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# Autoregressive Entity Retrieval (GENRE)

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# Introduction



## Entity Retrieval

### Applications On...

- Recommender System
  - Question Answering
  - Chatbots
- 
- > detect relevant vs irrelevant concepts
  - > find relevant retrieval components



**WIKIPEDIA**  
The Free Encyclopedia

# Introduction



## Entity Retrieval

Search : John Smith...



John Smith (actor)

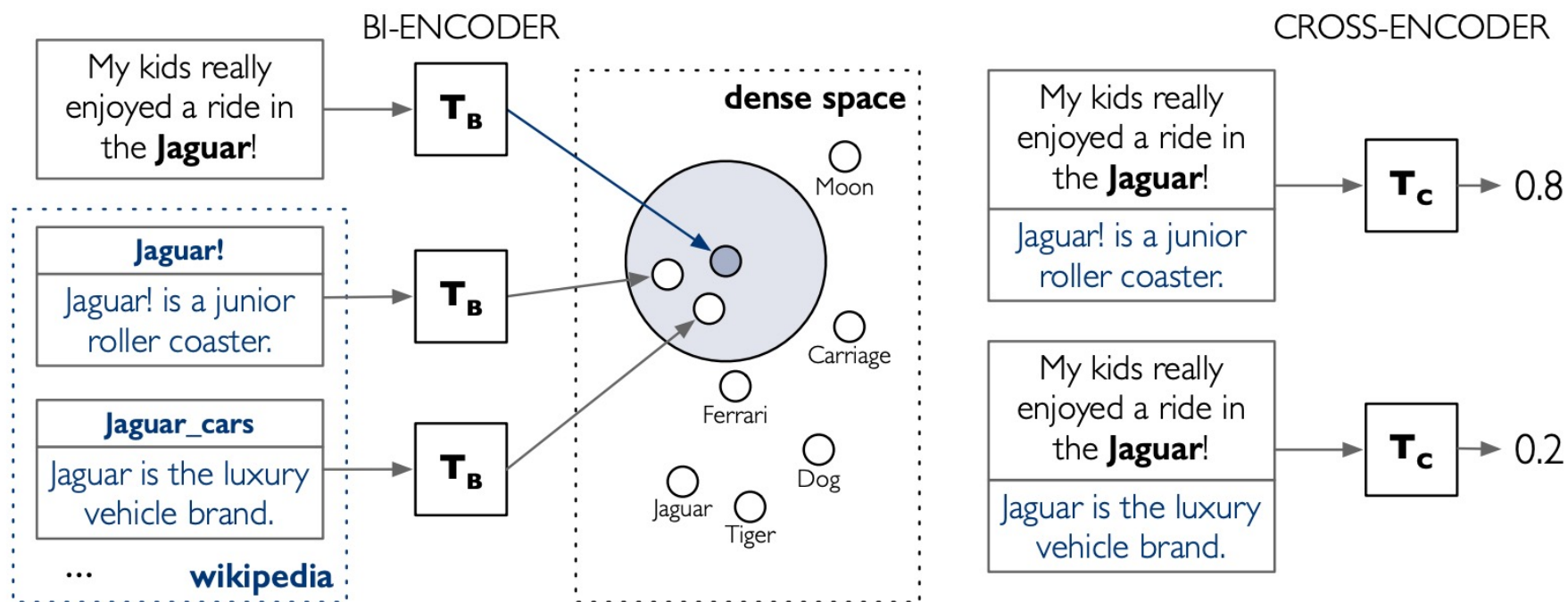


John Smith (astronomer)

& many more...

# Related Work

## BLINK

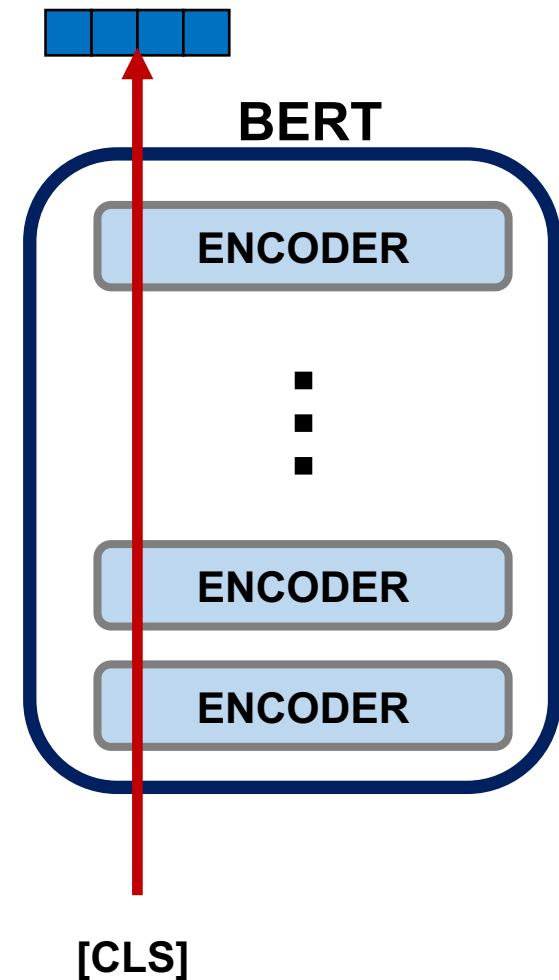


Wu et al., 2020. Scalable Zero-shot Entity Linking with Dense Entity Retrieval

# Related Work

## Dense Passage Retriever

- Bi-Encoder structure based on **BERT**
- Trainable Retriever (Pretrained Language Model)
- Uses the **output vector** corresponding to the **[CLS]** token
- Fine-tune to generate **dense embeddings**



Karpukhin et al., 2020. Dense Passage Retrieval for Open-Domain Question Answering

## Motivation

1. **Simple dot-product can miss fine-grained interactions between input & entity information**
  - Cross Encoder for re-ranking costly
2. **Large memory footprint needed to store dense vector embeddings (for MIPS)**
  - eg. ~24GB for 1024-D vectors for ~6M Wikipedia
3. **Arduous to subsample hard negative set @ training time**
  - Exact softmax over all entities very expensive
4. **Existing systems suffer from cold-start problem**
  - Entities with insufficient info

## Contribution

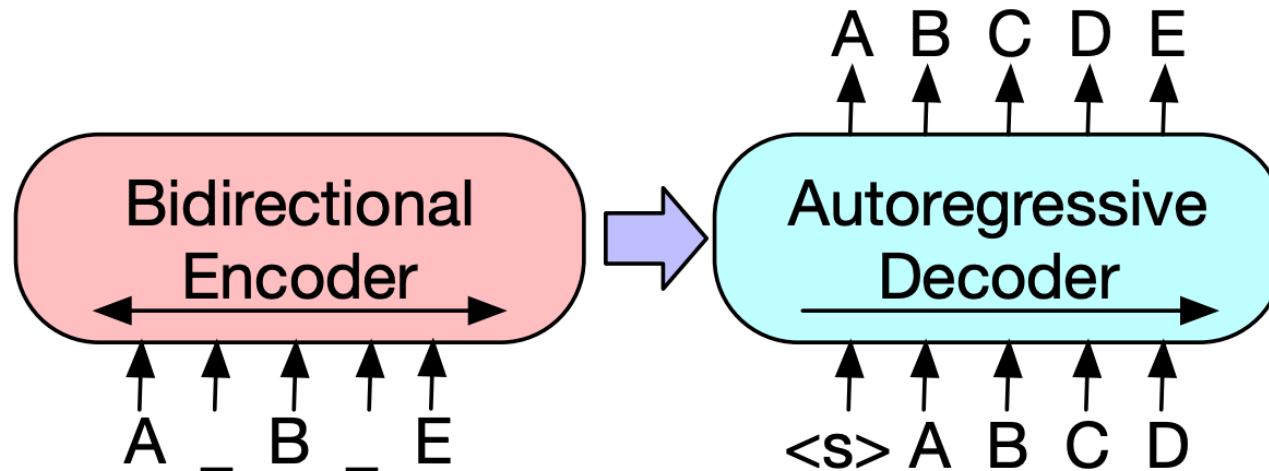
1. Propose **GENRE**, an **autoregressive** approach to directly capture relation between context & entity
2. Memory footprint magnitudes smaller corresponding to the **vocab size** (not entity count)
3. Exact softmax computed without the need to subsample negative data

# GENRE



## Architecture

BART (large)



### Pre-training

- Autoregressive denoising autoencoder

### Fine-tuning

- Generating entity names

$$p_{\theta}(y|x) = \prod_{i=1}^N p_{\theta}(y_i|y_{<i}, x)$$

### Inference

- Constrained Beam Search



## Examples

### Entity Disambiguation

Superman saved  
[START] Metropolis [END]



- 1 **Metropolis (comics)**
- 2 Metropolis (1927 film)
- 3 Metropolis-Hasting algorithm

(a) Type specification.

From 1905 to 1985 Owhango had a  
[START] railway station [END]



- 1 **Owhango railway station**
- 2 Train station
- 3 Owhango

(b) Composing from context.

[START] Farnese Palace [END]  
is one of the most important  
palaces in the city of Rome



- 1 **Palazzo Farnese**
- 2 Palazzo dei Normanni
- 3 Palazzo della Farnesina

(c) Translation.

## Examples

### Document Retrieval

What is the capital of Holland?



- 1 **Netherlands**
- 2 **Capital of the Netherlands**
- 3 **Holland**

(d) Entity normalization.

Which US nuclear reactor had a major accident in 1979?



- 1 **Three Mile Island accident**
- 2 **Nuclear reactor**
- 3 **Chernobyl disaster**

(e) Implicit factual knowledge.

Stripes had Conrad Dunn featured in it



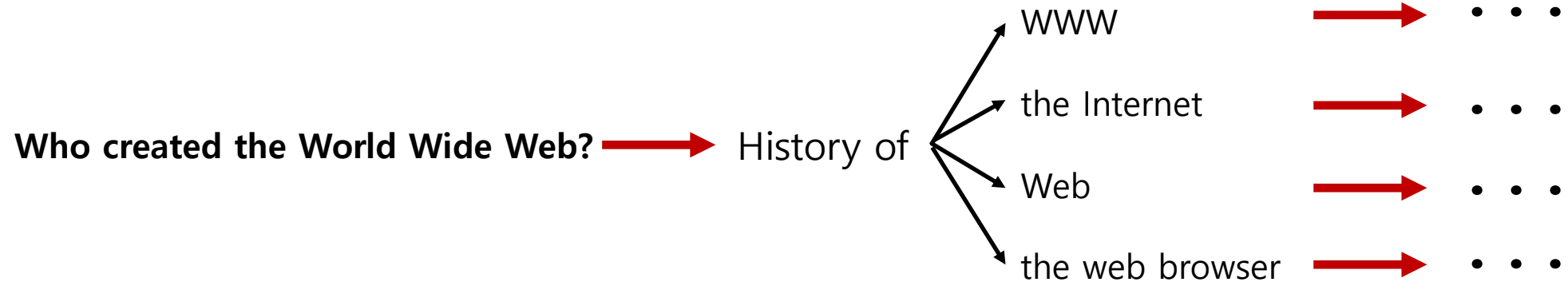
- 1 **Conrad Dunn**
- 2 **Stripes (film)**
- 3 **Kris Kristofferson**

(f) Exact copy.

## Method

(Beam Search)

**Objective** : generate valid entity names... -> **PROBLEM**

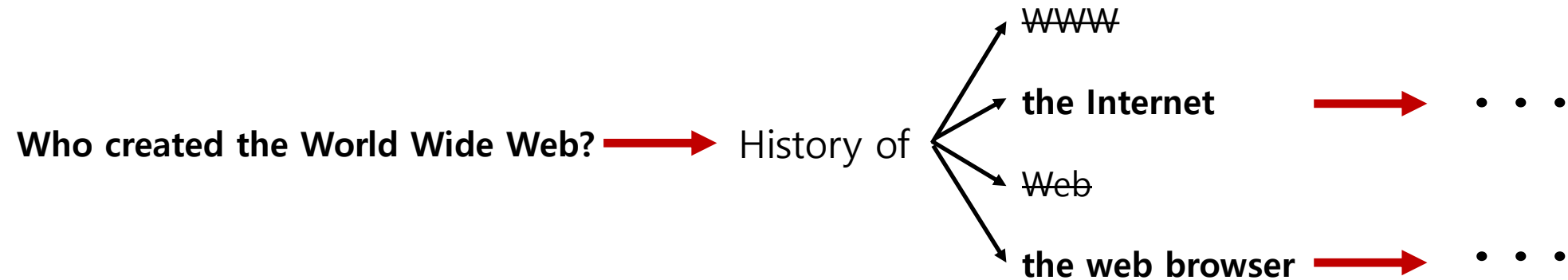


## Method

### Constrained Beam Search

**Objective** : generate valid entity names...

-> Constrain decoding search with a **prefix tree**



# Experiments



## Entity Disambiguation

```
1 ID: '87d95287-707e-4bd9-9633-ca0c611a4a3a_World_Without_Superma:8'
2 inputs: '[...] When Superman leaves Earth for New Krypton , he appoints , newly freed from
           the Phantom Zone , to take his place as guardian of [START-ENT] Metropolis [END-ENT
           ] . Mon-El assumes the secret identity of Johnathan Kent as a tribute to Clark \'s
           adoptive father , posing as Clark \'s cousin . [...]'
3 gold_output: 'Metropolis (comics)'
4 predicted_outputs: [
5     ( 'Metropolis_(comics)' , -0.09) ,
6     ( 'Themyscira_(DC_Comics)' , -1.09) ,
7     ( 'Metropolis_(disambiguation)' , -1.27) ,
8     ( 'Superman_(comic_book)' , -1.51) ,
9     ( 'Superman_(Earth-Two)' , -1.52)
10 ]
```

# Experiments



## Entity Disambiguation

Pre-train: BLINK dataset

Method	In-domain	Out-of-domain					Avg.
	AIDA	MSNBC	AQUAINT	ACE2004	CWEB	WIKI*	
Ganea & Hofmann (2017)	92.2	93.7	88.5	88.5	77.9	77.5	86.4
Guo & Barbosa (2018)	89	92	87	88	77	<u>84.5</u>	86.2
Yang et al. (2018a)	<b>95.9</b>	92.6	89.9	88.5	<b>81.8</b>	79.2	<u>88.0</u>
Shahbazi et al. (2019)	93.5	92.3	<u>90.1</u>	88.7	<u>78.4</u>	79.8	87.1
Yang et al. (2019)	93.7	<u>93.8</u>	88.2	<u>90.1</u>	75.6	78.8	86.7
Le & Titov (2019)	89.6	92.2	<b>90.7</b>	88.1	78.2	81.7	86.8
Fang et al. (2019)	<u>94.3</u>	92.8	87.5	<b>91.2</b>	78.5	82.8	87.9
BLINK w/o candidate set**	79.6	80.0	80.3	82.5	64.2	75.5	77.0
<b>GENRE</b>	93.3	<b>94.3</b>	89.9	<u>90.1</u>	77.3	<b>87.4</b>	<b>88.8</b>

# Experiments



## E2E Entity Linking

Plain Text -> Hypertext

Michelle Obama has  
launched ... as their White  
House challenger



[Michelle Obama](#) has  
launched ... as their [White  
House](#) challenger

# Experiments



## E2E Entity Linking

```
1 ID: '1106testa_SOCCER'
2 inputs: 'SOCCER – RESULT IN SPANISH FIRST DIVISION. MADRID 1996–08–31 Result of game ↘
         played in the Spanish first division on Saturday: Deportivo Coruna 1 Real Madrid 1.'
3 gold_output: 'SOCCER – RESULT IN [SPANISH](Spain) FIRST DIVISION . [MADRID](Madrid) ↘
               1996–08–31 Result of game played in the [Spanish](Spain) first division on Saturday ↘
               : Deportivo Coruna 1 [Real Madrid](Real Madrid C.F.) 1.'
4 predicted_output: 'SOCCER – RESULT IN [SPANISH](Spain) FIRST DIVISION . [MADRID](Madrid) ↘
                    1996–08–31 Result of game played in the [Spanish](Spain) first division on Saturday ↘
                    : [Deportivo](Deportivo de La Coruna) Coruna 1 [Real Madrid](Real Madrid C.F.) 1.'
5 gold_spans: [
6     [19, 7, 'Spain'],
7     [44, 6, 'Madrid'],
8     [91, 7, 'Spain'],
9     [147, 11, 'Real.Madrid.C.F. ']]
10 ]
11 predicted_spans: [
12     [19, 7, 'Spain'],
13     [44, 6, 'Madrid'],
14     [91, 7, 'Spain'],
15     [128, 9, 'Deportivo_de_La_Coruna'],
16     [147, 11, 'Real.Madrid.C.F. ']]
17 ]
18
```



# Experiments

## E2E Entity Linking

**Pre-train:** Abstract sections from Wikipedia

Method	In-domain			Out-of-domain					Avg.
	AIDA	MSNBC	Der	K50	R128	R500	OKE15*	OKE16*	
Hoffart et al. (2011)	72.8	65.1	32.6	55.4	46.4	<b>42.4</b>	<b>63.1</b>	0.0	47.2
Steinmetz & Sack (2013)	42.3	30.9	26.5	46.8	18.1	20.5	46.2	46.4	34.7
Moro et al. (2014)	48.5	39.7	29.8	<u>55.9</u>	23.0	29.1	41.9	37.7	38.2
Kolitsas et al. (2018)	<u>82.4</u>	<u>72.4</u>	34.1	35.2	<b>50.3</b>	38.2	<u>61.9</u>	<u>52.7</u>	53.4
Broscheit (2019)	79.3	-	-	-	-	-	-	-	
Martins et al. (2019)	81.9	-	-	-	-	-	-	-	
van Hulst et al. (2020) <sup>†</sup>	80.5	72.4	41.1	50.7	49.9	35.0	<b>63.1</b>	<b>58.3</b>	56.4
<b>GENRE</b>	<b>83.7</b>	<b>73.7</b>	<b>54.1</b>	<b>60.7</b>	46.7	<u>40.3</u>	56.1	50.0	<b>58.2</b>

# Experiments



## Page-level Document Retrieval

```
1 ID: 'sfq_18245 '  
2 inputs: "Which Florentine painter  
         1535–1607 used the name Bronzino  
         after the death of his 'uncle'?"  
3 gold_output: 'Bronzino '  
4 predicted_outputs: [  
5     ('Florence', -0.37),  
6     ('Bronzino', -0.62),  
7     ('Niccolo_Machiavelli', -0.64),  
8     ('Giorgio_de_Chirico', -0.71),  
9     ('Vitruvian_Man', -0.73)  
10 ]
```

(a) TriviaQA (open domain question answering).

# Experiments



## Page-level Document Retrieval

Train: KILT Dataset

Model	Fact Check.	Entity Disambiguation			Slot Filling		Open Domain QA				Dial.	Avg.
	FEV	AY2	WnWi	WnCw	T-REx	zsRE	NQ	HoPo	TQA	ELI5	WoW	
DPR + BERT	<u>72.9</u>	-	-	-	-	40.1	<b>60.7</b>	25.0	43.4	-	-	-
DPR	55.3	1.8	0.3	0.5	13.3	28.9	54.3	25.0	44.5	10.7	25.5	23.6
tf-idf	50.9	3.7	0.24	2.1	44.7	60.8	28.1	34.1	46.4	<u>13.7</u>	49.0	30.5
DPR + BART	55.3	75.5	45.2	46.9	13.3	28.9	54.3	25.0	44.4	10.7	25.4	38.6
RAG	61.9	72.6	48.1	47.6	28.7	53.7	59.5	30.6	48.7	11.0	<u>57.8</u>	47.3
BLINK + flair	63.7	<u>81.5</u>	<u>80.2</u>	<u>68.8</u>	<u>59.6</u>	<u>78.8</u>	24.5	<u>46.1</u>	<u>65.6</u>	9.3	38.2	<u>56.0</u>
<b>GENRE</b>	<b>83.6</b>	<b>89.9</b>	<b>87.4</b>	<b>71.2</b>	<b>79.4</b>	<b>95.8</b>	<u>60.3</u>	<b>51.3</b>	<b>69.2</b>	<b>15.8</b>	<b>62.9</b>	<b>69.7</b>

# Further Analysis



## Memory Footprint

Comparison between retrieval models on memory

Model	Memory	Param.	Index
DPR	70.9GB	220M	15B
RAG	40.4GB	626M	15B
BLINK	30.1GB	680M	6B
<b>GENRE</b>	<b>2.1GB</b>	<b>406M</b>	<b>17M</b>

1/14 BLINK  
1/34 DPR

Uses entity names only

# Further Analysis



## Ablation Study

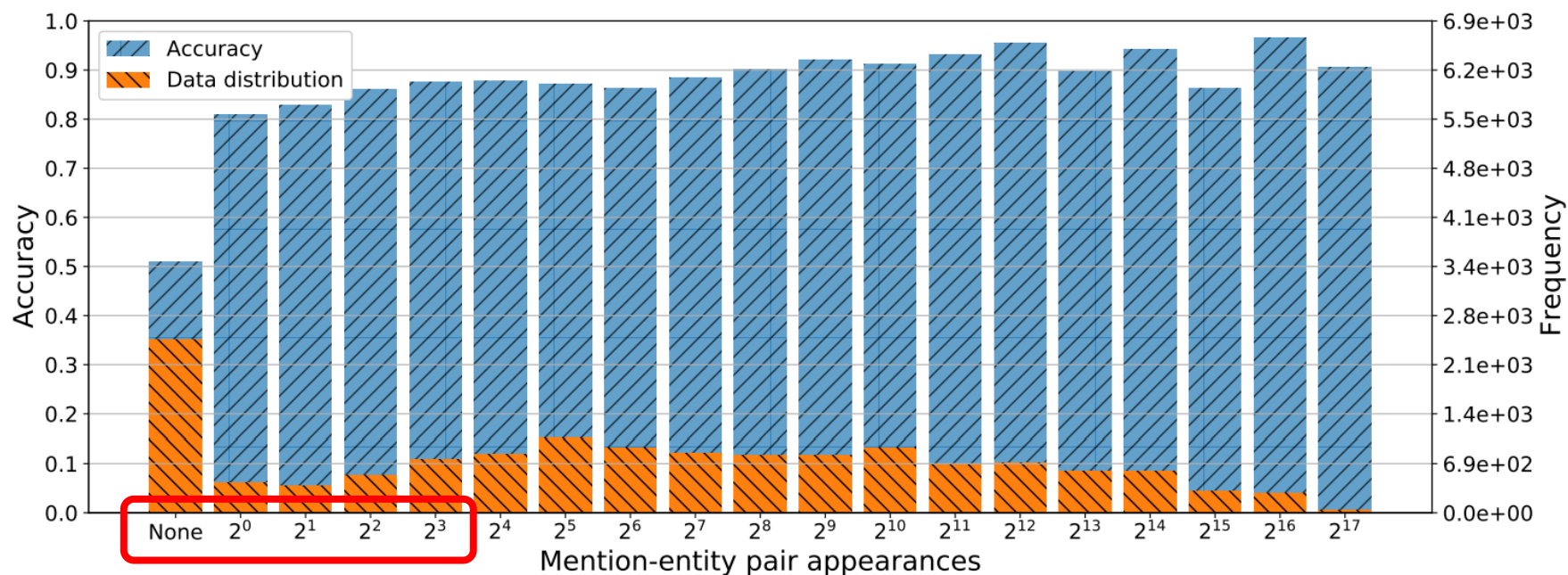
### Ablation on Entity Disambiguation

Method	In-domain	Out-of-domain					Avg.
	AIDA	MSNBC	AQUAINT	ACE2004	CWEB	WIKI*	
<b>GENRE</b>	93.3	<b>94.3</b>	89.9	<u>90.1</u>	77.3	<b>87.4</b>	<b>88.8</b>
Ablations							
GENRE only AIDA data	88.6	88.1	77.1	82.3	71.9	71.7	80.0
GENRE only BLINK data	89.3	93.3	90.9	91.1	76.0	87.9	88.1
GENRE w/o candidate set	91.2	86.9	87.2	87.5	71.1	86.4	85.1
GENRE w/o constraints	86.4	80.0	81.7	82.1	66.0	81.1	79.6

# Further Analysis

## Entity Frequency

### Accuracy per mention-entity pair frequency (on Entity Disambiguation)



# Further Analysis



## Cold Start

### 50 New Wikipedia Articles (2020)

- EM:  $19/50 = 38\%$
- GENRE's bias on exactly copying mention

Type (support)	BLINK	GENRE	IDs*
Exact match (1543)	97.8	96.6	76.0
Partial match (1531)	70.7	86.9	63.8
No match (322)	49.4	59.9	55.0
Total (3396)	81.0	88.8	68.5

# Conclusion



1. Propose **GENRE**, an **autoregressive** approach to directly capture relation between context & entity
2. Memory footprint magnitudes smaller corresponding to the **vocab size** (not entity count)
3. Exact softmax computed without the need to subsample negative data



**Q&A**