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# Paradigm Shift in NLP

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https://arxiv.org/abs/2109.12575

https://txsun1997.github.io/nlp-paradigm-shift/

### Outline

#### Introduction

- The Seven Paradigms in NLP
- Paradigm Shift in NLP Tasks
- Potential Unified Paradigms
- Conclusion

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### What is Paradigm?

#### Definition from Wikipedia

 In science and philosophy, a paradigm is a distinct set of concepts or thought patterns, including theories, research methods, postulates, and standards for what constitutes legitimate contributions to a field.

#### Definition in the context of NLP

• Paradigm is the general framework to model a class of tasks

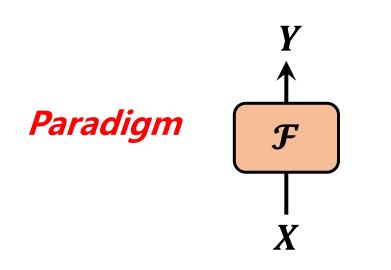
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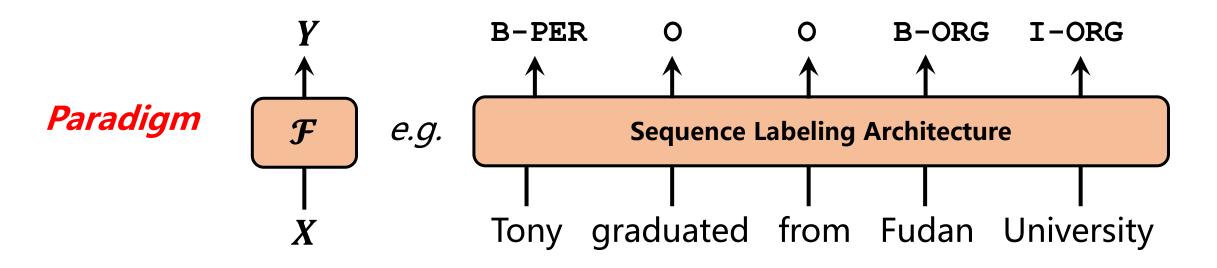
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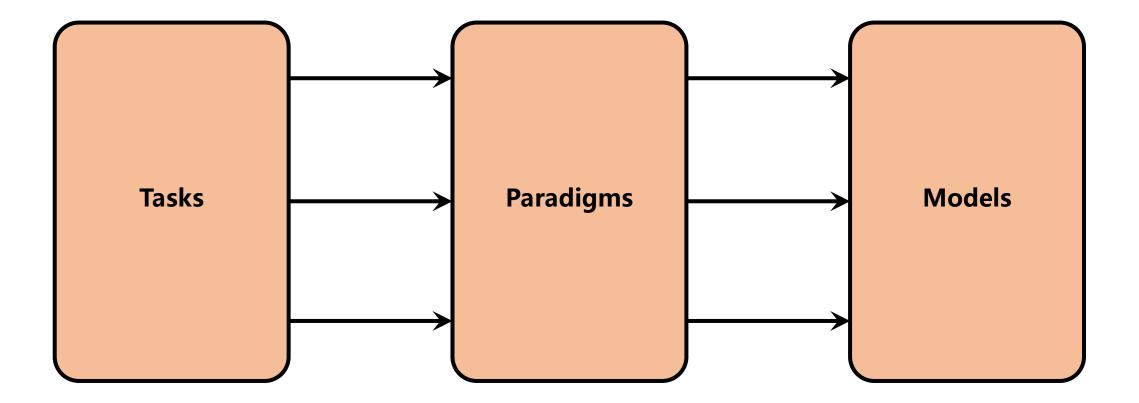
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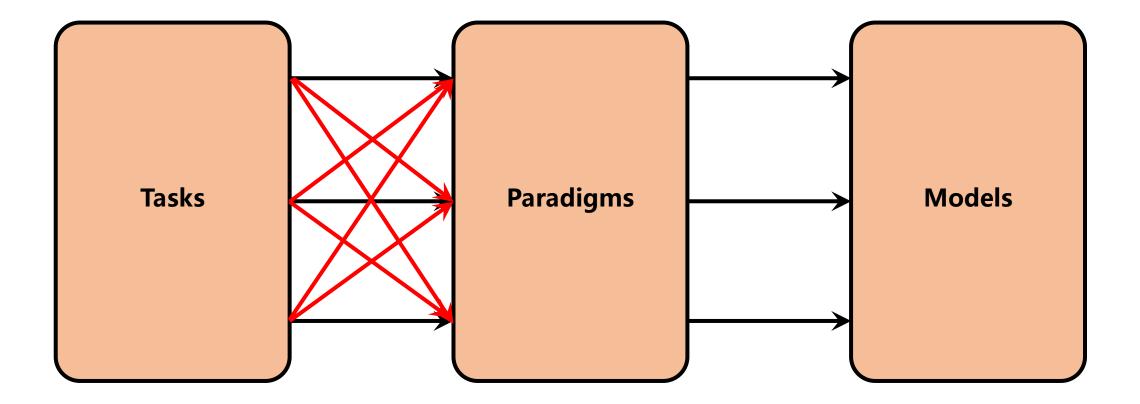
### Paradigms, Tasks, and Models

A Rough Illustration



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A Rough Illustration



### Outline

#### Introduction

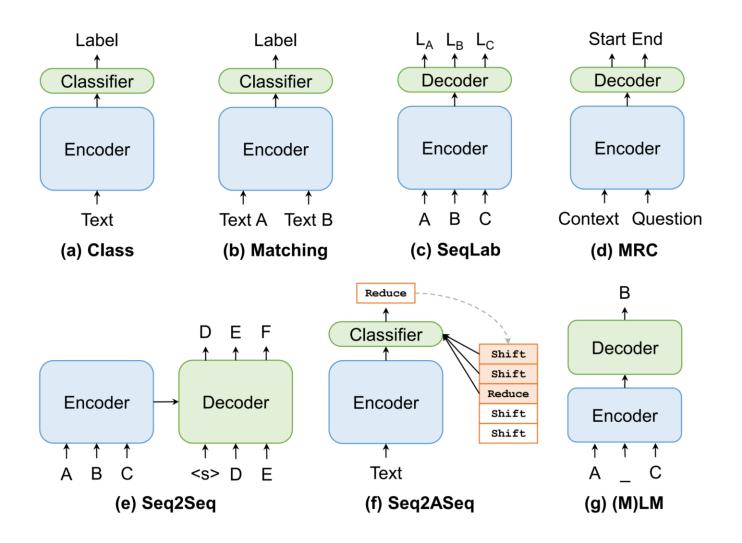
#### The Seven Paradigms in NLP

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### The Seven Paradigms in NLP

#### Seven Paradigms

- Class
- Matching
- SeqLab
- MRC
- Seq2Seq
- Seq2ASeq
- (M)LM



### **Classification (Class)**

#### • Paradigm

 $\mathcal{Y} = Cls(Enc(\mathcal{X})).$ 

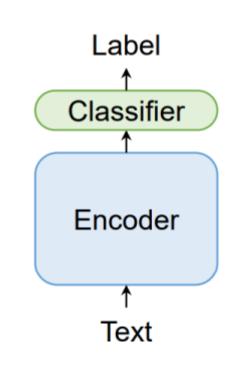
#### • Model

- $ENC(\cdot)$  : CNN, RNN, Transformers...
- $CLS(\cdot)$  : (max/average/attention) pooling + MLP

#### • Tasks

• ...

- Sentiment Analysis
- Spam Detection



## Matching

### Paradigm

 $\mathcal{Y} = \operatorname{Cls}(\operatorname{Enc}(\mathcal{X}_a, \mathcal{X}_b))$ 

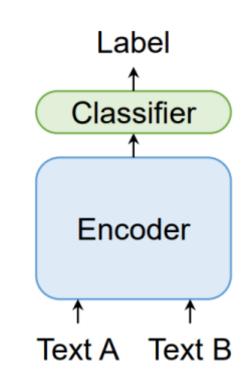
### • Model

- $ENC(\cdot)$  : encode the two texts separately or jointly
- $CLS(\cdot)$  : capture the interaction, and then prediction

#### • Tasks

• ...

- Natural Language Inference
- Similarity Regression



### Sequence Labeling (SeqLab)

#### • Paradigm

$$y_1, \cdots, y_n = \operatorname{Dec}(\operatorname{Enc}(x_1, \cdots, x_n))$$

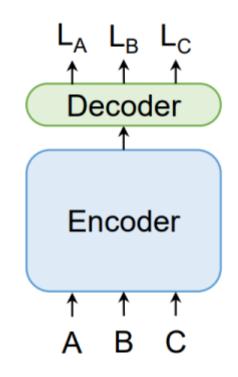
#### • Model

- $ENC(\cdot)$  : sequence model (RNN, Transformers...)
- $DEC(\cdot)$  : conditional random fields (CRF)

#### • Tasks

• ...

- Named Entity Recognition (NER)
- Part-Of-Speech Tagging



### Machine Reading Comprehension (MRC)

#### • Paradigm

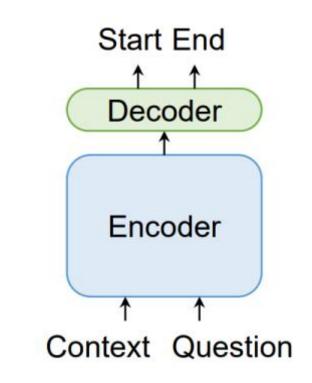
 $y_k \cdots y_{k+l} = \operatorname{Dec}(\operatorname{Enc}(\mathcal{X}_p, \mathcal{X}_q))$ 

#### • Model

- $ENC(\cdot)$  : CNN, RNN, Transformers...
- $DEC(\cdot)$  : start/end position prediction

#### • Tasks

Machine Reading Comprehension



### Sequence-to-Sequence (Seq2Seq)

#### • Paradigm

$$y_1, \cdots, y_m = \operatorname{Dec}(\operatorname{Enc}(x_1, \cdots, x_n))$$

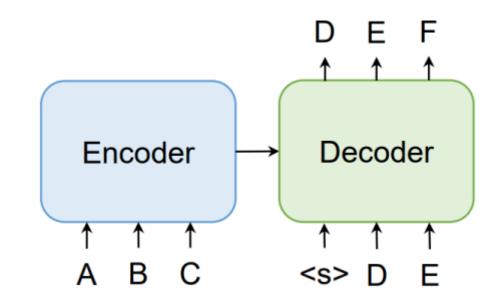
#### • Model

- $ENC(\cdot)$  : CNN, RNN, Transformers...
- $DEC(\cdot)$  : CNN, RNN, Transformers...

#### • Tasks

•

- Machine Translation
- End-to-end dialogue system



### Sequence-to-Action-Sequence (Seq2ASeq)

#### Paradigm

 $\mathcal{A} = \text{Cls}(\text{Enc}(\mathcal{X}), \mathcal{C})$ 

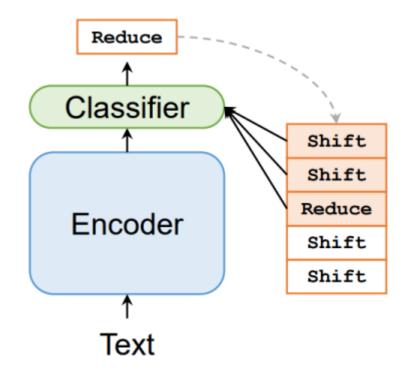
#### • Model

- $ENC(\cdot)$  : CNN, RNN, Transformers...
- $CLS(\cdot)$  : predict an action conditioned on a configuration and the input text

#### • Tasks

•

- Dependency Parsing
- Constituency Parsing



### (Masked) Language Model ((M)LM)

#### Paradigm

- LM:  $x_k = DEC(x_1, \cdots, x_{k-1})$
- MLM:  $\bar{x} = \text{Dec}(\text{Enc}(\tilde{x}))$

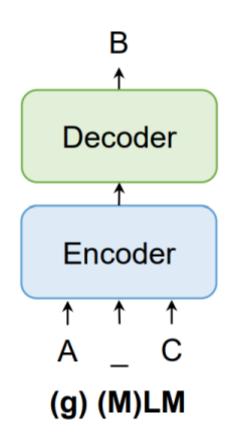
#### • Model

- $ENC(\cdot)$  : CNN, RNN, Transformers...
- $DEC(\cdot)$  : simple classifier, or a auto-regressive decoder

#### • Tasks

•

- Language Modeling
- Masked Language Modeling



### **Compound Paradigm**

- Complicated NLP tasks can be solved by combining multiple fundamental paradigms
- An Example
  - HotpotQA

#### Paragraph A, Return to Olympus:

[1] Return to Olympus is the only album by the alternative rock band Malfunkshun. [2] It was released after the band had broken up and after lead singer Andrew Wood (later of Mother Love Bone) had died of a drug overdose in 1990. [3] Stone Gossard, of Pearl Jam, had compiled the songs and released the album on his label, Loosegroove Records.

#### Paragraph B, Mother Love Bone:

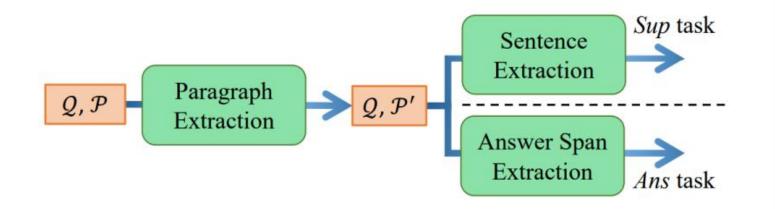
[4] Mother Love Bone was an American rock band that formed in Seattle, Washington in 1987. [5] The band was active from 1987 to 1990. [6] Frontman Andrew Wood's personality and compositions helped to catapult the group to the top of the burgeoning late 1980s/early 1990s Seattle music scene. [7] Wood died only days before the scheduled release of the band's debut album, "Apple", thus ending the group's hopes of success. [8] The album was finally released a few months later.

Q: What was the former band of the member of Mother Love Bone who died just before the release of "Apple"? A: Malfunkshun Supporting facts: 1, 2, 4, 6, 7

HotpotQA: A Dataset for Diverse, Explainable Multi-hop Question Answering. EMNLP 2018

### **Compound Paradigm**

- Complicated NLP tasks can be solved by combining multiple fundamental paradigms
- An Example
  - HotpotQA = Matching + MRC



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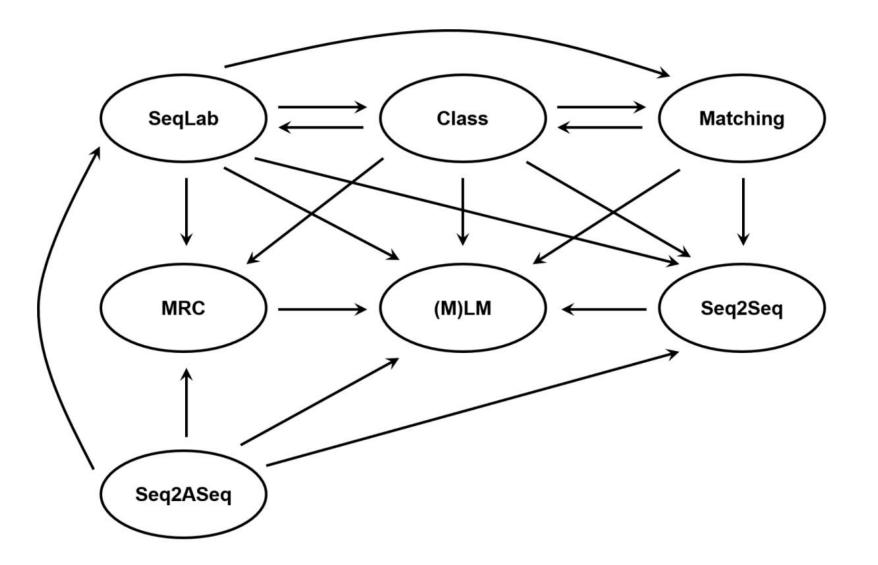
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Graph-free Multi-hop Reading Comprehension: A Select-to-Guide Strategy. https://arxiv.org/abs/2107.11823

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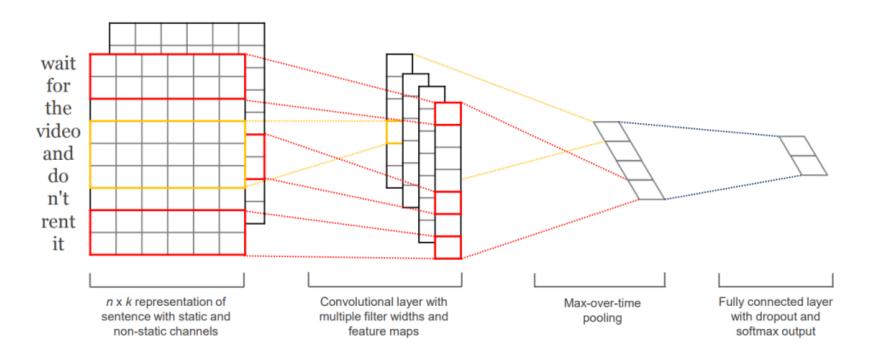


Task		Class	Matching	SeqLab	MRC	Seq2Seq	Seq2ASeq	(M) LM
тс	Input Output Example	$\begin{vmatrix} \mathcal{X} \\ \mathcal{Y} \\ \text{Devlin et al. (2019)} \end{vmatrix}$	$\mathcal{X}, \mathcal{L}$ $\mathcal{Y} \in \{0, 1\}$ Chai et al. (2020)			$\begin{vmatrix} \mathcal{X} \\ y_1, \cdots, y_m \\ \text{Yang et al. (2018a)} \end{vmatrix}$		$ \begin{array}{c} f_{prompt}(\mathcal{X}) \\ g(\mathcal{Y}) \\ \text{Schick and Schütze (2021a)} \end{array} $
NLI	Input Output Example	$ \begin{array}{c} \mathcal{X}_a \oplus \mathcal{X}_b \\ \mathcal{Y} \\ \text{Devlin et al. (2019)} \end{array} $	$\mathcal{X}_a, \mathcal{X}_b$ $\mathcal{Y}$ Chen et al. (2017b)			$f_{prompt}(\mathcal{X}_a, \mathcal{X}_b)$ $\mathcal{Y}$ McCann et al. (2018)		$f_{prompt}(\mathcal{X}_a, \mathcal{X}_b)$ $g(\mathcal{Y})$ Schick and Schütze (2021a)
NER	Input Output Example	$egin{array}{c} \mathcal{X}_{span} \ \mathcal{Y} \ Fu \ { m et al.} \ (2021) \end{array}$		$x_1, \cdots, x_n$ $y_1, \cdots, y_n$ Ma and Hovy (2016)	$ \begin{array}{c} \mathcal{X}, \mathcal{Q}_y \\ \mathcal{X}_{span} \\ \text{Li et al. (2020)} \end{array} $	$\begin{vmatrix} \mathcal{X} \\ (\mathcal{X}_{ent_i}, \mathcal{Y}_{ent_i})_{i=1}^m \\ \text{Yan et al. (2021b)} \end{vmatrix}$	$\begin{vmatrix} (\mathcal{X}, \mathcal{C}_t)_{t=0}^{m-1} \\ \mathcal{A} = a_1, \cdots, a_m \\ \text{Lample et al. (2016)} \end{vmatrix}$	
ABSA	Input Output Example	$egin{array}{c} \mathcal{X}_{asp} \ \mathcal{Y} \ Wang et al. (2016) \end{array}$	$\mathcal{X}, \mathcal{S}_{aux}$ $\mathcal{Y}$ Sun et al. (2019)		$ \begin{vmatrix} \mathcal{X}, \mathcal{Q}_{asp}, \mathcal{Q}_{opin\&sent} \\ \mathcal{X}_{asp}, \mathcal{X}_{opin}, \mathcal{Y}_{sent} \\ \text{Mao et al. (2021)} \end{vmatrix} $	$\begin{vmatrix} \mathcal{X} \\ (\mathcal{X}_{asp_i}, \mathcal{X}_{opin_i}, \mathcal{Y}_{sent_i})_{i=1}^m \\ \text{Yan et al. (2021a)} \end{vmatrix}$		$f_{prompt}(\mathcal{X})$ $g(\mathcal{Y})$ Li et al. (2021)
RE	Input Output Example	$ \begin{array}{c} \mathcal{X} \\ \mathcal{Y} \\ \text{Zeng et al. (2014)} \end{array} $			$ \begin{array}{c} \mathcal{X}, \mathcal{Q}_y \\ \mathcal{X}_{ent} \\ \text{Levy et al. (2017)} \end{array} $	$\begin{vmatrix} \mathcal{X} \\ (\mathcal{Y}_i, \mathcal{X}_{sub_i}, \mathcal{X}_{obj_j})_{i=1}^m \\ \text{Zeng et al. (2018)} \end{vmatrix}$		$f_{prompt}(\mathcal{X})$ $g(\mathcal{Y})$ Han et al. (2021)
Summ	Input Output Example		$(\mathcal{X}, \mathcal{S}_{cand_i})_{i=1}^n$ $\hat{\mathcal{S}}_{cand}$ Zhong et al. (2020)	$\mathcal{X}_1, \cdots, \mathcal{X}_n$ $\mathcal{Y}_1, \cdots, \mathcal{Y}_n \in \{0, 1\}^n$ Cheng and Lapata (2016)		$\begin{array}{l} \mathcal{X}, \mathcal{Q}_{summ} \\ \mathcal{Y} \\ \text{McCann et al. (2018)} \end{array}$		$\mathcal{X}, \mathrm{Keywords/Prompt}$ $\mathcal{Y}$ Aghajanyan et al. (2021)
Parsing	Input Output Example			$x_1, \cdots, x_n$ $g(y_1, \cdots, y_n)$ Strzyz et al. (2019)	$\begin{array}{l} \mathcal{X}, \mathcal{Q}_{child} \\ \mathcal{X}_{parent} \\ \text{Gan et al. (2021)} \end{array}$	$\begin{vmatrix} \mathcal{X} \\ g(y_1, \cdots, y_m) \\ \text{Vinyals et al. (2015)} \end{vmatrix}$	$\begin{vmatrix} (\mathcal{X}, \mathcal{C}_t)_{t=0}^{m-1} \\ \mathcal{A} = a_1, \cdots, a_m \\ \text{Chen and Manning (2014)} \end{vmatrix}$	$(\mathcal{X}, \mathcal{Y}_i)_{i=1}^k$ $\hat{\mathcal{Y}}$ Choe and Charniak (2016)

Table 1: Paradigms shift in natural language processing tasks. **TC**: text classification. **NLI**: natural language inference. **NER**: named entity recognition. **ABSA**: aspect-based sentiment analysis. **RE**: relation extraction. **Summ**: text summarization. **Parsing**: syntactic/semantic parsing. f and g indicate pre-processing and post-processing, respectively. In (M) LM,  $f(\cdot)$  is usually implemented as a template and  $g(\cdot)$  is a verbalizer. In parsing tasks,  $g(\cdot)$  is a function that reconstructs the structured representation (*e.g.* dependency tree) from the output sequence.  $\mathcal{L}$  means label description.  $\oplus$  means concatenation.  $\mathcal{X}_{asp}, \mathcal{X}_{opin}, \mathcal{Y}_{sent}$  mean aspect, opinion, and sentiment, respectively.  $\mathcal{S}_{aux}$  means auxiliary sentence.  $\mathcal{X}_{sub}, \mathcal{X}_{obj}$  stand for subject entity and object entity, respectively.  $\mathcal{S}_{cand}$  means candidate summary.  $\mathcal{C}_t$  is configuration t and  $\mathcal{A}$  is a sequence of actions. More details can be found in Section 3.

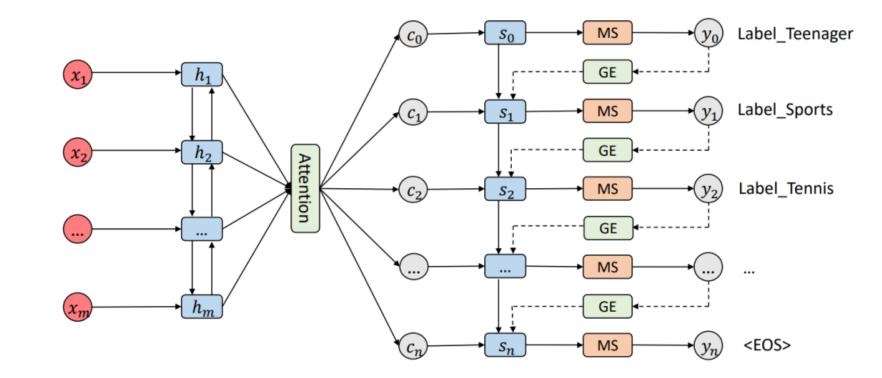
- Traditional Paradigm: Class
- Shifted to...
  - Seq2Seq
  - Matching
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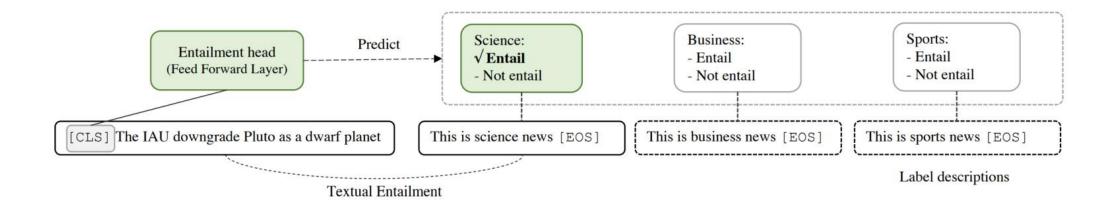
Convolutional Neural Networks for Sentence Classification. EMNLP 2014

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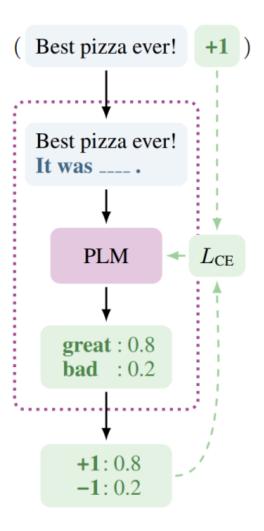
SGM: Sequence Generation Model for Multi-label Classification. COLING 2018

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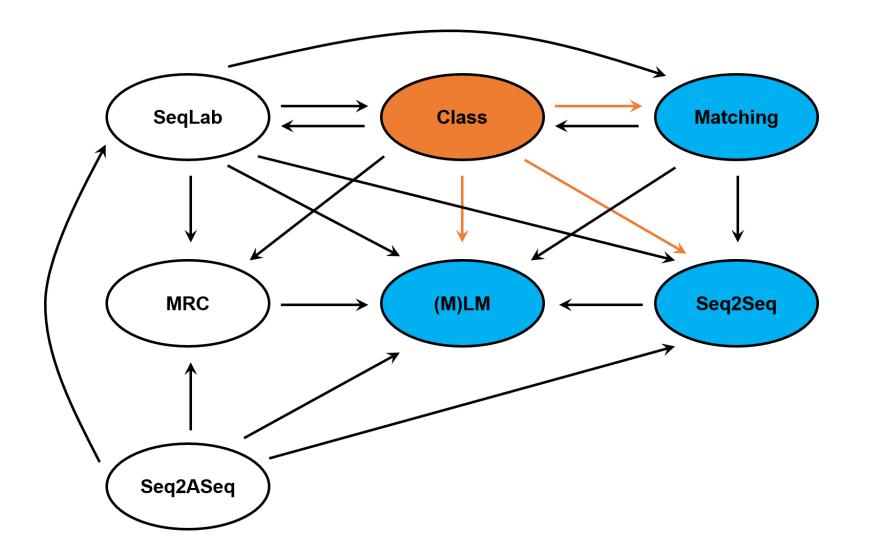


Entailment as Few-Shot Learner. https://arxiv.org/abs/2104.14690

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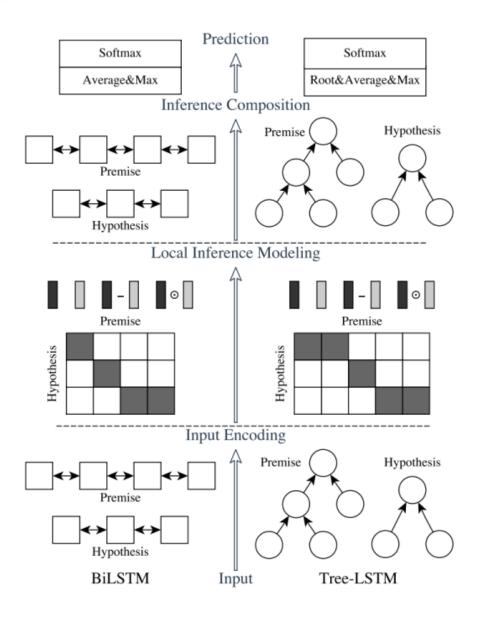


Exploiting Cloze Questions for Few Shot Text Classification and Natural Language Inference. EACL 2021



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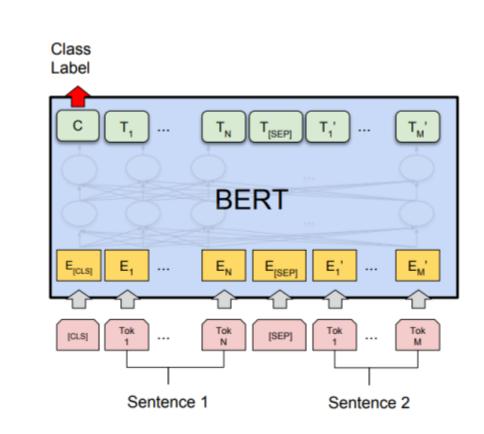
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Enhanced LSTM for Natural Language Inference. ACL 2017

### Traditional Paradigm: Matching

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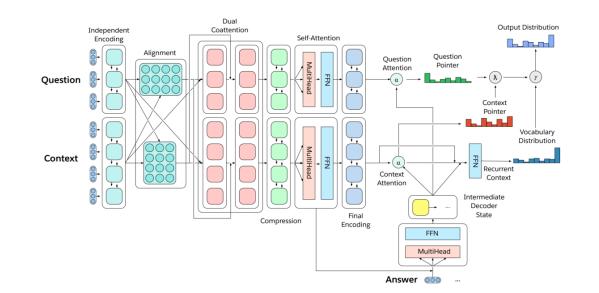
BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. NAACL 2019

#### Traditional Paradigm: Matching

### • Shifted to...

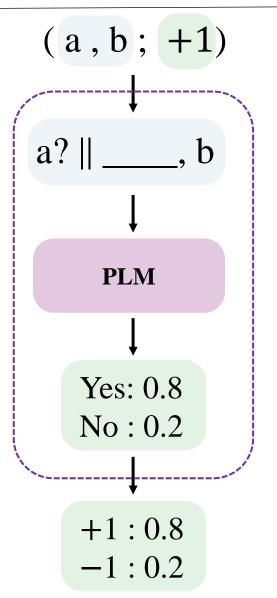
- Class
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Question	Context	Answer
Hypothesis: Product and geography are what make cream skimming work. Entailment, neutral, or contradiction?	Premise: Conceptually cream skimming has two basic dimensions – product and geography	Entailment

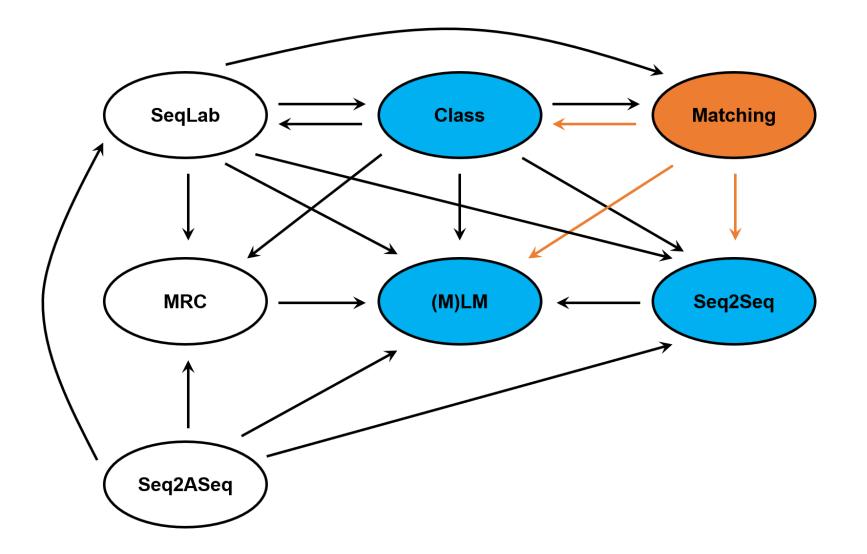


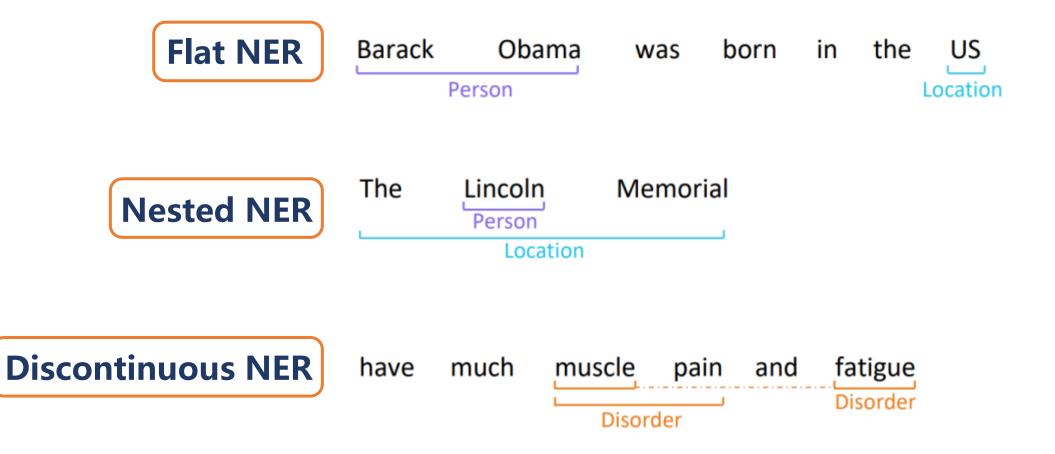
The Natural Language Decathlon: Multitask Learning as Question Answering. https://arxiv.org/abs/1806.08730

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Exploiting Cloze Questions for Few Shot Text Classification and Natural Language Inference. EACL 2021





#### Traditional Paradigm:

- SeqLab (Flat NER)
- Class (Nested NER)
- Seq2ASeq (Discontinuous NER)

### Shifted to / Unified in...

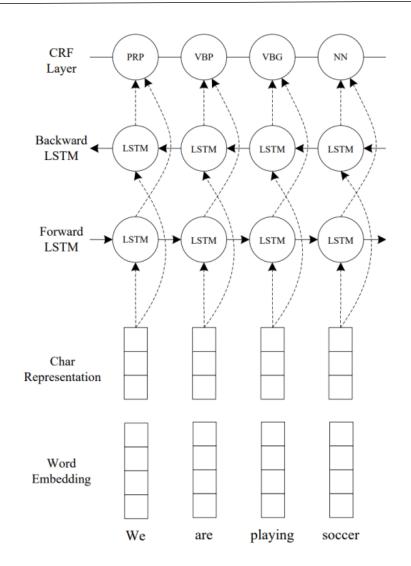
- Class (Flat&Nested NER)
- MRC (Flat&Nested NER)
- Seq2Seq (All)

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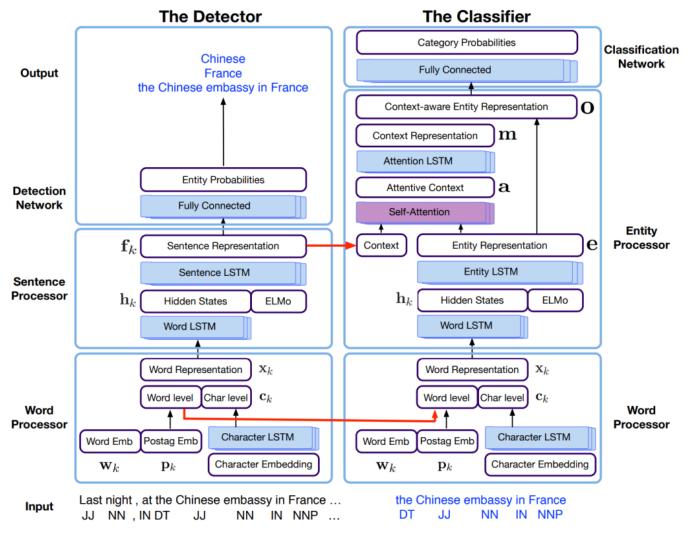
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End-to-end Sequence Labeling via Bi-directional LSTM-CNNs-CRF. ACL 2016

# Traditional Paradigm: SeqLab (Flat NER) Class (Nested NER) Seq2ASeq (Discontinuous NER) Shifted to / Unified in... Class (Flat&Nested NER) Sentence Processor

- MRC (Flat&Nested NER)
- Seq2Seq (All)

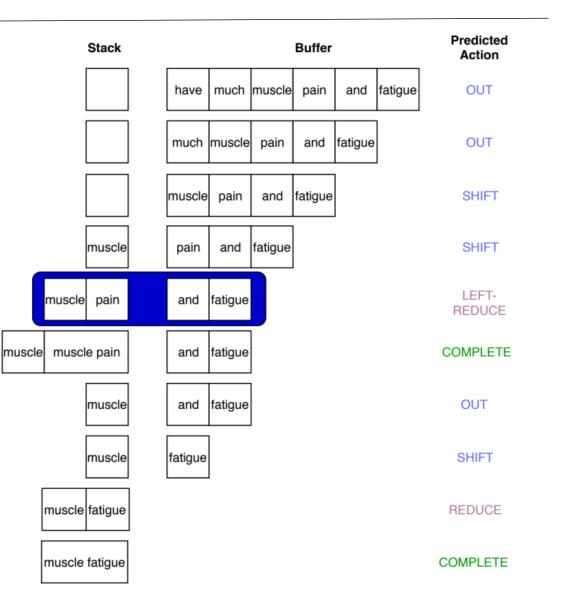


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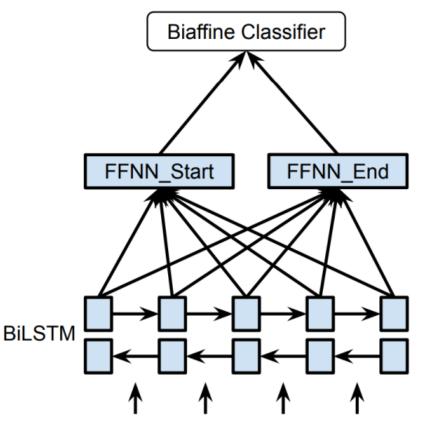
An Effective Transition-based Model for Discontinuous NER. ACL 2020

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BERT, fastText & Char Embeddings

Named Entity Recognition as Dependency Parsing. ACL 2020

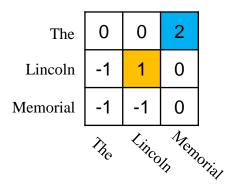
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#### Matrix (I×I×c) Labeling:



$$h_s(i) = \text{FFNN}_s(x_{s_i})$$
  

$$h_e(i) = \text{FFNN}_e(x_{e_i})$$
  

$$r_m(i) = h_s(i)^\top \mathbf{U}_m h_e(i)$$
  

$$+ W_m(h_s(i) \oplus h_e(i)) + b_m$$

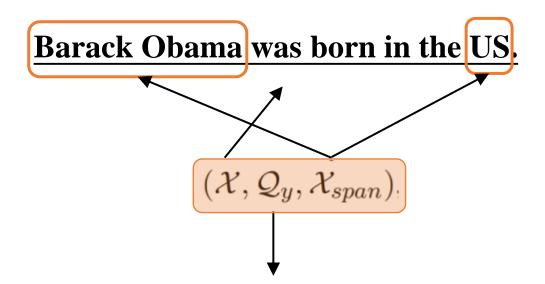
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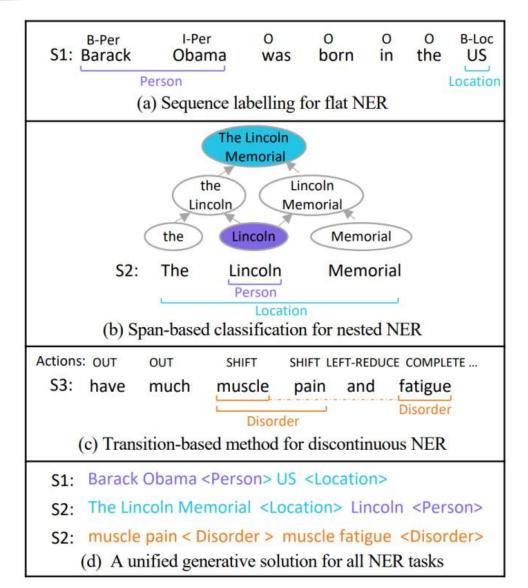
Entity	Natural Language Question
Location	Find locations in the text, including non-
	geographical locations, mountain ranges
	and bodies of water.
Facility	Find facilities in the text, including
	buildings, airports, highways and bridges.
Organization	Find organizations in the text, including companies, agencies and institutions.

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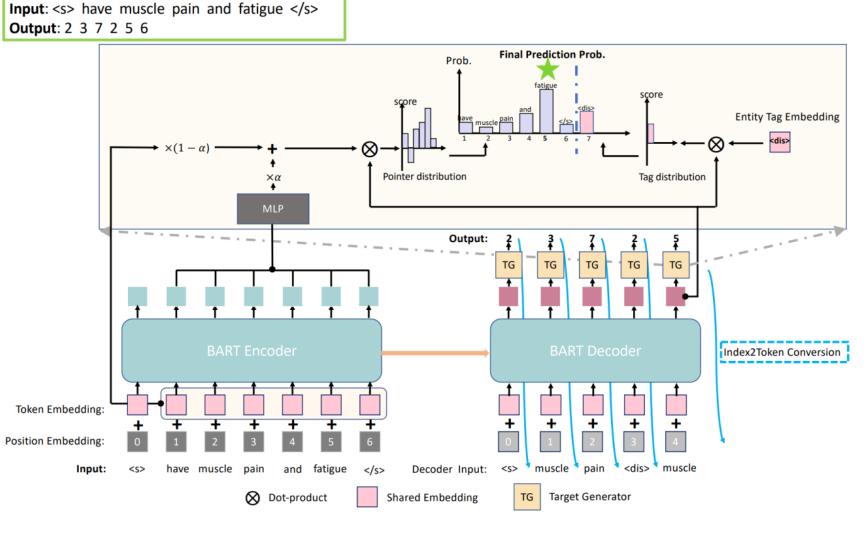


## Traditional Paradic

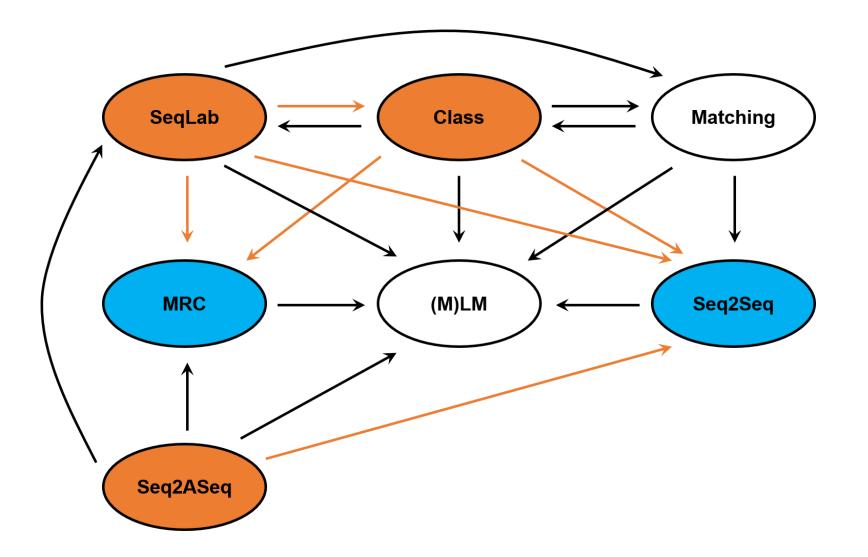
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- Class (Flat&Nested
- MRC (Flat&Nested
- Seq2Seq (All)



A Unified Generative Framework for Various NER Subtasks. ACL 2021



<b>a</b> <sub>1</sub> <i>o</i> <sub>1</sub>		<b>a</b> <sub>2</sub>	
Subtask	Input	Output	Tas
Aspect Term Extraction(AE)	S	<b>a</b> <sub>1</sub> , <b>a</b> <sub>2</sub>	Ext
<b>Opinion Term Extraction(</b> <i>OE</i> <b>)</b>	S	<i>o</i> <sub>1</sub> , <i>o</i> <sub>2</sub>	Ex
Aspect-level	<b>S</b> + <b>a</b> <sub>1</sub>	s <sub>1</sub>	Class
Sentiment Classification(ALSC)	<b>S</b> + <b>a</b> <sub>2</sub>	s <sub>2</sub>	Class
Aspect-oriented	<b>S</b> + <b>a</b> <sub>1</sub>	01	Erré
<b>Opinion Extraction</b> (AOE)	<b>S</b> + <b>a</b> <sub>2</sub>	02	Ext
Aspect Term Extraction and	S	( <b>a</b> <sub>1</sub> , s <sub>1</sub> ),	Extr
Sentiment Classification(AESC)	S	<b>(a<sub>2</sub>, s<sub>2</sub>)</b>	Class
Pair Extraction(Pair)	S	$(a_1, o_1), (a_2, o_2)$	Ext
Triplet Extraction(Triplet)	S	$(\mathbf{a_1}, o_1, \mathbf{s_1}), (\mathbf{a_2}, o_2, \mathbf{s_2})$	Extra Class

A Unified Generative Framework for Aspect-Based Sentiment Analysis. ACL 2021

#### Traditional Paradigm:

- SeqLab (AE, OE, AOE, ...)
- Class (ALSC...)

#### Shifted to / Unified in...

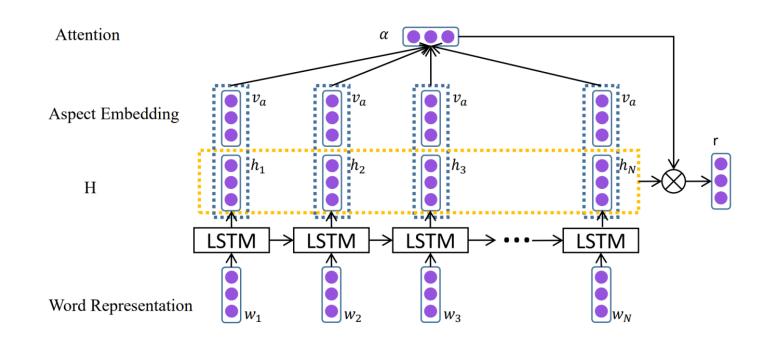
- Matching (ALSC)
- MRC (All)
- Seq2Seq (All)
- (M)LM (All)

#### Traditional Paradigm:

- SeqLab (AE, OE, AOE, ...)
- Class (ALSC...)

#### Shifted to / Unified in...

- Matching (ALSC)
- MRC (All)
- Seq2Seq (All)
- (M)LM (All)



Attention-based LSTM for Aspect-level Sentiment Classification. EMNLP 2016

#### Traditional Paradigm:

- SeqLab (AE, OE, AOE, ...)Class (ALSC...)
- Shifted to / Unified in...
  - Matching (ALSC)
  - MRC (All)
  - Seq2Seq (All)
  - (M)LM (All)

X: LOC1 is often considered the coolest area of London. Aspect: *Safety* 

- QA-M What do you think of the safety of LOC1? [X]
- NLI-M LOC1- safety. [X]
- QA-B The polarity of the aspect safety of LOC1 is positive. [X]

**NLI-B** LOC1- safety - positive. [X]

Utilizing BERT for Aspect-Based Sentiment Analysis via Constructing Auxiliary Sentence. NAACL 2019

#### Traditional Paradigm:

- SeqLab (AE, OE, AOE, ...)
- Class (ALSC...)

#### Shifted to / Unified in...

- Matching (ALSC)
- MRC (All)
- Seq2Seq (All)
- (M)LM (All)

#### Original training example:

- input text: The ambience was nice , but service was not so great.
- annotations: (ambience, nice, positive), (service, no so great, negative)

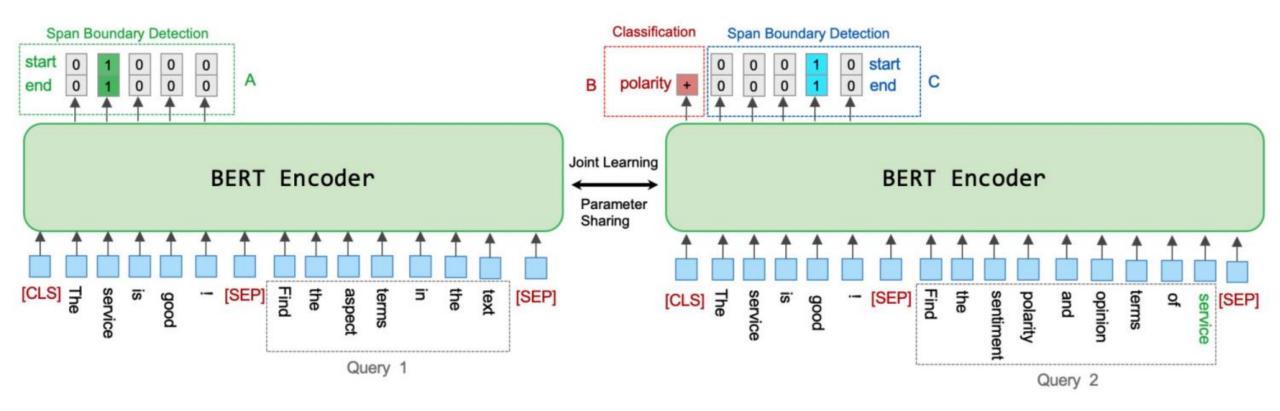
#### Converted training example 1:

- **query-1**: Find the *aspect terms* in the text.
- answer-1: ambience, service
- query-2: Find the sentiment polarity and opinion terms for ambience in the text.
- answer-2: (nice, positive)

#### **Converted training example 2:**

- query-1: Find the aspect terms in the text.
- answer-1: ambience, service
- query-2: Find the sentiment polarity and opinion terms for service in the text.
- answer-2: (not so great, negative)

#### Traditional Paradigm:



A Joint Training Dual-MRC Framework for Aspect Based Sentiment Analysis. AAAI 2021

#### Traditional Paradigm:

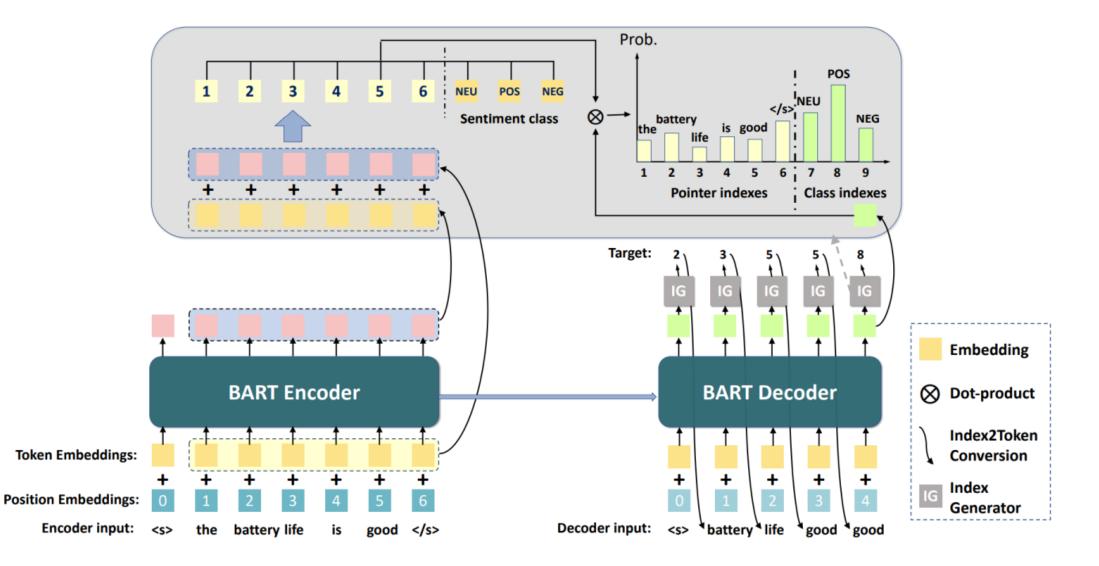
- SeqLab (AE, OE, AOE, ...)
- Class (ALSC...)

#### • Shifted to / Unified in...

- Matching (ALSC)
- MRC (All)
- Seq2Seq (All)
- (M)LM (All)

			Ł	Posi	tive	Posi	tive							Ро	sitiv	ve	
Token:	The	wine	list	is	inter	esting	and	has	good	value.	s, but	the	ser	vice	is	dre	adful
Position index:	0	1	2	3	4		5	6	7	8	9 10	11	12		13	14	
Carlet	1-		T														_

Target Sequence
1, 2, 12, 12,
4, 4, 7, 8, 14, 14,
<u>1</u> , <u>2</u> , POS,
<u>12</u> , <u>12</u> , POS,
<u>1</u> , <u>2</u> , 4, 4, 7, 8,
<u>12</u> , <u>12</u> , 14, 14,
1, 2, POS, 12, 12, NEG,
1, 2, 4, 4, 1, 2, 7, 8, 12, 12, 14, 14,
1, 2, 4, 4, POS, 1, 2, 7, 8, POS, 12, 12, 14, 14, POS,



A Unified Generative Framework for Aspect-Based Sentiment Analysis. ACL 2021

### Traditional Paradigm:

- SeqLab (AE, OE, AOE, ...)
- Class (ALSC...)

#### Shifted to / Unified in...

- Matching (ALSC)
- MRC (All)
- Seq2Seq (All)
- (M)LM (All)

The owners are great fun and the beer selection is worth staying for.

Consistency The owners are great fun? [MASK].

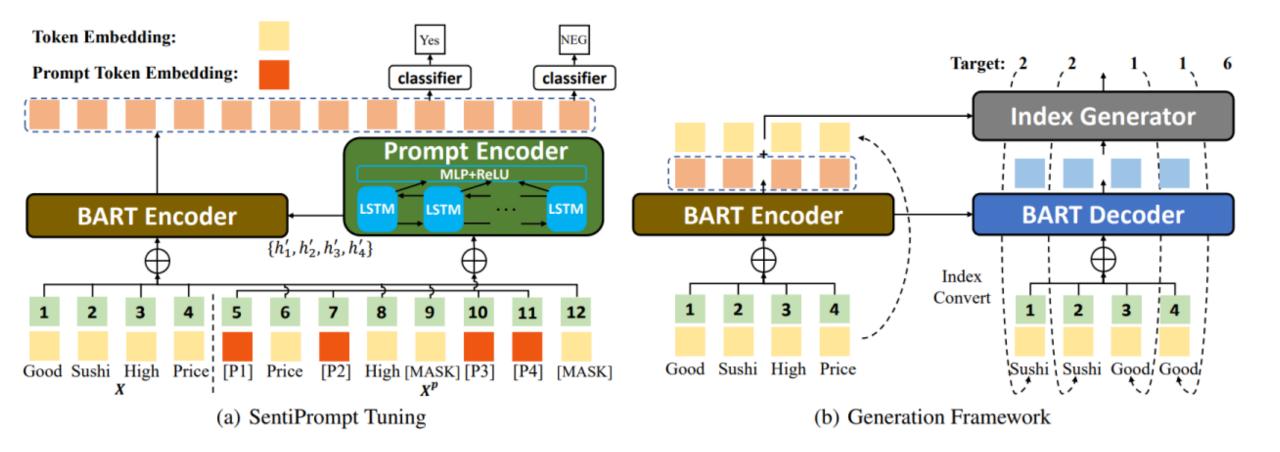
This is [MASK].

SentiPrompt: Sentiment Knowledge Enhanced Prompt-Tuning for Aspect-Based Sentiment Analysis. https://arxiv.org/abs/2109.08306

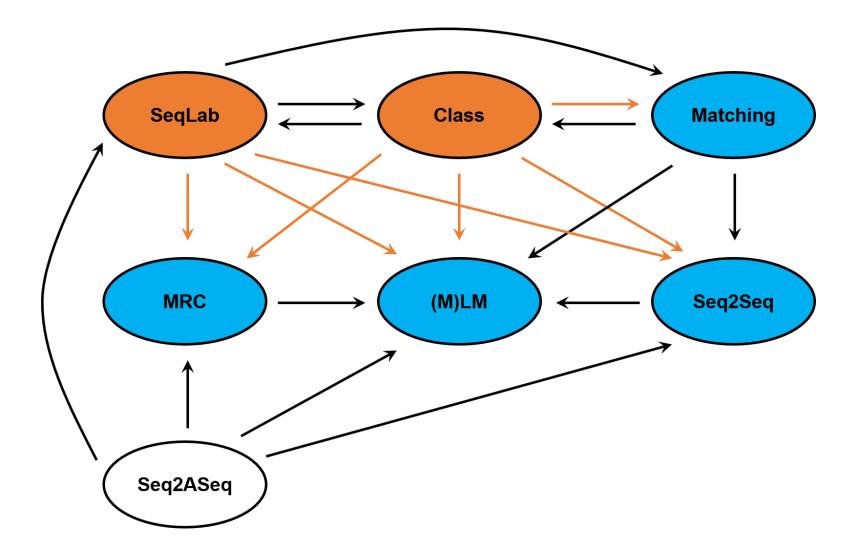
prompt

**Polarity** 

prompt



SentiPrompt: Sentiment Knowledge Enhanced Prompt-Tuning for Aspect-Based Sentiment Analysis. <u>https://arxiv.org/abs/2109.08306</u>



#### Traditional Paradigm:

- SeqLab (entity extraction)
- Class (relation classification)

#### • Shifted to / Unified in...

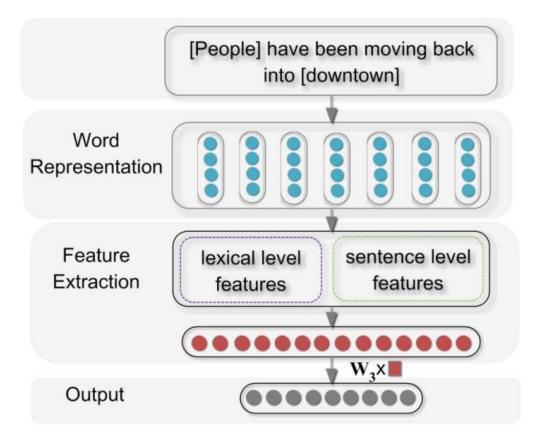
- Seq2Seq
- MRC
- (M)LM

#### Traditional Paradigm:

- SeqLab (entity extraction)
- Class (relation classification)

#### Shifted to / Unified in...

- Seq2Seq
- MRC
- (M)LM



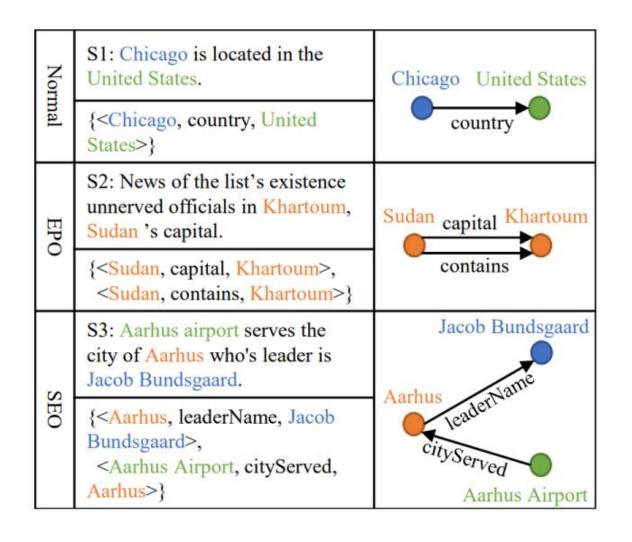
Relation Classification via Convolutional Deep Neural Network. COLING 2014

#### Traditional Paradigm:

SeqLab (entity extraction)Class (relation classification)

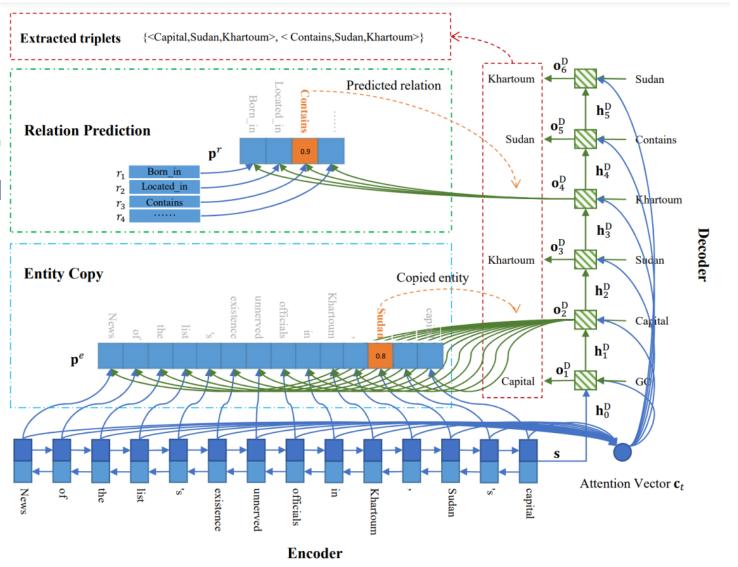
- Shifted to / Unified in...
  - Seq2Seq
  - MRC

• (M)LM



Extracting Relational Facts by an End-to-End Neural Model with Copy Mechanism. ACL 2018

- Traditional Paradigm
  - SeqLab (entity extracti
    Class (relation classific)
- Shifted to / Unified i
  - Seq2Seq
  - MRC
  - (M)LM



Extracting Relational Facts by an End-to-End Neural Model with Copy Mechanism. ACL 2018

#### Traditional Paradigm:

- SeqLab (entity extraction)
- Class (relation classification)
- Shifted to / Unified in...
  - Seq2Seq
  - MRC (entity prediction)
  - (M)LM

Relation	Question Template
	Where did <i>x</i> graduate from?
$educated\_at(x, y)$	In which university did x study?
	What is x's alma mater?
	What did x do for a living?
occupation(x, y)	What is <i>x</i> 's job?
	What is the profession of $x$ ?
	Who is x's spouse?
spouse(x, y)	Who did $x$ marry?
	Who is x married to?

Relation	Question	Sentence & Answers				
$educated\_at$	What is <b>Albert Einstein</b> 's alma mater?	Albert Einstein was awarded a PhD by the University				
	what is Albert Einstein's anna mater?	of Zürich, with his dissertation titled				
occupation	What did <b>Steve Jobs</b> do for a living?	Steve Jobs was an American businessman, inventor,				
	what did Steve Jobs do for a living?	and industrial designer.				
spouse	Who is Angela Merkel married to?	Angela Merkel's second and current husband is quantum				
	who is Angela Werker married to?	chemist and professor Joachim Sauer, who has largely				

#### Zero-Shot Relation Extraction via Reading Comprehension. CoNLL 2017

#### Traditional Paradigm:

SeqLab (entity extraction)

• Class (relation classification)

#### Shifted to / Unified in...

• Seq2Seq

• (M)LM

• MRC (triplet extraction)

#### Formulate RESUME

dataset as Multi-turn QA:

Q1 Person:	who is mentioned in the text?	A: $e_1$
Q2 Company:	which companies did $e_1$ work for?	A: $e_2$
Q3 Position:	what was $e_1$ 's position in $e_2$ ?	A: $e_3$
Q4 Time:	During which period did $e_1$ work for $e_2$ as $e_3$	A: $e_4$

Entity-Relation Extraction as Multi-Turn Question Answering. ACL 2019

#### Traditional Paradigm:

SeqLab (entity extraction)

• Class (relation classification)

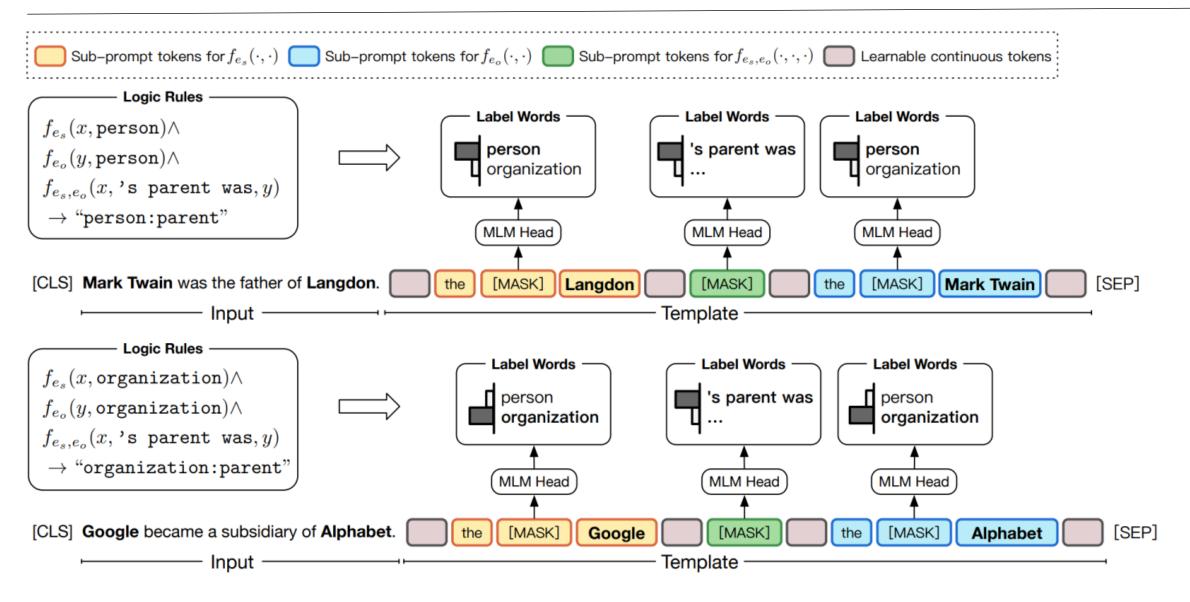
## Shifted to / Unified in...

- Seq2Seq
- MRC (triplet extraction)
- (M)LM

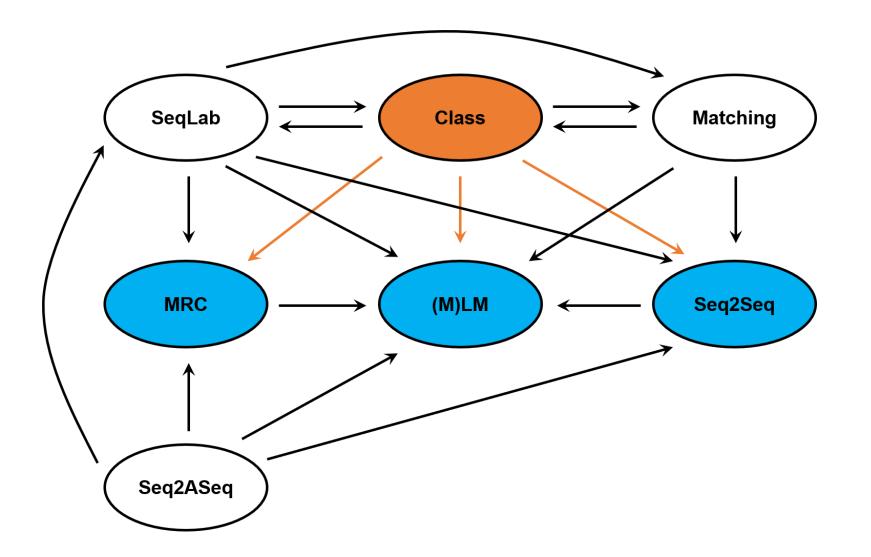
Mark Twain was the father of Langdon.

[p] the person Langdon [p] 's parent was
[p] the person Mark Twain [p].

PTR: Prompt Tuning with Rules for Text Classification. <u>https://arxiv.org/abs/2105.11259</u>



PTR: Prompt Tuning with Rules for Text Classification. https://arxiv.org/abs/2105.11259



#### Traditional Paradigm:

- SeqLab (extractive)
- Seq2Seq (abstractive)

#### Shifted to / Unified in...

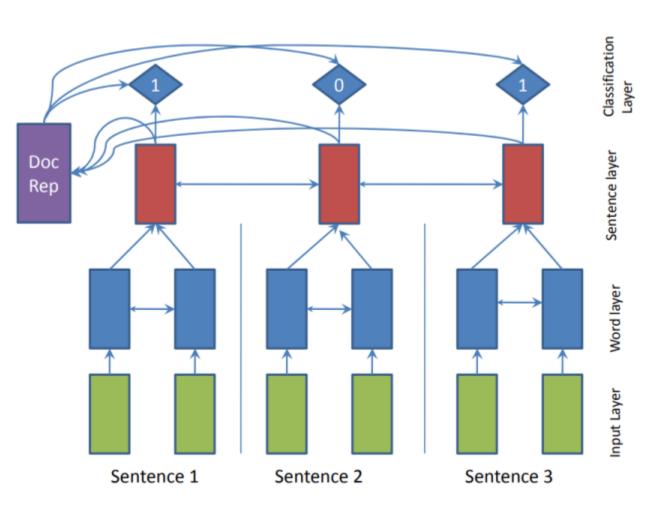
- Matching (extractive)
- (M)LM (abstractive)

#### Traditional Paradigm:

- SeqLab (extractive)
- Seq2Seq (abstractive)

#### Shifted to / Unified in...

- Matching (extractive)
- (M)LM (abstractive)



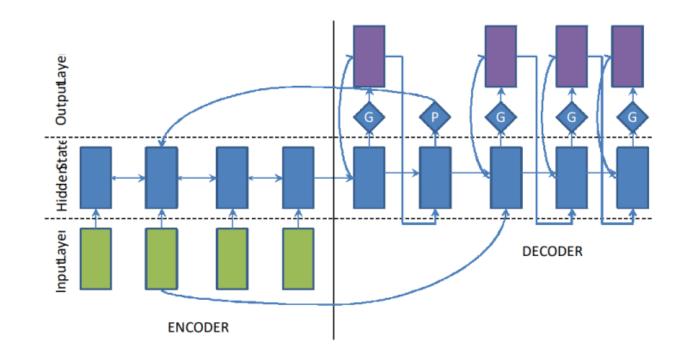
SummaRuNNer: A Recurrent Neural Network based Sequence Model for Extractive Summarization of Documents. AAAI 2017

#### Traditional Paradigm:

- SeqLab (extractive)
- Seq2Seq (abstractive)

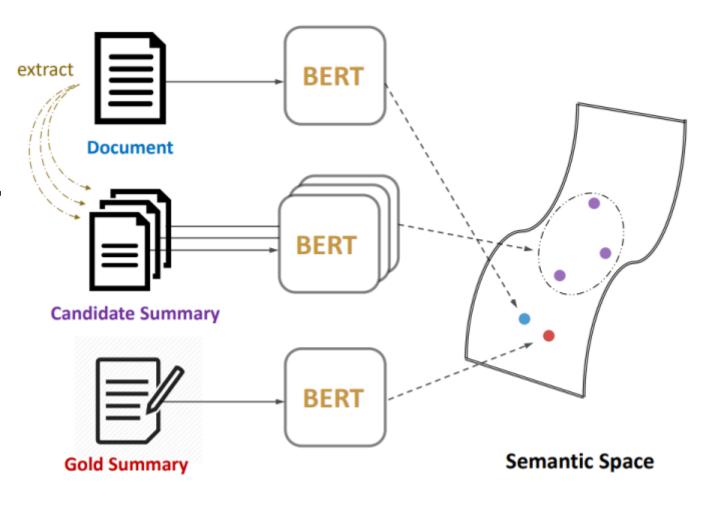
#### • Shifted to / Unified in...

- Matching (extractive)
- (M)LM (abstractive)



#### Traditional Paradigm:

- SeqLab (extractive)
- Seq2Seq (abstractive)
- Shifted to / Unified in...
  - Matching (extractive)
  - (M)LM (abstractive)



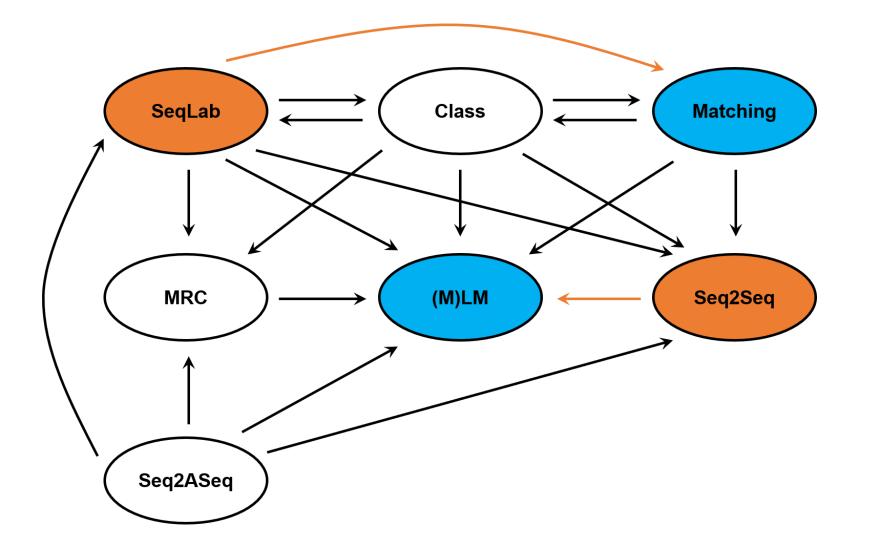
Extractive Summarization as Text Matching. ACL 2020

#### Traditional Paradigm:

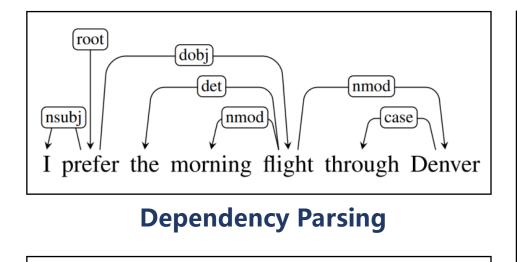
- SeqLab (extractive)
- Seq2Seq (abstractive)

#### Shifted to / Unified in...

- Matching (extractive)
- (M)LM (abstractive)

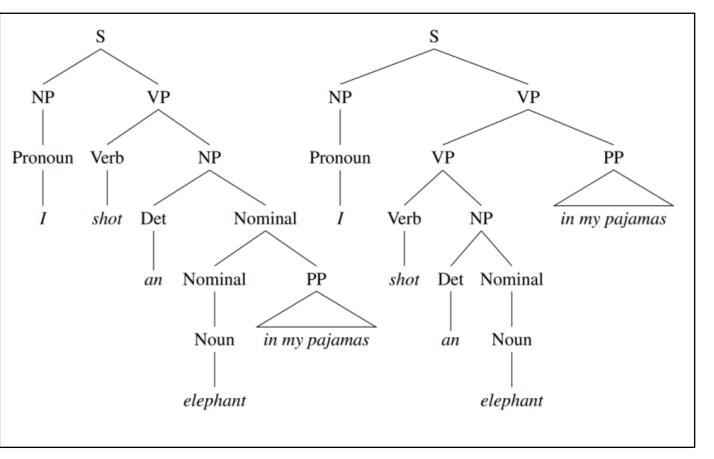


## **Paradigm Shift in Parsing**



which country had the highest carbon emissions last year

SELECT	country.name
FROM	country, co2_emissions
WHERE	<pre>country.id = co2_emissions.country_id</pre>
AND	co2_emissions.year = 2014
ORDER BY	co2_emissions.volume DESC
LIMIT	1;



#### **Constituency Parsing**

**Semantic Parsing** 

#### Traditional Paradigm:

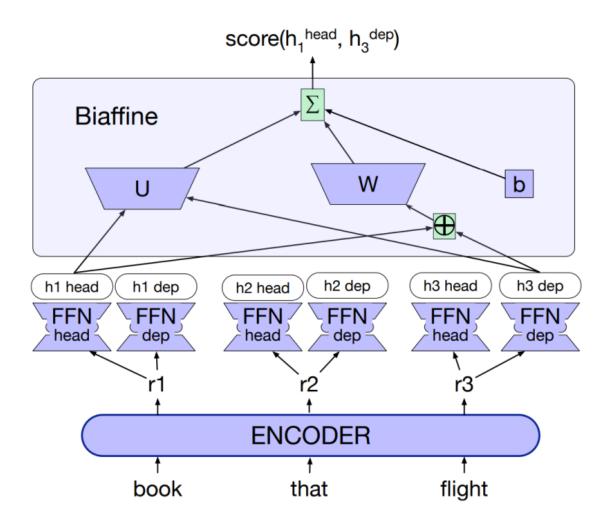
- Class (graph-based)
- Seq2ASeq (transition-based)
- Shifted to / Unified in...
  - SeqLab
  - Seq2Seq
  - (M)LM
  - MRC

### Traditional Paradigm:

- Class (graph-based)
- Seq2ASeq (transition-based)

### Shifted to / Unified in...

- SeqLab
- Seq2Seq
- (M)LM
- MRC

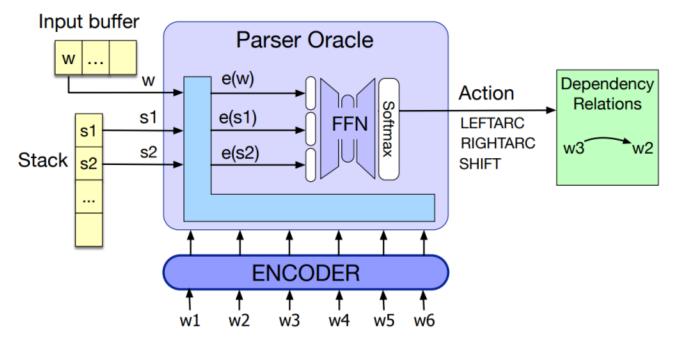


### Traditional Paradigm:

- Class (graph-based)
- Seq2ASeq (transition-based)

### Shifted to / Unified in...

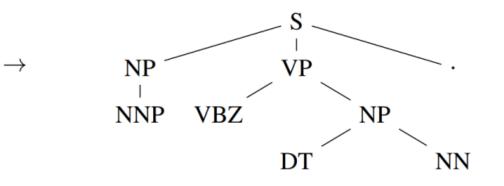
- SeqLab
- Seq2Seq
- (M)LM
- MRC



### Traditional Paradigm:

- Class (graph-based)
- Seq2ASeq (transition-based)
- Shifted to / Unified in...
  - SeqLab
  - Seq2Seq
  - (M)LM
  - MRC

**Linearize a parsing tree:** 



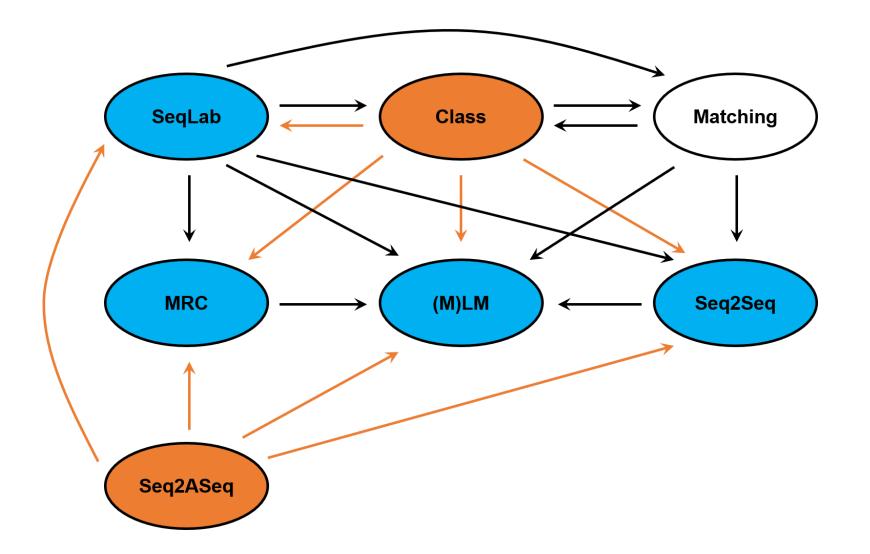
John has a dog.

 $\rightarrow$ 

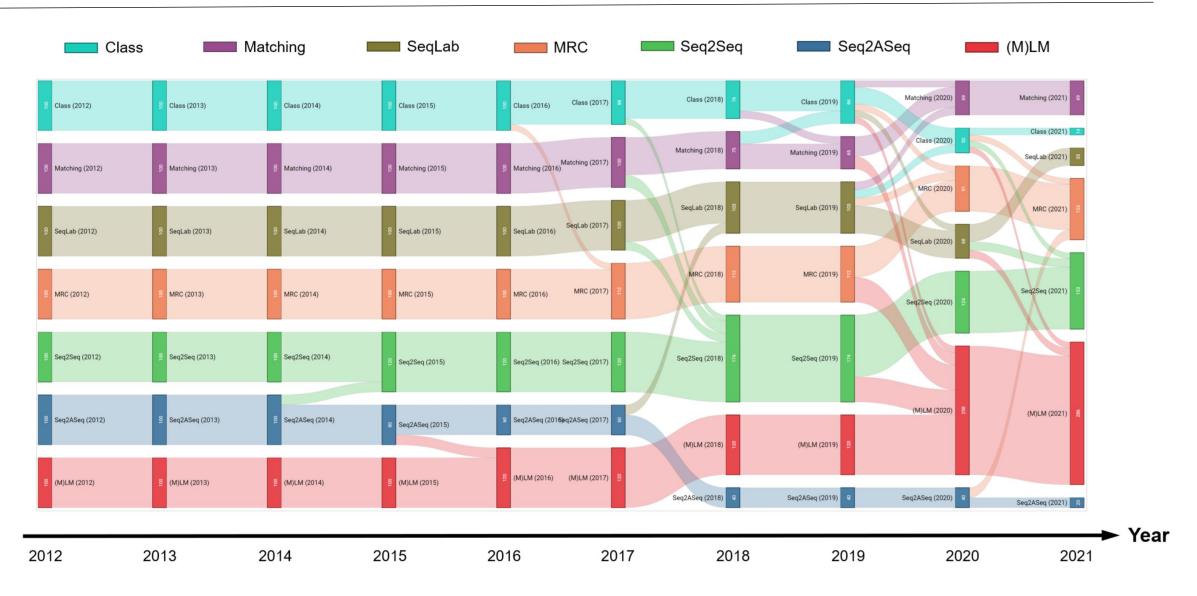
John has a dog.

 $(S (NP NNP)_{NP} (VP VBZ (NP DT NN)_{NP})_{VP} .)_{S}$ 

Grammar as a Foreign Language. NIPS 2015



## **Trends of Paradigm Shift**



#### Online version: https://txsun1997.github.io/nlp-paradigm-shift/sankey.html

# **Trends of Paradigm Shift**

#### More General and Flexible Paradigms are Dominating

- Traditional: Class, SeqLab, Seq2ASeq
- General: Matching, MRC, Seq2Seq, (M)LM

#### The Impact of Pre-trained LMs

• Formulate a NLP task as one that PLMs are good at!

### Outline

#### Introduction

- The Seven Paradigms in NLP
- Paradigm Shift in NLP Tasks

### Potential Unified Paradigms

Conclusion

# Why Unified Paradigm?

### Data Efficiency

• Task-specific models usually required large-scale annotated data, while unified models can achieve considerable performance with much less data

### Generalization

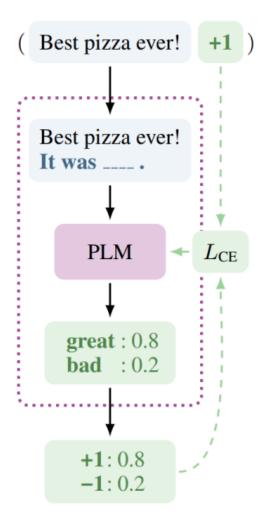
• Unified models can easily generalize to unseen tasks

#### • Convenience

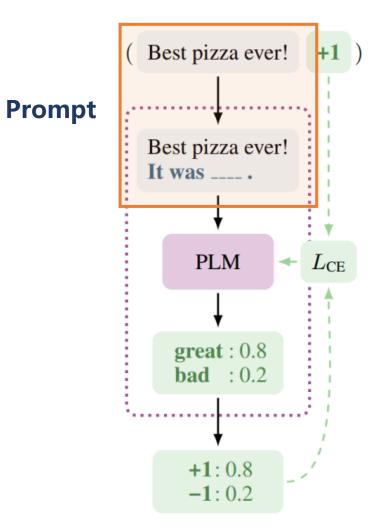
 Unified models are easier and cheaper to deploy and serve. They are born to be commercial black-box APIs

### **Potential Unified Paradigms**

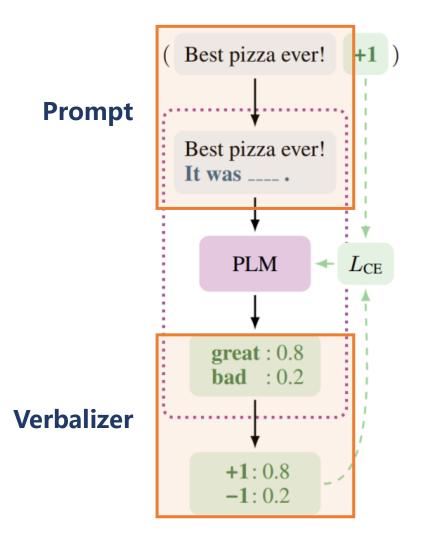
- (M)LM
- Matching
- MRC
- Seq2Seq



Exploiting Cloze Questions for Few Shot Text Classification and Natural Language Inference. EACL 2021



Exploiting Cloze Questions for Few Shot Text Classification and Natural Language Inference. EACL 2021



Exploiting Cloze Questions for Few Shot Text Classification and Natural Language Inference. EACL 2021

#### • Prompt

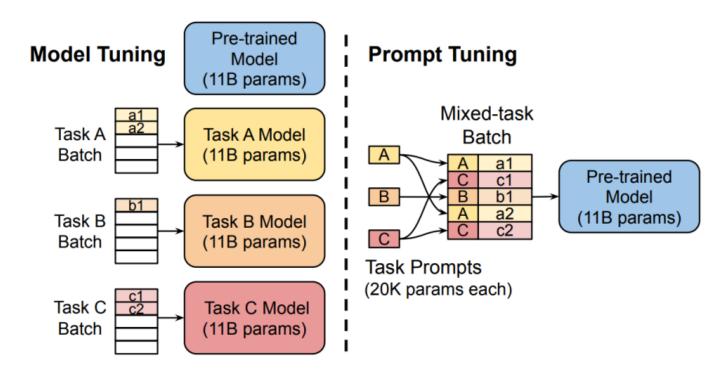
- Manually designed
- Mined from corpora
- Generated by paraphrasing
- Generated by another PLM
- Learned by gradient search/descent

### Verbalizer

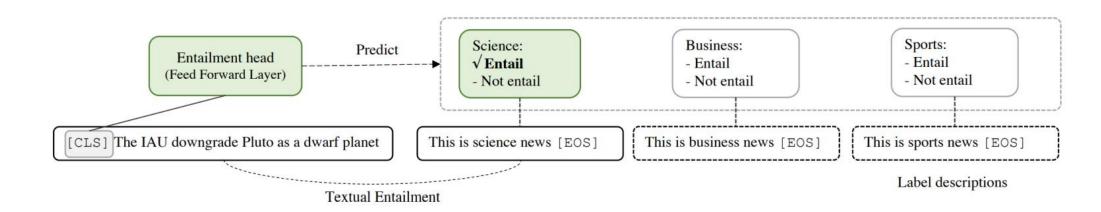
- Manually designed
- Automatically searched
- Constructed and refined with KB

#### Parameter-Efficient Tuning

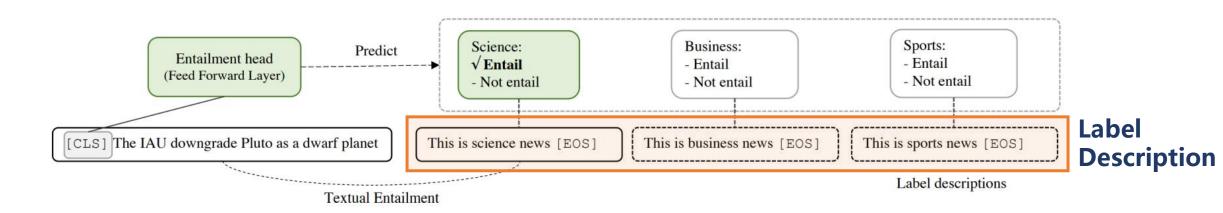
- Only tuning prompts can match the performance of fine-tuning
- Mixed-task inference

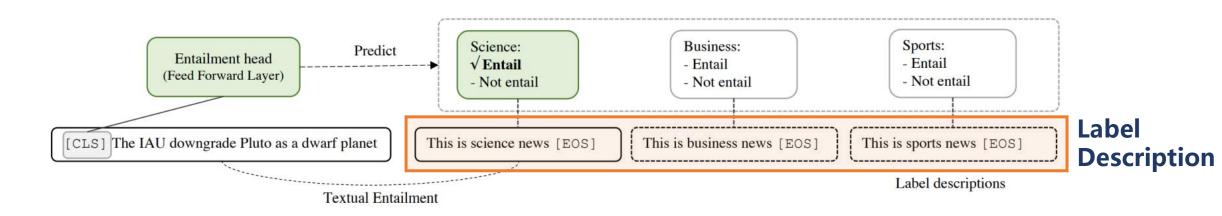


The Power of Scale for Parameter-Efficient Prompt Tuning. <u>https://arxiv.org/abs/2104.08691</u>



Entailment as Few-Shot Learner. https://arxiv.org/abs/2104.14690

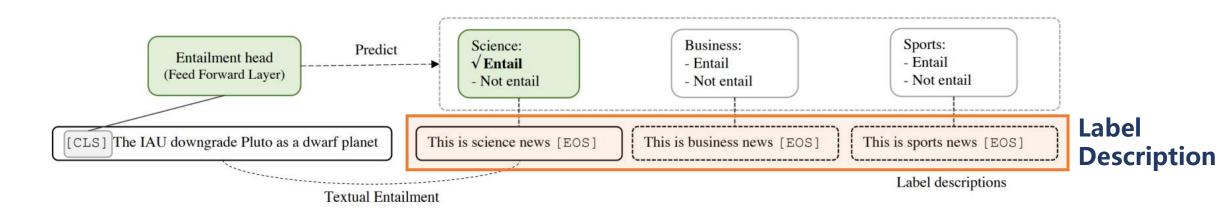




#### Label Description

- Manually designed (can be the same as prompt)
- Generated by reinforcement learning (Chai et al.)

Entailment as Few-Shot Learner. https://arxiv.org/abs/2104.14690



#### Label Description

- Manually designed (can be the same as prompt)
- Generated by reinforcement learning (<u>Chai et al.</u>)

#### The Entailment Model

• Fine-tuning a PLM on MNLI

Entailment as Few-Shot Learner. https://arxiv.org/abs/2104.14690

## (M)LM or Matching?

#### • (M)LM

- [MASK] -> MLM head, instead of randomly initialized classifier
- Require modifications of input (prompt) and output (verbalizer)
- Pre-trained LMs can be directly used (even zero-shot)
- Compatible with generation tasks

### Matching

- [CLS] -> MNLI/NSP head, instead of randomly initialized classifier
- Only label descriptions are required (less engineering!)
- Contrastive learning can be applied
- Suffer from domain adaption (due to the requirement of supervised data)
- Only support NLU tasks

### MRC

### A Highly General Paradigm

• A task can be solved as a MRC one as long as its input can be formulated as [context, question, answer].

#### Examples

Question	Context	Answer	Question	Context	Answer
What is a major importance of Southern California in relation to California and the US?	economic center for the state	major economic center	What has something experienced?	Areas of the Baltic that have experienced eutrophication.	eutrophication
What is the translation from English to German?	those of the planet is	Der Großteil der Erde ist Meerwasser	Who is the illustrator of Cycle of the Werewolf?	Cycle of the Werewolf is a short novel by Stephen King, featuring illustrations by comic book artist Bernie Wrightson.	Bernie Wrightson
What is the summary?	Radcliffe gains access to a	Harry Potter star Daniel Radcliffe gets £320M fortune	What is the change in dialogue state?	Are there any Eritrean restaurants in town?	food: Eritrean
Hypothesis: Product and geography are what make cream skimming work. Entailment, neutral, or contradiction?	Premise: Conceptually cream skimming has two basic dimensions – product and geography.	Entailment	What is the translation from English to SQL?	The table has column names Tell me what the notes are for South Australia	SELECT notes from table WHERE 'Current Slogan' = 'South Australia'
Is this sentence positive or negative?	A stirring, funny and finally transporting re-imagining of Beauty and the Beast and 1930s horror film.	positive	Who had given help? Susan or Joan?	Joan made sure to thank Susan for all the help she had given.	Susan

The Natural Language Decathlon: Multitask Learning as Question Answering. https://arxiv.org/abs/1806.08730

### MRC

### A Highly General Paradigm

• A task can be solved as a MRC one as long as its input can be formulated as [context, question, answer].

### MRC has been applied to many tasks...

 entity-relation extraction, coreference resolution, entity linking, dependency parsing, dialog state tracking, event extraction, aspect-based sentiment analysis...

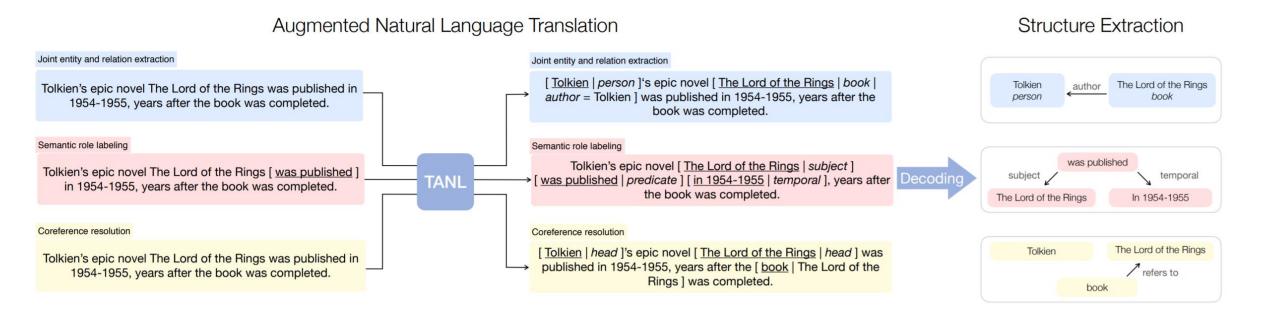
#### How to Utilize the Power of Pre-Training?

- All NLP tasks as open-domain QA?
- Dense Passage Retriever (DPR) may help (<u>REALM</u>, <u>RAG</u>, ...)
- Question  $\xrightarrow[retrieval]{}$  Context  $\xrightarrow[MRC]{}$  Answer

# Seq2Seq

#### A Highly General and Flexible Paradigm

• Suitable for complicated tasks (e.g. structured prediction, discontinuous NER, triplet extraction, etc.)



Structured prediction as translation between augmented natural languages. ICLR 2021

# Seq2Seq

### A Highly General and Flexible Paradigm

- Suitable for complicated tasks (e.g. structured prediction, discontinuous NER, triplet extraction, etc.)
- Powered by Pre-training
  - MASS, BART, T5...
- Compatible with (M)LM and MRC
- However...
  - High Latency at Inference Time (Non-autoregressive? Early exiting?)

### Outline

#### Introduction

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- Potential Unified Paradigms
- Conclusion

## Conclusion

### • (M)LM, aka prompt-based tuning, is exploding in popularity...

- Does the power come from the pre-trained MLM head?
- What if the classification head can be replaced with the NSP head, entailment head, or other classification/generation heads?
- What if pre-training can also boost other paradigms?

### More attention is needed on other promising paradigms

- Matching: less engineering, benefit from supervised data and contrastive learning
- MRC: general, interpretable
- Seq2Seq: compatibility, flexible to handle very complicated tasks



# Thank You!

### Any question or suggestion is welcome!

txsun19@fudan.edu.cn



https://txsun1997.github.io/nlp-paradigm-shift/