北京航空航天大學
BEIHANG UNIVERSITY

自然语言处理

人工智能研究院

主讲教师 沙磊

在语言模型中引入知识

Contents

- Techniques to add knowledge to LMs
  - 1. Add pretrained entity embeddings
  - 2. Use an external memory
  - 3. Modify the training data
- Evaluating knowledge in LMs

回顾：语言模型

- 标准语言模型，给出文本序列，预测下一个词
  - The students opened their _books_.
- 掩码语言模型（如BERT），根据双向的文本信息预测被掩码的token
  - I [MASK] to the [MASK].

went store

- 如上两种语言模型，都可以利用大量无标注语料库训练

回顾：语言模型用途

- 语言模型的用途：生成、评估句子的概率
  - Summarization
  - Dialogue
  - Autocompletion
  - Machine translation
  - Fluency evaluation
- 如今，LM也可以用来生成一些预训练的文本表示用来编码文本中的语义信息，提供给下游NLP任务使用
  - Text classification
  - Question answering
- 如果LM用海量文本预训练，可不可以直接被用作知识库？

What does a language model already know?

- iPod Touch is produced by _____ .
- London Jazz Festival is located in _____ .
- Dani Alves plays with _____ .
- Carl III used to communicate in _____ .
- Ravens can _____ .

Check out what BERT-Large predicts

What does a language model already know?

- iPod Touch is produced by Apple.
- London Jazz Festival is located in London .
- Dani Alves plays with Santos ->Barcelona.
- Carl III used to communicate in German ->Swedish.
- Ravens can fly .

Check out what BERT-Large predicts

预测看似合理，不一定符合事实

What does a language model know?

- Observation: predictions generally make sense (e.g. the correct types), but are not all factually correct.

- Why might this happen?
  - Unseen facts: some facts may not have occurred in the training corpora at all
  - Rare facts: LM hasn't seen enough examples during training to memorize the fact
  - Model sensitivity: LM may have seen the fact during training, but it was phrased in a different way than how we are testing, so the LM is confused
    - Fails to answer "x was created in y" but correctly answers "x was made in y"

- Takeaway: LMs have some knowledge, but fail to reliably recall knowledge
  - We will talk about how to address this key challenge facing LMs!

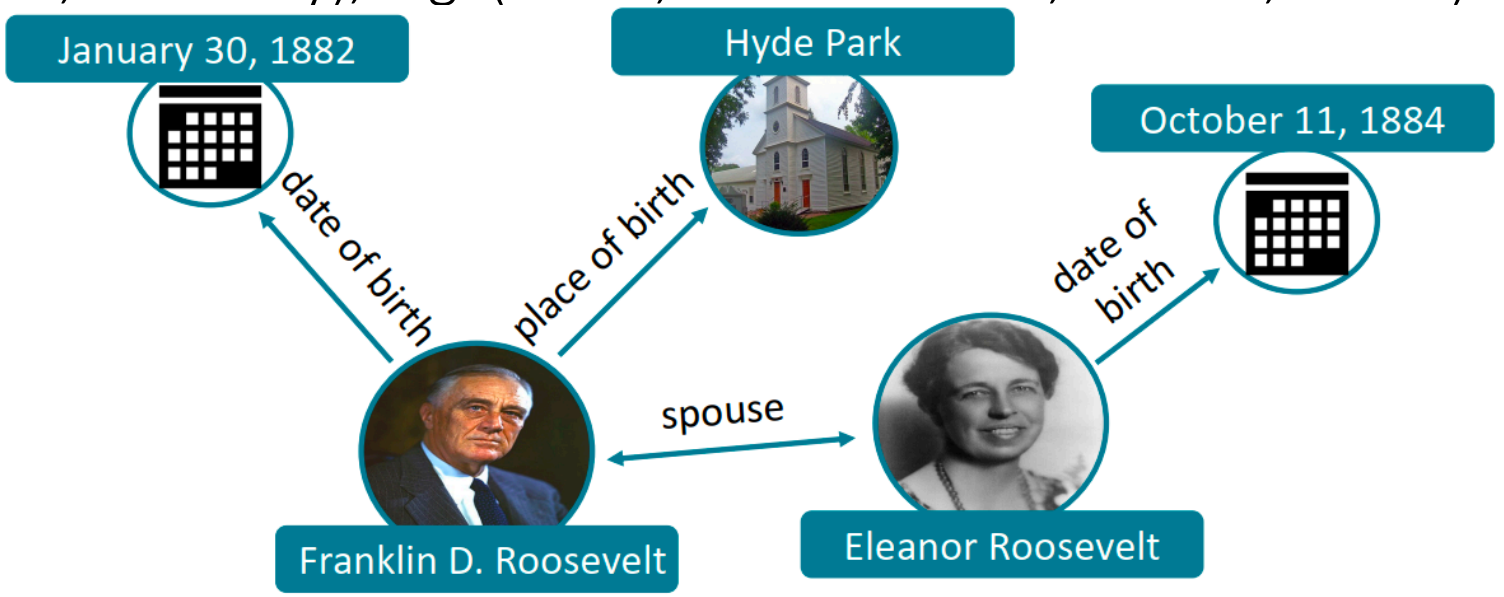
Why do we want to build knowledge-aware language models?

- LM's pretrained representations can benefit downstream tasks that leverage knowledge
  - e.g. Question answering and relation exaction (extracting the relations between two entities in a sentence) are much easier with knowledge about the entities
  - We'll come back to this when we talk about evaluation!

- Stretch goal: can LMs ultimately replace traditional knowledge bases?
  - Instead of querying a knowledge base with formal query (e.g. SQL), query the LM with a natural language prompt!
    - Of course, this requires LM to have high quality on recalling facts, and this is an active area of research

Traditional knowledge bases and how to query them

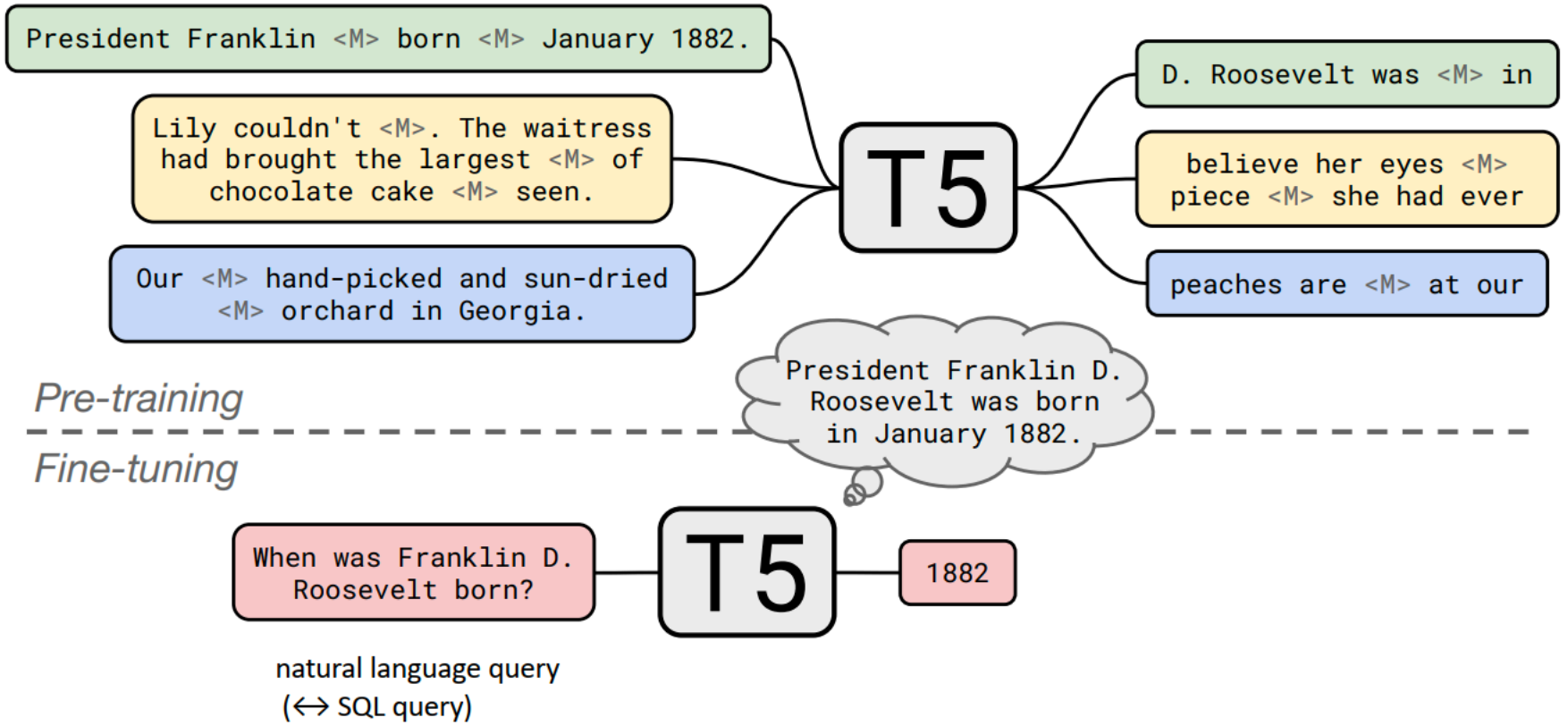
- Each Knowledge base entry can be written as a triple:
  - (parent entity, relation, tail entity), e.g. (“FDR”, “date of birth”, “Jan 30, 1882”)



- You can query knowledge base with a formal query such as SQL statement:
  - “What is the date of birth of FDR?”

How to query language models as knowledge bases

- Pretrain LM over unstructured text and then query with natural language.

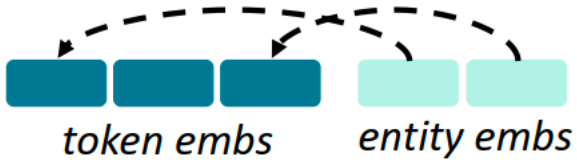


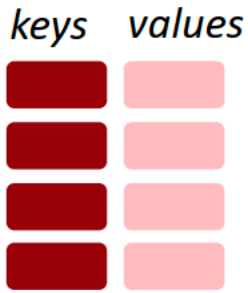
Advantages of using language models over traditional KBs

- LMs can be pretrained over large amounts of unstructured and unlabeled text
  - ↔ KBs typically require manual annotation
- LMs support more flexible natural language queries
  - Example: What does the final F in the song U.F.O.F. stand for?
    - Traditional KB may not have a specific relation "final F"; LM may learn it implicitly
- However, there are also many open challenges to using LMs as KBs:
  - Hard to interpret (it's unclear why LM produces this answer ↔ KB has provenance)
  - Hard to trust (LM may produce a realistic but incorrect answer ↔ KB either returns the correct answer or returns no answer)
  - Hard to modify (hard to update knowledge in LM ↔ KB is directly editable)
  - => Open up exciting opportunities for further research!

如何将知识加入LM中？

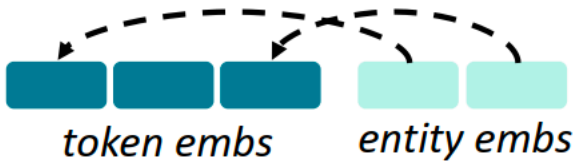
Techniques to add knowledge to LMs

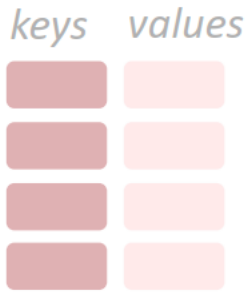




- Add pretrained entity embeddings
  - ERNIE
  - QAGNN/GreaseLM
- Use an external memory
  - KGLM
- Modify the training data
  - WKLM
  - ERNIE (another!), salient span masking

Techniques to add knowledge to LMs





- Add pretrained entity embeddings
  - ERNIE
  - QAGNN/GreaseLM
- Use an external memory
  - KGLM
- Modify the training data
  - WKLM
  - ERNIE (another!), salient span masking

Method 1: Add pretrained (entity) embeddings

- Observation: Facts about the world are usually in terms of entities
  - Example: Washington was the first president of the United States.
- However, the typical word embeddings we use do not have a notion of entities
  - We use different word embeddings for “U.S.A.”, “United States of America” and “America” even though they all refer to the same entity
- What if we assign a single embedding per entity?
  - Single entity embedding for “U.S.A.”, “United States of America” and “America”
- **Goal**: Get pretrained entity embeddings that encode factual knowledge, and add to language model
- Note: To use entity embeddings for text, we need to do a task called entity linking

Aside: What is entity linking?

(It's like looking up word in word embedding dictionary. But looking up entity mention in KB is a bit trickier, because string matching may not work..)

- Link mentions in text to entities in a knowledge base

mention *mention*

Washington was the first president of the United States.

candidate *candidate* *candidate*

Q23 (Wikidata)

Q1223 (Wikidata)

Q30 (Wikidata)

- Entity linking involves resolving ambiguous mentions (e.g. using context)
- Entity linking tells us which entity embeddings are relevant to the text

Method 1: Add pretrained entity embeddings

- Summary: Entity embeddings are like word embeddings, but for entities in a knowledge base!

George Washington = $\begin{pmatrix} 0.111 \\ -0.345 \\ 0.876 \\ -0.201 \end{pmatrix}$

- Many techniques for training entity embeddings:
  - Knowledge graph embedding methods (e.g., TransE)
  - Word-entity co-occurrence methods (e.g., Wikipedia2Vec)
  - Transformer encodings of entity descriptions (e.g., BLINK)
- Any of those entity embeddings can be used for the knowledge integration methods we will talk about today

Method 1: Add pretrained entity embeddings

- Question: How do we incorporate pretrained entity embeddings when they're from an different embedding space than the language model?

- Answer: Learn a fusion layer h that combines word info (from LM) and entity info

$$\boldsymbol{h}_j = F\left(\boldsymbol{W}_t \boldsymbol{w}_j + \boldsymbol{W}_e \boldsymbol{e}_k + b\right)$$

  - $\boldsymbol{w}_j$ is the embedding of word - in a sequence of words
  - $\boldsymbol{e}_k$ is the corresponding entity embedding
- Intuition: there's alignment between entities and words in the sentence such that projections $\boldsymbol{W}_t \boldsymbol{w}_j$ and $\boldsymbol{W}_e \boldsymbol{e}_k$ are in the same vector space

ERNIE: Enhanced Language Representation with Informative Entities[Zhang et al., ACL 2019]

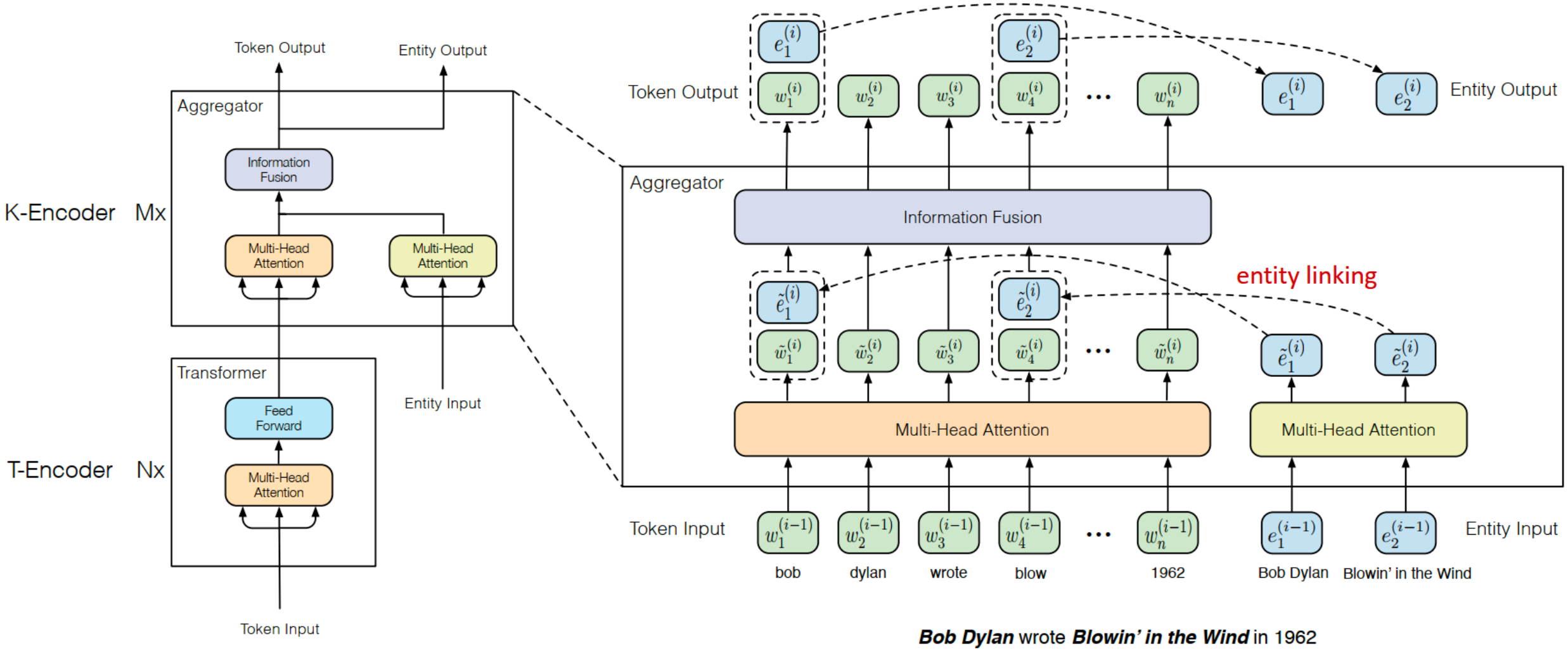
- Text encoder: multi-layer bidirectional Transformer encoder over the token in the sentence
- Knowledge encoder: each block is composed of:
  - Two self-attention layers – one for entity embeddings and one for token embeddings
  - A fusion layer to combine the output of the self-attention layers

$$\boldsymbol{h}_j = \sigma\left(\widetilde{\boldsymbol{W}}_t^{(i)}\widetilde{\boldsymbol{w}}_j^{(i)} + \widetilde{\boldsymbol{W}}_e^{(i)}\widetilde{\boldsymbol{e}}_k^{(i)} + \widetilde{\boldsymbol{b}}^{(i)}\right) \quad \text{fusion representation}$$

$$\boldsymbol{w}_j^{(i)} = \sigma\left(\boldsymbol{W}_t^{(i)}\boldsymbol{h}_j + \boldsymbol{b}_t^{(i)}\right) \quad \text{token embedding output (fed to next block)}$$

$$\boldsymbol{e}_k^{(i)} = \sigma\left(\boldsymbol{W}_e^{(i)}\boldsymbol{h}_j + \boldsymbol{b}_e^{(i)}\right) \quad \text{entity embedding output (fed to next block)}$$

ERNIE: Enhanced Language Representation with Informative Entities [Zhang et al., ACL 2019]



ERNIE: Enhanced Language Representation with Informative Entities [Zhang et al., ACL 2019]

- How to train? Pretrain jointly with three tasks:
  - Masked language model and next sentence prediction (i.e., BERT tasks)
  - Knowledge pretraining task (dEA): randomly mask some token-entity alignments and predict which entity in the sequence should be linked to the given token

$$p(e_j \mid w_i) = \frac{\exp(\boldsymbol{W}\boldsymbol{w}_i \cdot \boldsymbol{e}_j)}{\sum_{k=1}^{m} \exp(\boldsymbol{W}\boldsymbol{w}_i \cdot \boldsymbol{e}_k)}$$

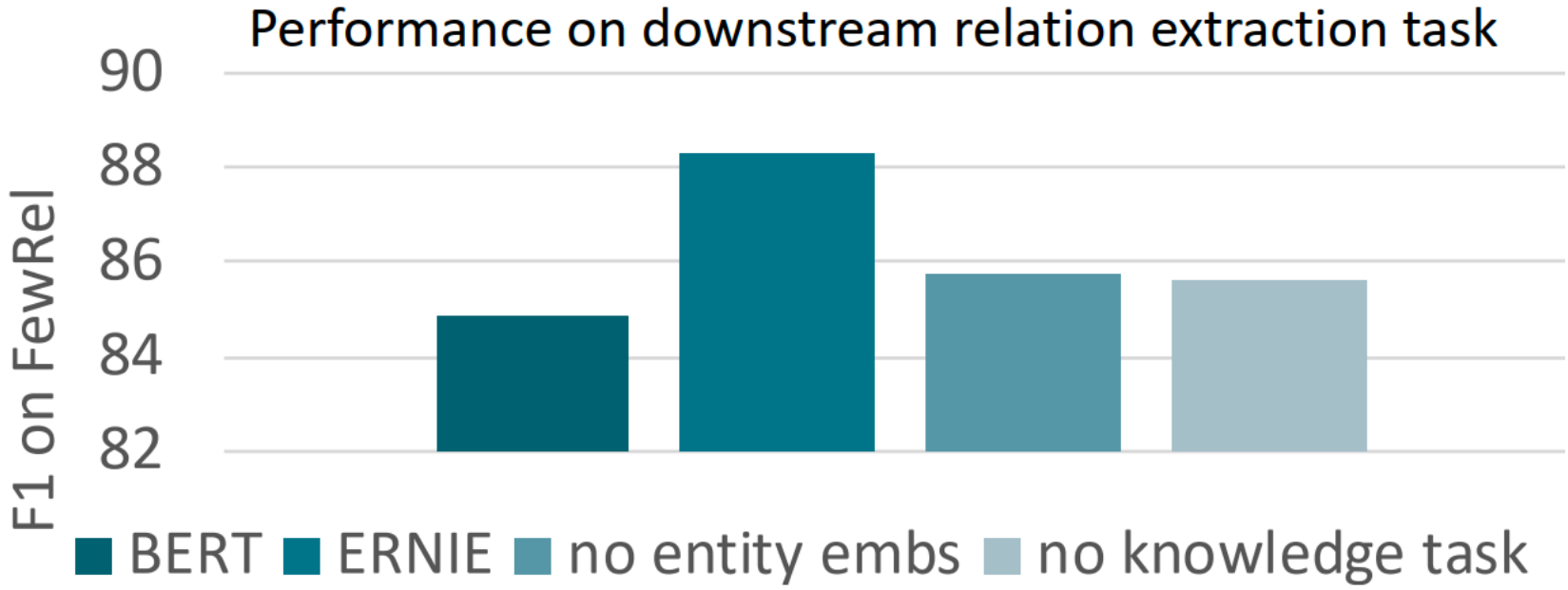
    - Motivations: better learn word-entity alignments; and prevent overfitting to pre-given (ground-truth) entity linking inputs
  - Final objective:

$$\mathcal{L}_{ERNIE} = \mathcal{L}_{MLM} + \mathcal{L}_{NSP} + \mathcal{L}_{dEA}$$

dEA named for denoising entity autoencoder from Vincent et al., ICML 2008.

ERNIE: Enhanced Language Representation with Informative Entities [Zhang et al., ACL 2019]

- Analysis to see the effect of model components (entity embs and knowledge task)
  - Knowledge pretraining task is necessary to make the most use of the pretrained entity embeddings.



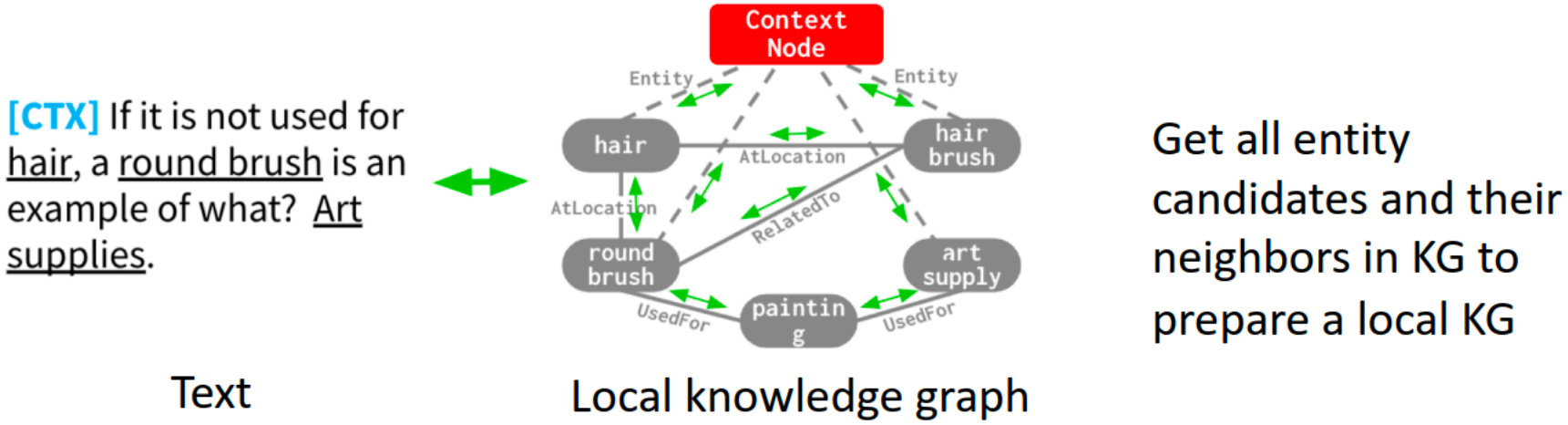
ERNIE: Enhanced Language Representation with Informative Entities[Zhang et al., ACL 2019]

- Strengths:
  - Combines entity + text info through fusion layers and a knowledge pretraining task
  - Improves performance on knowledge-intensive downstream tasks

- Limitation:
  - Needs to link each entity mention in input text to knowledge base in advance
    - For instance, "Bob Dylan wrote Blowin' in the Wind" needs entities linked to Wikidata knowledge base
    - It's challenging to get a good entity linker for any domain of text or tasks
    - We will next talk about a more recent method that mitigates this issue

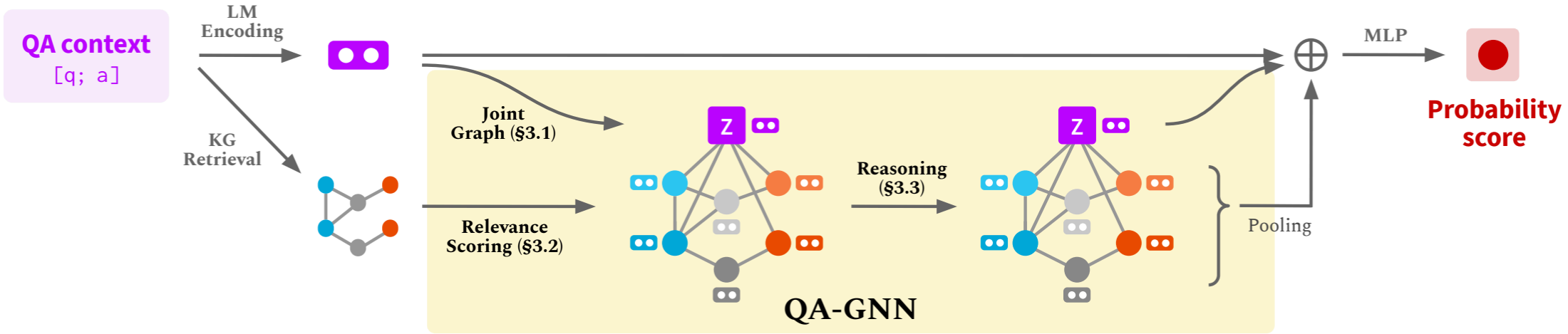
QAGNN/GreaseLM: Reasoning with Language Model and Knowledge Graph [Yasunaga et al. NAACL 2021; Zhang et al. ICLR 2022]

- **Key idea**: when adding entity embeddings to language model, dynamically update them together with neighbor or related entities in knowledge graph as well as text



- **Benefits**
  - Robust to non-perfect entity linking: can include all entity candidates and let the model figure out what to fuse
  - Better contextualize knowledge: helpful for joint reasoning about text and knowledge (e.g. question answering tasks)

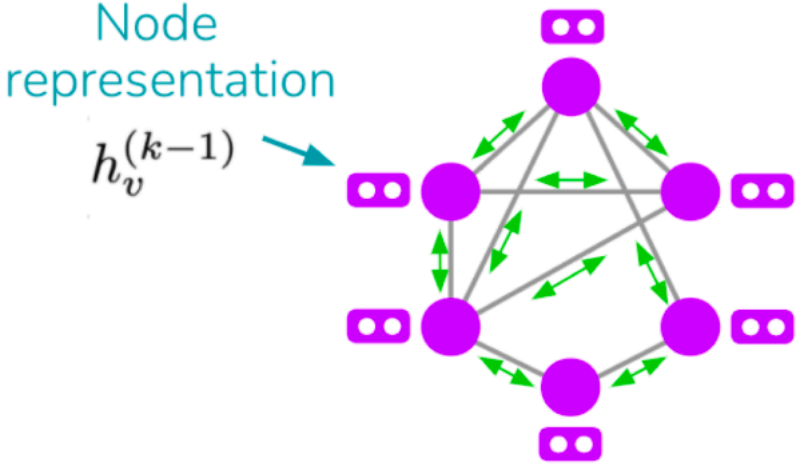
QAGNN



- Given a QA context (z), QAGNN connect it with the retrieved KG to form a joint graph (working graph; §3.1), compute the relevance of each KG node conditioned on z (§3.2; node shading indicates the relevance score), and perform reasoning on the working graph (§3.3).

QAGNN/GreaseLM: Reasoning with Language Model and Knowledge Graph [Yasunaga et al. NAACL 2021; Zhang et al. ICLR 2022]

- **Model architecture**:
- Text is encoded by a language model, knowledge graph (KG) is encoded by an graph neural network (GNN), and they are fused together for multiple rounds



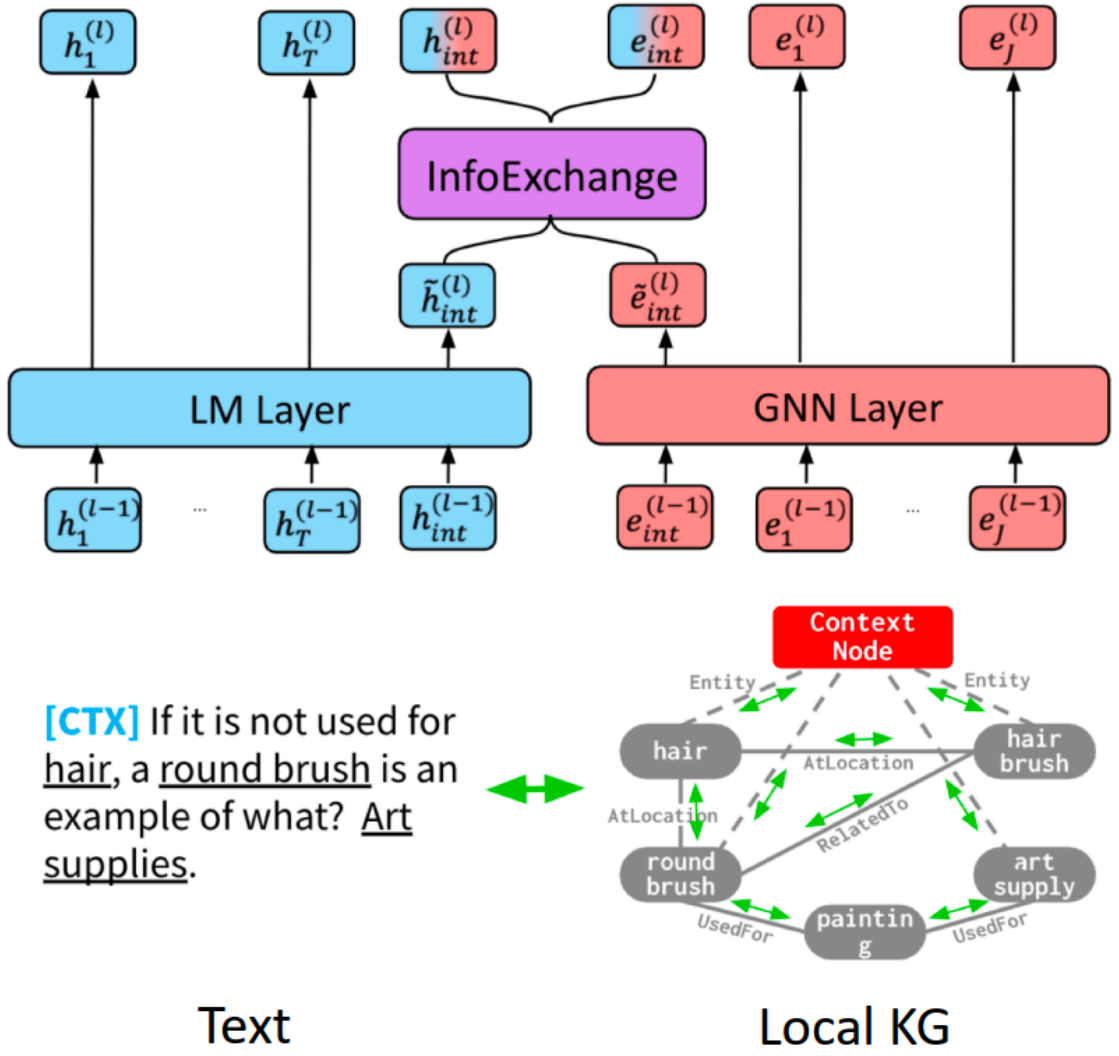
- What is GNN?
  - Neural network designed for encoding graph data.
  - GNN updates each node representation by aggregating message vectors from neighbor nodes.

$$a_v^{(k)} = \text{AGGREGATE}^{(k)}\left(\left\{h_u^{(k-1)} : u \in \mathcal{N}(v)\right\}\right)$$

$$h_v^{(k)} = \text{COMBINE}^{(k)}\left(h_v^{(k-1)}, a_v^{(k)}\right)$$

QAGNN/GreaseLM: Reasoning with Language Model and Knowledge Graph [Yasunaga et al. NAACL 2021; Zhang et al. ICLR 2022]

- **Model architecture**:
- Text is encoded by a language model, knowledge graph (KG) is encoded by an graph neural network (GNN), and they are fused together for multiple rounds



QAGNN/GreaseLM: Reasoning with Language Model and Knowledge Graph [Yasunaga et al. NAACL 2021; Zhang et al. ICLR 2022]

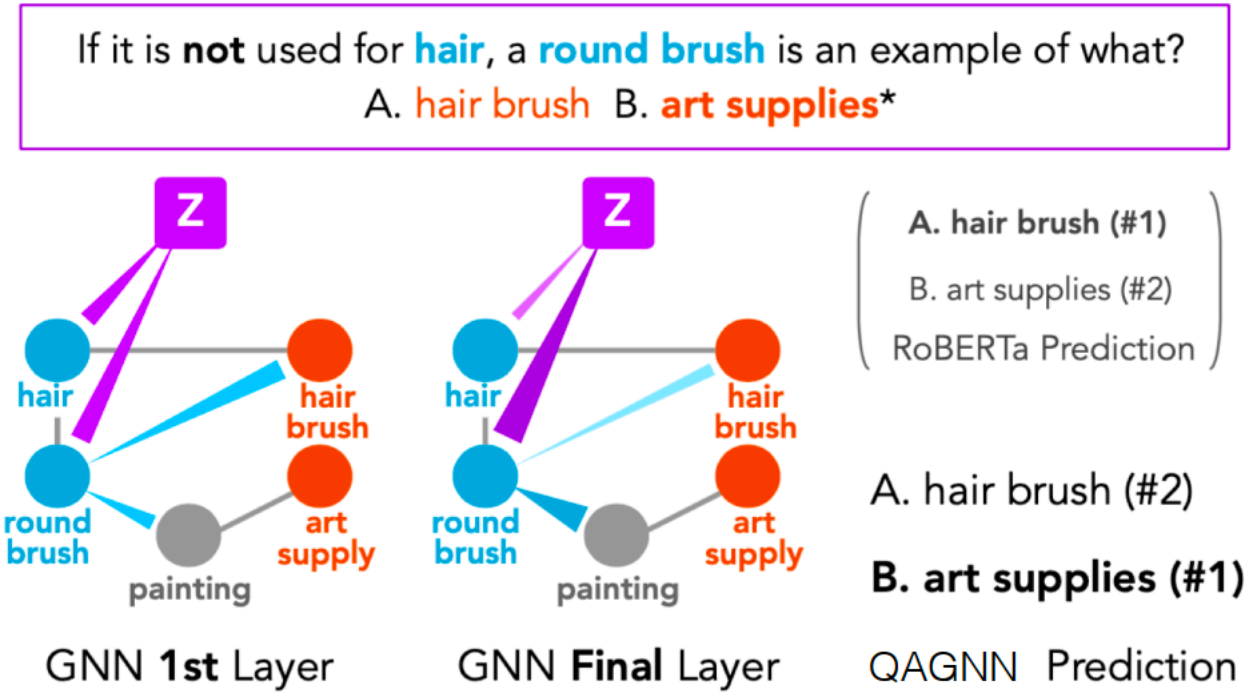
- **Quantitative result**: QAGNN and GreaseLM outperform previous BERT-based models on knowledge-intensive question answering tasks

Model	CommonsenseQA	OpenBookQA	MedQA
BERT-Large	55.4	60.4	-
RoBERTa-Large	68.7	64.8	35.0
SapBERT-Base	-	-	37.2
QAGNN	73.4	**67.8**	38.0
GreaseLM	**74.2**	66.9	**38.5**

Devlin et al., NAACL 2019 & Liu et al., 2019 & Liu et al., NAACL 2021 & Yasunaga et al., NAACL 2021 & Zhang et al., ICLR 2022

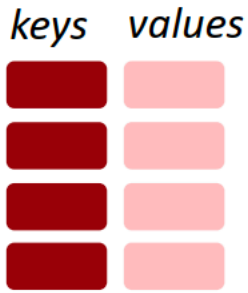
QAGNN/GreaseLM: Reasoning with Language Model and Knowledge Graph [Yasunaga et al. NAACL 2021; Zhang et al. ICLR 2022]

- Qualitative example:
- By grounding language model to knowledge graph, models learn to perform structured reasoning (e.g. handling negation correctly)
- Vanilla LMs don't handle negation well.. [Kassner et al., ACL 2020]
- New insight on how KG can help LM
  - Provide background knowledge
  - Provide scaffold for reasoning



- After several layers of fusion, attention weight from text over hair decreases, but attention weight over round brush and painting increases, adjusting for the negation in text

Techniques to add knowledge to LMs



- Add pretrained entity embeddings
  - ERNIE
  - QAGNN/GreaseLM
- Use an external memory
  - KGLM
- Modify the training data
  - WKLM
  - ERNIE (another!), salient span masking

Method 2: Use an external memory

- Previous methods rely on the pretrained entity embeddings to encode the factual knowledge into the language model.
  - Pros: Convenient, as you can just plug in any available entity embeddings
  - Cons: if the KB is modified, you may need to re-train the entity embeddings and model
- Question: Are there more direct ways to provide factual knowledge for LM?
- Answer: Yes! Give the model access to an external memory (a key-value store for KG triples or facts) in a way that is independent of learned model parameters
- Advantages:
  - Can directly update facts in the external memory without re-training the model
  - Interpretable
    - It's more visible which fact in external memory the LM used to make prediction ($\leftrightarrow$ it's harder to debug model predictions if we use entity embeddings)

External memory? → Memory Network

- 模型主要包含一系列的记忆单元（可以看成是一个数组，每个元素保存一句话的记忆）和I，G，O，R四个模块。

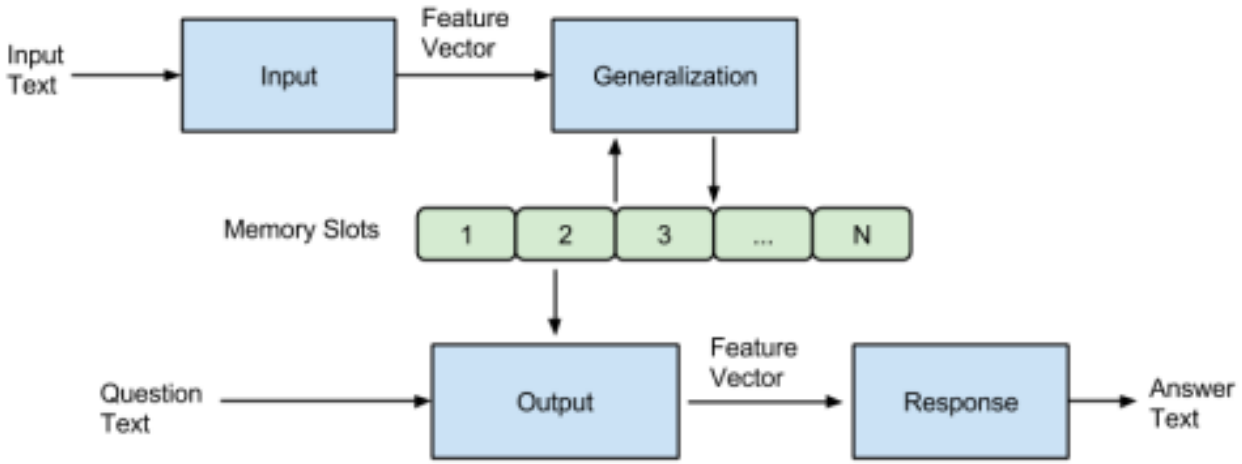
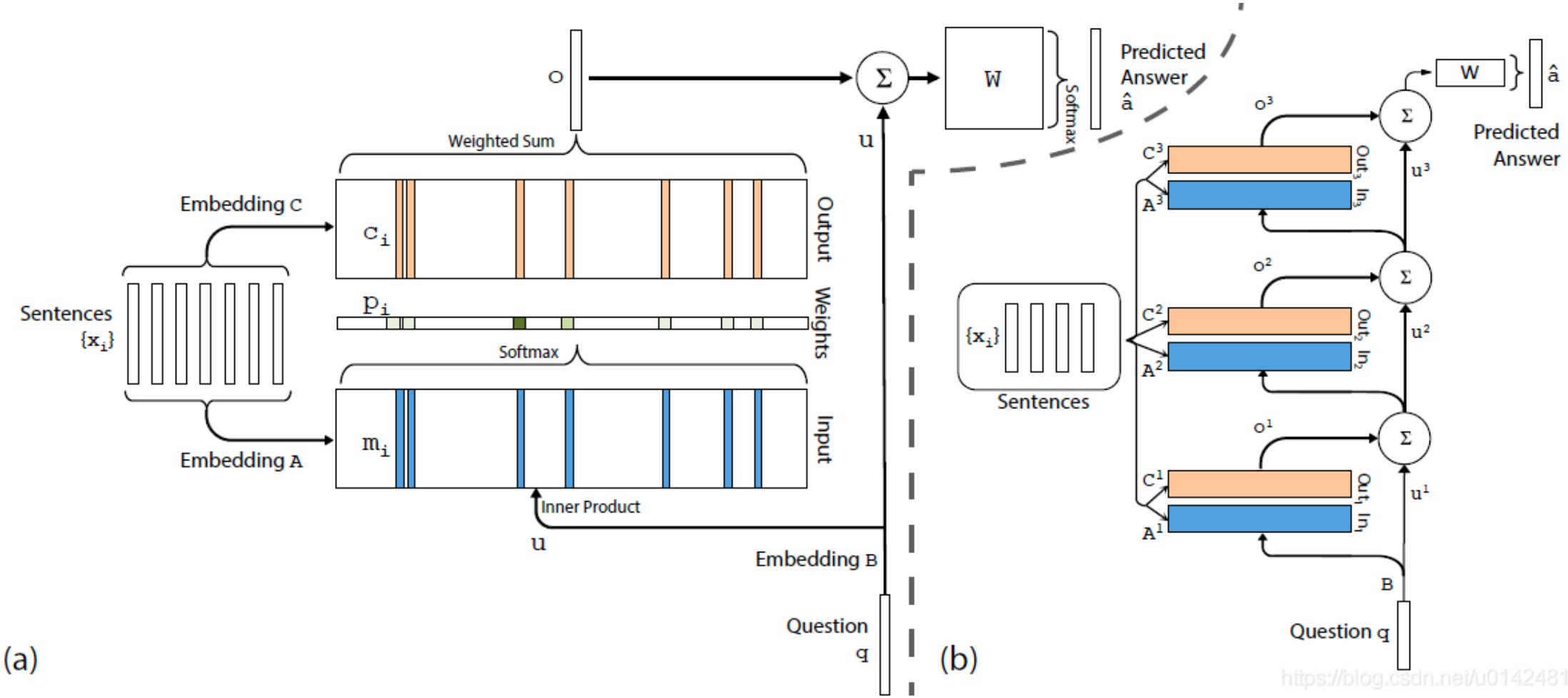


Figure 3: Memory Network architecture.

- I: (input feature map)：用于将输入转化为网络里内在的向量。（可以利用标准预处理，例如，文本输入的解析，共参考和实体解析。 还可以将输入编码为内部特征表示，例如，从文本转换为稀疏或密集特征向量）
- G: (generalization)：更新记忆。在最初始版本的实现里，只是简单地插入记忆数组里。也可以设计新的情况，包括了记忆的忘记，记忆的重新组织。(最简单的G形式是将I（x）存储在存储器中的“slot”中)
- O: (output feature map)：从记忆里结合输入，把合适的记忆抽取出来，返回一个向量。每次获得一个向量，代表了一次推理过程。
- R: (response)：将该向量转化回所需的格式，比如文字或者answer。

https://arxiv.org/pdf/1410.3916.pdf

End-To-End Memory Networks



Barack‘s Wife Hillary: Using Knowledge-Graphs for Fact-Aware Language Modeling (KGLM) [Logan et al., ACL 2019]

- Key idea: condition the language model on a knowledge graph (KG) when predicting next word
- Recall that (standard) language models predict the next word given previous words:

$$P\left(x^{(t+1)} \middle| x^{(t)}, \ldots, x^{(1)}\right)$$

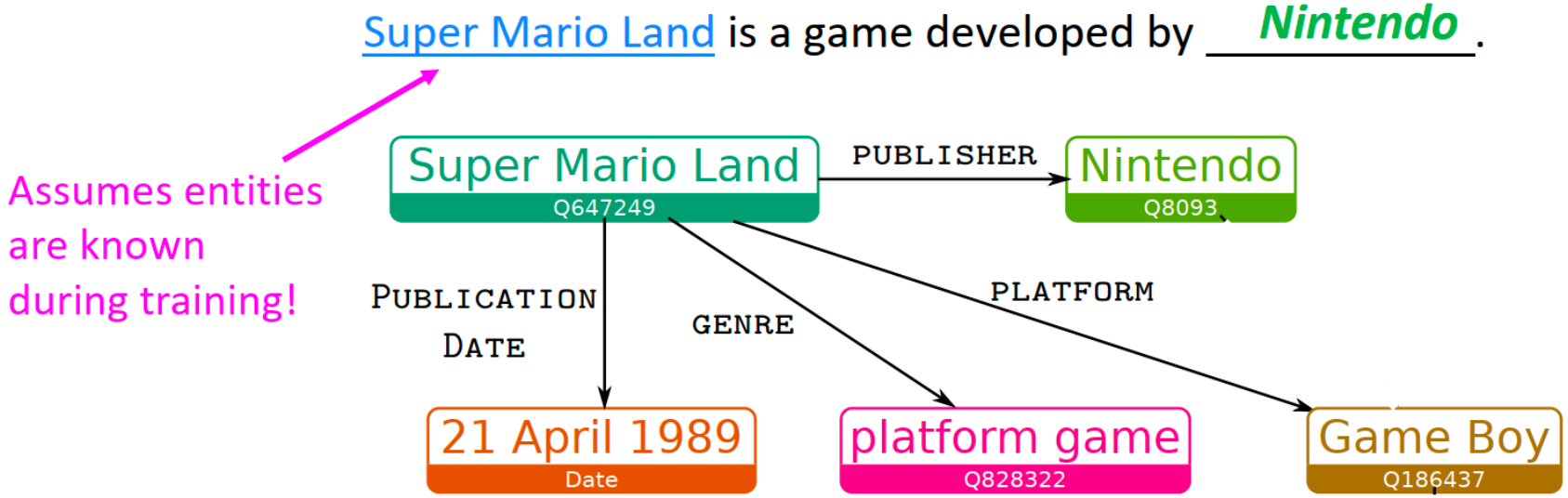
- Goal: predict the next word and entity using both the previous word and entity info

$$P\left(x^{(t+1)}, \mathcal{E}^{(t+1)} \middle| x^{(t)}, \ldots, x^{(1)}, \mathcal{E}^{(t)}, \ldots, \mathcal{E}^{(1)}\right)$$

  - $\mathcal{E}^{(t)}$ is the set of KG entities mentioned at timestep

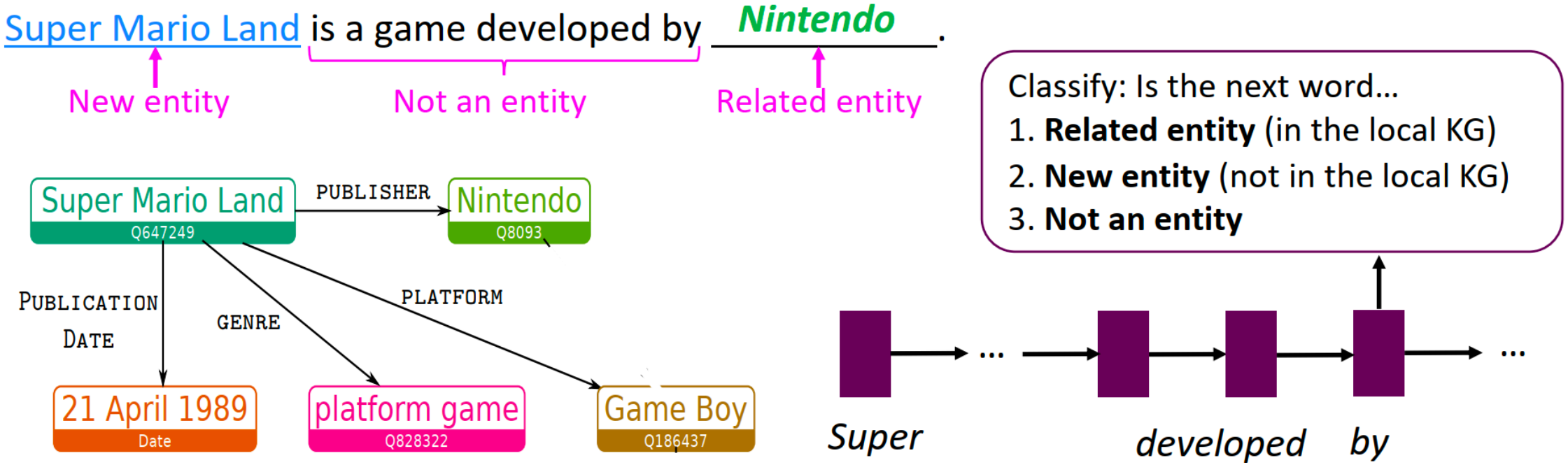
KGLM [Logan et al., ACL 2019]

- Method: Build a local knowledge graph as you iterate over the sequence
  - Local KG is a subset of the full KG with only entities relevant to the sequence so far



  - Local KG can provide a strong signal for predicting what comes as the next word
- How can the LM know when to use the local KG vs standard LM to predict the next word?

KGLM [Logan et al., ACL 2019]



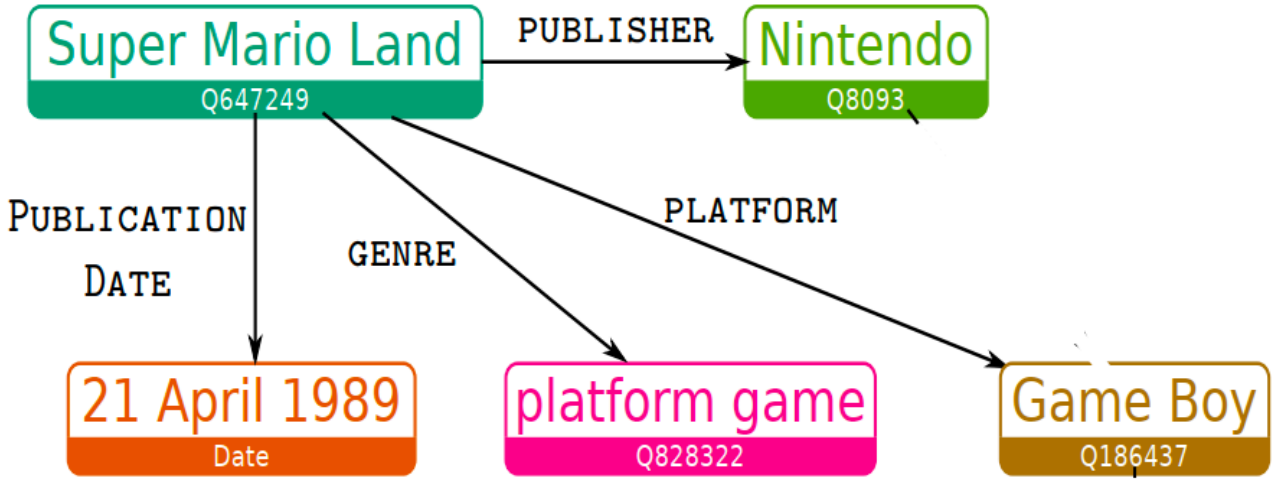
- Instead of predicting next word directly, use the LM hidden state to first predict the type of the next word (3 classes)
- Once we predict the word type, how to predict the next entity and word in each of the 3 scenarios?

KGLM [Logan et al., ACL 2019]

Super Mario Land is a game developed by Nintendo.

New entity | Not an entity | Related entity

- 1. Related entity case (in the local KG)



KG triple = (parent entity, relation, tail entity)

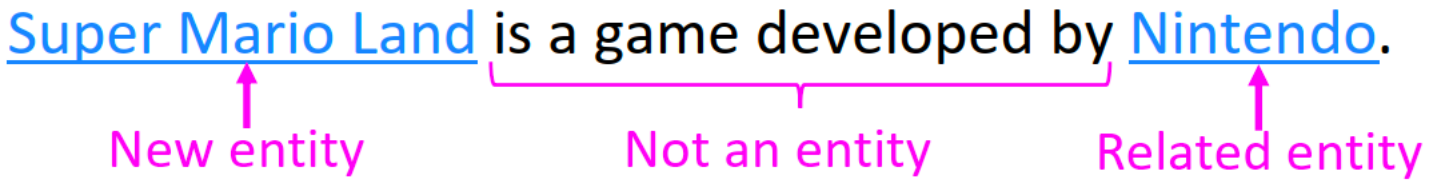
Example

Top scoring parent entity: "Super Mario Land"

Top scoring relation: "publisher"

-> Next entity is "Nintendo", due to KG triple (Super Mario Land, *publisher,* Nintendo).

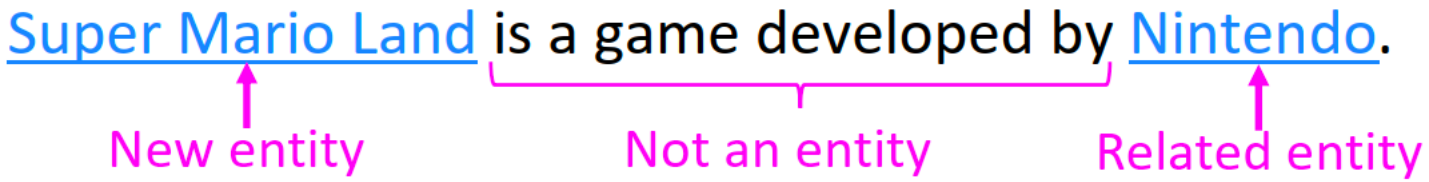
KGLM [Logan et al., ACL 2019]



- 1. Related entity case (in the local KG)
- Find the top-scoring parent and relation in the local KG using the LM hidden state and entity and relation embeddings
  - $P(p_t) = \text{softmax}(\boldsymbol{v_p} \cdot \boldsymbol{h_t})$ where $\boldsymbol{p_t}$ is a potential parent entity, $\boldsymbol{v_p}$ is the corresponding entity embedding, and $\boldsymbol{h_t}$ is from the LM hidden state
  - Similarly for predicting top relation
- **Next entity will be:** tail entity from KG triple (top parent entity, top relation, tail entity)
- **Next word will be:** most likely next token over the standard vocabulary expanded to include the tail entity and its aliases[1]

[1] Phrases that could all refer to Nintendo (e.g. Nintendo, Nintendo Co., Koppai)

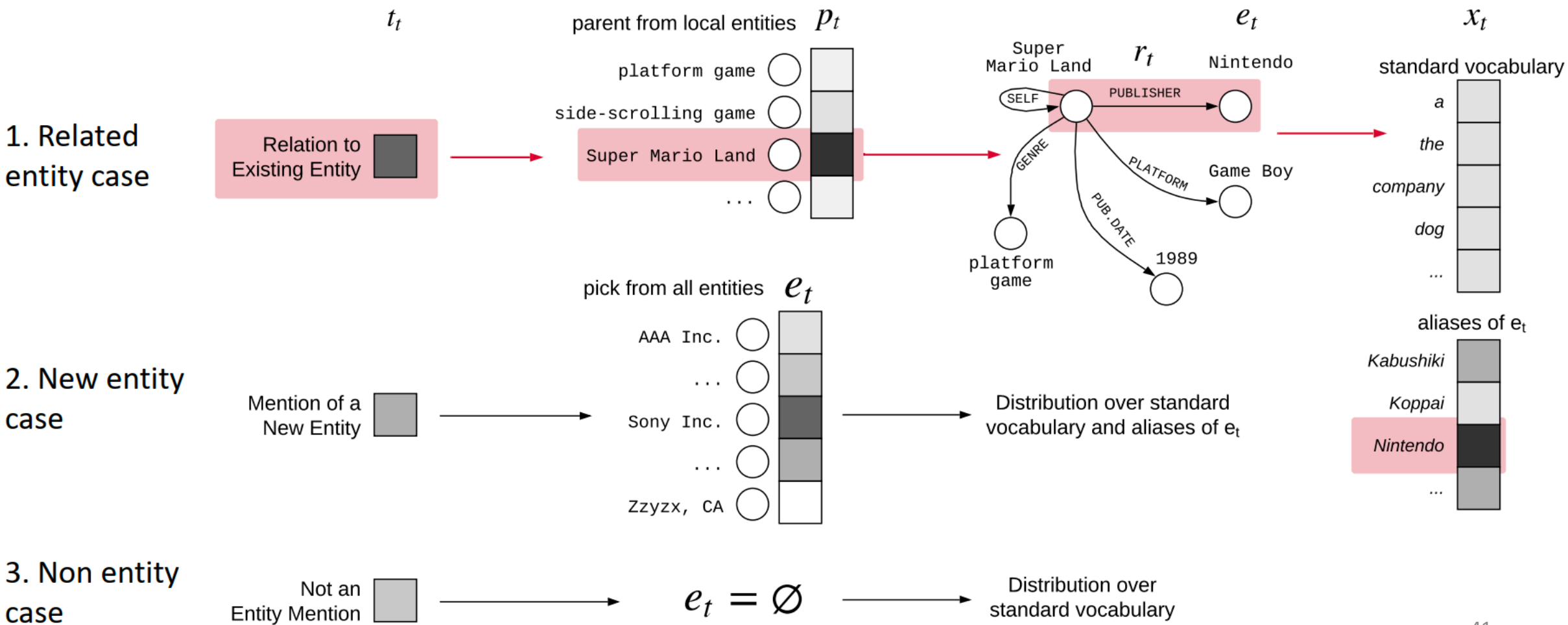
KGLM [Logan et al., ACL 2019]



- 2. New entity case (not in the local KG)
  - Find the top-scoring entity in the full KG using the LM hidden state and entity embeddings
  - **Next entity will be**: the predicted top-scoring entity
  - **Next word will be:** most likely next token over standard vocabulary + entity aliases
- 3. Not an entity case
  - **Next entity will be**: None
  - **Next word will be:** most likely next token over standard vocabulary

KGLM [Logan et al., ACL 2019]

Super Mario Land is a 1989 side-scrolling platform video game developed and published by Nintendo



KGLM [Logan et al., ACL 2019]

- Outperforms GPT-2 and AWD-LSTM[Merity et al., ICLR 2018] on a fact completion task ("fill-in-the-blank")

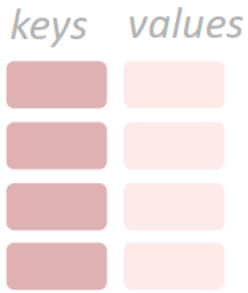
- Qualitatively, KGLM tends to predict more specific tokens, whereas GPT-2 predicts more common, generic tokens

- Supports modifying/updating facts!
  - Modifying the KG has a direct change in the LM predictions

  - Barack Obama was born on _____.
  - **KG triples:** **Most likely next word:**
  - (Barack Obama, birthDate, 1961-08-04) "August", "4", "1961"
  - (Barack Obama, birthDate, 2013-03-21) "March", "21", "2013"

- External memory can help LMs to do factually-grounded text generation!

Techniques to add knowledge to LMs



- Add pretrained entity embeddings
  - ERNIE
  - QAGNN/GreaseLM
- Use an external memory
  - KGLM
- Modify the training data
  - WKLM
  - ERNIE (another!), salient span masking

Method 3: Modify the training data

- Previous methods incorporated knowledge explicitly through pretrained embeddings and/or an external memory.

- Question: Can knowledge also be incorporated implicitly through the unstructured text?
- Answer: Yes! Mask or corrupt the data to introduce additional training tasks that require factual knowledge.

- Advantages:
  - No need for additional memory/computation (e.g. no need to carry a local KG)
  - No need for modifying the architecture (e.g. no need for a fusion layer)

Pretrained Encyclopedia: Weakly Supervised Knowledge Pretrained Language Model (WKLM) [Xiong et al., ICLR 2020]

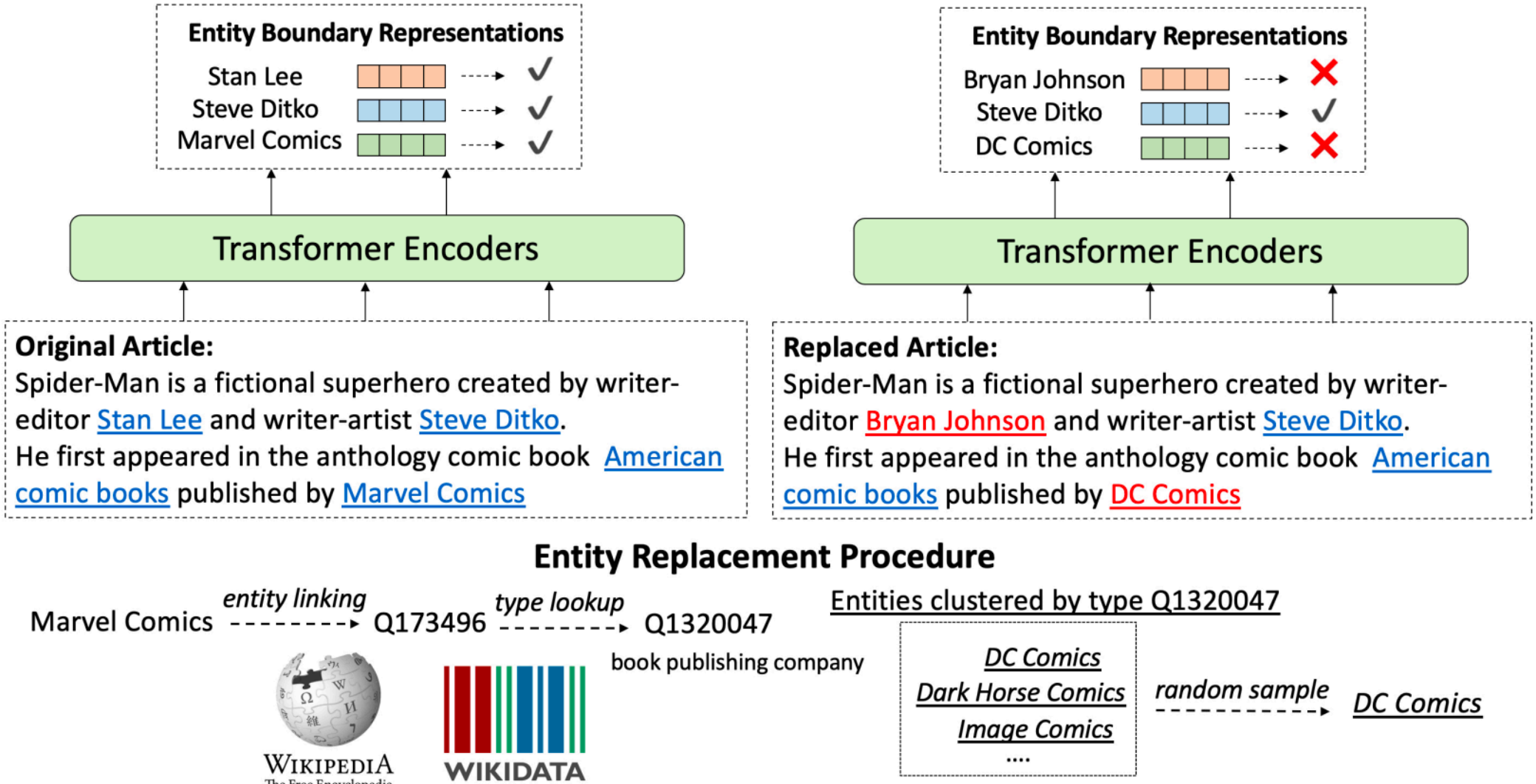
- Key idea: train the model to distinguish between true and false knowledge
- Method: Replace mentions in the text with mentions that refer to different entities of the same type to create negative knowledge statements
  - Make the model predicts whether entity has been replaced or not
  - Need type-constraint to enforce linguistically correct replacement. Otherwise the model may trivially predict "replaced" using linguistic signal instead of knowledge

True knowledge statement: J.K. Rowling is the author of Harry Potter.

Negative knowledge statement: J.R.R. Tolkien is the author of Harry Potter.

- => Requires the model to have background knowledge to be able to distinguish!

WKLM [Xiong et al., ICLR 2020]



WKLM [Xiong et al., ICLR 2020]

- **Training**: Uses an entity replacement loss (binary classification) to train the model to distinguish between true and false mentions

$$\mathcal{L}_{entRep} = \mathbb{I}_{e \in \mathcal{E}^+} \log P(e \mid C) + (1 - \mathbb{I}_{e \in \mathcal{E}^+}) \log(1 - P(e \mid C))$$

where e is an entity, C is the context, and $\mathcal{E}^+$ represents a true entity mention

- Total loss is the combination of standard masked language model loss (MLM) and the entity replacement loss.

$$\mathcal{L}_{WKLM} = \mathcal{L}_{MLM} + \mathcal{L}_{entRep}$$

- MLM is defined at the token-level; entRep is defined at the entity-level
  - Treating a whole entity (could be multi-word) instead of a token as one unit can make LMs more knowledge-aware

WKLM [Xiong et al., ICLR 2020]

- Improves over BERT and GPT-2 in fact completion tasks
- Improves over ERNIE on downstream tasks
- Ablation experiments (see the effect of model components, MLM and EntRep)
  - EntRep loss is essential because it makes WKLM outperform BERT
  - MLM loss is also essential for downstream task performance
  - On knowledge-intensive tasks, WKLM even outperforms training BERT longer with just MLM loss

Model	SQuAD (F1)	TriviaQA (F1)	Quasar-T (F1)	FIGER (acc)
WKLM	91.3	56.7	49.9	60.21
WKLM w/o MLM	87.6	52.5	48.1	58.44
BERT + 1M Updates	91.1	56.3	48.2	54.17

Much worse without MLM

Much worse training for longer, compared to using the entity replacement loss

Learn inductive biases through masking

- Besides corrupting data, another idea is: can we just do clever masking to help the LM learn factual knowledge?
  - ERNIE[1]: Enhanced Representation through Knowledge Integration, Sun et al., arXiv 2019
    - Uses phrase-level and entity-level masking, and shows improvements on downstream NLP tasks
  - How Much Knowledge Can You Pack Into the Parameters of a Language Model?, Roberts et al., EMNLP 2020
    - Uses "salient span masking" (Guu et al., ICML 2020) to mask out salient spans (i.e. named entities and dates)
    - Shows that salient span masking improves T5's performance on QA tasks

另外一个ERNIE

Another ERNIE from Baidu

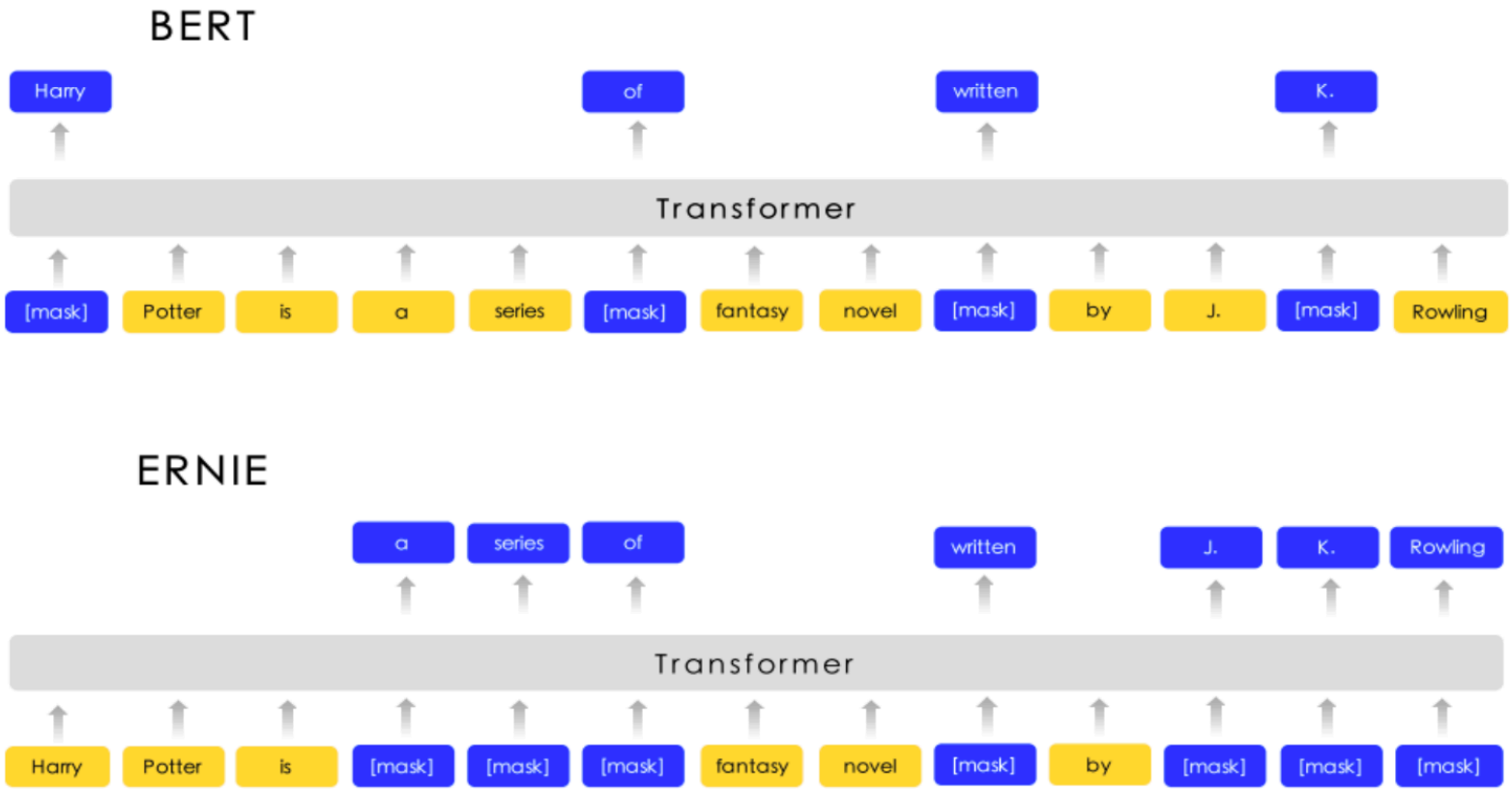


Figure 1: The different masking strategy between BERT and ERNIE

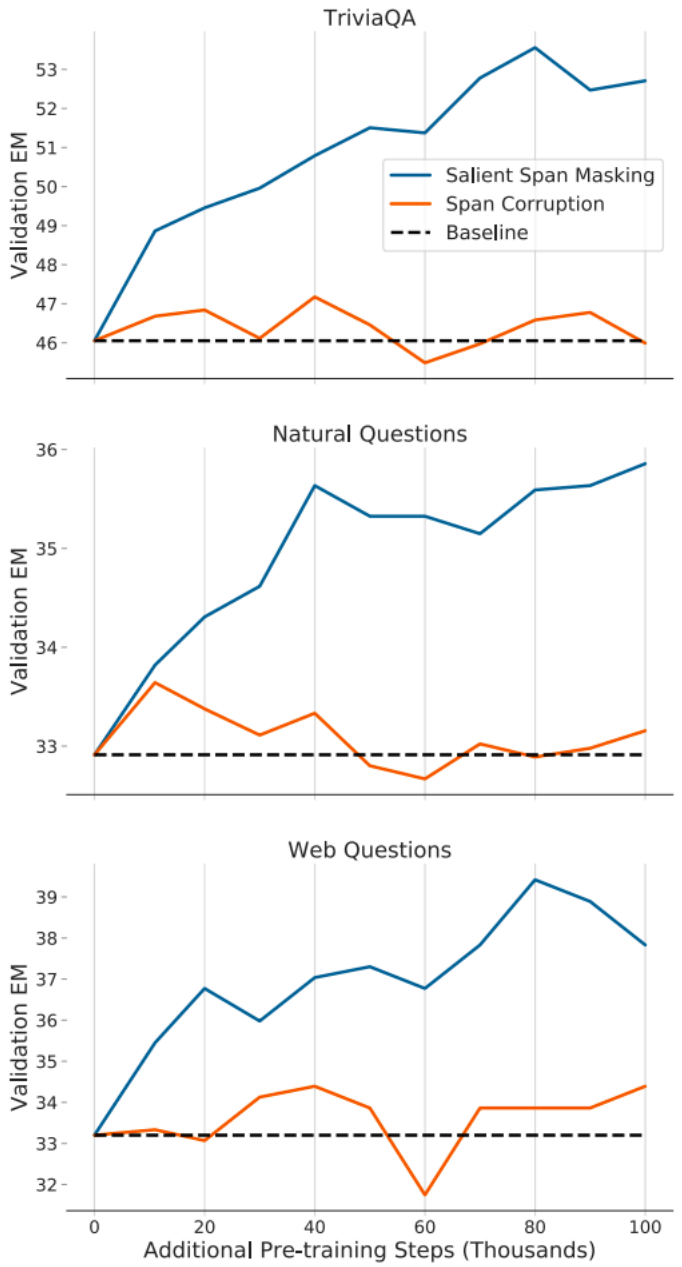
ERNIE: Enhanced Representation through Knowledge Integration, Sun et al, 2019

Salient span masking

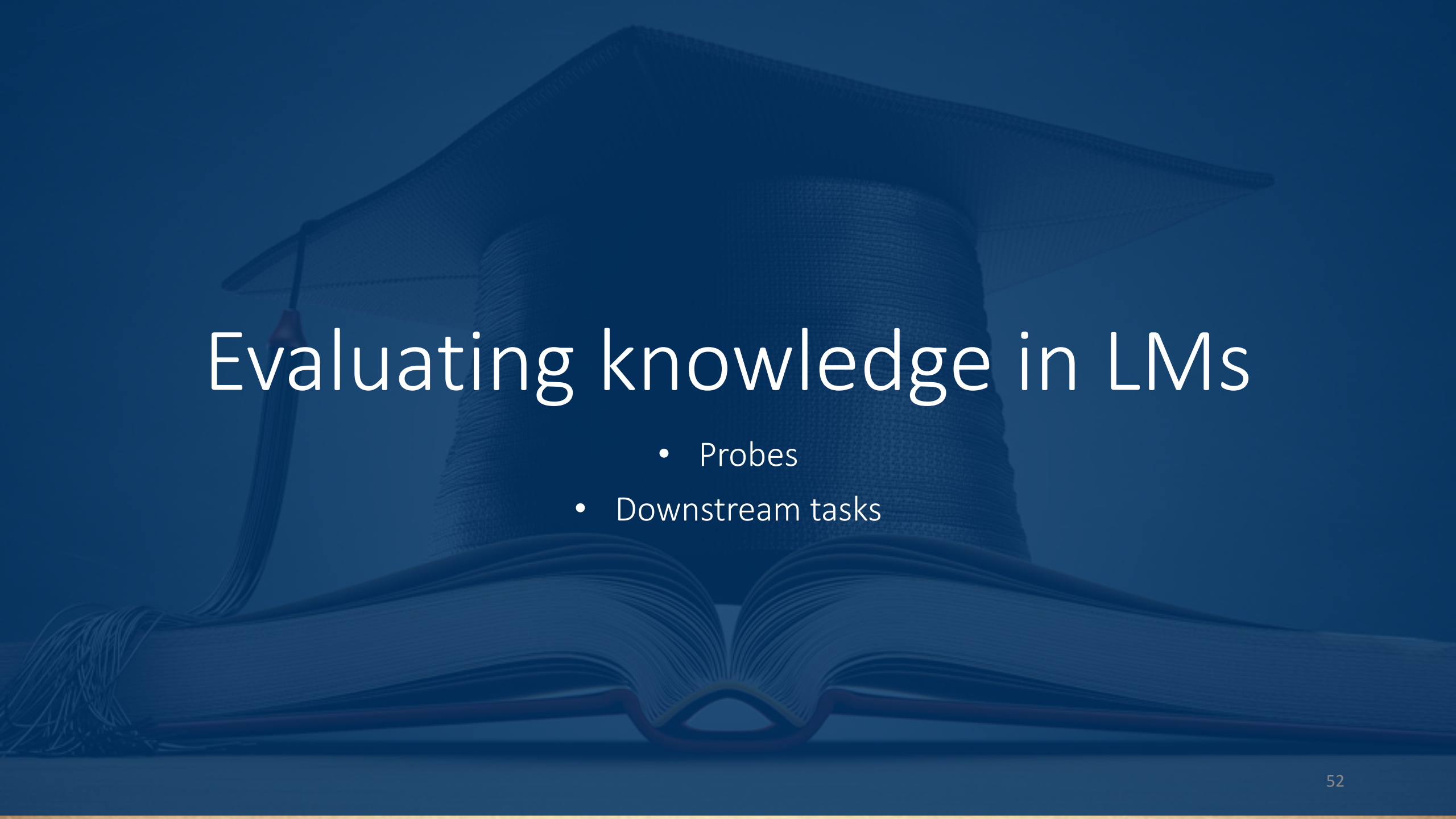
- Salient span masking has been shown to outperform other masking or corruption strategies on QA and document retrieval tasks.
- QA/Retrieval performance on NaturalQuestions

Masking technique	Exact Match	Retrieval Recall @5
Random uniform masks (BERT)	32.3	24.2
Random span masks (SpanBERT)	35.3	26.1
Salient span masking	**38.2**	**38.5**

REALM, Guu et al., ICML 2020



Roberts et al., EMNLP 2020



Evaluating knowledge in LMs

- Probes
- Downstream tasks

Probes

LAnguage Model Analysis (LAMA) Probe [Petroni et al., EMNLP 2019]

- Idea: How much relational (commonsense and factual) knowledge is already in off-the-shelf language models?
  - Without any additional training or fine-tuning

- Manually constructed a set of "cloze" statements (fill-in-the-blank) to assess a model's ability to predict a missing token.
- Examples:
  - The theory of relativity was developed by [MASK].
  - The native language of Mammootty is [MASK].
  - Ravens can [MASK].
  - You are likely to find a overflow in a [MASK].

LAnguage Model Analysis (LAMA) Probe [Petroni et al., EMNLP 2019]

- Generate cloze statements from KG triples and question-answer pairs in QA datasets
- Goal: evaluate knowledge in off-the-shelf pretrained LMs (Note: this means they may have used different pretraining corpora)
- Compare the unsupervised LMs to supervised relation extraction (RE) and QA systems

Mean precision at one (P@1)

BERT struggles on N-to-M relations

Corpus	DrQA	RE baseline	ELMo	ELMo (5.5B)	GPT2 (300M)	GPT2 (1.5B)	BERT-base	BERT-large
Google-RE	-	7.6	2.0	3.0	4.9	6.5	9.8	**10.5**
T-REx	-	**33.8**	4.7	7.1	20.3	25.1	31.1	32.2
ConceptNet	-	-	6.1	6.2	9.7	12.8	15.6	**19.2**
SQuAD	**37.5**	-	1.6	4.3	5.9	11.5	14.1	17.4

LMs are NOT finetuned!

LAnguage Model Analysis (LAMA) Probe [Petroni et al., EMNLP 2019]

- Using LAMA library, you can try out examples to assess knowledge in popular/your favorite LMs!
- https://github.com/facebookresearch/LAMA
- The cat is on the [MASK]

bert:

	Top10 predictions	
0	phone	-2.345
1	floor	-2.630
2	ground	-2.968
3	couch	-3.387
4	move	-3.649
5	roof	-3.651
6	way	-3.718
7	run	-3.757
8	bed	-3.802
9	left	-3.965

index	token	log_prob	prediction	log_prob	rank@1000
1	The	-5.547	.	-0.607	14
2	cat	-0.367	cat	-0.367	0
3	is	-0.019	is	-0.019	0
4	on	-0.001	on	-0.001	0
5	the	-0.002	the	-0.002	0
6	[MASK]	-14.321	phone	-2.345	-1
7	.	-0.002	.	-0.002	0

LAnguage Model Analysis (LAMA) Probe [Petroni et al., EMNLP 2019]

- Limitations of the LAMA probe:
  - Hard to understand why models perform well when they do
    - LM could just be memorizing word co-occurrence patterns rather than "understanding" the cloze statement and "recalling" knowledge
    - LM could just be identifying similarities between the surface forms of the subject and object (e.g., Pope Clement VII has the position of pope)
  - LMs are sensitive to the phrasing of the statement
    - e.g. sometimes rephrasing the template makes LMs suddenly perform better
    - But LAMA has only one manually defined template for each relation
    - This means probe results are a lower bound on knowledge encoded in the LM
- We will talk about two works that address these limitations

LAnguage Model Analysis (LAMA) Probe [Petroni et al., EMNLP 2019]

- Limitations of the LAMA probe:
  - Hard to understand why models perform well when they do
    - LM could just be memorizing word co-occurrence patterns rather than "understanding" the cloze statement and "recalling" knowledge
    - LM could just be identifying similarities between the surface forms of the subject and object (e.g., Pope Clement VII has the position of pope)
  - LMs are sensitive to the phrasing of the statement
    - e.g. sometimes rephrasing the template makes LMs suddenly perform better
    - But LAMA has only one manually defined template for each relation
    - This means probe results are a lower bound on knowledge encoded in the LM
- We will talk about two works that address these limitations

A More Challenging Probe: LAMA-UnHelpful Names (LAMA-UHN) [Poerner et al., EMNLP 2020]

- Key idea: Remove the examples from LAMA that can be answered without relational knowledge

- Motivation: BERT may rely on surface forms of entities to make predictions
  - String match between subject and object
  - "Revealing" person name: Name can be a (possibly incorrect) prior for native language, nationality, etc.
- Removing these examples helps to evaluate whether BERT is really knowing the fact

- With LAMA-UHN, BERT's score drops ~8%
  - Knowledge-enhanced model E-BERT drops only <1%

Native language of French-speaking actors according to BERT

Person Name	BERT
Jean Marais	French
Daniel Ceccaldi	Italian
Orane Demazis	Albanian
Sylvia Lopez	Spanish
Annick Alane	English

LAnguage Model Analysis (LAMA) Probe [Petroni et al., EMNLP 2019]

- Limitations of the LAMA probe:
  - Hard to understand why models perform well when they do
    - LM could just be memorizing word co-occurrence patterns rather than "understanding" the cloze statement and "recalling" knowledge
    - LM could just be identifying similarities between the surface forms of the subject and object (e.g., Pope Clement VII has the position of pope)
  - LMs are sensitive to the phrasing of the statement
    - e.g. sometimes rephrasing the template makes LMs suddenly perform better
    - But LAMA has only one manually defined template for each relation
    - This means probe results are a lower bound on knowledge encoded in the LM
- We will talk about two works that address these limitations

Developing better prompts to query knowledge in LMs [Jiang et al., TACL 2020]

- Problem: LMs may know the fact, but fail on completion tasks (LAMA) due to the query phrasing
  - Pretraining text may have had different sentence structures/contexts than the query
    - Example: “The birth place of Barack Obama is Honolulu, Hawaii” (pretraining corpus) versus “Barack Obama was born in _____” (query)
- Solution
  - Generate more LAMA prompts by mining templates from Wikipedia and generating paraphrased prompts by using back-translation
    - Increases the chance of getting a prompt similar to what was seen in pretraining
  - Ensemble prompts: LM’s output probability is averaged over different prompts

Developing better prompts to query knowledge in LMs [Jiang et al., TACL 2020]

- Results: Performance on LAMA for BERT-large increases 7% when using top-performing query for each relation. Ensembling leads to another 4% gain.
  - Original LAMA really was a lower bound on knowledge encoded in LM!
- Small changes in the query phrasing lead to large gains.
  - LMs are very sensitive to the query phrasing => research opportunity for robust LM!

ID	Modifications	Acc. Gain
P413	x plays in→at y position	+23.2
P495	x was created→made in y	+10.8
P495	x was→is created in y	+10.0
P361	x is a part of y	+2.7
P413	x plays ~~in~~ y position	+2.2

Downstream tasks

Knowledge-intensive downstream tasks

- Measures how well the knowledge-enhanced LM transfers its knowledge to downstream tasks
- Unlike probes, this evaluation usually involves finetuning the LM on downstream tasks, like evaluating BERT on GLUE tasks
- Common knowledge-intensive tasks:
  - Relation extraction
    - Example: [Bill Gates] was born in [Seattle]; label: “city of birth”
  - Entity typing
    - Example: [Alice] has donated billions to eradicate malaria; label: “philanthropist”
  - Question answering
    - Example: “What kind of forest is the Amazon?”; label: “moist broadleaf forest

Relation extraction performance on TACRED

- Knowledge-enhanced systems (ERNIE, KnowBERT) improve over previously state-of-the-art models for relation extraction

Model	LM	Precision	Recall	F1
C-GCN	-	69.9	63.3	66.4
BERT-LSTM-base	BERT-Base	73.3	63.1	67.8
ERNIE (Zhang et al.)	BERT-Base	70.0	66.1	68.0
KnowBert-W+W	BERT-Base	**71.6**	**71.4**	**71.5**

Peters et al., EMNLP 2019

Entity typing performance on OpenEntity

- Knowledge-enhanced LMs (ERNIE, KnowBERT) improve over prior LSTM and BERT-Base models on entity typing
- Impressively, previous models (NFGEC, UFET) were designed for entity typing

Model	Precision	Recall	F1
NFGEC (LSTM)	68.8	53.3	60.1
UFET (LSTM)	77.4	60.6	68.0
BERT-Base	76.4	71.0	73.6
ERNIE (Zhang et al.)	78.4	72.9	75.6
KnowBert-W+W	**78.6**	**73.7**	**76.1**

Zhang et al., ACL 2019 & Peters et al., EMNLP 2019

Knowledge-intensive Question Answering

- Knowledge-enhanced LMs (QAGNN, GreaseLM) improve over previous BERT-based models on question answering

Model	CommonsenseQA	OpenBookQA	MedQA
BERT-Large	55.4	60.4	-
RoBERTa-Large	68.7	64.8	35.0
SapBERT-Base	-	-	37.2
QAGNN	73.4	**67.8**	38.0
GreaseLM	**74.2**	66.9	**38.5**

Devlin et al., NAACL 2019 & Liu et al., 2019 & Liu et al., NAACL 2021 & Yasunaga et al., NAACL 2021 & Zhang et al., ICLR 2022

Summary of Evaluation

- Probes
  - Evaluate the knowledge already present in models without more training
  - Challenging to construct benchmarks that really test factual knowledge
  - Challenging to construct the query prompts used in the probe
- Downstream tasks
  - Evaluate the usefulness of the knowledge-enhanced representation in applications
  - Typically requires finetuning the LM further on the downstream task
  - Less direct way to evaluate the knowledge in the LM, but perhaps more practically useful in terms of applications

Other exciting progress!

- Retrieval-augmented language models
  - REALM, Guu et al., ICML 2020
  - RAG, Lewis et al., NeurIPS 2020
  - Retro, Borgeaud et al., 2022
- Modifying knowledge in language models
  - Fast Model Editing at Scale, Mitchell et al., 2021
- More knowledge-aware pretraining for language models
  - KEPLER, Wang et al., TACL 2020
- More efficient knowledge systems
  - NeurIPS Efficient QA challenge
- Better knowledge benchmarks
  - KILT, Petroni et al., NAACL 2021

Thank you