POLARIS PROJECT

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2024.03

PART 0 CONTENTS

POLARIS Project

Chapter 1.

Polaris Project

About Polaris Project

1 Introduction

- Apache AsterixDB is developed by UC Irvine, UC Riverside, UC San Diego, and Couchbase
- Open source big data management system
- IDALab and Big data group in UCI co-research on Apache AsterixDB project
- Design and implement AsterixDB admin dashboard and contribute on Apache top-level project

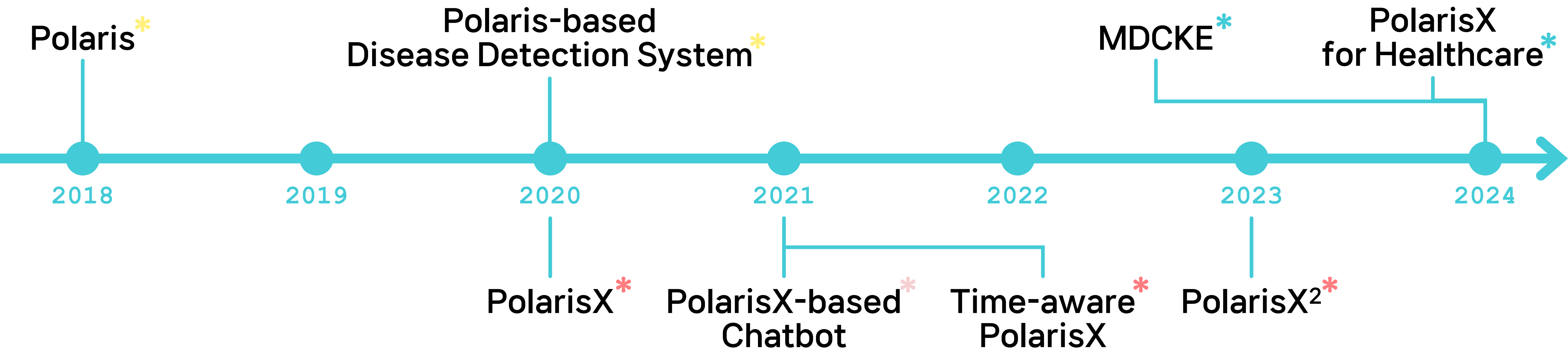
2 Polaris Project

- A research project that can guide navigators to find the knowledge they need in a sea of big data, much like the North Star guides navigators

3 History

- Start from 2018

* : Real-time analytics system
* : Auto-growing knowledge graph
* : Application (based on PolarisX)
* : Post-PolarisX



Chapter 2.

Polaris

Polaris

: Social Media Contents based Sentiment Analysis and Prediction System

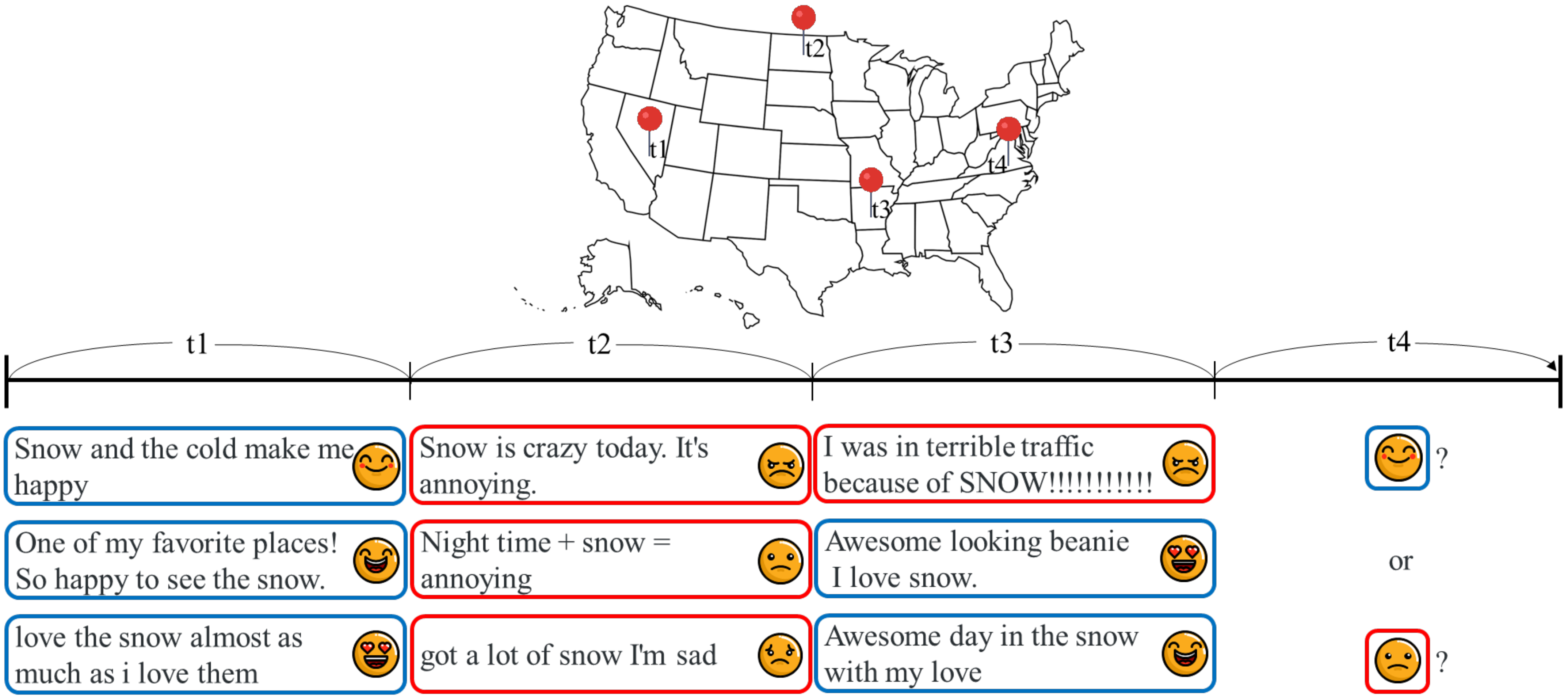
SoYeop Yoo, JeIn Song, and OkRan Jeong

Expert Systems With Applications 105 (2018) pp.102 – 111
https://authors.elsevier.com/c/1Wxau3PiGT7gAi

PART 1 INTRODUCTION

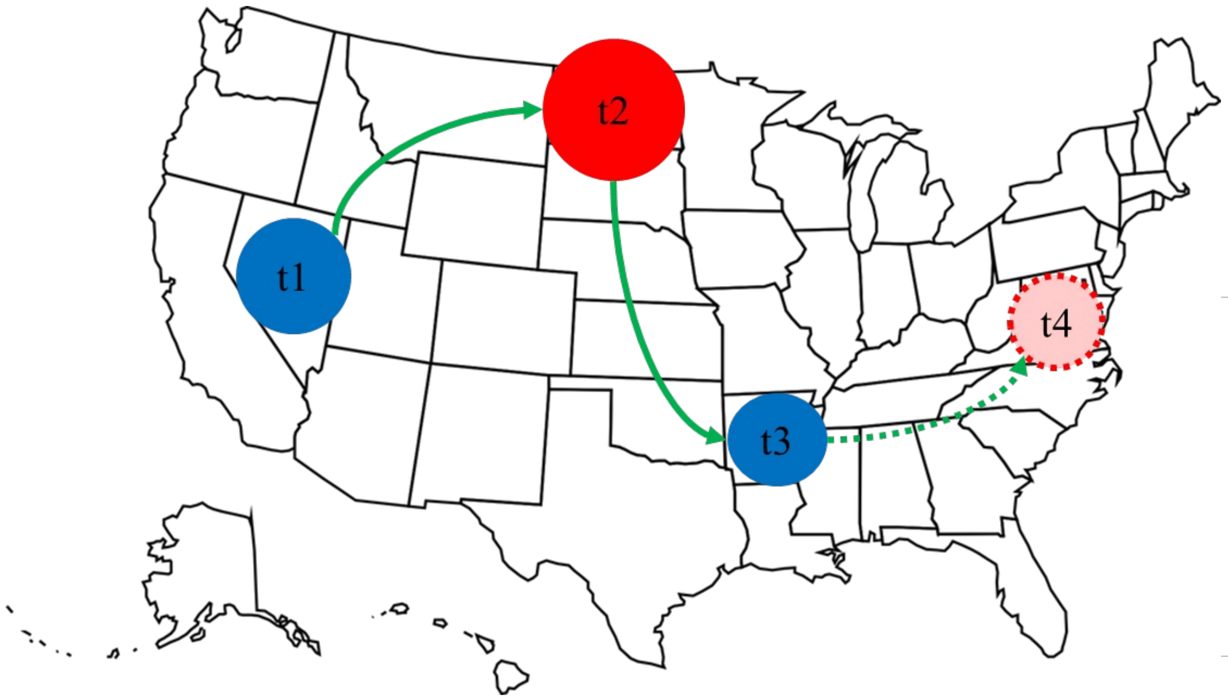
Social Media Contents based Sentiment Analysis and Prediction System

1 Motivation



1 Motivation

➢ Polaris: Social media contents based sentiment analysis and prediction system



Efficiency on cost
Use AsterixDB to handle social media contents efficiently

Sentimental path
Enable a user can obtain insight at a glance by analyzing trajectory and sentiment together

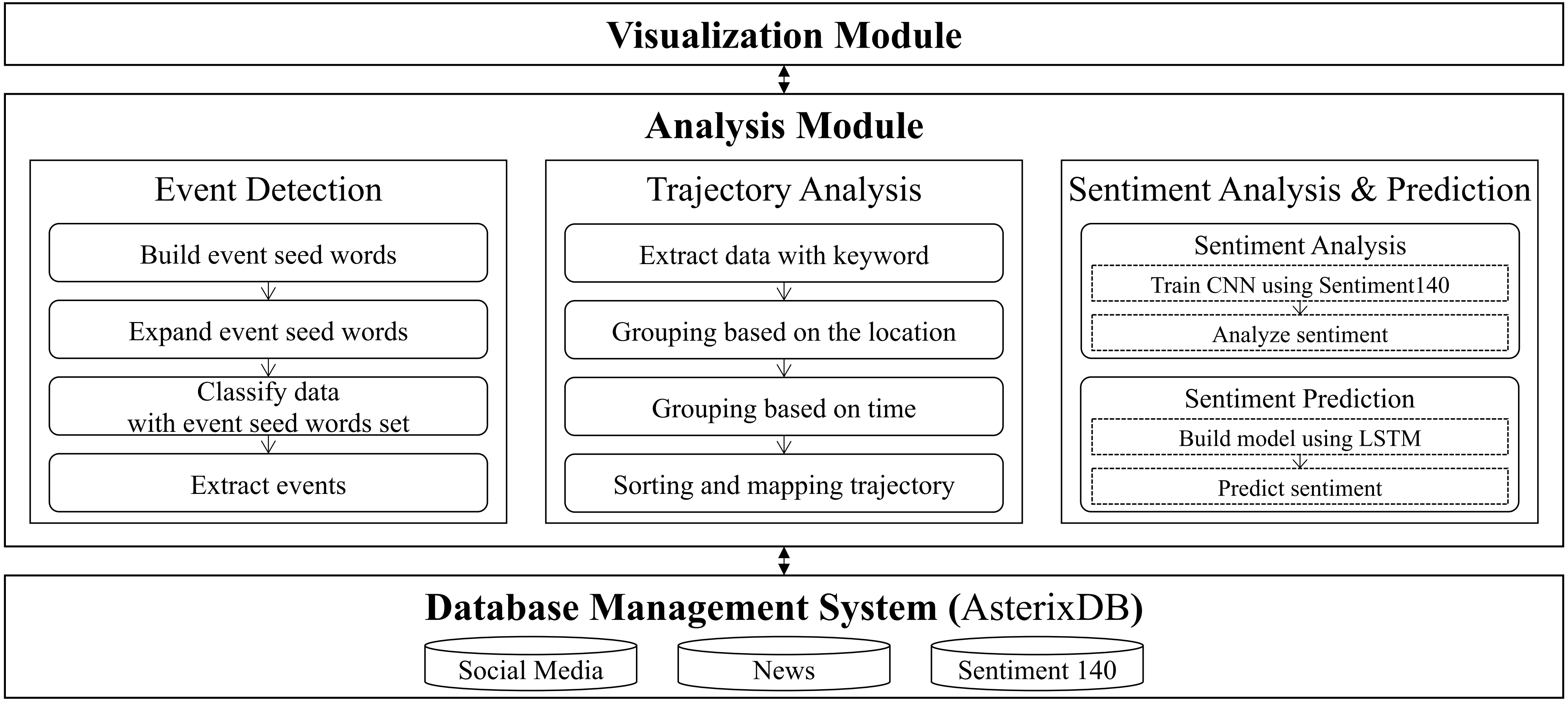
Deep learning on sentimental path
Use recent deep learning techniques (CNN and LSTM)

1 Polaris

- Polaris is the name of our proposed system
- It is a novel system for analyzing and predicting users' sentimental trajectories for events and showing the results

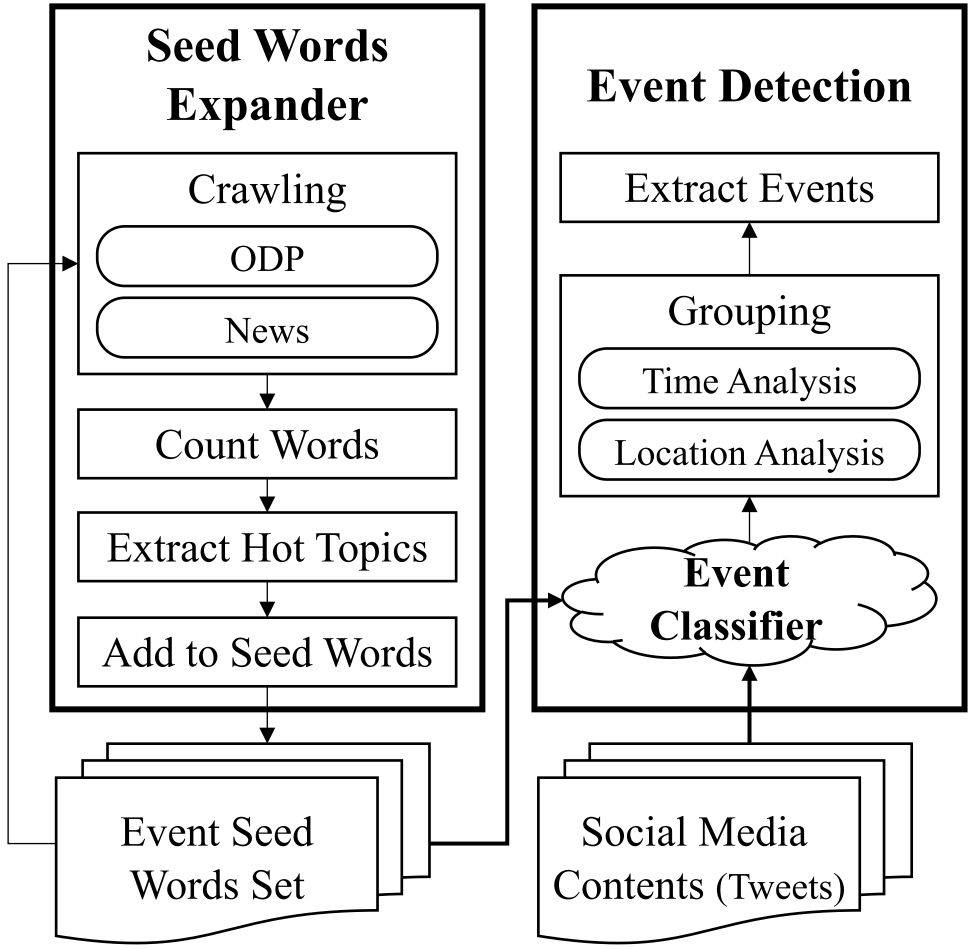
1 Polaris

≻ Overall Structure



2 Event Detection and Trajectory Analysis

- Event detection
  - Use social media contents as a sensor of event detection
  - Seed words are used for event detection; { crime, disaster, accident }



2 Event Detection and Trajectory Analysis

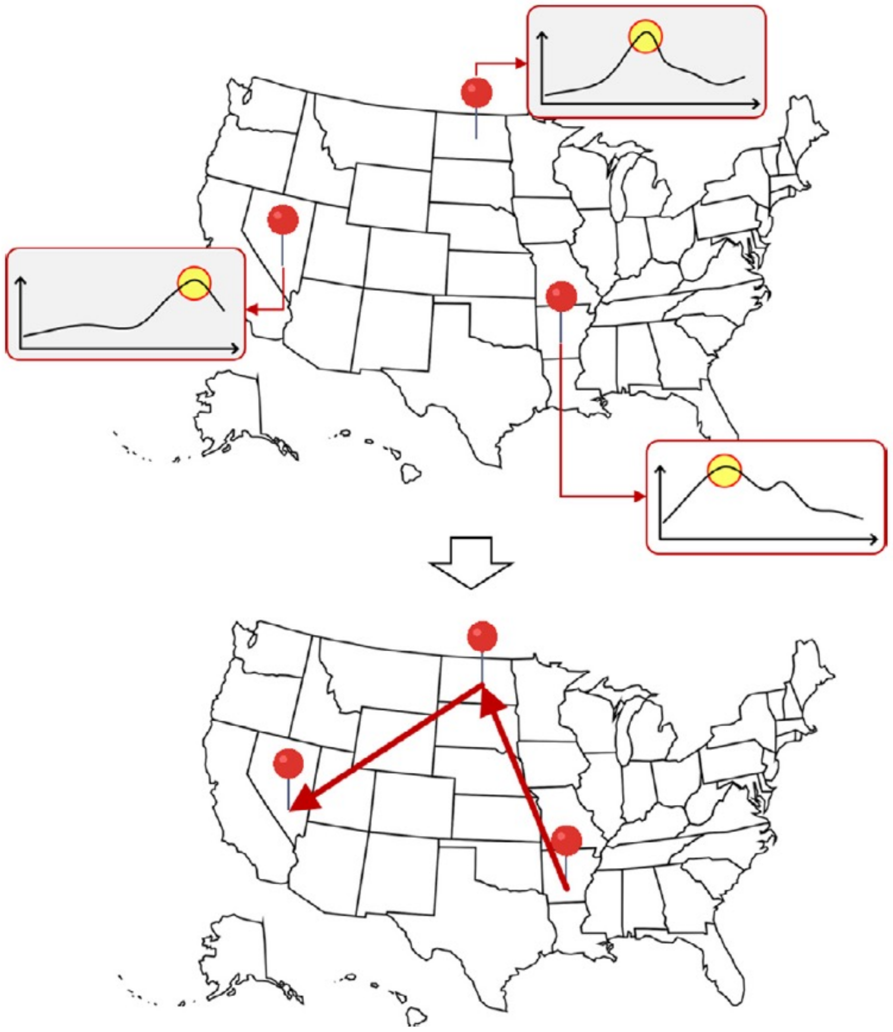
- Detect event based on 'Crime, Disaster, Accident' events
  - Seed words: { crime, disaster, accident }
  - "TEDAS: a Twitter based Event Detection and Analysis System" (Li, Rui, et al. 2012)
- Make event-word-set using word2vec model
- Then, weight on some features
  - Has number? (ex. 5 people died)
  - Has time? (ex. 14:30 am)
  - Has @ or #?

PART 2 POLARIS

Social Media Contents based Sentiment Analysis and Prediction System

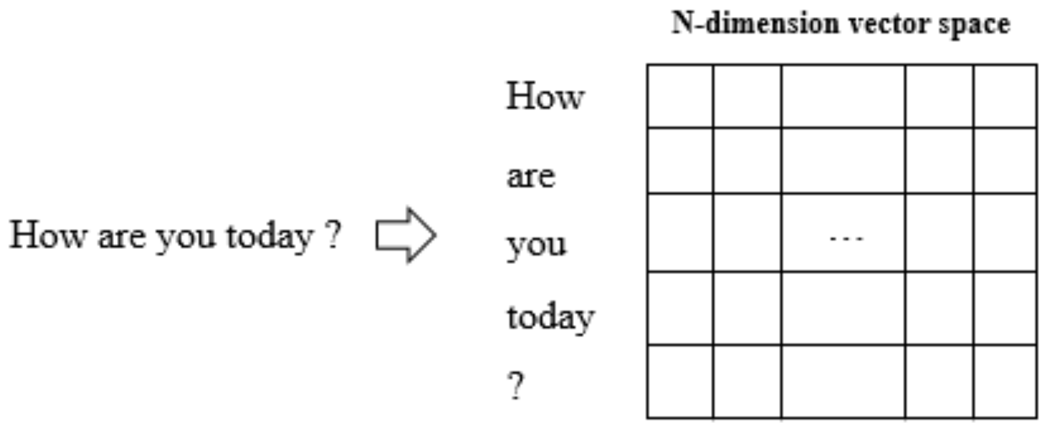
2 Event Detection and Trajectory Analysis

- Trajectory analysis
  - Event trajectories are the results of analysis of the paths which events are propagated through the analysis of the time and area where certain events are occurred



2 Sentiment Analysis

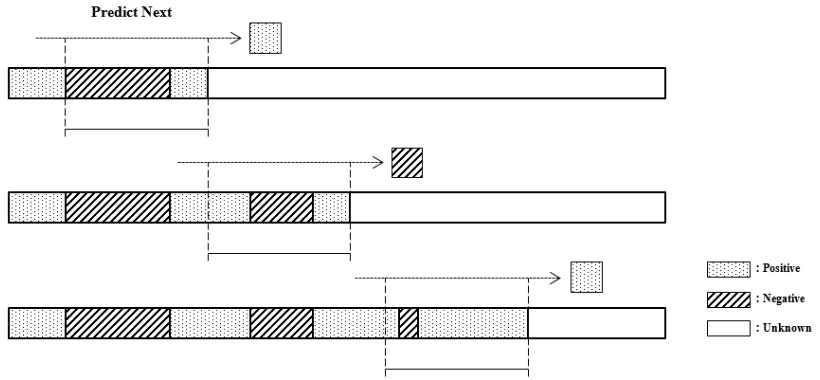
- Sentiment analysis
  - We use machine learning to analyze the sentiment of users for the events occurred
  - The sentiment classification model is trained using the CNN (Convolutional Neural Networks) for sentence classification (Kim, 2014)
- Training CNN
  - Training set: 700,000 positive, 700,000 negative
  - Data source: Sentiment140



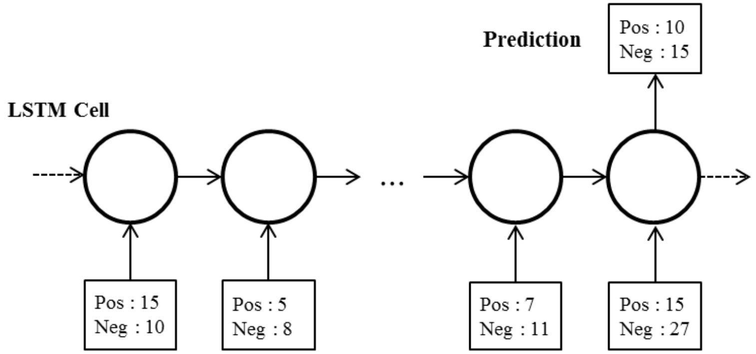
3 Sentiment Prediction

≻ Sentiment prediction

- The concept of time window is used for sentimental path prediction
- We set the window size to 7 days



- We predict users' sentiment based on LSTM (Long Short-Term Memory)



1 Implementation Environment and Data Set

- Environment
  - Ubuntu 14.04
  - Intel Xeon CPU E5-2620 v3 (X 2)
  - 500GB SSD
  - 32G memory
  - GTX970 GPU

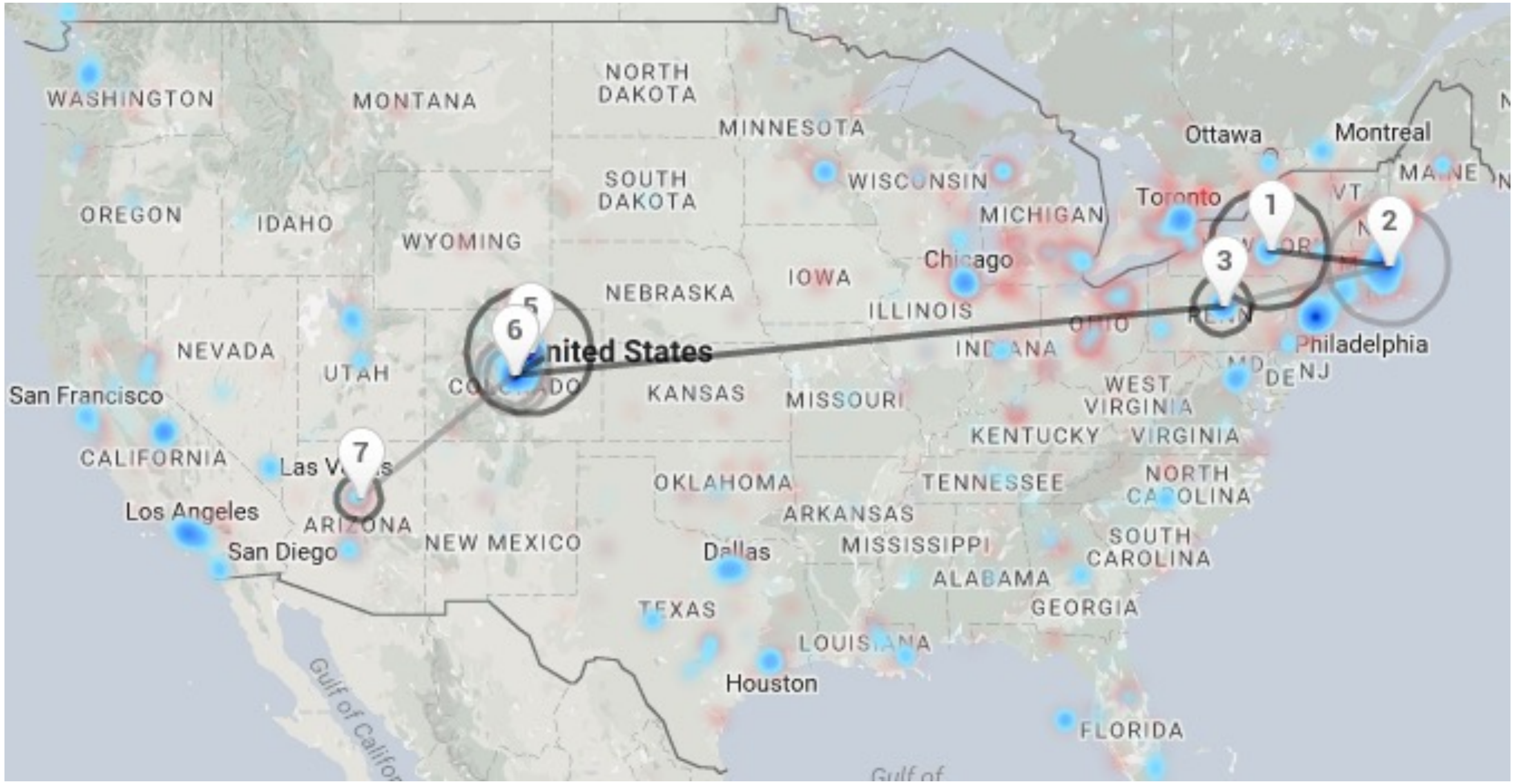
- Data set
  - US tweet data
    - → 40 million tweets
    - → 04/01/2016 ~ 04/30/2016
  - Sentiment 140
    - → 800,000 positive data
    - → 800,000 negative data

2 Implementation

➢ Event detection result

2 Implementation

- Sentimental path analysis result for 'snow'

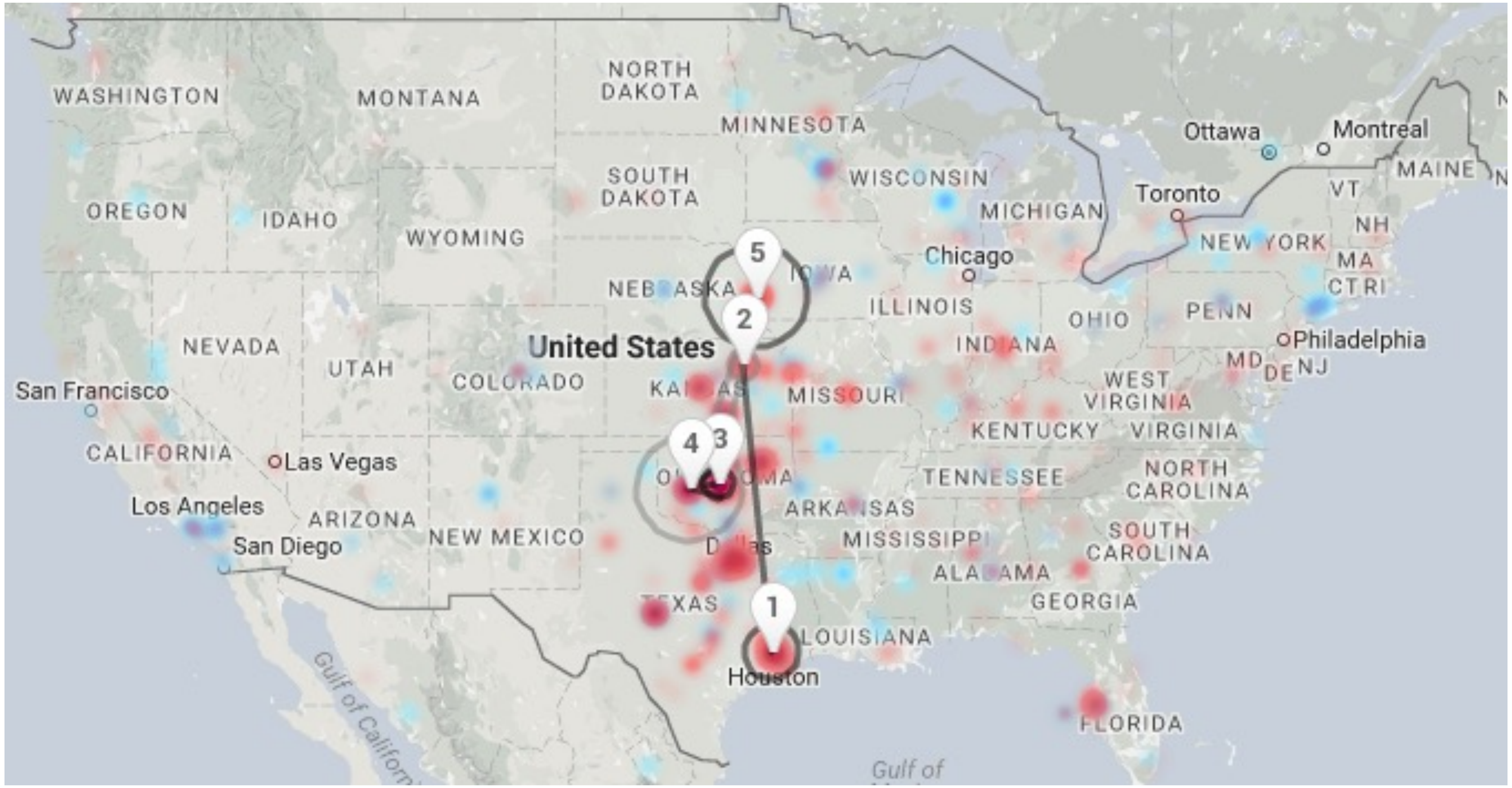


PART 3 **IMPLEMENTATION AND EXPERIMENTS**

Social Media Contents based Sentiment Analysis and Prediction System

2 Implementation

➢ Sentimental path analysis result for 'tornado'



3 Experiments

- Experiment on sentiment analysis
  - Accuracy according to vocabulary size

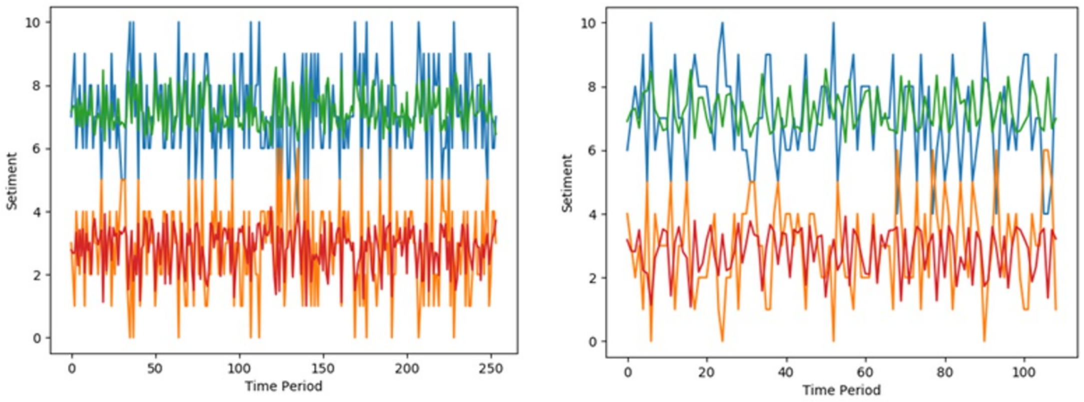
Vocabulary Size	Epoch 1	Epoch 2	Epoch 3	Epoch 4	Epoch 5
20000	0.8050	0.8318	0.7611	0.7802	0.7489
30000	0.7818	0.8311	0.7921	0.7695	0.7667
40000	0.8173	0.8456	0.8012	0.7937	0.7875
50000	0.8095	0.8329	0.7808	0.7746	0.7699
60000	0.7886	0.8329	0.7749	0.7842	0.7743

  - Comparison result of sentiment analysis model with other machine learning methods

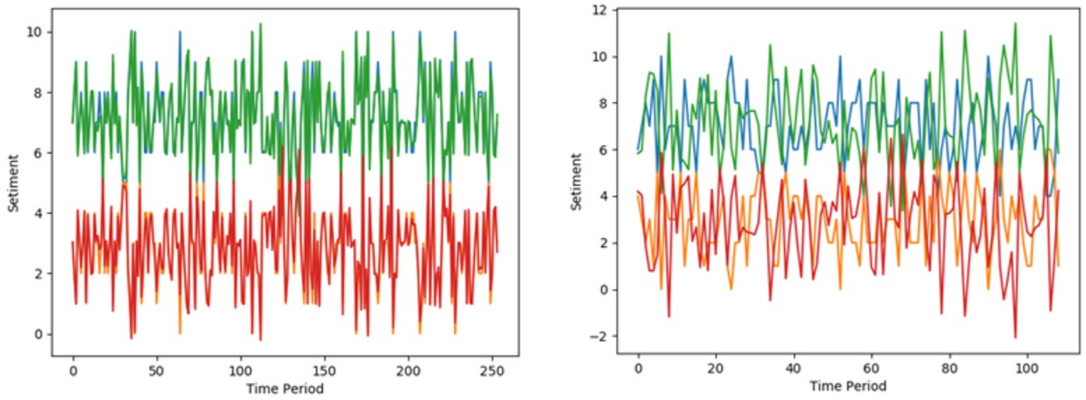
Model	Naïve-Bayes	SVM	Random Forest	Proposed Model
Precision	0.76	0.77	0.76	0.839
Recall	0.76	0.77	0.76	0.845
F-1 Score	0.75	0.77	0.76	0.841

3 Experiments

- Experiment on sentiment prediction
  - Left side: training data
  - Right side: test data
  - Blue line: answer of positive
  - Green line: prediction of positive
  - Orange line: answer of negative
  - Red line: prediction of negative



(a) At iteration 1500



(b) At iteration 4500

1 Conclusion

- We propose a system to analyze social media contents in real time
- We use AsterixDB to efficiently manage the social media contents
- We propose and implement Polaris that finds events in real time to analyze and predict users' sentimental paths

2 Usage

- Polaris can be utilized for disaster notice service for earthquakes and tsunamis or real time traffic accident informing service
- It also can be applied to social events too, it can be used for diverse marketing programs

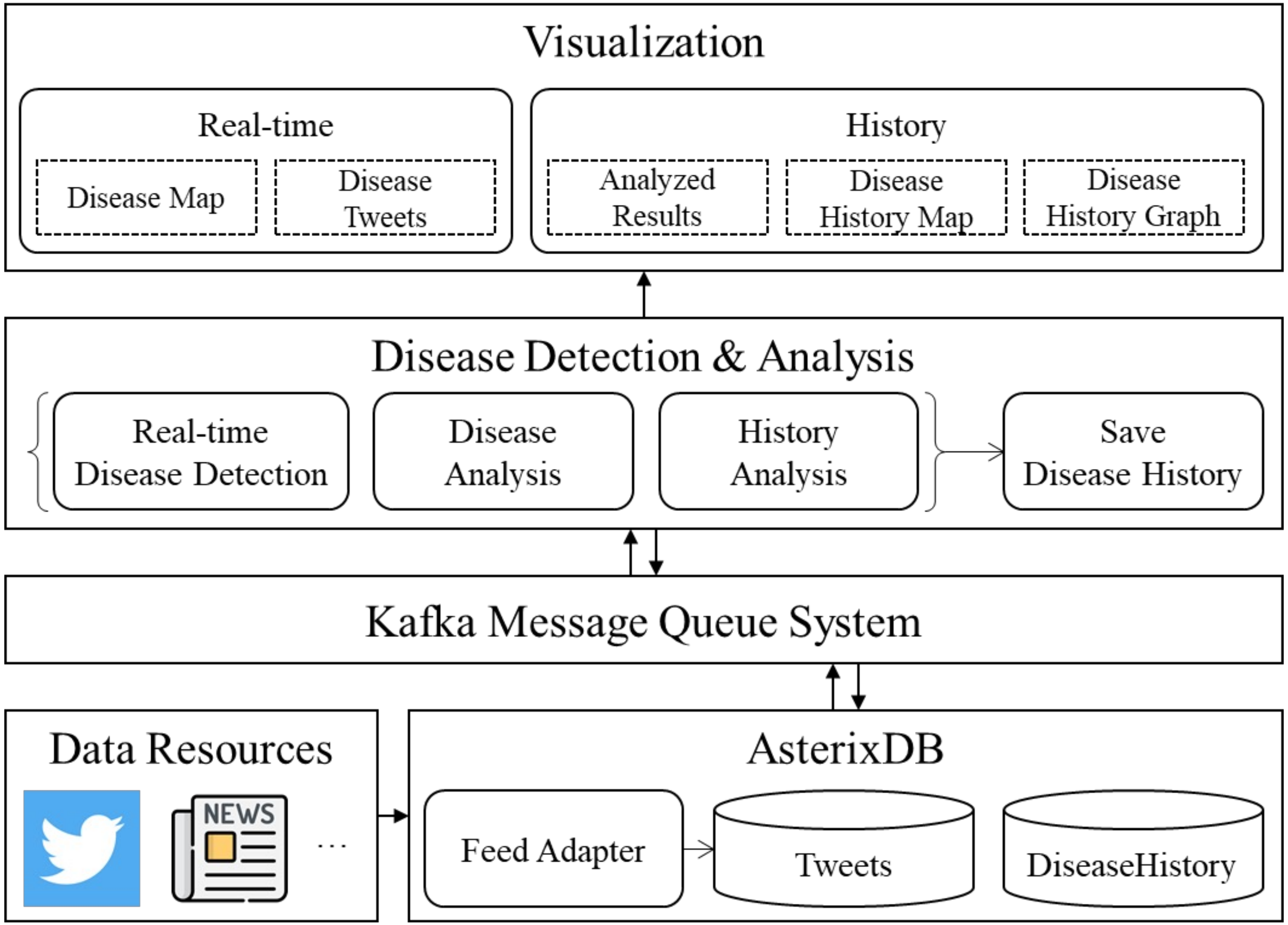
Polaris-based Disease Detection System

: Real-time disease detection and analysis system using social media contents

SoYeop Yoo, DaeHo Kim, SungMin Yang and OkRan Jeong

International Journal of Web and Grid Services, Vol. 16, No. 1, pp. 22-38, 2020
https://doi.org/10.1504/IJWGS.2020.106103

1 Overall Structure



1 Real-time Disease Detection

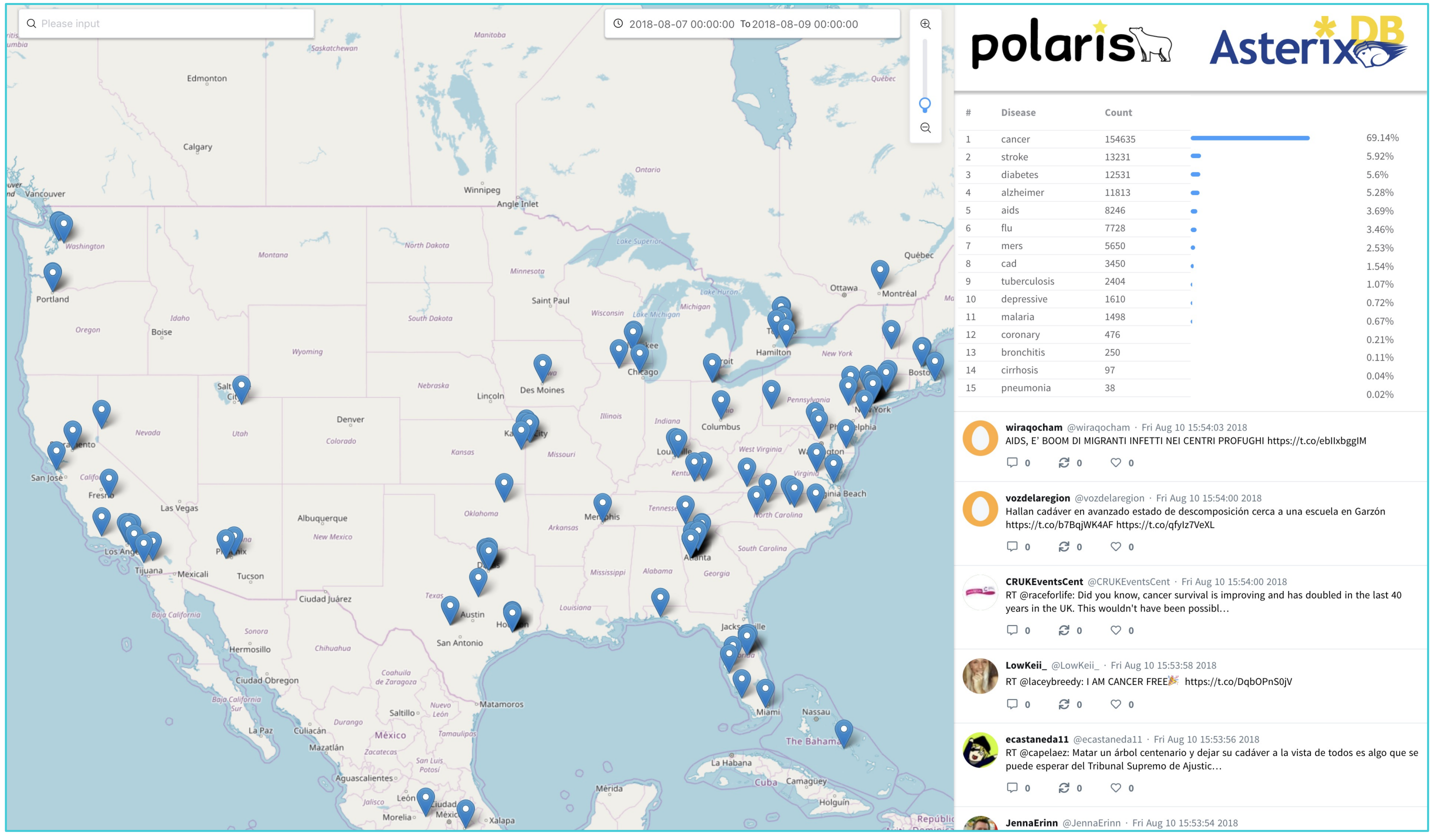
- 15 diseases
  - coronary artery disease (CAD), stroke, flu, pneumonia, bronchitis, diabetes mellitus, Alzheimer's, tuberculosis, cirrhosis, cancer, AIDS, malaria, depressive disorder, measles, MERS
  - (ref) ICD-11 from WHO, https://www.healthline.com/health/top-10-deadliest-diseases#tb, https://list25.com/25-deadliest-diseases-in-human-history/
- Real-time detection
  - Apache Kafka
  - Apache AsterixDB
    - → Feed Adapter to crawl Twitter streaming data
    - → UDF (User Defined Function) to detect diseases

PART 2 POLARIS FOR DISEASE DETECTION

Polaris Project for Disease Detection

2 Disease History

- History
  - Save the detected tweets into history
  - Get results of the specific time

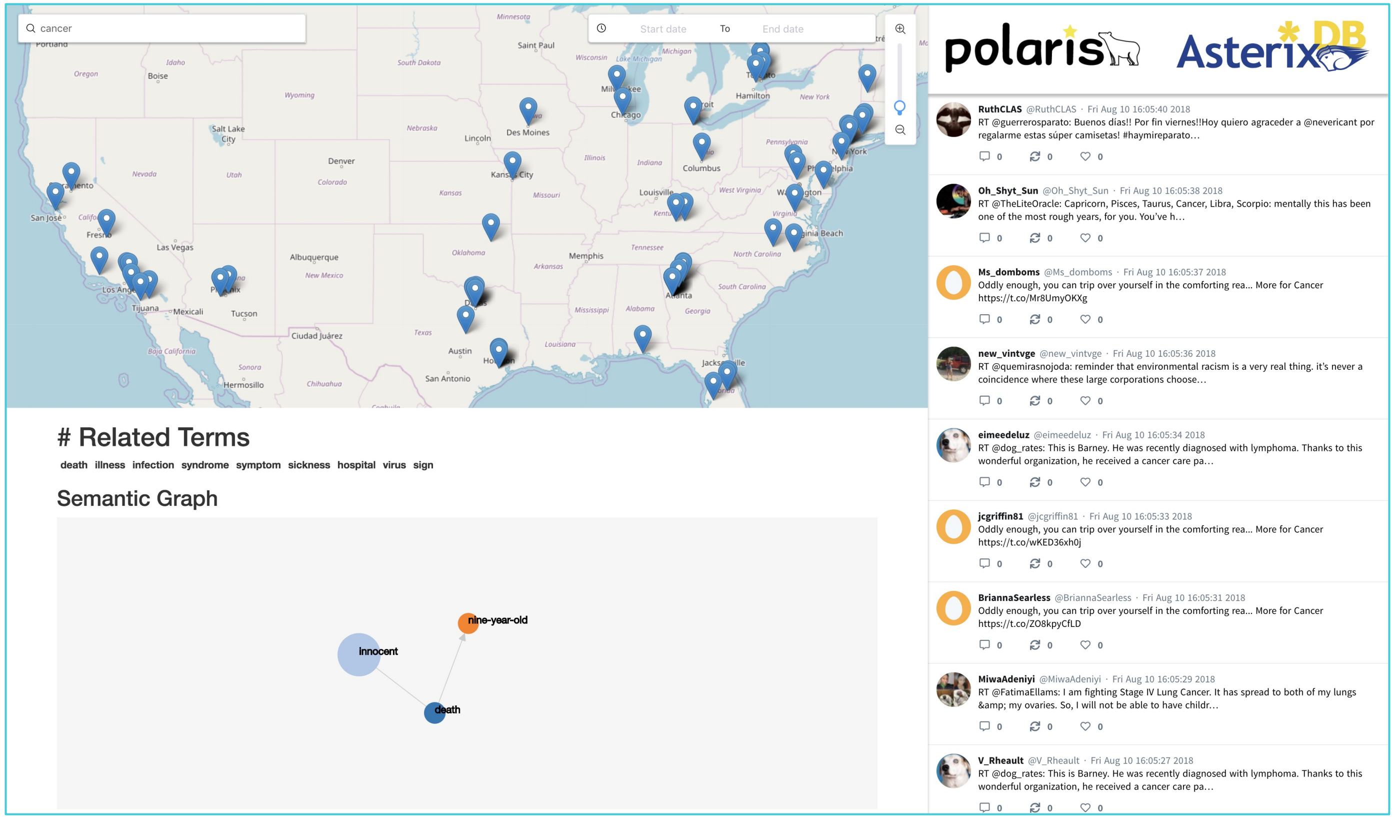


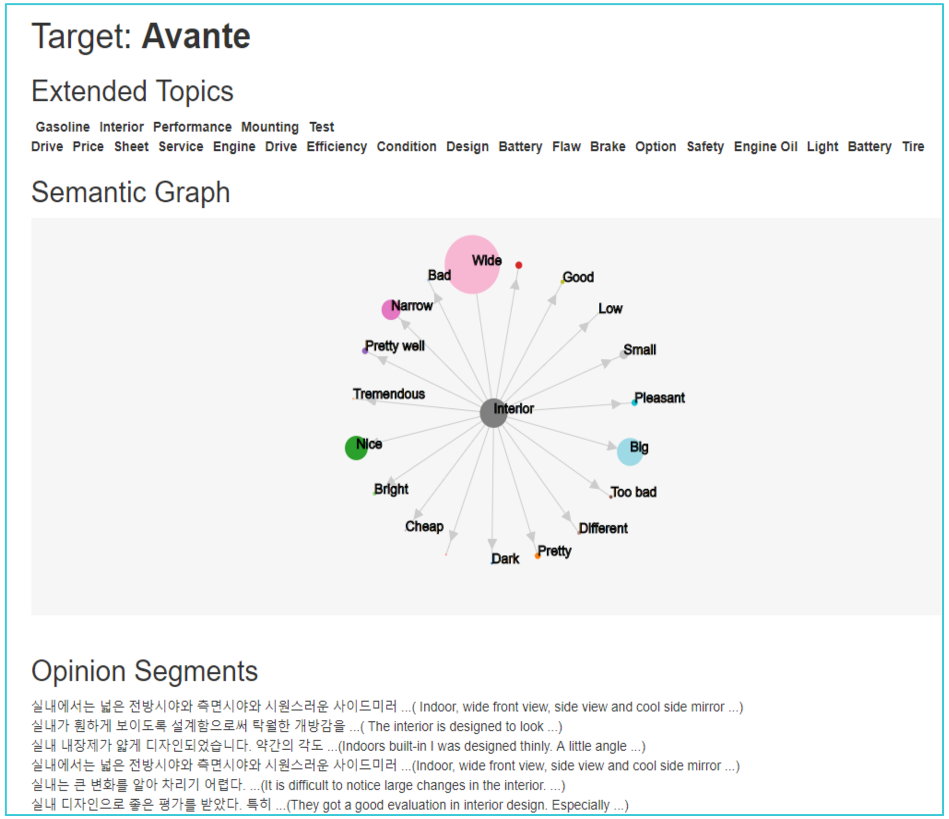
PART 2 POLARIS FOR DISEASE DETECTION

Polaris Project for Disease Detection

3 Disease Analysis

- Semantic analysis
  - Analysis opinions using semantic (PolarisX)





Chapter 3.

PolarisX

PolarisX

: Automating the Expansion of a Knowledge Graph

SoYeop Yoo, and OkRan Jeong

Expert Systems with Applications, Vol. 141, 2020.
https://doi.org/10.1016/j.eswa.2019.112965

1 Introduction

- Object of research
  - Expand the knowledge graph automatically not only to rapidly expand the knowledge base for any human language, but also to support neologisms
- Limitations of the existing knowledge graphs
  - The existing knowledge base is rather limited in size and scope for most of the human languages
  - It is not able to support in a timely manner neologisms that form a part of the human common sense
  - Examples of neologisms

Word	Past	Now
Apple	a kind of fruit	IT brand
Ford	a location where a stream is shallow	motor company
Gangnam style	lifestyle associated with the Gangnam district of Seoul	K-pop by PSY
Trump	playing card	the 45^{th} president of the United States
Google	company name	search for information on the Web

1 Introduction

- Our approaches
  - Three major components
    - → The social crawler to expand data resource
    - → The semantic analyzer to determine new relationships using the fine-tuned BERT
    - → The knowledge miner to build and extend the knowledge graph

2 Motivation

Input: selfie

Existing Knowledge Graph-based System

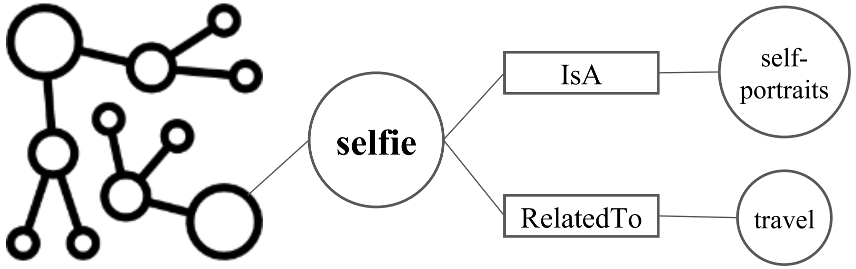
Finding 'selfie' in
the existing knowledge graph

…?

PolarisX-based System:

Auto-growing Knowledge Graph-based System

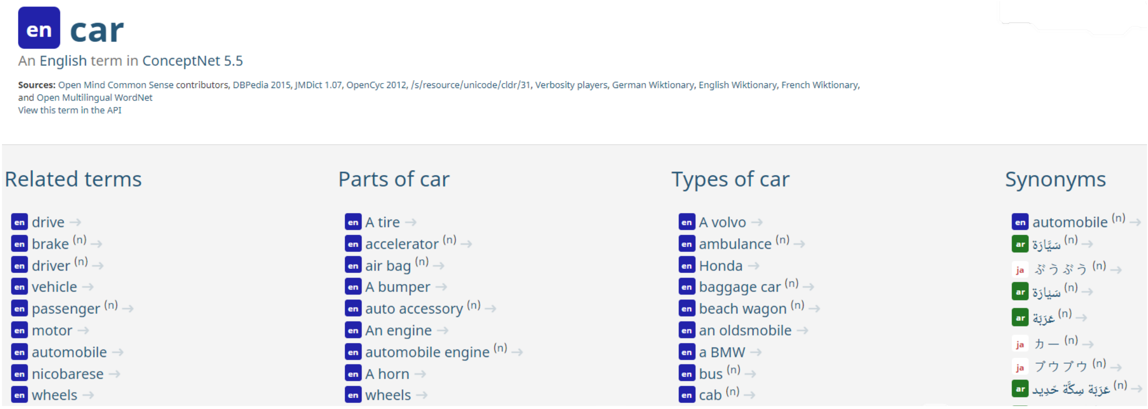
Finding 'selfie' in
PolarisX(An Auto-growing Knowledge Graph)



{ selfie, *IsA*, self-portraits }
{ selfie, *RelatedTo*, travel }

1 Knowledge Graph: ConceptNet

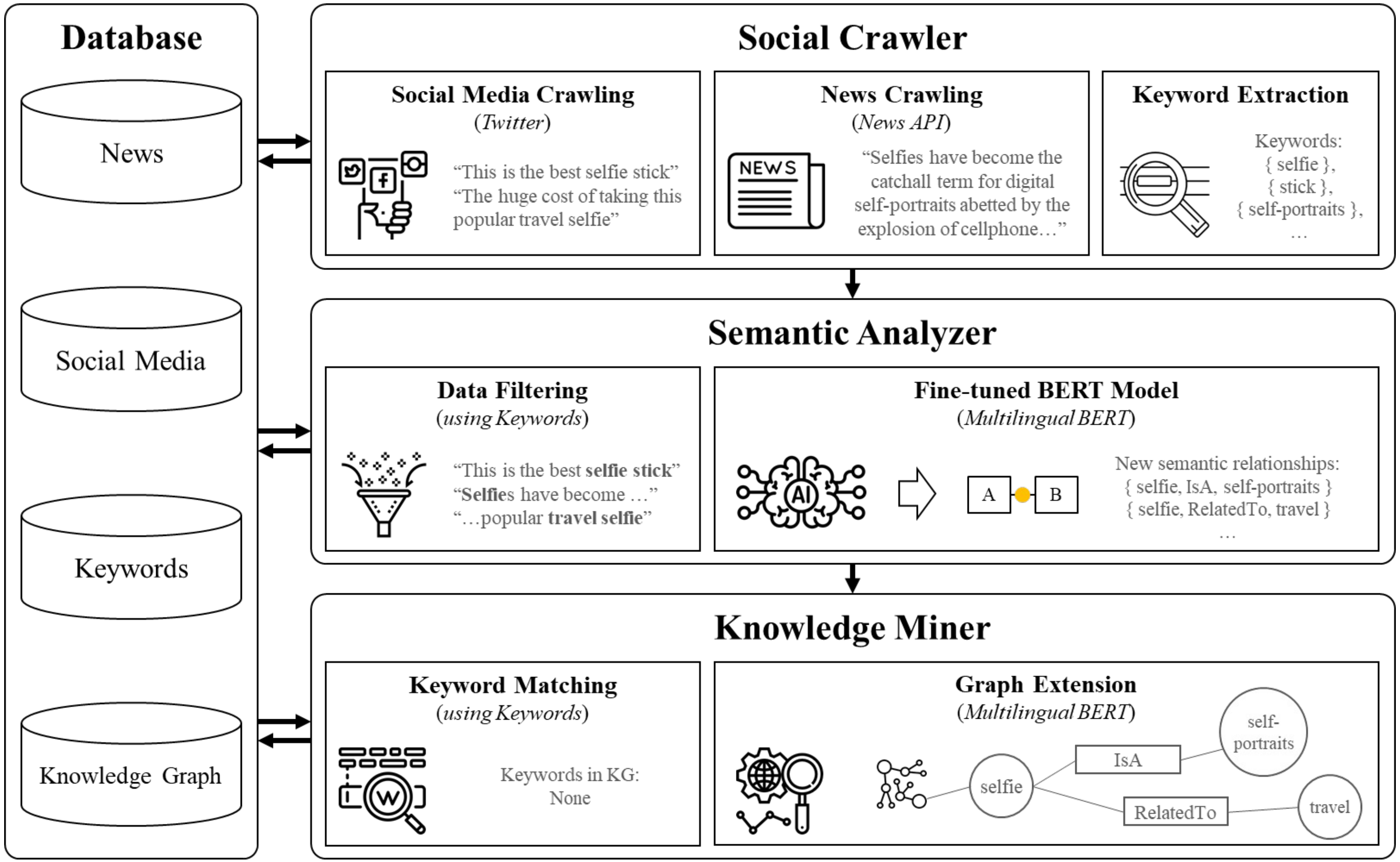
- ConceptNet
  - A freely-available semantic network, designed to help computers understand the meanings of words that people use



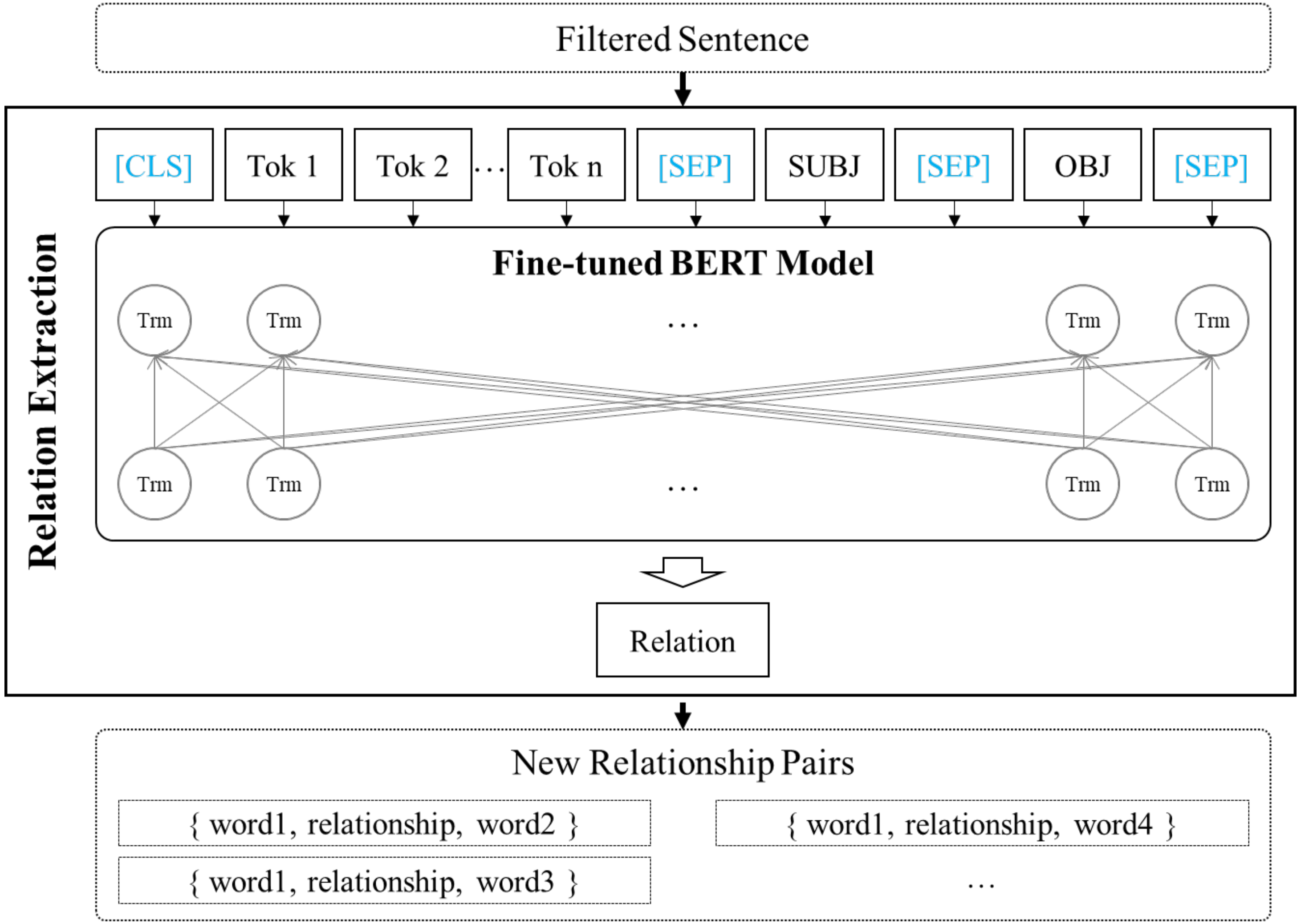
- Problem of ConceptNet

Core Languages		Common Languages	
Language	Num. of Words	Language	Num. of Words
English	1,803,873	Czech	129,183
French	3,023,144	Filipino	17,620
Italian	1,078,629	Korean	47,268
Japanese	363,663	Slovak	29,768
Chinese	242,746	Turkish	65,892

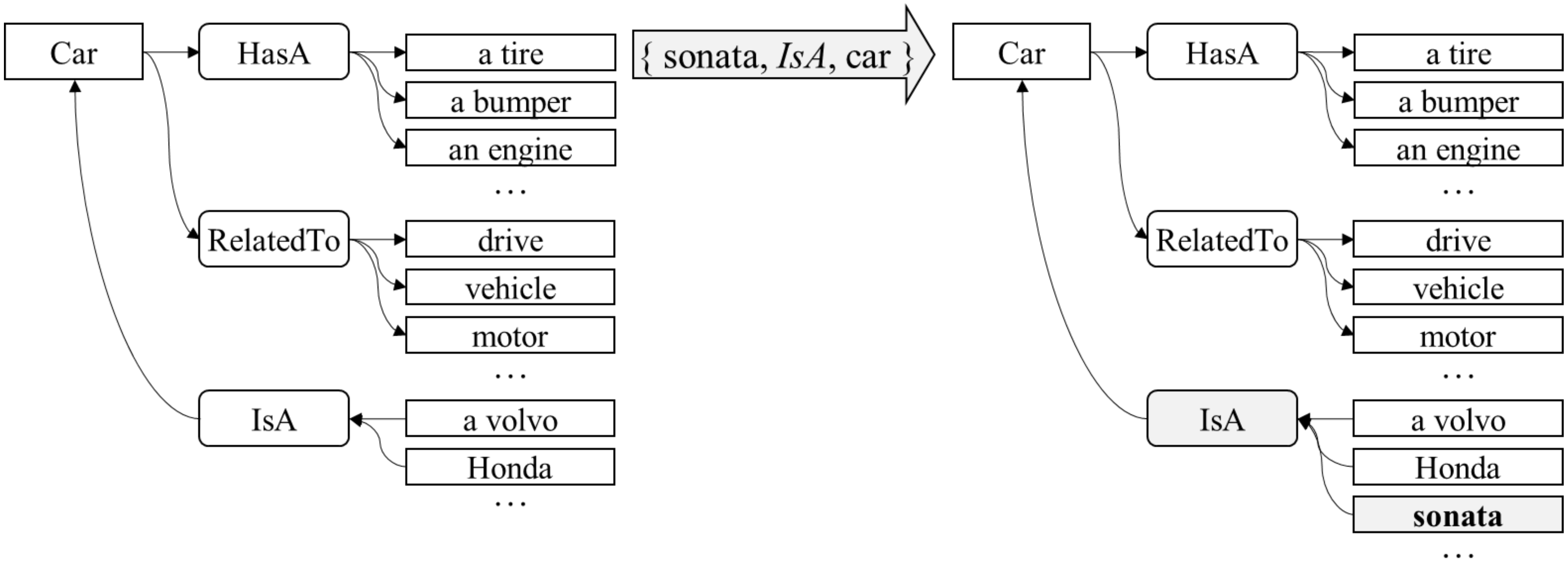
2 Architecture



3 Semantic Analyzer using the fine-tuned BERT model



4 Expanding the ConceptNet Knowledge Graph using PolarisX



1 Experiment Result

- Experiment on extension of knowledge graph
  - Using data
    - Tweets: 2.5 million (2018/08/08 ~ 2018/08/14)
    - News: 35,000
  - Comparison result of with the existing knowledge graphs

Knowledge Graphs	# of Relations	# of Edges
DBpedia (English)	2,813	176,043,129
YAGO	77	25,946,870
NELL	425	432,845
OpenCyc	18,526	2,413,894
Probase	1	20,757,545
PolarisX (+ ConceptNet)	40	32,871,573

1 Experiment Result

- Experiment on accuracy of semantic analyzer
  - TACRED data
  - We use 'BERT-Base, Multilingual Cased' model
  - Environment: Google colab TPU

  - Comparison result on TACRED dataset

Models	Precision	Recall	F1 score
Logistic Regression (Y. Zhang, Qi, and Manning 2018)	73.5	49.9	59.4
PA-LSTM (Y. Zhang et al. 2017)	65.7	64.5	65.1
C-GCN+PA-LSTM (Y. Zhang, Qi, and Manning 2018)	71.3	65.4	68.2
BERT-based model (our model)	79.1	72.6	75.7

Time-Aware PolarisX

: Auto-Growing Knowledge Graph

YeonSun Ahn, and OkRan Jeong

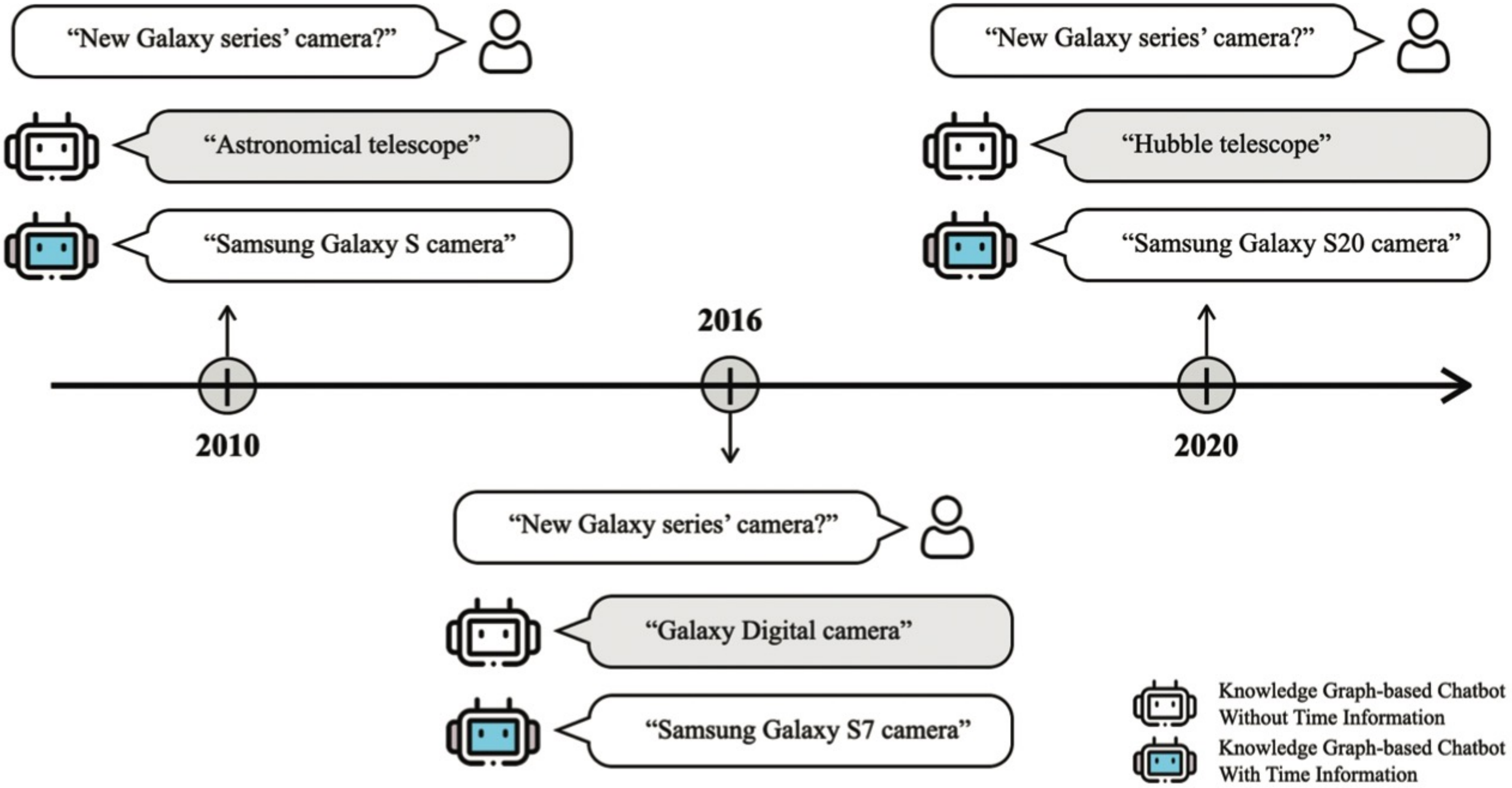
Computers, Materials & Continua, Vol. 67, No. 3, pp. 2807-2817, 2021
https://doi.org/10.32604/cmc.2021.015636

1 Introduction

- Knowledge graph
  - Considers knowledge to be the relationship between entities
  - Expresses knowledge in the form of <h, r, t>
    - → the triple of 'head entity,' 'relation,' and 'tail entity'
  - The core of NLP tasks, such as Q&A and semantic analysis

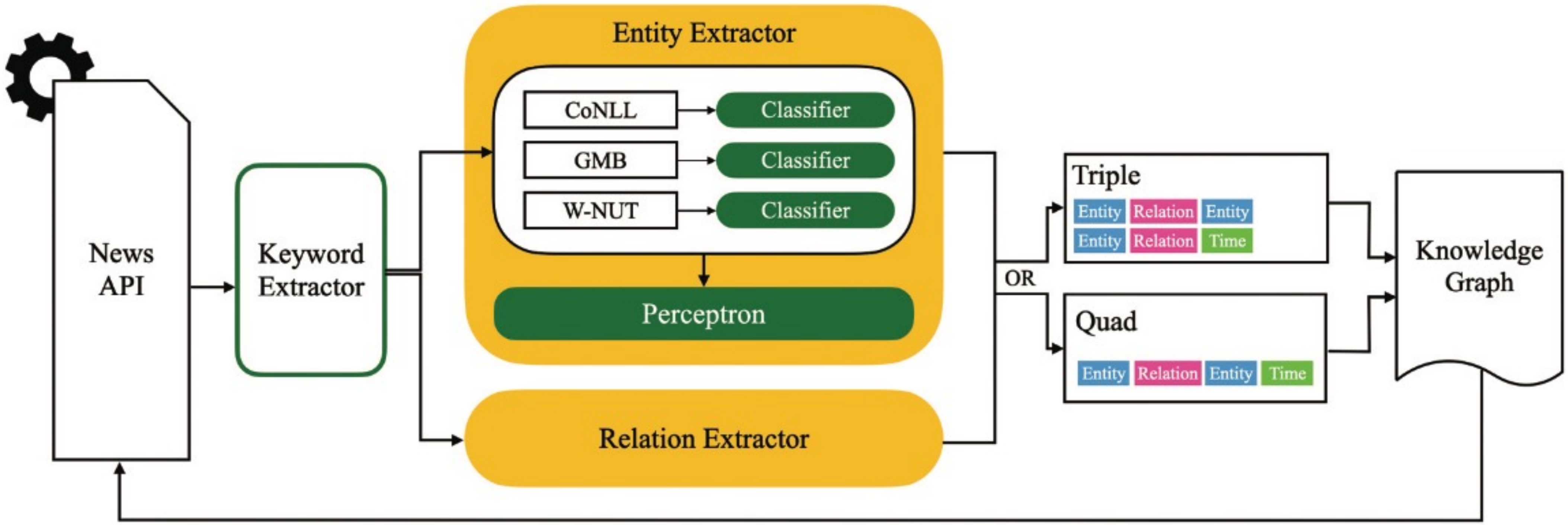
- Limitations
  - Static
    - → cannot cover all human knowledge because stored knowledge is fixed
  - Not considering time information

2 Motivation



1 Time-Aware PolarisX

- Build knowledge graph automatically, including time information, and continuously expands
- Overall architecture



1 Construction

- Entity extraction
  - The ensemble NER tagger
    - Groningen Meeting Bank (GMP) corpus
    - CoNLL2003
    - Noisy User-generated Text (W-NUT 17')
  - Datasets for NER models

Dataset	Total words	Used words (%)	Total sentences	Used sentences (%)
GMB	1,047,059	261,391 (25%)	47,958	11,990 (25%)
CoNLL2003	36,424	7,163 (20%)	12,735	2,539 (20%)
W-NUT 17'	3,596	1,127 (31%)	1,634	552 (34%)

  - Named entity tags

Dataset	Tags
GMB	Art, Per, Tim, Org, Nat, Eve, Geo, Gpe, O
CoNLL2003	PER, ORG, LOC, MISC, O
W-NUT 17'	Corporation, creative-work, group, location, person, product
For ensemble NER	Person, organization, location, time indicator

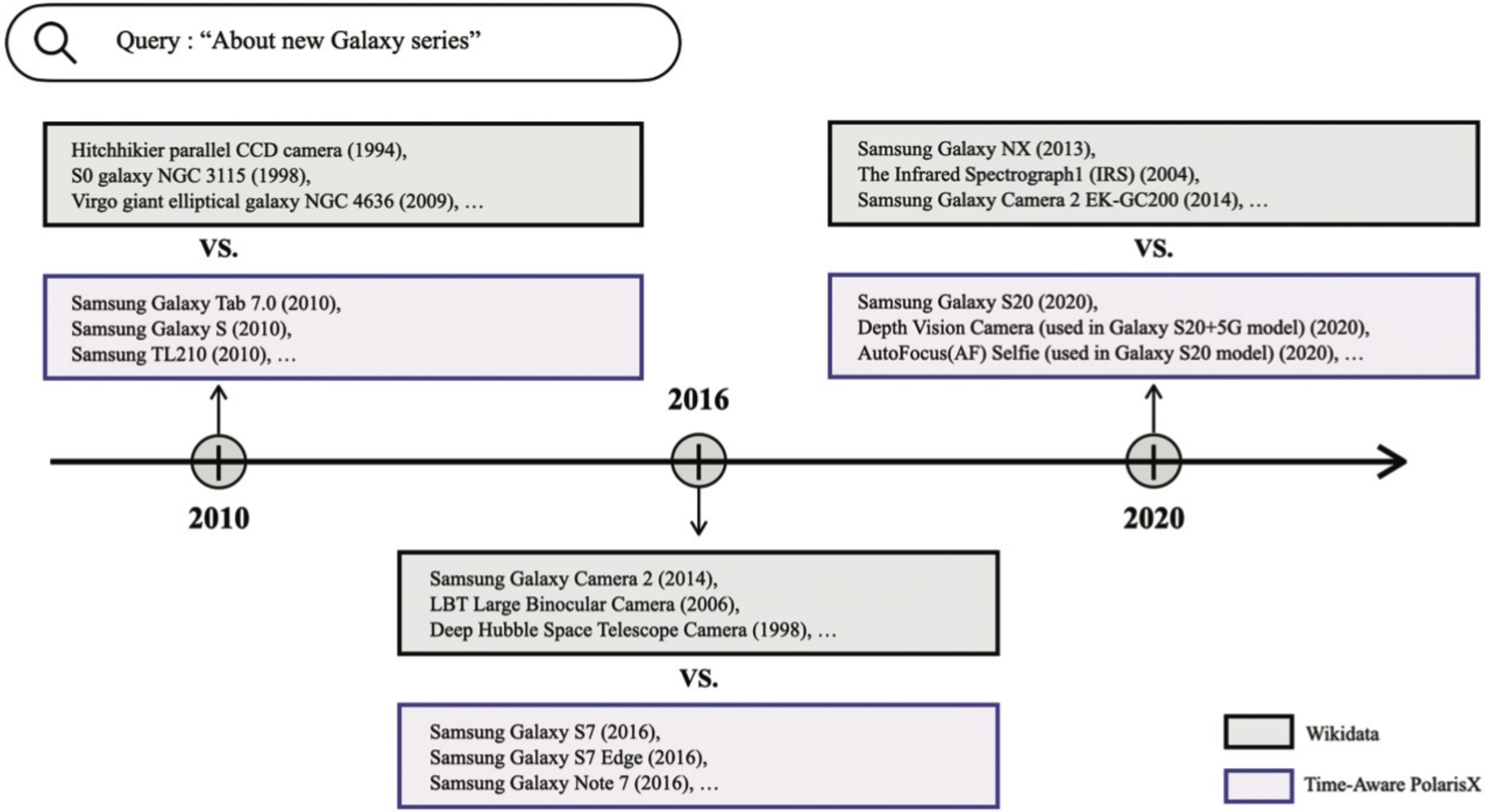
1 Construction

- Relation extraction
  - BERT-based model is used as the PolarisX
  - Instead of TACRED dataset used in PolarisX, Time-Aware PolarisX uses YAGO3
    - YAGO3: a semantic knowledge graph built from large-scale WordNet and Wikipedia, with time information
  - YAGO3 relations and selected relations

Relations
isLeaderOf, hasOfficialLanguage, imports, dealsWith, hasNeighbor, **isInterestedIn**, exports, hasCurrency, **hasCapital**, hasAcademicAdvisor, **isKnownFor**, **owns**, **isCitizenOf**, **isLocatedIn**, hasMusicalRole, edited, isConnectedTo, **actedIn**, **participatedIn**, isPoliticianOf, wroteMusicFor, hasChild, isAffiliatedTo, hasGender, **playsFor**, **directed**, **influences**, **hasWonPrize**, hasWebsite, **livesIn**, **wasBornIn**, **created**, **diedIn**, **isMarriedTo**, **happenedIn**, **worksAt**, **graduatedFrom**

2 Comparison Experiments

- Comparison of search results for knowledge graphs
  - The results of searching for 'A new Galaxy Series' on Wikidata, and Time-Aware PolarisX



2 Comparison Experiments

- Comparison of NER models
  - Results

GMB	F1-score	CoNLL2003	F1-score	W-NUT 17’	F1-score
CRF [31]	0.46	LUKE	0.94	Arcada [34]	0.399
Bi-LSTM [32]	0.48	ACE	0.936	SJTU-Adapt [35]	0.404
Multi-layer Perceptron	0.60	CNN Large [33]	0.935	SpinningBytes [36]	0.407
BERT	0.67	Biaffine-NER	0.935	UH-RiTUAL [37]	0.418
Our model*	**0.70**	**BERT-Large***	**0.928**	**Our model***	**0.448**

2 Comparison Experiments

- The change of authenticity over time
  - Comparing YAGO3 with time-aware PolarisX-extended YAGO3

Knowledge graph	Year	Examples of entity
YAGO3	2009~2011	Samsung_Galaxy_Spica (2009), Samsung_Galaxy_S (2010), Samsung_Galaxy_Note (2011), ...
	2012~2014	Samsung_Galaxy_S3 (2012), Samsung_Galaxy_S4 (2013), Samsung_Galaxy_Note_4 (2014), ...
	2015~2017.04	Samsung_Galaxy_S6_Edge (2015), Samsung_Galaxy_J5 (2016), Samsung_Galaxy_S8 (2017), ...
Time-Aware PolarisX	2018	Samsung_Galaxy_AR_Emoji (2018), Samsung_Galaxy_S9 (2018), Samsung_Galaxy_Watch (2018), ...
	2019	Samsung_Galaxy_S10 (2019), Samsung_Galaxy_Buds (2019), Samsung_Galaxy_Fold (2019), ...
	2020	Samsung_Galaxy_S20 (2020), Samsung_Galaxy_S20_Plus (2020), Samsung_Galaxy_Z_Flip (2020), ...

PolarisX^2

: Auto-Growing Context-Aware Knowledge Graph

YeonSun Ahn, SoYeop Yoo, and OkRan Jeong

International Journal of Web and Grid Services, Vol. 19, No. 2, pp. 137-155, 2023
https://doi.org/10.1504/ijwgs.2023.131215

1 Introduction

- Limitations of the existing knowledge graphs
  - Most knowledge graphs rarely correspond to numerical information
  - Most relation extraction modules utilized can extract only one relation from one sentence

- We propose PolarisX^2, a Polaris Experienced Expander
  - Utilize type information
  - Perform entity and relation extraction at a 2-stage

1 Motivation

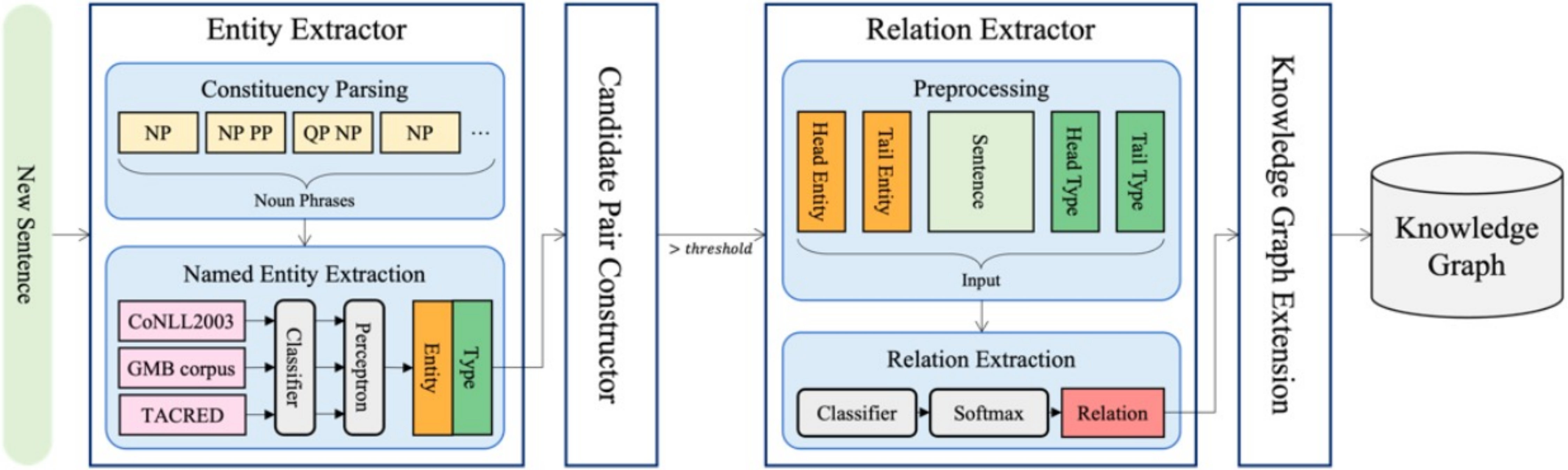
370 million schoolchildren are missing *the free school meals* that they rely on.

- Existing knowledge graph

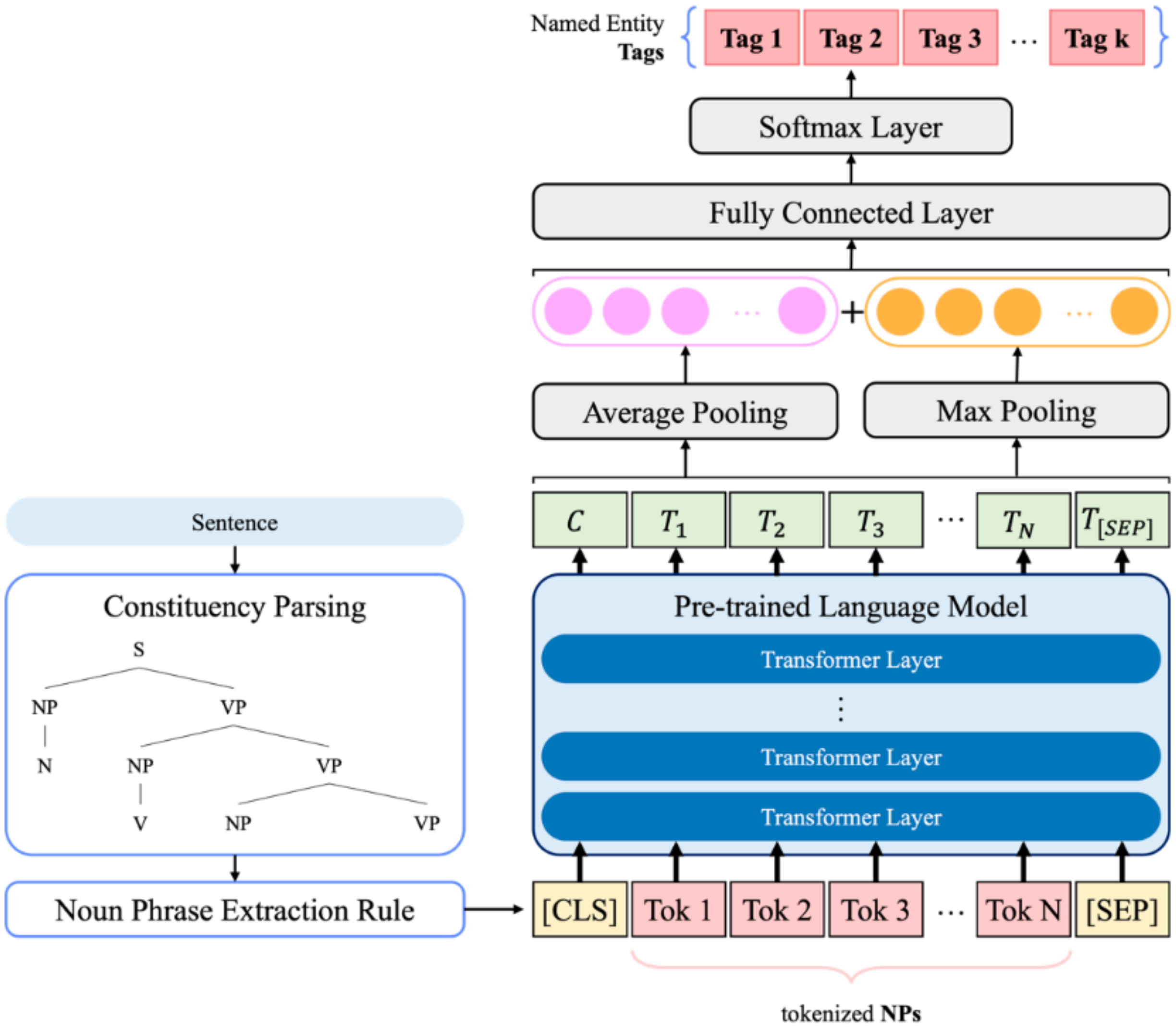
  { schoolchildren, are missing, the free school meals }

  - This knowledge cannot be said to be the correct information, because it is seen as a generalized knowledge that all schoolchildren cannot receive free school meals
  - In addition, knowledge { 370 million schoolchildren, rely on, the free shool meals } also can be extracted

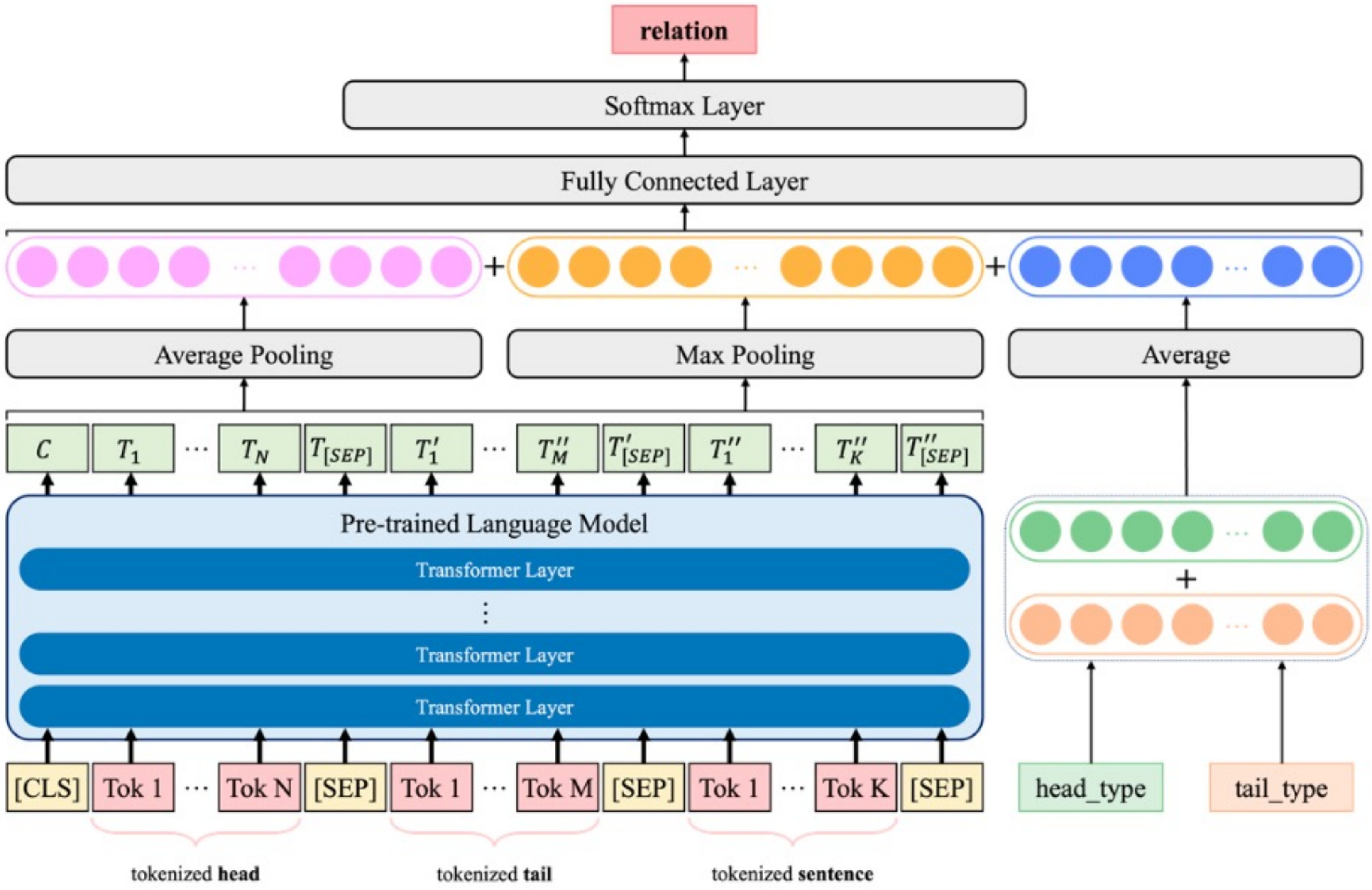
2 Overall Architecture



3 Entity Extraction



5 Relation Extraction



1 Entity Extraction

≻ Datasets

– Statistics

Dataset	*Num. of words*	*Num. of sentences*
CoNLL-2003	302,811	22,137
GMB corpus	1,048,575	47,959
TACRED	3,866,863	106,264

– Named entity tags

Dataset	*Tags*
CoNLL-2003	PER, ORG, LOC, MISC, O
GMP corpus	Art, Per, Tim, Org, Nat, Eve, Geo, Gpe, O
TACRED	ORDINAL, PERSON, ORGANISATION, DURATION, LOCATION, PERCENT, SET, MONEY, DATE, NUMBER, TIME, MISC
Ensemble NER (ours)	Person, organisation, location, time indicator, number, others

1 Entity Extraction

➢ Results

Dataset	*Model*	*F1-score*
CoNLL-2003	ACE + document-context (Wang et al., 2021c)	94.6
	LUKE (Suchanek et al., 2007)	94.3
	Cross-sentence context (Luoma and Pyysalo, 2020)	93.7
	Ours	*95.1*
GMB corpus	BERT-base	67.0
	CRF	710
	Bi-LSTM + CRF	79.3
	Ours	*84.8*
TACRED	*Ours*	*94.0*

2 Relation Extraction

➢ Results

Model	*Precision*	*Recall*	*F1-score*
PA-LSTM (Zhang et al., 2017)	65.7	64.5	65.1
C-GCN + PA-LSTM (Zhang et al., 2018)	71.3	65.4	68.2
BERTEM + MTB (Soares et al., 2019)	-	-	71.5
KEPLER (Wang et al., 2021b)	70.4	73.0	71.7
K-Adapter (Wang et al., 2021a)	68.9	75.4	72.0
DeNERT-KG (Yang et al., 2020)	*71.8*	73.1	72.4
LUKE (Suchanek et al., 2007)	70.4	75.1	72.7
PolarisX^2 (our ensemble)	70.2	*75.5*	*72.8*

PolarisX-Bot

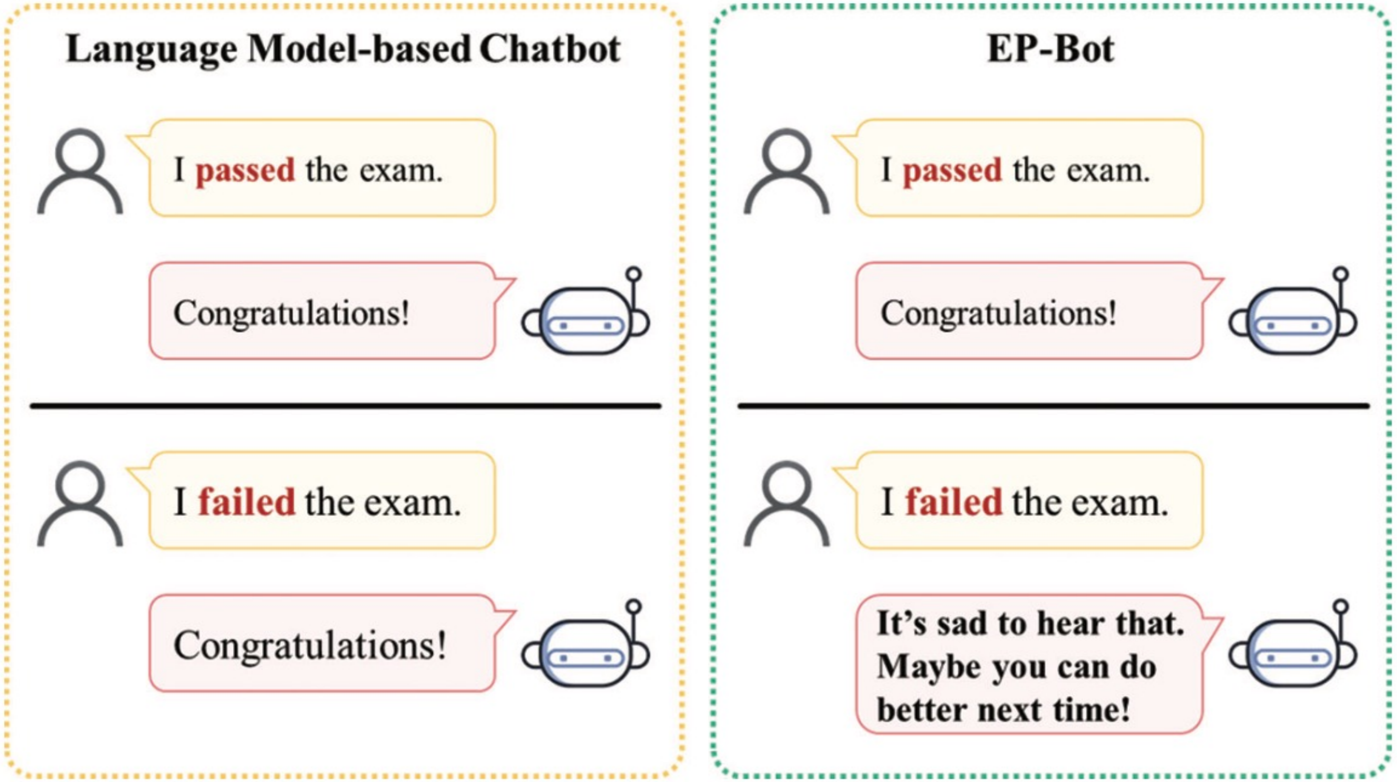
: EP-Bot: Empathetic Chatbot Using Auto-Growing Knowledge Graph

SoYeop Yoo, and OkRan Jeong

Computers, Materials & Continua, Vol. 67, No. 3, pp. 2807-2817, 2021
https://doi.org/10.32604/cmc.2021.015634

1 Introduction

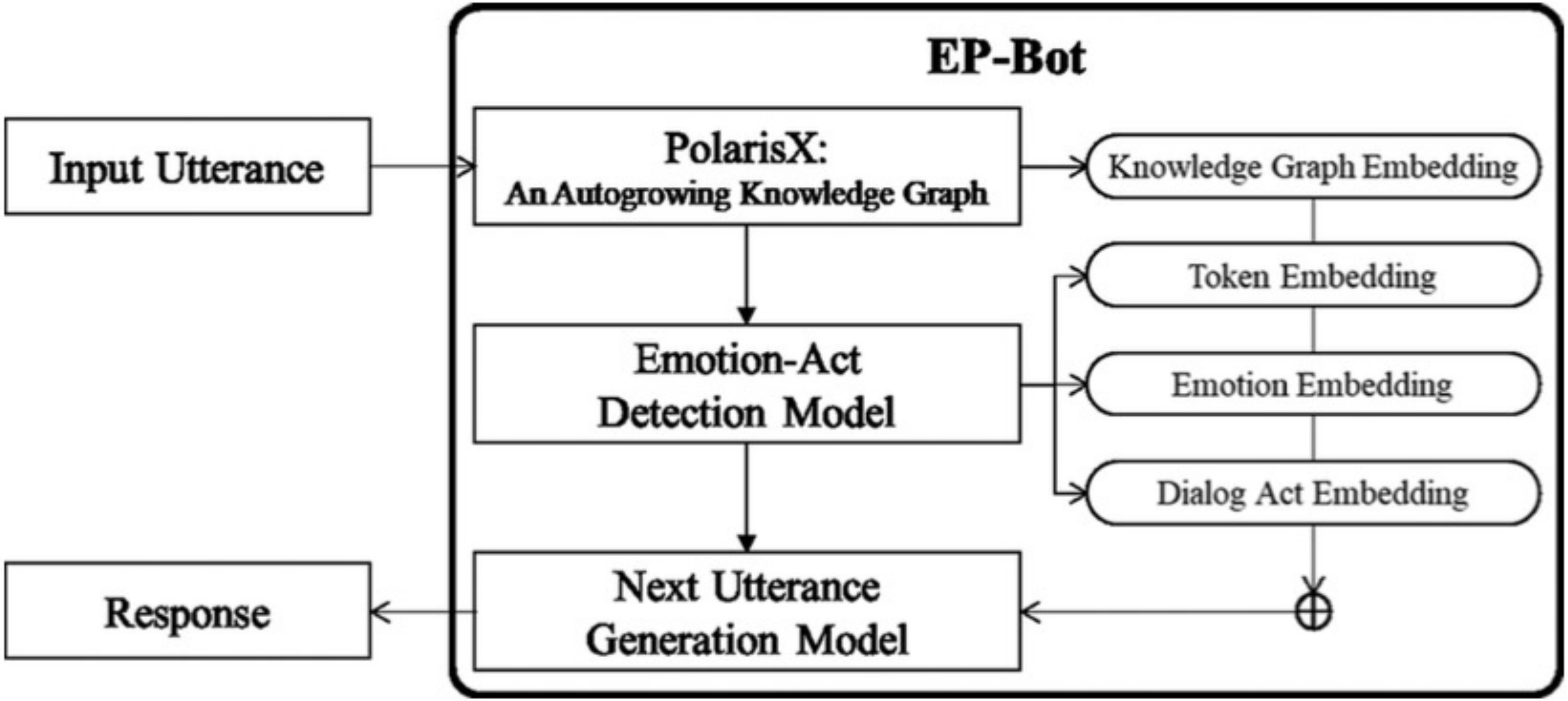
- Conversation
  - It is not just for information acquisition but also has various meanings, such as emotional exchange and interaction
- Motivating example



1 PolarisX-Bot

- EP-Bot
  - An emotion-based chatbot that enables both information acquisition and daily conversation
  - We use PolarisX, an automatically extended knowledge graph, to provide information and generate appropriate answers

2 Overall Structure



3 Emotion-Act Detection Model using PolarisX

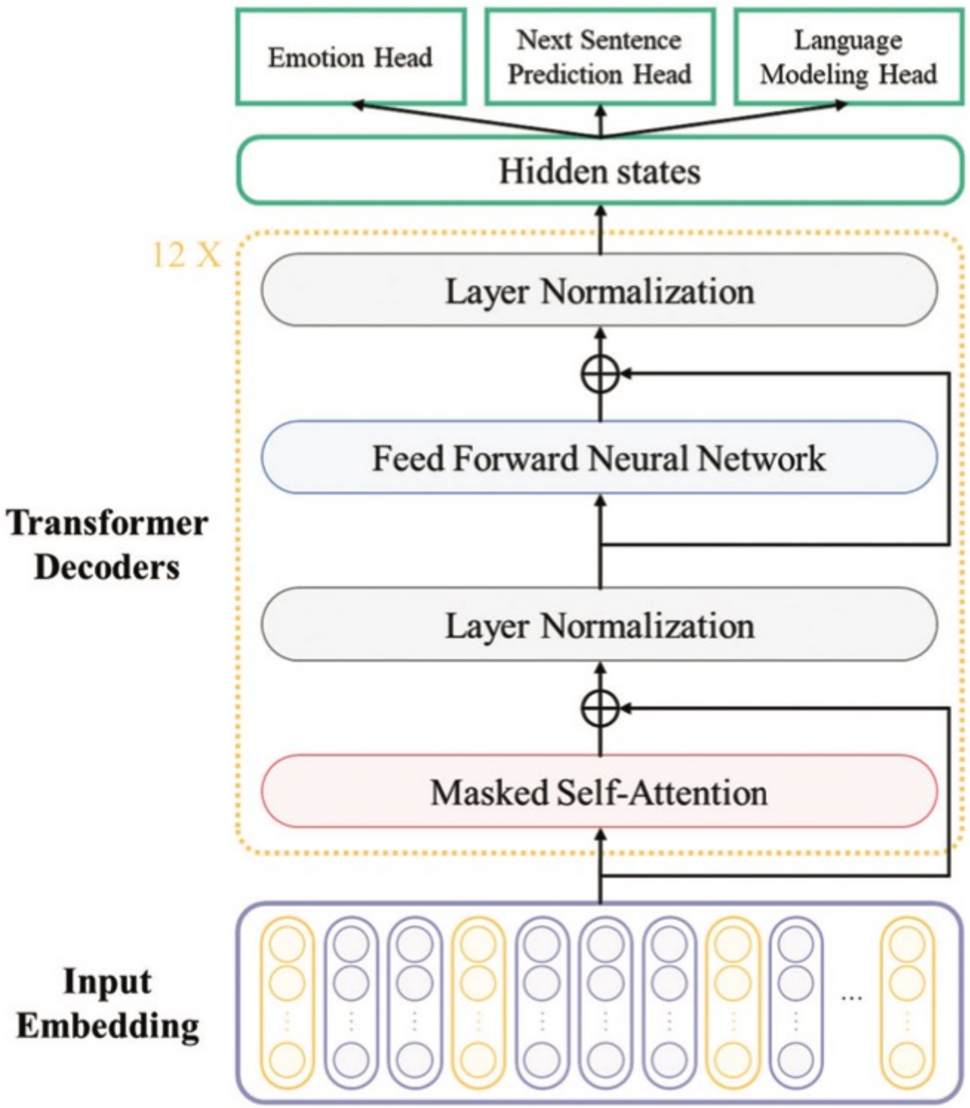
- Information extraction
  - Information about relationships with entities in sentences
  - Dialogue action information to respond to a person's intentions
  - Emotion information to help identify a person's emotions
- Input representation
  - Used in the emotion-act detection model
  - ALBERT model is utilized

Input Utterance	[CLS]	I	am	worried	about	something	[SEP]	What	is	that	[SEP]
KG Embedding	E_{UNK}	E_{I}	E_{am}	E_{worry}	E_{about}	$E_{something}$	E_{UNK}	E_{what}	E_{is}	E_{that}	E_{UNK}
Emotion Embedding	E_{UNK}	E_{fear}	E_{fear}	E_{fear}	E_{fear}	E_{fear}	E_{UNK}	E_{happy}	E_{happy}	E_{happy}	E_{UNK}
Dialog Act Embedding	E_{UNK}	E_{inform}	E_{inform}	E_{inform}	E_{inform}	E_{inform}	E_{UNK}	$E_{question}$	$E_{question}$	$E_{question}$	E_{UNK}
Token Embedding	E_{UNK}	E_{I}	E_{am}	$E_{worried}$	E_{about}	$E_{something}$	E_{UNK}	E_{what}	E_{is}	E_{that}	E_{UNK}

PolarisX-Bot

3 Next Utterance Generation Model

- Model
  - GPT-based model to generate the next sentence
  - Input embedding uses
    - knowledge graphs
    - emotions
    - dialog act
    - token embedding



1 Environment and Dataset

- Environment
  - Ubuntu 18.04
  - AMD Ryzen Threadripper 1940X 16-Core processor
  - NVIDIA GeForce RTX 2080 SUPER
- Dataset
  - DailyDialog
    - 13,118 multi-turn conversations (2~7 turns) by two speakers
    - Each turn contains the utterance, emotion, and act data

2 Evaluation of Emotion-Act Detection Model

≻ Results

Model	Emotion-F1	Act-F1	Average-F1
Baseline			
Electra-small	83.12	82.95	83.03
BERT-base	83.44	82.48	82.96
ALBERT-base	83.42	82.70	83.06
With KG Embedding			
Electra-small	83.51	84.07	83.79
BERT-base	84.09	84.04	84.06
ALBERT-base	**85.64**	**84.65**	**85.14**

3 Evaluation of Next Utterance Generation Model

≻ Results

Model	Hit@1	PPL	F1	BLEU
Models without emotion				
Seq2Seq + Attention	9.41	129.3	10.22	5.58
Transformer ranker	17.20	–	26.37	15.79
OpenAI GPT without emotion	75.01	10.19	18.2	3.755
Models with emotion				
EmpTransfo	77.25	10.63	19.39	3.99
EmpTransfo + action + topic	78.47	9.04	17.27	2.45
EP-bot without KG, act	71.49	9.90	14.43	3.70
EP-bot	**78.69**	**8.22**	**18.52**	**4.23**

Chapter 4.

Post-PolarisX

MDCKE

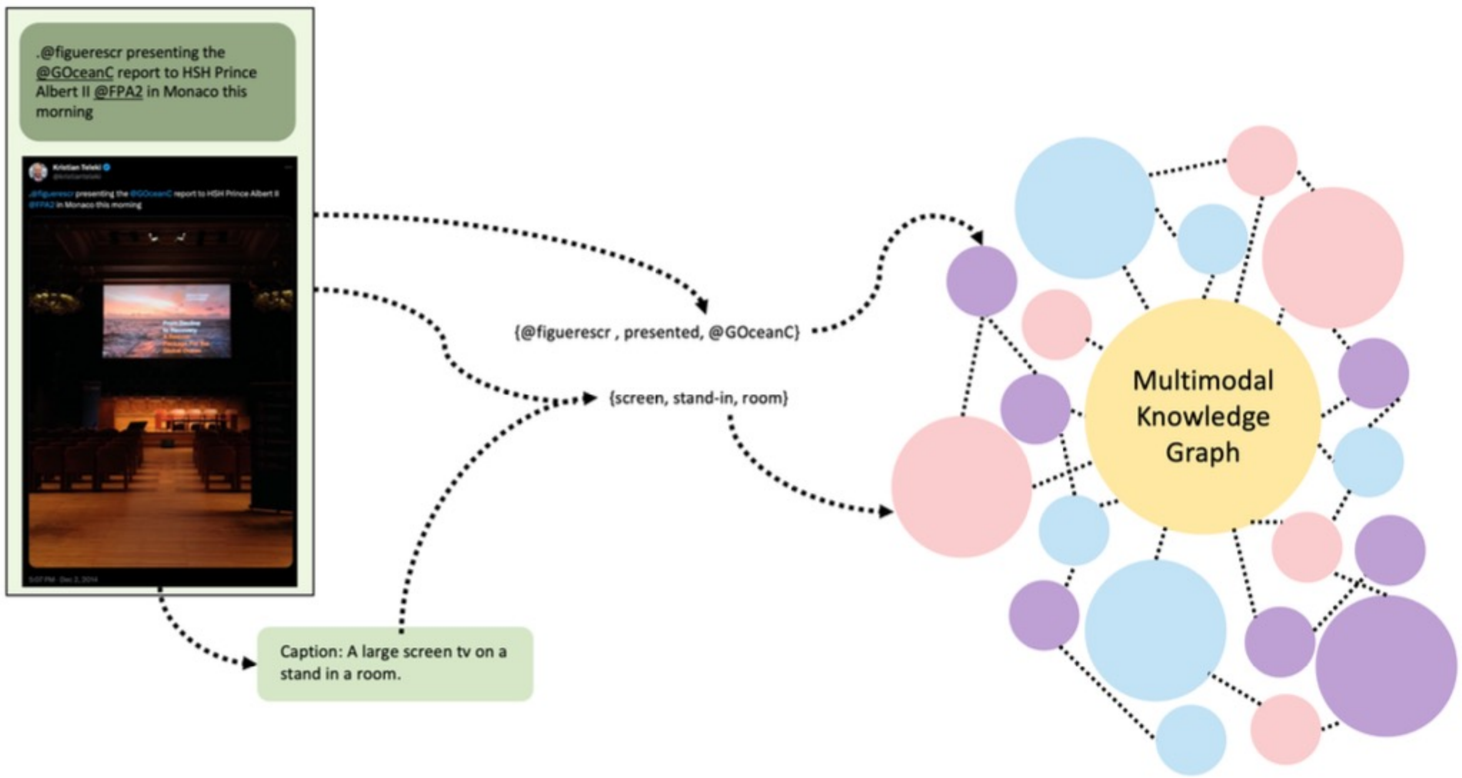
: A multimodal deep-context knowledge extractor that integrates contextual information

Hyojin Ko, Joon Yoo, and OkRan Jeong

Alexandria Engineering Journal (Under Review)

1 Introduction

- Numerous knowledge graphs
  - Constructed by associating image and text data extracted from disparate sources
  - BUT, show insufficient triplets, constrained to the entities and relations within the sentence
- Motivating example



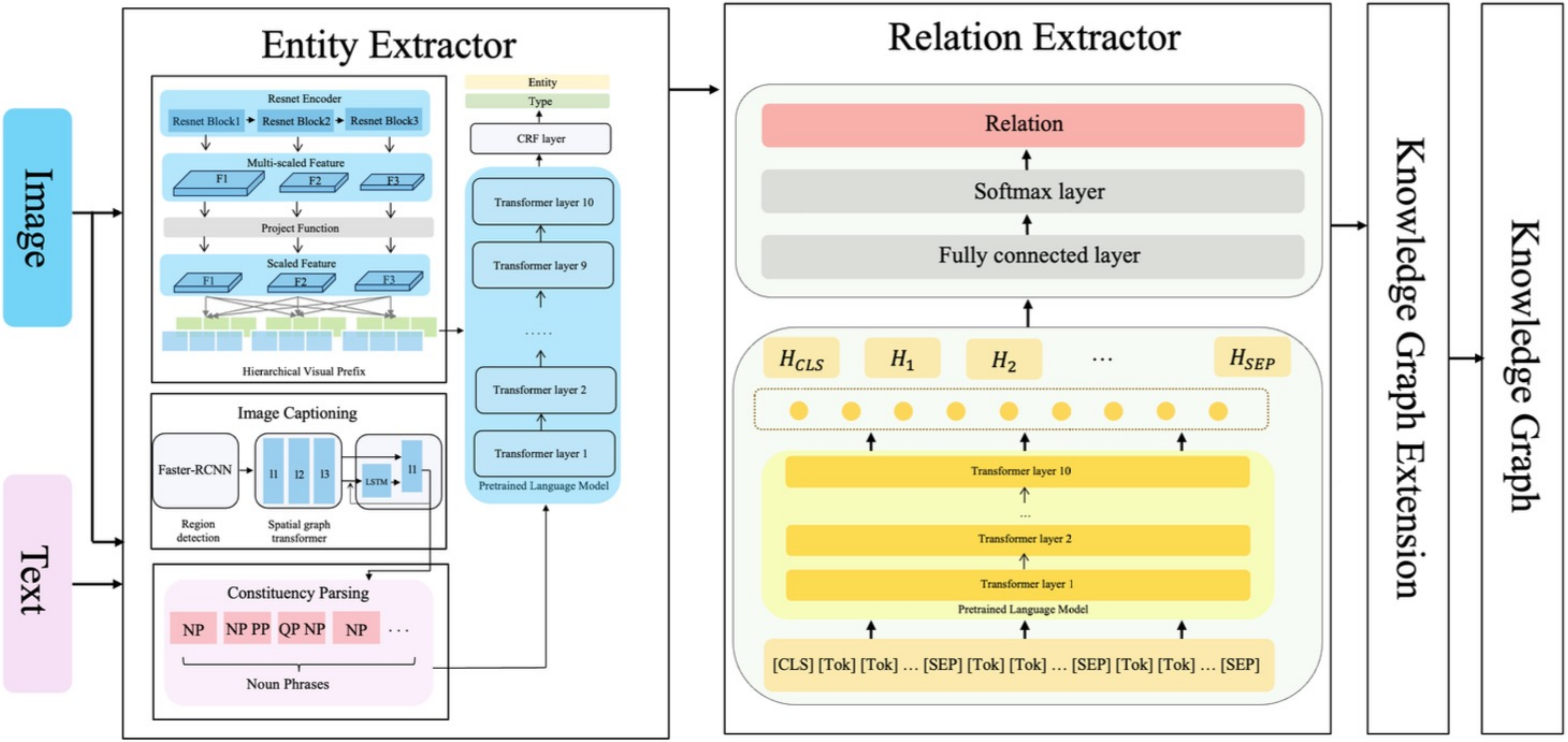
1 Proposed Methods

- MDCKE
  - Multimodal Deep-Context Knowledge Extractor

- Main contributions
  - Two-stage information extraction module is introduced that adapts its processing approach based on the presence of other data types
  - Image information is recontextualized by fully integrating image context information
  - By fusing generated image captions as additional semantic information along with image-text features from the original data and treating them as visual connections

MDCKE

2 Overall Structure



1 Datasets

- Datasets
  - MSCOCO
    - → Image captioning dataset for pretraining the captioning model
  - CoNLL, GMB
    - → Datasets for pretraining the language model, BERT
  - Twitter2015
    - → Experiment dataset for the NER task
  - MNRE
    - → Experiment dataset for the RE task

2 Results

- Utility of deep contextual information
  - NER results on the Twitter2015 dataset with/without annotation

	Twitter2015			Twitter2015+Caption		
	Precision	**Recall**	**F1**	**Precision**	**Recall**	**F1**
LOC	74.45	91.57	89.41	92.23	91.69	**91.88**
MISC	44.86	64.45	52.90	45.44	49.89	47.56
ORG	76.68	77.46	79.16	77.75	94.37	**85.25**
PER	80.60	90.11	84.03	85.92	87.86	**86.91**

  - Top 5 classes of RE result on the MNRE dataset with/without annotation

Top@5 classes	MNRE			Top@5 classes	MNRE+Caption		
	Precision	**Recall**	**F1**		**Precision**	**Recall**	**F1**
/loc/loc/contain	88.76	91.15	89.94	/per/misc/present_in	89.98	91.47	**90.72**
/per/per/peer	82.37	81.63	81.99	/per/per/peer	83.35	94.92	**88.76**
/per/misc/present_in	80.90	82.19	81.54	/per/org/member_of	89.77	87.27	88.49
/per/misc/nationality	81.43	79.36	80.37	/misc/misc/part_of	83.99	80.37	82.13
/per/misc/awarded	81.62	78.44	80.00	/loc/loc/contain	81.17	81.07	81.11

2 Results

- Comparison results
  - On the Twitter2015 and MNRE dataset results

Modality	Model	Twitter2015			MNRE		
		Precision	Recall	F1	Precision	Recall	F1
Text	**BiLSTM+CRF+CNN**[59]	60.89	66.08	63.38	-	-	-
	ELMo+CRF[60]	65.33	65.11	65.22	-	-	-
	BERT+CRF[61]	70.74	67.23	68.39	-	-	-
	PCNN[62]	-	-	-	60.88	58.68	58.24
	MTB[63]	-	-	-	59.92	59.60	59.76
Text+Image	**RpBERT-BiLSTM-CRF**[11]	70.03	69.93	69.87	-	-	-
	MoRE[65]	-	-	-	65.64	69.09	67.21
	VisualBERT[67]	95.42	58.33	72.39	59.10	63.38	61.20
	MEGA[66]	70.33	74.76	72.48	69.22	65.52	59.86
	HVPNeT[41]	71.67	71.73	76.29	88.90	83.36	82.93
	Ours	75.35	81.71	**78.31**	85.32	86.53	**86.02**

Modality	Model	Twitter2015			MNRE		
		Precision	Recall	F1	Precision	Recall	F1
Text w.Caption	BiLSTM+CRF+CNN[59]	65.82	68.89	67.21	-	-	-
	ELMo+CRF[60]	69.14	70.31	69.61	-	-	-
	BERT+CRF[61]	73.66	70.03	**71.69**	-	-	-
	PCNN[62]	-	-	-	64.48	63.41	**63.94**
	MTB[63]	-	-	-	62.76	62.80	62.78
Text+Image w.Caption	RpBERT-BiLSTM-CRF[11]	67.70	66.75	67.22	-	-	-
	MoRE[65]	-	-	-	66.80	63.48	65.09
	VisualBERT[67]	70.78	74.35	72.51	60.06	69.84	64.58
	MEGA[66]	76.96	75.26	76.09	62.28	60.78	61.41
	HVPNeT[41]	80.32	81.79	78.66	89.41	87.19	**88.30**
	Ours	80.32	84.67	**82.44**	89.04	77.19	83.02

PolarisX for Healthcare

Ongoing Project

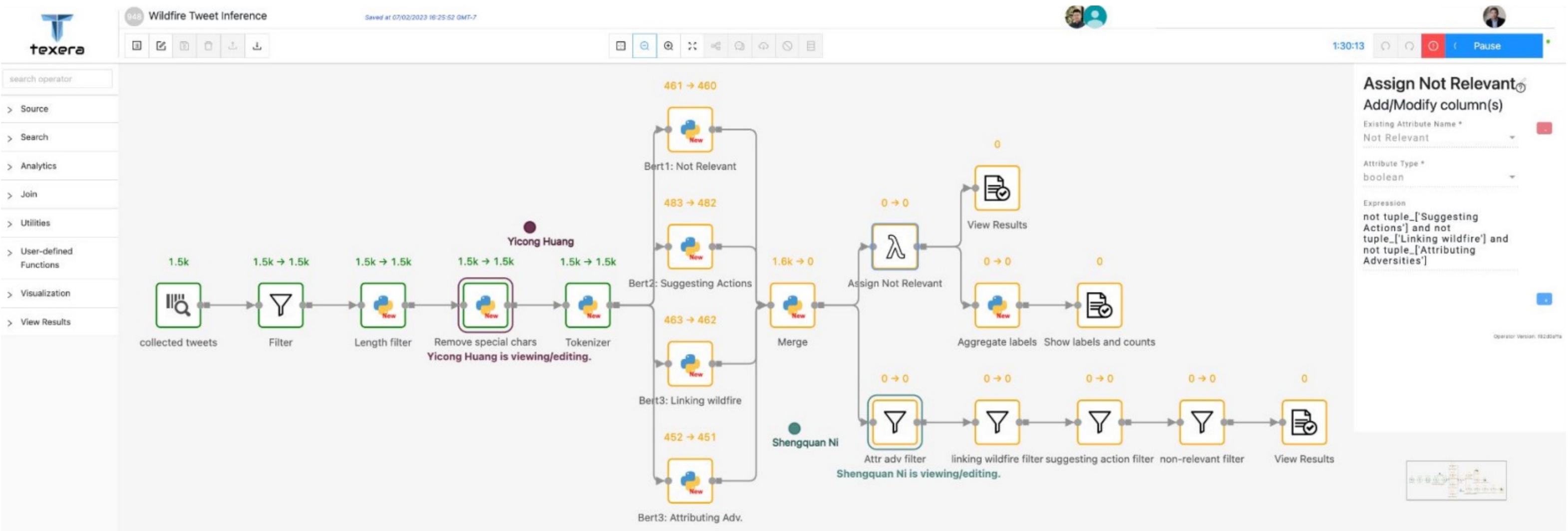
1 Motivation

- Characteristics to consider for applying AI in healthcare
  - Be able to handle multimodal data
  - Need to process large amounts of data quickly and efficiently
  - Should product explainable and reliable results
  - Collaborate with non-IT experts (ex. doctors, nurses, and so on)

2 TEXERA

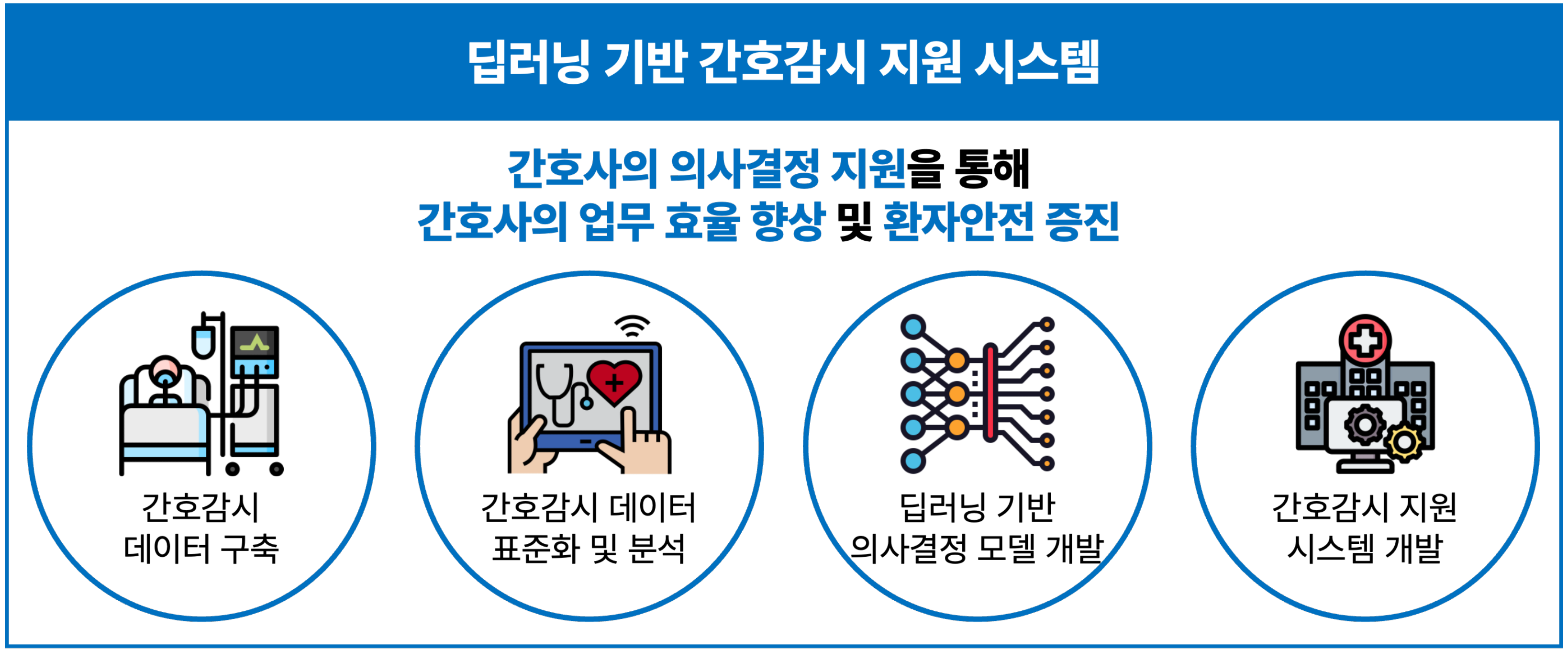
- UCI ISG AsterixDB Project
- Support scalable computation and enable advanced AI/ML techniques
- Goals
  - Provide data analytics as cloud services
  - Provide a browser-based GUI to form a workflow without writing code
  - Allow non-IT people to do data analytics
  - Support collaborative data analytics
  - Allow users to interact with the execution of a job
  - Support huge volumes of data efficiently

texera



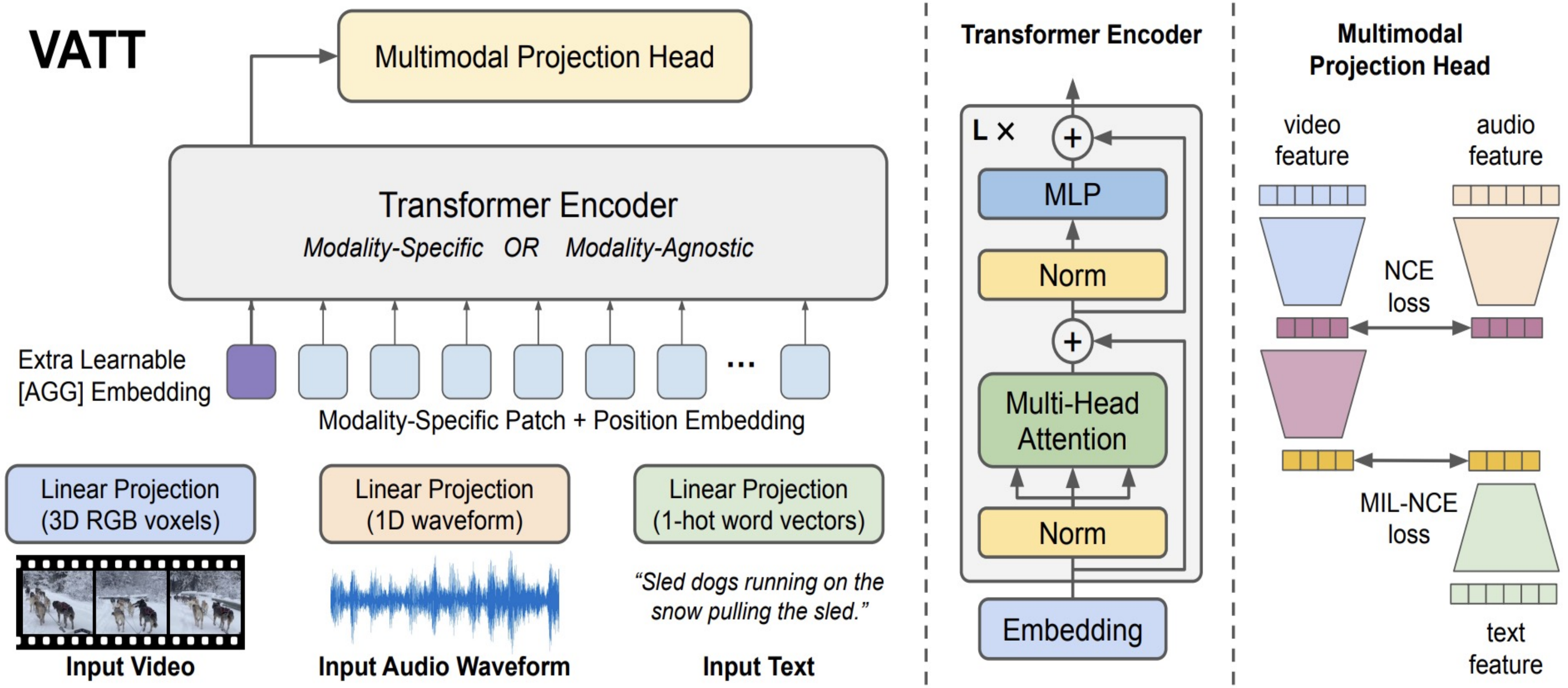
1 Nursing Surveillance Decision-making System

- Deep learning-based nursing surveillance decision-making system



2 VATT Model

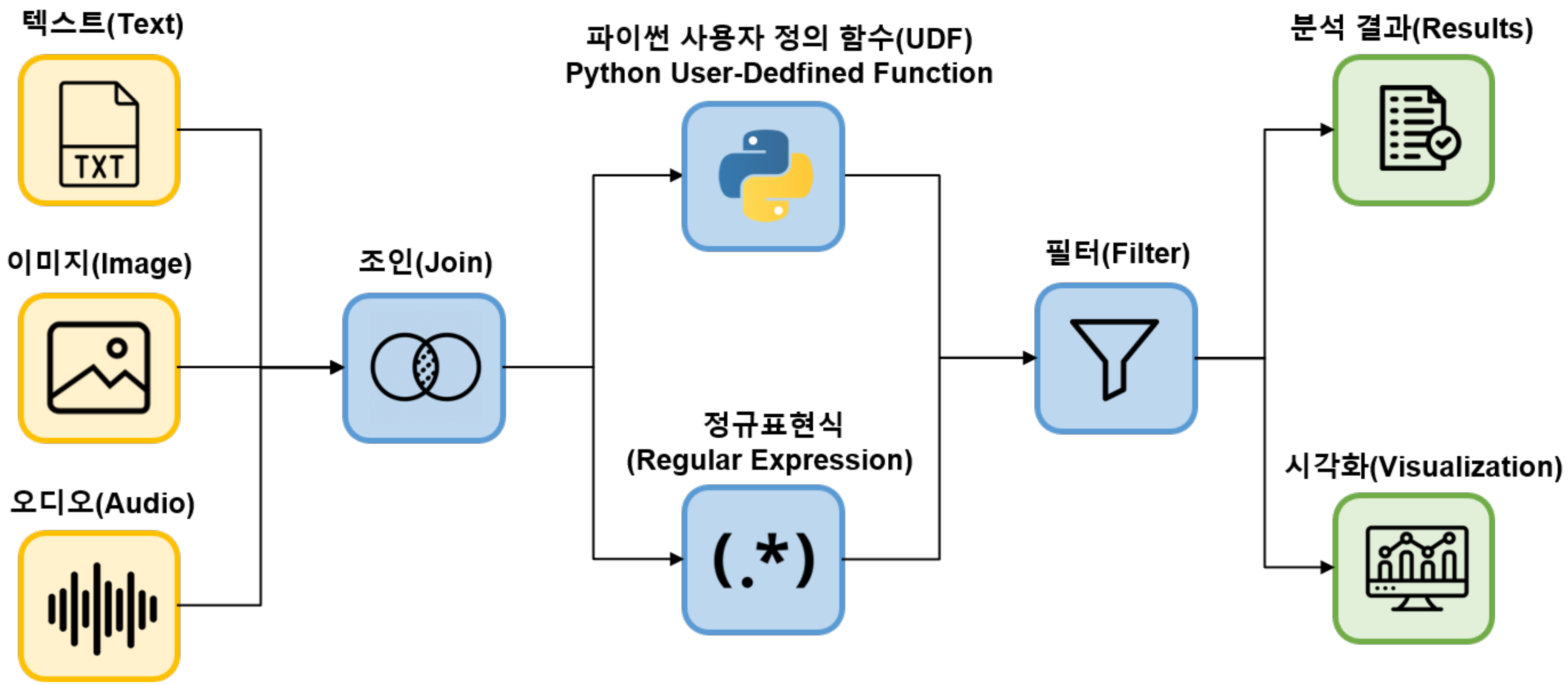
- Baseline model for multimodal data processing by learning nursing surveillance data that contains a combination of number and natural language



VATT: Transformers for Multimodal Self-Supervise Learning for Raw Video, Audio and Text, 35th NIPS, 2021 (Hassan Akbari, et al.)

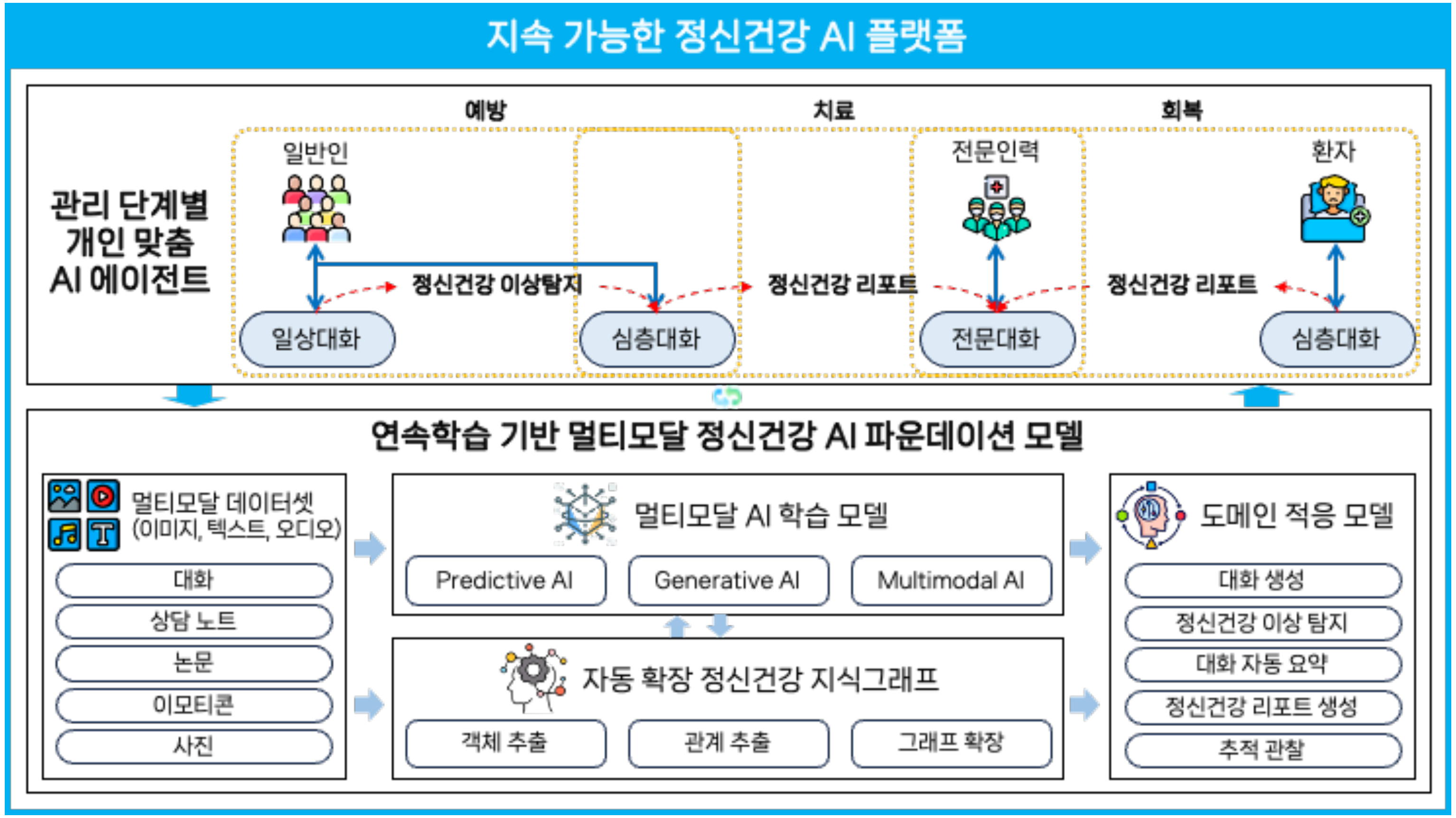
1 Mental Health AI Analytics System

- Multimodal AI analytics system for mental health based on Texera



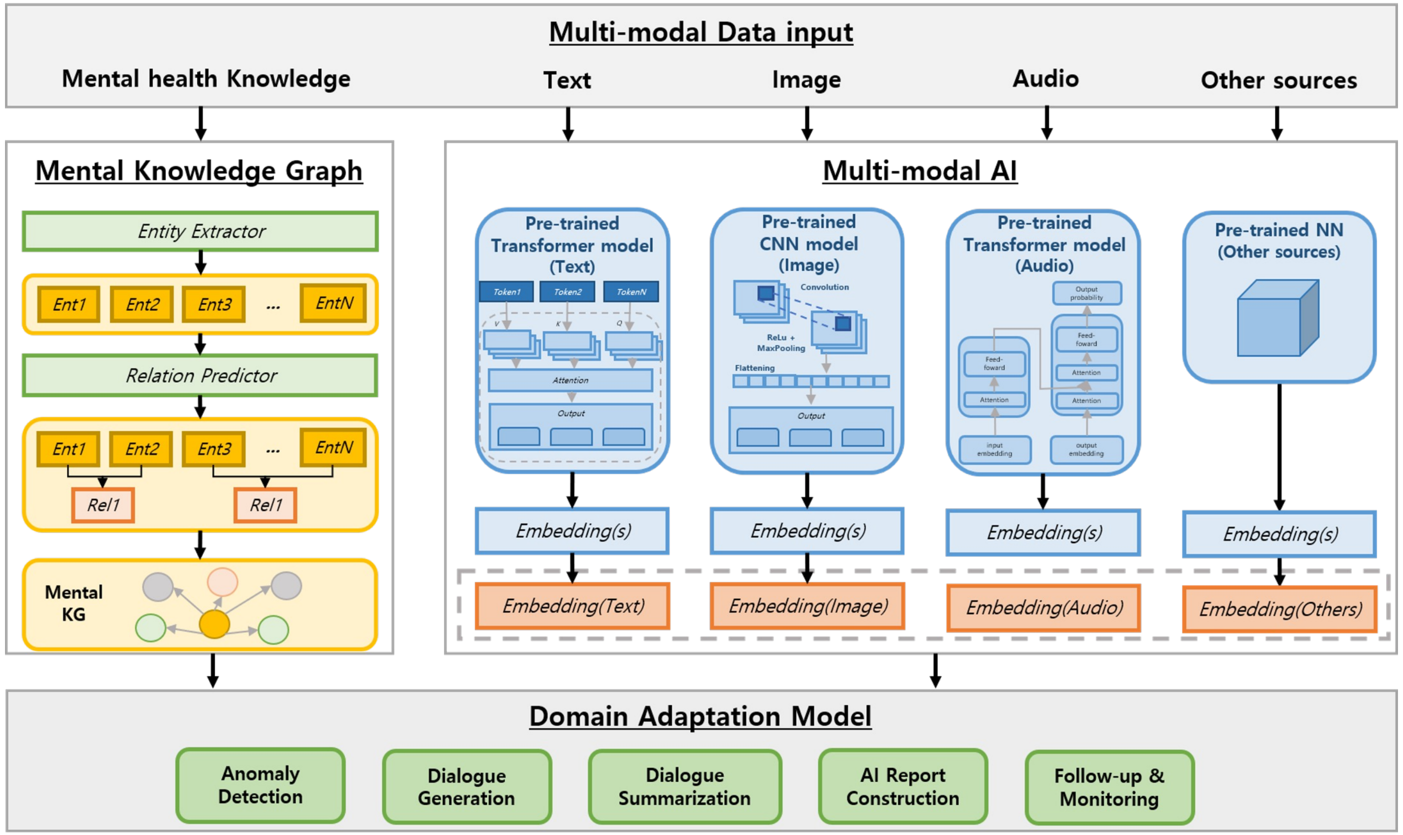
2 Mental Health AI Platform

- Multimodal AI platform based on continual learning to support all stages of mental healthcare



3 Mental Health AI Foundation Model

- Auto-growing mental knowledge graph
  + Multi-modal AI learning model
  + Domain adaptation model



THANK YOU

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2024.03