Towards Cognitive Assistant Systems for Emergency Response

PIs: Homa Alemzadeh (ECE), John Stankovic (CS), Ronald Williams (ECE)

Presented By:

Sarah Masud Preum, PhD Candidate, UVa, CS

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Team

Prof. Homa Alemzadeh
ECE/CpE, UVa

Prof. John Stankovic
CS, UVa

Prof. Ronald Williams
ECE, UVa

1. Sarah Masud Preum, PhD candidate, CS, UVa
2. Sile Shu, MS student, ECE, UVa
3. Mustafa Hotaki, MS student, ECE, UVa
4. Arif Imtiaz, PhD student, CS, UVa
5. Annie Chapman, Undergrad, CS, UVa
6. Jui Tao Tsai, Undergrad, CS, UVa
7. Elizabeth Shelton, Undergrad, CS, UVa
8. Haydon Pitchford, First Responder, TJEMS

EMS Protocols

Medical history (EHR)

EMS transcription database

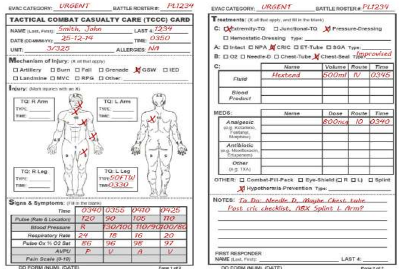
911 Call record

EMS radio call

EMS Intervention

Conversations with bystanders and victims

- Information overload
  - Collecting, analyzing, prioritizing
- Recording and summarizing information
- Decision making and execution

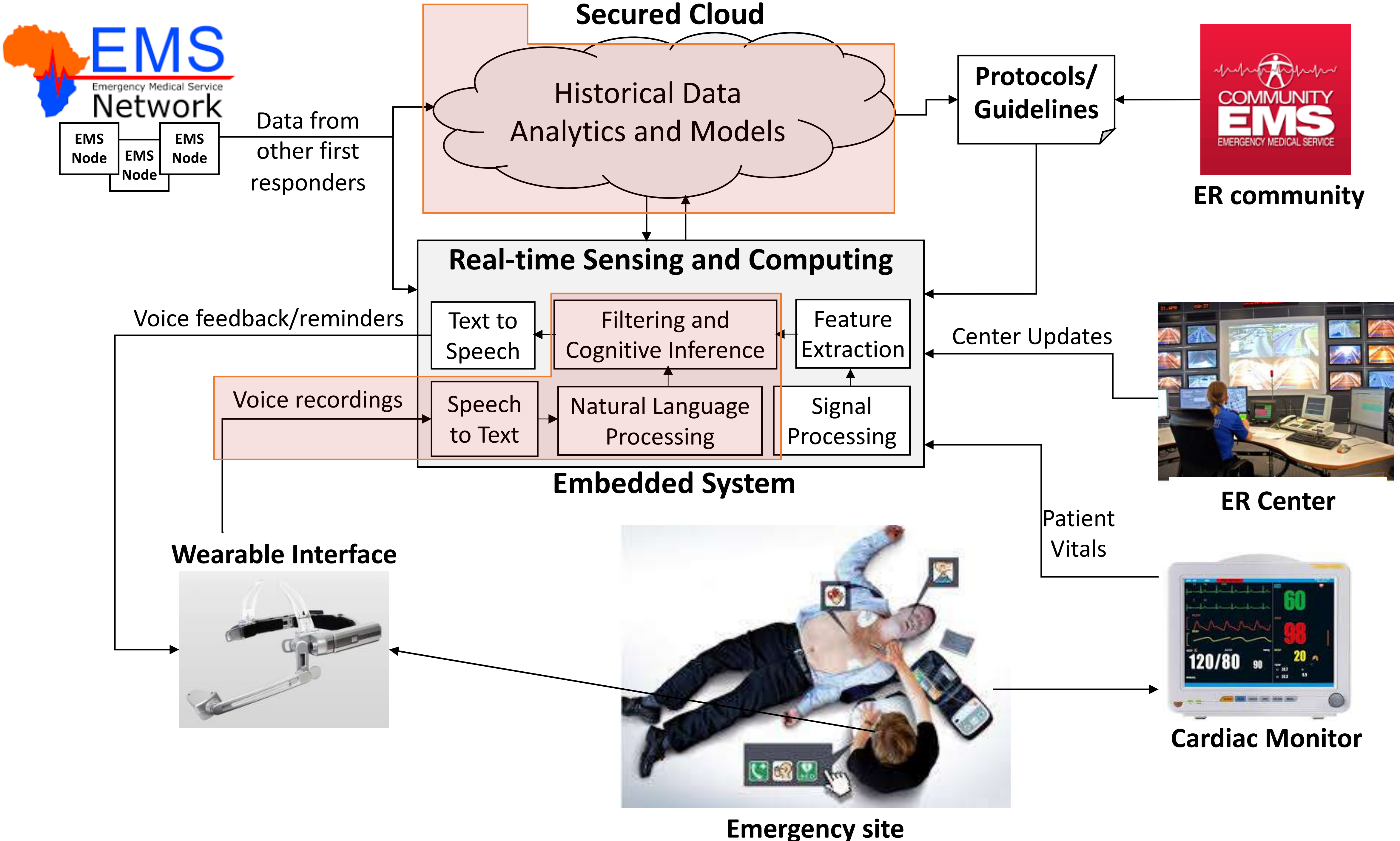


EMS Incident Report

CognitiveEMS:
A Cognitive Assistant System for EMS

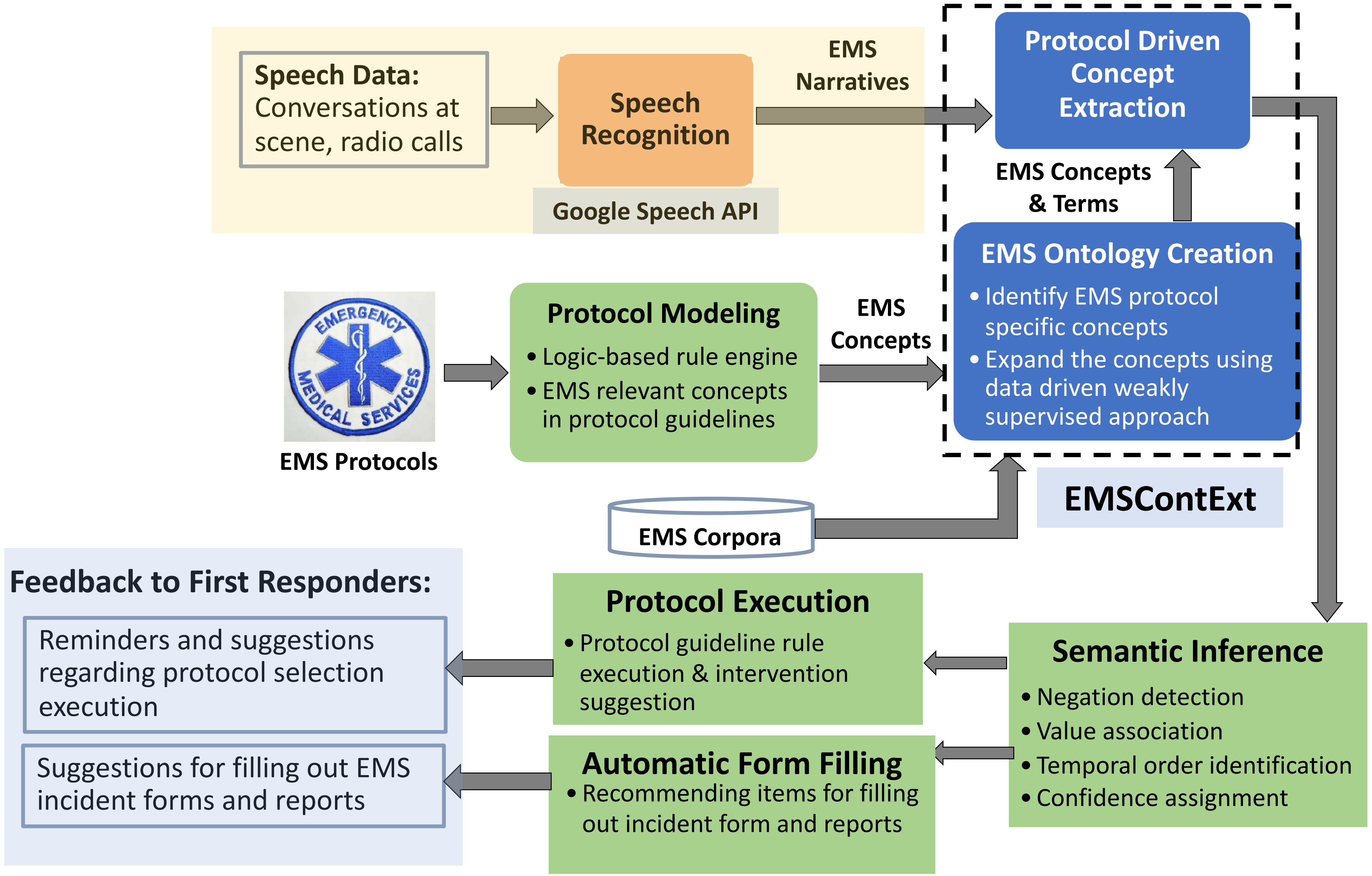
- **Resilient data analytics**
- Automated ***collection*** and ***analysis*** of data from incident scene
- **Filtering** and **aggregation** of in-situ/public data
- Providing dynamic data-driven feedback on effective response actions

- **Anytime real-time sensing and computing**
- **Embedded** system architecture for **real-time** data analytics
- **Dynamic reconfiguration** for resiliency



EMS
Emergency Medical Service
Network
EMS Node
EMS Node
EMS Node
Data from other first responders
Secured Cloud
Historical Data Analytics and Models
Protocols/ Guidelines
COMMUNITY EMS
EMERGENCY MEDICAL SERVICE
ER community
Real-time Sensing and Computing
Voice feedback/reminders
Text to Speech
Filtering and Cognitive Inference
Feature Extraction
Center Updates
Voice recordings
Speech to Text
Natural Language Processing
Signal Processing
Embedded System
ER Center
Patient Vitals
Wearable Interface
Cardiac Monitor
Emergency site

Protocol-Driven EMS Decision Support Pipeline



Challenges: Speech Recognition in Emergency Scenes

- Noisy environment
    - Word/phrase deletion, insertion, substitution
    - Lack of context-awareness:
        - Male-mail
    - Inaccurate numerical value identification
        - four hundred eighty (480) → four eighty →for eighty (for 80)
        - two hundred eighty (280) → hundred eighty → (180)
- Network failure
- Resource constraint

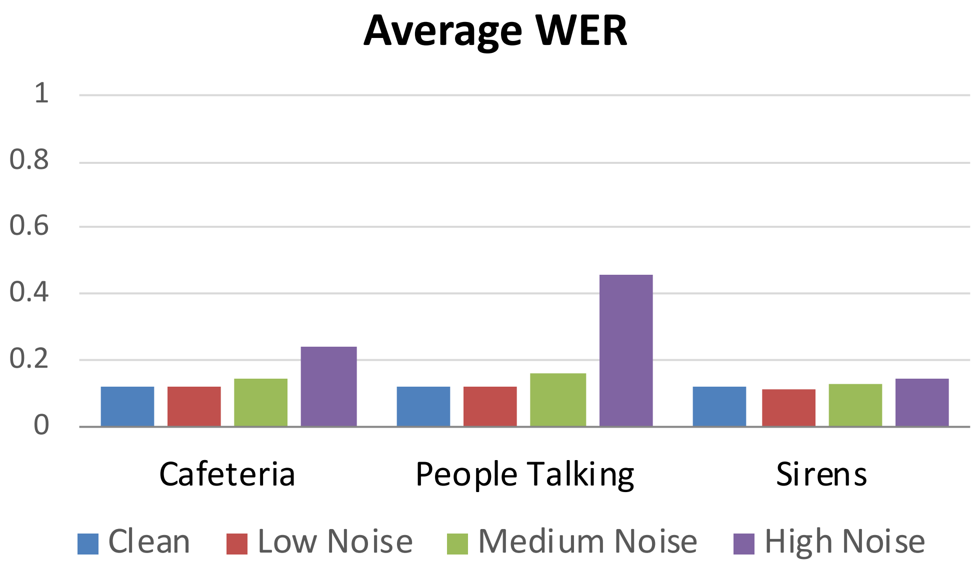
N: total words
I: # of inserted words
D: # of deleted words
S: # of substituted words

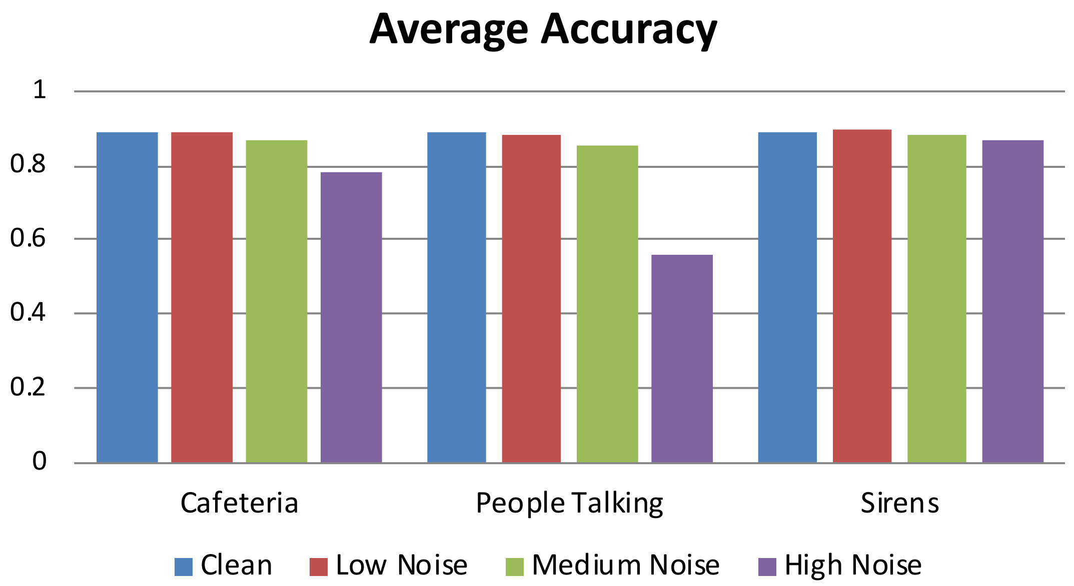
$$WER = \frac{I + D + S}{N}$$

Environment		PocketSphinx	Google	Microsoft	IBM
Noise-free	**WER**	0.80	**0.19**	0.24	0.45
	Runtime (sec)	2.48	**2.72**	3.42	5.34
Noisy	**WER**	1.05	**0.39**	0.62	0.89
	Runtime (sec)	3.41	**3.00**	3.38	9.84

Table I: Average WER and Runtime for Speech-to-Text tools

Noisy Speech Recognition: Google Speech API





N: total words
I: # of inserted words
D: # of deleted words
S: # of substituted words

$$WER = \frac{I + D + S}{N}$$

$$Accuracy = \frac{N - D - S}{N}$$

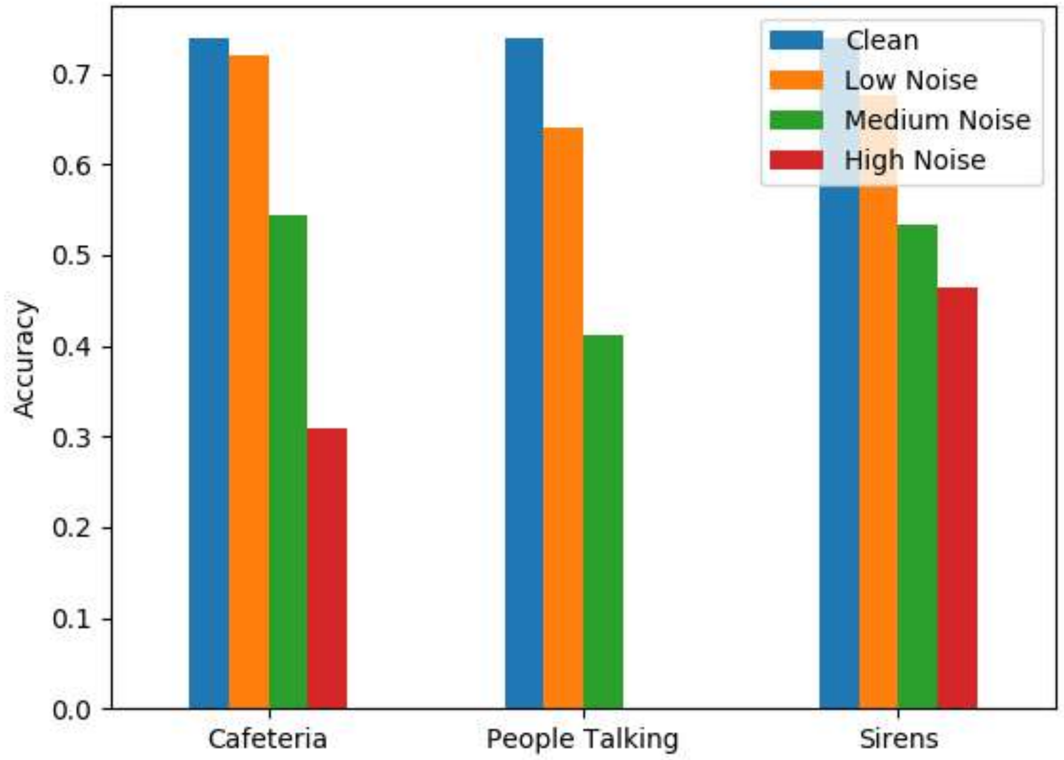
Noisy Speech Recognition: Google Speech API on Benchmark Dataset

- **TIMIT Acoustic-Phonetic Continuous Speech Corpus**
- A noise-free dataset containing 6,300 audio files of sentences read by people from different regions of the United States
- Average Word Error Rate (WER) is less than 10%

Noisy Speech Recognition: Mozilla DeepSpeech

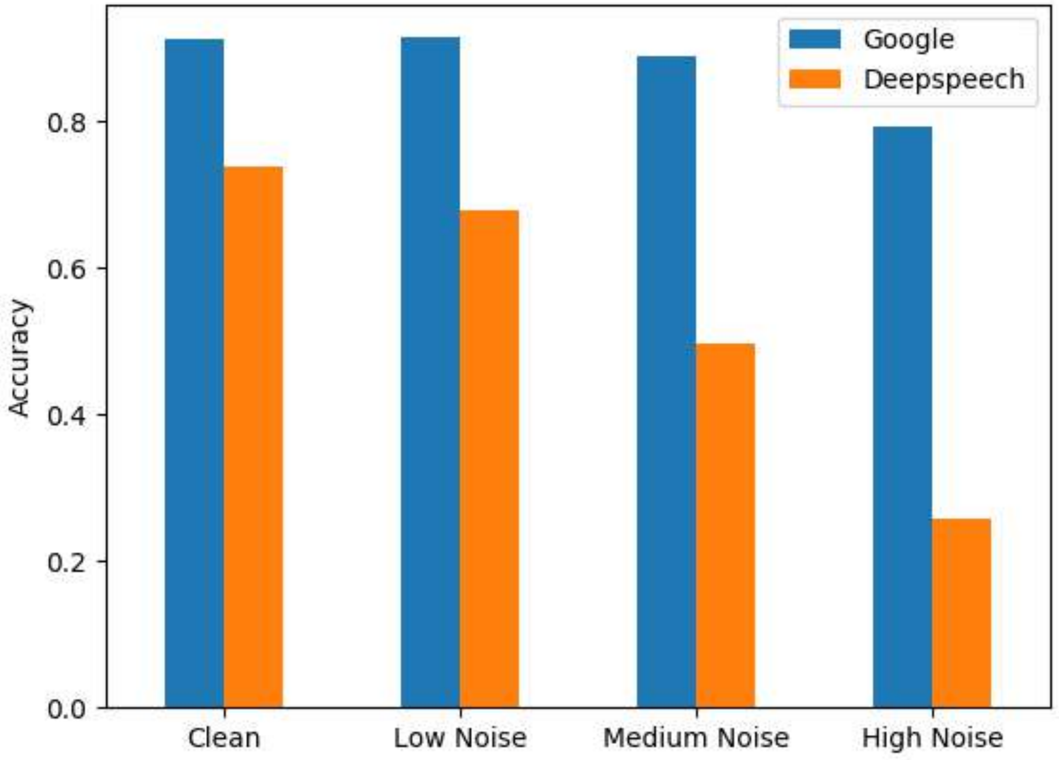
Challenge: Robustness

Mozilla DeepSpeech : Open source, standalone, state-of-art, trainable, offline

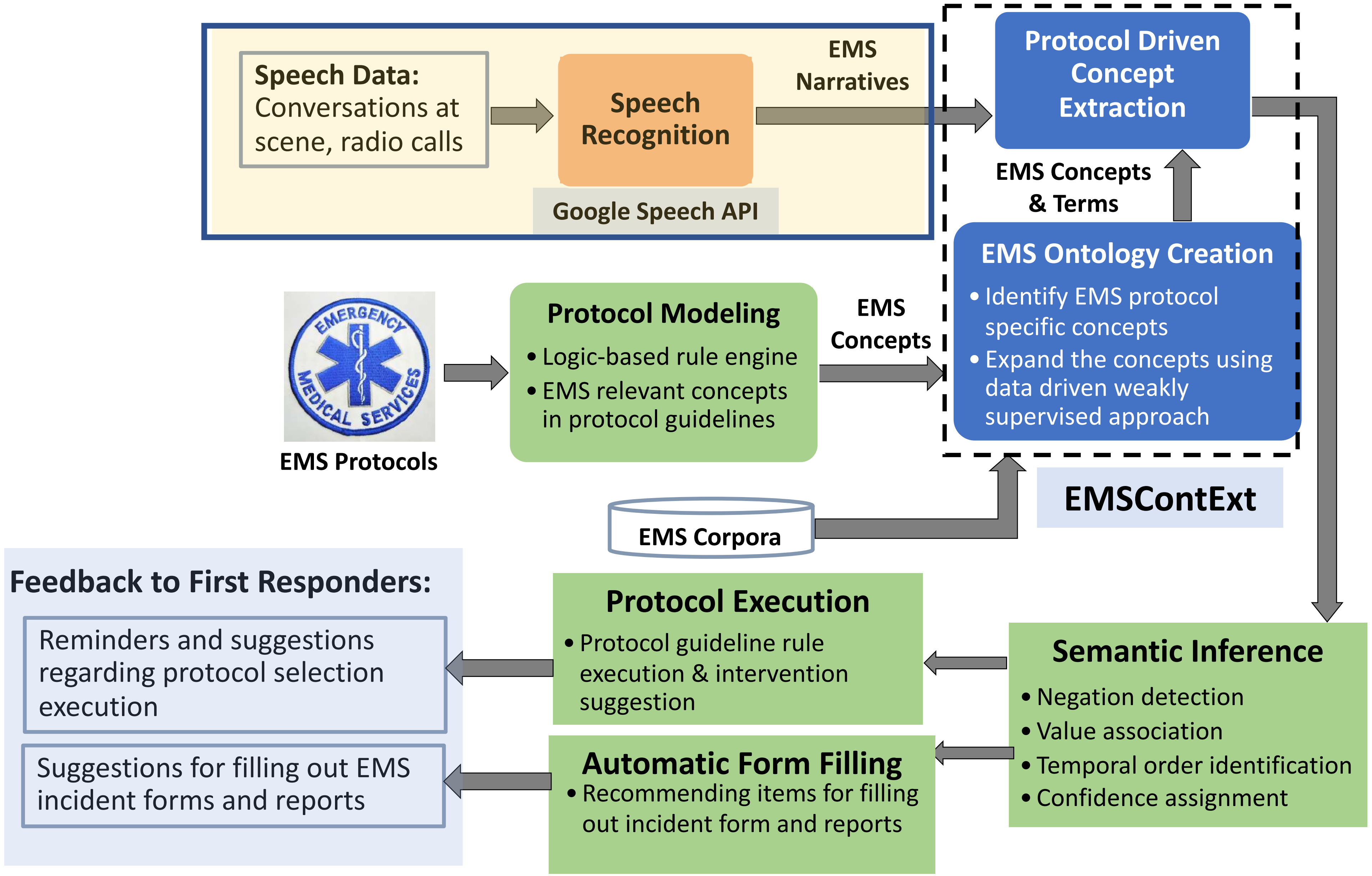


Noisy Speech Recognition: Mozilla DeepSpeech vs Google API

- Improving the performance of DeepSpeech
  - Preprocessing and post processing
  - Use both Google speech API and DeepSpeech



Protocol-Driven EMS Decision Support Pipeline



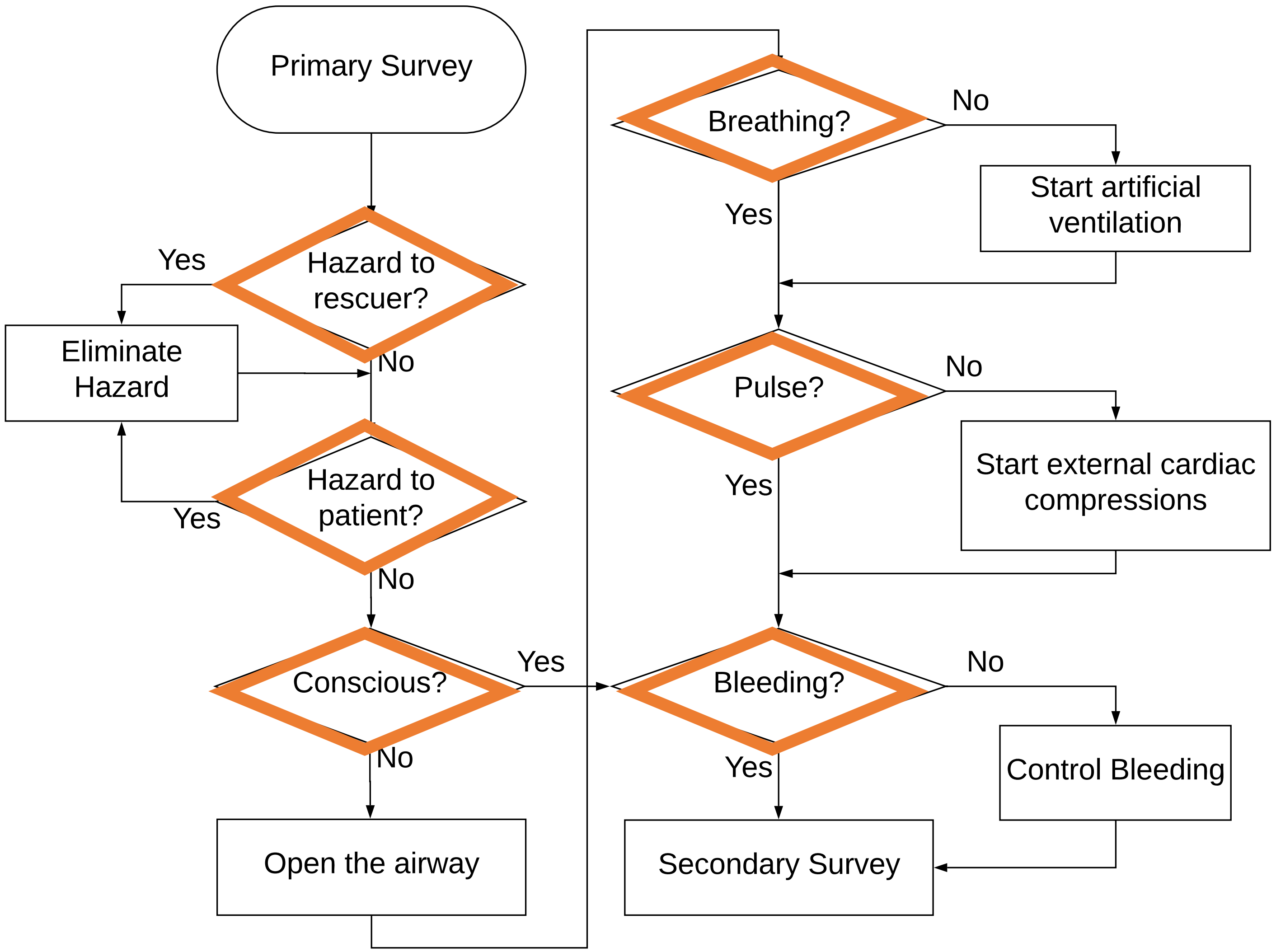
EMS Protocols

- **100+ EMS protocols**
  - General
    - Primary survey, secondary survey protocols
  - Regional
    - Cardiac, Cardiac Arrest, Environmental, Medical, Neuro, Respiratory, OB/GYN, Injury
  - Protocols vary in structure, complexity, and volume of co

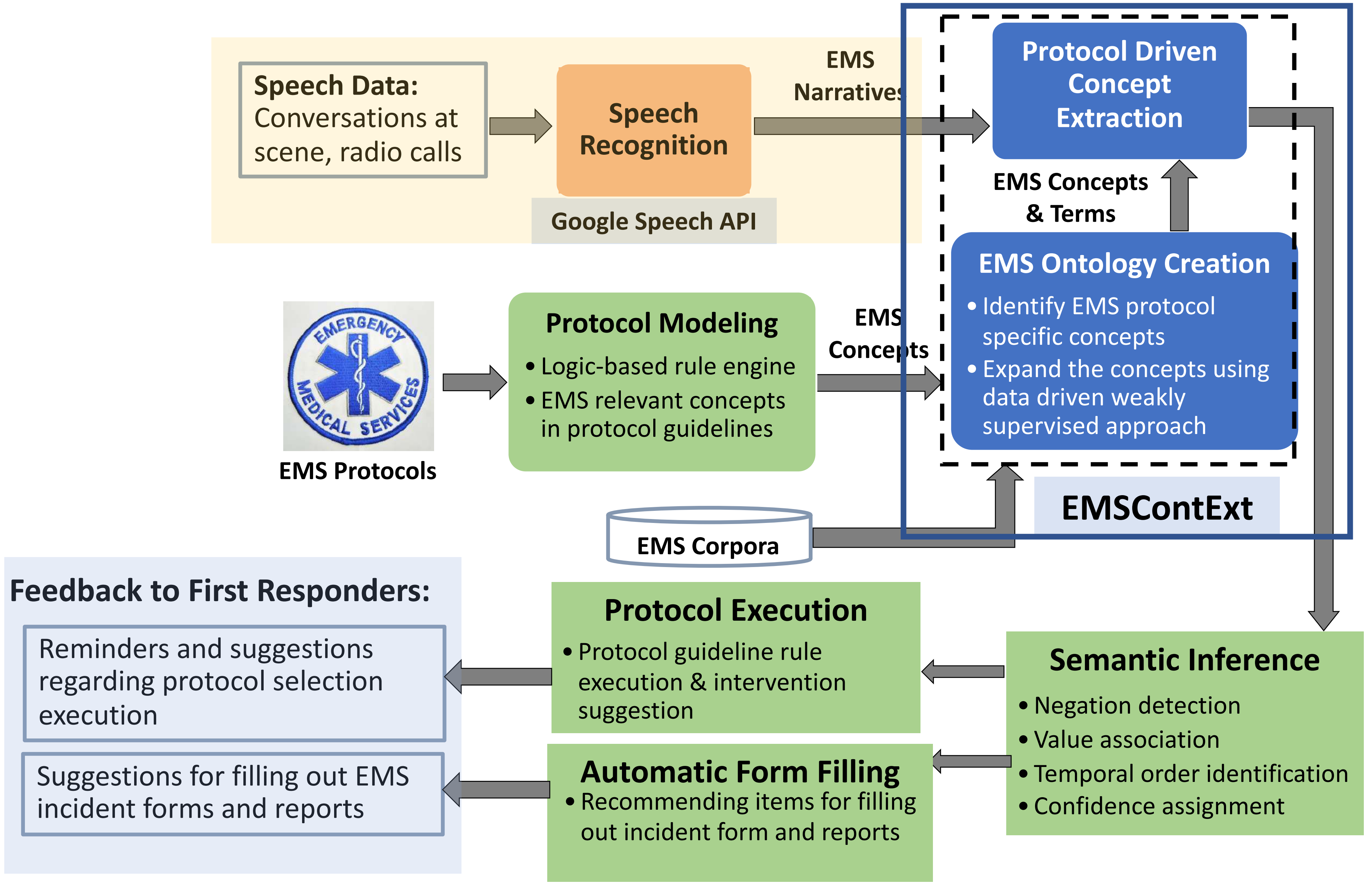
Old Dominion EMS Alliance

- **66 commonly used protocols from ODEMSA Protocols**
  - **TJEMS, WV EMS**

Primary Survey Protocol

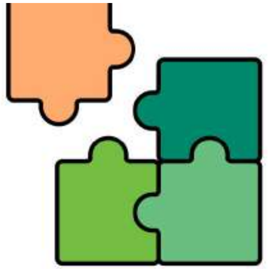


Protocol-Driven EMS Decision Support Pipeline



Challenges: Protocol Driven Concept Extraction

- Lexical variation
  - Respirations: resp., respiration, respiratory, rr, etc.
  - Conscious → LOC, unconscious, awake and oriented
- Domain mismatch
  - From general domain to EMS domain
    - Example: sob
  - From medical domain to EMS domain
    - Example: A+OX4
- Low resource
  - No publicly available textual corpus
  - Lack of annotated data
    - Expensive annotation in terms of time and expertise
- Lightweight and robust solution
  - Network failure and device constraint



Challenges: Protocol Driven Concept Extraction

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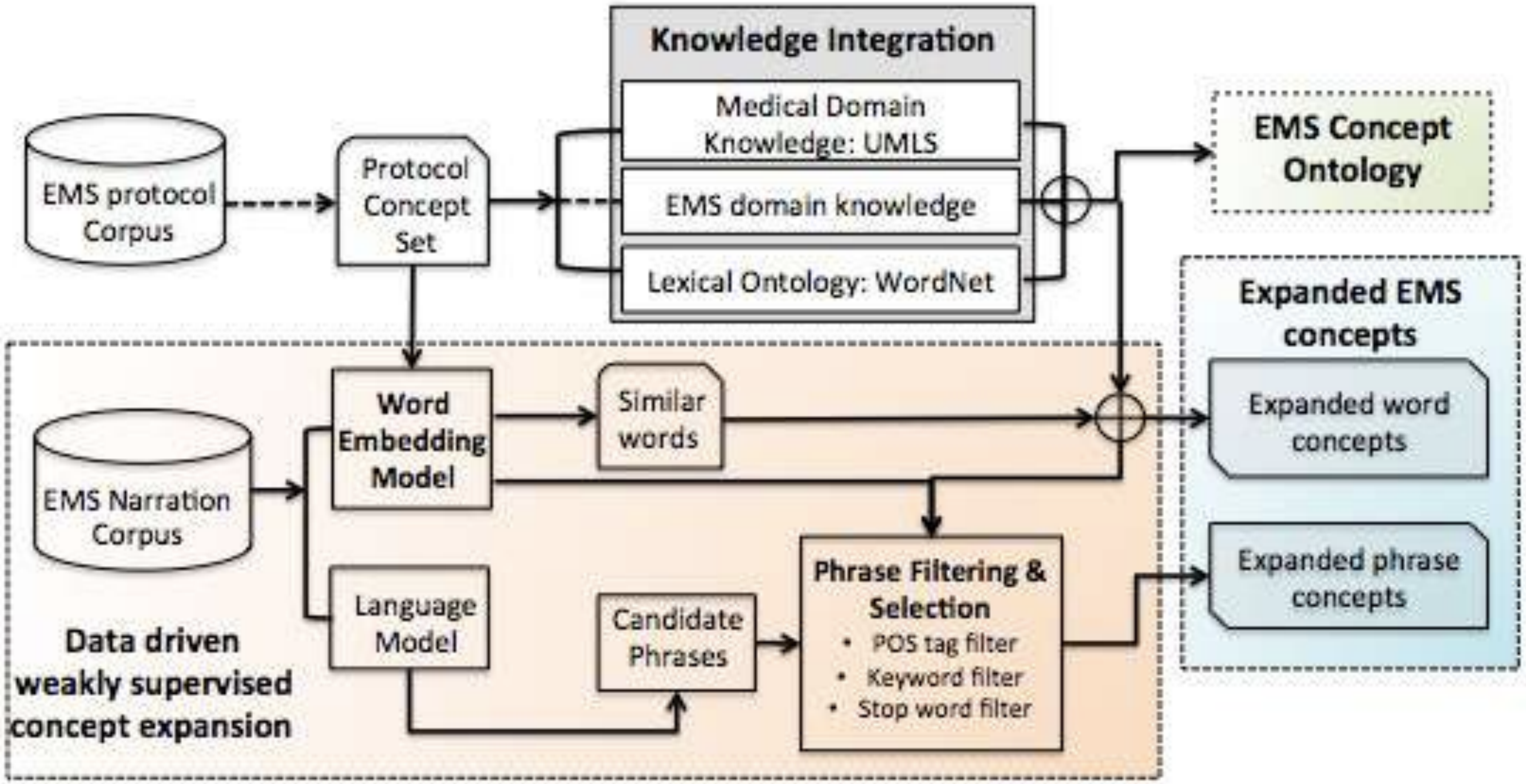
One-time knowledge integration from multiple relevant knowledge bases

Data-driven weakly supervised approach for expanding EMS concepts

Reduce data annotation effort and automatic concept annotation

EMS Protocol Driven Lexicon Expansion



Evaluation of Concept Extraction: Datasets

	Textual Dataset	Size of Dataset	Number of Sentences
1	Richmond Ambulance Authority (RAA)	8000 narrations	216K+
2	Online EMS forum	1403 narrations	20K+
3	I2B2	5733 narrations	302K+
4	MIMIC III	2434 narrations	38K+
5	EMS (Union of 1 and 2)	9434 narrations	237K+
6	Medical (Union of 3 and 4)	8167 narrations	340+
7	EMS + Medical (Union of 5 and 6)	17,570 narrations	577K+

Evaluation of Concept Extraction: Comparing with the State-of-the-art Medical Concept Extraction Tool

- **Our weakly supervised approach outperforms the state-of-the-art, supervised approach, MetaMap**
  - 33% and 16% higher recall in RAA and EMS Forum datasets respectively
  - 3 times higher F1 score

Evaluation of Concept Extraction: Impact of Knowledge Integrated Lexicon Expansion

- **Knowledge-Integrated Lexical Expansion**
- Lexical knowledge base, WordNet
- Medical knowledge base, UMLS
- EMS knowledge base

Test Data	Lexical	Medical	EMS
RAA	1081	1776	45
EMSForum	2598	7984	304

The number of original protocol specific terms expanded by different components of the EMS ontology for the two test datasets.

Evaluation of Concept Extraction: Impact of Knowledge Integrated Lexicon Expansion

- Different knowledge bases contribute uniquely
- Combination of all three knowledge bases results in the best performance for both datasets
- But using only knowledge-integrated approach is not enough
  - Many concepts are still not extracted

Test Data	Knowledge	Recall	F1
RAA	Lexical	0.5479	0.5938
	Medical	0.3425	0.4145
	EMS	0.1381	0.2377
	Lexical+ Medical+EMS	**0.7134**	**0.6133**
	EMSContExt	**0.8538**	**0.8182**
EMS Forum	Lexical	0.1876	0.2883
	Medical	0.222	0.3036
	EMS	0.1469	0.2344
	Lexical+ Medical+EMS	**0.2702**	**0.3639**
	EMSContExt	**0.8255**	**0.842**

Evaluation of Concept Extraction: Impact of Data-driven Lexicon Expansion

- Distributional semantic model for finding semantic similarity
  - Word2Vec: word embedding model
- Training the model on training datasets from different domains
  - GoogleNews: general news article
  - Medical corpus: I2B2 + MIMIC III
  - EMS corpus: RAA + EMS Forum

Evaluation of Concept Extraction: Impact of Data-driven Lexicon Expansion

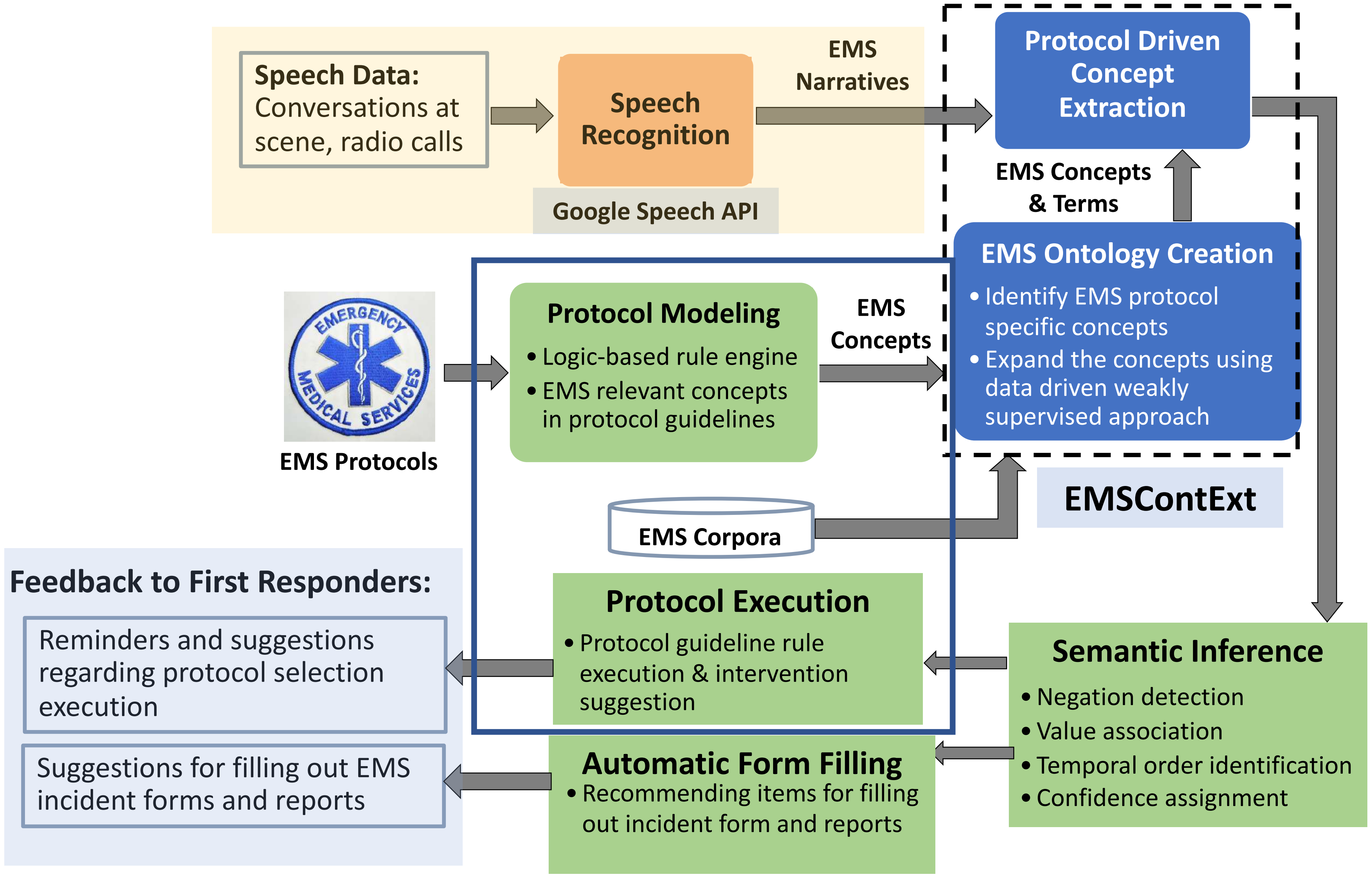
- Using domain specific data for training results in the best performance

  - **Comparing with generic textual training data**
  - RAA: 2 times increase in recall
  - EMS Forum: 2 times increase in recall

  - **Comparing with medical textual training data**
  - RAA: 29% increase in recall
  - EMS Forum: 6% increase in recall

Test Data	Model	Recall	F1
RAA	EMS	**0.6148**	0.5477
	Medical	0.4745	0.5139
	EMS+Medical	0.4827	0.5635
	GoogleNews	0.2587	0.3189
	EMSContExt	**0.8538**	**0.8182**
EMS Forum	EMS	**0.647**	0.6694
	Medical	0.6074	0.6518
	EMS+Medical	0.6091	0.6965
	GoogleNews	0.2712	0.3338
	EMSContExt	**0.8255**	**0.842**

Protocol-Driven EMS Decision Support Pipeline



EMS Protocol Modeling and execution

- **Protocol modeling:** Behavior tree model with confidence score
  - Assign confidence to the evidences gathered from input text
  - Calculate confidence score of the suggested interventions

- **Protocol execution**
  - Weakly supervised knowledge-driven model to perform protocol selection and intervention suggestion
  - Supervised data-driven approach to perform end-to-end intervention suggestion

Behavior Tree (BT): Background

Fig. 1.22: The JIBO social robot has an SDK based on BTs.

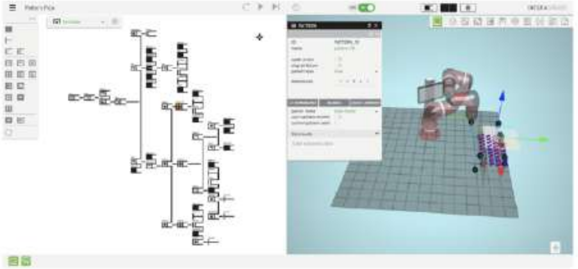
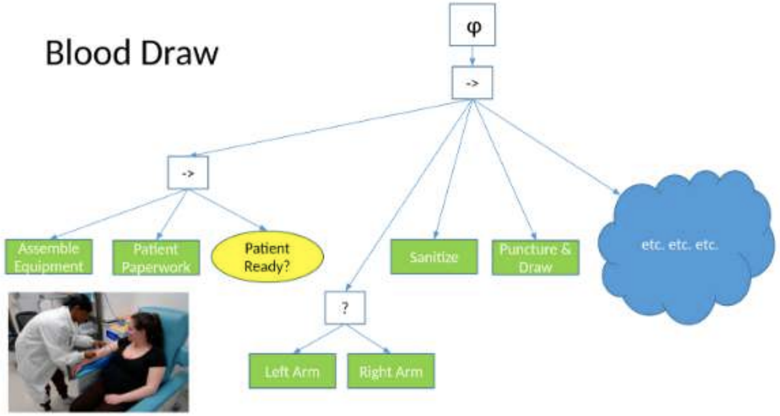
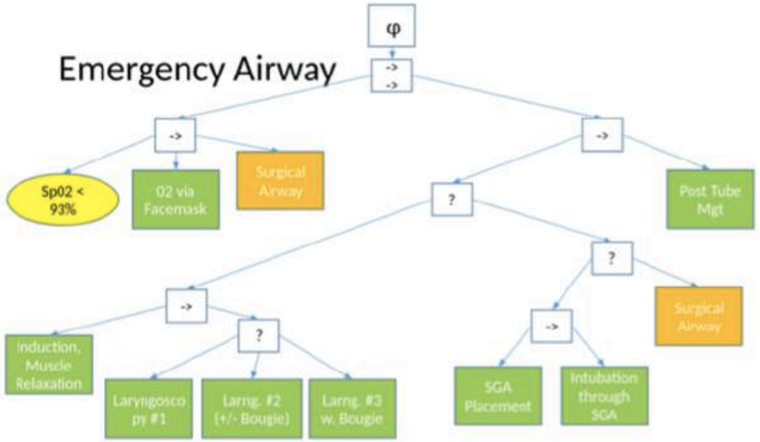


Fig. 1.20: Intera's BT (left) and simulation environment (right).[10]

M. Colledanchise and P. Ogren. *Behavior trees in robotics and AI, an introduction*. 2017.

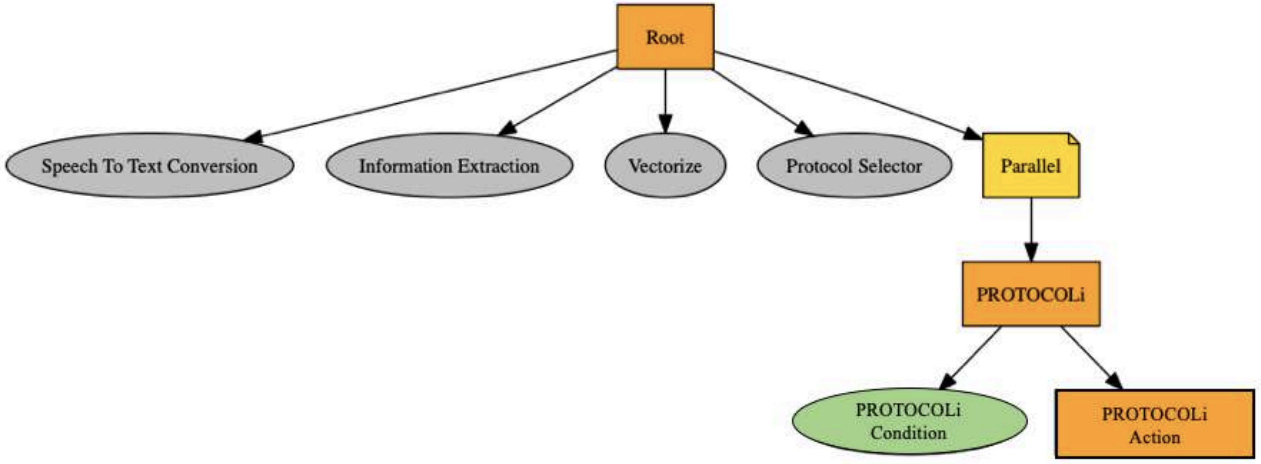


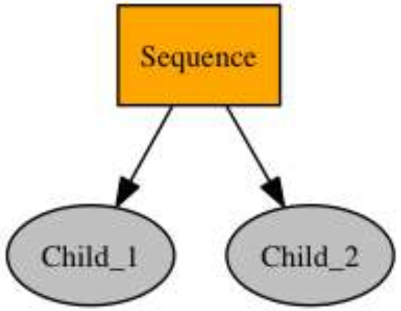


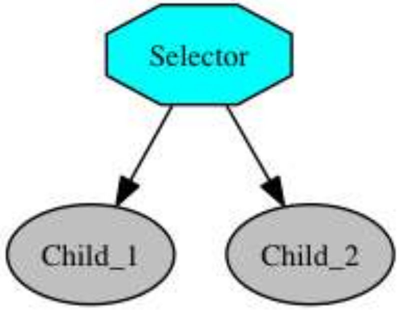
Hannaford, Blake, et al. *Behavior Trees as a Representation for Medical Procedures.* 2018.

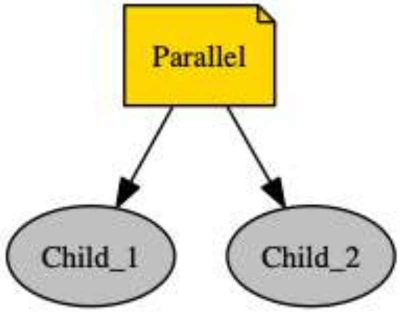
Behavior Tree Framework for EMS Protocol Modeling and Execution

- **Semi-supervised approach**



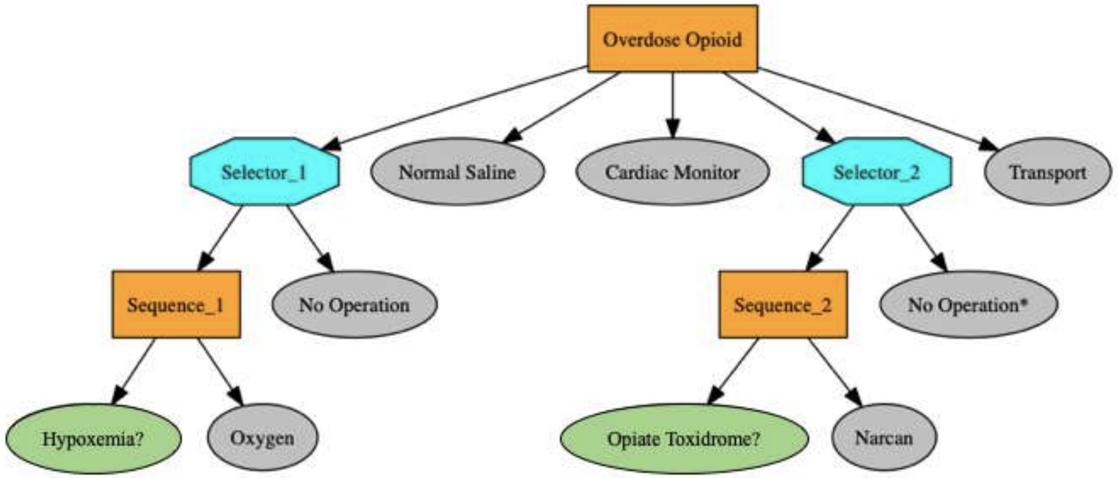






Behavior Tree Framework for EMS Protocol Modeling and Execution

- **Semi-supervised approach**
- **EMS protocols modeled using behavior trees and logic rules**
  - Input: current patient status
    - “not breathing”
  - Output: recommended action based on protocol
    - “start artificial ventilation”



Information Extraction: Sample Output from MetaMap

- UMLS concept extraction
- Concept filtering
- Negation detection
- Value retrieval

MMI indexing score with a maximum score of 1000, which indicates the relevance of the UMLS concept

UMLS Concept Unique Identifier (CUI)

```
ConceptMMI(index='00000000', mm='MMI', score='16.19', preferred_name='Respiratory rate', cui='C0231832', semtypes='[c
lna]', trigger='["Breathing rate"-tx-1-"breathing rate"-noun-0]', location='TX', pos_info='162/9,177/4', tree_codes='
E01.370.600.875.875;G09.772.770.755.730')
```

- UMLS concept (preferred name)
- Actual text
- Speech tagger
- Negation Flag: ‘1’ if consider negated

StartPos/Length

Information Extraction: Unified Concept Framework

$$(C_i : P_{i,t}, V_{i,t}, T_{i,t}, Conf(C_i, t), t)$$

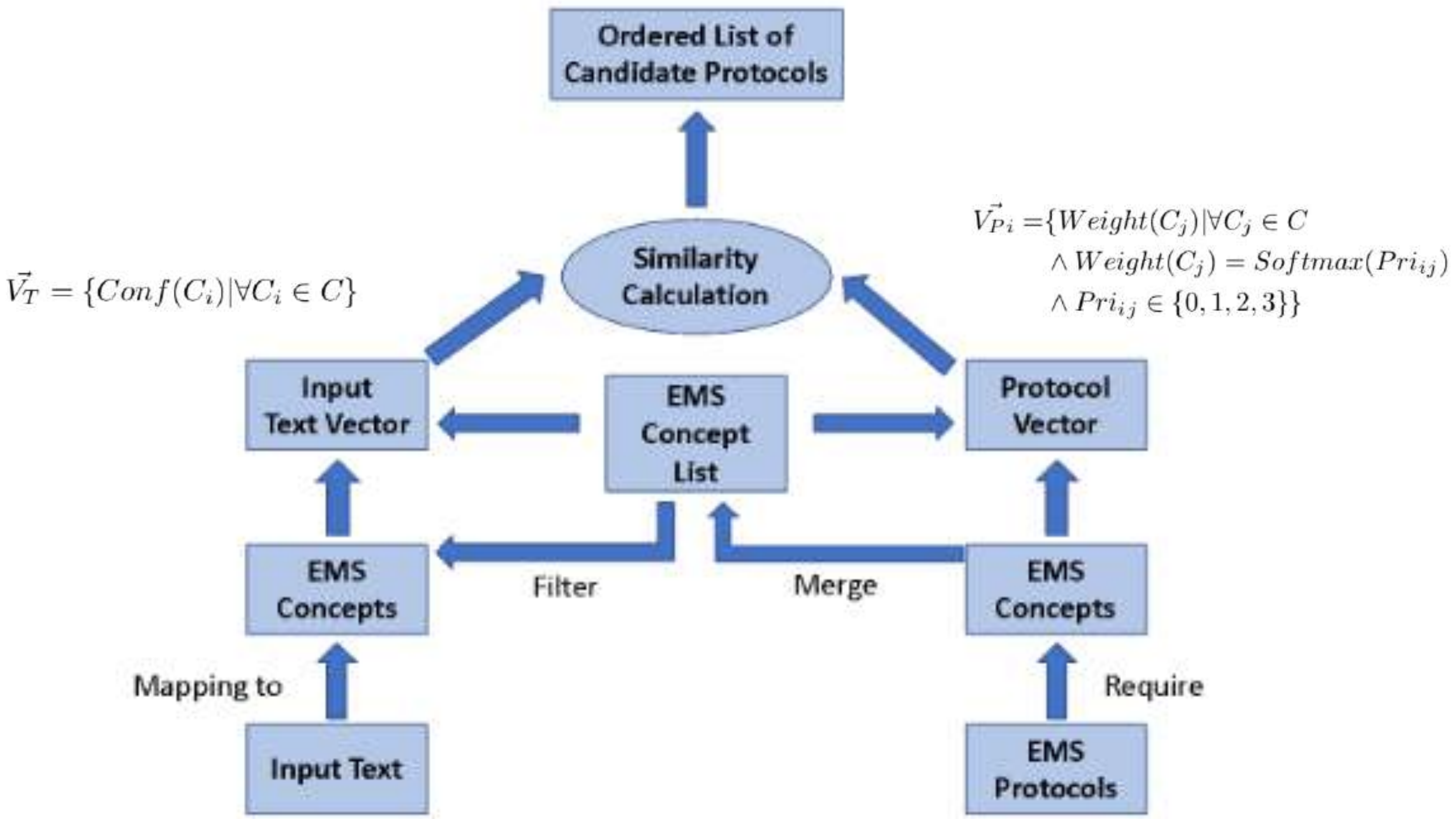
- $Conf(C_i, t)$ is a normalized score in range [0, 1000] representing the confidence that the concept C_i appears in the given speech
- $Conf(C_i, t)$ is derived from the confidence scores from MetaMap and Google Speech API. We assume they are independent from each other

$$Conf(C_i) = Conf_G(C_i) \cdot mmScore(C_i)$$

```
this is paramedic Smith we are transporting
a 36 year old male complaining of shortness
of breath he also complains of non radiating
sharp chest pain on expiration symptoms
began 1 hour ago after exercising he
attempted to use his inhaler without relief
```

```
(breath,True,expiration,expiration,694.0,1)
(pain,True,of chest pain,of chest pain,772.0,1)
(gender,True,male,male,573.0,1)
(age,True,36,year,573.0,1)
```

Protocol Selection: Vectorization



Protocol Selection: Similarity Calculation

[0.772, 0.694, 0, 0, 0, 0, 0]

[Pain, Breath, Nausea, Pulse, Pale, Fever, heart rate]

CP: [1,1,1,0,1,0,0]
Res: [0,1,0,0,0,1,1]
AP: [1,0,1,1,0,0,0]

```
(breath,True,expiration,expiration,694.0,1)
(pain,True,of chest pain,of chest pain,772.0,1)
(gender,True,male,male,573.0,1)
(age,True,36,year,573.0,1)
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this is paramedic Smith we are transporting
a 36 year old male complaining of shortness
of breath he also complains of non radiating
sharp chest pain on expiration symptoms
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```
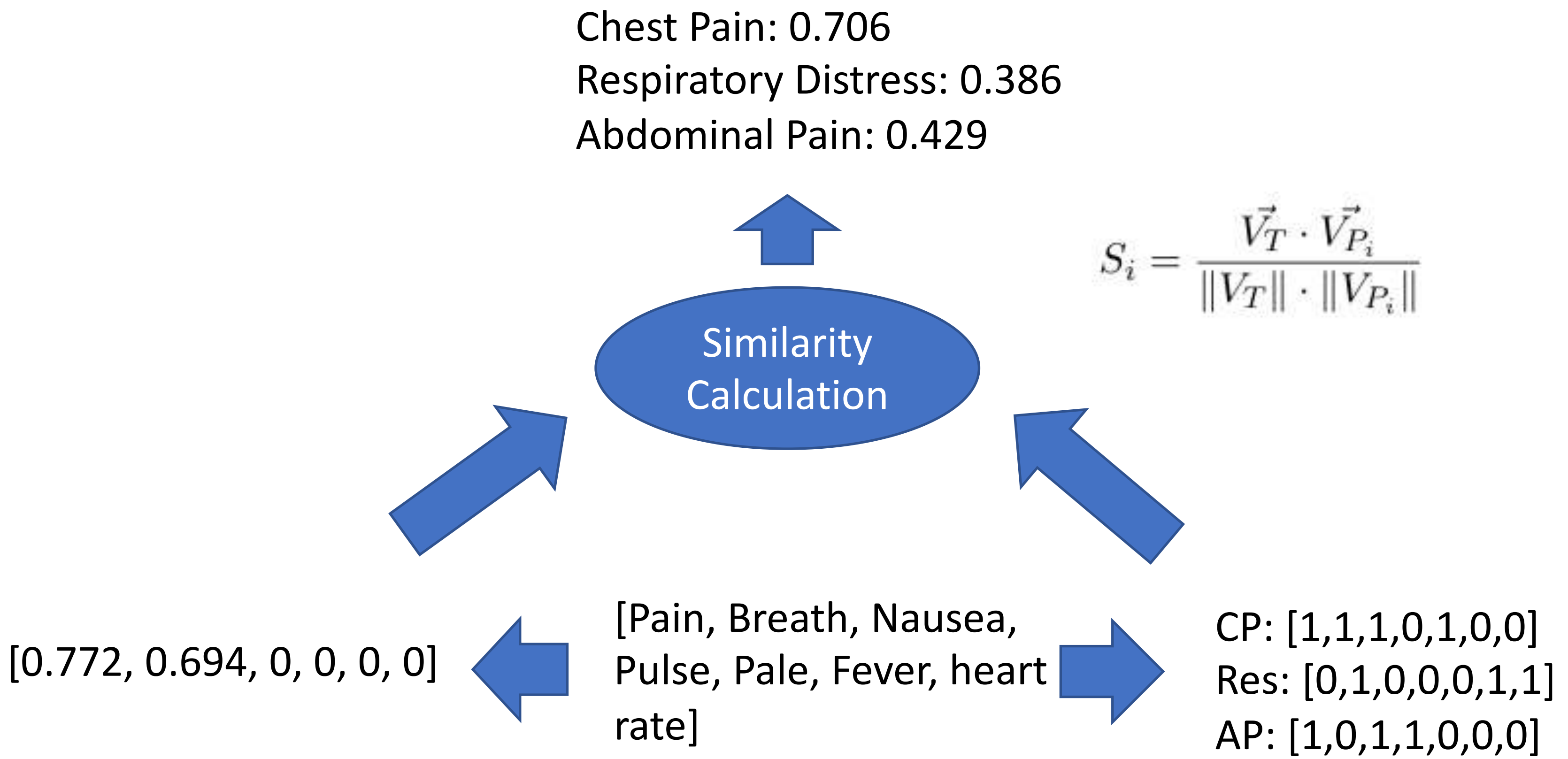
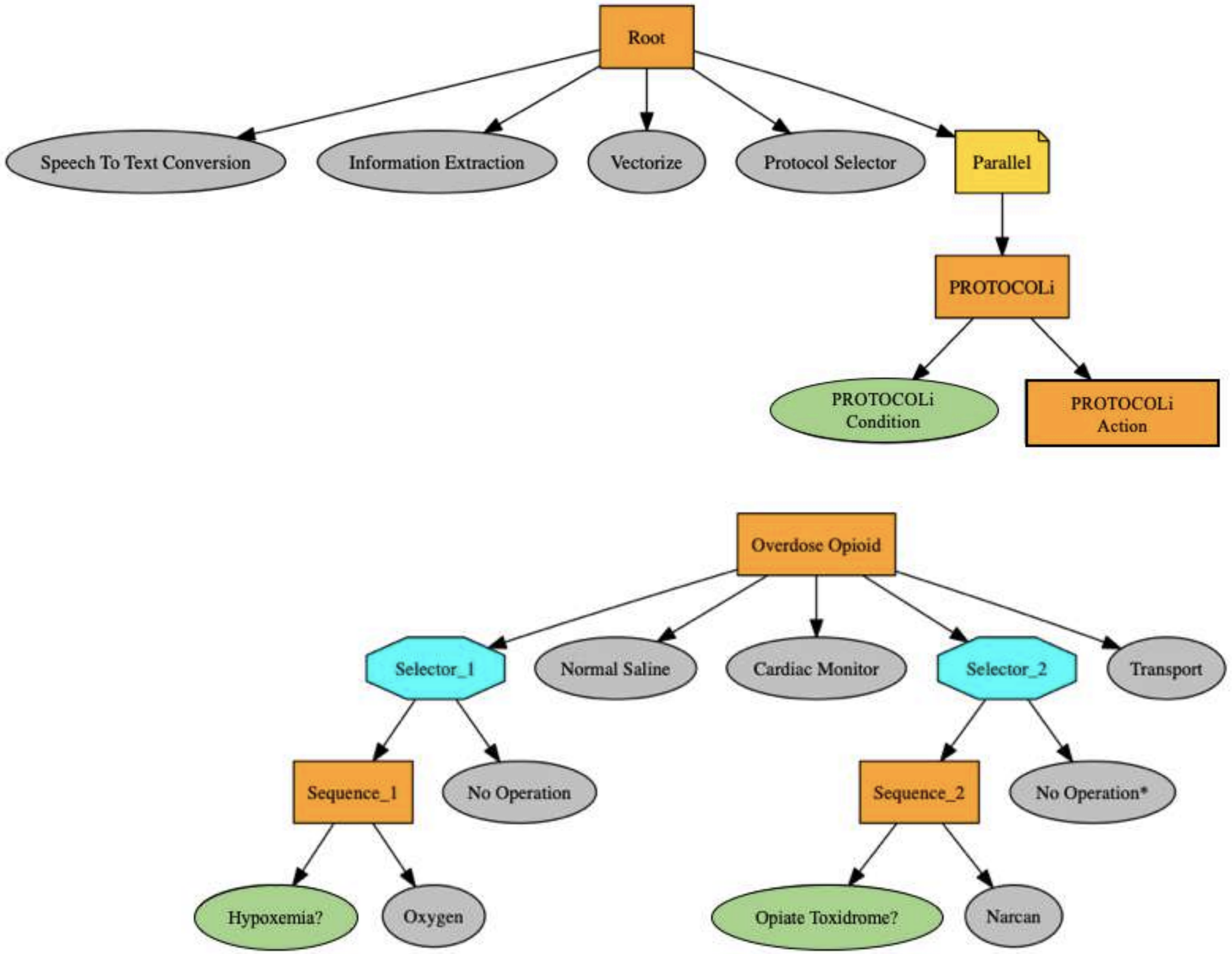

Chest Pain
Respiratory Distress
Abdominal Pain

Protocol Selection: Similarity Calculation



$$S_i = \frac{\vec{V_T} \cdot \vec{V_{P_i}}}{\|V_T\| \cdot \|V_{P_i}\|}$$

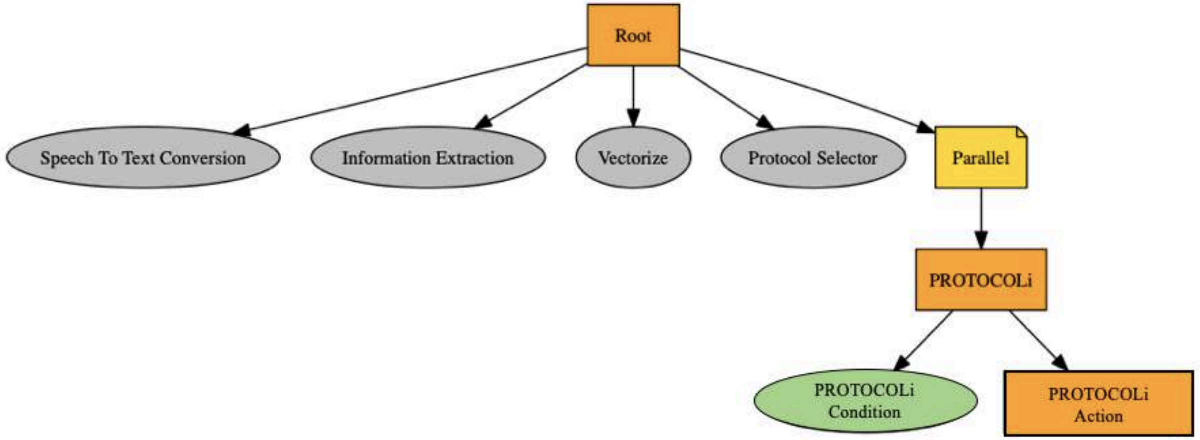
Protocol Execution - Intervention Suggestion

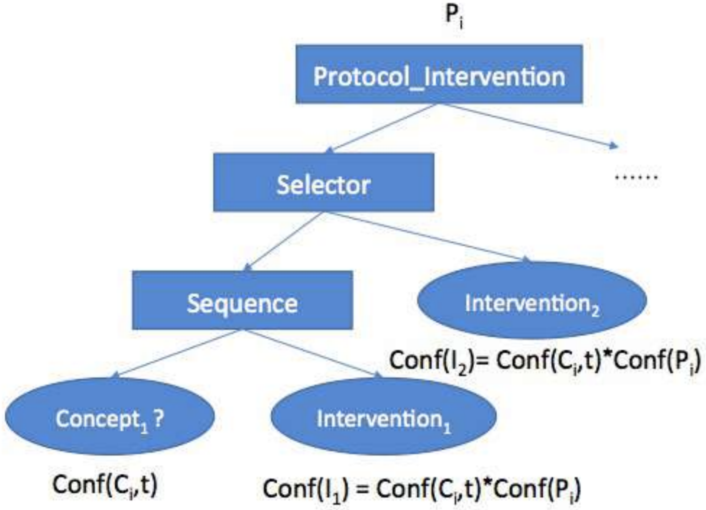


- Searching the action nodes in the selected sub-trees
- Yield interventions along with a confidence score
- Independence assumption when calculating the confidence score

Protocol Execution – Confidence Score Propagation and Risk Assessment

- **Confidence score:**
- Risk assessment
- Filtering
- Presenting to responders





$$P(P_i) = \begin{cases} \frac{S_i}{\sum S_j} & \forall P_j \in Candi \\ 0 & \text{otherwise} \end{cases}$$

Protocol Selection and Execution: Example

Structured Vital Signs:

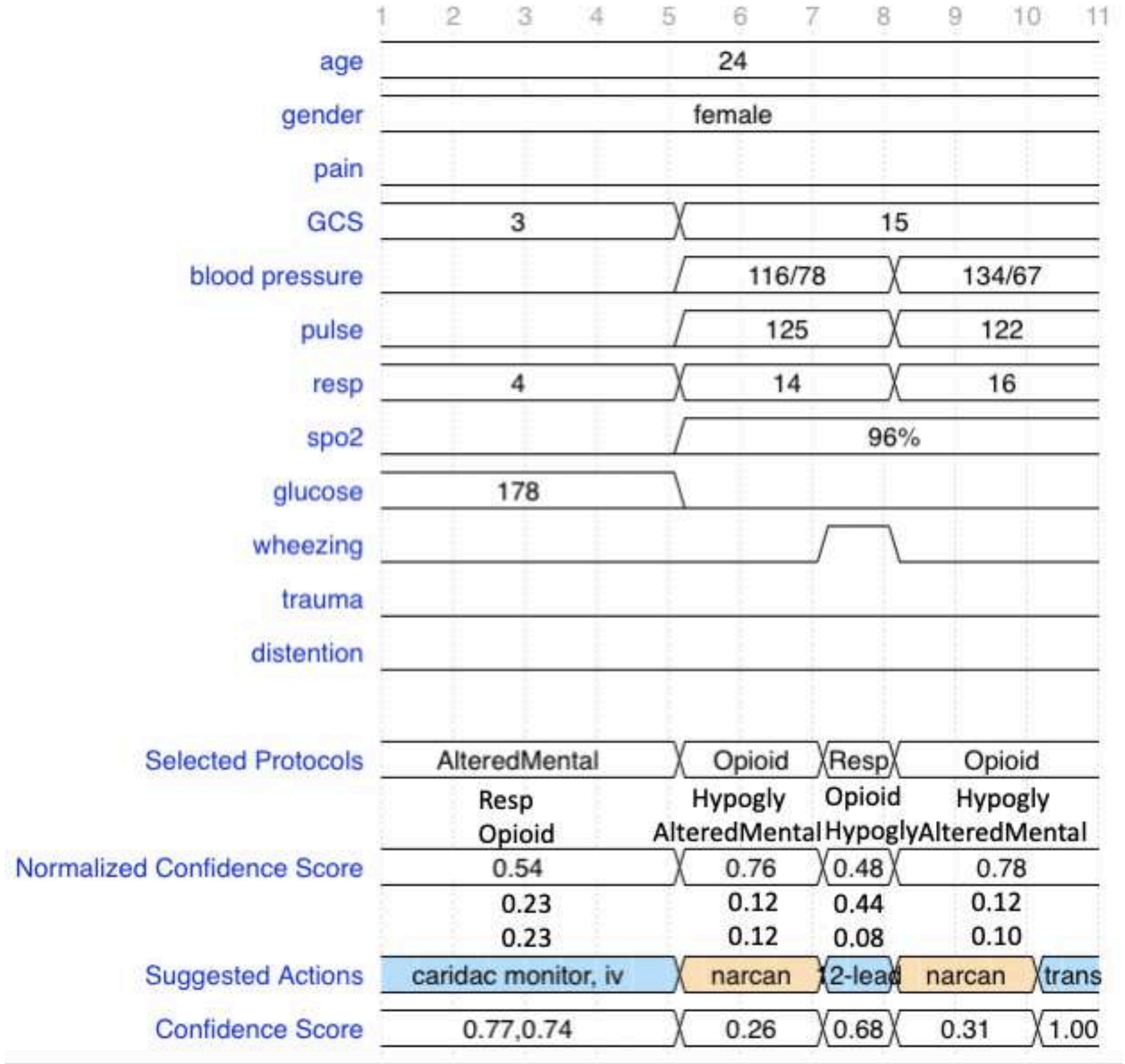
{23:44:00: Pulse-0 Resp-4 BP-0/0 GCS-3 Glucose-178 SPO2-0 Pain-0 EKG-Other (Not Listed)}
{23:57:00: Pulse-125 Resp-14 BP-116/78 GCS-15 Glucose-0 SPO2-96 Pain-0 EKG-Sinus Tachycardia}
{00:15:00: Pulse-122 Resp-16 BP-134/67 GCS-15 Glucose-0 SPO2-96 Pain-0 EKG

Input Text:

1: D- Dispatched priority 1 for a 24 year old female reported to be unconscious.
2: A- Patient was located in a parking lot off Broad Rock BV. Upon our arrival to the scene, patient was lying supine on the ground unconscious and unresponsive. Patient appeared unstable.
3: R-PD already on scene standing around patient. C- Patient's chief complaint - Overdose.
4: H- Patient found by bystander. According to patient, she sniffed heroin around 1030 tonight. Patient remembers she was with some friends in a car but doesn't remember what happened afterwards. Patient was compliant and answered all questions from EMS and R-PD. Patient's has a history of asthma. Patient is allergic to sulfa, penicillin, amoxicillin.
5: Patient initially A&O*0, GCS 3 (E1V1M1). After giving Narcan patient was A&O*4, GCS 15 (E4V5M6).
6: AIRWAY: initially non-patent-obstructed by tongue. Patent after gaining consciousness. BREATHING: initially noted to be agonal. After gaining consciousness, breathing noted to be normal rate with normal depth. CIRCULATION: No obvious bleeding.
7: NEURO: Grossly intact. SKIN: Cyanotic upon patient contact. After gaining consciousness normal color, normal temp, dry, capillary refill <2 seconds. PULSE: Radial strong and regular. HEENT: Pupils PERRL. No signs of trauma noted. NECK: No JVD, edema, tracheal deviation. No signs of trauma noted. LUNG SOUNDS: clear bilateral. CHEST: rise and fall equal. No signs of trauma noted.
8: ABDOMEN: no noted distention or palpable masses present. No signs of trauma noted. PELVIS: Intact, stable, no deformities. No signs of trauma noted. EXTREMITIES: Pt. has good PMS in all extremities. Pt. able to move all extremities. No signs of trauma noted. BACK: No signs of trauma noted.
9: R- Basic vital signs obtained. Hospital contact without orders. Cardiac monitor. ETCO2. 12-lead- Sinus Tach. Glucometer used to check blood sugar- 178. IV established, 20G in left AC saline lock. O2 given 15 lpm via BVM (assisted ventilation), room air during transport.
10: Medication administration: 0.5 mg Narcan IV- patient gained consciousness.

Extracted Concepts:

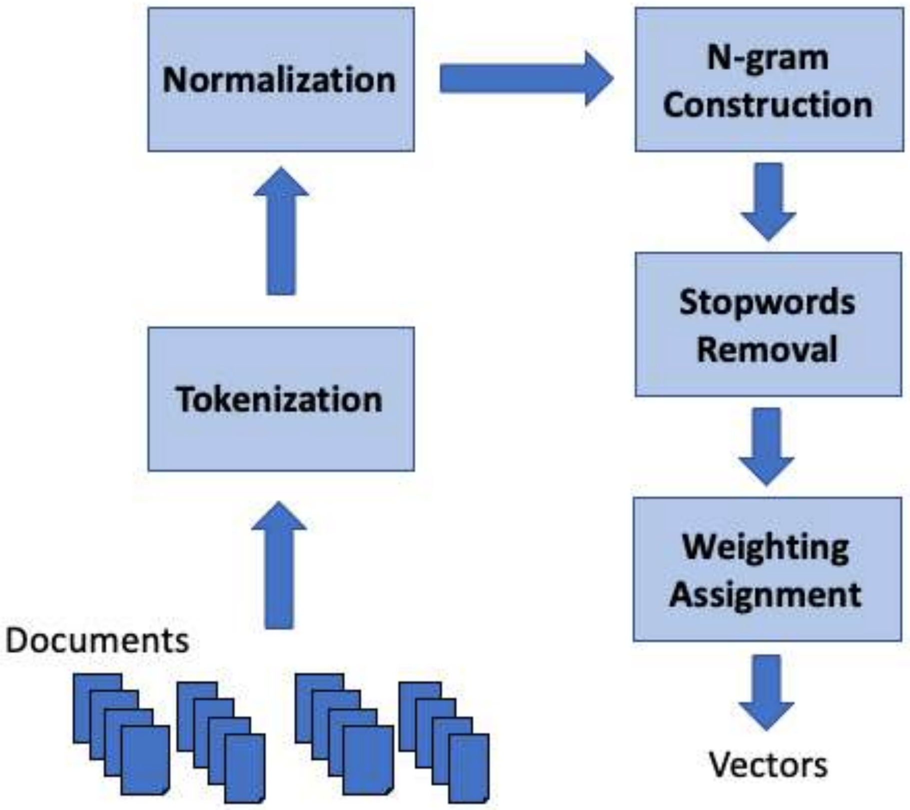
```
(bradypnea;True;4;Resp;1000.0;0)
(loss of consciousness;True;unconscious;unconscious;1000.0;1)
(decreased mental status;True;3;GCS;1000.0;5)
(tachycardia;True;122;Pulse;1000.0;0)
(dysrhythmia;False;125;EKG;1000.0;0)
(trauma;False;trauma;trauma;604.0;8)
(wheezing;True;lung sounds;lung sounds;983.0;7)
(tachycardia;True;122;Pulse;1000.0;0)
(distension;True;distention;distention;861.0;8)
```



Supervised end-to-end
Protocol Specific Intervention Suggestion

Features:
- N-gram
- Unigram
- Concepts

Classifiers for multi-label classification:
- Decision Tree
- Random Forest
- SVM



Evaluation: Protocol Selection and Execution (Intervention Suggestion)

- 8000+ EMS records with intervention labels from RAA

Priority	CallType	ChiefComplaint	Impression	Vitals	Interventions	Narrative	Outcome
1	Syncope/Unconscious	{Poisoning/Overdo	{Abuse of Narcotic	{14:26:42: Pulse-11	{14:21:00: Assist V	D: "unconscious/fainting" A: Arrived to find	Patient Refused Transp
1	Breathing Problems	{Respiratory - SOB}	{Respiratory - Asth	{10:51:58: Pulse-1(	{10:51:58: Cardiac	M992 was dispatched for a female with diffic	Treated, Transported b
3	Pregnancy/Childbirth	{Abdominal Pain - (	{GI/GU - Abdomina	{07:25:24: Pulse-82	{07:26:00: Cardiac	D: Dispatched for female pt having abdomina	Treated, Transported b

- Performance Metrics
  - ❖ Precision, recall, F1 score
  - ❖ Weighted and Micro Averaging

$$P_{micro} = \frac{\sum TP_i}{\sum TP_i + \sum FP_i}$$

$$R_{micro} = \frac{\sum TP_i}{\sum TP_i + \sum FN_i}$$

$$F_{micro} = \frac{2 \cdot P_{micro} \cdot R_{micro}}{P_{micro} + R_{micro}}$$

$$P_{weighted} = \frac{\sum P_{C_i} \cdot C_i}{\sum C_i}$$

$$R_{weighted} = \frac{\sum R_{C_i} \cdot C_i}{\sum C_i}$$

$$F_{weighted} = \frac{2 \cdot P_{weighted} \cdot R_{weighted}}{P_{weighted} + R_{weighted}}$$

- Safety Criticality Metric: Risk factor

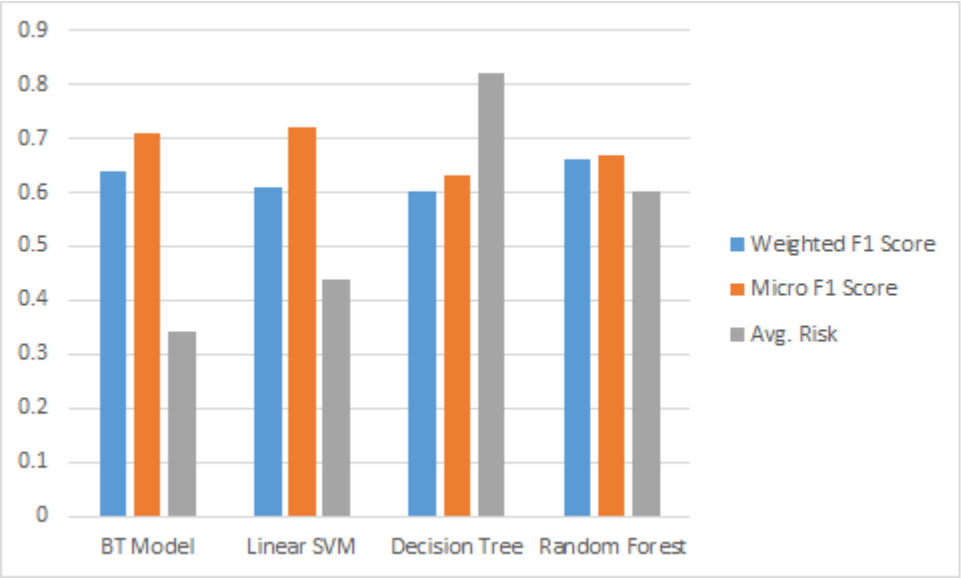
$$Avg.\ Normalized\ Risk = \frac{1}{n} \frac{\sum Conf(I_i) \cdot Risk(I_i)}{|I|}$$

Evaluation: Intervention Suggestion using Supervised ML

Model		Precision	Recall	F1 Score	Avg. Risk Factor
SVM	N-gram	0.89	0.77	0.83	0.32
	Unigram	0.92	0.88	0.90	0.24
	Concept	0.81	0.64	0.72	0.44
Random Forest	N-gram	0.88	0.66	0.76	0.46
	Unigram	0.91	0.71	0.80	0.42
	Concept	0.76	0.60	0.67	0.60
Decision Tree	N-gram	0.77	0.75	0.76	0.45
	Unigram	0.84	0.82	0.82	0.28
	Concept	0.64	0.61	0.63	0.82

Evaluation: Intervention Suggestion using Supervised ML vs B-Tree Model

- Compare the performance of B-Tree model and ML models
  - Comparable (or even better) F1 score in intervention prediction
  - Lowest avg. normalized risk factor



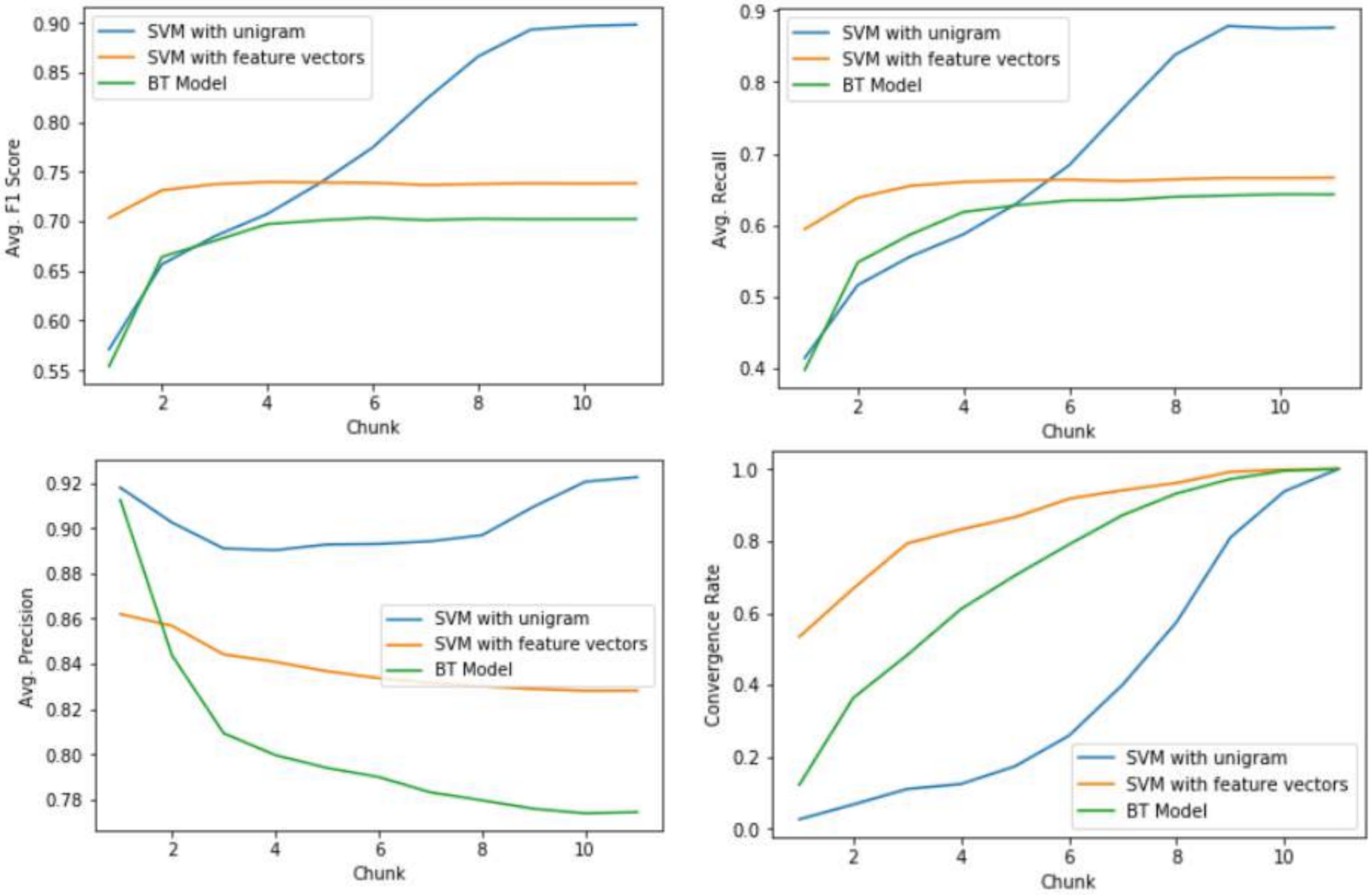
Evaluation: Intervention Suggestion for streaming input

- Simulate the streaming speech input by splitting each report into text chunks
- Record the outputs after each text chunk was fed in
- Concern about the reliability of intermediate interventions suggestions provided to the first responders.

$$ConvergenceRate(k) = 1 - \frac{\sum_{i=1}^{I} |Pred(k)_i - Pred(n)_i|}{I}$$

Evaluation: Intervention Suggestion for streaming input

- ML models outperform the BT model
- ML model with unigram vector show a large convergence in the last chunks, which is another evidence of the bias on the intervention prediction

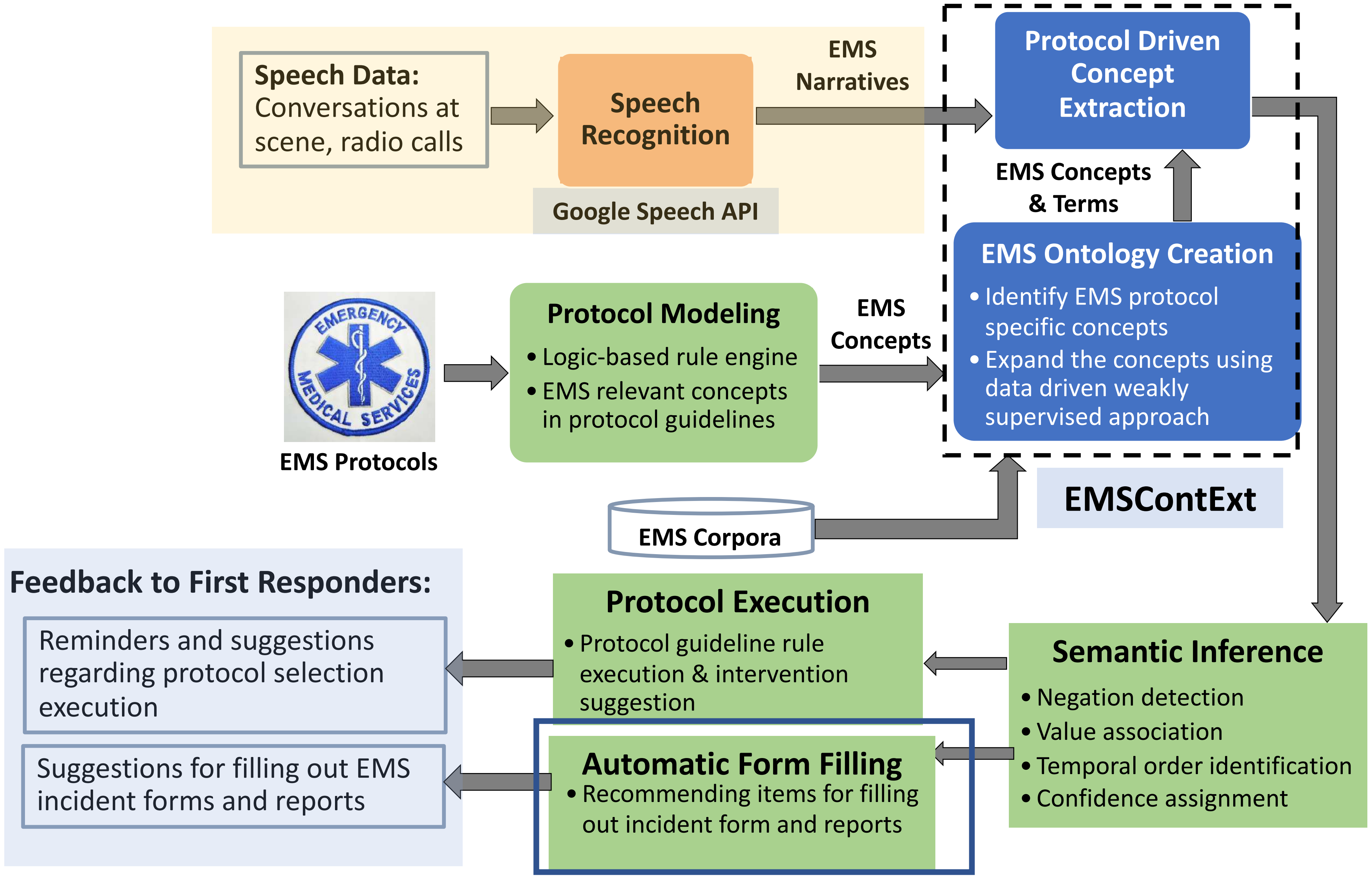


Evaluation: Protocol Intervention Prediction

- Comparing effect of our concept extraction approach with MetaMap
  - Better accuracy: more customized and domain-adapted
    - 6% increase in weighted recall and 4% increase in weighted F1 score
  - Significantly faster execution time: 6 times faster

Method	Weighted Recall	Weighted Precision	Weighted F1-score	Execution Time (sec/case)
MetaMap	0.654	0.642	0.648	11.98
Knowledge-integrated approach	0.575	0.579	0.577	**1.76**
Data-driven approach	0.652	**0.695**	0.673	**0.71**
Our Concept Extraction Approach	**0.698**	0.655	**0.676**	**2.01**

Protocol-Driven EMS Decision Support Pipeline



FIRE RESCUE

ALBEMERLE COUNTY

460 Stagecoach Drive, Suite F
Charlottesville, VA 22902-6489

Phone: (434)296-5833 - OEMS Agency #00939

INITIAL PATIENT CARE REPORT

PPCR will be available on Hospital Bridge within 24 hours

PATIENT INFORMATION

NAME: Martha Alex Morgan			
ADDRESS: 123 lake street			
CITY: New York		STATE: New York	ZIP: 22903.
DOB: Aug 15 , 2000		SSN: 456789456	
AGE: 53	SEX: M	FACILITY: UVA MJH OTHER- SQUARE Hosp.	

MEDICAL INFORMATION

CHIEF COMPLAINT: Chest Pain, Headache,

HPI: Myocardial Infarction, Systemic arterial pressure, Glaucoma,

PMH: ASTHMA COPD CHF CAD MI RENAL FAILURE CVA DIABETES HTN SZ

MEDS: Aspirin, Ibuprofen,

ALLERGIES: No allergies mentioned here. Patient has no allergies on any medicine.

PE/RX/TX: Given Aspirin , dose 4 counts 81 mg ,

Given Ibuprofen , dose 9 counts 99 mg ,

CALL INFORMATION

CALL INFORMATION		INCIDENT#: 65897
UNIT#: 7854	EMP. ID	DATE: Aug 15 , 2003
AIC: Kevin Brown	037	DISPATCHED: 12:45 AM
DRIVER: Micheal	0456	RESPONDING: 12:50 AM
ATT1: Douglus	0123	ON SCENE: 12:55 AM
ATT2: Jason	014	PT. CONTACT: 1:00 AM
RESPONSE LOCATION		LEAVE SCENE: 1:05 AM
123 Baker Street , New York , ZIP: 22903		ARRIVE DEST.: 1:10 AM
INITIAL LOC: Charlottesville.	PT. WEIGHT: 49LBS	LEAVE DEST.:1:15 AM
		RETURN SERVICE:1:45 AM

INITIAL VITAL SIGNS

TIME	3:00pm	GLUCOSE	34 mg/dl	GCS	E	3	V	98	M	65	=	110
RESP	16	BP	120/70	EKG	43							
PULSE	78	SPO2	93	ETCO2	76mm Hg				TEMP	106		

TIME	LOC	PULSE	RESP	BP	EKG	SPO2	ETCO2
5:00pm	ivy rd	73	76	120/70	43	93	76
6:00pm	ivyy rd	763	766	120/760	463	963	766

PROCEDURES

PROCED.	LOCATION	SIZE	ATT.	SUC.	TIME	EMP. ID	OTHER
p377	ivy rud	74	john cuosta	yes	9:00pm	0291	non then
p37	ivy rd	4	john costa	yes	8:00pm	021	none then

MEDICATIONS ADMINISTRATED:

MEDICATION	DOSE GIVEN/ROUTE	TIME	EMP. ID	AMOUNT WASTED	WITNESS INT.
aspirin	4 counts 81 mg	1:00pm	011	2 mg	john costa
ibuprofen	9 counts 99 mg	2:00pm	099	9 mg	joh9n c9osta

SIGNATURES:

AIC: Robert **MD: Andy**

NARCOTIS ACCOUNTED FOR: funny and hizibizi.

STARTING MILEAGE:128 **ENDING MILEAGE:158** **TOTAL MILEAGE:30.0**

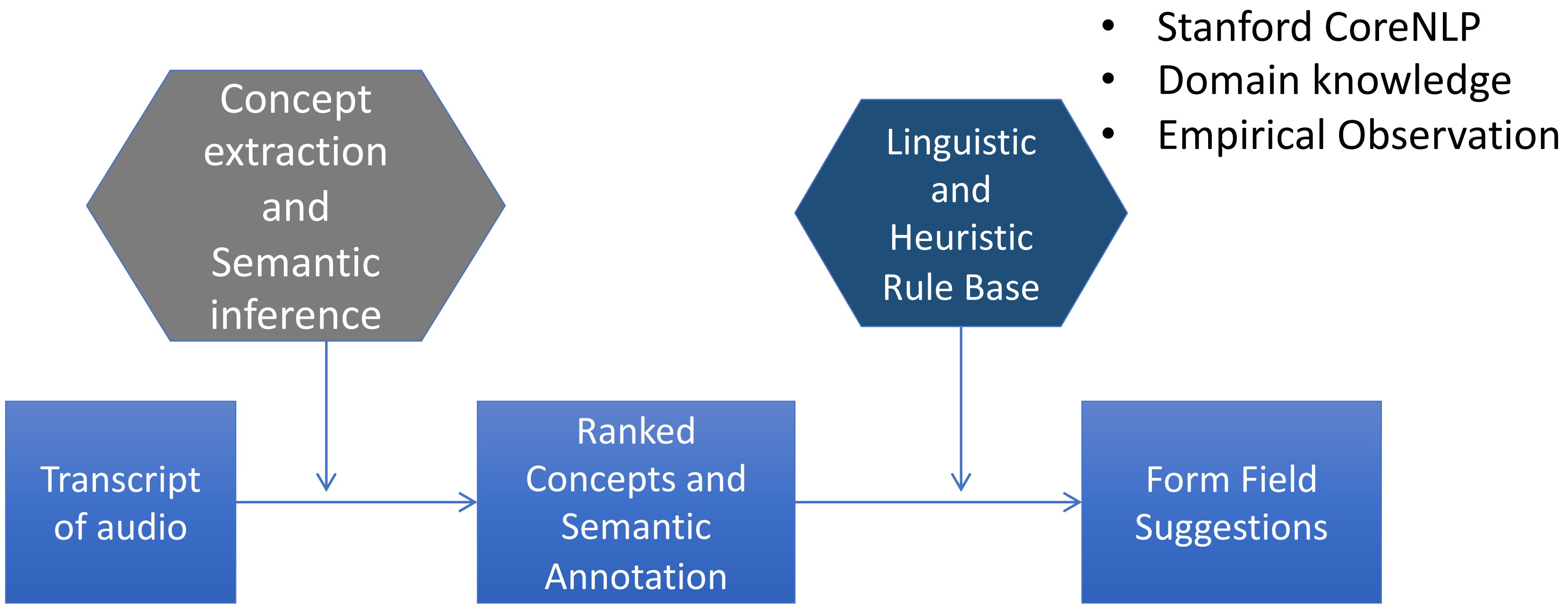
DRUG BOX USED-#.451 **NEW:345**

Automatic Suggestion Generation for Form Filling

"A 911 call came for an old women who had severe chest pain. Reaching the spot, the EMS personnel found out that the patient is fading away. Her blood pressure is low and pulse is irregular. She had been feeling feverish lately and never had asthma before. She denied having shortness of breath…"

- Chief Complaint
- History of Present Illness

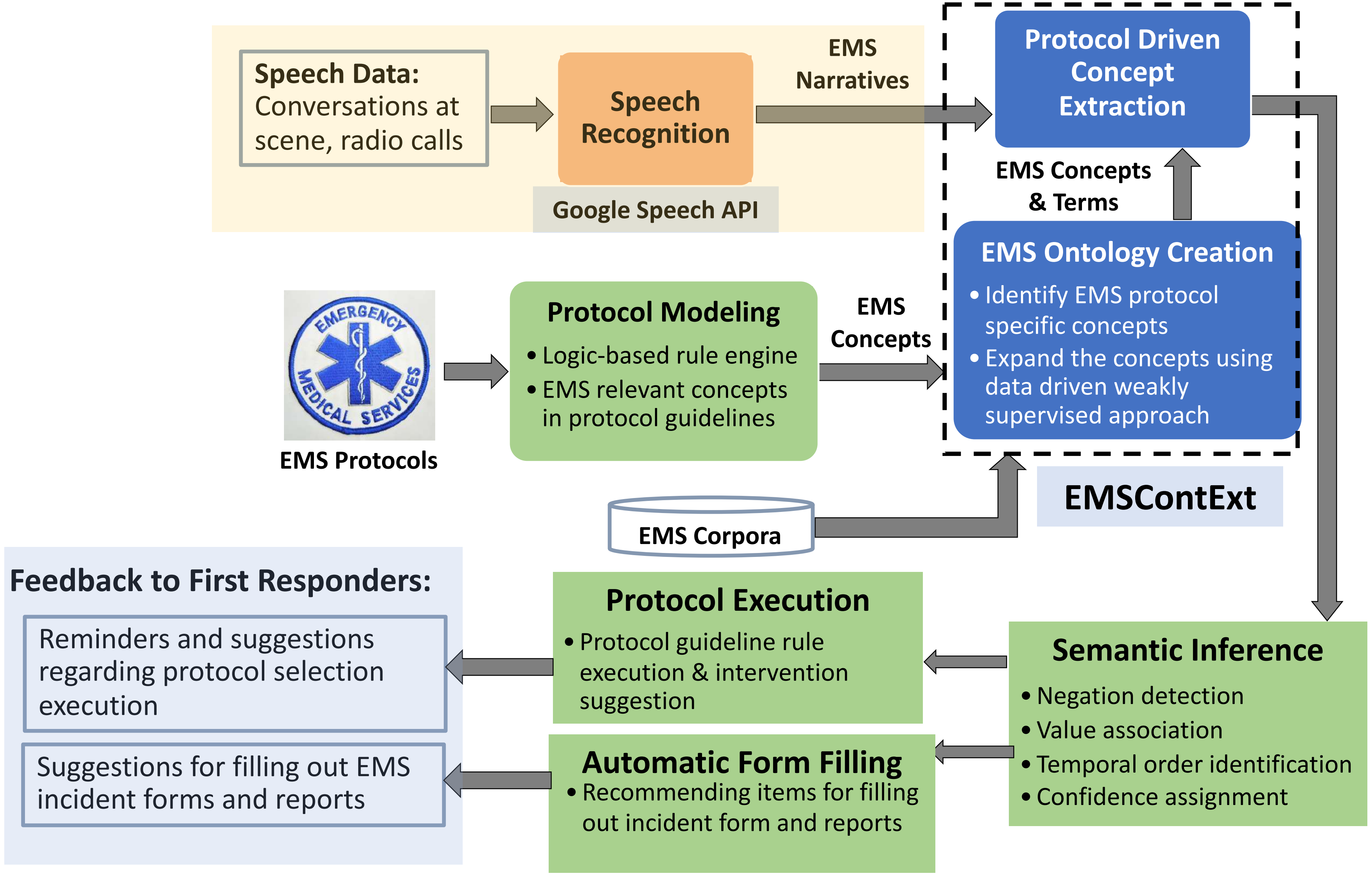
GRACE: Generating Summary Report Automatically for Cognitive Assistance in Emergency Response (V1)

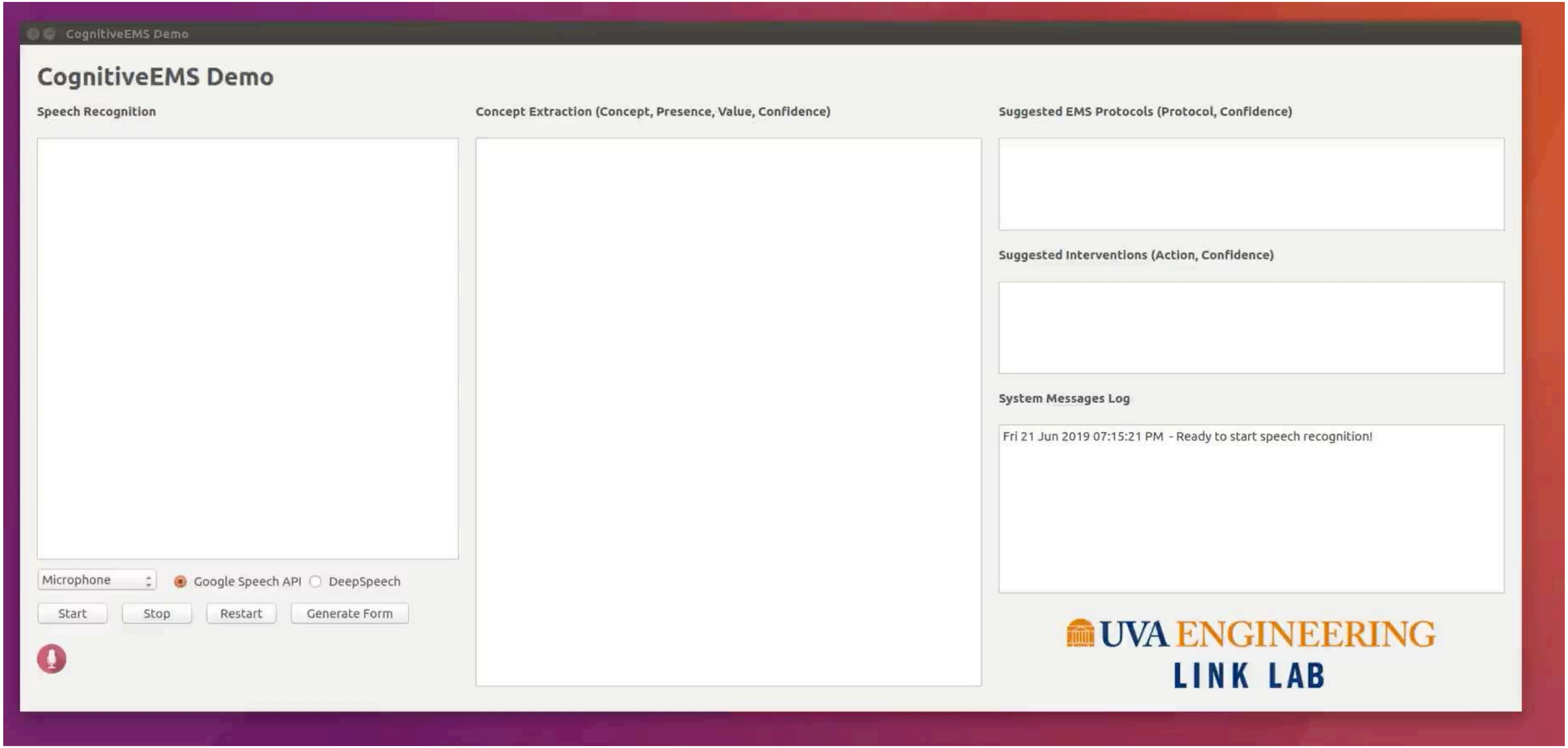


Preliminary Evaluation: Automatic Form Filling

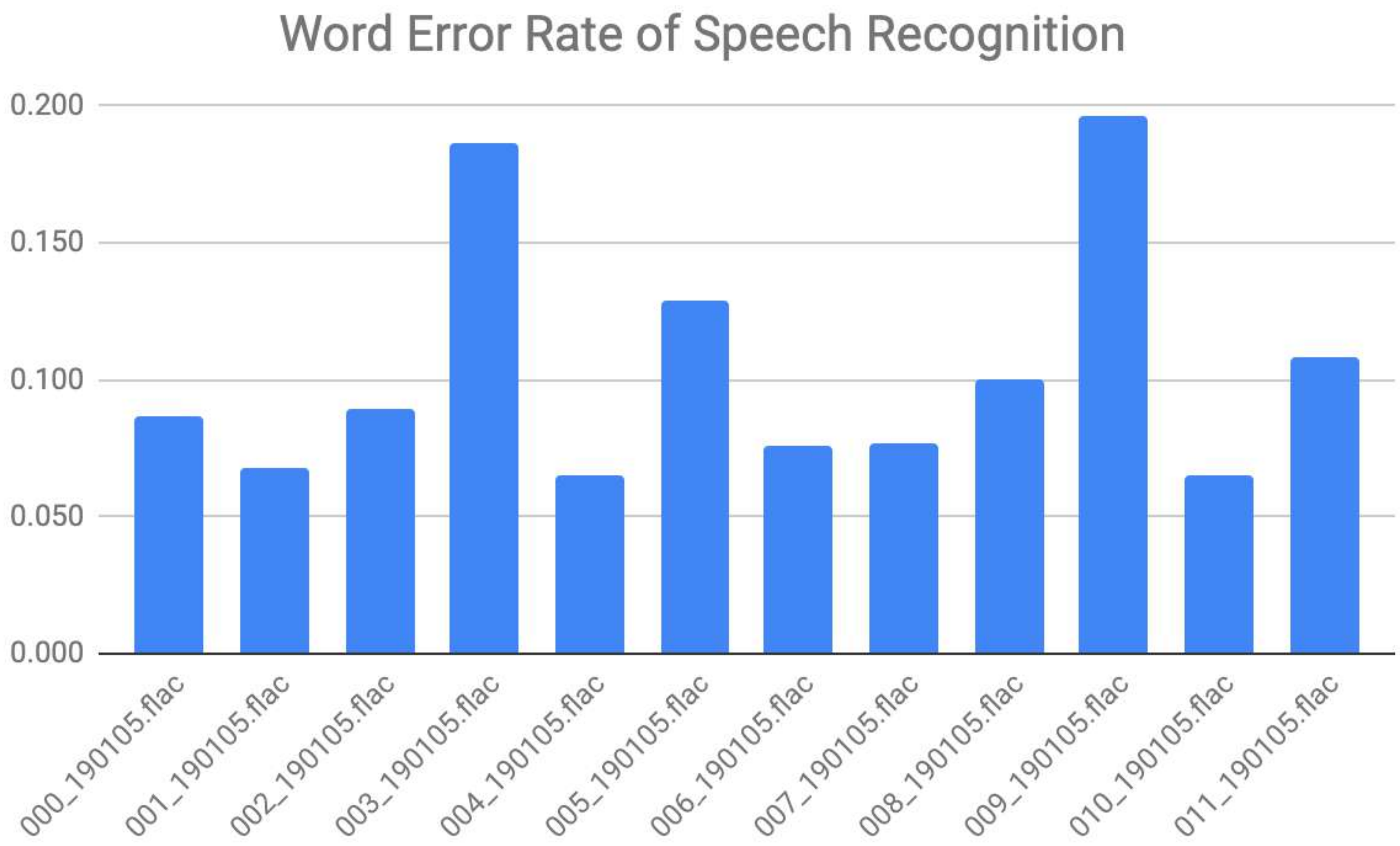
Information field	Precision	Recall	F1-score
Gender	100	72	83.72
Age	100	100	100.00
Chief complaints	100	93	96.37
Allergies	50	50	50.00
HPI	84	55	66.47
PMH	42	82	55.55
Medication name	20	10	13.33
Medication dosage	66	100	79.52
PE/TX/RX	88	56	68.44
Vital signs	100	97	98.48
Procedure name	81	95	87.44

Protocol-Driven EMS Decision Support Pipeline

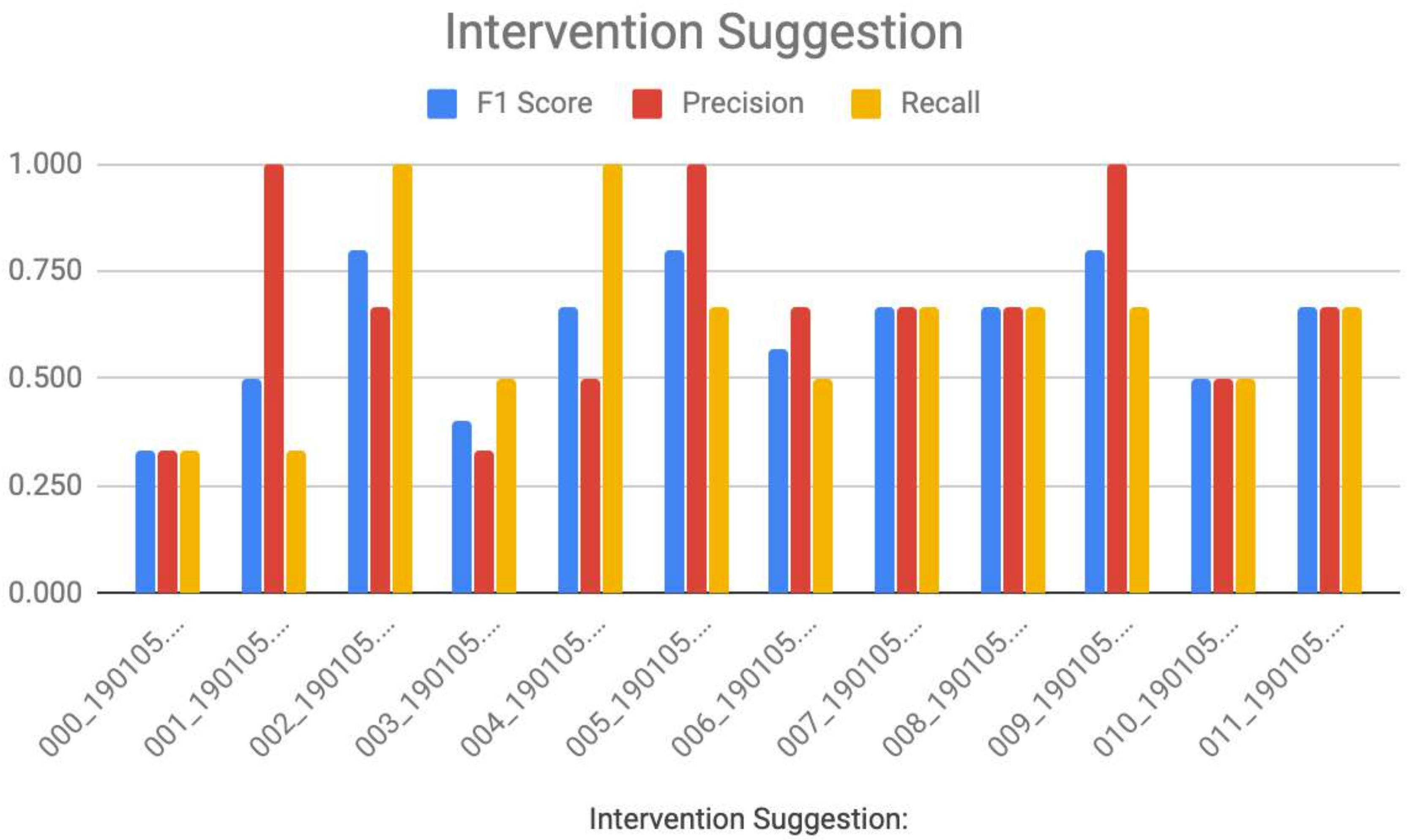



CognitiveEMS Demo
CognitiveEMS Demo
Speech Recognition
Concept Extraction (Concept, Presence, Value, Confidence)
Suggested EMS Protocols (Protocol, Confidence)
Suggested Interventions (Action, Confidence)
System Messages Log
Fri 21 Jun 2019 07:15:21 PM - Ready to start speech recognition!
Microphone
Google Speech API
DeepSpeech
Start
Stop
Restart
Generate Form
UVA ENGINEERING
LINK LAB

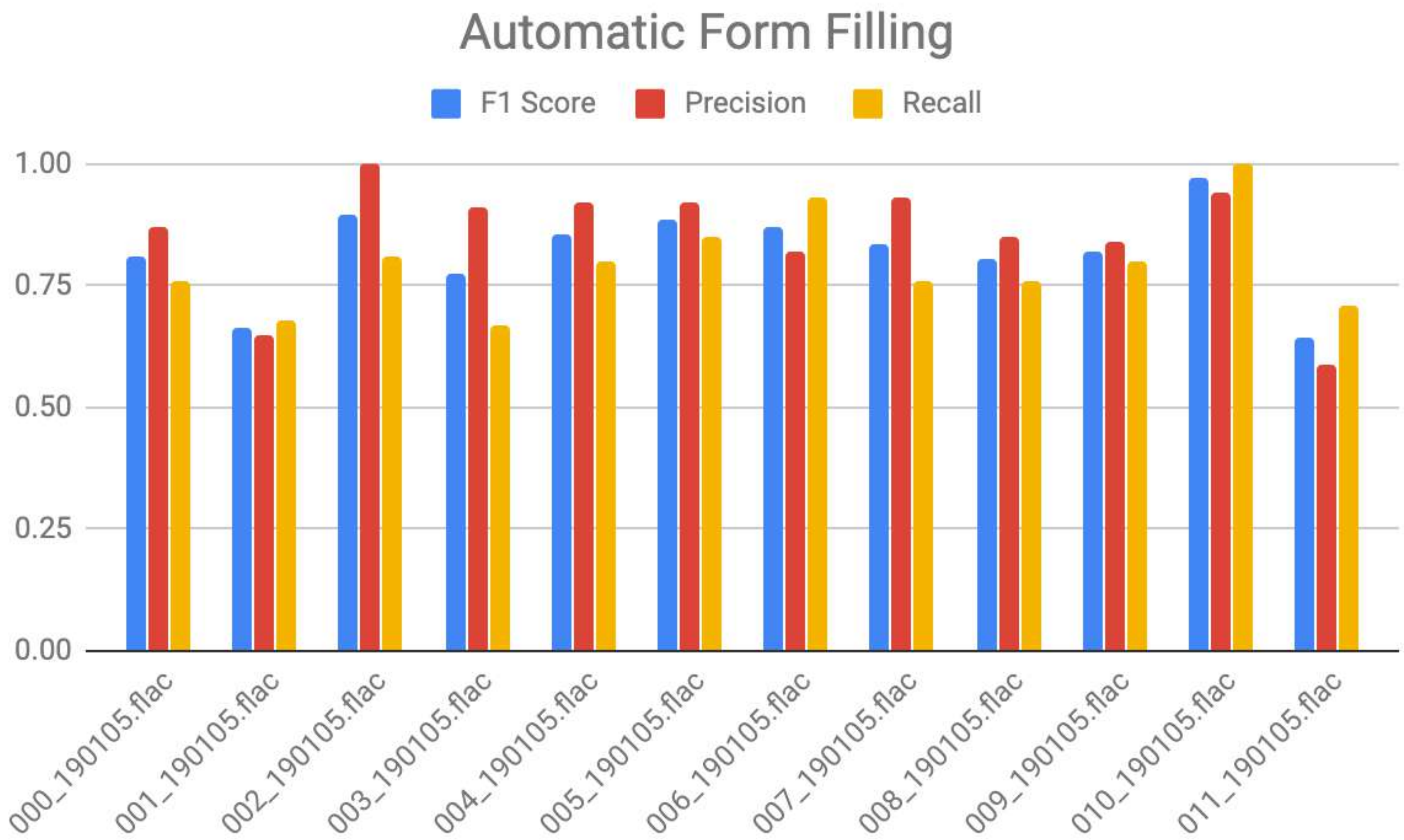
Evaluating the End-to-end Protocol-Driven EMS Decision Support Pipeline: Speech Recognition



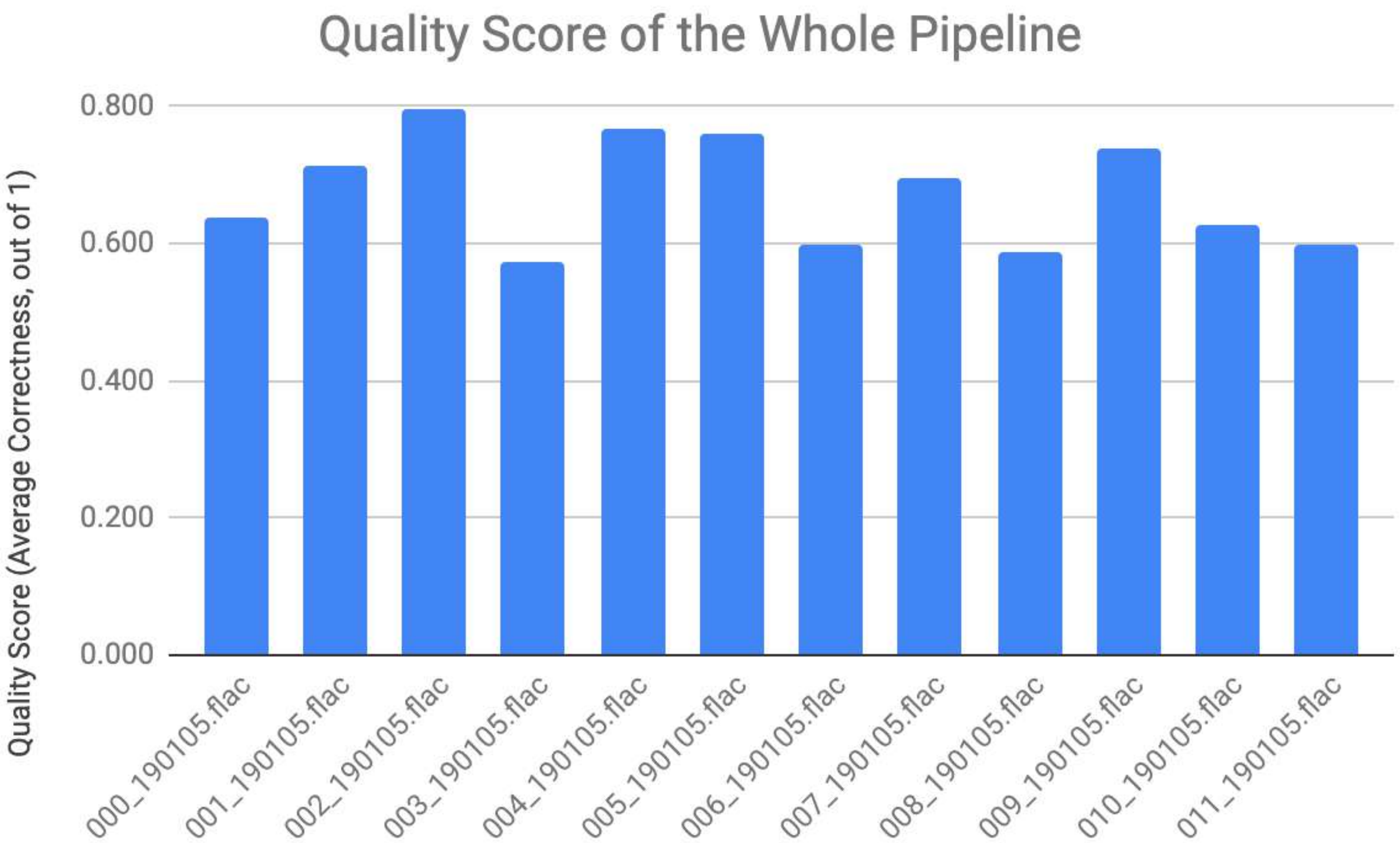
Evaluating the End-to-end Protocol-Driven EMS Decision Support Pipeline: Intervention Suggestion



Evaluating the End-to-end Protocol-Driven EMS Decision Support Pipeline: Automatic Form Filling



Evaluating the End-to-end Protocol-Driven EMS Decision Support Pipeline



Ongoing Work

- **Speech Recognition**
  - Improve robustness and resiliency: Pre-processing and post-processing
  - Retraining Mozilla DeepSpeech with domain knowledge
- **Semantic Inference**
  - Value association
  - Information validation
- **Protocol Modeling and Execution**
  - Go beyond the BT model and try some probabilistic model
  - Improve the module for streaming data
- **Real-world testing**
  - Improve the wireless device to process everything on a wearable device

Publications

- Shu, S., Preum, S., Pitchford, H., Williams, R., Stankovic, J., & Alemzadeh, H. Behavior Tree Cognitive Assistant System for Emergency Medical Services. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2019
- Preum, S., Rahman, A., Ji, Y., Stankovic, J., & Alemzadeh, H. CognitiveEMS: A Cognitive Assistant System for Emergency Medical Services. Under Submission to an NLP venue, 2019
- Preum, S., Shu, S., Hotaki, M., Williams, R., Stankovic, J., & Alemzadeh, H. CognitiveEMS: A Cognitive Assistant System for Emergency Medical Services. Proc. of 7th IEEE Workshop on Medical Cyber Physical Systems (MedCPS), CPS Week, 2018
- Preum, S., Shu, S., Ting, J., Lin, V., Williams, R., Stankovic, J., & Alemzadeh, H. (2018, April). Towards a cognitive assistant system for emergency response. ACM/IEEE 9th International Conference on Cyber-Physical Systems (ICCPS), 2018

Code and data repository: https://github.com/UVA-DSA/EMS-pipeline

Thanks

North Garden
Fire Department

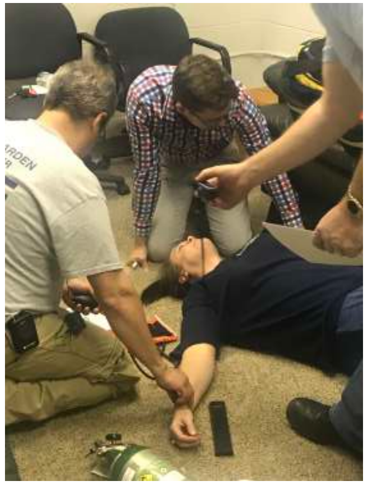
Office of Emergency
Medical Services

Thomas Jefferson
EMS Council (TJEMS)

Richmond
Ambulance Authority

National Institute of
Standards and Technology
U.S. Department of Commerce

Thanks



Opioid overdose

Chest Pain

Volunteer Members of
North Garden Fire Department

Respiratory Distress

Seizure

Come back for the

Next Session

2:40 PM

Backup Slides

Ongoing Work / Challenges: Semantic Inference

- **For protocol modeling and execution and automatic form filling**
- Negation detection: limitation of existing negation detection tools
- Missing punctuation: since ASR does not provided punctuated text
  - Sentence boundary: example
- Value association: mapping a numerical value to its entity correctly
- Chronological ordering of information
  - Differentiating between PMI and HPI
- Information validation
- Co-reference resolution
- Speaker identification for multi-person conversational context

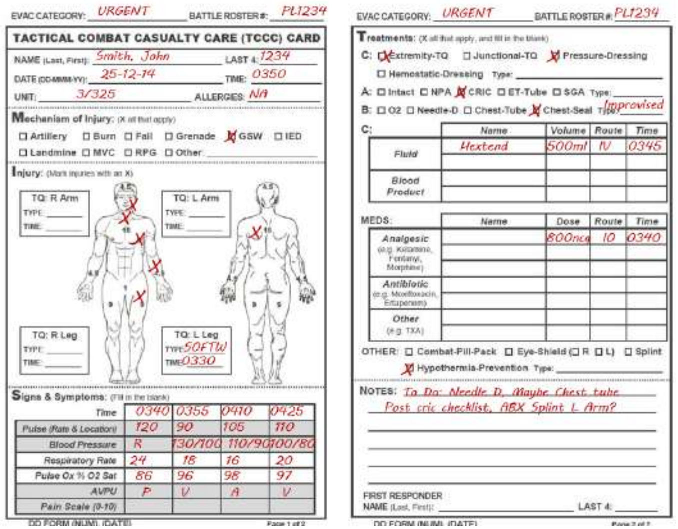
EMS radio call

Conversations with bystanders and victims

Medical history (EHR)

911 Call record

EMS Protocols



EVAC CATEGORY: URGENT BATTLE ROSTER #: PL1234

TACTICAL COMBAT CASUALTY CARE (TCCC) CARD

NAME (Last, First): Smith, John LAST 4: 1234
DATE (DD-MMM-YY): 25-12-14 TIME: 0350
UNIT: 3/325 ALLERGIES: NA

Mechanism of Injury: (X all that apply)
☐ Artillery ☐ Burn ☐ Fall ☐ Grenade ☒ GSW ☐ IED
☐ Landmine ☐ MVC ☐ RPG ☐ Other

Injury: (Mark injuries with an X)

TQ: R Arm TYPE: TIME:
TQ: L Arm TYPE: TIME:
TQ: R Leg TYPE: TIME:
TQ: L Leg TYPE: SOFTW TIME: 0330

Signs & Symptoms: (Fill in the blank)

Time	0340	0355	0410	0425
Pulse (Rate & Location)	120	90	105	110
Blood Pressure	R	130/100	110/90	100/80
Respiratory Rate	24	18	16	20
Pulse Ox % O2 Sat	86	96	98	97
AVPU	P	V	A	V
Pain Scale (0-10)				

DD FORM (NUM), (DATE) Page 1 of 2

EVAC CATEGORY: URGENT BATTLE ROSTER #: PL1234

Treatments: (X all that apply, and fill in the blank)
C: ☒ Extremity-TQ ☐ Junctional-TQ ☒ Pressure-Dressing
☐ Hemostatic-Dressing Type:
A: ☐ Intact ☐ NPA ☒ CRIC ☐ ET-Tube ☐ SGA Type:
B: ☐ O2 ☐ Needle-D ☐ Chest-Tube ☒ Chest-Seal Type: Improvised

C:	Name	Volume	Route	Time
Fluid	Hextend	500ml	IV	0345
Blood Product				

MEDS:	Name	Dose	Route	Time
Analgesic (e.g. Ketamine, Fentanyl, Morphine)		800mcg	IO	0340
Antibiotic (e.g. Moxifloxacin, Ertapenem)				
Other (e.g. TXA)				

OTHER: ☐ Combat-Pill-Pack ☐ Eye-Shield (☐ R ☐ L) ☐ Splint
☒ Hypothermia-Prevention Type:

NOTES: To Do: Needle D, Maybe Chest tube
Post cric checklist, ABX Splint L Arm?

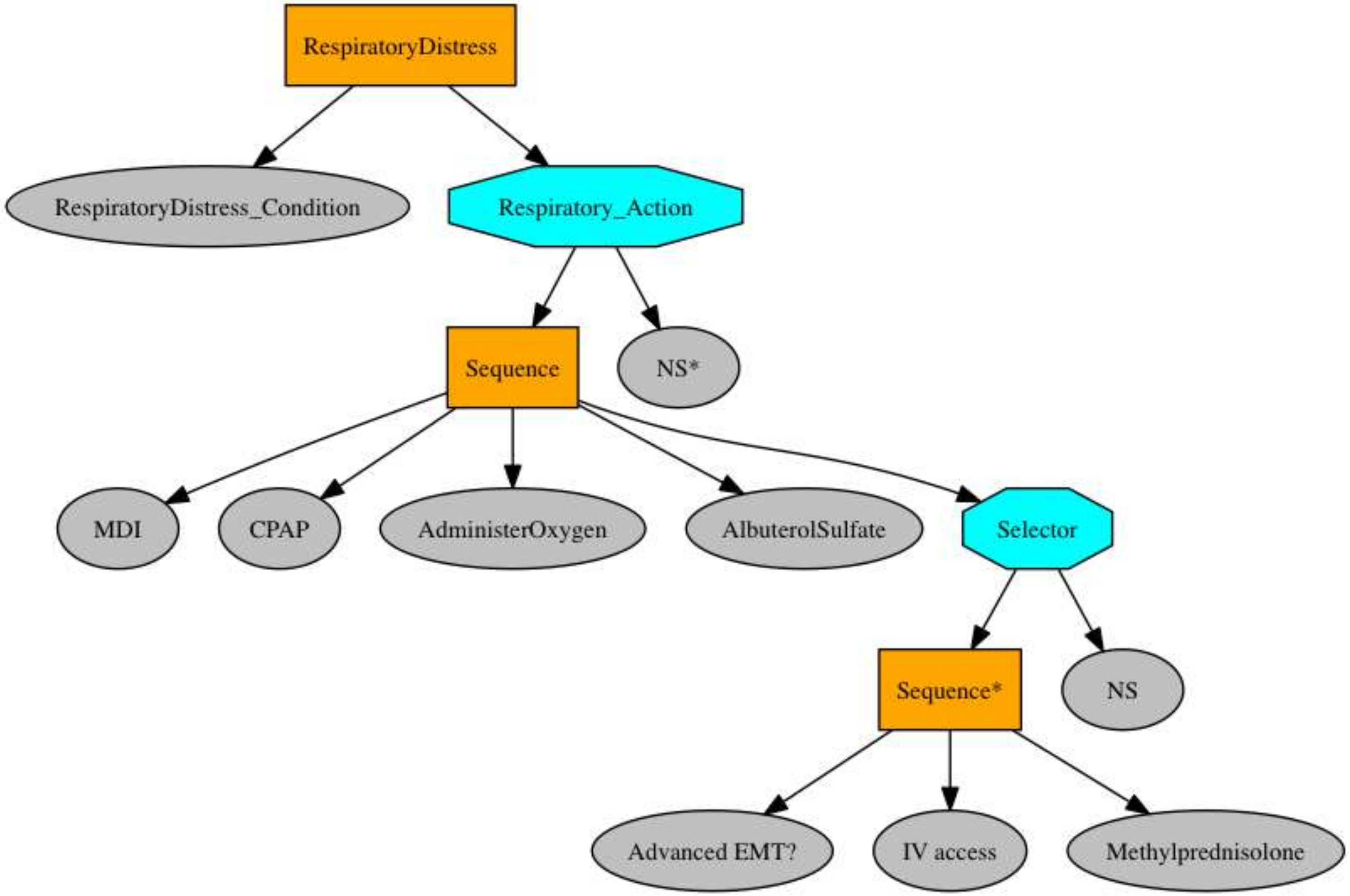
FIRST RESPONDER
NAME (Last, First): LAST 4:

DD FORM (NUM), (DATE) Page 2 of 2

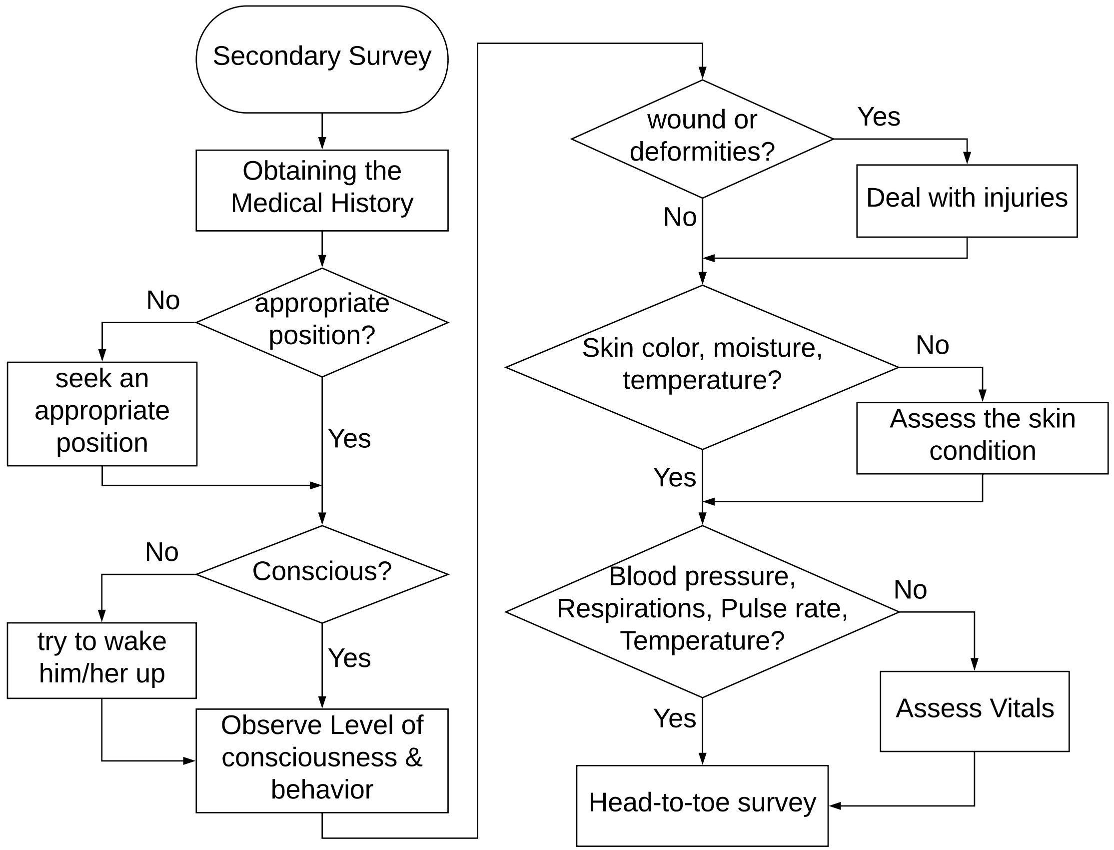
EMS Incident Report/ Form

- Information overload
  - Collecting, analyzing, prioritizing
- Recording and summarizing information
- Decision making and execution
  - Iterative / feedback loop based

Respiratory Distress Behavior Tree Model



Secondary Survey Protocol



Big EMS Data

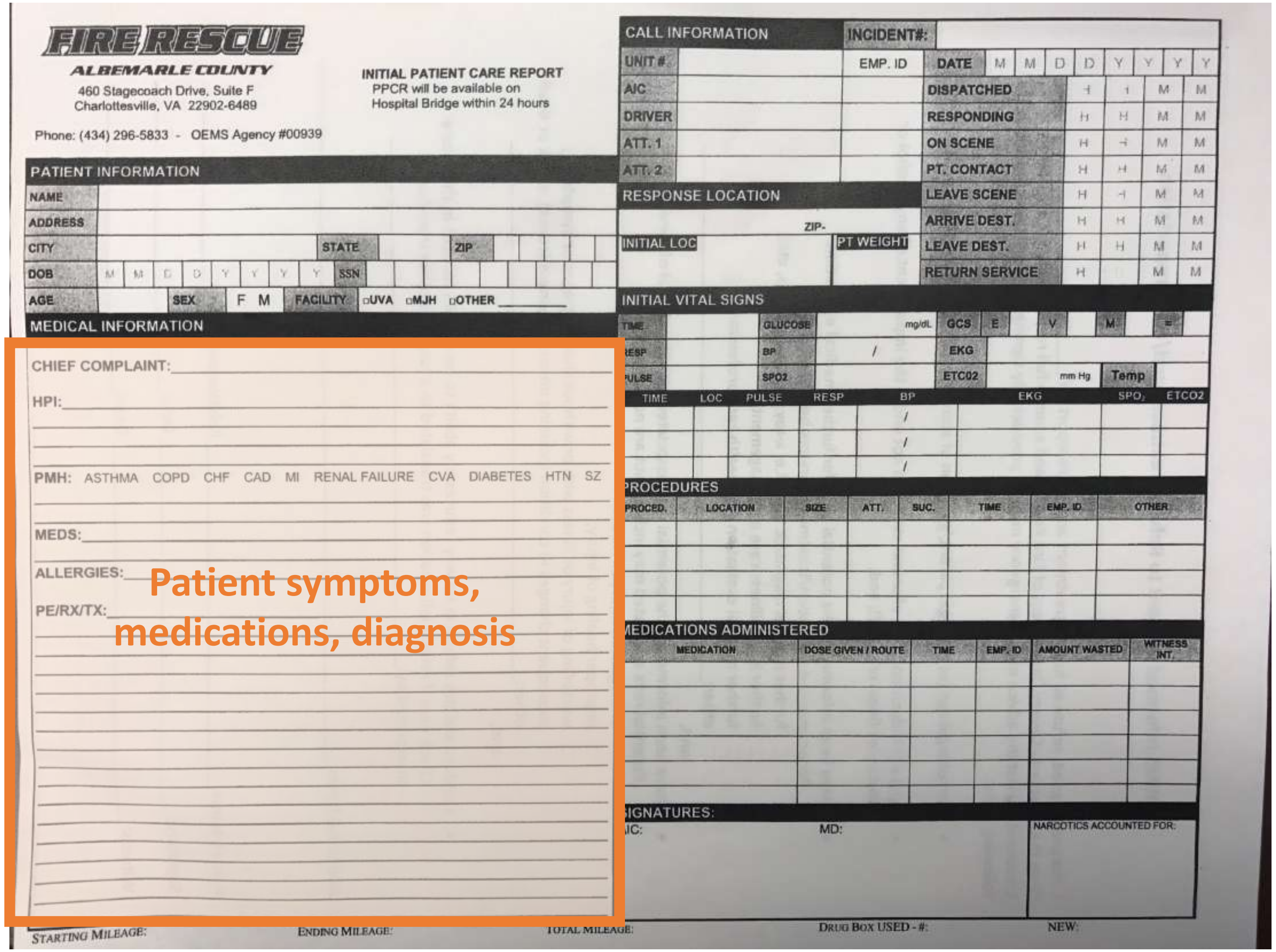
- Over 19,400 credentialed EMS agencies
- 826,000 credentialed EMS professionals
- Over 36,698,000 EMS events were responded to in 2009*

- **Variety of data sources at incident scene:**
  - Observations and communications with center/other responders
  - Sensor data from wearables, mobile, IoT devices
  - Physiological data from patient monitors/medical devices
  - Public data (e.g., protocol guidelines, audio, video, social media)

* *G. Mears, et al., "2011 National EMS Assessment (Report No. DOT HS 811 723)," Washington, DC: National Highway Traffic Safety Administration.*

Challenges in Data Analytics

- **Manually reported**
  - Incomplete
  - Inaccurate
- **Unstructured format**
  - Textual reports
  - Voice communications
  - Voice calls
- **Cognitive overload**
- **Resiliency**



FIRE RESCUE
ALBEMARLE COUNTY
460 Stagecoach Drive, Suite F
Charlottesville, VA 22902-6489
Phone: (434) 296-5833 - OEMS Agency #00939

INITIAL PATIENT CARE REPORT
PPCR will be available on
Hospital Bridge within 24 hours

CALL INFORMATION | INCIDENT#:
UNIT # | EMP. ID | DATE M M D D Y Y Y Y
A/C | DISPATCHED
DRIVER | RESPONDING
ATT. 1 | ON SCENE
ATT. 2 | PT. CONTACT
RESPONSE LOCATION | LEAVE SCENE
ZIP- | ARRIVE DEST.
INITIAL LOC | PT WEIGHT | LEAVE DEST.
RETURN SERVICE

PATIENT INFORMATION
NAME
ADDRESS
CITY | STATE | ZIP
DOB M M D D Y Y Y Y | SSN
AGE | SEX F M | FACILITY □UVA □MJH □OTHER

MEDICAL INFORMATION
CHIEF COMPLAINT:
HPI:
PMH: ASTHMA COPD CHF CAD MI RENAL FAILURE CVA DIABETES HTN SZ
MEDS:
ALLERGIES:
PE/RX/TX:

INITIAL VITAL SIGNS
TIME | GLUCOSE mg/dL | GCS E V M =
RESP | BP / | EKG
PULSE | SPO2 | ETC02 mm Hg | Temp
TIME | LOC | PULSE | RESP | BP | EKG | SPO2 | ETCO2

PROCEDURES
PROCED. | LOCATION | SIZE | ATT. | SUC. | TIME | EMP. ID | OTHER

MEDICATIONS ADMINISTERED
MEDICATION | DOSE GIVEN / ROUTE | TIME | EMP. ID | AMOUNT WASTED | WITNESS INT.

SIGNATURES:
AIC: | MD: | NARCOTICS ACCOUNTED FOR:

STARTING MILEAGE: | ENDING MILEAGE: | TOTAL MILEAGE: | DRUG BOX USED - #: | NEW:

EMS Protocol Selection and Execution

Observations/Communications

Time

*EMS Advanced Life Support (ALS) unit dispatched for a **male** patient **unresponsive** in a fast-food restaurant. Patient's estimated to be in his **early twenties**. Patient's **medical history is unknown**.*

Universal Patient Care/Initial Patient Care Protocol

- Scene safety/personal protective equipment
- Primary Assessment with initial interventions ("ABC"s)

*He is seated and slumped with his head resting on his arms on a table. His **LOC is unresponsive** with a **Glasgow Coma Scale (GCS) score of 3**. He is **breathing at a rate of 16 BPM**. His **heart rate is 96 BPM**. His **radial pulse is not palpable**; his pulse is palpated at the left carotid artery. No unusual marks, discoloration, or deformities are noted. Patient noted to be somewhat **diaphoretic**.*

Supplemental O2 (Oxygen Administration Guideline)

- 2ndary assessment: vitals, pain, medical history, glucometry

*The glucometer reports a **blood sugar level of 15 mg/dL**. This is a critically low level that requires rapid intervention.*

*The caller reports that the patient purchased a large orange juice and sat down at the table. The orange juice is observed on the table, and it appears that none has been consumed. The manager reports that he noticed the patient with his head on the table and **had not moved for 45 mins** after purchasing the orange juice. The manager was unable to wake the patient at that time, and called 911.*

Altered Mental Status Protocol

- IV/IO/Vascular Access
- Glucagon 1 mg IM if no IV access
- Repeat IV Access
- Dextrose 50% 25 grams slow IV push

The patient's LOC starts to improve. He starts to make some sounds and move as he begins to wake.

- Second D50 slow IV push – administered due to glucometer reading and positive response to first dose

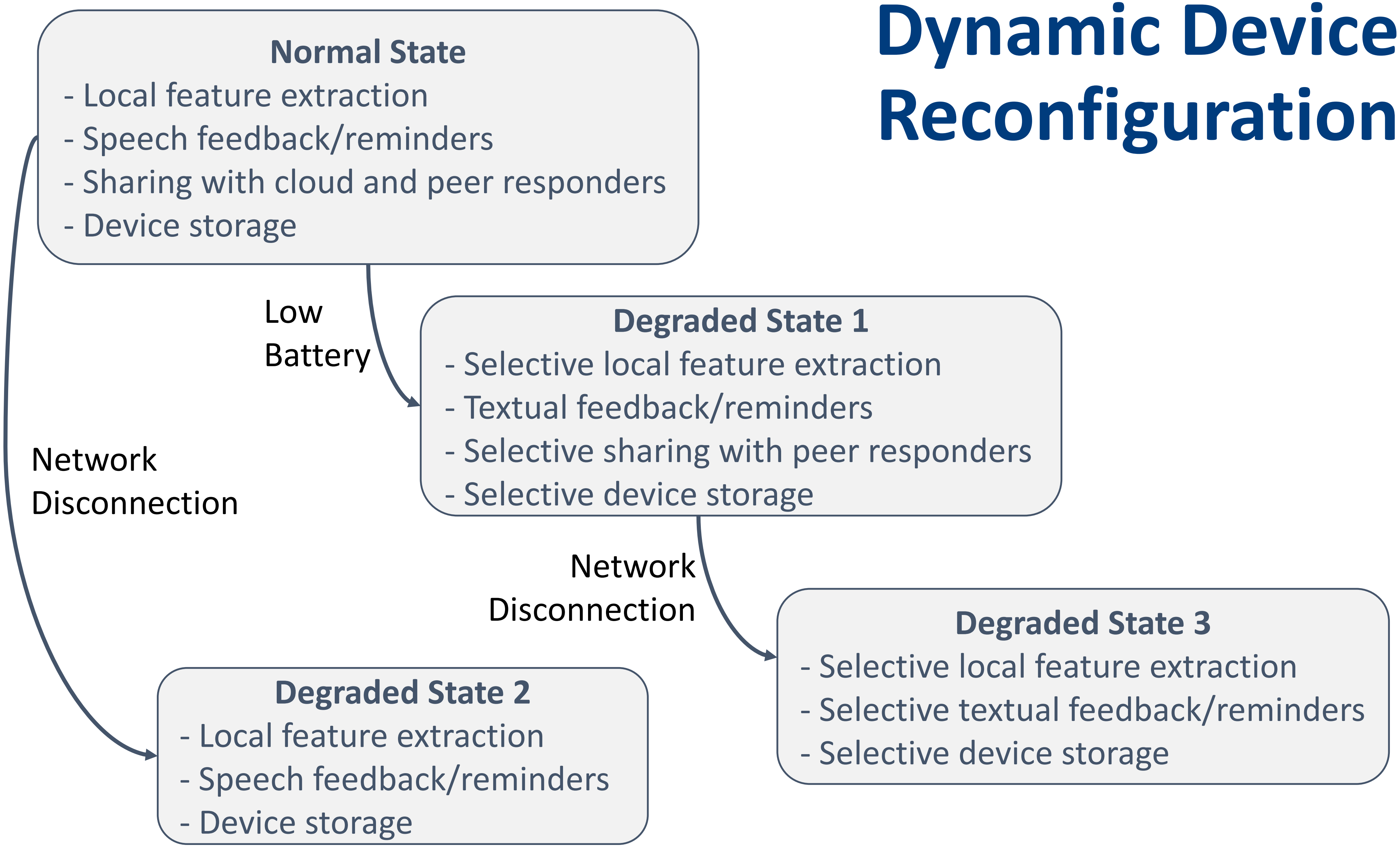
*A few minutes after **administration of the D50**, the patient appears awake but groggy.*

*Within few moments, patient becomes **completely awake** and oriented but **without memory of the event**. The patient states that he **feels fine**. The patient reports that he is a **type 1 diabetic** and he had **not eaten today**. He had no recollection of buying the orange juice or how he arrived at the restaurant.*

Medical: Hypotension/Shock (non-trauma)

- Hypovolemia must be corrected prior to dopamine infusion.
- Identify and manage underlying cause.

Dynamic Device Reconfiguration



Future Work

- Develop classification model for different form fields
- Generate editable Forms
- Interface GRACE with ImageTrend