Conducting an emulation of “Remote crowd sourcing”:
    - Evaluating whether anonymous remote volunteers can correct errors in “tags assigned by SME”
    - Evaluating whether anonymous remote volunteers can extract “detailed physical addresses of disaster locations” from tweets
  - Conducting an agent-based simulation of “On-site crowd sourcing”:
    - Evaluating whether a team of registered/anonymous on-site volunteers can check the credibility of each Event Report
    - Evaluating whether “deterrent based on identification/peer pressure” can enhance trustworthiness of registered/anonymous on-site volunteers in conducting credibility check

Effectiveness of Remote crowdsourcing

- **Objective:** Evaluating how remote crowdsourcing correct errors of "tags in SMPs" assigned by SME
- **Approach:**
  - Chooses randomly 1000 disaster-related SMPs tagged "rescue" and "non-rescue" and evaluates how many corrected SMPs meet the condition of event report
  - Evaluates whether physical address is extracted (corrected) from the content of the "SMP where physical location is not identified by SME"
- **Observation:** Confirmed that the credibility of tagged SMPs can enhanced by a large number of remote anonymous volunteers

	Number of Extracted Event Reports (original)	Number of Extracted Event Reports (corrected)
Rescue	28	12
Non-Rescue	84	47

Wrong tags were corrected by remote volunteers, which extracted trustworthy 59 event reports out of 1000 tagged tweets.

	Corrected Non-rescue to Rescue	Corrected Rescue to Non-Rescue
Rescue	N/A	6
Non-Rescue	0	N/A

Six wrong Rescue tag were corrected by remote volunteers.

	Exact home address level	Street/town level with landmark	Street/town level without landmark
Rescue	4	0	2
Non-Rescue	7	17	13

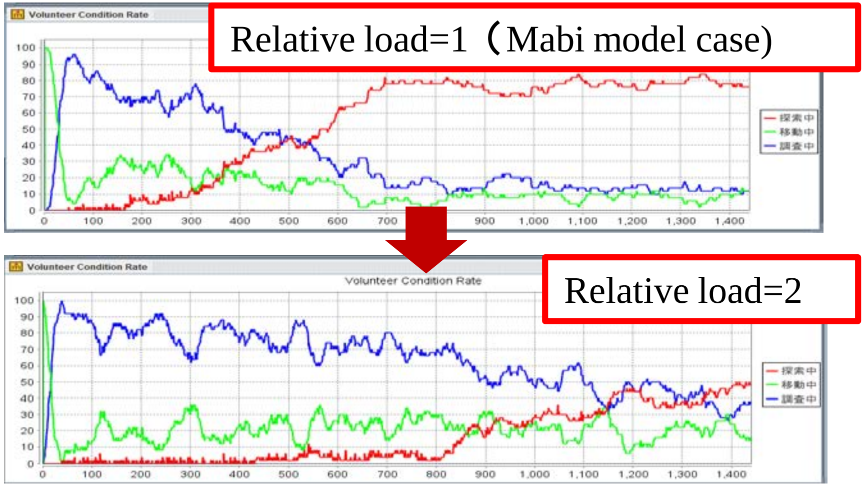
A tweet with a detailed address is likely to be an event report.

Effectiveness of On-site crowdsourcing

- **Objective:** Evaluating how on-site crowdsourcing checks credibility of event reports
- **Approach:**
  - Simulates the behavior of registered/anonymous on-site volunteer teams in disaster areas through agent-based simulation, based on Western Japan Heavy Rain, July 2018
  - Conducts simulations that take into account “deterrent based on identification” and “deterrent based on peer pressure”.
- **Observation:** Clarified the effect of the ratio of registered on-site volunteers on the accuracy of credibility check and the effect of the relative load (depending on amount of Event Reports, number of teams, area of disaster site) on the speed of information cleansing.

Ratio of registered on-site volunteers	True Rate	False Rate
0 %	75.0%	25.0%
12.5%	77.3%	22.7%
25%	86.4%	13.6%
50%	95.8%	4.2%

Accuracy of credibility check is greatly improved when the volunteers includes more than 1/4 of registered volunteers.



The time required for credibility check increases as the relative load per volunteer team increases. The result can contribute to estimate the number of people required according to the load in each affected area.

Conclusion and Plan of the Future

- Summary
  - Designed the architecture, DiReCt, so that timely delivery of the right information to the right people can improve outcomes and save lives
  - Designed architectural components and integrated them
  - Evaluated the architecture based on data from SMPs
- Plan of the Future
  - Write the paper based on the integrated architecture and further evaluation

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