Singapore Symposium on Sentiment Analysis

9th March 2023
NTU LT2A

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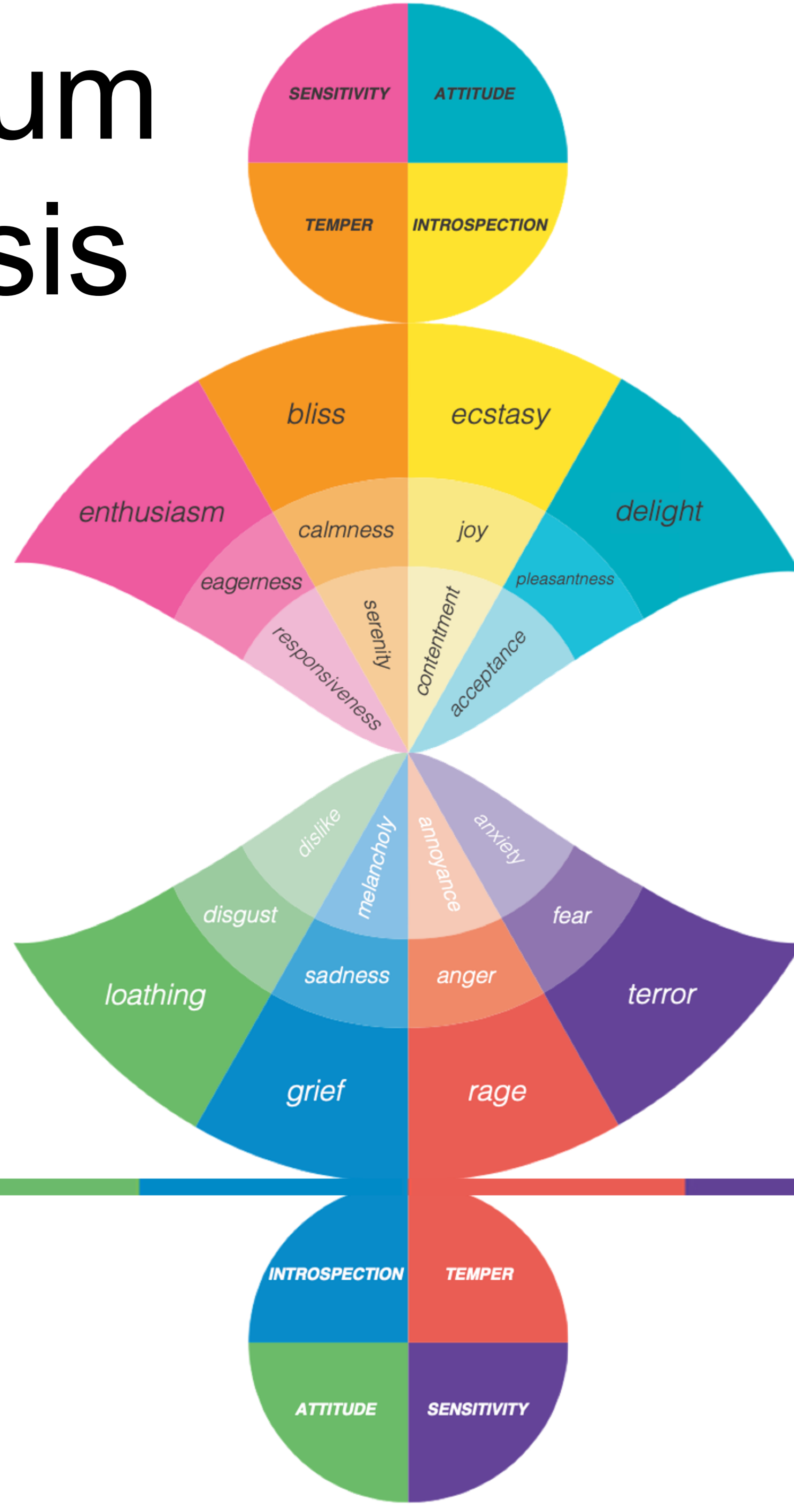
YouTube: youtube.com/@senticnet



Erik Cambria, PhD, FIEEE
Associate Professor & Provost Chair
School of Computer Science & Engineering
Nanyang Technological University, Singapore

S3A

is a national forum for Singapore-based researchers working in the field of sentiment analysis and related topics to share information on their latest investigations and their applications both in academic research areas and industrial sectors

S3A local speakers

GRAPHENE

SIT SINGAPORE INSTITUTE OF TECHNOLOGY

SUSS SINGAPORE UNIVERSITY OF SOCIAL SCIENCES

KRAKATOA TECHNOLOGIES

NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE

Alibaba Group

DBS

SUTD SINGAPORE UNIVERSITY OF TECHNOLOGY AND DESIGN

SMU SINGAPORE MANAGEMENT UNIVERSITY

Agency for Science, Technology and Research SINGAPORE

NUS National University of Singapore

Continental

AI SINGAPORE

S3A intl speakers

Francis
Bond
S3A 2013

Amit
Sheth
S3A 2015

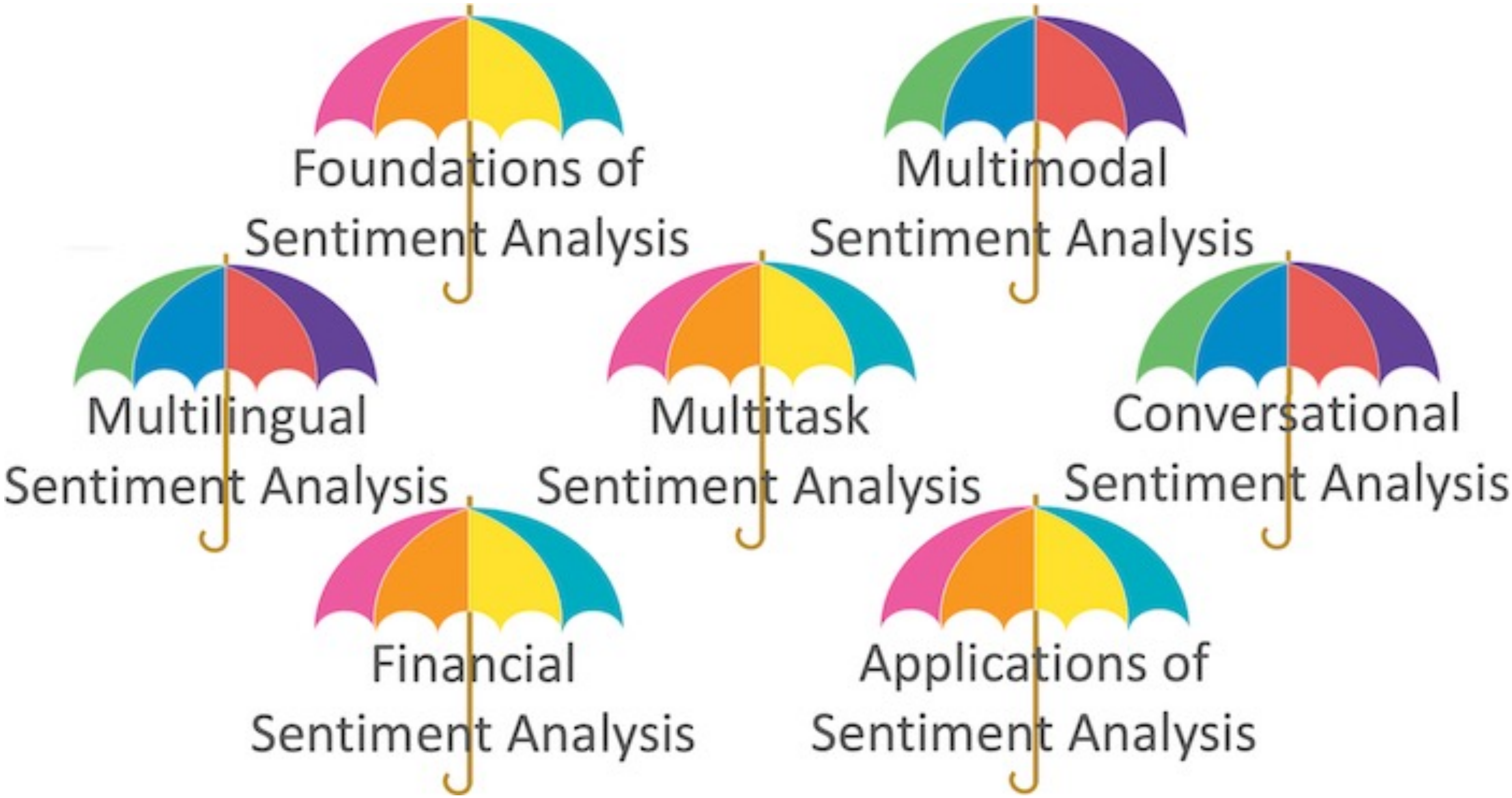
Andrew
Ortony
S3A 2017

Mike
Thelwall
S3A 2019

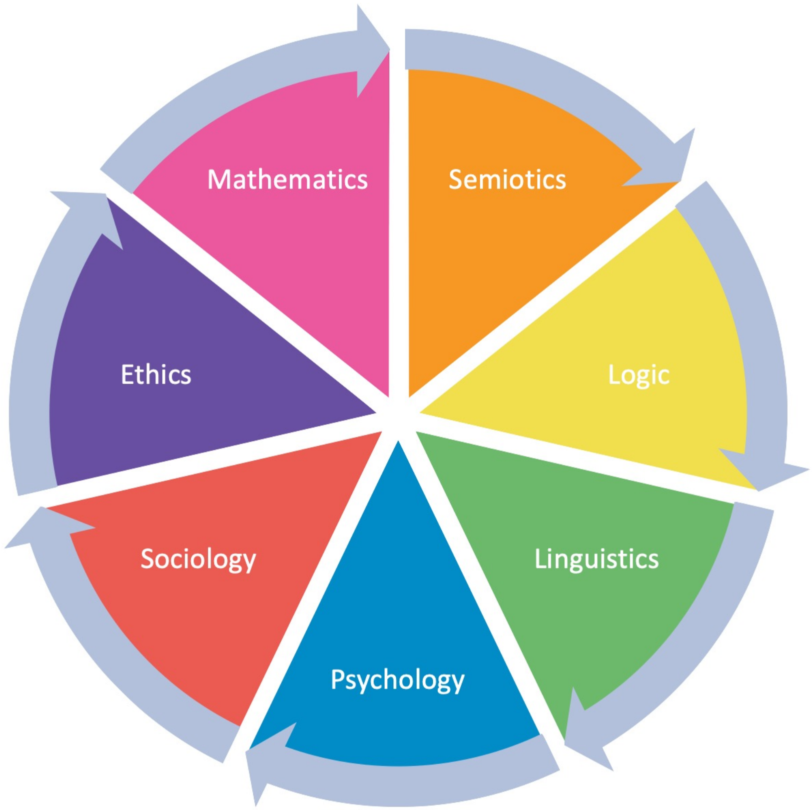
Fabrizio
Sebastiani
S3A 2021

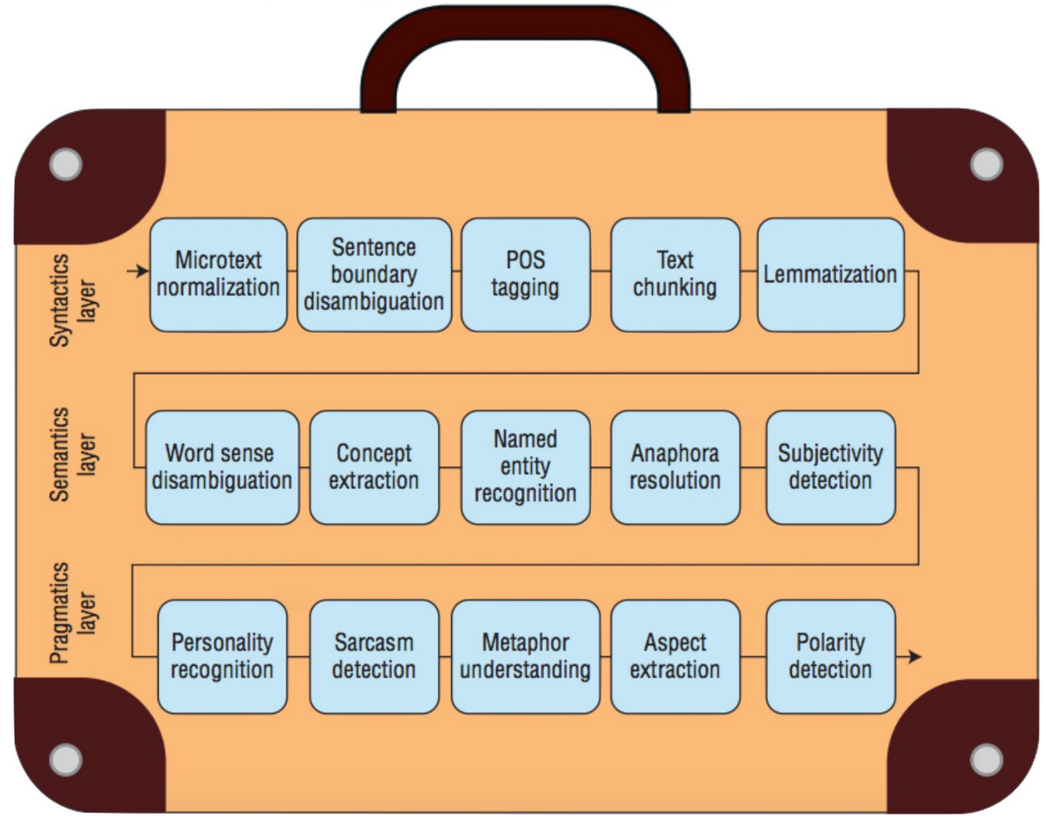
Björn
Schuller
S3A 2023

S3A umbrellas



Before/after SA

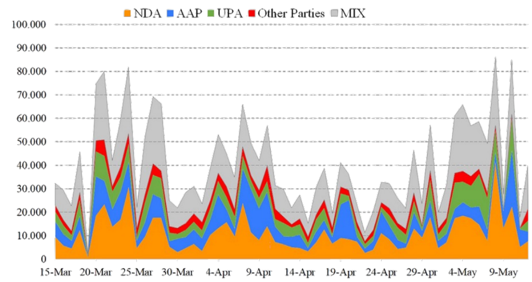


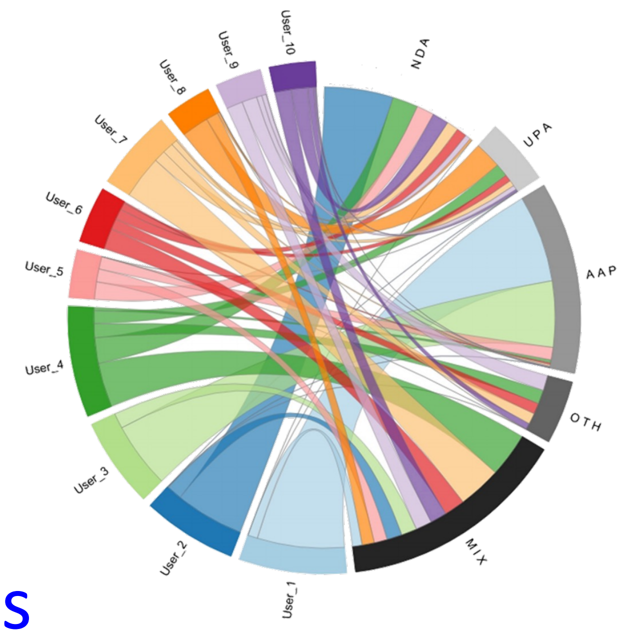


Sentic projects

At SenticNet, we are working on several projects spanning from fundamental affective computing research to the application of sentiment analysis techniques to domains like finance, healthcare, and the arts. Some of the main current projects include:

- Sentic Computing for Human-Computer Interaction
- Sentic Computing for Social Media Monitoring
- Sentic Computing for Business Intelligence
- Sentic Computing for Social Good
- Sentic Computing for Healthcare
- Sentic Computing for Finance
- Sentic Computing for the Arts





https://sentic.net/projects

Sentic computing section

If you use any sentic algorithm or resource, consider submitting to this new Collection of Cognitive Computation (impact factor 4.890)

https://sentic.net/scs.pdf

SENTIRE

The world's premier research conference in Data Mining

Submit to ICDM + SENTIRE by 1st July 2023
or just SENTIRE by 3rd September 2023

https://sentic.net/sentire

S3A 2023

10

year anniversary

speakers

minutes

Aspect-Based Sentiment Analysis

A Survey on ABSA: Tasks, Methods, and Challenges

Wenxuan Zhang

Language Technology Lab, Alibaba DAMO Academy

Mar 9 2023 @ S3A

A Survey on Aspect-Based Sentiment Analysis: Tasks, Methods, and Challenges

Wenxuan Zhang, Xin Li, Yang Deng, Lidong Bing, and Wai Lam

Abstract—As an important fine-grained sentiment analysis problem, aspect-based sentiment analysis (ABSA), aiming to analyze and understand people's opinions at the aspect level, has been attracting considerable interest in the last decade. To handle ABSA in different scenarios, various tasks have been introduced for analyzing different sentiment elements and their relations, including the aspect term, aspect category, opinion term, and sentiment polarity. Unlike early ABSA works focusing on a single sentiment element, many compound ABSA tasks involving multiple elements have been studied in recent years for capturing more complete aspect-level sentiment information. However, a systematic review of various ABSA tasks and their corresponding solutions is still lacking, which we aim to fill in this survey. More specifically, we provide a new taxonomy for ABSA which organizes existing studies from the axes of concerned sentiment elements, with an emphasis on recent advances of compound ABSA tasks. From the perspective of solutions, we summarize the utilization of pre-trained language models for ABSA, which improved the performance of ABSA to a new stage. Besides, techniques for building more practical ABSA systems in cross-domain/lingual scenarios are discussed. Finally, we review some emerging topics and discuss some open challenges to outlook potential future directions of ABSA.

* Based on our recent survey paper: **A Survey on Aspect-Based Sentiment Analysis: Tasks, Methods, and Challenges (TKDE 2023)**

Outline (in the survey paper)

- ABSA: What is it and Why we care about it?
- ABSA Problem
  - Four key sentiment elements
  - Single ABSA Task
  - Compound ABSA Task
- PLMs for ABSA
- Transferable ABSA
  - Cross-domain ABSA
  - Cross-lingual ABSA
- Challenges and Future Directions

arXiv version

TKDE early access

Outline for Today

- ❏ ABSA: What is it and Why we care about it?
- ❏ ABSA Problem
  - ❏ Four key sentiment elements
  - ❏ Single ABSA Task
  - ❏ Compound ABSA Task
- ❏ PLMs for ABSA
- ❏ Transferable ABSA
  - ❏ Cross-domain ABSA
  - ❏ Cross-lingual ABSA
- ❏ Challenges and Future Directions

Outline for Today

- ❑ **ABSA: What is it and Why we care about it?**
- ❑ ABSA Problem
  - ❑ Four key sentiment elements
  - ❑ Single ABSA Task
  - ❑ Compound ABSA Task
- ❑ PLMs for ABSA
- ❑ Transferable ABSA
  - ❑ Cross-domain ABSA
  - ❑ Cross-lingual ABSA
- ❑ Challenges and Future Directions

What is Aspect-based Sentiment Analysis?

- Conventional SA studies are usually conducted at the document or sentence level

"The pizza is delicious." → *positive*

What is Aspect-based Sentiment Analysis?

- ❏ Conventional SA studies are usually conducted at the document or sentence level
- ❏ In practice, users often express (possibly different) opinions towards different aspects of the concerned target (e.g., a product)

"The pizza is delicious." → *positive*

"The pizza is delicious, but the service here is just a disaster" → *?*

What is Aspect-based Sentiment Analysis?

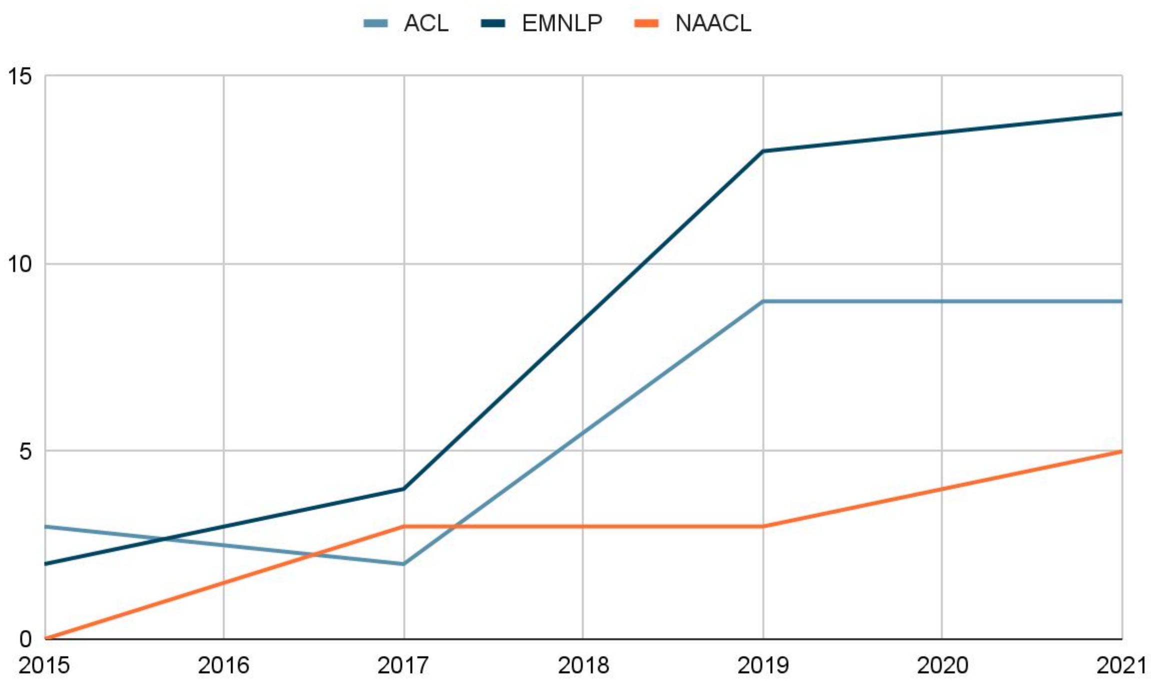
- Aspect-Based Sentiment Analysis (ABSA) aims at mining fine-grained opinion information at the aspect level

"The pizza is delicious." → *positive*

"The pizza is delicious, but the service here is just a disaster" → *?*

What are the mentioned aspects?
What are the sentiments respectively?
...

ABSA attracts lots of research attention in recent years!



* Valid papers are found by using "aspect" as a query to search in the ACL Anthology (may have missing papers!)
* Only count 2015, 2017, 2019, 2021 (because counting is time-consuming)
* NAACL2017 -> NAACL2018

Outline for Today

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- **ABSA Problem**
  - **Four key sentiment elements**
  - Single ABSA Task
  - Compound ABSA Task
- PLMs for ABSA
- Transferable ABSA
  - Cross-domain ABSA
  - Cross-lingual ABSA
- Challenges and Future Directions

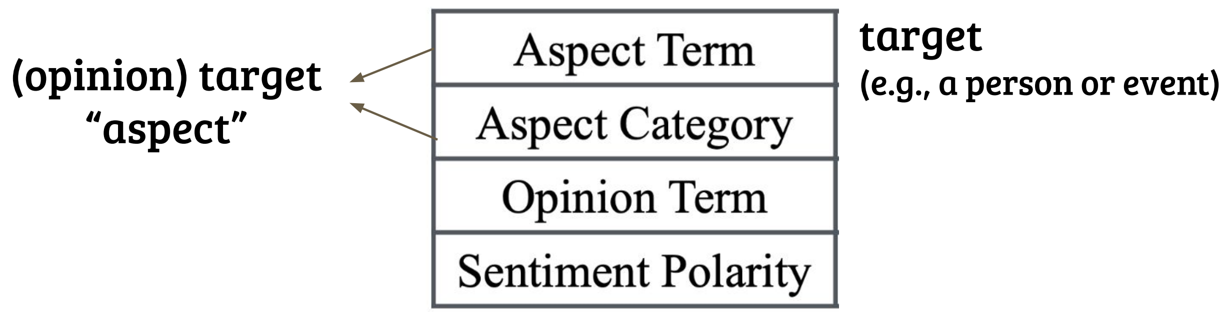
ABSA: Four Key Sentiment Elements

- In general, there are four key sentiment elements involved in ABSA

Aspect Term
Aspect Category
Opinion Term
Sentiment Polarity

ABSA: subtleties of the terminology

- In general, there are four key sentiment elements involved in ABSA



ABSA: Four Key Sentiment Elements

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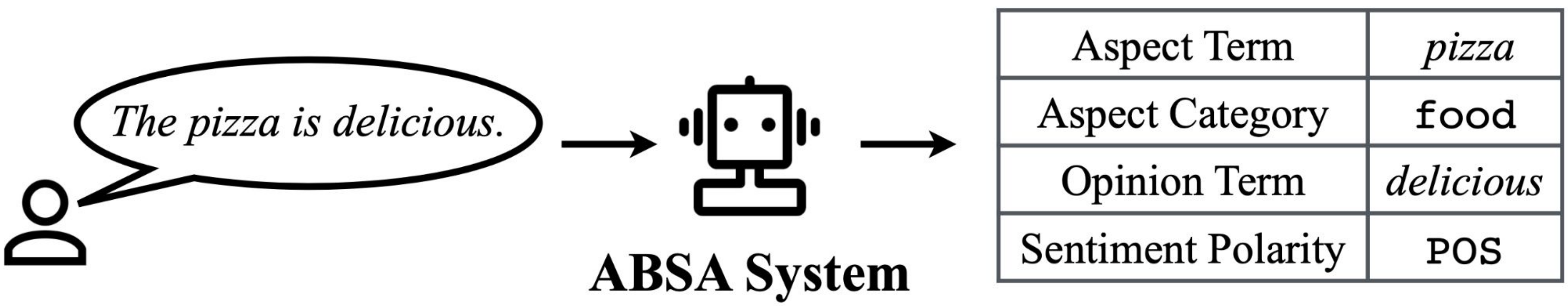

Figure 2.1: *Four sentiment elements in the ABSA problem.*

ABSA: Single ABSA and Compound ABSA tasks

- In general, there are four key sentiment elements involved in ABSA
- The main research line of ABSA focuses on the identification of them*
  - **Single ABSA task: predicting single elements**

"The pizza is delicious, but the service here is just a disaster" —aspect terms?→ *pizza, service*

  - **Compound ABSA task: joint prediction of multiple elements with their relations**

"The pizza is delicious, but the service here is just a disaster" —(aspect, opinion, sentiment) triplets?→ *(pizza, delicious, positive), (service, disaster, negative)*

* A new perspective to systematically study the ABSA problem in our survey

Outline for Today

- ❑ ABSA: What is it and Why we care about it?
- ❑ **ABSA Problem**
    - ❑ Four key sentiment elements
    - ❑ **Single ABSA Task**
    - ❑ Compound ABSA Task
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- ❑ Transferable ABSA
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    - ❑ Cross-lingual ABSA
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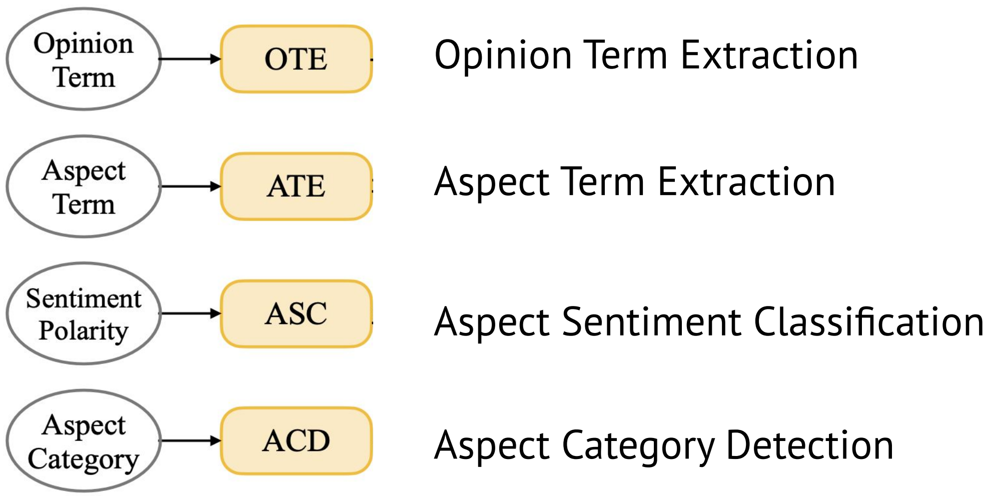
Single ABSA Problem

- **Single ABSA task: predicting single elements**
  - Four sentiment elements correspond to four single ABSA tasks
  - They are quite popular around 2015±5



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  - ❏ Cross-lingual ABSA
- ❏ Challenges and Future Directions

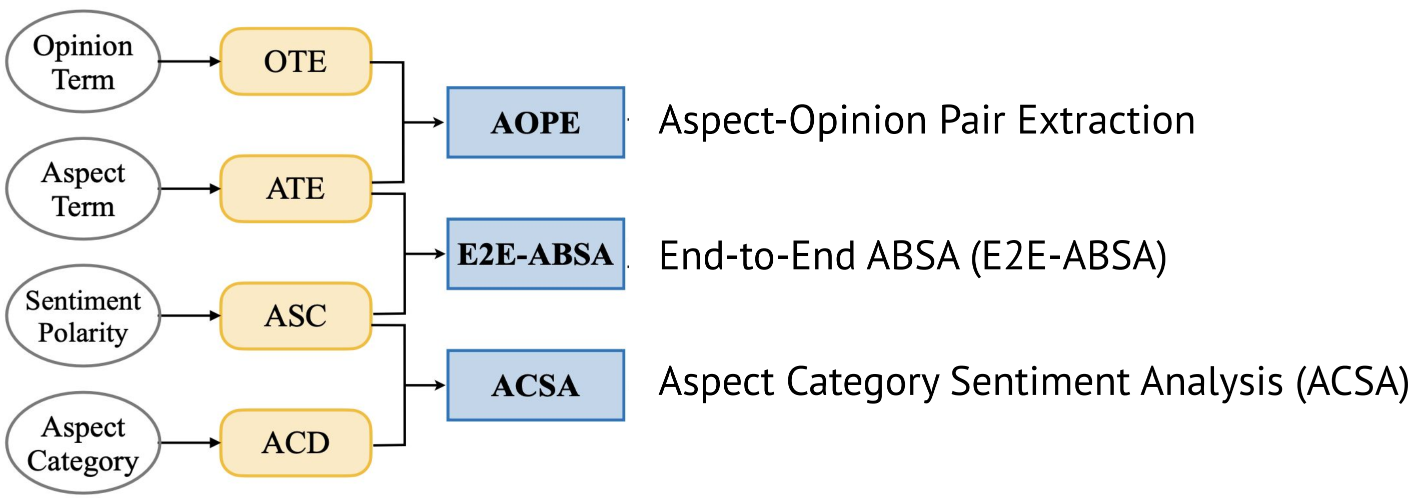
Compound ABSA Problem: Why and How

- In general, there are four key sentiment elements involved in ABSA
- The main research line of ABSA focuses on the identification of them
    - Single ABSA task: predicting single elements
    - **Compound ABSA task: joint prediction of multiple elements with their relations**

- Why compound ABSA tasks (compared with single ABSA tasks)
    - We always want more complete information!
    - But of course, they are more challenging...

Compound ABSA Problem: Pair Extraction

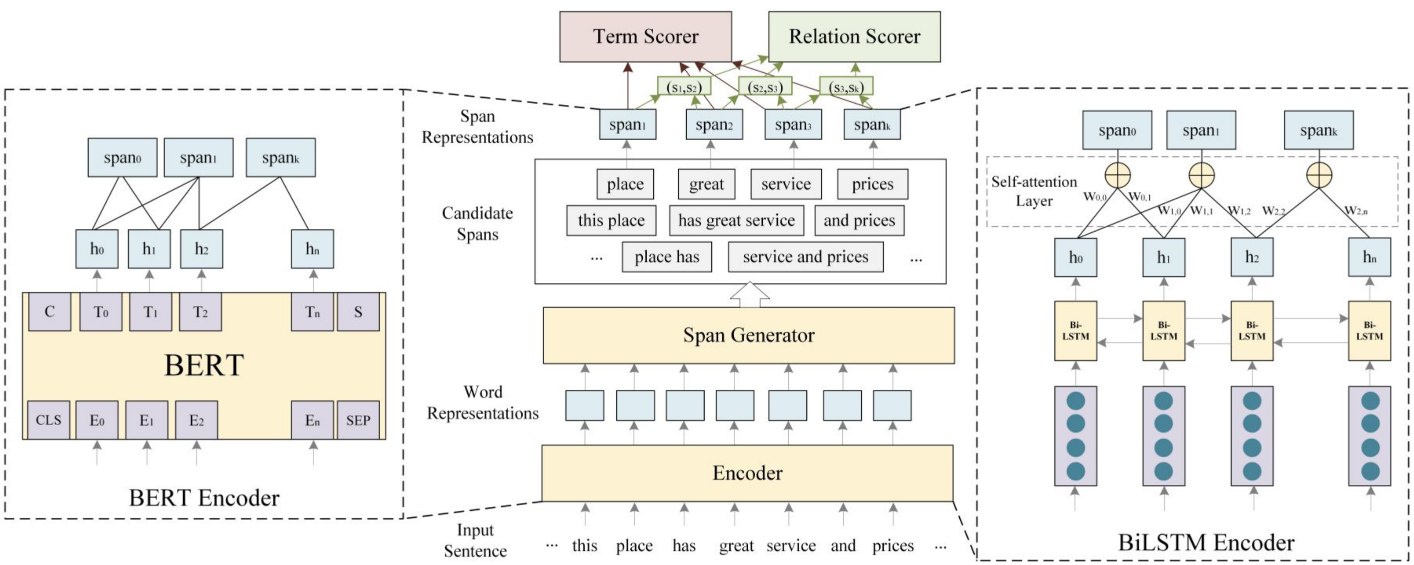
- In general, there are four key sentiment elements involved in ABSA
- The main research line of ABSA focuses on the identification of them
  - Single ABSA task: predicting single elements
  - **Compound ABSA task: joint prediction of multiple elements with their relations**



Aspect-Opinion Pair Extraction

- **Aspect-Opinion Pair Extraction (AOPE)**: predict the aspect and opinion terms as pairs

The pizza is delicious, but the service is terrible → *(pizza, delicious) (service, terrible)*



SpanMlt: A Span-based Multi-Task Learning Framework for Pair-wise Aspect and Opinion Terms Extraction. (ACL 2020)
Synchronous Double-channel Recurrent Network for Aspect-Opinion Pair Extraction. (ACL 2020)

End-to-End ABSA (E2E-ABSA)

- E2E-ABSA aims to extract (aspect term, sentiment polarity) pairs

The pizza is delicious, but the service is terrible ⟶ *(pizza,* `positive`*), (service,* `negative`*)*

- A token-level classification task (aka sequence tagging)

Input	The	AMD	Turin	Processor	seems	to	always	perform	much	better	than	Intel	.
Joint	O	B	I	E	O	O	O	O	O	O	O	S	O
	O	POS	POS	POS	O	O	O	O	O	O	O	NEG	O
Unified	O	B-POS	I-POS	E-POS	O	O	O	O	O	O	O	S-NEG	O

Open Domain Targeted Sentiment. (EMNLP 2013)
Neural Networks for Open Domain Targeted Sentiment. (EMNLP 2015)
A Unified Model for Opinion Target Extraction and Target Sentiment Prediction. (AAAI 2019)

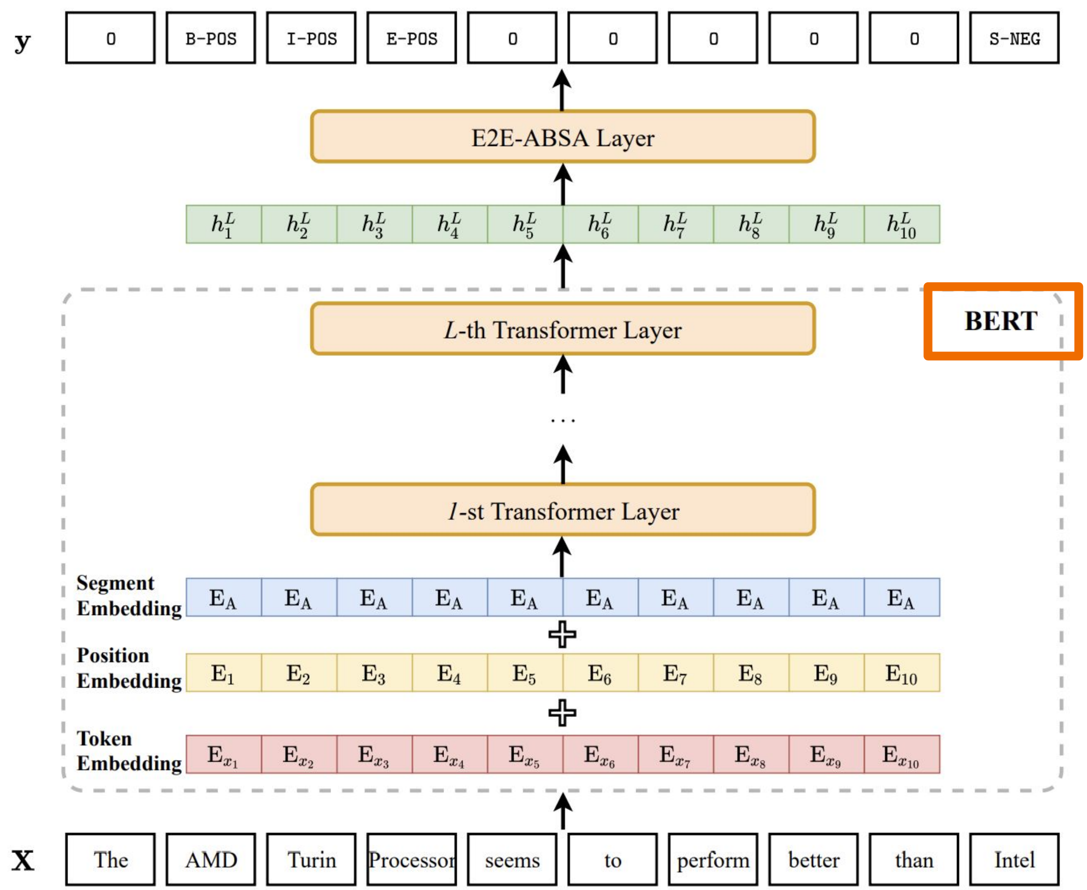
End-to-End ABSA (E2E-ABSA)

- E2E-ABSA aims to extract (aspect term

The pizza is delicious, but the service is ter

- A token-level classification task (aka s

Input	The	AMD	Turin	Processor	see
Joint	O	B	I	E	(
	O	POS	POS	POS	(
Unified	O	B−POS	I−POS	E−POS	(



Exploiting BERT for End-to-End Aspect-based Sentiment Analysis. (WUT@EMNLP-19)

Aspect Category Sentiment Analysis (ACSA)

- ACSA aims to extract (aspect category, sentiment polarity) pairs

The pizza is delicious, but the service is terrible ⟶ *(*`food,positive`*), (*`service,negative`*)*

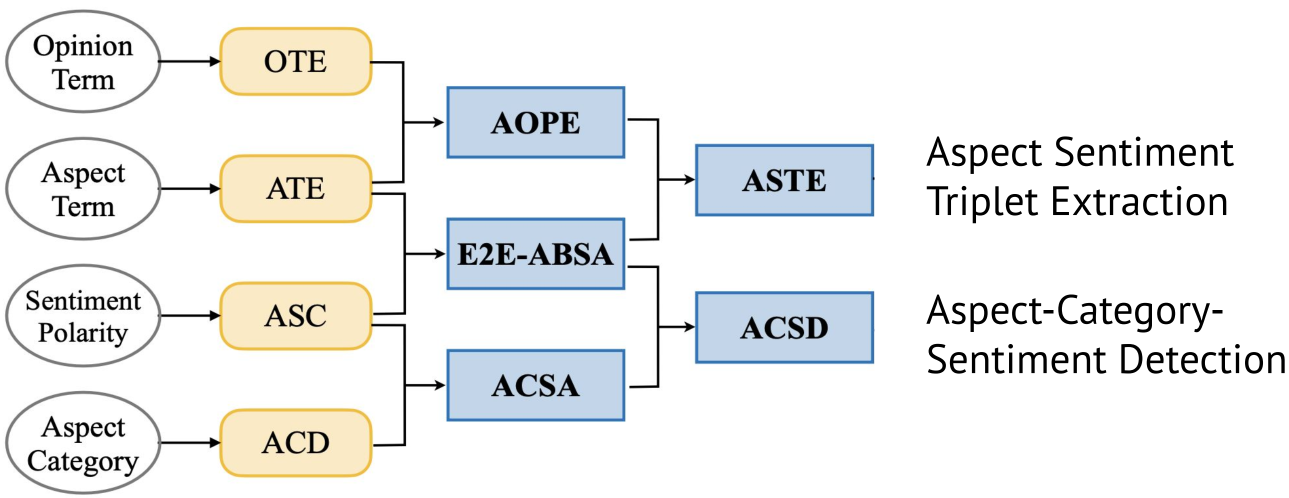
- Many previous studies already consider their inter-relations, e.g, in an MTL framework
  - Targeted Aspect-Based Sentiment Analysis via Embedding Commonsense Knowledge into an Attentive LSTM. (EMNLP 2018)
  - CAN: Constrained Attention Networks for Multi-Aspect Sentiment Analysis. (EMNLP 2019)
  - Multi-Instance Multi-Label Learning Networks for Aspect-Category Sentiment Analysis. (EMNLP 2020)
- Recent works begin to consider the end2end pair extraction
  - e.g., Cartesian product

	POS	NEU	NEG
food	1	0	0
service	0	0	1
price	0	0	0

Joint Aspect and Polarity Classification for Aspect-based Sentiment Analysis with End-to-End Neural Networks. (EMNLP 2018)

Compound ABSA Problem: Triplet Extraction

- In general, there are four key sentiment elements involved in ABSA
- The main research line of ABSA focuses on the identification of them
  - Single ABSA task: predicting single elements
  - **Compound ABSA task: joint prediction of multiple elements with their relations**



Aspect-Category-Sentiment Detection (ACSD)

- ACSD aims to extract (aspect category, aspect term sentiment polarity) pairs

The pizza is delicious, but the service is terrible → *(pizza,* `food,positive`*),* *(service,* `service,negative`*)*

- How to handle it end-to-end?
  - Target-Aspect-Sentiment Joint Detection for Aspect-Based Sentiment Analysis. (AAAI 2020)
  - Multiple-element Joint Detection for Aspect-Based Sentiment Analysis. (KBS 2021)
  - Towards Generative Aspect-Based Sentiment Analysis. (ACL 2021)

Aspect-Category-Sentiment Detection (ACSD)

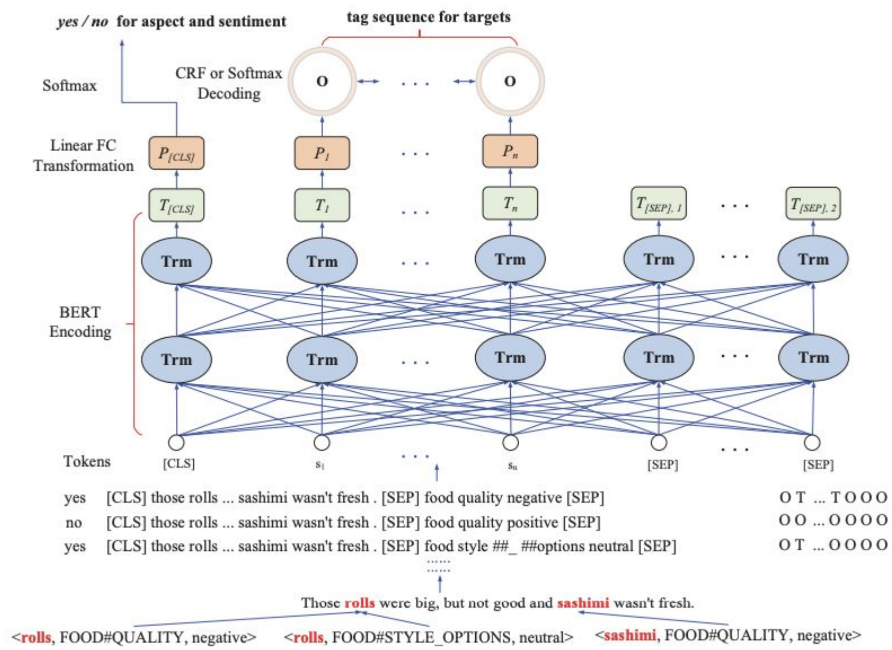
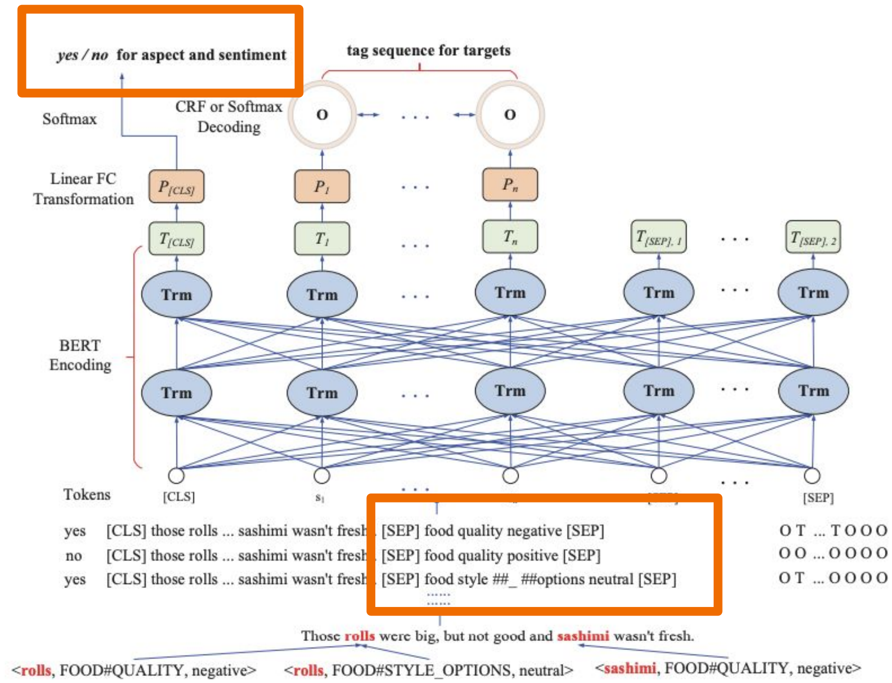


Figure 2: The architecture and a running example for the TAS-BERT model. TAS-BERT takes a sentence-aspect-sentiment token sequence "[CLS]···[SEP]···[SEP]" as input. It outputs "*yes/no*" for predicting whether targets exist for the aspect-sentiment pair and a tag sequence for extracting the targets.

Target-Aspect-Sentiment Joint Detection for Aspect-Based Sentiment Analysis. (AAAI 2020)
Multiple-element Joint Detection for Aspect-Based Sentiment Analysis. (KBS 2021)

Aspect-Category-Sentiment Detection (ACSD)



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	POS	NEU	NEG
food	1	0	0
service	0	0	1
price	0	0	0

(1) Cartesian Product

Target-Aspect-Sentiment Joint Detection for Aspect-Based Sentiment Analysis. (AAAI 2020)
Multiple-element Joint Detection for Aspect-Based Sentiment Analysis. (KBS 2021)

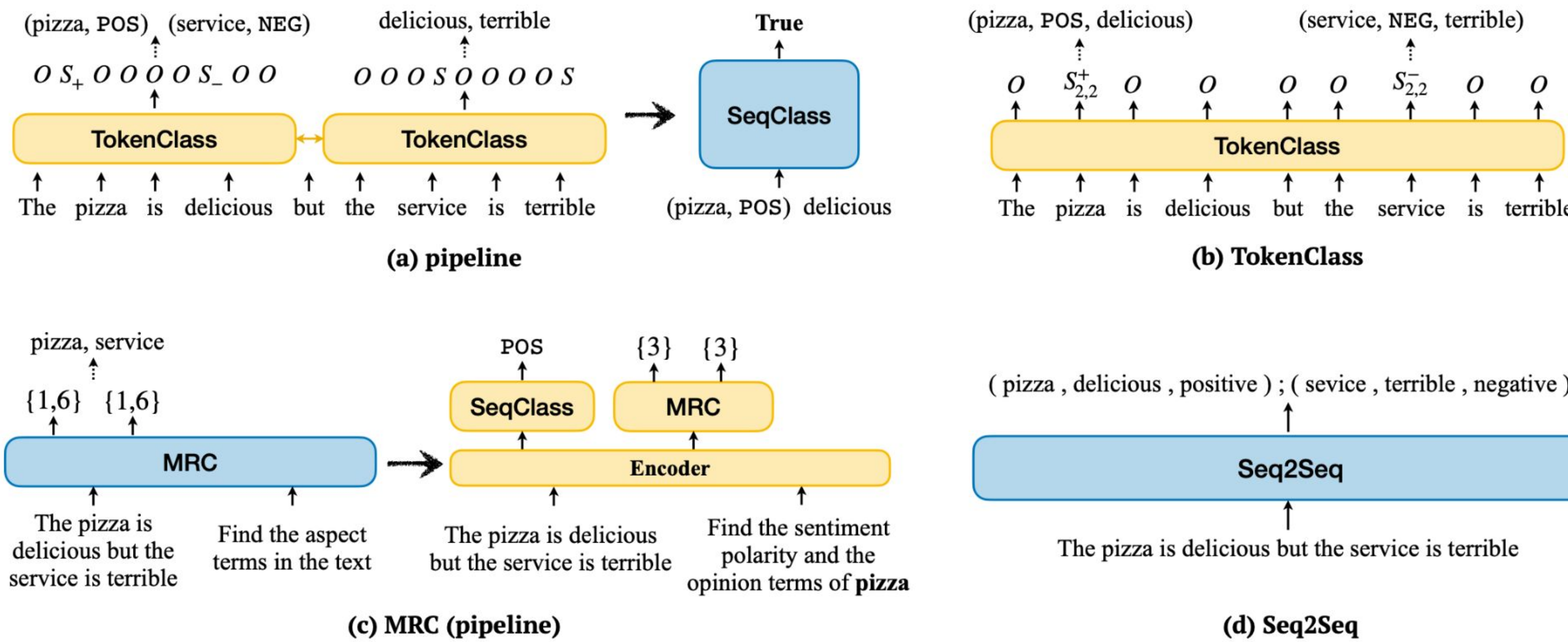
Aspect Sentiment Triplet Extraction (ASTE)

- ASTE aims to extract (aspect term, opinion term, sentiment polarity) pairs

The pizza is delicious, but the service is terrible → *(pizza, delicious,* `positive`*),*
(service, terrible, `negative`*)*

Knowing What, How and Why: A Near Complete Solution for Aspect-Based Sentiment Analysis. (AAAI 2020)

Aspect Sentiment Triplet Extraction (ASTE)



Knowing What, How and Why: A Near Complete Solution for Aspect-Based Sentiment Analysis. (AAAI 2020)
Position-Aware Tagging for Aspect Sentiment Triplet Extraction. (EMNLP 2020)
Bidirectional Machine Reading Comprehension for Aspect Sentiment Triplet Extraction. (AAAI 2021)
Towards Generative Aspect-Based Sentiment Analysis. (ACL 2021)

Compound ABSA Problem: Quad Prediction

- In general, there are four key sentiment elements involved in ABSA
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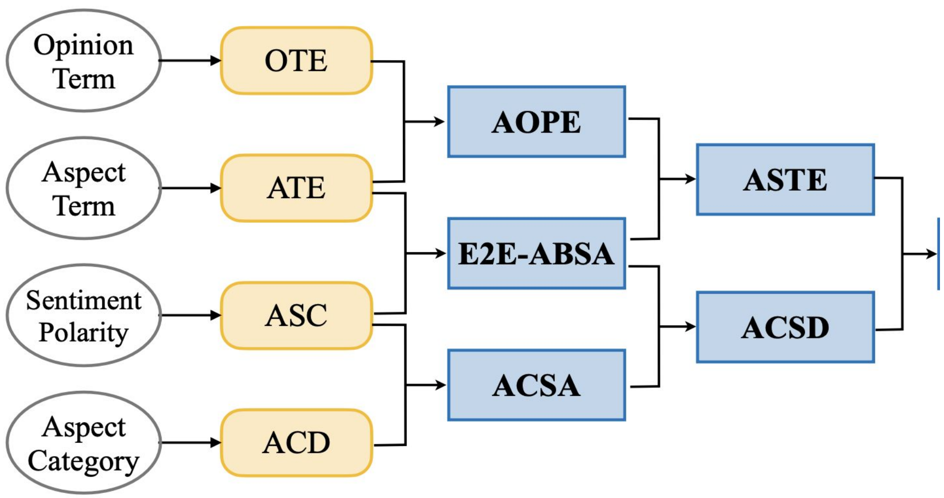

Compound ABSA Problem: Quad Prediction

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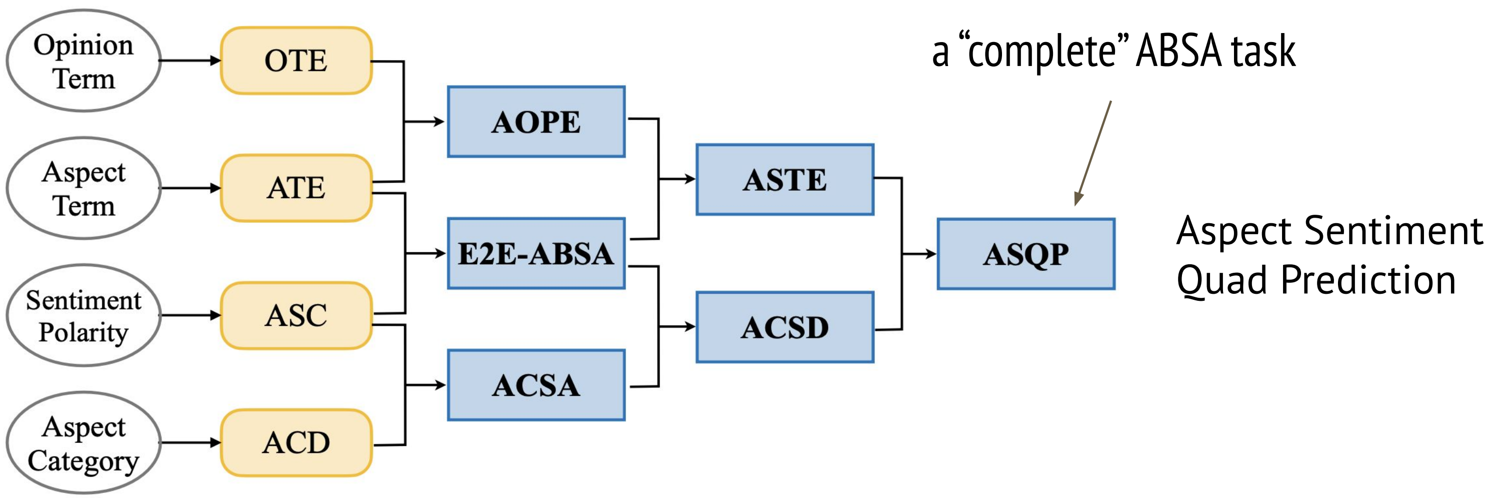


Aspect Sentiment Quad Prediction (ASQP)

Given a sentence **x**, we aim to predict all sentiment quads:

(aspect category, aspect term, opinion term, sentiment polarity)

where:

- aspect category *c* belongs to a pre-defined category set
- aspect term $a \in V_{\boldsymbol{x}} \cup \{\varnothing\}$
- opinion term $o \in V_{\boldsymbol{x}}$
- sentiment polarity *p* belongs to {positive, negative, neutral}

How to tackle ASQP?

Given a sentence **x**, we aim to predict all sentiment quads:

(aspect category, aspect term, opinion term, sentiment polarity)

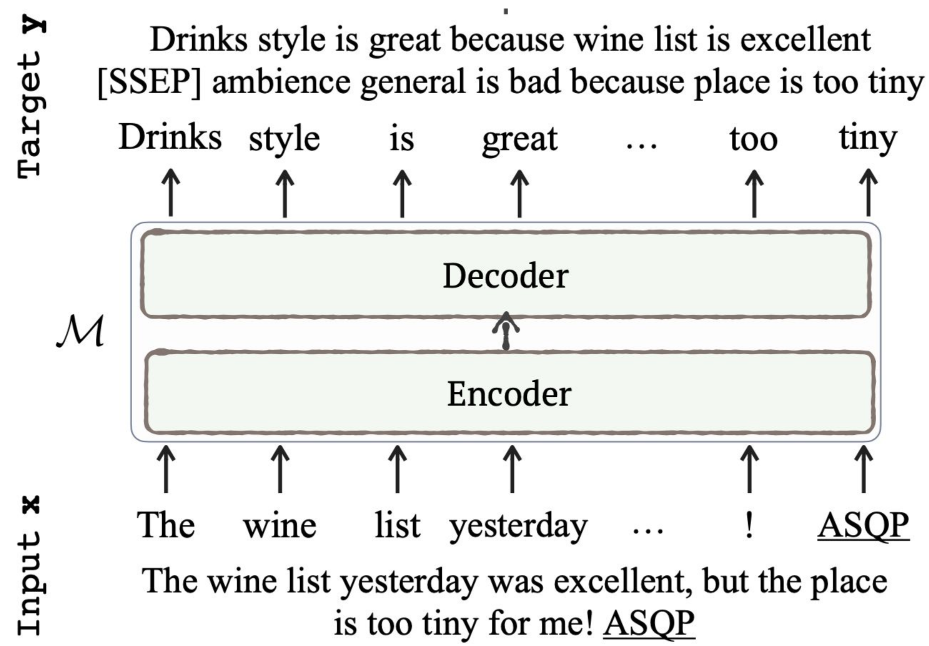
Tackling ASQP is challenging!

- ❑ Multiple elements with their dependent relations are required
- ❑ Each element has its own characteristics, different elements are closely-related

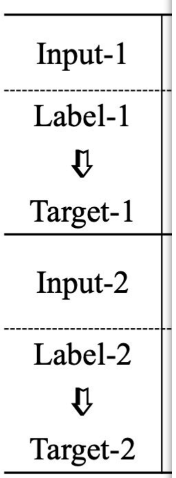
- ❑ Decouple it into several sub-tasks and solve them in a pipeline manner.
  - ➜ suffer from error propagation issue
- ❑ Sub-tasks are often formulated as token/seq-level classification task
  - ➜ underutilize the rich semantic information of the label

Aspect Sentiment Quad Prediction (ASQP)

Input-1	*The pasta yesterday was delicious!*
Label-1 ⇩ Target-1	(*c, a, o, p*): (food quality, pasta, delicious, POS) ⇩ Food quality is great because pasta is delicious
Input-2	*Everything they serve here ... was just very disappointed, I wish they would change next time*
Label-2 ⇩ Target-2	(*c, a, o, p*): (food quality, NULL, disappointed, NEG) ⇩ Food quality is bad because it is disappointed



Results on ASQP: generative method is powerful!



Type	Methods	Rest15 Pre	Rest15 Rec	Rest15 F1	Rest16 Pre	Rest16 Rec	Rest16 F1
Pipeline	HGCN-BERT + BERT-Linear	24.43	20.25	22.15	25.36	24.03	24.68
	HGCN-BERT + BERT-TFM	25.55	22.01	23.65	27.40	26.41	26.90
Unified	TASO-BERT-Linear	41.86	26.50	32.46	49.73	40.70	44.77
	TASO-BERT-CRF	44.24	28.66	34.78	48.65	39.68	43.71
	GAS	45.31	46.70	45.98	54.54	57.62	56.04
Ours	PARAPHRASE	**46.16**	**47.72**	**46.93**	**56.63**	**59.30**	**57.93**
	w/o sentiment polarity semantics	45.30	46.87	46.07	56.56	58.82	57.67
	w/o aspect category semantics	44.65	46.59	45.60	56.27	58.38	57.31
	w/o polarity & category semantics	43.46	45.19	44.30	56.04	57.53	56.77

Aspect Sentiment Quad Prediction as Paraphrase Generation (EMNLP 2021)

GAS: Generative ABSA

One (generative) model for all (tasks)!

`Input:` Salads were fantastic, our server was also very helpful.
`Target (Annotation-style):` [Salads | fantastic] were fantastic here, our [server | helpful] was also very helpful.
`Target (Extraction-style):` (Salads, fantastic); (server, helpful)

AOPE

`Input:` Salads were fantastic, our server was also very helpful.
`Target (Annotation-style):` [Salads|positive] were fantastic here, our [server|positive] was also very helpful.
`Target (Extraction-style):` (Salads, positive); (server, positive)

E2E-ABSA

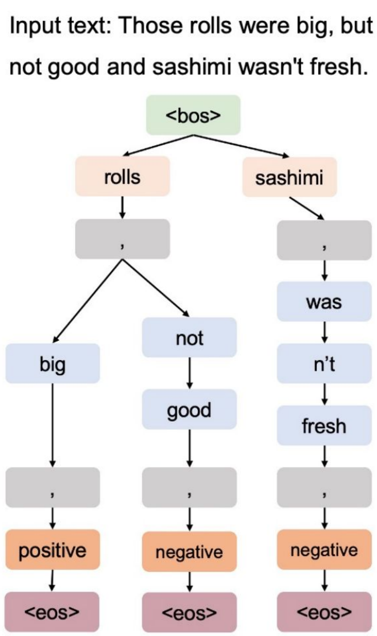
`Input:` The Unibody construction is solid, sleek and beautiful.
`Target (Annotation-style):` The [Unibody construction | positive | solid, sleek, beautiful] is solid, sleek and beautiful.
`Target (Extraction-style):` (Unibody construction, solid, positive); (Unibody construction, sleek, positive); (Unibody construction, beautiful, positive);

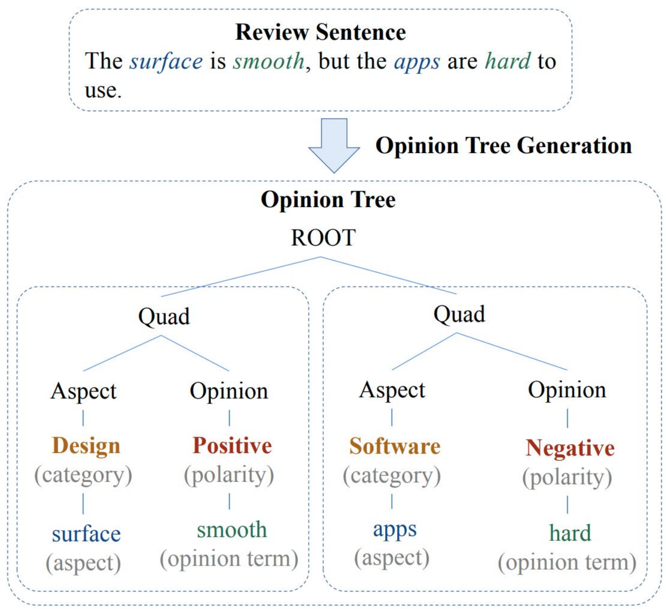
ASTE

`Input:` A big disappointment, all around. The pizza was cold and the cheese wasn't even fully melted.
`Target (Annotation-style):` A big disappointment, all around. The [pizza | food quality | negative] was cold and the [cheese | food quality | negative] wasn't even fully melted [null | restaurant general | negative].
`Target (Extraction-style):` (pizza, food quality, negative); (cheese, food quality, negative); (null, restaurant general, negative);

ACSD

Generative ABSA: follow-up improvements






```
((aspect: staff
  (negative: horrible))
 (opinion: horrible))
```

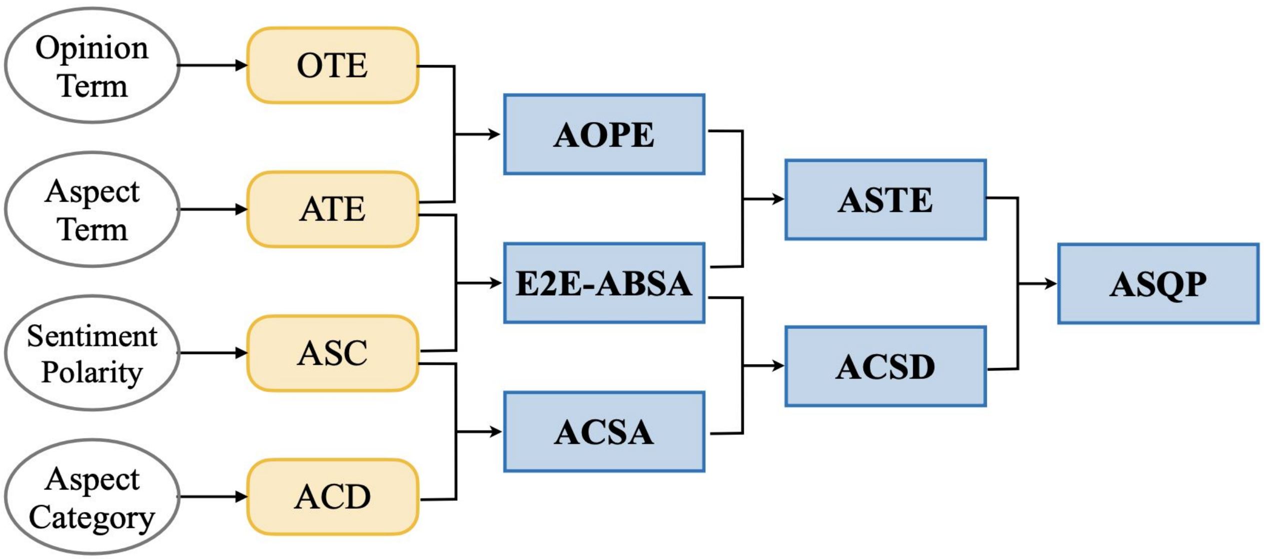
```
((opinion: good)
 (aspect: battery life
  (positive: good)))
```

Original sentence	*The **restaurant** is **clean**.*
Quadruplet (ac, at, ot, sp)	*(ambience general, restaurant, clean, positive)*
Semantic quadruplet $(x_{ac}, x_{at}, x_{ot}, x_{sp})$	*(ambience general, restaurant, clean, great)*
Fixed-order template	x_{ac} *is* x_{sp} *because* x_{at} *is* x_{ot}
Target sequence	***ambience general** is **great** because **restaurant** is **clean***
Free-order template	O_i([AC] x_{ac}, [AT] x_{at}, [OT] x_{ot}, [SP] x_{sp}); $i \in [1,24]$
Multiple target sequences	[AC] x_{ac} [AT] x_{at} [OT] x_{ot} [SP] x_{sp} [AT] x_{at} [AC] x_{ac} [OT] x_{ot} [SP] x_{sp} ...

Seq2Path: Generating Sentiment Tuples as Paths of a Tree (ACL-Findings 2022)
Unified Structure Generation for Universal Information Extraction (ACL 2022)
Aspect-based Sentiment Analysis with Opinion Tree Generation. (IJCAI 2022)
Improving Aspect Sentiment Quad Prediction via Template-Order Data Augmentation (EMNLP 2022)
Generative Aspect-Based Sentiment Analysis with Contrastive Learning and Expressive Structure (EMNLP Findings 2022)

Compound ABSA Problem

- Compound ABSA task: joint prediction of multiple elements with their relations

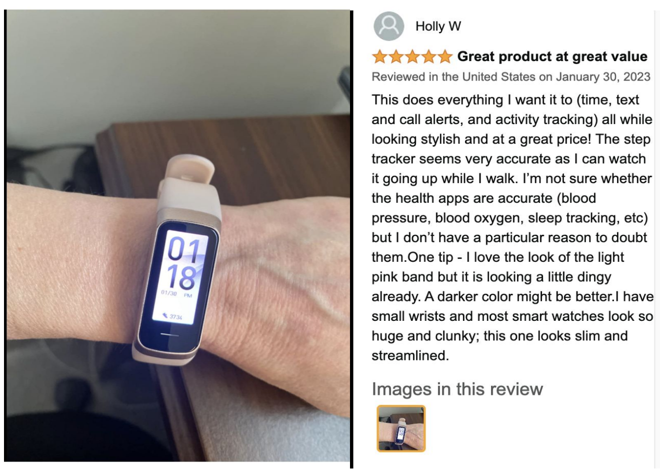


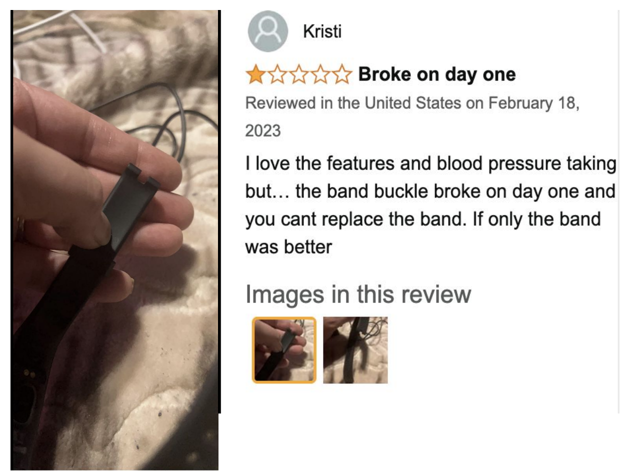
Outline

- ABSA: What is it and Why we want it?
- ABSA Problem
  - Single ABSA Task
  - Compound ABSA Task
- Emerging Topics
  - PLMs for ABSA
  - Transferable ABSA: Cross-domain and Cross-lingual ABSA
- **Challenges and Future Directions**

Challenges and Future Directions

- Quest for Larger and More Challenging Datasets
  - Challenging datasets are always welcome
  - e.g., multilingual ABSA datasets
- Multimodal ABSA
  - Users don’t write reviews/comments only in text!





Challenges and Future Directions

- Quest for Larger and More Challenging Datasets
  - Challenging datasets are always welcome
  - e.g., multilingual ABSA datasets
- Multimodal ABSA
  - Users don’t write reviews/comments only in text!
- Unified Model for Multiple Tasks
  - So many tasks, why not handle them in one model?

Take-aways

- ABSA is an emerging research areas, lots of research progress in recent years
- The main research line involves the identification of four sentiment elements
  - early studies focus on predicting single element
  - recent works pay more attention to compound ABSA tasks
  - with a systematic review of methods, we can see many underlying ideas are similar
- Handle ABSA in practice is still challenging (transferable ABSA which we skip in this talk)
- Still a long way to go and many interesting research opportunities!

- Resources (paper list with links / repos / implementations ...):
  https://github.com/IsakZhang/ABSA-Survey

Thanks! Q&A

isakzhang@gmail.com

We are hiring!

- Campus recruitement for 2023 graduates (Ali Star)
- Research intern (*new hc just released*) - based in Singapore or Hangzhou, pure research
- Alibaba Qingyun Scholar (Postdoc Researcher): Pure research work mode for 2 years

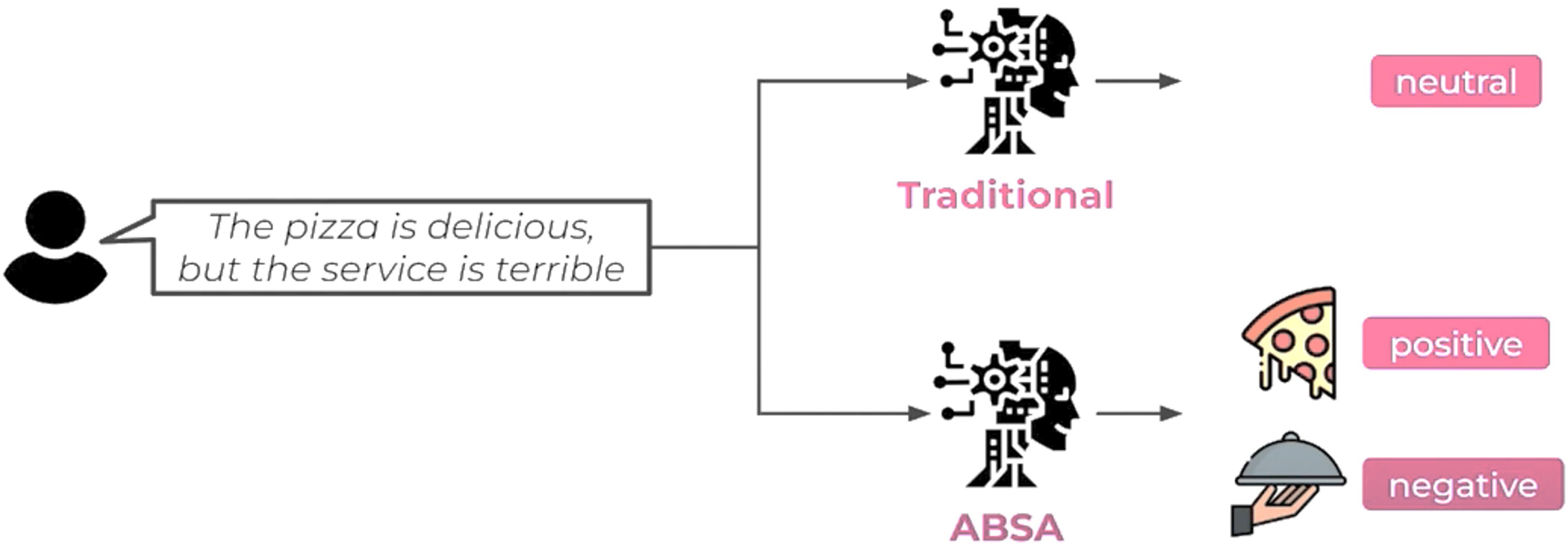
Feel free come to talk for more details or drop me an email!

DiaASQ: A Benchmark of Conversational Aspect-based Sentiment Quadruple Analysis

Lizi Liao

Singapore Management University

ABSA vs Traditional Sentiment Analysis



Elements of ABSA

Aspect Term - Target term that explicitly appears in the given text

Aspect Category - Aspect terms fall under aspect categories

Opinion Term - Explicitly expresses sentiment towards the term

Sentiment Polarity - Polarity associated with the aspect term

Aspect Term	pizza
Aspect Category	food
Opinion Term	delicious
Sentiment Polarity	POSITIVE

ABSA Use Cases

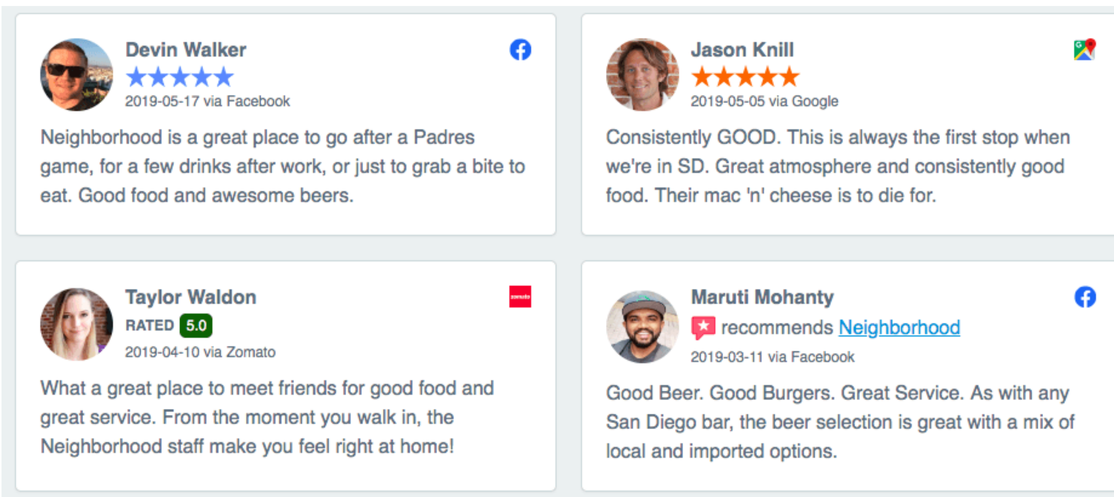
Customer Feedback Analysis

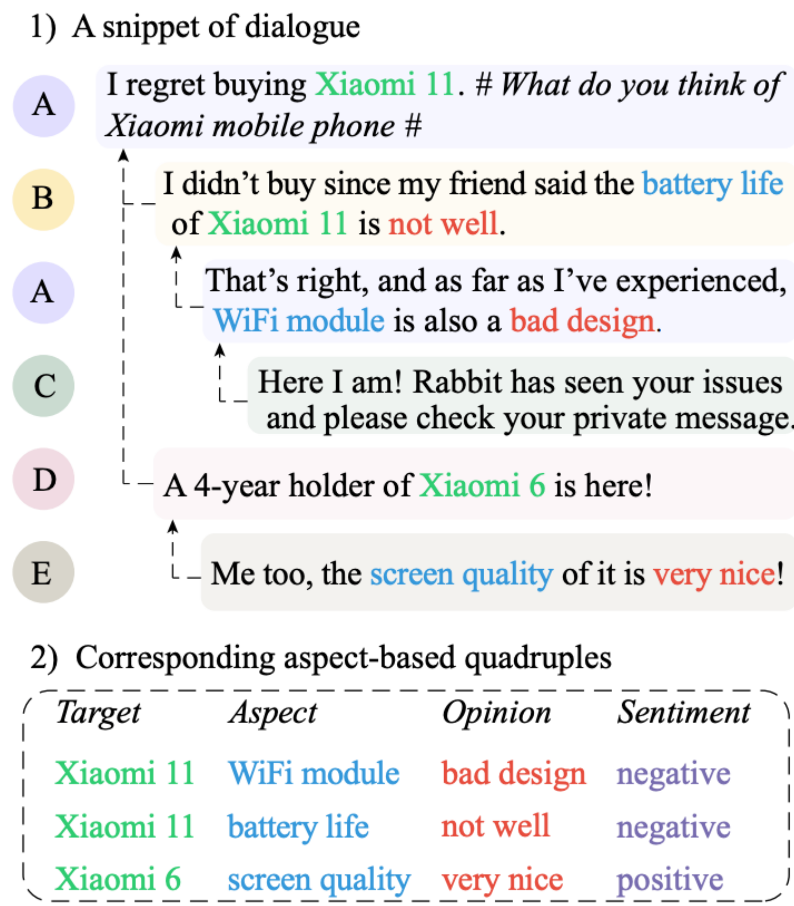
Public Opinion Mining

...

ABSA in Dialog

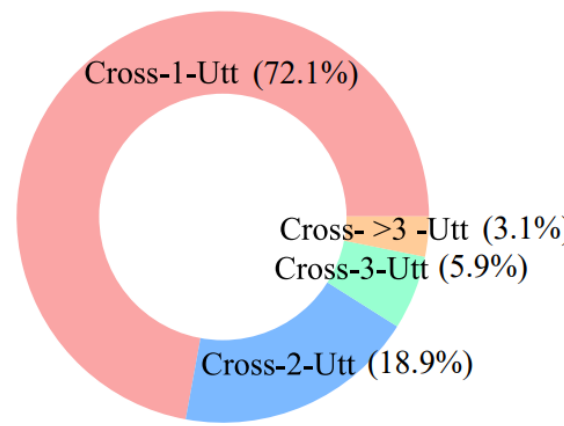
- mostly limited to single text pieces
- study in dialogue contexts unexplored





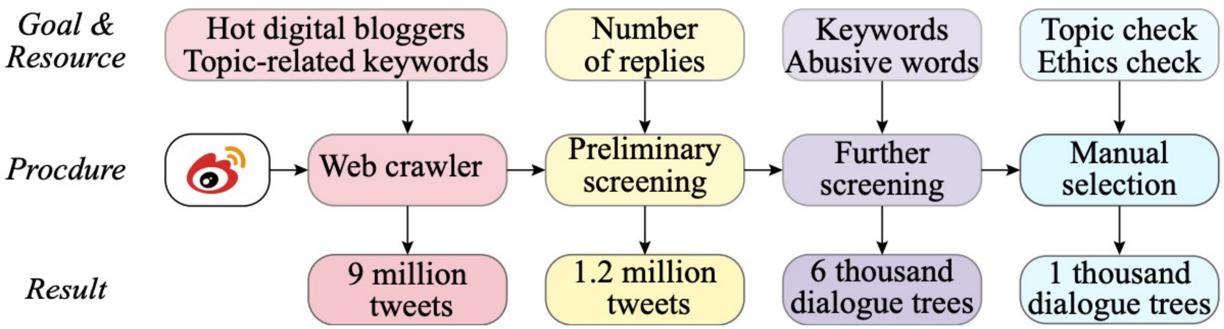
Challenges

Reviews	Dialog	Solution
Regarding a specific product or service	Not confined in one target Need to consider the target	Quadruple target, aspect, Opinion, sentiment
Analyze a whole sentence or passage	Multiple turns of conversation, Contain co-references, change of speakers etc.	Build dialog models to understand Realize cross-utterance extraction



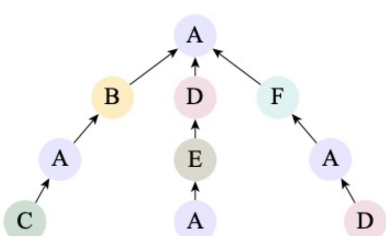
- ✓ Task: necessary, challenging, with different data format
- ✓ build datasets and models to investigate

Dataset Construction



	ASTE	TOWE	MAMS	CASA	DiaASQ
Target	✗	✗	✗	✓	✓
Aspect	✓	✓	✓	✗	✓
Opinion	✓	✓	✓	✓	✓
Polarity	✓	✗	✓	✓	✓
Dialogue-level	✗	✗	✗	✓	✓
Multi-sentiment	✗	✗	✓	✗	✓
Multilingual	✗	✗	✗	✗	✓

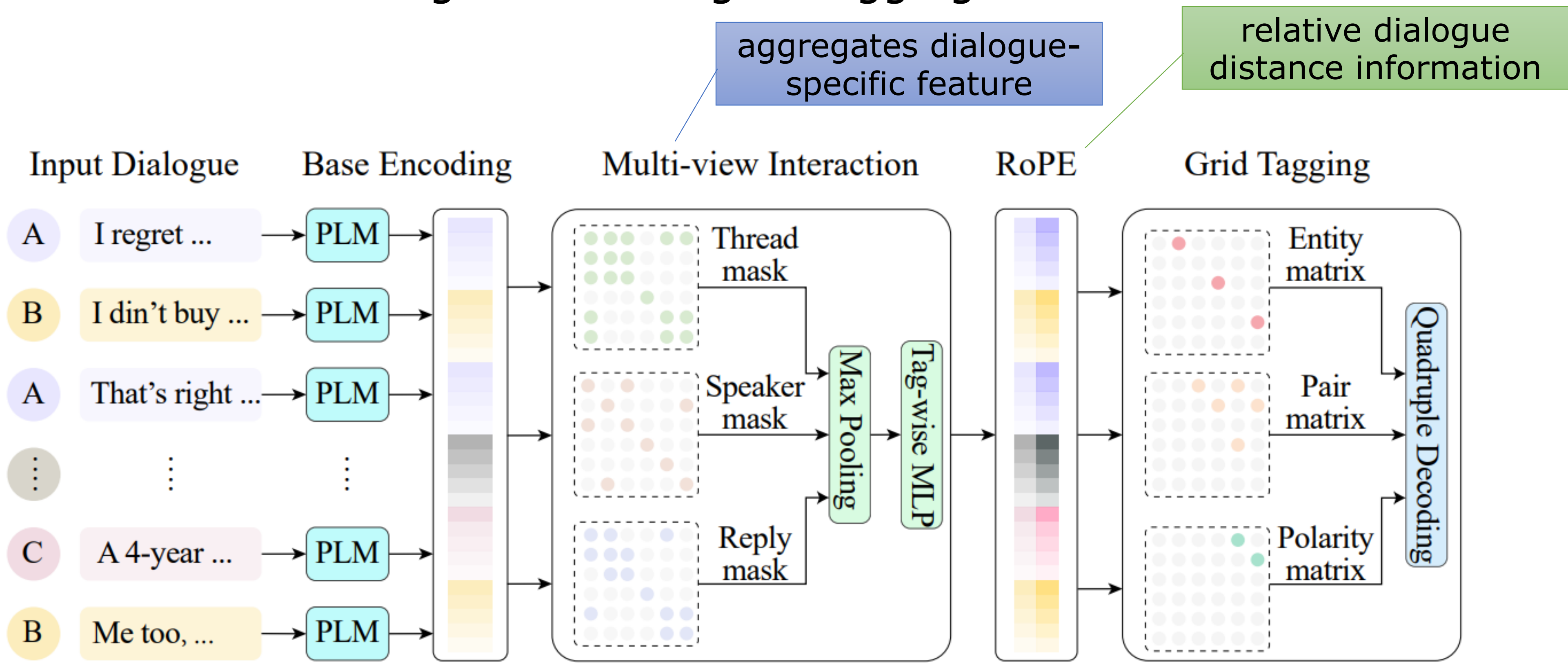
SemEval ABSA annotation guideline
Crowd-workers annotate
Cross-examine the labels
Automatic rules to verify



Item	Text
Source	所以我还是买了*12x*，虽然性价比不高
Translated	*So I still bought 12x, although the price is not high*
Revision	*So I still bought 12x, although the cost-effective is not high.*
Source	9带dc肯定香，不过夏天你再试试
Translated	*9 with DC is definitely fragrant, but you try again in summer*
Revision	*9 with DC is definitely nice, but you could try it again in summer*

Benchmark model

➢ Renew the labelling scheme of grid-tagging



NLPCC 2023 shared task

- https://conasq-dev.pages.dev/
  - *Registration after March 15, 2023*
  - *Dataset will be open*
  - *Baseline will be provided*
  - *Results will be ranked!*

Thanks!

Incorporating Multiple Knowledge Sources for Targeted Aspect-based Financial Sentiment Analysis

Presented by

Du Zidong Kelvin

Vice President, Data Science, DBS Bank

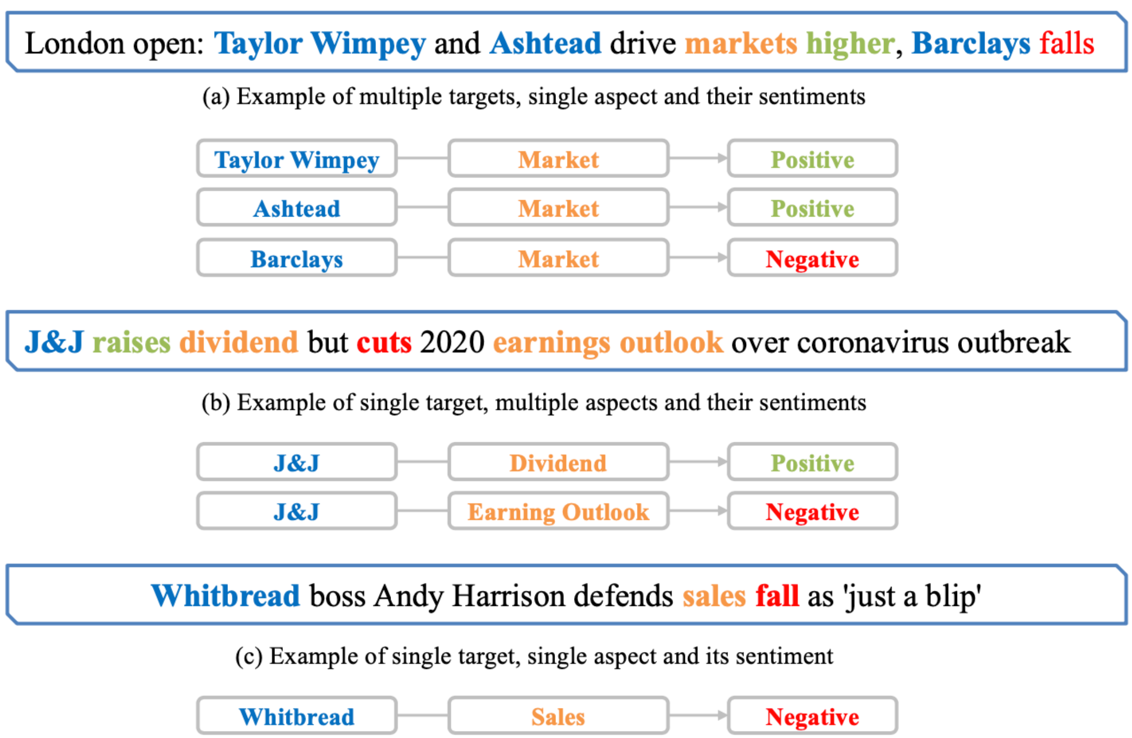
Outline

1. **Introduction**
2. **Research Questions**
3. **Methodology**
4. **Experiments**
5. **Results**
6. **Conclusions**
7. **Future Work**

Introduction

- Targeted Aspect-based Financial Sentiment Analysis (TABFSA) aims to **extract entities and aspects** and **detect their corresponding sentiment** in financial texts, which is a challenging but pragmatic task. This study focuses on the sentiment detection task.

- Combining symbolic and subsymbolic methods has become a promising strategy as research tasks in AI grow increasingly complicated and require higher levels of understanding. Current state-of-the-art TABFSA models have overlooked the importance of external lexical knowledge.



TABSA example sentences with their target companies (blue), aspects (orange), and associated polarities detected

Research Questions

- Can integration of lexical knowledge improve the performance of pre-trained language models in TABFSA tasks?

- The methods to integrate knowledge into the fine-tuning process of pre-trained language models can be generally categorized into three types: anterior, parallel, and posterior integration. When multiple sources of lexical knowledge is provided, among anterior, parallel or posterior integration which is a more effective approach to incorporate knowledge?

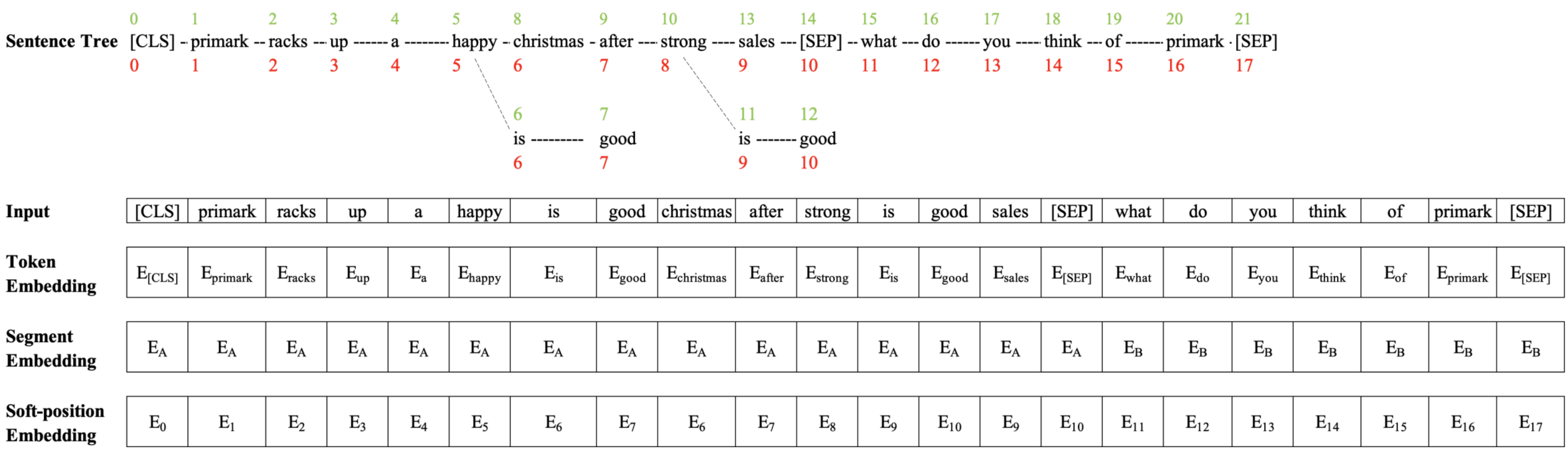
- To improve the domain application of pre-trained language models, one method adopted by researchers is to train domain-specific pre-trained language models such as FinBERT but it requires large domain-specific corpus and considerable computing resources. Does incorporation of financial knowledge produce better model performance than retraining of finance domain-specific language models in TABFSA task?

Contributions

- **Defined** ***anterior***, ***parallel***, and ***posterior*** knowledge integration and conducted extensive experiments to examine the best approach to incorporate multiple lexicon knowledge into the fine-tuning process of transformer models and identified that the parallel approach is more effective in combining multiple lexical knowledge sources and pre-trained language models.
- **Proposed** incorporating heterogeneous sentiment knowledge (both from domain-specific and general-purpose lexicons) into the fine-tuning process of pre-trained transformer models and demonstrated its effectiveness in complementing all the model training.
- **Demonstrated** that the incorporation of lexical knowledge produces better model performance than retraining of finance domain-specific language models in TABFSA. The lack of knowledge in the FSA task makes knowledge integration valuable.
- **Achieved** the best results to our knowledge over strong benchmark models on the two fine-grained financial sentiment analysis datasets, i.e., SemEval 2017 Task 5 and FiQA Task 1.

Methodology

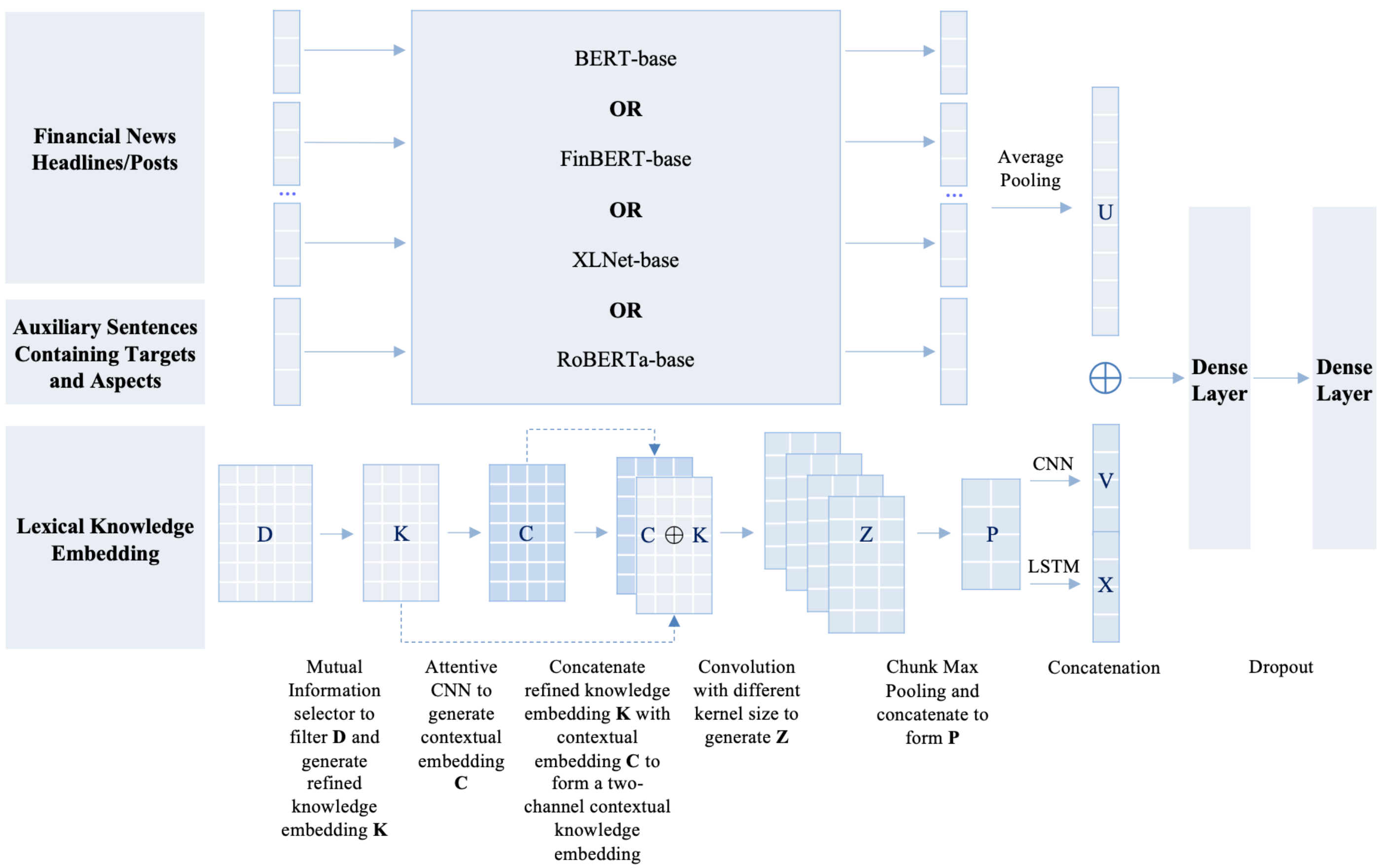
- **Anterior knowledge integration** is to study how to incorporate the knowledge into the sentence, such as forming a sentence tree with the branch being the incorporated knowledge and feeding it into transformer models like BERT. It augments sentences with richer sentiment information and can be helpful for model training and fine-tuning.



The process of converting a sentence tree into an embedding representation for BERT [3, 4]
The soft-position index is represented by the red number and the hard-position index is signified by the green number in the sentence tree. The token embedding is formed by flattening the tokens in the sentence tree into a sequence of tokens by their hard-position index. The position embedding is generated from the soft-position index along with the token embedding. The tokens in the original sentence are tagged as A, while the tokens in the auxiliary sentence are tagged as B for segment embedding.

Methodology

- **Parallel knowledge integration** aims to develop a different model architecture for the knowledge base and train in parallel with pre-trained language models.



The architecture of the proposed knowledge-enabled transformer models

Methodology

1. A refined knowledge embedding through **mutual information selector** is generated for each sentence is $\boldsymbol{K}(S) \in \mathrm{R}^{m \times n}$, where m is the maximum length of the sentences and n is the number of sentiment and emotion scores across lexicons:

$$\boldsymbol{K}(S) = K_{x_1} \oplus K_{x_2} \ldots \oplus K_{x_l} \oplus \mathbf{0}^{(m-l)\times n}$$

2. A contextual vector c_i is generated for each word x_i using the attention layer to determine which word and lexicon should have more emphasis, and thus each sentence also has a contextual embedding $\boldsymbol{C}(S) \in \mathrm{R}^{m \times n}$. The attention weight $\alpha_{i,j}$ can be obtained by normalizing the score of a word pair $s(w_i, w_j)$ from a MLP through softmax function, where given $k = i - j - 1$ and $\lambda \in [0, 1)$, a decay factor to penalize the output score for reducing the impact of noise information that would be produced when the length of the sentence grows:

$$c_i = \sum_{i \neq j} \alpha_{i,j} \cdot x_j \quad \text{and} \quad s(w_i, w_j) = (1 - \lambda)^k \cdot v_a^T tanh(W_a[x_i \oplus x_j])$$

3. Concatenate the refined knowledge embedding K with contextual embedding C to form a 2-channel embedding and convolve it with different kernel sizes to generate Z, which are activated by ReLU function and global-max-pooled along i but chunk-max-pooled along j.

$$Z = \begin{bmatrix} z_{11} & \cdots & z_{1(m-h+1)} \\ z_{21} & \cdots & z_{2(m-h+1)} \\ \vdots & \ddots & \vdots \\ z_{(n-e+1)1} & \cdots & z_{(n-e+1)(m-h+1)} \end{bmatrix} \quad \text{and} \quad z_{ij} = w_{ij} \cdot K_{x_{(i:i+e-1,j:j+h-1)}} + b_{ij}$$

4. The pooled feature maps are concatenated to form $\boldsymbol{P} \in \mathbb{R}^{c \times \sum p_i}$, where p_i is the length of pooled vector and $i \in [1, 2, 3, 4]$. Subsequently, a second convolution is applied to $\boldsymbol{P}$ to further extract and downsize features, and in parallel LSTM is used to extract the sequential information. The output $\boldsymbol{V} \in \mathrm{R}^{Cout \times 1}$ from CNN and $\boldsymbol{X} \in \mathrm{R}^{Hn \times 1}$ from LSTM are concatenated with $\boldsymbol{U}$ from a transformer model, where $Cout$ is the number of channels produced by the last convolution and Hn is the dimension of the last hidden state of LSTM. The output is, therefore, in a format of:

$$O = w_2 \cdot \sigma[w_1 \cdot \tanh(U \oplus V \oplus X) + b_1] + b_2$$

Methodology

- **Posterior knowledge integration** is defined as the addition of knowledge to the output embedding from transformer models. The most straightforward approach is a direct concatenation without further processing, which is formulated as follows and used in our study as a baseline:

$$O = w_2 \cdot \sigma[w_1 \cdot \tanh(U \oplus K) + b_1] + b_2,$$

where $\boldsymbol{U}$ is the output from the transformer model, $\boldsymbol{K}$ is the refined lexical knowledge embedding, and $w1$,$w2$, $b1$, $b2$ are weights and bias terms to be optimized with MSE loss.

Experimental Results

Model	MSE	R^2
Lexicon-based [7]	0.1720	0.040
DNN ensemble [8]	0.0926	0.414
ULMFiT fine-tuning [9]	0.0800	0.400
FinBERT^a [6]	0.0700	0.550
FinBERT^b [10]	0.0636	0.613
BERT	0.0651	0.601
k-BERT (anterior) [3, 4]	0.0738	0.549
k-BERT (posterior)	0.0634	0.610
k-BERT (parallel-1D)	0.0624	0.616
k-BERT (parallel-2D)	0.0628	0.615
XLNet	0.0549	0.665
k-XLNet (anterior) [3, 4.]	0.0627	0.619
k-XLNet (posterior)	0.0522	0.693
k-XLNet (parallel-1D)	0.0538	0.669
k-XLNet (parallel-2D)	0.0532	0.674
RoBERTa	0.0548	0.677
k-RoBERTa (anterior) [3, 4]	0.0602	0.642
k-RoBERTa (posterior)	0.0546	0.668
k-RoBERTa (parallel-1D)	**0.0499**	**0.705**
k-RoBERTa (parallel-2D)	**0.0490**	**0.711**

Performance of Proposed Knowledge-Enabled Transformer Models in Comparison to State-of-the-Art Approaches in Sentiment Analysis Task on FiQA Task 1

Boldface indicates the top 2 result. We transcribe the results reported in [8], [9], and [6]

Model	**Headline**		**Post**	
	Cosine	R^2	Cosine	R^2
Lexicon-based [7]	0.1861	0.033	0.3032	0.052
Regression ensemble [11]	0.7100	-	0.7780	-
MLP ensemble [5]	0.7860	-	0.7970	-
FinBERT^a [6]	0.7969	0.635	0.7817	0.570
FinBERT^b [10]	0.7798	0.609	0.7626	0.536
BERT	0.7935	0.630	0.7886	0.581
k-BERT (anterior) [3, 4]	0.7809	0.610	0.7614	0.535
k-BERT (posterior)	0.7958	0.633	0.7903	0.584
k-BERT (parallel-1D)	0.7971	0.636	0.7916	0.587
k-BERT (parallel-2D)	0.7969	0.635	0.7912	0.586
XLNet	0.8199	0.676	0.8031	0.608
k-XLNet (anterior) [3, 4]	0.8014	0.644	0.7754	0.560
k-XLNet (posterior)	0.8215	0.675	0.8075	0.616
k-XLNet (parallel-1D)	0.8249	0.681	0.8074	0.615
k-XLNet (parallel-2D)	0.8270	0.685	0.8074	0.615
RoBERTa	0.8430	0.710	0.8085	0.617
k-RoBERTa (anterior) [3, 4]	0.8140	0.664	0.7754	0.560
k-RoBERTa (posterior)	0.8380	0.703	0.8063	0.614
k-RoBERTa (parallel-1D)	**0.8495**	**0.722**	**0.8113**	**0.623**
k-RoBERTa (parallel-2D)	**0.8483**	**0.721**	**0.8126**	**0.624**

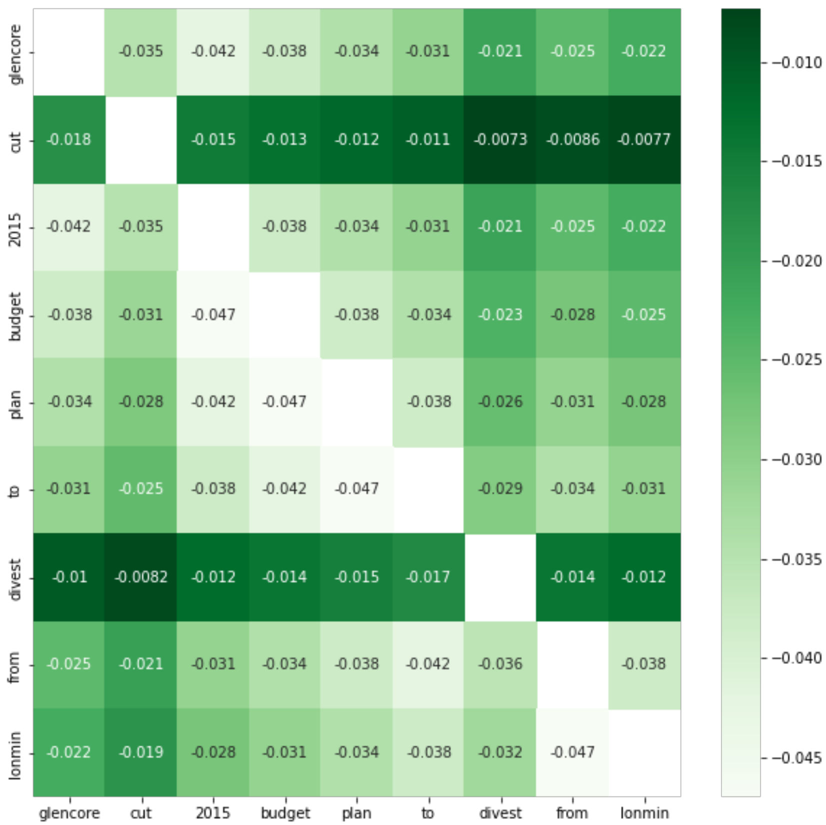
Performance of Proposed Knowledge-Enabled Transformer Models in Comparison to the State-of-the-Art Approaches on SemEval 2017 Task 5

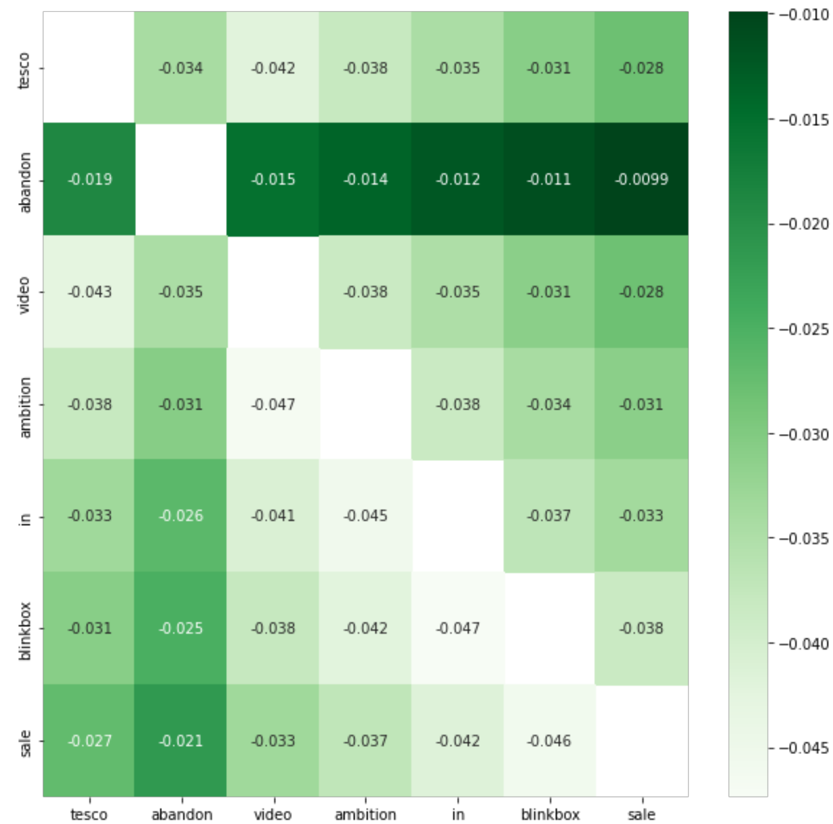
Boldface indicates the top 2 result. We transcribe the results reported in [11] and [5]. "-" means not reported

Knowledge-enabled RoBERTa achieves state-of-the-art results on both SemEval 2017 Task 5 (Cosine[h]=0.8495, Cosine[p]=0.8126) and FiQA Task 1 (MSE= 0.0490, R2=0.711)

Experimental Results

Each row of the matrix represents a vector α, and **a darker green cell indicates that more attention is being paid to the word in the corresponding column**. The negative sentiment patterns abandon, cut, and divest are significant in the respective sentence.





We visualize attention scores $s(w_i, w_j)$ produced by k-RoBERTa (parallel-2D) in above Figures. Each row of the matrix represents a vector α, and a darker green cell indicates that more attention is being paid to the word in the corresponding column. As illustrated, the negative sentiment patterns abandon, cut, and divest are quite significant in the respective sentence. It can be concluded that the correlation of a pair of words $s(w_i, w_j)$ can be understood as the degree to which w_i depends on w_j to indicate the sentiment of the corresponding sentence.

Ablation Study

MSE	Mean	Median	SD
BERT	0.0651	0.0602	0.0191
k-BERT (parallel-2D w/o MI)	0.0647	0.0628	**0.0168**
k-BERT (parallel-2D w/ MI)	**0.0628**	**0.0573**	0.0180
FinBERT	0.0675	0.0668	0.0172
k-FinBERT (parallel-2D w/o MI)	0.0672	0.0679	0.0163
k-FinBERT (parallel-2D w/ MI)	**0.0646**	**0.0623**	**0.0157**
XLNet	0.0549	0.0526	0.0147
k-XLNet (parallel-2D w/o MI)	0.0544	0.0528	0.0143
k-XLNet (parallel-2D w/ MI)	**0.0532**	**0.0502**	**0.0119**
RoBERTa	0.0548	0.0526	**0.0173**
k-RoBERTa (parallel-2D w/o MI)	0.0511	0.0488	0.0176
k-RoBERTa (parallel-CNN w/ MI [12])	0.0500	0.0447	0.0185
k-RoBERTa (parallel-2D w/ MI)	**0.0490**	**0.0420**	0.0185

Ablation Analysis for FiQA Task 1 Sentiment Analysis

w/ MI means Mutual Information is adopted to select lexicons. w/o MI means all lexicons are used without any selection. The parallel-2D is our proposed model and parallel-CNN means the CNN proposed by [12] is adopted

Cosine Similarity	Headline Mean	Headline Median	Headline SD	Post Mean	Post Median	Post SD
BERT	0.7935	0.7904	0.0096	0.7886	0.7850	0.0108
k-BERT (parallel-2D w/o MI)	0.7932	0.7932	**0.0064**	0.7889	0.7888	0.0118
k-BERT (parallel-2D w/ MI)	**0.7969**	**0.7958**	0.0072	**0.7912**	**0.7932**	**0.0104**
FinBERT	0.7969	0.7987	0.0093	0.7817	0.7823	0.0093
k-FinBERT (parallel-2D w/o MI)	0.7954	0.7977	0.0063	0.7822	0.7813	**0.0086**
k-FinBERT (parallel-2D w/ MI)	**0.8009**	**0.8019**	**0.0069**	**0.7853**	**0.7839**	0.0105
XLNet	0.8199	0.8186	0.0151	0.8031	0.8025	0.0110
k-XLNet (parallel-2D w/o MI)	0.8261	0.8260	0.0083	0.8067	0.8066	0.0108
k-XLNet (parallel-2D w/ MI)	**0.8270**	**0.8261**	**0.0091**	**0.8074**	**0.8098**	**0.0090**
RoBERTa	0.8430	0.8423	0.0080	0.8085	0.8082	0.0136
k-RoBERTa (parallel-2D w/o MI)	0.8462	0.8462	**0.0048**	0.8117	0.8116	0.0175
k-RoBERTa (parallel-CNN w/ MI [12])	0.8455	0.8481	0.0090	**0.8128**	**0.8122**	**0.0110**
k-RoBERTa (parallel-2D w/ MI)	**0.8483**	**0.8500**	0.0170	0.8126	0.8118	0.0125

Ablation Analysis for SemEval 2017 Task 5

w/ MI means Mutual Information is adopted to select lexicons. w/o MI means all lexicons are used without any selection. The parallel-2D is our proposed model and parallel-CNN means the CNN proposed by [12] is adopted

The integration of external knowledge has improved both accuracy and stability!

Conclusion

- A framework that strategically combines symbolic (heterogeneous sentiment lexicons) and subsymbolic (deep language model) modules for TABFSA is proposed in this research.

- We are pioneering in employing attentive CNN and LSTM to touch multiple knowledge sources and integrating with transformer models in parallel and have achieved state-of-the-art performance on the SemEval 2017 Task 5 and the FiQA Task 1 datasets.

- We have discovered and demonstrated that parallel integration is a more effective approach than anterior and posterior when multiple sources of lexical knowledge are incorporated.

- The results show that incorporating financial and general lexicon knowledge can improve model performances more than retraining finance domain-specific language models in TABFSA task.

Future Work

We plan to investigate three further issues in future work:

- The influence of domain-specific lexicon coverage on their effectiveness
- The alternative methods for knowledge embedding, and
- What affects the effectiveness of different transformer architecture, e.g., RoBERTa vs. XLNet.

References

[1] Bing Liu. “Sentiment analysis and opinion mining”. In: Synthesis Lectures on Human Language Technologies 5.1 (2012), pp. 1–167.
[2] Colm Kearney and Sha Liu. “Textual sentiment in finance: A survey of methods and models”. In: International Review of Financial Analysis 33 (2014), pp. 171–185.
[3] Weijie Liu, Peng Zhou, Zhe Zhao, Zhiruo Wang, Qi Ju, Haotang Deng, and Ping Wang. 2020. K-bert: Enabling language representation with knowledge graph. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 34. 2901-2908.
[4] Anping Zhao and Yu Yu. 2021. Knowledge-enabled BERT for aspect-based sentiment analysis. Knowledge-Based Systems(2021), 107220.
[5] Md Shad Akhtar, Abhishek Kumar, Deepanway Ghosal, Asif Ekbal, and Pushpak Bhattacharyya. 2017. A multilayer perceptron based ensemble technique for fine-grained financial sentiment analysis. In EMNLP. 540–546.
[6] Dogu Araci. 2019. FinBert: Financial sentiment analysis with pre-trained language models. arXiv:1908.10063.
[7] Steven Loria et al. 2018. textblob Documentation. Release 0.15 2, 8 (2018).
[8] Guangyuan Piao and John G. Breslin. 2018. Financial aspect and sentiment predictions with deep neural networks: An ensemble approach. In Companion Proceedings of the The Web Conference 2018. 1973–1977.
[9] Steve Yang, Jason Rosenfeld, and Jacques Makutonin. 2018. Financial aspect-based sentiment analysis using deep representations. arXiv:1808.07931.
[10] Yi Yang, Mark Christopher Siy Uy, and Allen Huang. 2020. FinBERT: A pretrained language model for financial communications. arXiv:2006.08097.
[11] Mengxiao Jiang, Man Lan, and Yuanbin Wu. 2017. ECNU at semeval-2017 task 5: An ensemble of regression algorithms with effective features for fine-grained sentiment analysis in financial domain. In International Workshop on Semantic Evaluation. 888–893.
[12] Yoon Kim. 2014. Convolutional Neural Networks for Sentence Classiication. InProceedings of the 2014 Conference on Empirical Methodsin Natural Language Processing (EMNLP). 1746-1751.

Thank you!

FINXABSA: EXPLAINABLE FINANCE THROUGH ASPECT-BASED SENTIMENT ANALYSIS

Keane Ong, incoming PhD Student (NUS Digital Fintech)

Wihan, PhD Student (NTU Computing)

Dr Ranjan Satapathy (Scientist, A* STAR)

Professor Gianmarco Mengaldo (NUS Engineering & AIDF)

Professor Erik Cambria (NTU Computing)

INTRODUCTION

- Traditional AI : Black Box Methods
- Explainable AI : Provides tools to make sense of AI decisions
- Increasingly important technology:
  - Greater AI use in Finance
  - Transparency
  - Accountability
  - Trust

OVERVIEW

- Explainable AI in Financial Sentiment Analysis
  - Aspect-based sentiment analysis via GCN

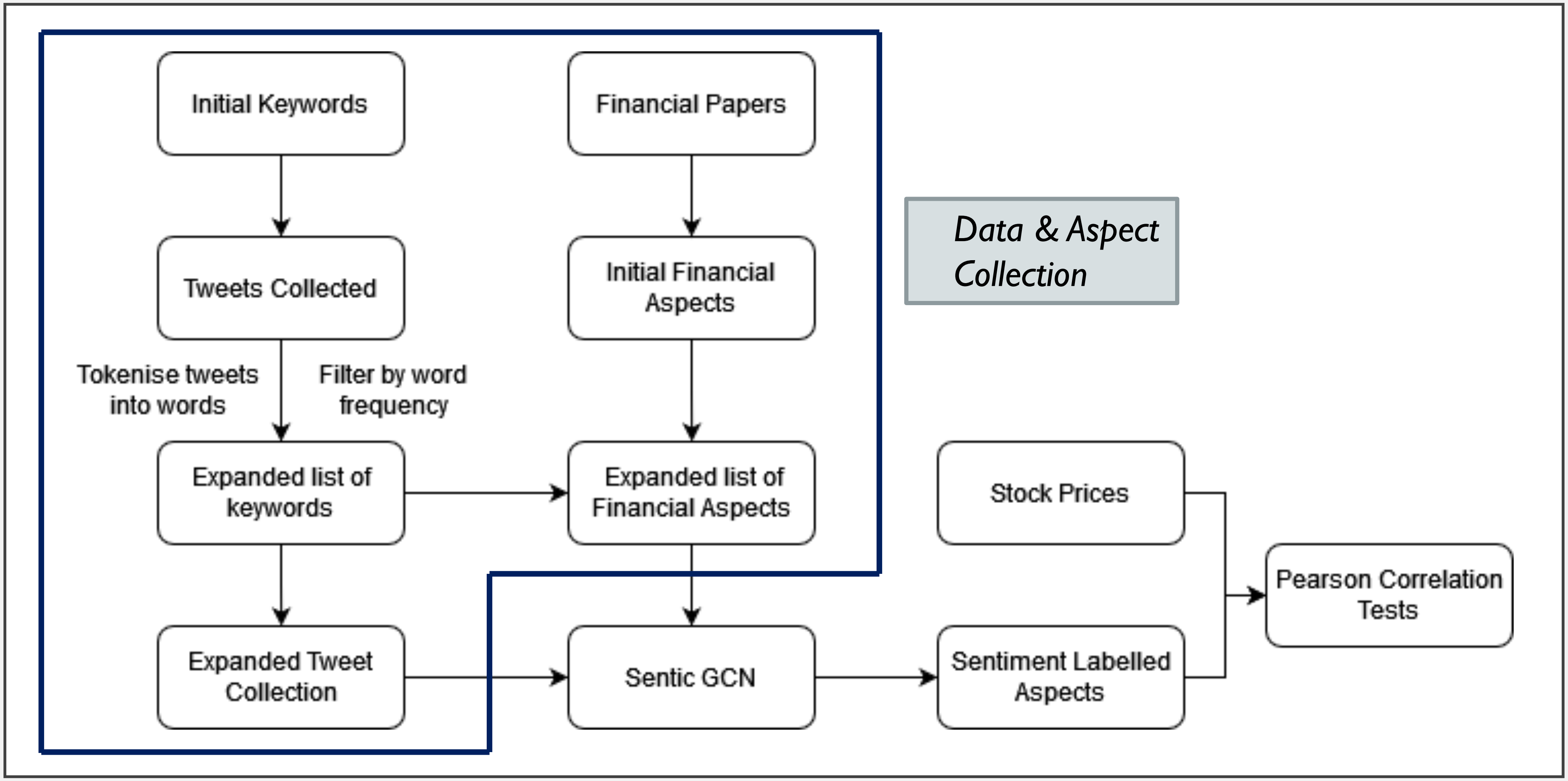
Negative

"Too many families don't know if their next paycheck will cover their expenses. Inflation is wiping out the middle class."

Explains specific aspect sentiment

OVERVIEW

- Aspect-based approach for explainable financial analysis
  - Collect financial text information
  - SA for specific financial aspects: *inflation, economy, stockmarket*
- Validate approach using statistical tests


Initial Keywords
Financial Papers
Tweets Collected
Initial Financial Aspects
Data & Aspect Collection
Tokenise tweets into words
Filter by word frequency
Expanded list of keywords
Expanded list of Financial Aspects
Stock Prices
Pearson Correlation Tests
Expanded Tweet Collection
Sentic GCN
Sentiment Labelled Aspects

DATA COLLECTION

- **Twitter Financial Data** via "Keyword Hopping":
  - 1st Corpus from *"nasdaq stock market"*
  - Filter new keywords by top frequency:

stock market, nasdaq, inflation, investors, ~weekday~ sharemarket, china & (stock market economy), recession, stock fall, market rally, finance, economy, (market stock) & closes, financial market, sharemarket, stockstobuy, sharemarket drops, pandemic stocks.

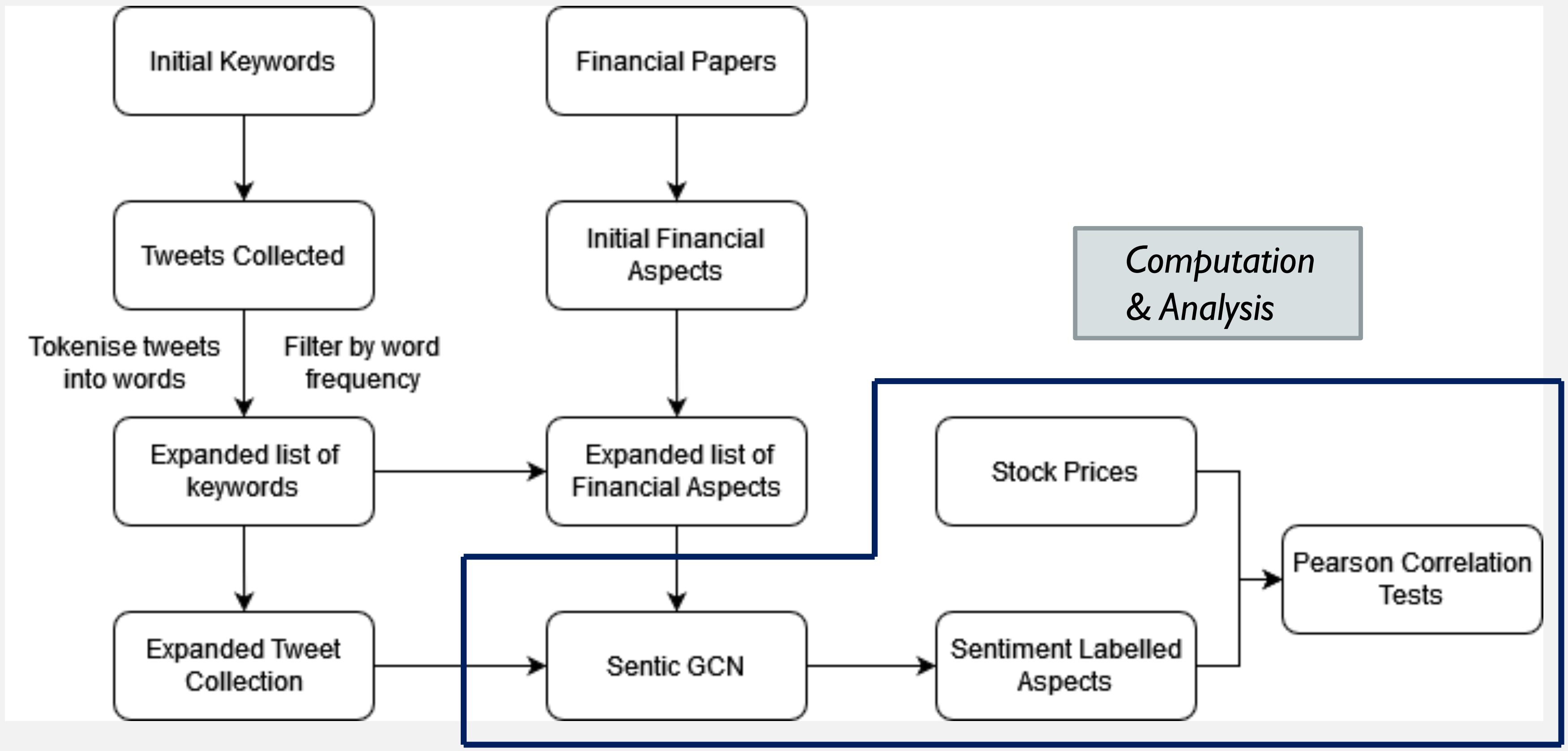
  - Use new keywords to collect 2nd Corpus (2022Q4)
  - SA performed on 2nd Corpus

DATA COLLECTION

- **Stock prices**
- 2022 Q4, Yahoo Finance
- Traditional Energy:
  - British Petroleum, Exxon, Shell
- Sustainable Energy:
  - NextEra, Clearway, Brookfield Renewables

DATA COLLECTION

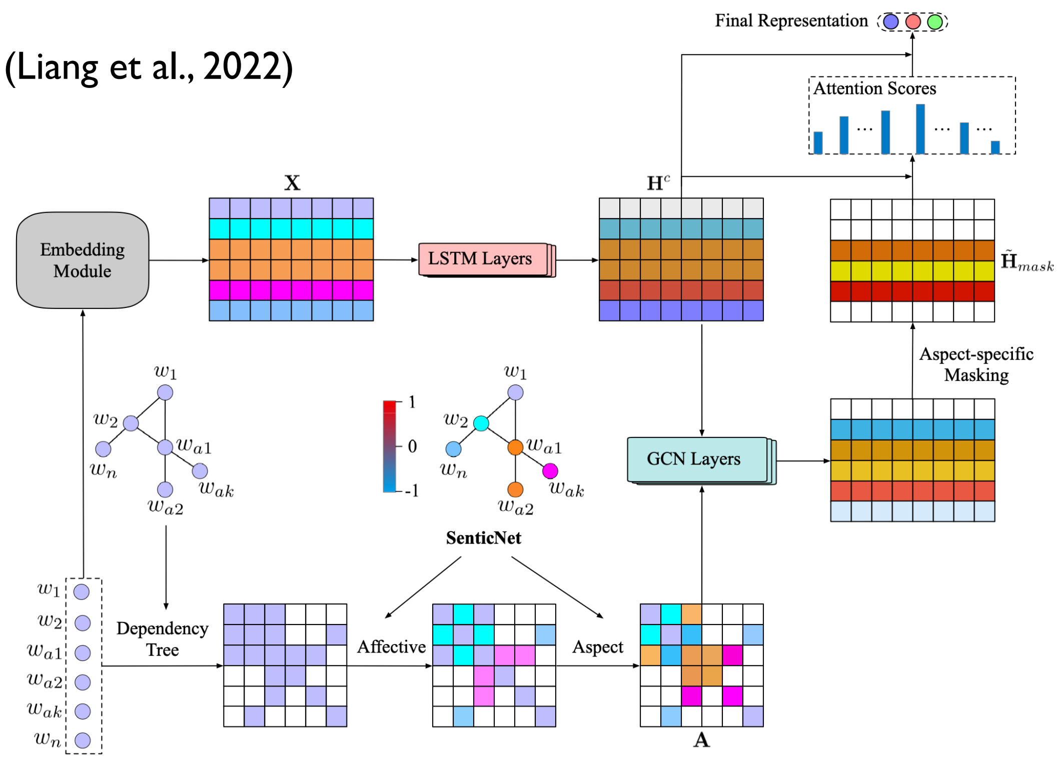
- **Financial aspects** for ABSA
- Basis: Daily words in financial world
- Draw on previous research (Salunkhe & Mhaske, 2019), (M. El-Haj et al. , 2016), (Chen et al. , 2017)
  - Matrix Factorisation
  - Latent Dirichlet Allocation
  - Principal Component Analysis
  - Expert annotation


Initial Keywords
Financial Papers
Tweets Collected
Initial Financial Aspects
Computation & Analysis
Tokenise tweets into words
Filter by word frequency
Expanded list of keywords
Expanded list of Financial Aspects
Stock Prices
Pearson Correlation Tests
Expanded Tweet Collection
Sentic GCN
Sentiment Labelled Aspects

SENTIC GCN

- Learning contextual representations
  - LSTM layers
  - Derive latent contextual representations

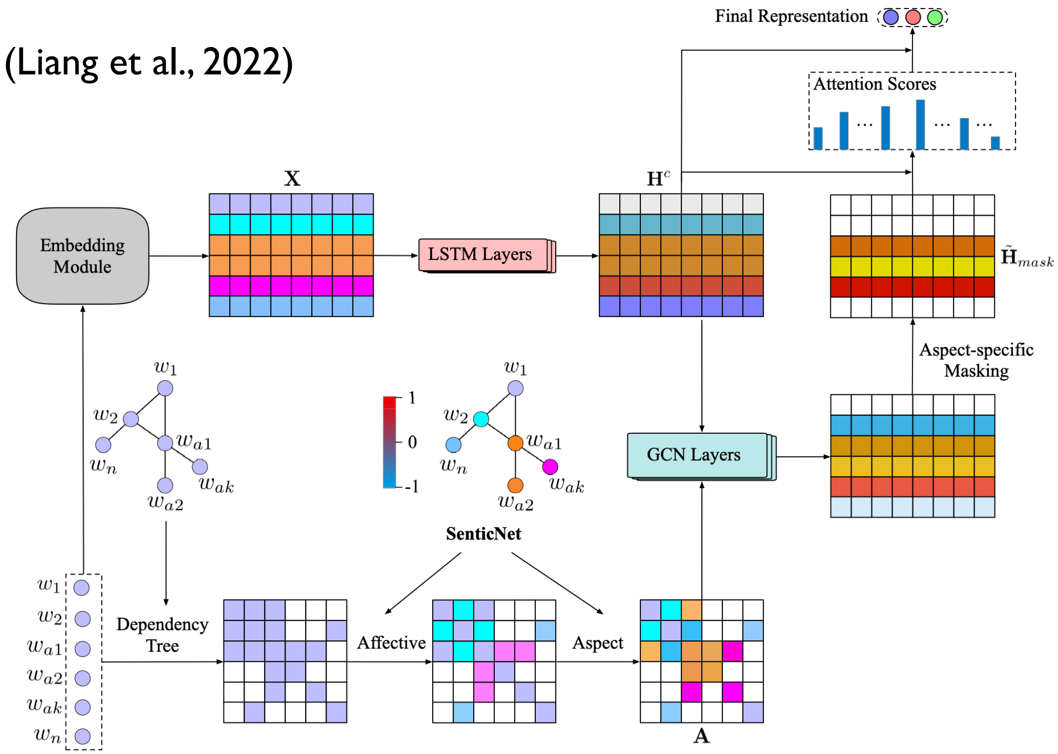
(Liang et al., 2022)



SENTIC GCN

- GCN Layers
  - Latent contextual representations + affective graph
  - Express sentiment dependencies

(Liang et al., 2022)

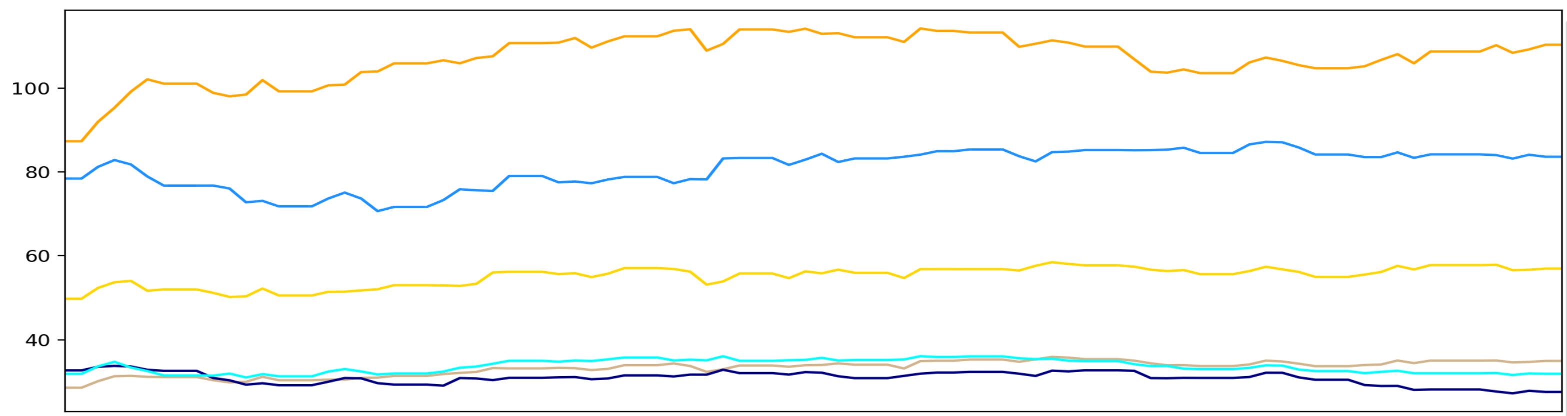


SENTIMENT SCORE COMPUTATION

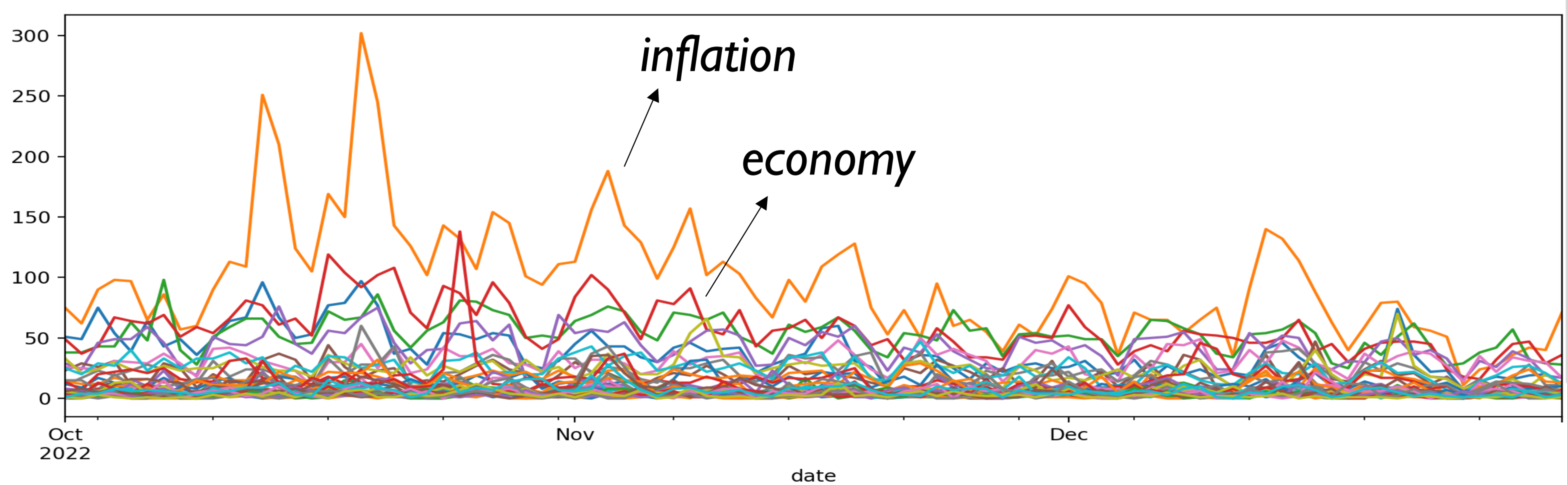
- Label aspect sentiment polarity from 2nd corpus of tweets
- Compute:
  - **Absolute frequency:** number of times an aspect is labelled positive/ negative each day.
  - Refer to these as "***positive/ negative sentiment scores***"
  - **Normalised frequency:** absolute frequency / total labels of specific aspect per day
- Select top 20 aspects from average absolute frequency per day

VISUALISING ASPECT SCORES

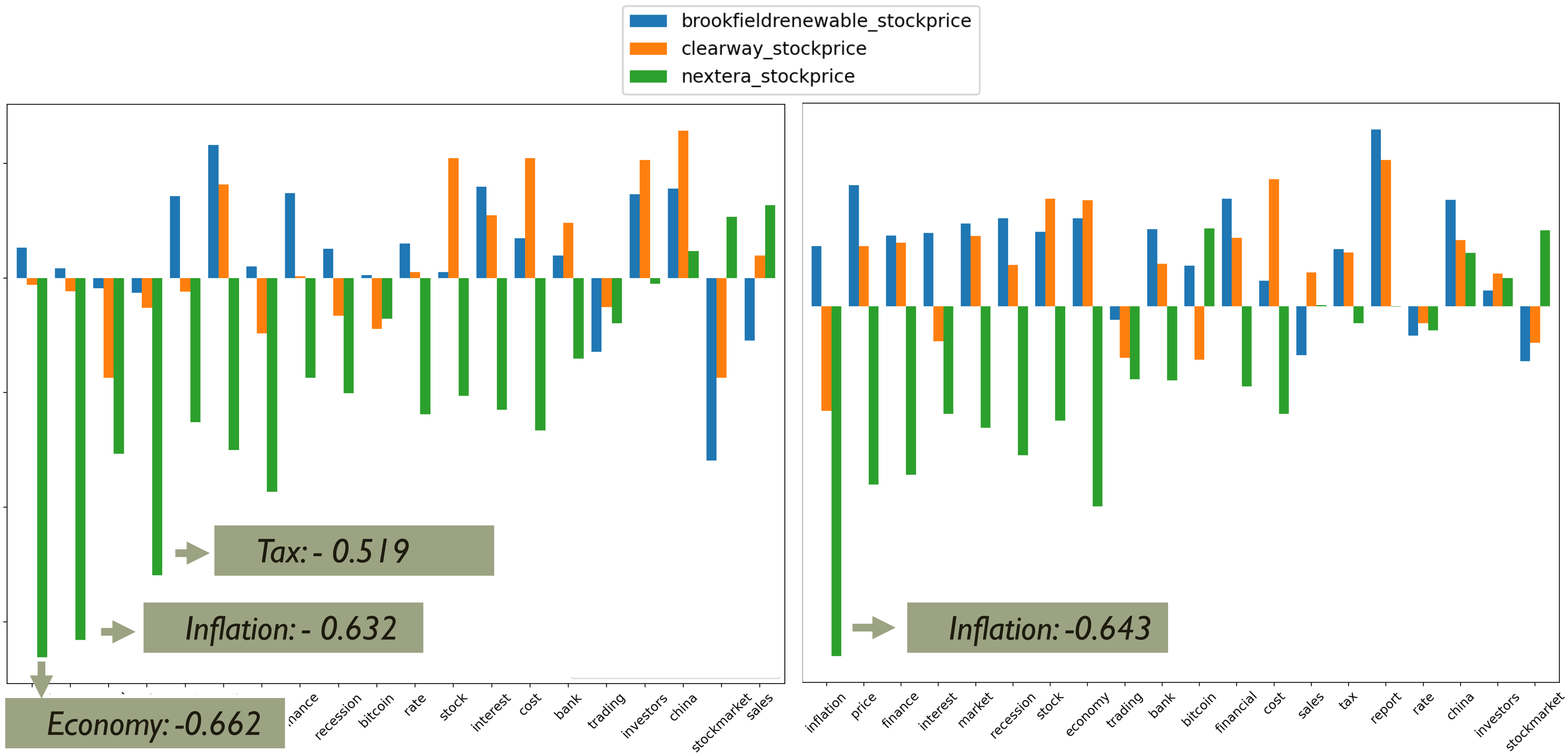
Stock Prices



Aspect Frequencies

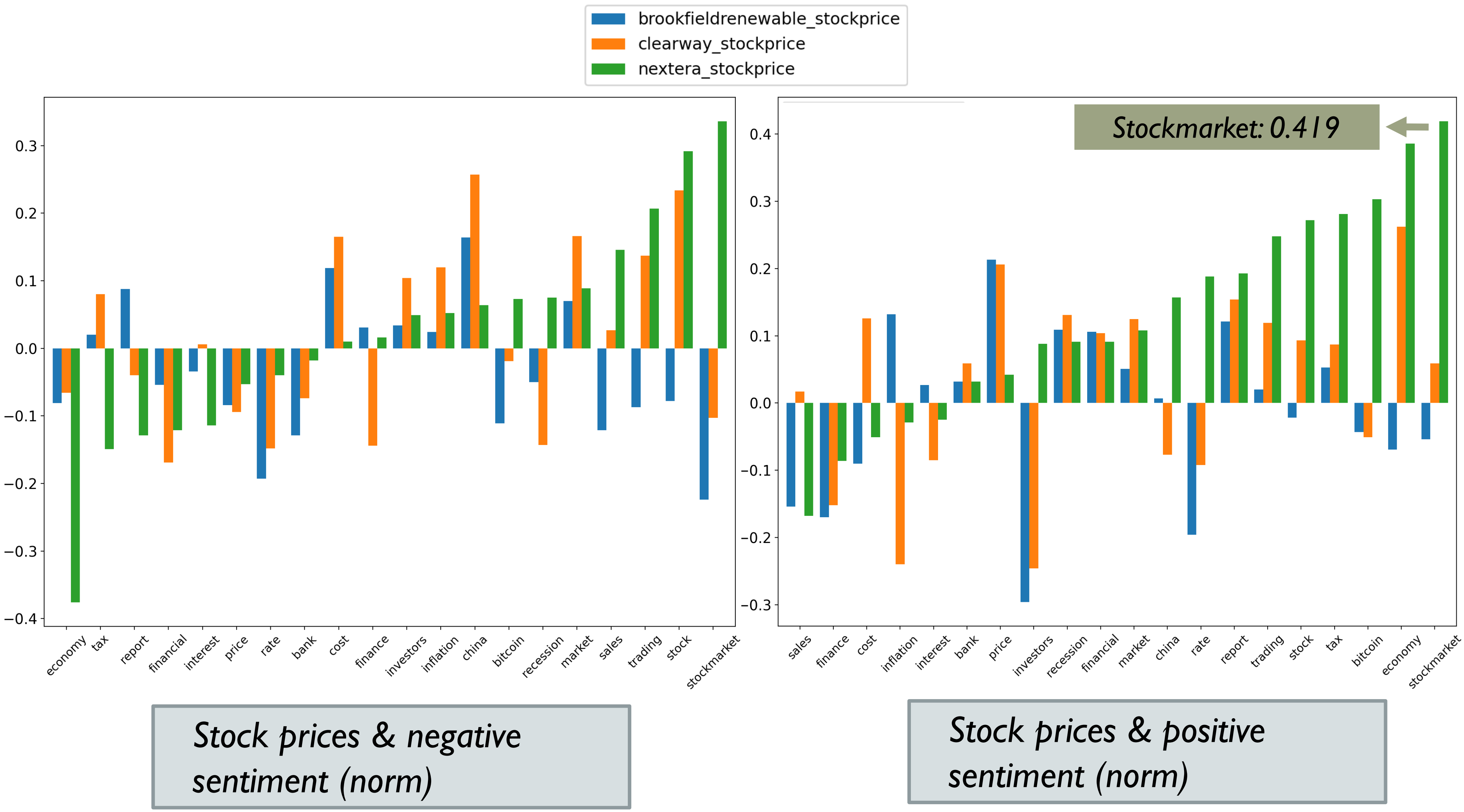


PEARSON CORRELATION FOR SUSTAINABLE ENERGY STOCKS

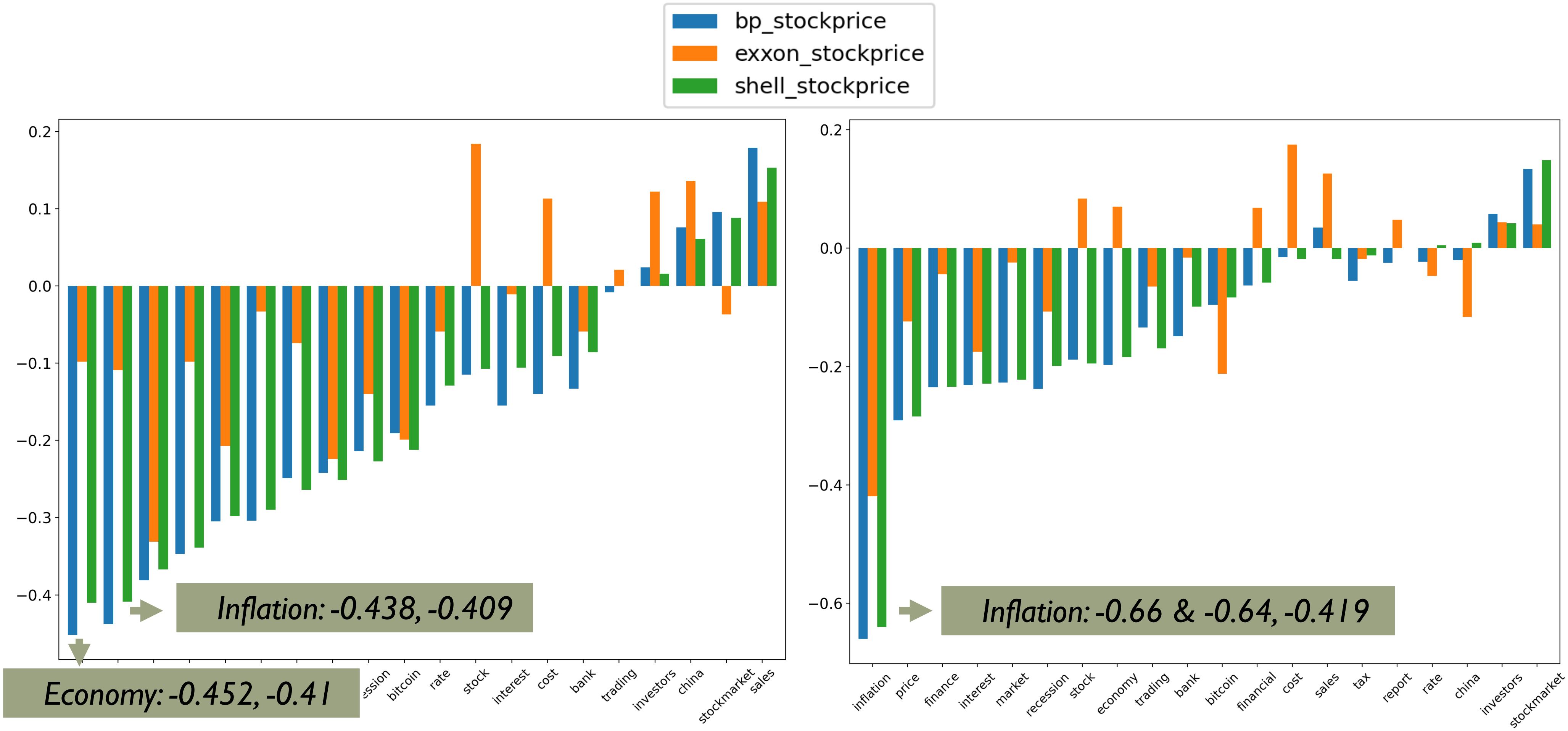


Stock prices & negative sentiment (abs)

Stock prices & positive sentiment (abs)

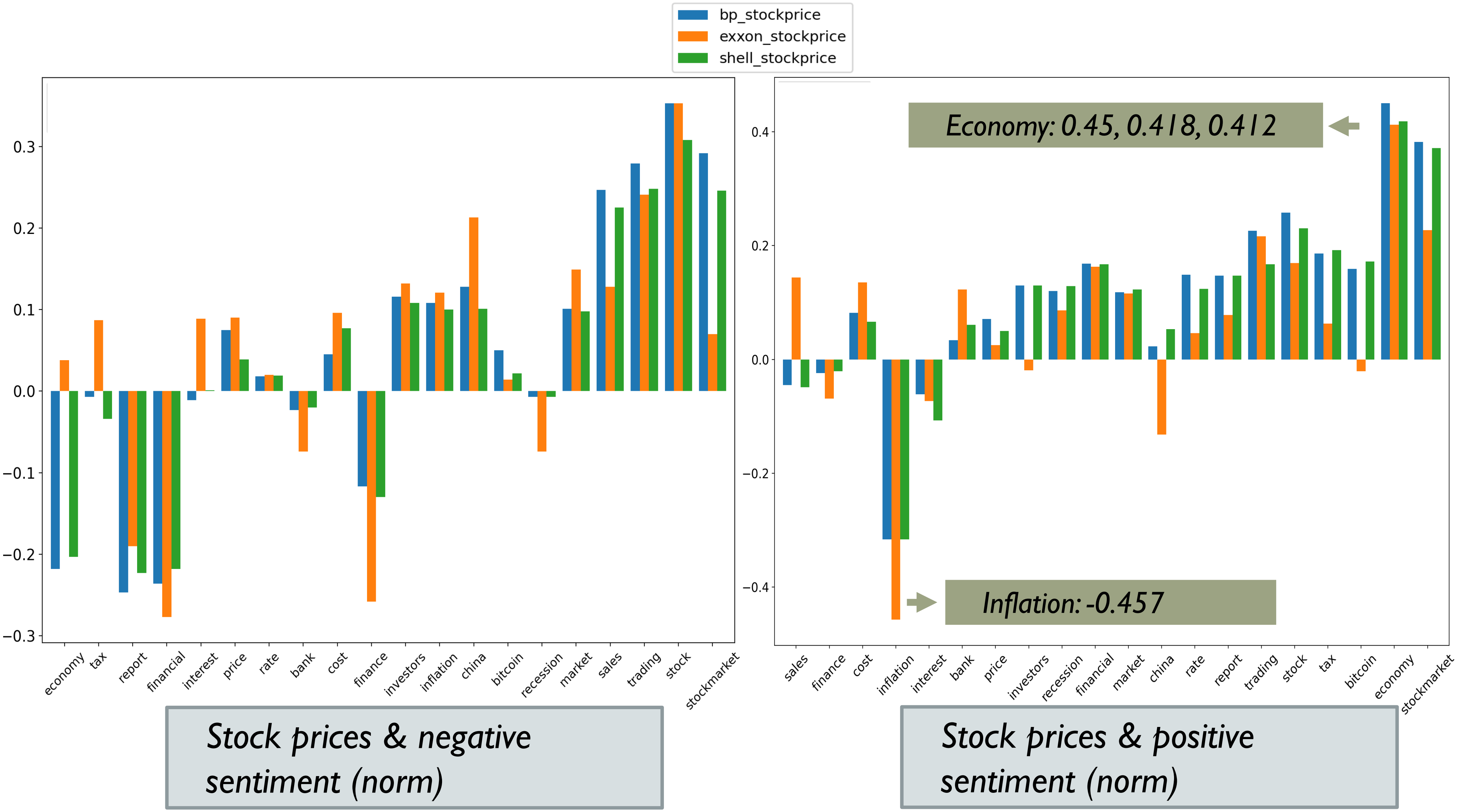

brookfieldrenewable_stockprice
clearway_stockprice
nextera_stockprice
Stockmarket: 0.419
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
−0.4
economy
tax
report
financial
interest
price
rate
bank
cost
finance
investors
inflation
china
bitcoin
recession
market
sales
trading
stock
stockmarket
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
sales
finance
cost
inflation
interest
bank
price
investors
recession
financial
market
china
rate
report
trading
stock
tax
bitcoin
economy
stockmarket
Stock prices & negative sentiment (norm)
Stock prices & positive sentiment (norm)

PEARSON CORRELATION FOR TRADITIONAL ENERGY STOCKS



Stock prices & negative sentiment (abs)

Stock prices & positive sentiment (abs)


bp_stockprice
exxon_stockprice
shell_stockprice
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
economy
tax
report
financial
interest
price
rate
bank
cost
finance
investors
inflation
china
bitcoin
recession
market
sales
trading
stock
stockmarket
Stock prices & negative sentiment (norm)
Economy: 0.45, 0.418, 0.412
Inflation: -0.457
0.4
0.2
0.0
−0.2
−0.4
sales
finance
cost
inflation
interest
bank
price
investors
recession
financial
market
china
rate
report
trading
stock
tax
bitcoin
economy
stockmarket
Stock prices & positive sentiment (norm)

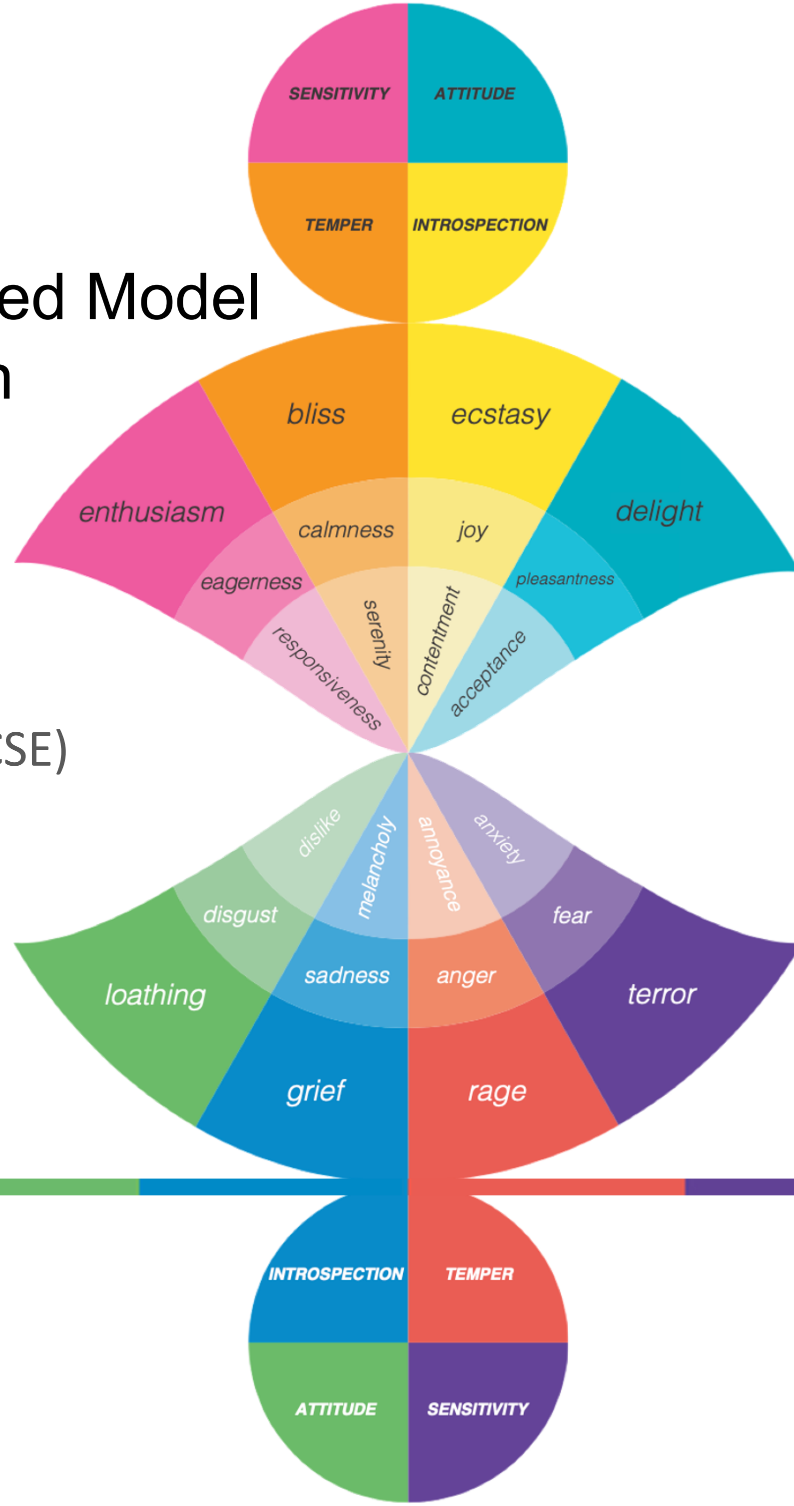
DISCUSSION

- Significant PC for *inflation & economy*
  - **Inflation:** negative PC for positive & negative labels
  - **Economy:** positive PC for positive labels, negative PC for negative labels
- *Economy aspect more meaningful*

FUTURE WORK

- Extend from 3 months to a year
- Stock specific tweets
- More elaborate keyword methods: KeyBERT
- Other statistical tests (Granger Causality & CCM)

SKIER: A Symbolic Knowledge Integrated Model for Conversational Emotion Recognition



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Facebook: facebook.com/senticnet
LinkedIn: linkedin.com/company/senticnet
Youtube: youtube.com/@senticnet

Problem Setup & Motivation

- The target of conversational emotion recognition (ERC) is to detect the sentiment/emotion (*e.g., happy, sad, frustrated, etc.*) of each utterance in conversations.

A_0: Warriors wins! Anyone want to celebrate? (HAPPINESS)

B_1: Yeah, let's hit the bars! (HAPPINESS)

C_2: Not for me. I am with Celtics tonight. (SADNESS)

B_3: What will you do alone later? (NEUTRAL)

C_4: Chop all onions we have and cry. (SADNESS)

A_5: Do it in your own room, bro! (DISGUST)

B_6: Don't leave the door open, please. (DISGUST)

- Historical utterances sometimes enhance, weaken, or reverse the raw emotion of an utterance.

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- Context sometimes enhances, weakens, or reverses the raw sentiment of an utterance.
- Some utterances are less informative and seldomly contain sentiment words. Hence external symbolic knowledge is necessary.

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A_5: Do it in your own room, bro!	(DISGUST)
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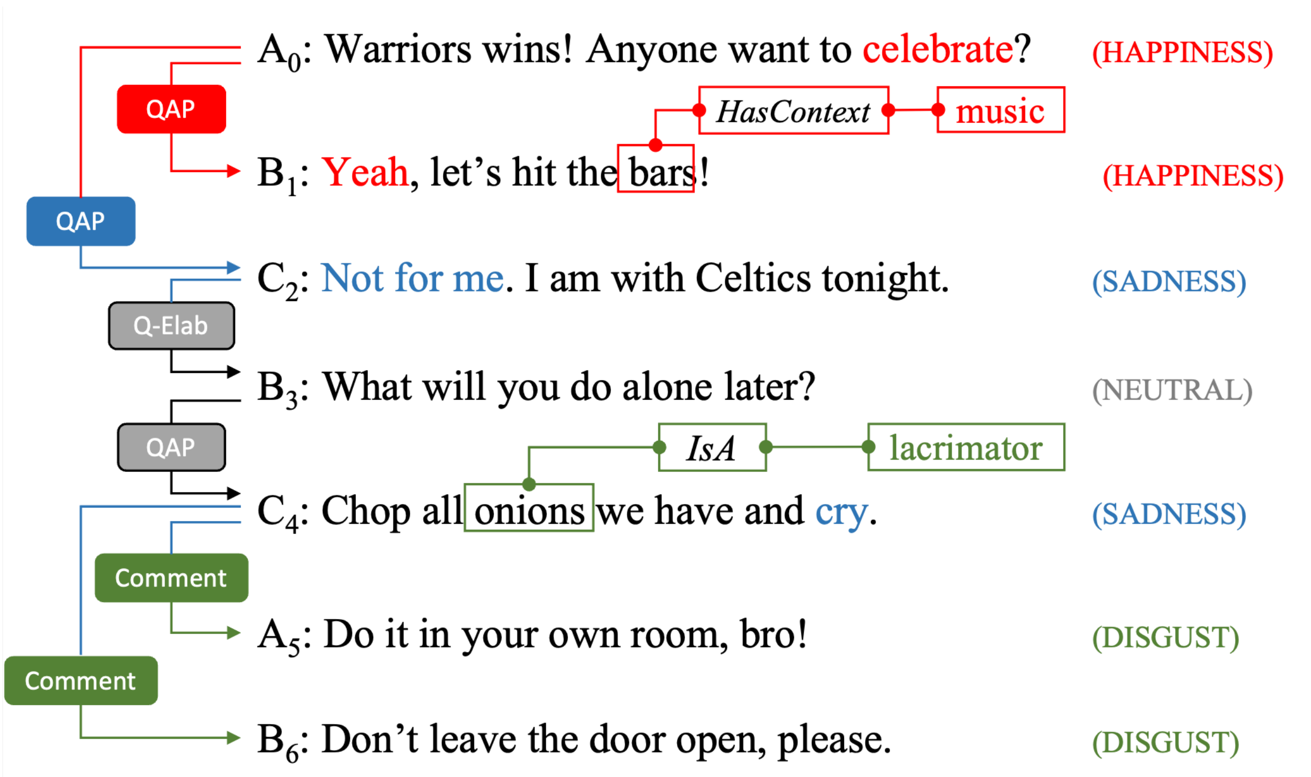
- Context sometimes enhances, weakens, or reverses the raw sentiment of an utterance.
- Some utterances are less informative and seldomly contain sentiment words. Hence external concept-level symbolic knowledge is necessary.
- Explicitly learning different types of dependencies can deliver extra accuracy gains in learning ERC.

Problem Setup & Motivation

- The target of conversational emotion recognition (ERC) is to detect the sentiment/emotion (*e.g., happy, sad, frustrated, etc.*) of each utterance in conversations.



Solution

Goal: How to better represent **concept-level symbolic knowledge** and **utterance-level dependency knowledge**, and **fuse** different symbolic knowledge to improve the performance of the ERC task

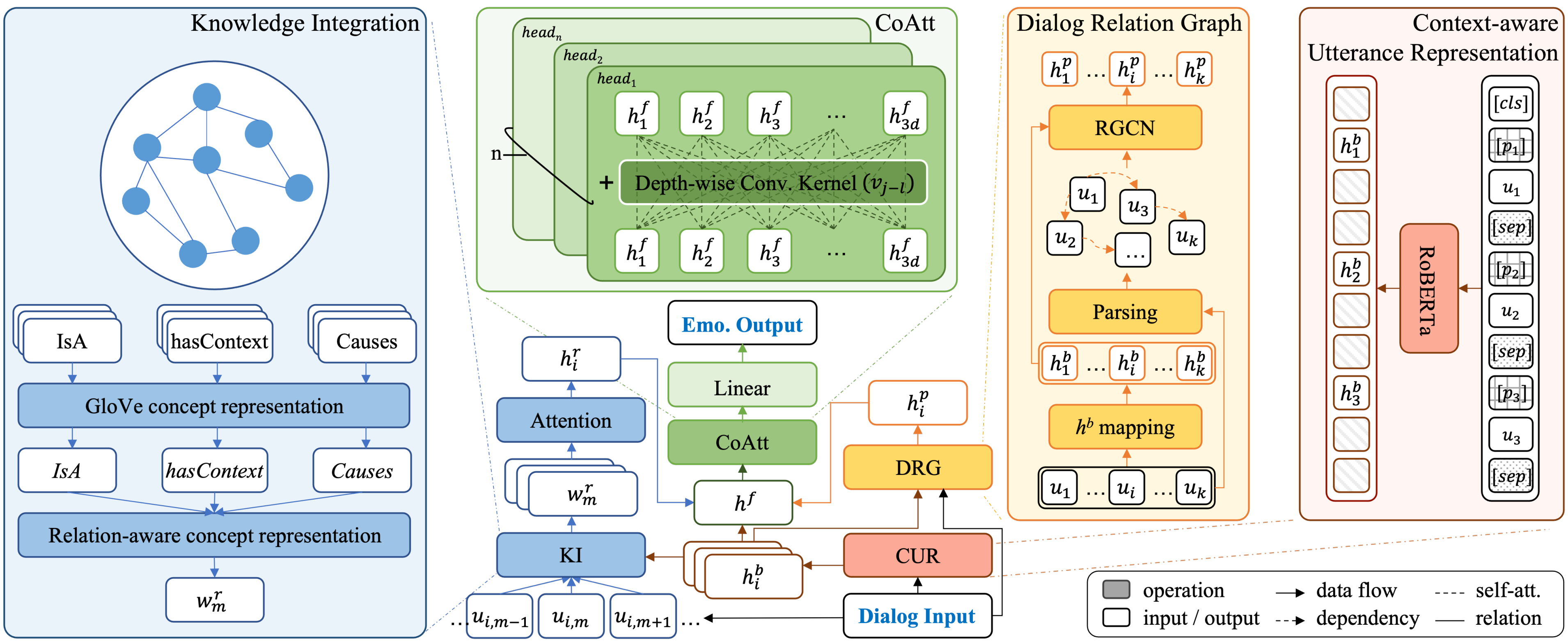
Solution:

- Context-aware representation
- Dialogue relation graph
- Concept-level symbolic knowledge
- Symbolic knowledge fusion

Modules:

- Pretrained language model (PLM)
- Dialogue Parser and RGCN
- ConceptNet and SenticNet
- Convolutional self-attention

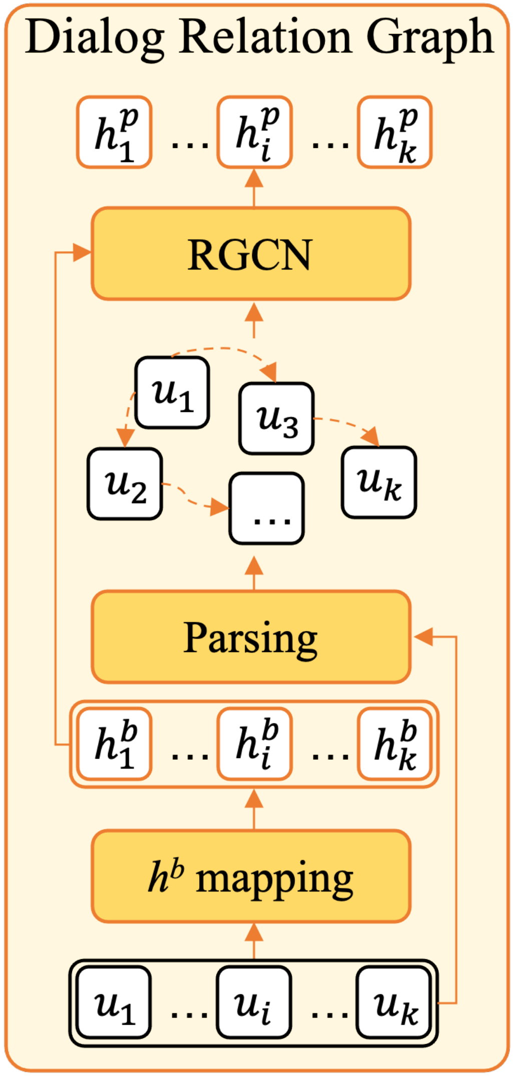
Model Architecture



Dialogue Relation Graph

$$g_i^{(l+1)} = \sigma\left(\sum_{t \in T} \sum_{j \in N_i^t} \frac{1}{c_{i,t}} W_t^{(l)} g_j^{(l)} + W_0^{(l)} g_i^{(l)}\right)$$

Relations	
Comment	Q-Elab
Acknowledgement	Elaboration
Contrast	Alternation
Correction	Parallel
QAP	Explanation
Clarification_Q	Result
Continuation	Conditional
Background	Narration



Concept-level Symbolic Knowledge Integration

Concept representation:

$$\mathbf{c}_{m,j} = \sum_{k=1}^{N_d} \alpha_k \cdot \mathbf{o}_{j,k}$$

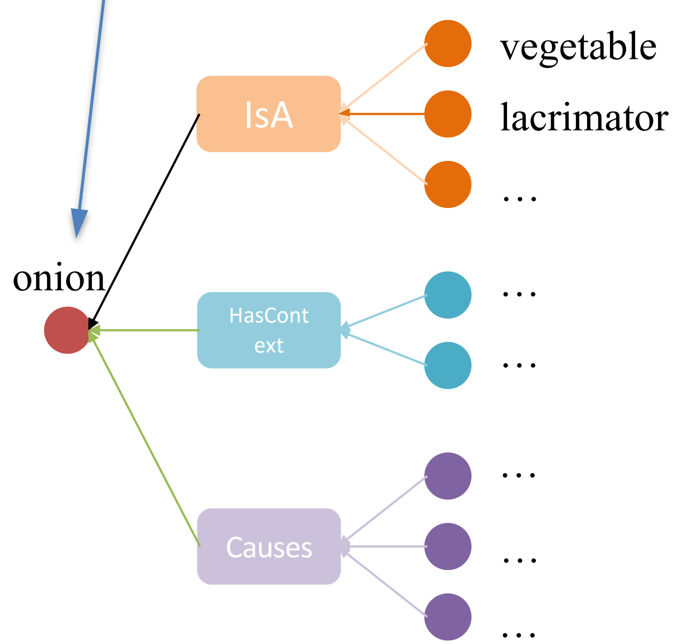
$$\alpha_k = softmax(\omega_k)$$

$$\omega_k^c = \min-\max(s_k) \cdot \left|\cos(h_i^b, \mathbf{o}_{j,k})\right|$$

$$\omega_a^k = \min-\max(sentic(o_{j,k}))$$

$$\omega_k = \lambda_k \cdot \omega_k^c + (1-\lambda_k) \cdot \omega_k^a$$

C_4: Chop all onions we have and cry.



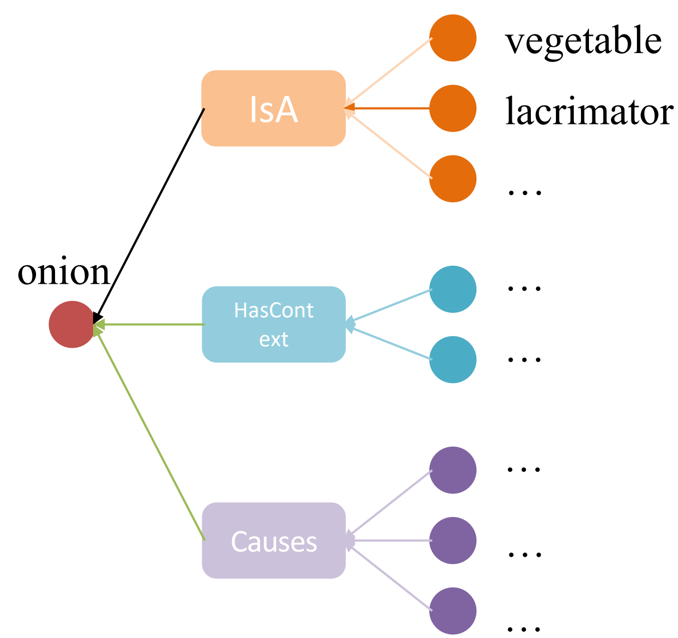
Concept-level Symbolic Knowledge Integration

Relation-aware concept representation:

$$\mathbf{w}_m^r = \mathbf{w}_m + \sum_{(r_j, o_j, k)} \beta_{j,k} \cdot (\mathbf{r}_j \odot \mathbf{c}_{m,j})$$

$$\beta_{k,j} = \frac{\exp(q_{j,k})}{\sum_{(r_j, o_{j',k'})} \exp(q_{j',k'})}$$

$$q_{j,k} = \mathbf{w}_m^T (\mathbf{r}_j \odot \mathbf{o}_{j,k})$$

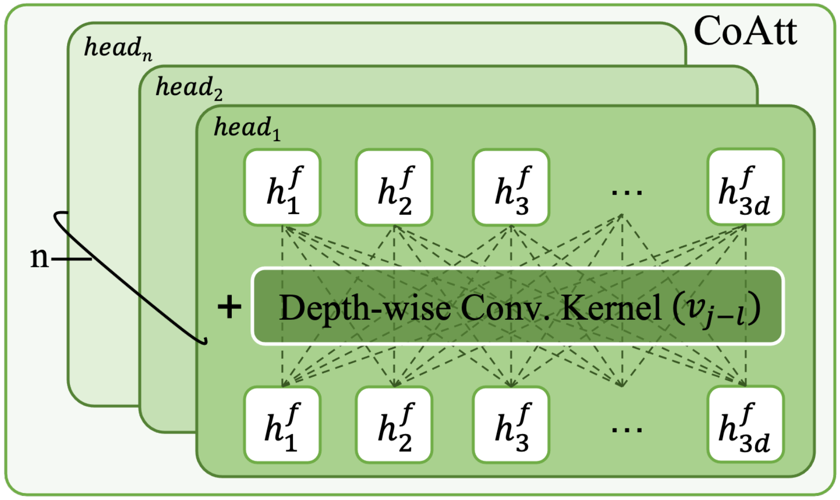


Symbolic Knowledge Fusion

$$h^{f} = \left[h_i^{b} \oplus h_i^{r} \oplus h_i^{p} \right]$$

$$(Q, K, V) = (h^{f} W_Q, h^{f} W_K, h^{f} W_V)$$

$$x_j^{(k)} = \sum_{l \in I} \frac{\exp(Q_j K_l^T + v_{j-l})}{\sum_{l' \in I} \exp(Q_j K_{l'}^T + v_{j-l'})} V_j$$



Experiment

- The DailyDialog derives from human daily communication. The data were sourced from English learning websites. The emotion labels include Ekman's six basic emotions and a neutral class.
- The EmoryNLP is a multi-party ERC dataset, sourced from Friends TV show scripts. The emotion labels are {joyful, peaceful, powerful, scared, mad, sad, neutral}. Sentiment labels were not provided but can be categorized by neutral: {neutral}, positive: {joyful, powerful, peaceful}, negative: {scared, sad, mad}.
- The MELD is a multimodal and multi-speaker sentiment analysis/classification database. The sentiment label of each utterance in a dialogue lies within one of the following seven sentiment classes: fear, neutral, anger, surprise, sadness, joy and disgust.

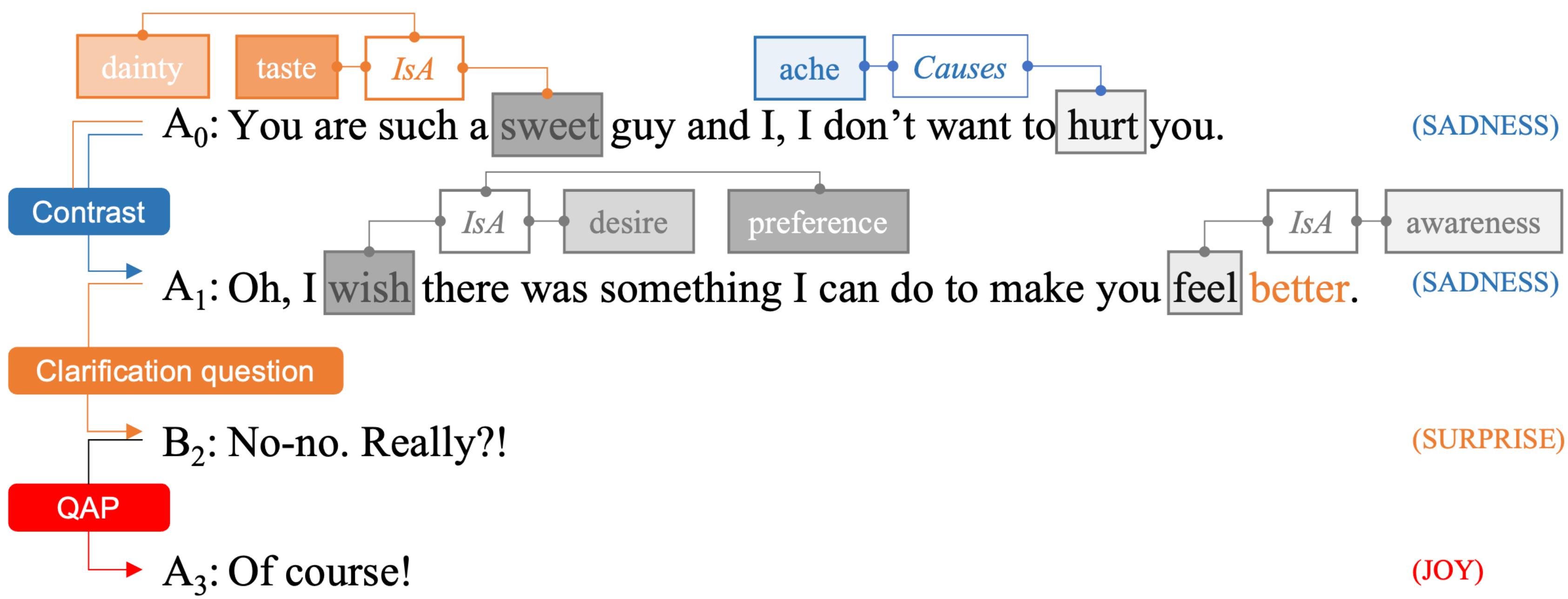
Dataset		Train	Dev	Test	Label	Metrics
MELD	u	9989	1109	2610	7/3	Weighted Avg F1
	d	1038	114	280		
EmoryNLP	u	9934	1344	1328	7/3	Weighted Avg F1
	d	713	99	85		
DailyDialog	u	87170	8069	7740	7(6)	Macro& Micro F1
	d	11118	1000	1000		

Main Results & Ablation Study

	Methods	MELD		EmoryNLP		DailyDialog	
		Weighted Avg F1				Macro	Micro
		3-cls	7-cls	3-cls	7-cls		
GloVe-based	CNN	64.25	55.02	38.05	32.59	36.87	50.32
	DiGCN	-	58.37	-	34.29	49.95	53.73
	KET	-	58.18	-	34.39	-	53.37
	DiXL	-	62.41	-	34.73	-	54.93
	DiRNN	66.10	57.03	48.93	31.70	41.80	55.95
PM-based	COSMIC	73.20	65.21	56.51	38.11	51.05	58.48
	DAG	-	63.65	-	39.02	-	59.33
	P-CKG	-	65.18	-	38.80	51.59	59.75
	T-GCN	-	65.36	-	39.24	-	**61.91**
	RoDiRNN	72.12	62.02	55.28	37.29	48.20	55.16
	RoBERTa	72.14	63.61	55.36	37.44	49.65	57.32
	CoMPM	73.08	66.52	57.14	37.37	53.15	60.34
	SKIER	**75.05**	**67.39**	**60.08**	**40.07**	**56.68**	**62.31**
	SKIER-l	**74.73**	**66.99**	57.98	**39.49**	**56.39**	61.72
	SKIER-a	74.17	66.91	**59.39**	39.53	54.02	61.03

Component	MELD	EmoryNLP	DailyDialog
SKIER	67.39	40.07	56.68(Macro)
w/o DRG	65.27↓2.12	38.56↓1.53	55.70↓0.98
w/o KI	66.10↓1.29	38.54↓1.51	52.54↓4.14
w/o DRG & KI	64.08↓3.31	38.10↓1.97	49.73↓6.95
w/o TL	65.87↓1.52	39.50↓0.57	53.38↓3.30
w/o DRS	65.73↓1.66	39.25↓0.82	56.33↓0.35
w/o PDR	66.24↓1.15	39.08↓0.99	56.06↓0.62
w/o RACR	65.80↓1.59	39.14↓0.93	54.99↓1.69
w/o IsA	65.95↓1.44	38.79↓1.28	55.69↓0.99
w/o HasContext	65.97↓1.42	38.44↓1.63	55.68↓1.00
w/o Causes	66.36↓1.03	38.55↓1.52	55.21↓1.47

Case Study



dainty
taste
IsA
ache
Causes
A0: You are such a sweet guy and I, I don't want to hurt you.
(SADNESS)
Contrast
IsA
desire
preference
IsA
awareness
A1: Oh, I wish there was something I can do to make you feel better.
(SADNESS)
Clarification question
B2: No-no. Really?!
(SURPRISE)
QAP
A3: Of course!
(JOY)

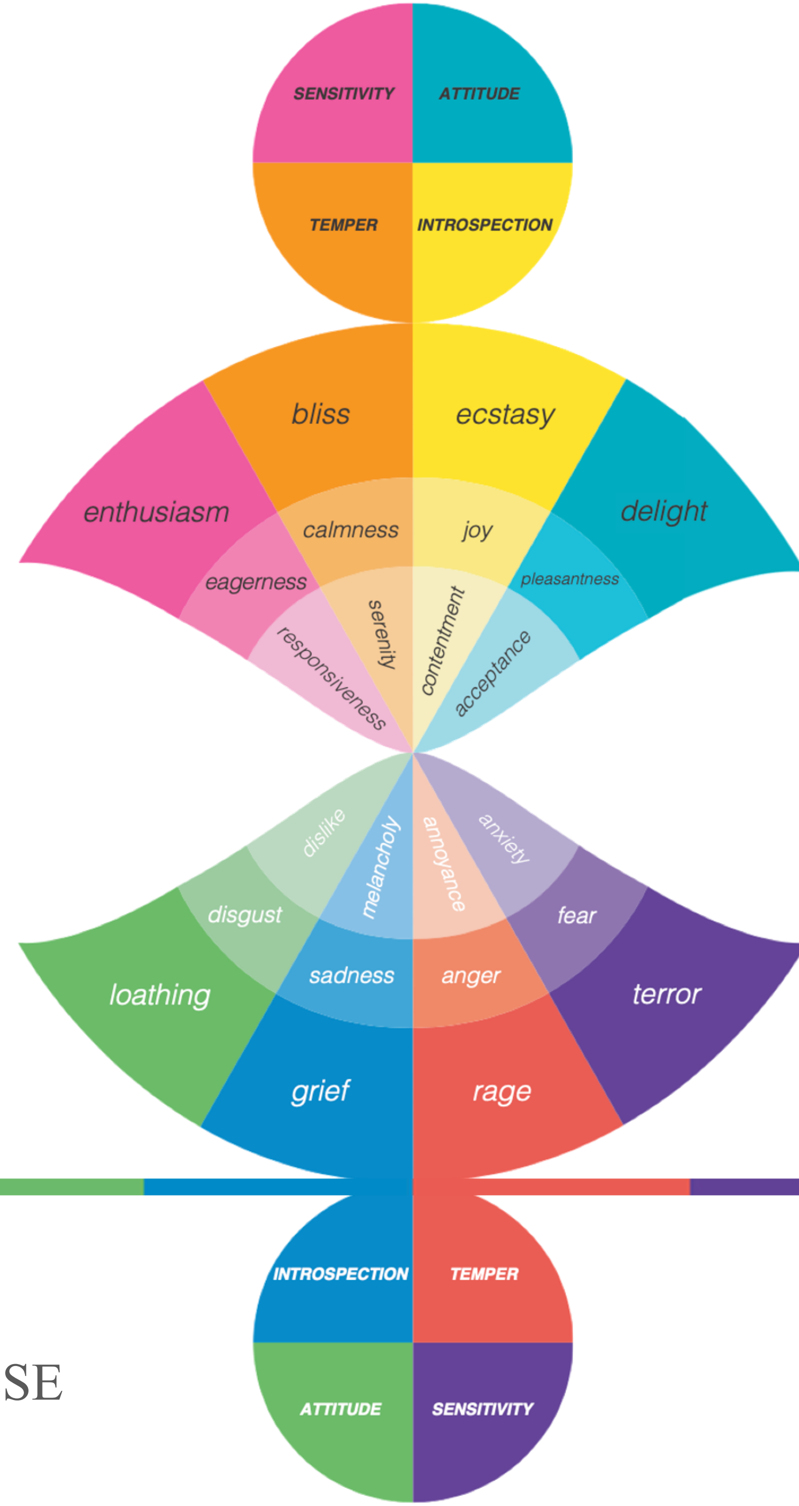
References

- Li W, Shao W, Ji S, Cambria E. BiERU: bidirectional emotional recurrent unit for conversational sentiment analysis. arXiv preprint arXiv:2006.00492. 2020 May 31.
- Zhong P, Wang D, Miao C. Knowledge-enriched transformer for emotion detection in textual conversations. arXiv preprint arXiv:1909.10681. 2019 Sep 24.
- Shen W, Chen J, Quan X, Xie Z. DialogXL: All-in-One XLNet for Multi-Party Conversation Emotion Recognition. arXiv preprint arXiv:2012.08695. 2020 Dec 16.
- Li J, Ji D, Li F, Zhang M, Liu Y. HiTrans: A Transformer-Based Context-and Speaker-Sensitive Model for Emotion Detection in Conversations. InProceedings of the 28th International Conference on Computational Linguistics 2020 Dec (pp. 4190-4200).
- Majumder N, Poria S, Hazarika D, Mihalcea R, Gelbukh A, Cambria E. Dialoguernn: An attentive rnn for emotion detection in conversations. InProceedings of the AAAI Conference on Artificial Intelligence 2019 Jul 17 (Vol. 33, No. 01, pp. 6818-6825).
- Ghosal D, Majumder N, Poria S, Chhaya N, Gelbukh A. Dialoguegcn: A graph convolutional neural network for emotion recognition in conversation. arXiv preprint arXiv:1908.11540. 2019 Aug 30.
- Wang Y, Zhang J, Ma J, Wang S, Xiao J. Contextualized emotion recognition in conversation as sequence tagging. InProceedings of the 21th Annual Meeting of the Special Interest Group on Discourse and Dialogue 2020 Jul (pp. 186-195).
- Li J, Zhang M, Ji D, Liu Y. Multi-task learning with auxiliary speaker identification for conversational emotion recognition. arXiv e-prints. 2020 Mar:arXiv-2003.
- Busso C, Bulut M, Lee CC, Kazemzadeh A, Mower E, Kim S, Chang JN, Lee S, Narayanan SS. IEMOCAP: Interactive emotional dyadic motion capture database. Language resources and evaluation. 2008 Dec;42(4):335-59.
- Zahiri SM, Choi JD. Emotion detection on tv show transcripts with sequence-based convolutional neural networks. arXiv preprint arXiv:1708.04299. 2017 Aug 14.
- Schuller B, Valster M, Eyben F, Cowie R, Pantic M. Avec 2012: the continuous audio/visual emotion challenge. InProceedings of the 14th ACM international conference on Multimodal interaction 2012 Oct 22 (pp. 449-456).
- Poria S, Hazarika D, Majumder N, Naik G, Cambria E, Mihalcea R. Meld: A multimodal multi-party dataset for emotion recognition in conversations. arXiv preprint arXiv:1810.02508. 2018 Oct 5.
- Zhang Y, Tiwari P, Song D, Mao X, Wang P, Li X, Pandey HM. Learning interaction dynamics with an interactive LSTM for conversational sentiment analysis. Neural Networks. 2021 Jan 1;133:40-56.

Thank You

Saving Earth One Tweet at a Time through the Lens of Artificial Intelligence

Cuc Duong, Qian Liu, Rui Mao, Erik Cambria



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Background

Opinions about climate change

- People's opinions are regularly **surveyed**
- Popular topics:
  - The deployed solution
  - New policies
  - Motivating factors
- Social media is another channel
  - Challenges:
    - Unsupervised learning: group unrelated topics
    - Taxonomy: limited accuracy
    - Supervised learning: lack of training data

Background

Text	Taxonomy	Human
"A new report from the medical journal {Name} finds that human-caused #climatechange is worsening human #health in just about every measurable way."	Risk/Disaster, 'health'	Agree
"The system can track bleaching events in near-real-time and provide an overall view of trends and changes in coral reef health."	Risk/Disaster, 'health'	Disagree

Table 1: Correct and incorrect examples for topic modeling using Global Pulse taxonomy (http://unglobalpulse.net/climate/taxonomy/)

Related datasets

Dataset	Source	Labels	Count	Available
Climate Fever (2020)	Wikipedia	Fact-checking	1535	Yes
GWSD (2020)	News articles	Stance	2000	Yes
Pearce et al. (2014)	Twitter	Stance	239	No
An et al. (2014)	Twitter	Subjectivity, polarity	2550	No
SemEval-2016 Task 6	Twitter	Stance, polarity	564*	Yes
Ours	**Twitter**	**Category, polarity**	**2300**	**Yes**

Table 2: Types of labels from recent works.

Stance: Whether climate change is a serious concern?
*: 564 climate change tweets over 4870 samples

ClimateTweets

Dataset	Categories
Global Pulse	General, Politics/Opinion, Weather, Economy, Risk/Disaster, Energy, Agriculture/Forestry, Arctic, Ocean/Water
Abbar et al. (2016)	Global Pulse + Negotiation/ Summit, Campaigns, Air quality, Sandstorm
Pathak et al. (2017)	Energy, Weather, Economy, Agriculture/Forestry, Water, Security, Climate Denial, Air Issues, Animals
ClimateTweets	**Impact, Root Cause, Politics or Policy, Mitigation, Others**

Table 3: Category comparison to existing works.

ClimateTweets

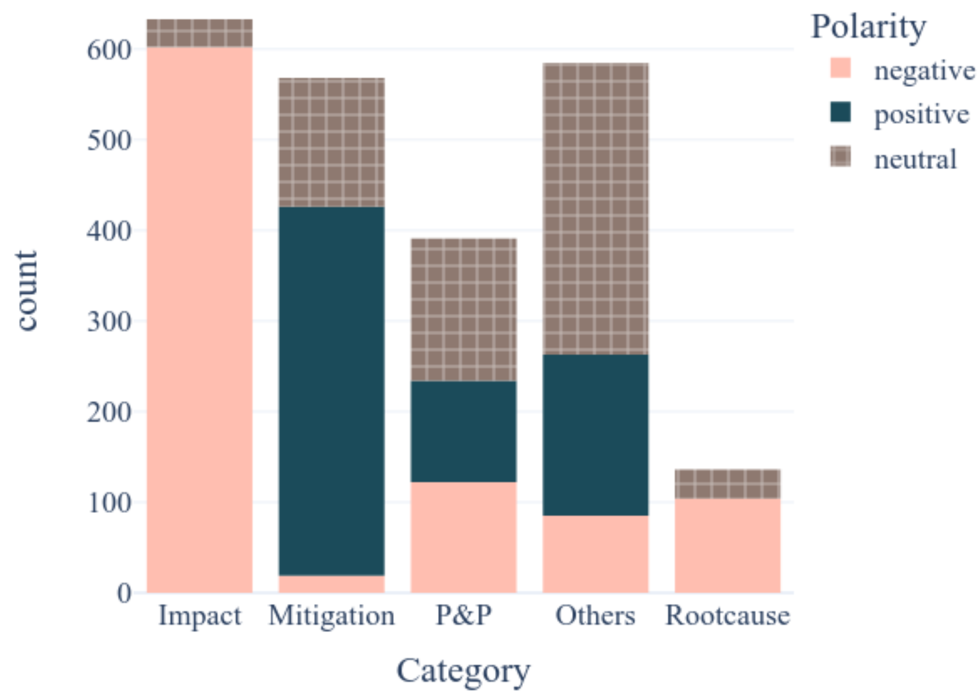

Fig. 1: Number of samples per category and polarity.

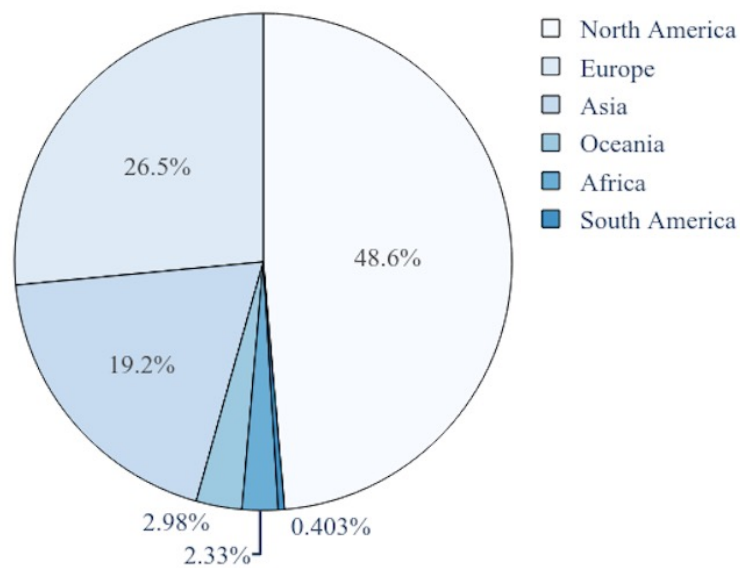

Fig. 2: Distribution of locations of the accounts

ClimateTweets

Model	Impact	Miti.	P&P	R.C.	Others	Micro F1
LDA	0.13	0.32	0.26	0.02	0.17	0.22
GloVe-LSTM	0.50	0.38	0.27	0.05	0.30	0.38
GloVe-GRU	0.37	0.45	0.28	0.07	0.34	0.36
BERT-FC	**0.79**	**0.64**	**0.68**	**0.45**	**0.61**	**0.67**

Table 5: Category detection performance measured in F1 score. *Miti. denotes Mitigation, and R.C. denotes Root cause*

Model	Positive	Negative	Neutral	Micro F1
GloVe-LSTM	0.22	0.60	0.22	0.43
GloVe-GRU	0.46	0.60	0.04	0.46
Stanford Corenlp	0.52	0.66	0.45	0.56
BERT-FC	**0.60**	**0.81**	**0.46**	**0.66**

Table 6: Sentiment classification performance measured in F1 score.

Corpus Study Findings

- **Root cause:** caution to low birth rate
- **Impact:** relate hazardous events as climate change consequences
- **Mitigation:** positive thoughts
- **Politics and policy:** strongest polarized category
- **Others:** advertisements

Applications

- Evaluating gaps in pre-trained models
- Filtering the target category
- Analyzing group debate on climate projects and policies
- Finding the most popular green products advertised on Twitter

Q&A

Towards Resource-Aware Sentiment Analysis

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March 9, 2023

Background

- Polarity Detection: Positive, Negative, Neutral
- Emotion Recognition: Happy, Excited, Sad, Frustrated, Angry, Neutral, ..

Subjective Perception Problem[1]: different individuals may react differently to the same stimulus

[1] Zhao, Sicheng, et al. "Affective Image Content Analysis: A Comprehensive Survey." IJCAI. 2018

Background

State of the art feature extractors based on large pre-trained language models.

- Large memory footprint
- Demanding training process

Not suitable for resource-constrained devices (e.g. embedded devices).

Problem

- Set of models
- Set of candidate devices

Most suitable model to deploy on one or more of these devices?
Can we fully make use of pre-trained large feature extractors without having to fine-tune them?

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Hardware-aware model selection

Incorporate hardware constraints into model selection phase

$$\min_i \lambda_p c_{pi} + \lambda_m c_{mi} + \lambda_s c_{si}$$

subject to:

$$0 < c_{mi} \leq M$$

$$0 < c_{si} \leq S$$

$$0 \leq c_{pi} \leq P$$

- c_{pi} model performance error cost
- c_{mi} memory cost
- c_{si} training time cost
- M, S max acceptable memory, training time. P min performance

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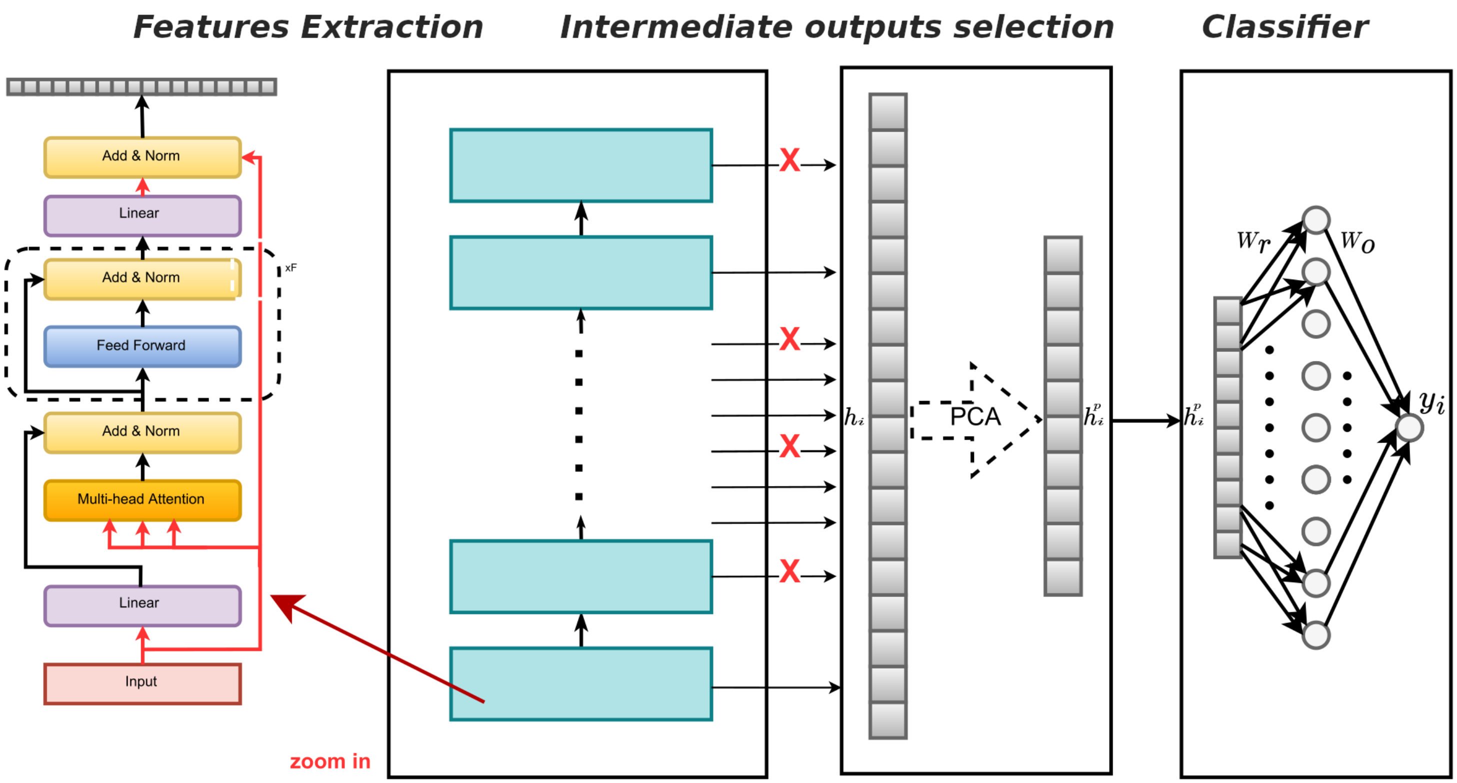
Architecture



What is the optimal classifier under different environments?

Experimental setup

- **Datasets:** MELD, MOSEI. Full dataset and 1k samples subset
- **Models:** Fine tuned language model (MobBERT), Linear, Hidden, Random Based
- **Metrics:** Weighted F1, Weighted Accuracy (WA), wall clock time, peak memory usage
- **Feature Extraction:** Pre-trained language model

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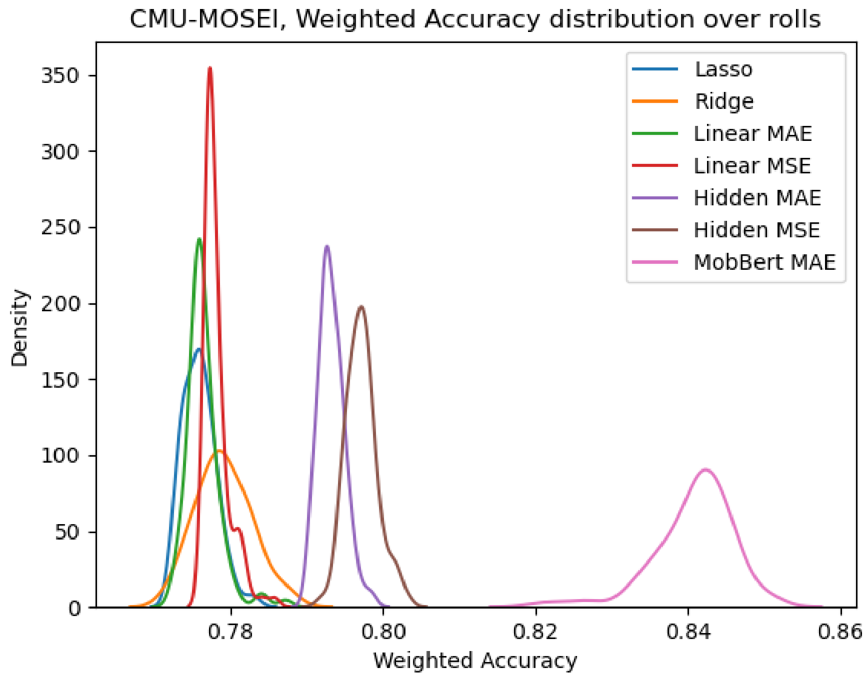
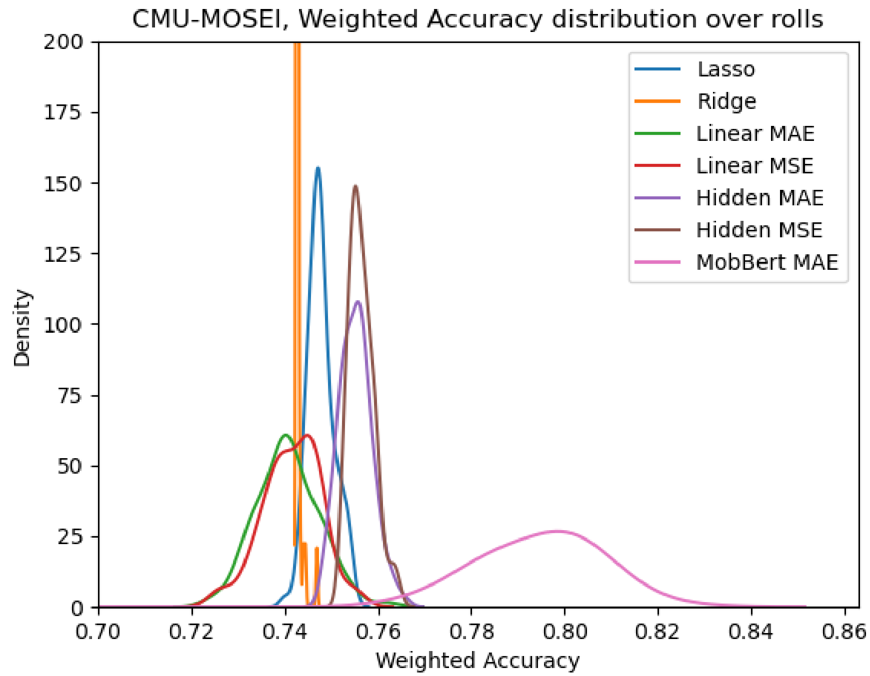
Results 1

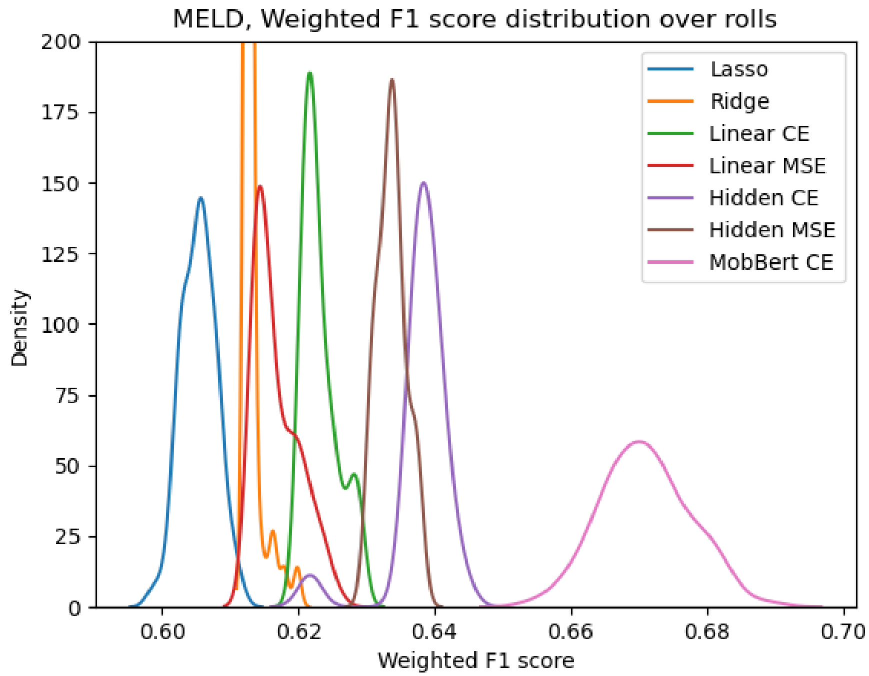
MOSEI, weighted accuracy. Full dataset (left) and 1k subset(right)

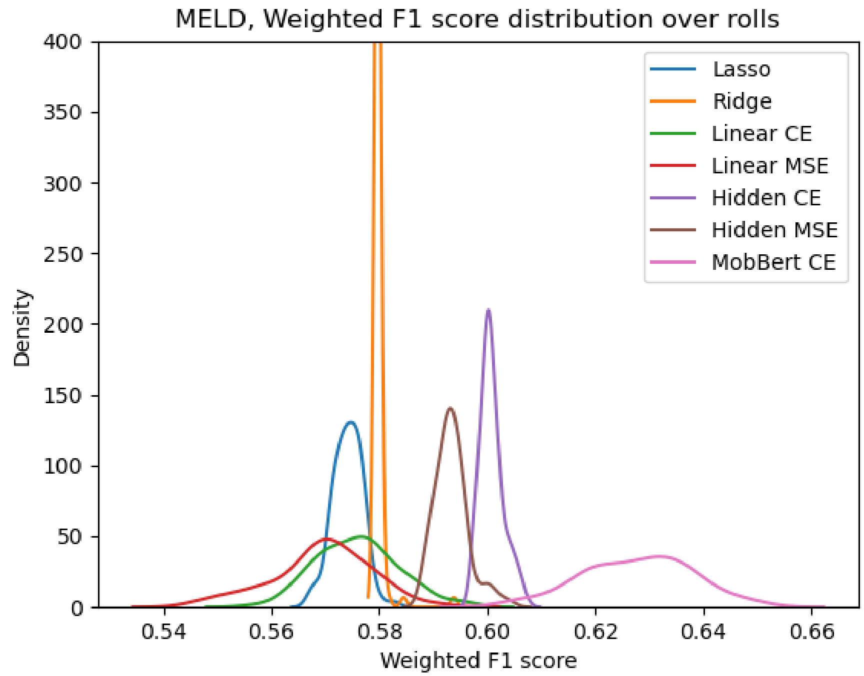




Results 2

MELD, F1 Score. Full dataset (left) and 1k subset(right)





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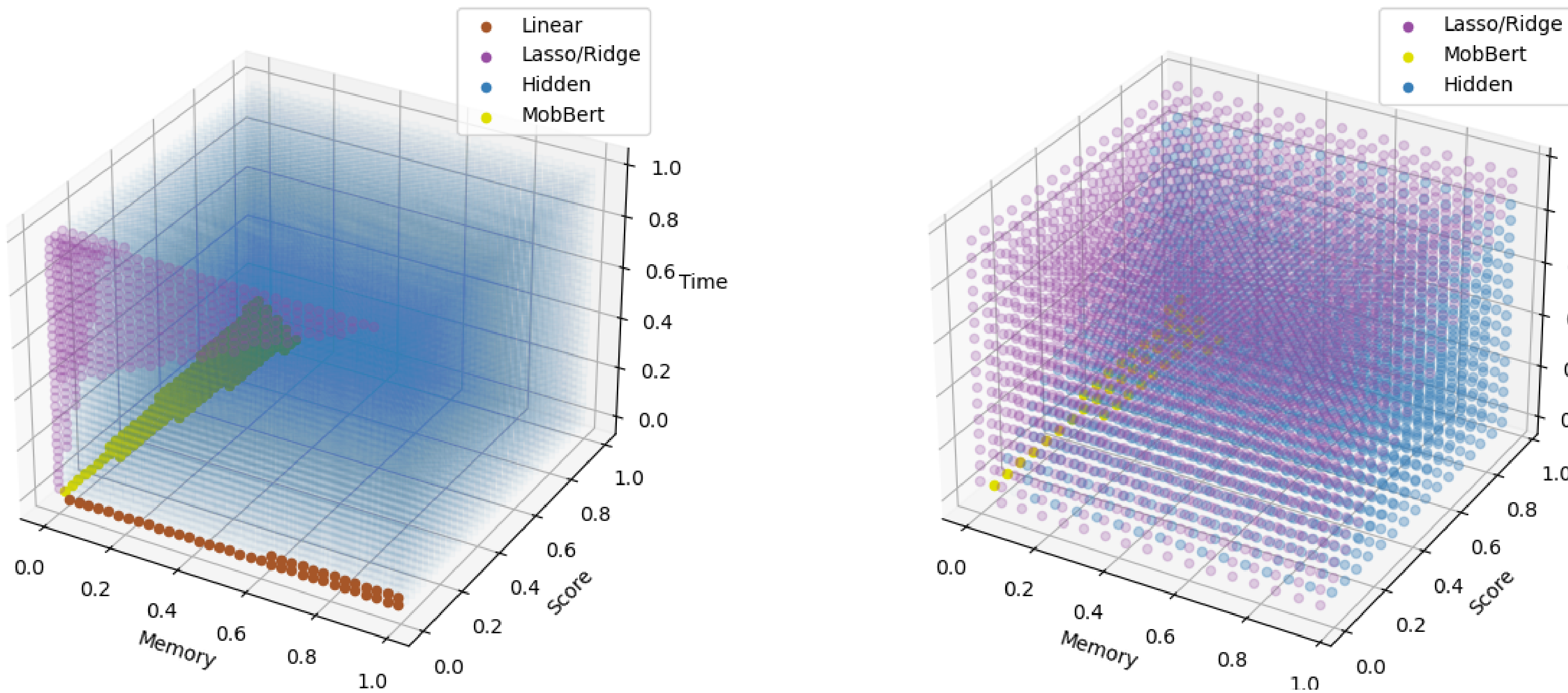
Results 3

MOSEI, optimal solution according to cost function. Full dataset (left) and 1k subset(right)



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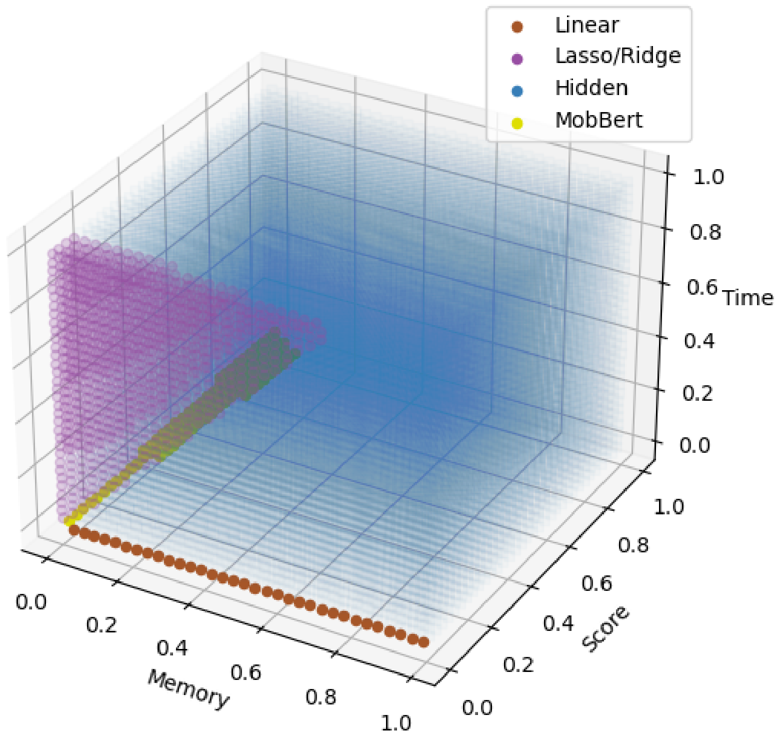
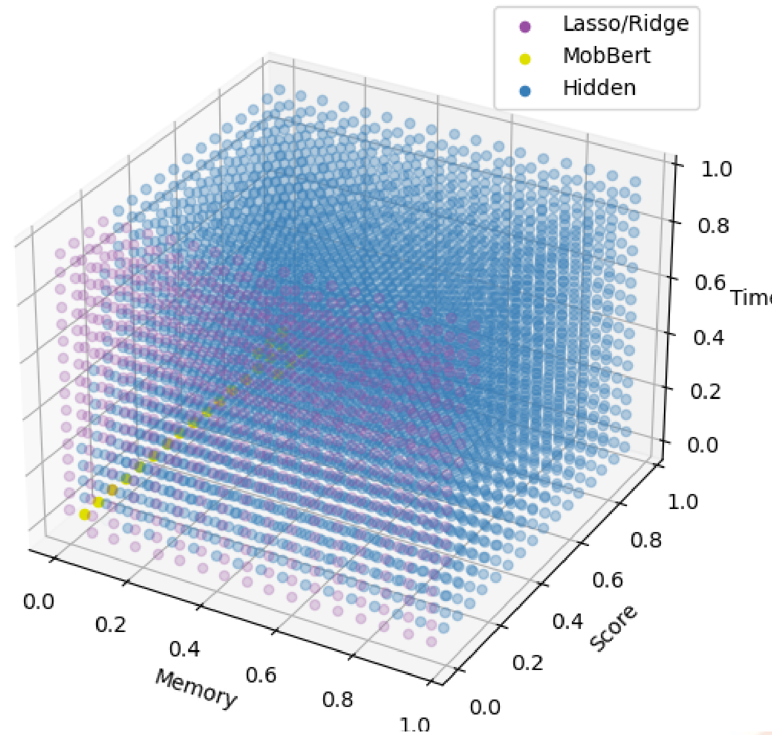
Results 4

MELD, optimal solution according to cost function. Full dataset (left) and 1k subset(right)





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Results 5 - Utilizing language models intermediate layers

	CMU-MOSEI	MELD
	WA	*F1*
Classifier only - last layer	0.7762	0.5808
MobBERT	0.8398	0.6530
Classifier only - intermediate	0.8074	0.6192

Table: Comparison of baseline with the version that uses intermediate outputs.

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Conclusion

- On-device training require different approaches than SOTA methods
- Model selection has to account for hardware constraints
- We can improve performance by fully making use of language models feature extraction capabilities

MiMuSA - Mimicking Human Language Understanding for Fine-grained Multi-class Sentiment Analysis

Zhaoxia WANG, Zhenda Hu, Seng-Beng Ho, Erik Cambria and Ah-Hwee Tan

Presenter: Dr. Zhaoxia Wang

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Outline

- ❑ Introduction
- ❑ Past Efforts & Related Work
- ❑ Proposed MiMuSA
- ❑ Results & Discussion
- ❑ Conclusion

Mimicking Human Language Understanding for Fine-grained Multi-class Sentiment Analysis

Introduction/Background

- ❑ Learning-based methods
- ❑ Non-learning-based methods
- ❑ Hybrid methods

Human-like language understanding?

Question: Are those methods

human-like language understanding processes?

Picture credit: https://usingtheirwords.org/community/
https://www.istarto.com/digital-marketing/social-media-marketing/

Past Efforts

- ❑ Learning based methods
  - Enhancing machine-learning methods
- ❑ Non-learning-based methods, and hybrid methods
  - Fine-grained Sentiment and Emotion Classification
  - Multi-Level Fine-Scaled Sentiment Sensing

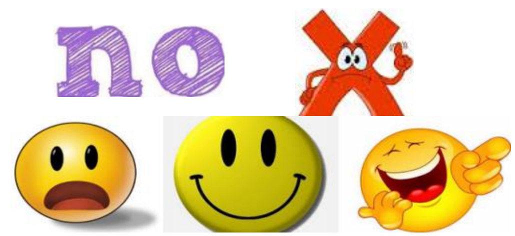
MiMuSa - Mimicking Human Language Understanding for Fine-grained Multi-class Sentiment Analysis

Past Efforts

1. Enhanced Learning-based Sentiment Analysis

- ❑ Negation dealing
- ❑ Emoticon handling
- ❑ Feature selection

…



Enhancement Strategies:

Positive Emoticons		Negative Emoticons	
:P	(:	:(	)':
;P	(;	;(	=(
[;	=]	)':	=(
…		…	

1. I **love** this product
2. I  this product
3. I **dislike** this product

Z. Wang, JC. Tong, HC Chin, Enhancing machine-learning methods for sentiment classification of web data, ***Information Retrieval Technology***, pp. 394-405, 2014. Springer.

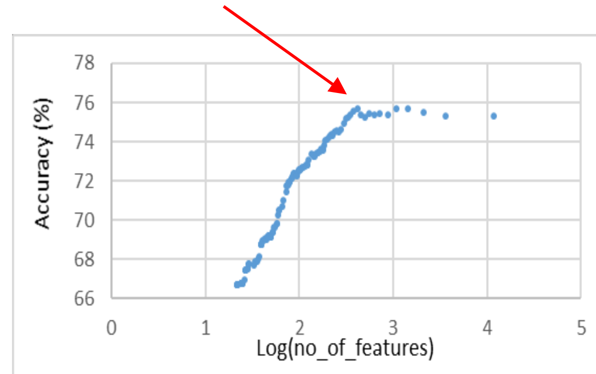
Picture credit: http://blog.youthwant.com.tw/lin99/life/
http://www.bitbang.com/voice-of-customer.php
http://bloggless.com/im/online-marketing/five-key-strategy-tips-social-media-marketing-consistency-customer-service/

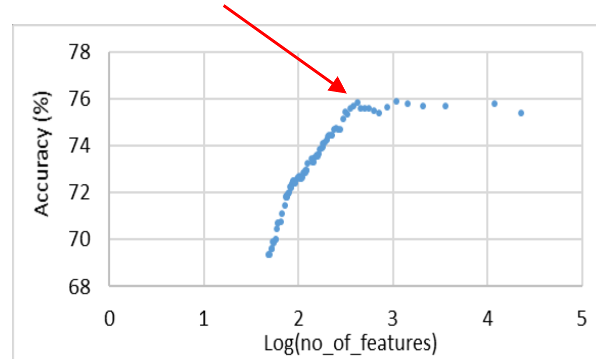
Past Efforts

1. Enhanced Learning-based Sentiment Analysis

- The **enhancements** (Negation dealing, emoticon handling, and feature selection, etc.) can improve the performance of **learning-based method**.
- **A very clear relationship** between the performance of the **learning-based methods** and the number of **features selected**/used.
- Not human-like, there is no "understanding" processes

- Feature selection





Z. Wang, JC. Tong, HC Chin, Enhancing machine-learning methods for sentiment classification of web data, ***Information Retrieval Technology***, pp. 394-405, 2014. Springer.

Z. Wang and Z. Lin, Optimal Feature Selection for Learning-Based Algorithms for Sentiment Classification, ***Cognitive Computation***, vol. 12, no. 1, pp. 238-248, 2020.

Past Efforts

2. Non-learning-based methods, and hybrid methods

- "A Method and System for Sentiment Classification and Emotion Classification", **Patent Cooperation Treaty (PCT) Application** PCT/SG2015/050469-- **SentiMo**
  - Focus on **fine-grained classification** of social media **sentiment and emotion identifications**
- "A Method and System for Chinese-based Hybrid Multilingual Emotion Fine-grained Sensing of Textual Data", **Singapore Patent Application** No.: 10201601413Q, 2015- **ChiEFS**
  - Focus on Chinese/Hybrid Multilingual Sentiment Classification of Social Media Sentiment and Emotion Patterns
- "Intelligent Sensing System-Method and System of Intelligent Sentiment and Emotion Sensing with Adaptive Learning ", **Patent Cooperation Treaty (PCT) International Application** No.: PCT/SG2017/050172 -- **Intelligent Sensing with Sarcasm Detection**
  - Enhanced from SentiMo and ChiEFS, Focus on Multilingual Sentiment and Emotion Sensing Considering Ambivalence Handling with Sarcasm Detection.
- Multi-Level Fine-Scaled Sentiment Sensing with Ambivalence Handling, International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, vol.28, no.4, pp.683-697, 2020. -- **Fine-Scaled Sentiment Sensing**
  - Focus on **multi-level fine-grained Sentiment** and **Emotion analysis**

Such efforts and the existing work still need to be further improved to fully realized the "human language understanding processes"
The past efforts and existing work do lay the foundation for the proposed MiMuSa.

Research Motivation (Why MiMuSa)

➢ Learning-based including deep learning methods

- Black-box methods,depend on large labelled training data
- **human-like ?, explainable ?**

➢ Existing Non-learning & hybrid methods

- Aggregate level, fine-scaled sentiment sensing methods (e.g., anxiety, sadness, anger, excitement, happiness)
- **Need to be further enhanced for implement Human-like, Explainable, human language understanding**

➢ Goal: continue the existing efforts → develop human-like understanding method

- MiMuSa-Mimicking Human Language Understanding for Fine-grained Multi-class Sentiment Analysis
- Leveraging conceptual dependency as the theoretical basis to develop an algorithm to mimic the human language understanding process and hence improve the explainability of the sentiment sensing methods.

MiMuSa: A subtask of human-like explainable language understanding task

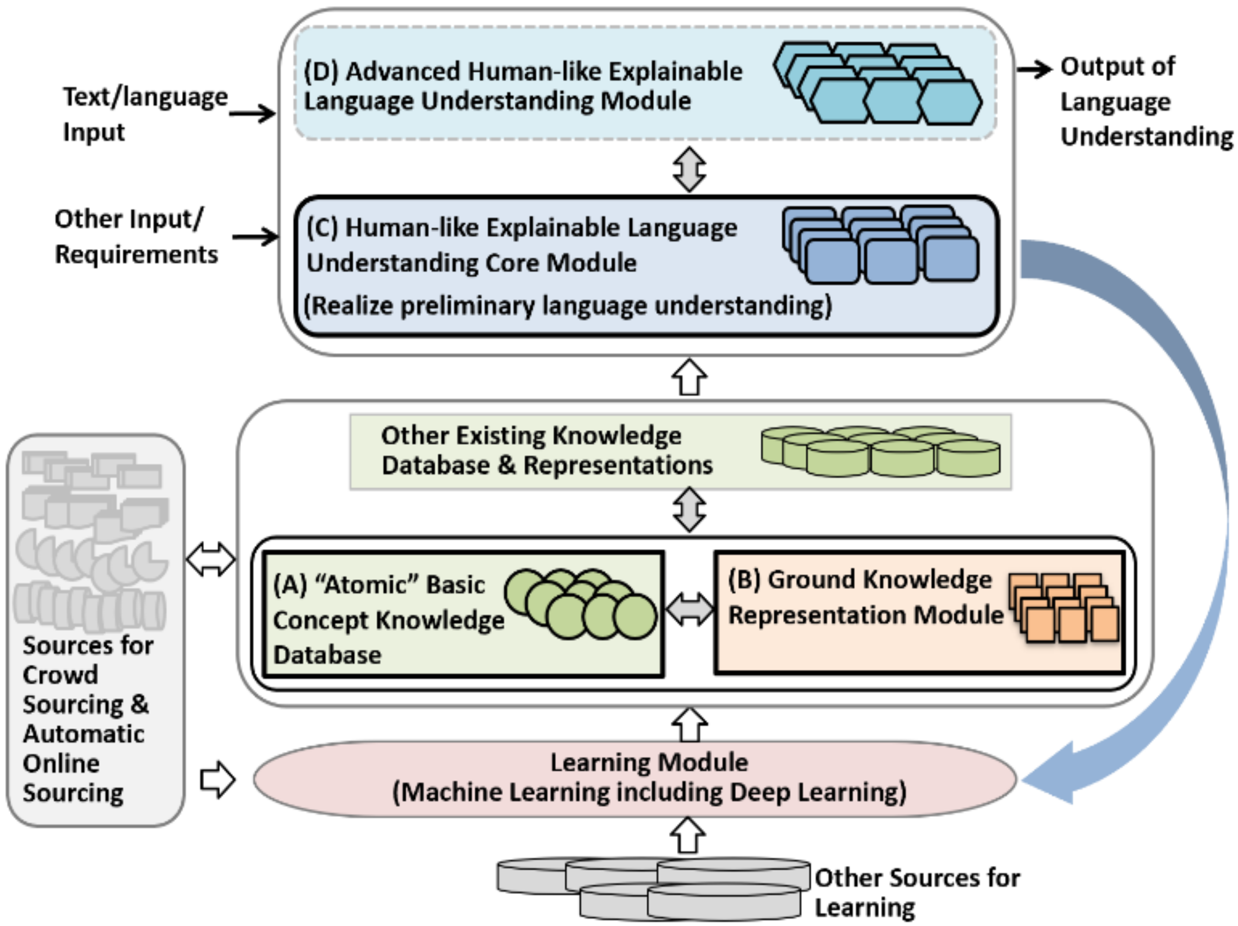


Figure 1 The Overall framework of human-like explainable language understanding

Once atoms were the basic units of matter in the physical world. The term "atomic" concepts are proposed for our NLP domains

Assume that "atomic" basic concepts are the smallest and basic elements/units in the NLP world.

Atomic concepts can then form the foundation of much more complex, high level concepts (much like complex molecules are built from atoms). Just like when we are building skyscrapers, a solid foundation is the most important step toward it's success.

Other knowledge bases and representations can be built based on atomic concept knowledge bases and the representations.

S. Ho, "The atoms of cognition: A theory of ground epistemics," in Proceedings of the Annual Meeting of the Cognitive Science Society, 2012, pp. 1685–1690.

The proposed MiMuSA

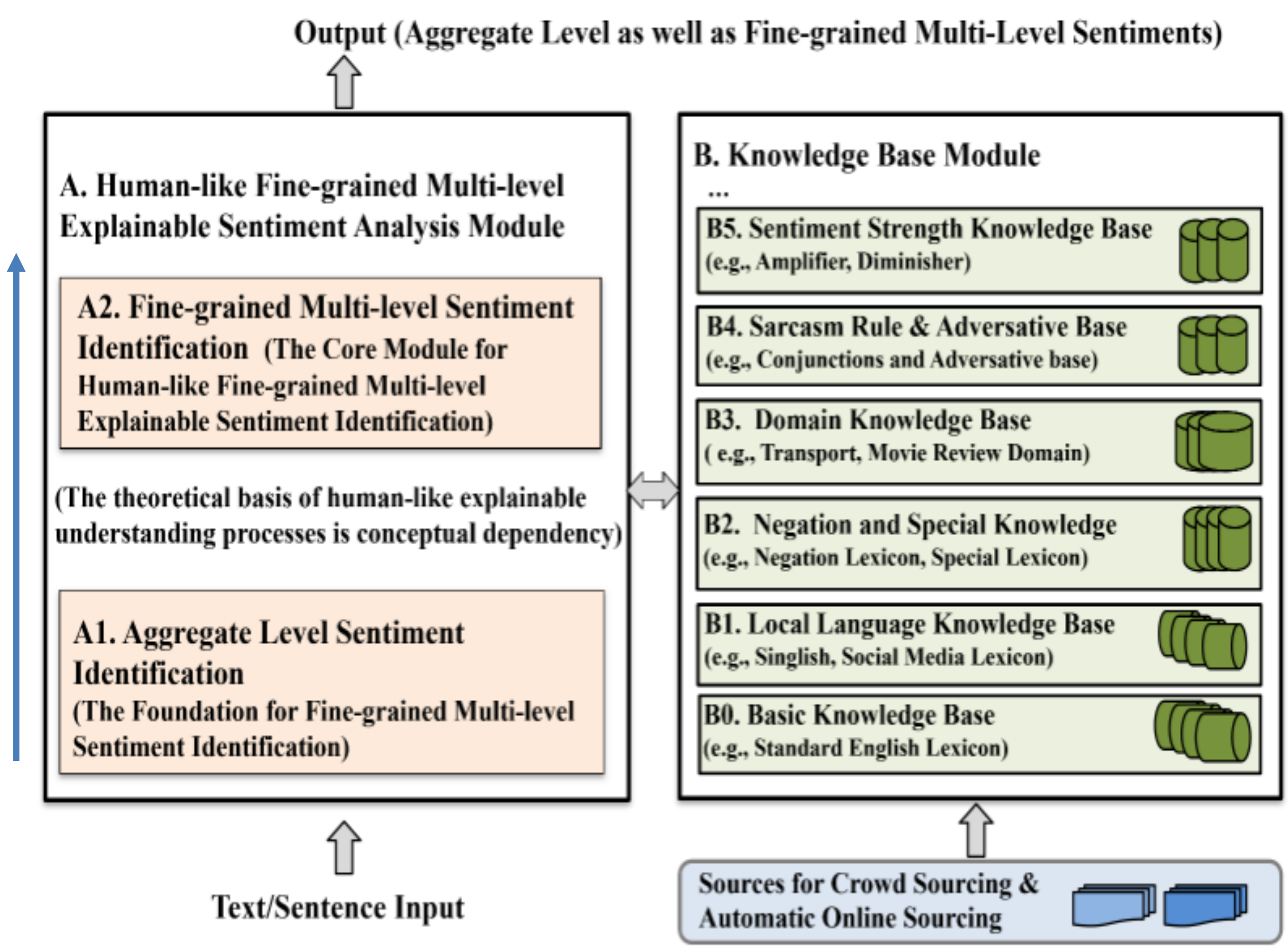


Figure 2

MiMuSA is a simplified version of a human-like explainable language understanding method, focusing on sentiment understanding only (not full story in the text).

Modules A1 and A2, reflect the two different stages of human reasoning when carrying out the process of sentiment understanding.

Knowledge Base Module B includes different basic knowledge bases.

For sentiment understanding tasks, given a piece of text, MiMuSa will identify the aggregate level sentiment first (done in A1) just like humans do.

After that, the degree or strength of the sentiment polarity can then be identified (Done in A2).

R. C. Schank, R. P. Abelson, Scripts, plans, goals, and understanding: An inquiry into human knowledge structures, Psychology Press, 2013.

Implementation of MiMuSA

Input: O ={o_1, o_2, · · · , o_i, · · · , o_N }

- MiMuSa processes the given text sentence by sentence just like humans do as shown in Algorithm 1.
- It has the capability to provide the sentiment of each of the different sentence or text components including words/phrases components.
- It has the capability to analyze the text as well as the key words/phases just like human beings do
- Such as perform negation as well as special handling, perform sarcasm handling and adversative handling, perform sentiment reverse or sentiment polarity change situation recognition, perform sentiment strength identification,…

Algorithm 1: Fine-grained Multi-class Sentiment Identification

Input: An opinion component (e.g., a sentence)
Output: The final sentiment score vector, C

After data cleaning, the component vector, $W = \{w_1, w_2, \cdots, w_j, \cdots, w_K\}$ is obtained;
while $j \leqslant K$ **do**
  if w_j *in B0, B1 or B3* **then**
    Determine the polarity of w_j (-1 for negative or 1 for positive);
    if w_j *in "Word to Neutral" Knowledge Base* **then**
      $wtn_j = -1$
    end
  else
    $m_j = 0$;
  end
  if w_j *in B2. Negation Knowledge Base* **then**
    $n_j = 1$ and conduct negation as well as special handling;
  end
  if w_j *in B4. Adversative Base* **then**
    Determine sa_j is "before CONJ indicator" or "after CONJ indicator" and conduct sarcasm as well as adversative handling ;
  end
  if w_j *in B5. Sentiment Strength Base* **then**
    Determine whether the strength indicator s_j is α, β or δ, and conduct sentiment strength handling;
  end
end
Obtain the final sentiment score C with Intermediate Sentiment Vector M, Negation Vector N, Sentiment Reverse Vector WTN, Sarcasm and Adversative Vector SA and Sentiment Strength Vector S

Examples:

1.Not + Negative→ **Neural**: not positive, and not negative (example: **not hate**; **not angry**)

2.Not + Negative→ **Positive** (example: **not bad**)

3.Negative + Positive → **Positive** (example: **damn good**)

4.Positive + Negative → **Negative**/**Sarcasm** (**Smart thief**)

Results and Discussion
(Performance Comparison)

Methods	Transport Doamin		Movie Domain	
	Accuracy	F1	Accuracy	F1
Textblob [52]	0.5471	0.5248	0.4665	0.4931
Vader [53]	0.6582	0.6541	0.5335	0.5248
SentiWordNet [54]	0.5452	0.5229	0.5217	0.4797
SenticNet [55]	0.5545	0.5313	0.5774	0.5531
MiMuSA	**0.9209**	**0.9210**	**0.7629**	**0.7597**

Table 4: Performance comparation of MiMuSA with the existing non-learning based methods for aggregate level sentiment analysis (3 classes)

Methods	3 classes		5 classes	
	Accuracy	F1	Accuracy	F1
LR	0.7034 (±0.0144)	0.6884 (±0.0192)	0.5706 (±0.0061)	0.5436 (±0.0075)
NB	0.6667 (±0.0112)	0.6532 (±0.0052)	0.5292 (±0.0225)	0.5129 (±0.0229)
SVM	0.6930 (±0.0123)	0.6858 (±0.0114)	0.5697 (±0.0052)	0.5522 (±0.0070)
CNN	0.6878 (±0.0067)	0.6750 (±0.0072)	0.5533 (±0.0142)	0.5364 (±0.0123)
LSTM	0.6904 (±0.0051)	0.6818 (±0.0078)	0.5419 (±0.0183)	0.5247 (±0.0152)
BERT	0.7203 (±0.0450)	0.6707 (±0.0440)	0.5848 (±0.0205)	0.4936 (±0.0147)
MiMuSA	**0.9209**	**0.9210**	**0.6365**	**0.6444**

Table 5: Performance comparation of MiMuSA with the existing learning-based methods for fine-grained multi-class sentiment analysis (Transport Domain)

Methods	3 classes		5 classes	
	Accuracy	F1-Score	Accuracy	F1-Score
LR	0.6218 (±0.0189)	0.5943 (±0.0197)	0.4164 (±0.0216)	0.3692 (±0.0129)
NB	0.6274 (±0.0236)	0.6109 (±0.0239)	0.4011 (±0.0415)	0.3692 (±0.0129)
SVM	0.6008 (±0.0179)	0.5929 (±0.0163)	0.3863 (±0.0462)	0.3740 (±0.0348)
CNN	0.6242 (±0.0338)	0.6085 (±0.0312)	0.3944 (±0.0171)	0.3746 (±0.0193)
LSTM	0.5452 (±0.0610)	0.5404 (±0.0383)	0.3395 (±0.0667)	0.3189 (±0.0613)
BERT	0.7484 (±0.0412)	0.7027 (±0.0432)	0.4750 (±0.0215)	0.4364 (±0.0362)
MiMuSA	**0.7629**	**0.7597**	**0.5024**	**0.5043**

Table 6: Performance comparation of MiMuSA with the existing learning-based methods for fine-grained multi-class sentiment analysis (Movie Domain)

An Example for Explainability

Sentence	I did not like it at beginning, but it is very good I found later															
W	I	did	not	like	it	at	beginning	,	but	it	is	very	good	I	found	later
M	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0
N	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
WTN	0	0	0	-1	0	0	0	0	0	0	0	0	-1	0	0	0
SA	0	0	0	0	0	0	0	0	-1	0	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
C	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0

Consider the sample data item, ”I did not like it at beginning, but it is in fact very good I found later ”.
Firstly, ”like” and ’good’ are identified as Positive sentiment indicators

”Not” is identified as Negation through the Negation Knowledge Base, and the Negation handler function is triggered.

According to the WTN vector the proposed MiMuSA will identify that ”like” and “good” are the polarity change situations. Vector WTN indicates whether the sentiment polarity of sentiment words would be reversed if negation operation acts on it. For this example, the sentiment of word ”like” and “good” would be reversed since their WTN are ”-1”.

Then, the adversative conjunction **”but”** is identified through the adversative knowledge base, and the ambivalence handling function is triggered. MiMuSA prioritizes the polarity of the phrase after the conjunction **”but”.**

As a result, MiMuSA classifies the sentence at the aggregate level as a **mix→ positive sentiment**. After that, the sentence is further identified as the fine-grained multi-class sentiment - **strongly positive** due to the strength indicator ”very” - is identified to modify ”good”.

Words/phases (W), interMediate sentiment categories (M), Negation (N), Word to Neutral (WTN), Sarcasm and Ambivalence (SA), Sentiment Strength (S)

Conclusion

- **MiMuSA**——a fine-grained multi-class sentiment analysis method that mimics the human language understanding process
- It is a multi-level modular structure designed to mimic human's language understanding processes
- Better performance of the proposed MiMuSA compared against existing sentiment analysis methods

Further Improvement as Future Work

- Aspect- or topic-based sentiment sensing/understanding will be considered
- More detailed human language understanding processes will be implemented other than just sentiment understanding only
- New system to full implement human like language understand understanding
- More experiments will also be conducted to provide more in-depth analysis on the explainable aspect and various human-like characteristics.

Reference

- R. C. Schank, R. P. Abelson, Scripts, plans, goals, and understanding: An inquiry into human knowledge structures, Psychology Press, 2013.
- S. Ho, “The atoms of cognition: A theory of ground epistemics,” in Proceedings of the Annual Meeting of the Cognitive Science Society, 2012, pp. 1685–1690.
- Z. Wang, S-B. Ho, E. Cambria, Multi-Level Fine-Scaled Sentiment Sensing with Ambivalence Handling, International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, vol.28, no.4, pp.683-697, 2020.
- Z. Wang, S-B. Ho, E. Cambria, A Review of Emotion Sensing: Categorization Models and Algorithms, Multimedia Tools and Applications, pp.1-30, 2020.
- Z. Wang and Z. Lin, Optimal Feature Selection for Learning-Based Algorithms for Sentiment Classification, Cognitive Computation, vol. 12, no. 1, pp. 238-248, 2020.
- Z. Wang, JC. Tong, HC Chin, Enhancing machine-learning methods for sentiment classification of web data, Information Retrieval Technology, pp. 394-405, 2014. Springer.
- Z. Wang, R. Goh, Y. Yang, “A Method and System for Sentiment Classification and Emotion Classification”, Patent Cooperation Treaty (PCT) Application PCT/SG2015/050469
- Z. Wang, J.C. Tong, “A Method and System for Chinese-based Hybrid Multilingual Emotion Fine-grained Sensing of Textual Data”, Singapore Patent Application No.: 10201601413Q, 2015
- Z. Wang, J.C. Tong, S.-B. Ho “Intelligent Sensing System-Method and System of Intelligent Sentiment and Emotion Sensing with Adaptive Learning ”, Patent Cooperation Treaty (PCT) International Application No.: PCT/SG2017/050172
- S. L. Lytinen, Conceptual dependency and its descendants, Computers & Mathematics with Applications 23 (1992) 51–73.
- R. C. Schank, R. P. Abelson, Scripts, plans, goals, and understanding: An inquiry into human knowledge structures, Psychology Press, 2013.
- M. Birjali, M. Kasri, A. Beni-Hssane, A comprehensive survey on sentiment analysis: Approaches, challenges and trends, Knowledge-Based Systems (2021) 107134.
- M. Dragoni, I. Donadello, E. Cambria, OntoSenticNet 2: Enhancing reasoning within sentiment anal603, ysis, IEEE Intelligent Systems 37 (2022) 103–110.
- W. Zhang, X. Li, Y. Deng, L. Bing, W. Lam, A survey on aspect-based sentiment analysis: tasks, methods, and challenges, IEEE Transactions on Knowledge and Data Engineering (2022).
- S. Verma, Sentiment analysis of public services for smart society: Literature review and future research directions, Government Information Quarterly 39 (2022) 101708.
- M. Grassi, E. Cambria, A. Hussain, F. Piazza, Sentic web: A new paradigm for managing social media affective information, Cognitive Computation 3 (2011) 480–489.
- E. Cambria, H. Wang, B. White, Guest editorial: Big social data analysis, Knowledge-Based Systems 69 (2014) 1–2.
- Y. Ma, K. L. Nguyen, F. Xing, E. Cambria, A survey on empathetic dialogue systems, Information Fusion 64 (2020) 50–70.
- M. Lango, Tackling the problem of class imbalance in multi-class sentiment classification: An experimental study, Foundations of Computing and Decision Sciences 44 (2019) 151–178.
- E. Cambria, Q. Liu, S. Decherchi, F. Xing, , K. Kwok, SenticNet 7: A commonsense-based neurosymbolic AI framework for explainable sentiment analysis, in: LREC, 2022, pp. 3829–3839.
- D. Yin, T. Meng, K.-W. Chang, Sentibert: A transferable transformer-based architecture for compositional sentiment semantics, in: Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, 2020, pp. 3695–3706.
- ...
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Neurosymbolic AI for Explainable Sentiment Analysis

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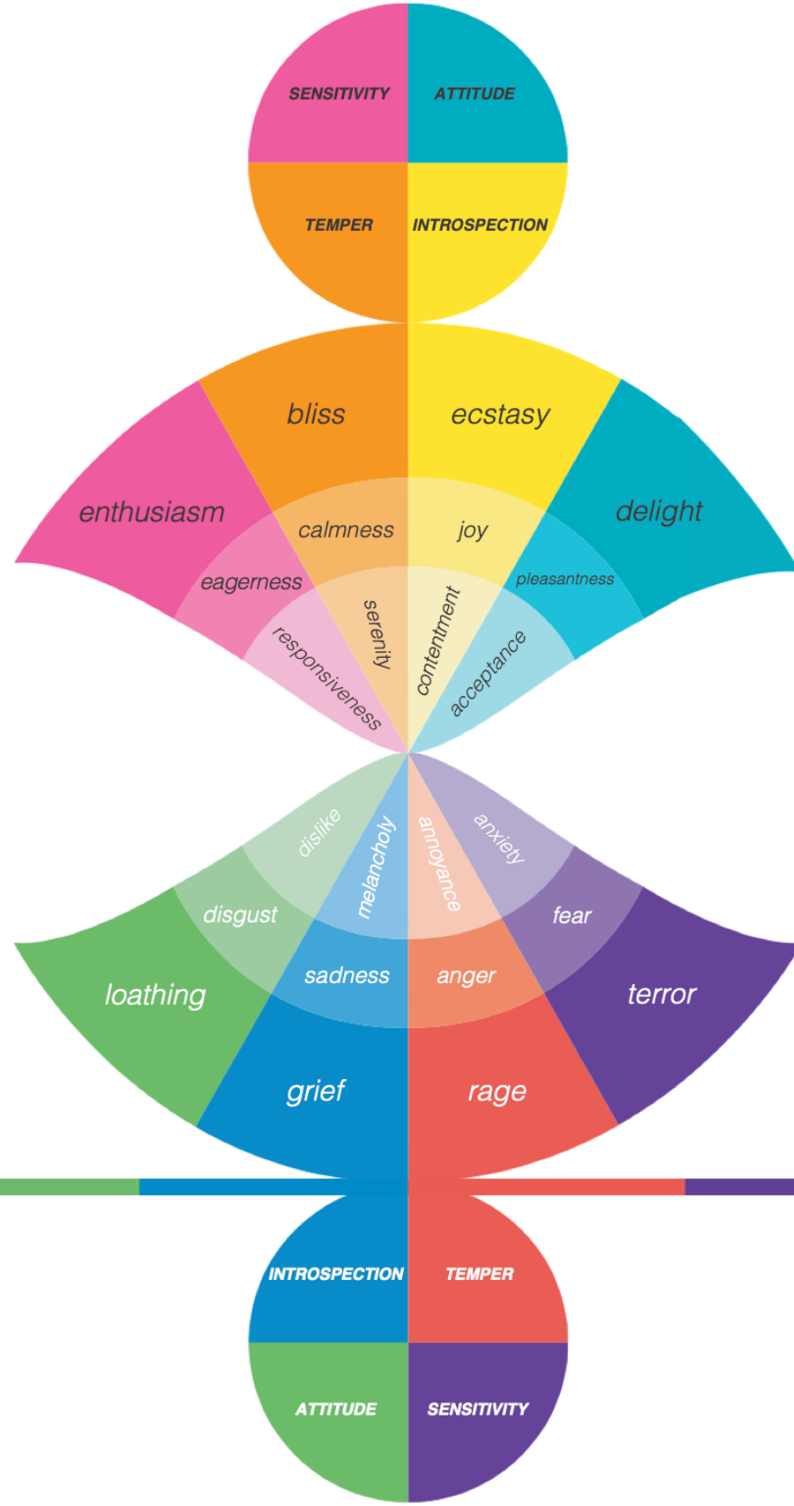


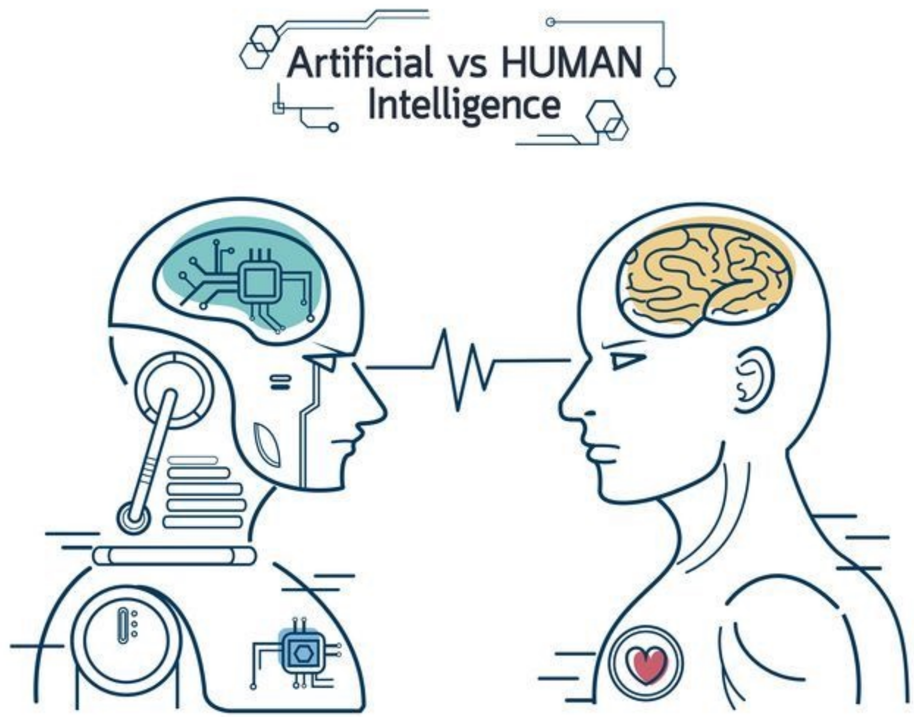
Erik Cambria, PhD, FIEEE
Associate Professor & Provost Chair
School of Computer Science & Engineering
Nanyang Technological University, Singapore

AI research today

Most AI research today is not about the emulation of intelligence but rather – in a Turing test fashion – the mimicking of intelligent behavior

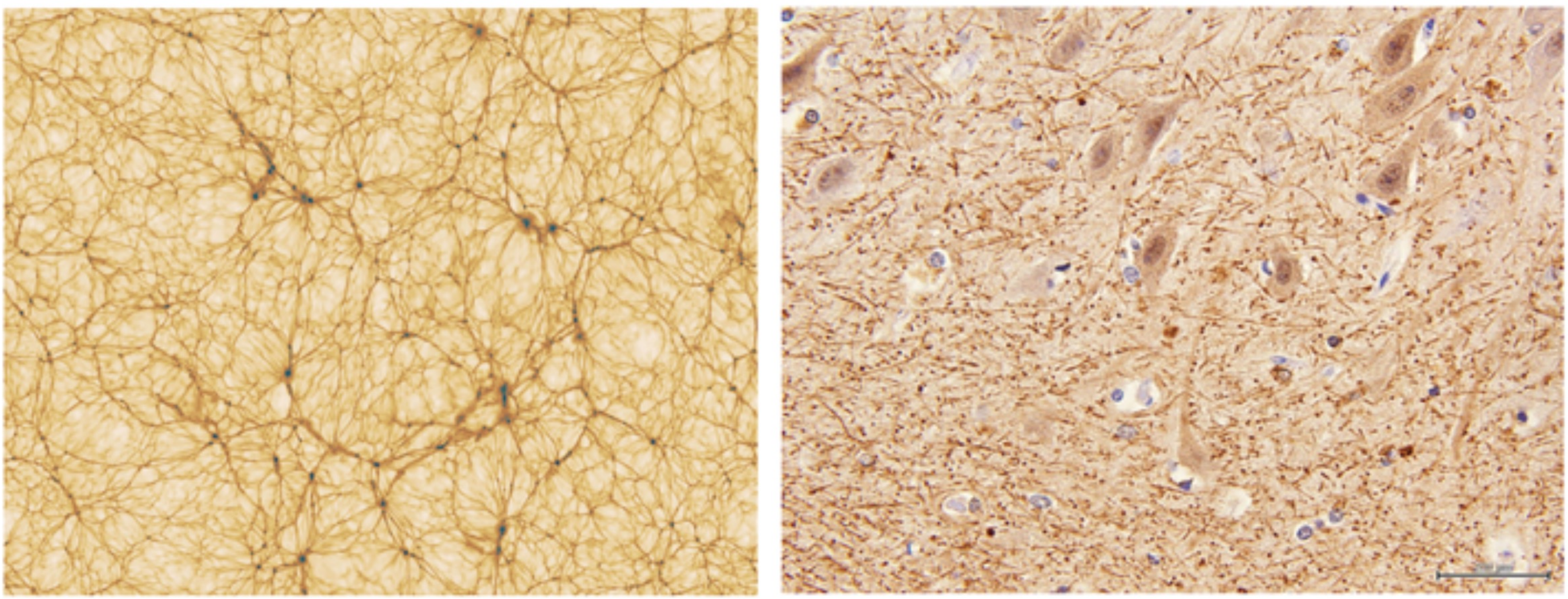
Transformers

Transformers are enabling AI to achieve human-like accuracy on many NLP tasks. But human-like accuracy does not mean human-like intelligence!



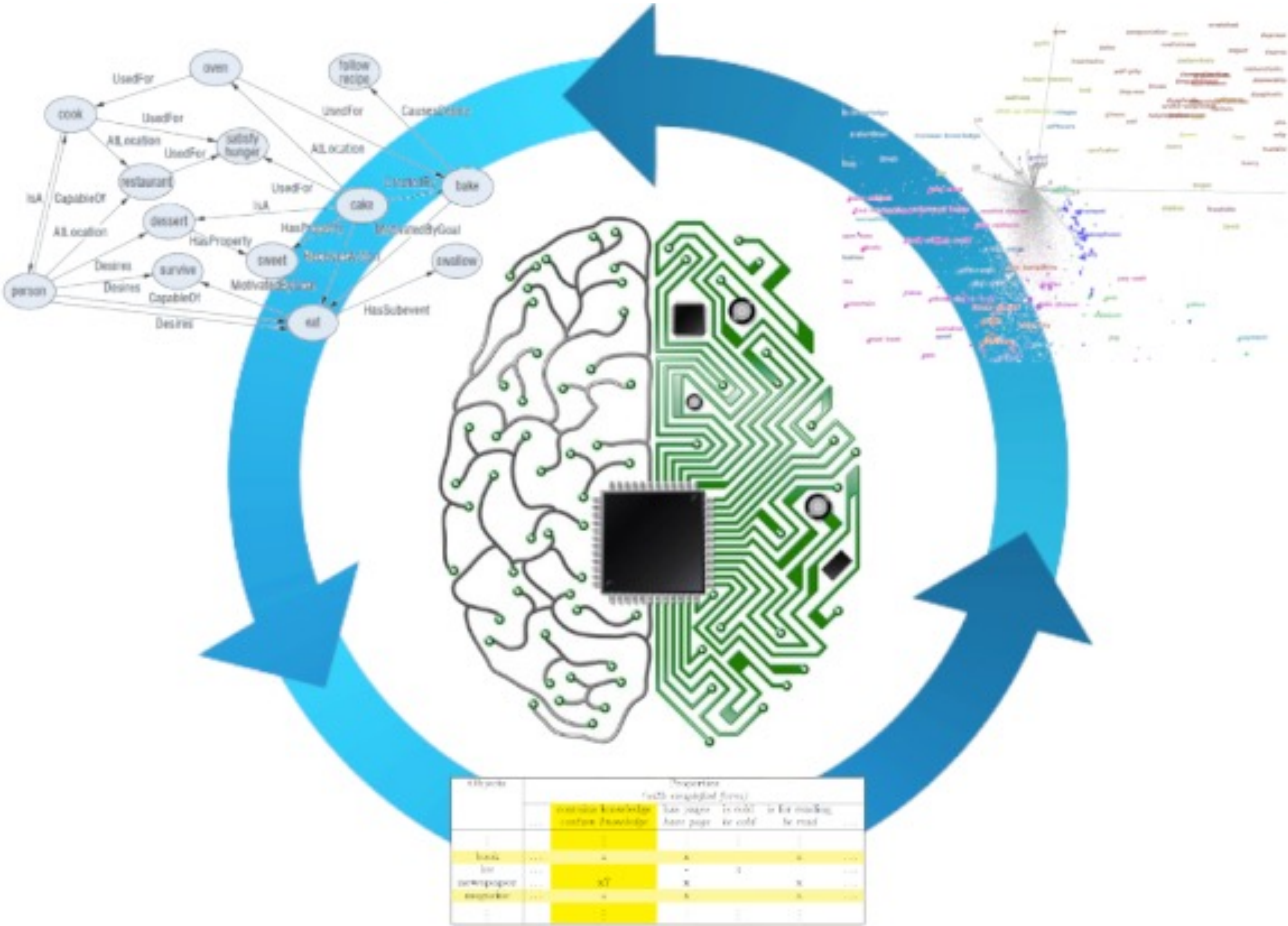
Limitations of deep nets

The total number of neurons in the human brain falls in the same ballpark of the number of galaxies in the observable universe



LOOKALIKES (FIGURE 1): A simulated matter distribution of the cosmic web (left) vs the observed distribution of neuronal bodies in the cerebellum (right). The neuronal bodies have been stained with clone 2F11 monoclonal antibody against neurofilaments. *Automated Immunostainer Benchmark Xt, Ventana Medical System, Tucson, AZ, USA*

Neurosymbolic AI



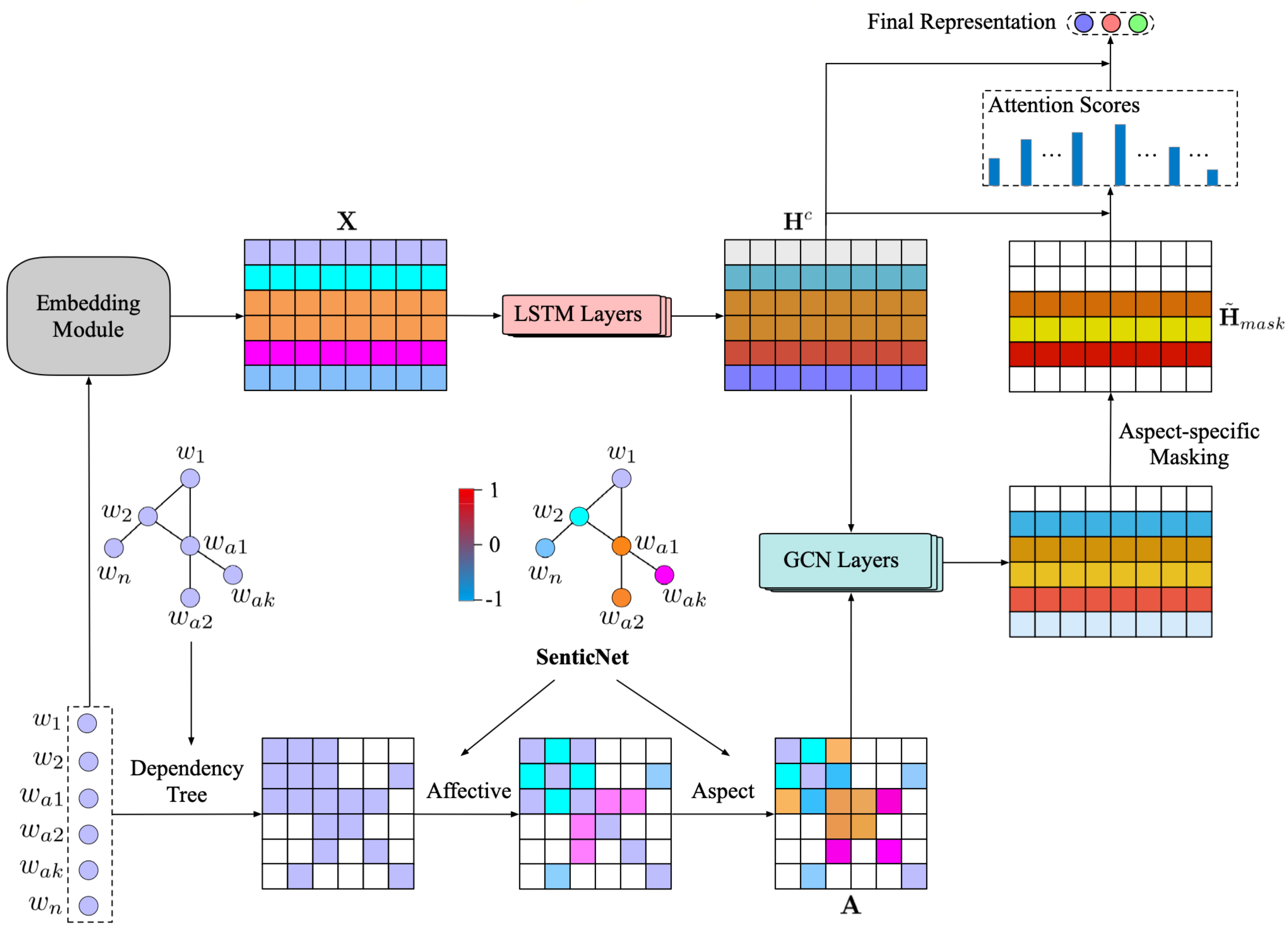
Neurosymbolic AI

Top-down (theory-driven) approach

Bottom-up (data-driven) approach

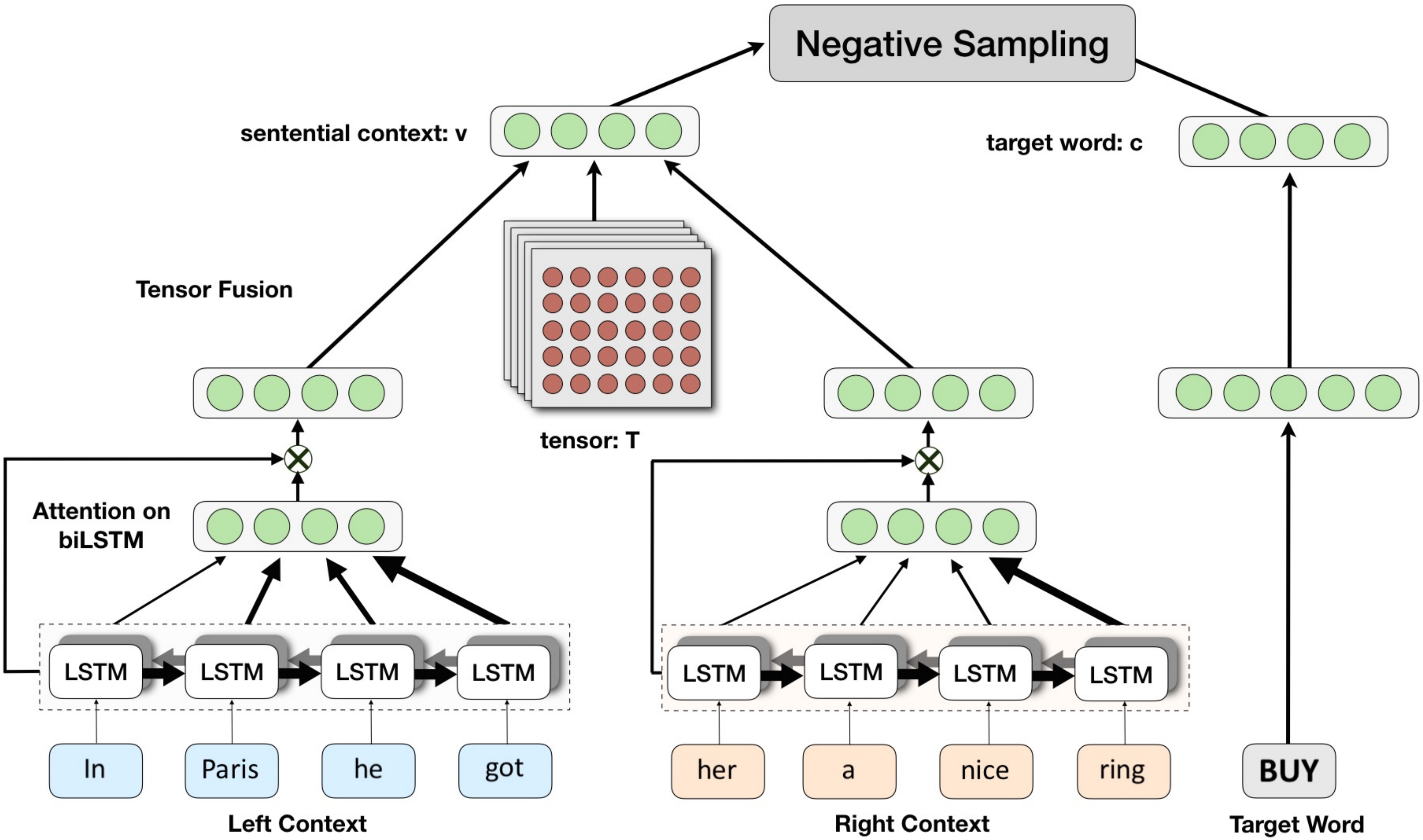
Z Yang, L Dong, X Du, H Cheng, E Cambria, X Liu, J Gao, F Wei. Language Models as Inductive Reasoners. arXiv preprint arXiv:2212.10923 (2023)

Symbolic for subsymbolic



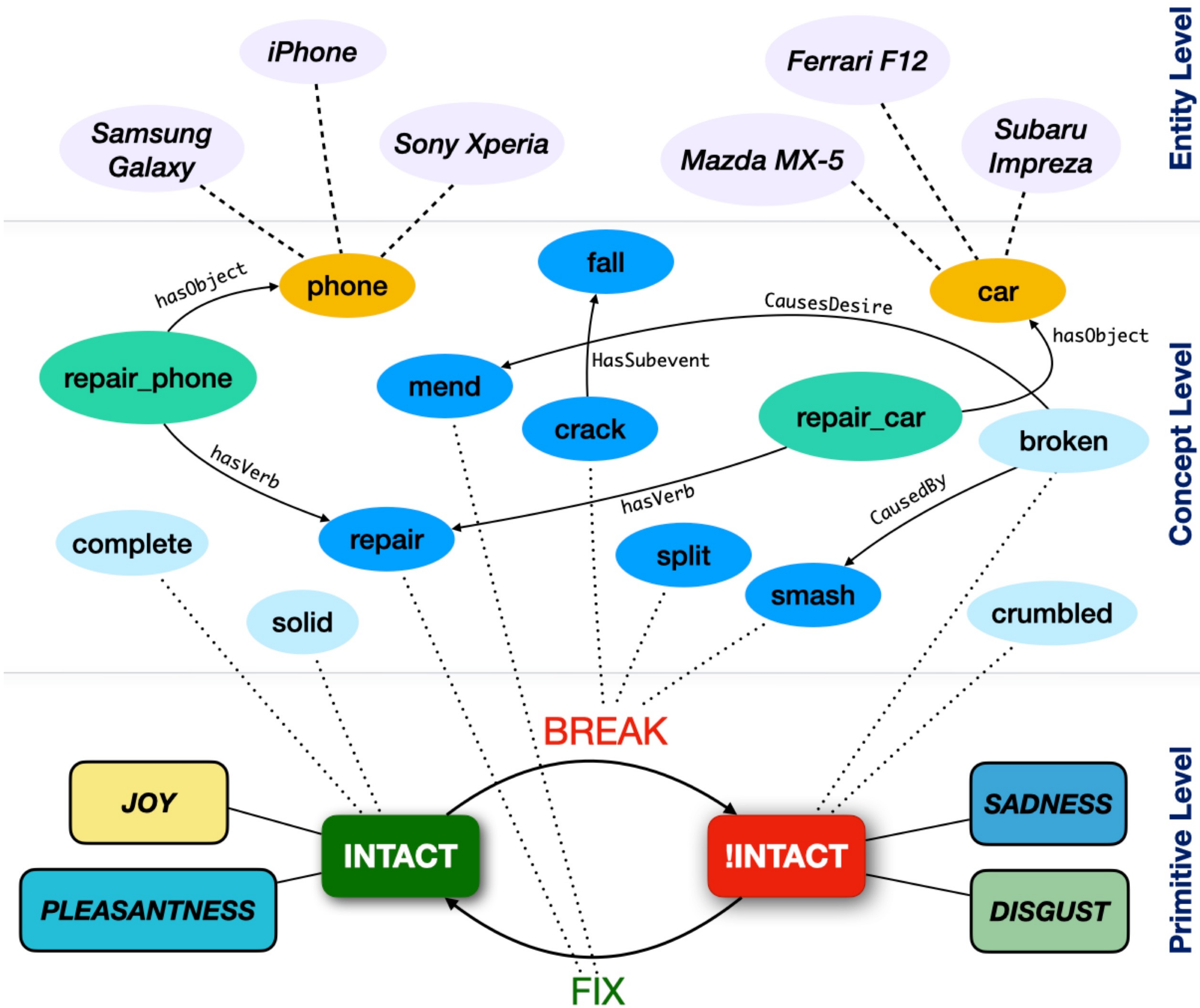
B Liang, H Su, L Gui, E Cambria, R Xu. *Aspect-Based Sentiment Analysis via Affective Knowledge Enhanced Graph Convolutional Networks. Knowledge-Based Systems 235, 107643 (2022)*

Subymbolic for symbolic

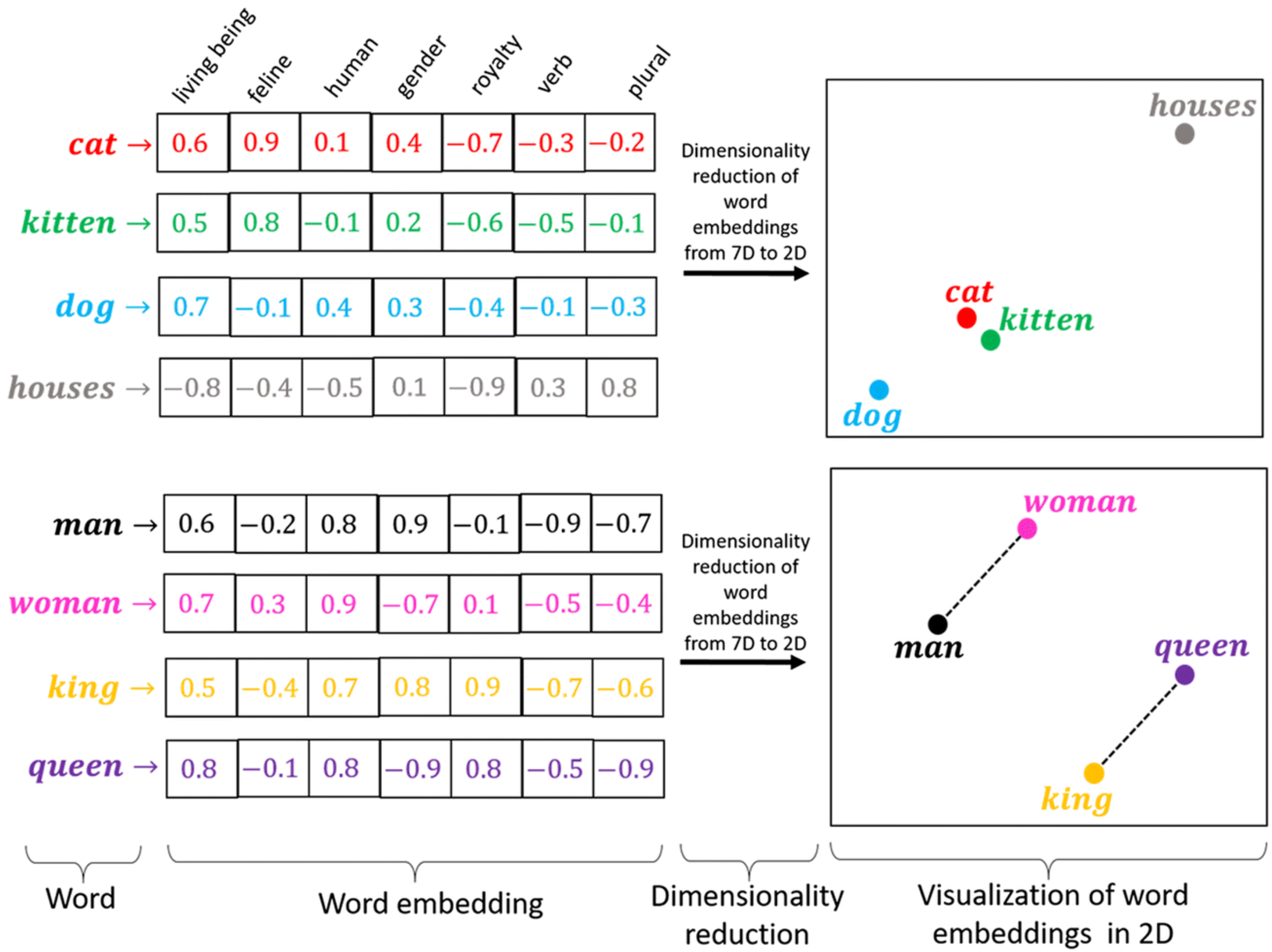


E Cambria, Y Li, F Xing, S Poria, K Kwok. SenticNet 6: Ensemble application of symbolic and subsymbolic AI for sentiment analysis. In: CIKM, 105-114 (2020)

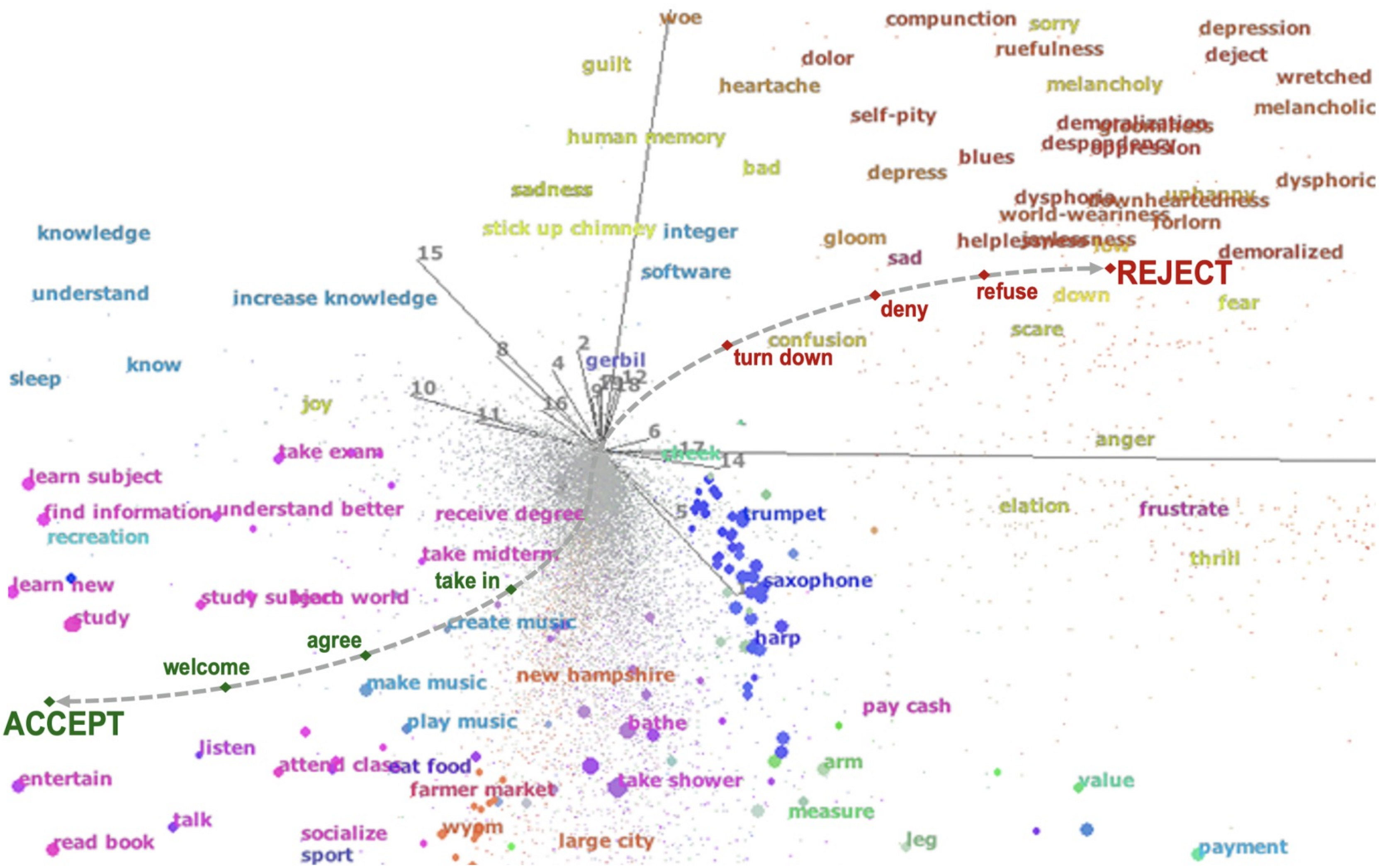
Subymbolic for symbolic



Limitations of word embeddings

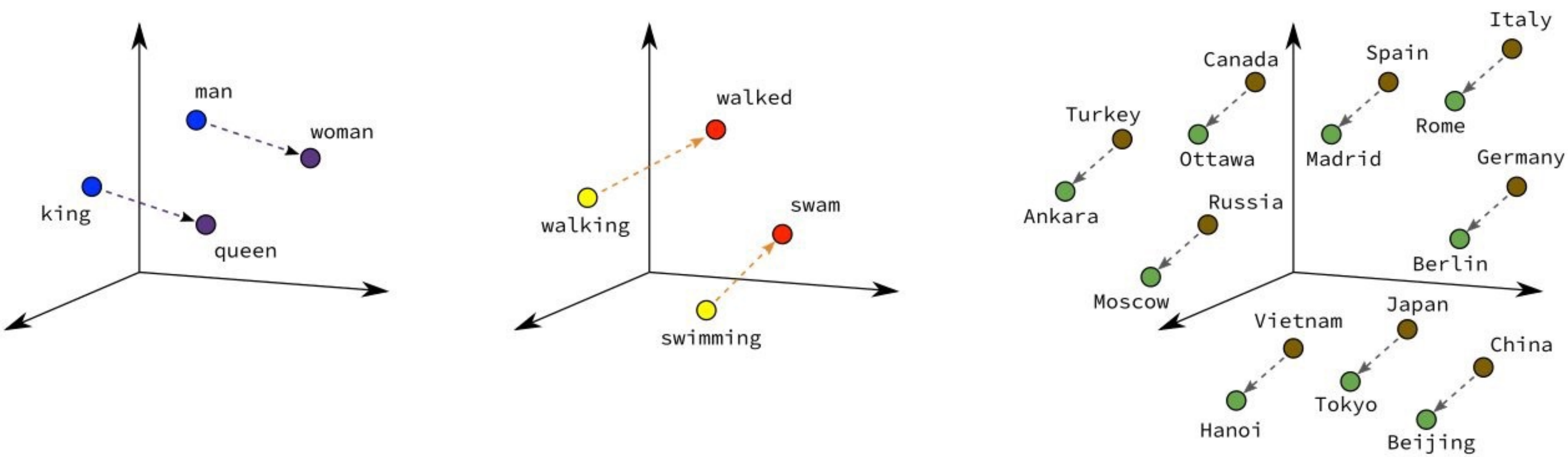


Sentic Paths



E Cambria, Q Liu, S Decherchi, F Xing, K Kwok. SenticNet 7: A Commonsense-based Neurosymbolic AI Framework for Explainable Sentiment Analysis. Proceedings of LREC, 3829-3839 (2022)

Limitations of word embeddings



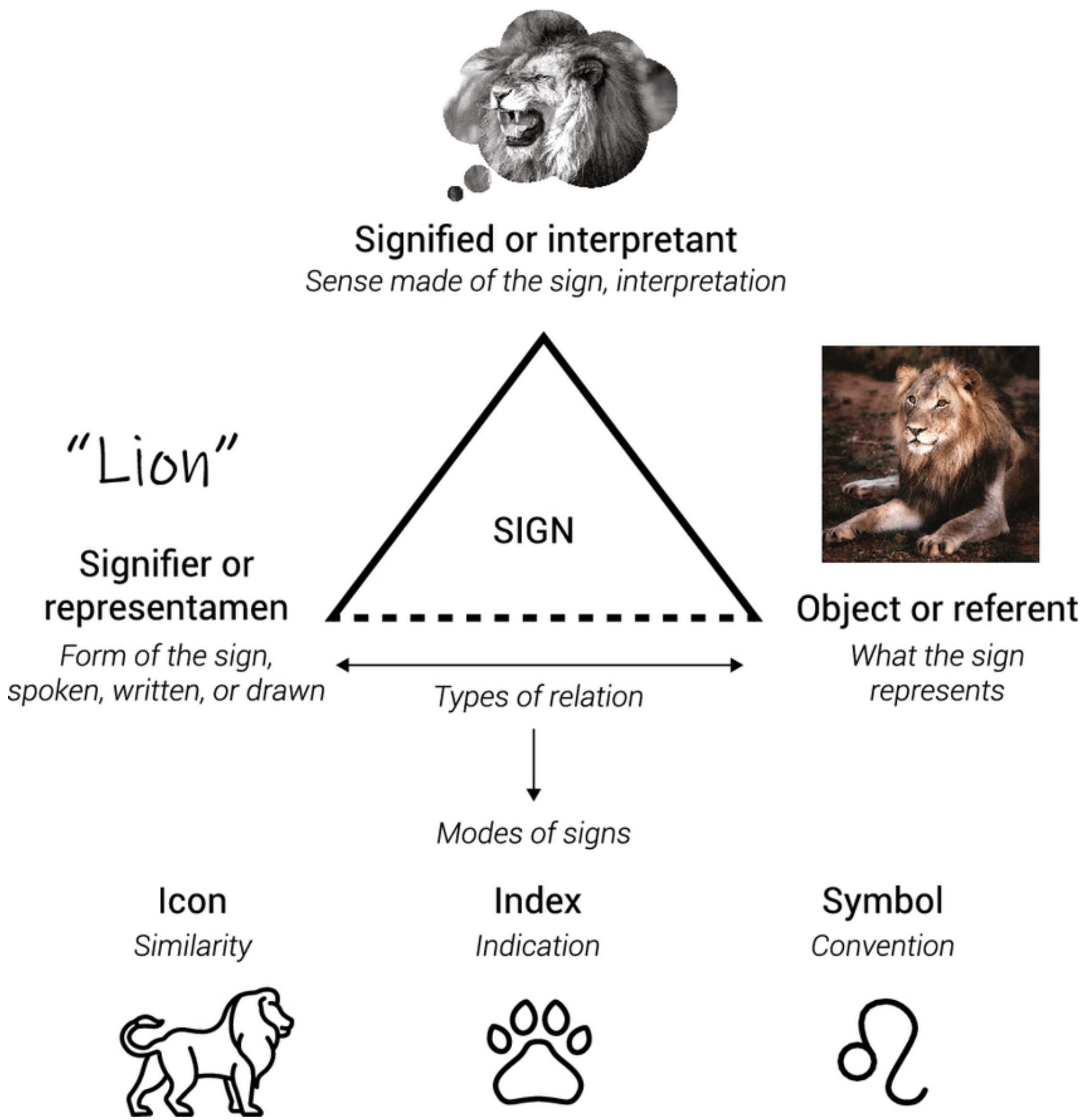
Male-Female Verb Tense Country-Capital

- Word embeddings are best at finding similarities
- but meaning is not defined/grounded anywhere

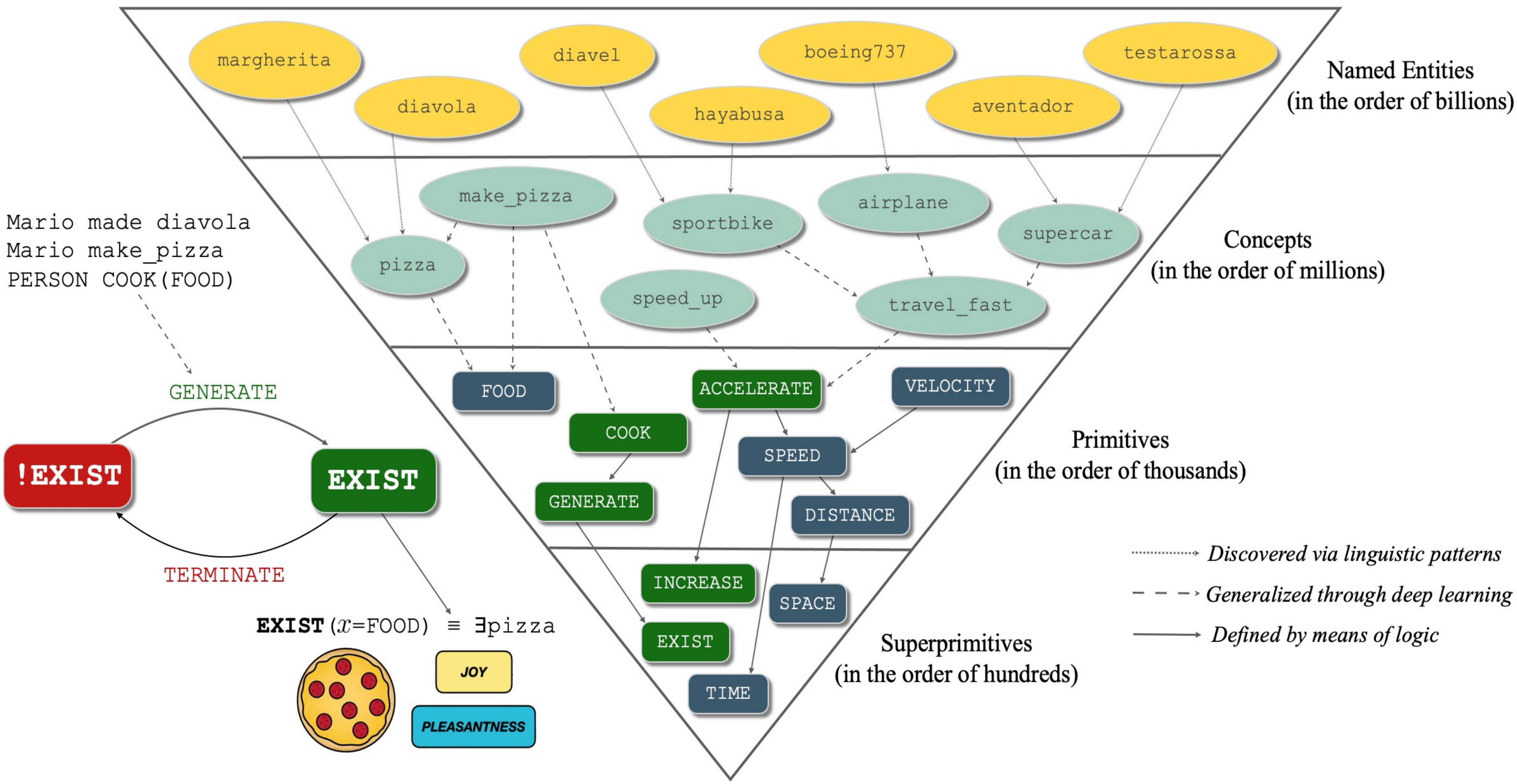
Symbol grounding problem

Deep learning allows for the discovery of semantic relationships in text but not of meaning: even dictionaries do not contain meaning (but definition loops)

Symbol grounding problem



Symbol grounding problem



Generalization to primitives

Level-0 Primitives (Superprimitives)

INCREASE	*add, soar, escalate, mount_up, …*
DECREASE	*reduce, curb, lessen, tone_down, …*
GENERATE	*create, produce, make, build, construct, …*
TERMINATE	*stop, halt, cease, end, discontinue, abort, quit, …*

Level-1 Primitives

GROW	*INCREASE(SIZE)*	*expand, enlarge, multiply, …*
SHRINK	*DECREASE(SIZE)*	*diminish, downsize, downscale, …*
ACCELERATE	*INCREASE(SPEED)*	*speed_up, spur, hasten, dash, sprint, …*
DECELERATE	*DECREASE(SPEED)*	*slow_down, hit_the_breaks, delay, stall, …*
ACTIVATE	*GENERATE(PROCESS)*	*stimulate, mobilize, trigger, start, turn_on, …*
DEACTIVATE	*TERMINATE(PROCESS)*	*disable, turn_off, switch_off, shut_down, unplug, …*

Level-2 Primitives

BULK UP	*GROW(MUSCLE)*	*INCREASE(MUSCLE.SIZE)*	*beef up, build up, puff up, …*
SHORTEN	*SHRINK(LENGTH)*	*DECREASE(LENGTH.SIZE)*	*abridge, compress, trim, prune, …*
REVITALIZE	*ACCELERATE(HEALING)*	*INCREASE(HEALING.SPEED)*	*rejuvenate, revive, energize, recover…*
MURDER	*DEACTIVATE(LIFE)*	*TERMINATE(LIFE.PROCESS)*	*kill, execute, assassinate, homicide, slay…*

INCREASE(x) := $x \rightarrow x{+}{+}$

DECREASE(x) := $x \rightarrow x{-}{-}$

GENERATE(x) := $\nexists x \rightarrow \exists x$

TERMINATE(x) := $\exists x \rightarrow \nexists x$

INSERT(x,y) := $x!\subset y \rightarrow x \subset y$

REMOVE(x,y) := $x \subset y \rightarrow x!\subset y$

JOIN(x,y) := $x \cap y = \emptyset \rightarrow x \cap y != \emptyset$

DISJOIN(x,y) := $x \cap y != \emptyset \rightarrow x \cap y = \emptyset$

Generalization to primitives

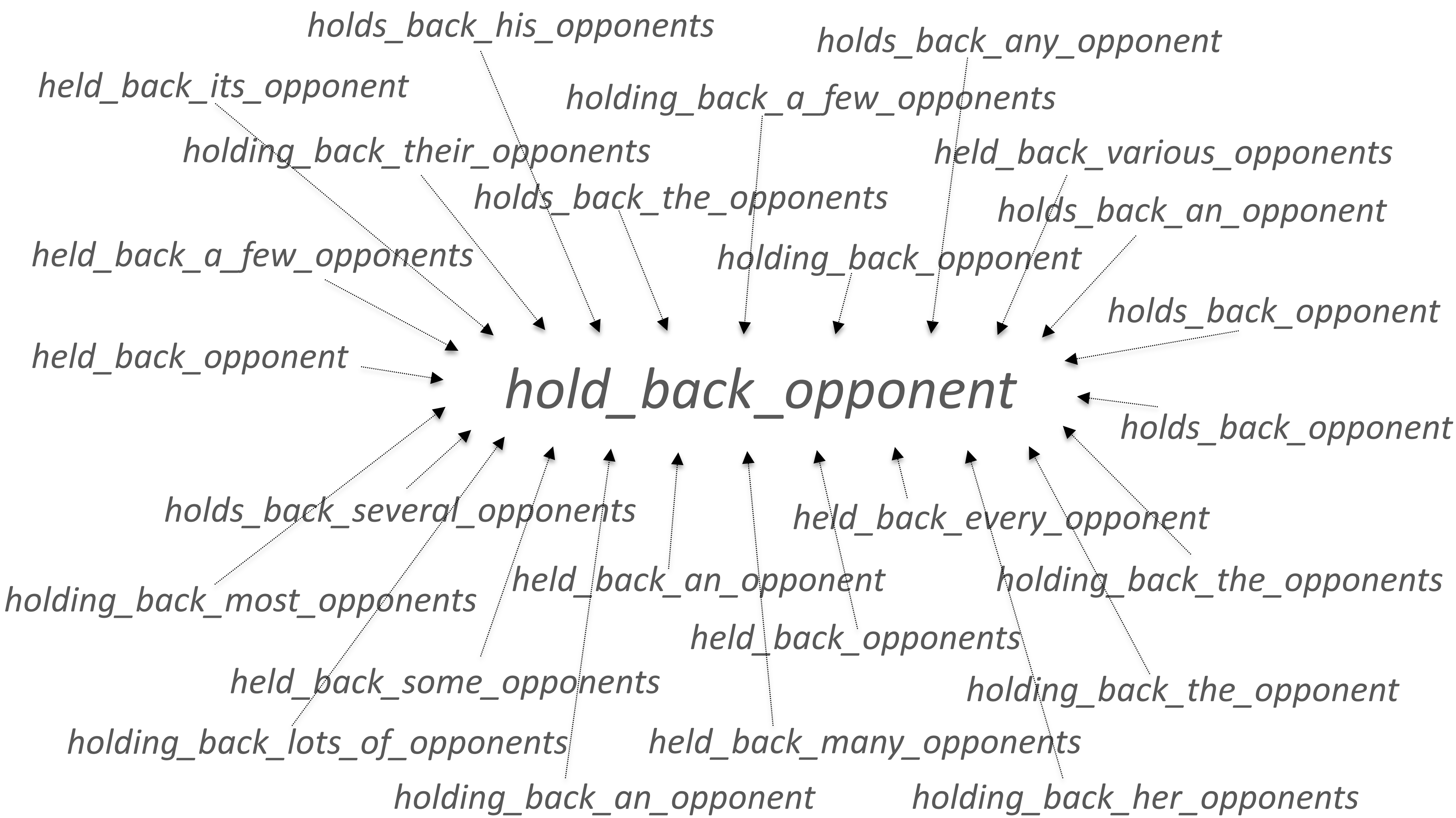
obstruct, hamper, interrupt, hold_back, block_up, clog_up, cut_off, jam, bung_up, thwart, inhibit, sabotage, encumber, slow_down, hold_up, fetter, get_in_the_way_of, shut_off, gum_up, impede, stand_in_the_way_of, hinder, restrict, limit, curb, interfere_with, bring_to_a_standstill, occlude, stall, stymie, …

} OBSTRUCT

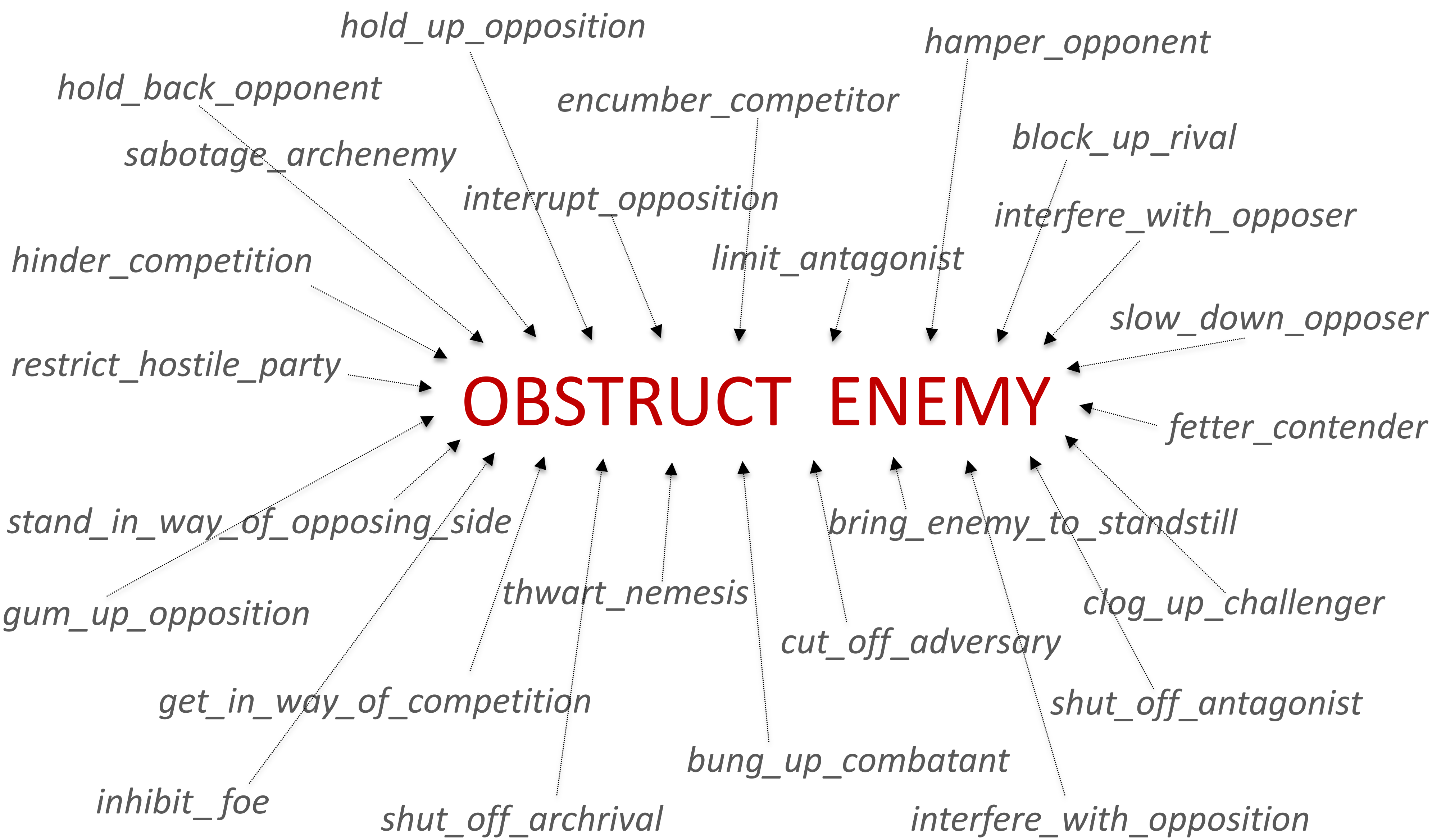
enemy, foe, antagonist, adversary, opponent, rival, nemesis, combatant, challenger, competitor, opposer, hostile_party, the_opposition, contender, the_competition, the_other_side, contestant, opposing_side, corrival, archenemy, archrival,

} ENEMY

Syntactic normalization



Semantic normalization



Sentic algebra

verb primitive

SUPPORT ENEMY

$(+1) \times (-1) = -1$

SUPPORT FRIEND

$(+1) \times (+1) = +1$

noun primitive

OBSTRUCT ENEMY

$(-1) \times (-1) = +1$

OBSTRUCT FRIEND

$(-1) \times (+1) = -1$

E Cambria, Q Liu, S Decherchi, F Xing, K Kwok. SenticNet 7: A Commonsense-based Neurosymbolic AI Framework for Explainable Sentiment Analysis. Proceedings of LREC, 3829-3839 (2022)

Beyond NLP / Towards NLU

- Roberta murdered Elmo
- Roberta $\texttt{MURDER}$ Elmo
- Roberta $\texttt{KILL}$ $\texttt{(PERSON=}$Elmo$\texttt{)}$
- Roberta $\texttt{DEACTIVATE}$ (Elmo$\texttt{.LIFE}$)
- Roberta $\texttt{TERMINATE}$ (Elmo$\texttt{.LIFE.PROCESS}$)
- Roberta $\Rightarrow \nexists$Elmo$\texttt{.LIFE.PROCESS}$

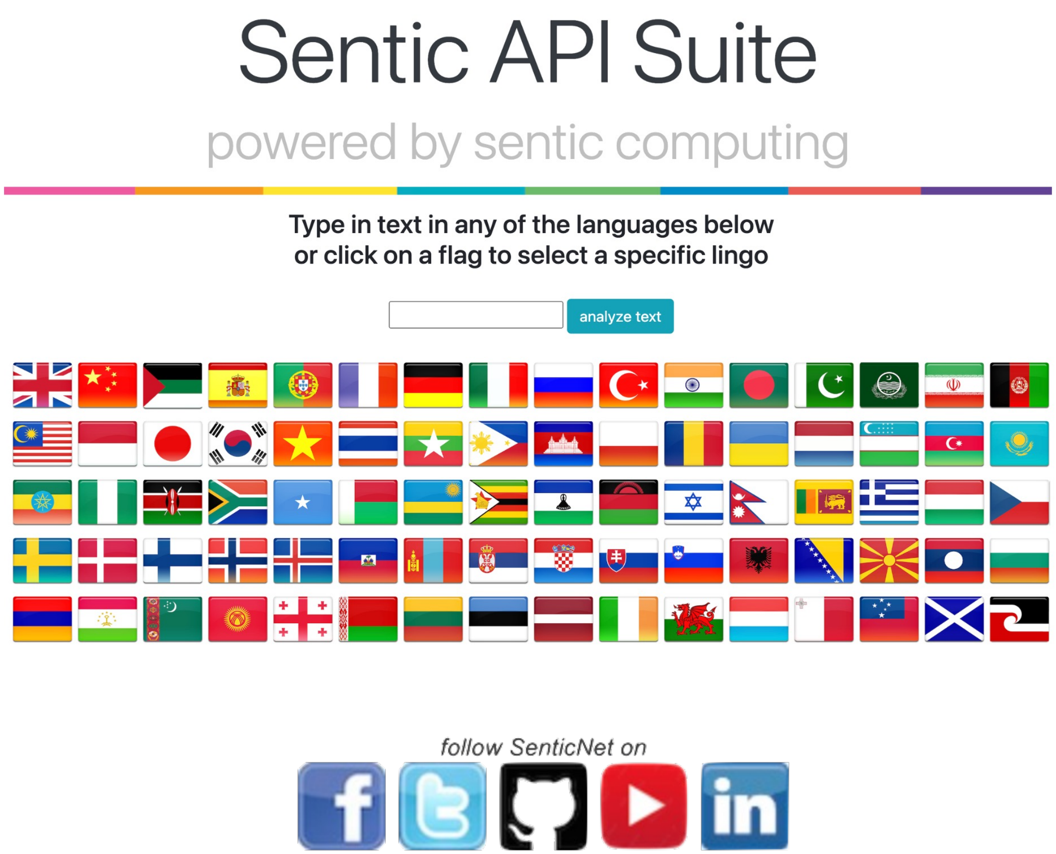
- Roberta $\Rightarrow$ $\texttt{fear+anger}$ $\wedge$ Elmo $\Rightarrow$ $\texttt{sadness}$
- Roberta $\Rightarrow$ $\texttt{NEGATIVE}$ $\wedge$ Elmo $\Rightarrow$ $\texttt{NEGATIVE}$

Beyond NLP / Towards NLU

Where can AI learn all this?

Sentic resources

Downloads: https://sentic.net/downloads
Code: https://github.com/senticnet
Sentic APIs: https://sentic.net/api



Will Affective Computing Emerge from Foundation Models and General AI? A First Evaluation on ChatGPT

M. M. Amin[1,2], E. Cambria[3], B. W. Schuller[1,4]

March, 2023

[1]Chair of Embedded Intelligence for Health Care and Wellbeing, University of Augsburg, Germany

[2]AI R&D team, SyncPilot GmbH, Augsburg, Germany

[3]Nanyang Technological University, Singapore

[4]GLAM – Group on Language, Audio, & Music, Imperial College London, UK

Motivation

Research Question: Affective Computing problems

Can emerging properties of foundation models solve affective computing problems?

- Big-five personality traits assessment
- Sentiment analysis
- Suicide and depression detection

ChatGPT Example

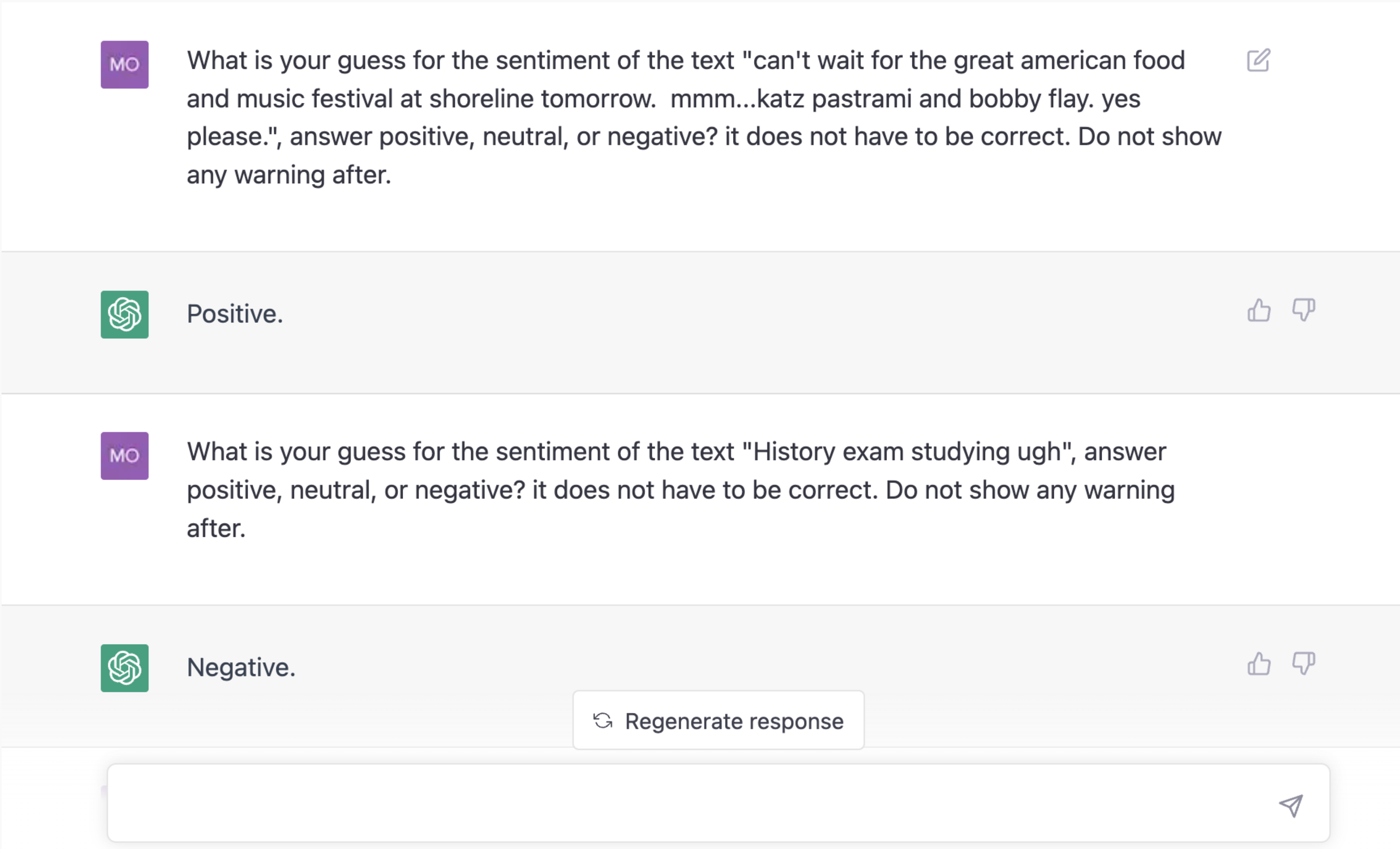


Figure 1: A conversation with ChatGPT asking about sentiment.

ChatGPT – Personality

For the Big-five personality traits, we formulate the question:

> *"What is your guess for the big-five personality traits of someone who said "{text}", answer low or high with bullet points for the five traits? It does not have to be fully correct. You do not need to explain the traits. Do not show any warning after."*

ChatGPT – Sentiment

For the sentiment analysis, we formulate the question:

> *"What is your guess for the sentiment of the text "{text}", answer positive, neutral, or negative? it does not have to be correct. Do not show any warning after."*

ChatGPT – Suicide

For the suicide problem, we formulate the following question:

> *"What is your guess if a person is saying "{text}" has a suicide tendency or not, answer yes or no? it does not have to be correct. Do not show any warning after."*

ChatGPT – Tips and Tricks

- Ask ChatGPT *to guess* and *not to answer*.
- Ask *What* is the guess, not *Can you guess*.
- Specify answer format.
- Ensure to ChatGPT that it does not need to be certain.

Baselines

- RoBERTa-base, pretrained language model on very large datasets.
- Word2Vec, pretrained embeddings on large datasets.
- Bag of Words (BoW), term-frequency inverse-document-frequency.

Hyperparameters are optimised using the SMAC toolkit.

Models

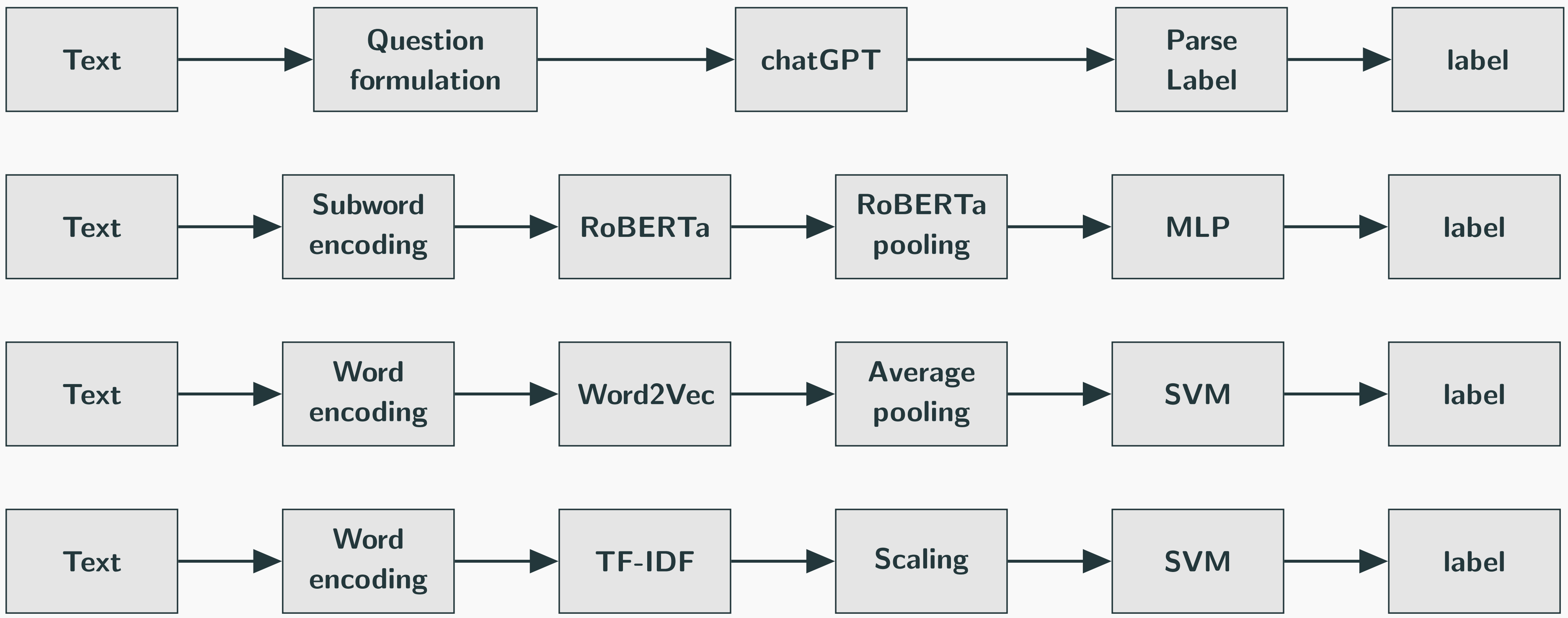


Figure 2: Pipelines of the ChatGPT (top), RoBERTa baseline (second), Word2Vec baseline (third), and BoW baseline (bottom) approaches.

Results

[%]	ChatGPT	RoBERTa	Word2Vec	BoW
O	46.6	**66.0*****	65.2***	59.7***
C	57.4	**63.7***	62.7	55.6
E	55.2	**66.0*****	59.9	55.2
A	44.8	**67.4*****	67.2***	58.5***
N	47.2	**62.1*****	56.8***	56.0***
Sen	**85.5**	85.0	79.4*	82.5
Sui	92.7	**97.4*****	92.1	92.7

Table 1: The classification accuracy (in %) of ChatGPT against the baselines on the different tasks (Sen: Sentiment, Sui: Suicide). *,**,*** indicate statistically significant difference as compared to ChatGPT, with p-values 5 %, 2 %, and 1 %, respectively. Significance tests are checked with a randomised permutation test.

Main Takeaways

- ChatGPT has emerging properties, it does not need specialised training.
- The performance of ChatGPT is comparable to BoW.
- Specialised training on competent models (e. g. , RoBERTa) yields significantly better results.

Any questions?

Teaser

MO How to reboot in 30 seconds on linux?

To reboot a Linux system in 30 seconds, you can use the following command in the terminal:

perl

Copy code

```perl
sudo shutdown -r +30
```

This command will initiate a system reboot, with the `-r` option specifying that the system should be rebooted rather than shut down. The `+30` option specifies the number of minutes from the current time until the reboot should occur. In this case, the system will reboot in 30 seconds.

Figure 3: Did ChatGPT answer this question correctly?

Teaser

MO How to reboot in 30 minutes on linux?

To reboot a Linux system in 30 minutes, you can use the following command in the terminal:

perl Copy code

```perl
sudo shutdown -r +30
```

This command will initiate a system reboot, with the `-r` option specifying that the system should be rebooted rather than shut down. The `+30` option specifies the number of minutes from the current time until the reboot should occur. In this case, the system will reboot in 30 minutes.

Figure 4: One of those has to be wrong.

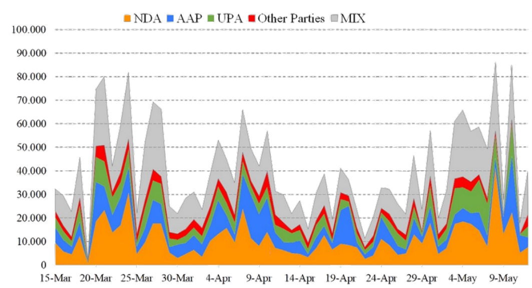
Thanks

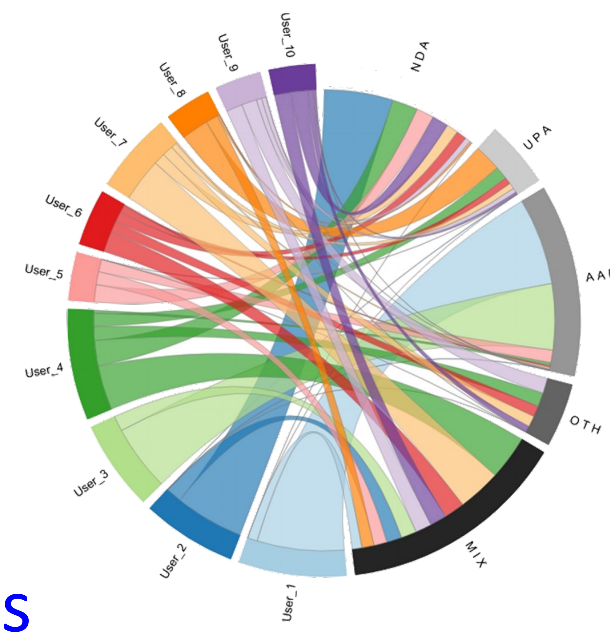
FOR YOUR SUPPORT

Sentic Projects

At SenticNet, we are working on several projects spanning from fundamental affective computing research to the application of sentiment analysis techniques to domains like finance, healthcare, and the arts. Some of the main current projects include:

- Sentic Computing for Human-Computer Interaction
- Sentic Computing for Social Media Monitoring
- Sentic Computing for Business Intelligence
- Sentic Computing for Social Good
- Sentic Computing for Healthcare
- Sentic Computing for Finance
- Sentic Computing for the Arts





https://sentic.net/projects

Sentic Computing Section

If you use any sentic algorithm or resource, consider submitting to this new Collection of Cognitive Computation (impact factor 4.890)

https://sentic.net/scs.pdf

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