Natural Language Processing with Deep Learning
CS224N/Ling284

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Lecture 13: Integrating Knowledge in Language Models

Slides coauthored with Megan Leszczynski

Lecture Plan (Integrating Knowledge in Language Models)

1. Recap of language models (LMs) and what do they know? [15 mins]
2. Techniques to add knowledge to LMs
    1. Add pretrained entity embeddings [20 mins]
    2. Use an external memory [15 mins]
    3. Modify the training data [15 mins]
3. Evaluating knowledge in LMs [20 mins]

Announcements:

- Project Milestone out today; due next Thursday
- Project Proposal feedback available on GradeScope by Thursday
- Hope your final projects are going well – stop by office hours for any questions or help!

Recap: LMs

- Standard language models predict the next word given a sequence of text and compute the probability of a sequence

The students opened their **books** *.*

- Masked language models (e.g., BERT) predict a masked token in a sequence of text using bidirectional context

went ***store***

I [MASK] to the [MASK].

- In both cases, language models can be trained over large amounts of unlabeled text, without any human annotation

Recap: LMs

- LMs are used for many tasks involving generating or evaluating the probability of text:
  - Summarization
  - Dialogue
  - Autocompletion
  - Machine translation
  - Fluency evaluation

- Recently, LMs are also commonly used to generate pretrained representations of text that encode some notion of language understanding for downstream NLP tasks
  - Text classification
  - Question answering

- Today: If an LM is trained over large amounts of text, can it even be used as a knowledge base?

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 ________.

Examples taken from [Petroni et al., EMNLP 2019]

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__.

Predictions generally look reasonable, but are not always factually correct!

Examples taken from [Petroni et al., EMNLP 2019]

Check out what BERT-Large predicts

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"

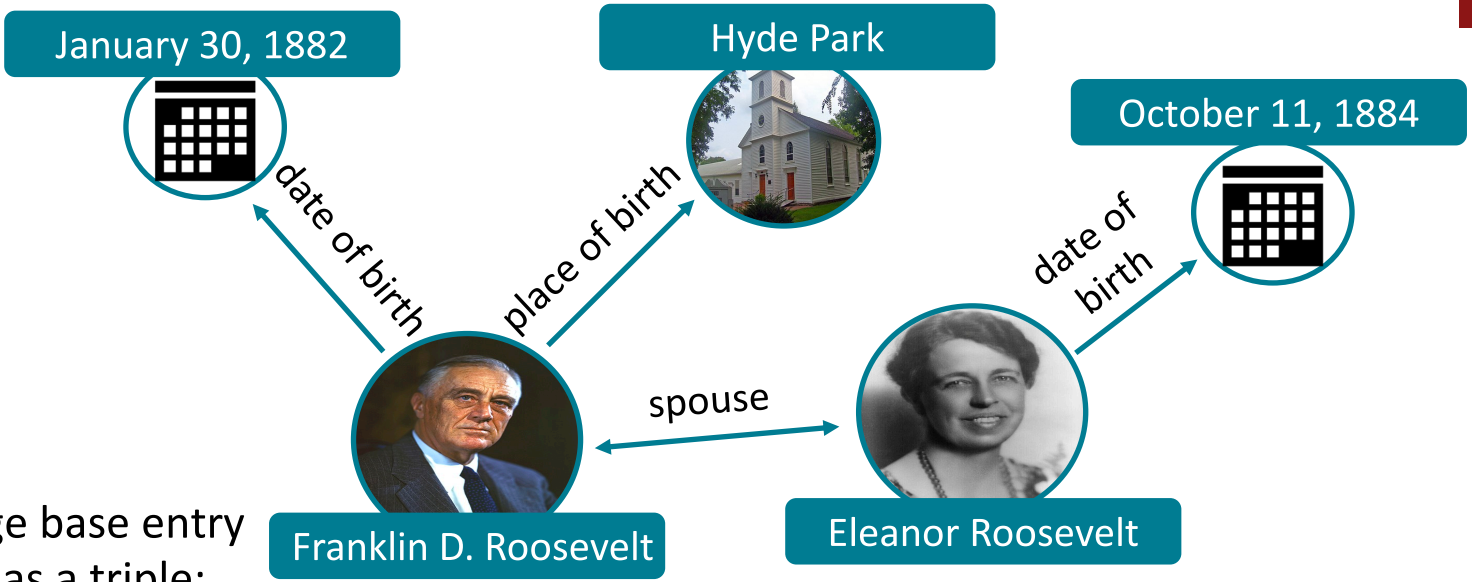
- Takeaway: LMs have *some* knowledge, but fail to *reliably* recall knowledge
  - We will talk about how to address this key challenge facing LMs!

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")

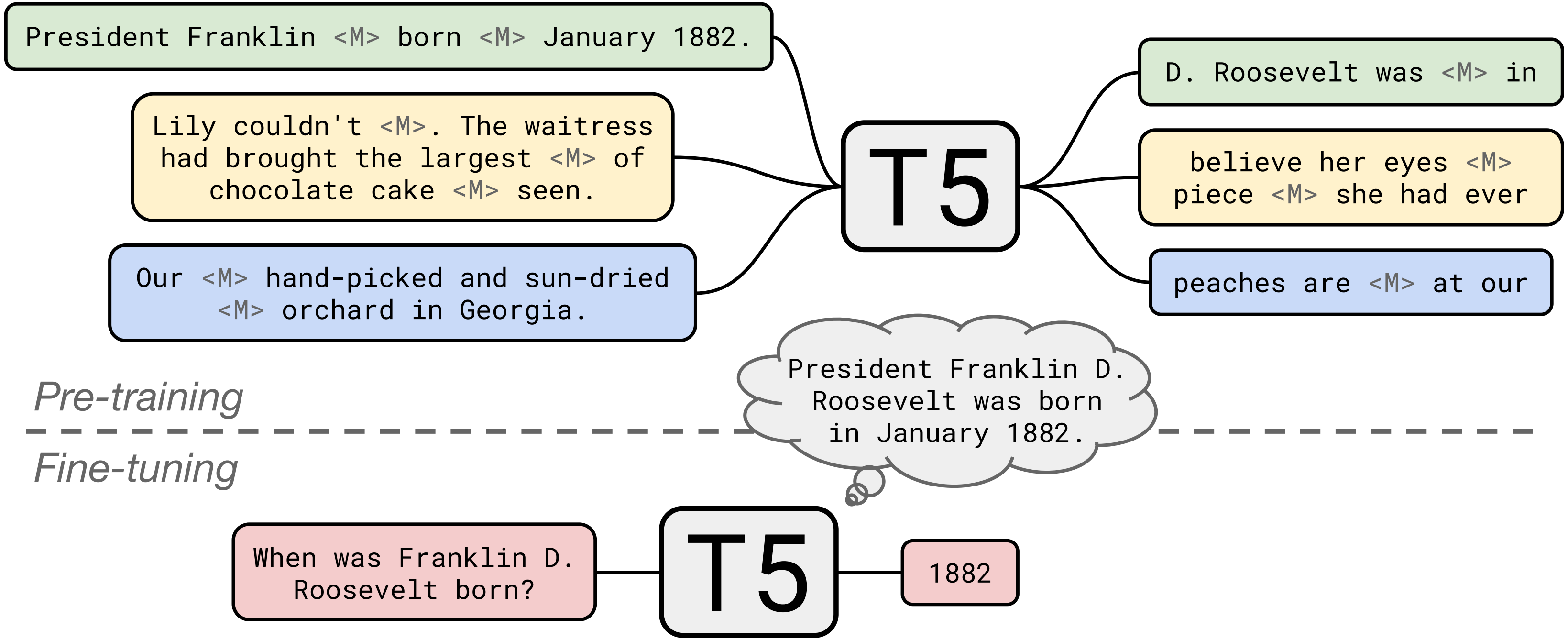
- You can query knowledge base with a formal query such as SQL statement:

  "What is the date of birth of FDR?"

```
SELECT date of birth
WHERE person = "Franklin D. Roosevelt"
```

How to query language models as knowledge bases

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



natural language query
(⟷ SQL query)

Roberts et al., EMNLP 2020

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

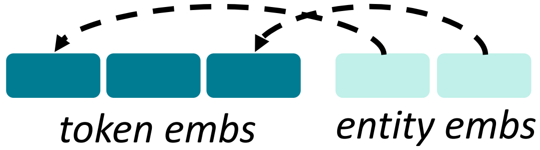
- LMs support more flexible natural language queries
  - Example: *What does the final F in the song U.F.O.F. stand for?*
    - Traditional KB may not have a specific relation “final F”; LM *may* learn it implicitly

- 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!

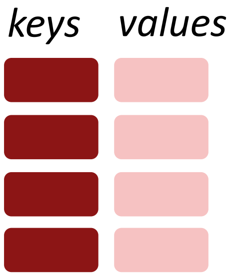
Section 2:
Techniques to add knowledge to LMs

Techniques to add knowledge to LMs



Add pretrained entity embeddings

- ERNIE
- QAGNN/GreaseLM



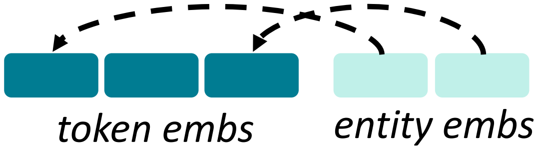
Use an external memory

- KGLM

Modify the training data

- WKLM
- ERNIE (another!), salient span masking

Techniques to add knowledge to LMs



Add pretrained entity embeddings

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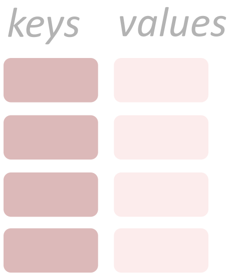

Use an external memory

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Modify the training data

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- ERNIE (another!), salient span masking

Method 1: Add pretrained embeddings

entity

- 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?

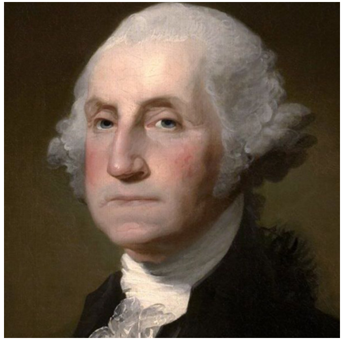
(It's like looking up word in word embedding dictionary. But looking up entity mention in KB is a bit trickier, because string matching may not work..)

- Link mentions in text to entities in a knowledge base

mention *mention*

<u>Washington</u> was the first president of the <u>United States</u>.

candidate

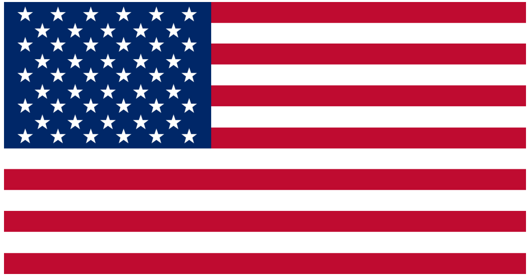


Q23 (Wikidata)

candidate

Q1223 (Wikidata)

candidate



Q30 (Wikidata)

- Entity linking involves resolving ambiguous mentions (e.g. using context)

- Takeaway: Entity linking tells us which entity embeddings are relevant to the text

More resources: Orr et al., CIDR 2021 & Li et al., EMNLP 2020

Method 1: Add pretrained entity embeddings

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

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

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

Bordes et al., NeurIPS 2013 & Yamada et al., 2020 & Wu et al., EMNLP 2020

Method 1: Add pretrained entity embeddings

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

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

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

- $\boldsymbol{w}_j$ is the embedding of word j 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

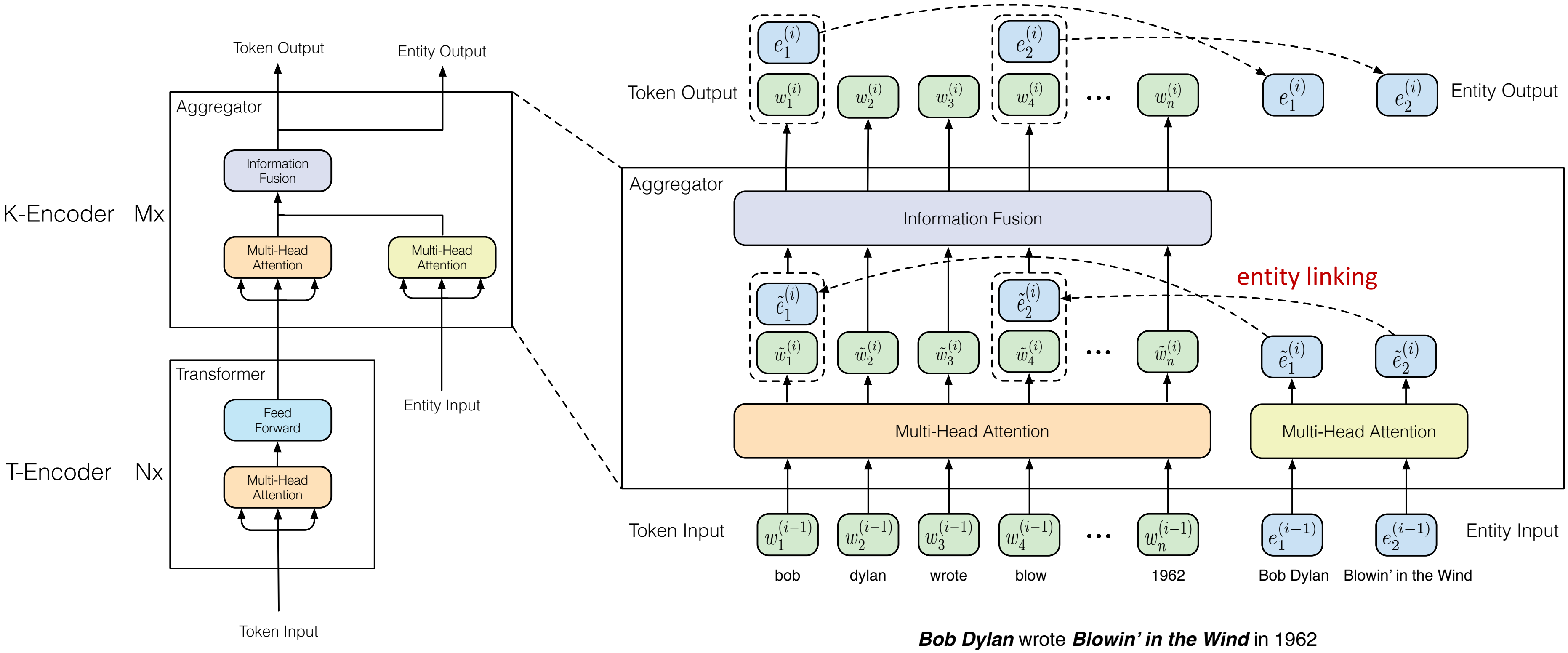
$$\boldsymbol{h}_j = \sigma\left(\widetilde{\boldsymbol{W}}_t^{(i)} \tilde{\boldsymbol{w}}_j^{(i)} + \widetilde{\boldsymbol{W}}_e^{(i)} \tilde{\boldsymbol{e}}_k^{(i)} + \tilde{\boldsymbol{b}}^{(i)}\right)$$ fusion representation

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

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

ERNIE: Enhanced Language Representation with Informative Entities

[Zhang et al., ACL 2019]



(a) Model Achitecture

(b) Aggregator

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[1]): 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:

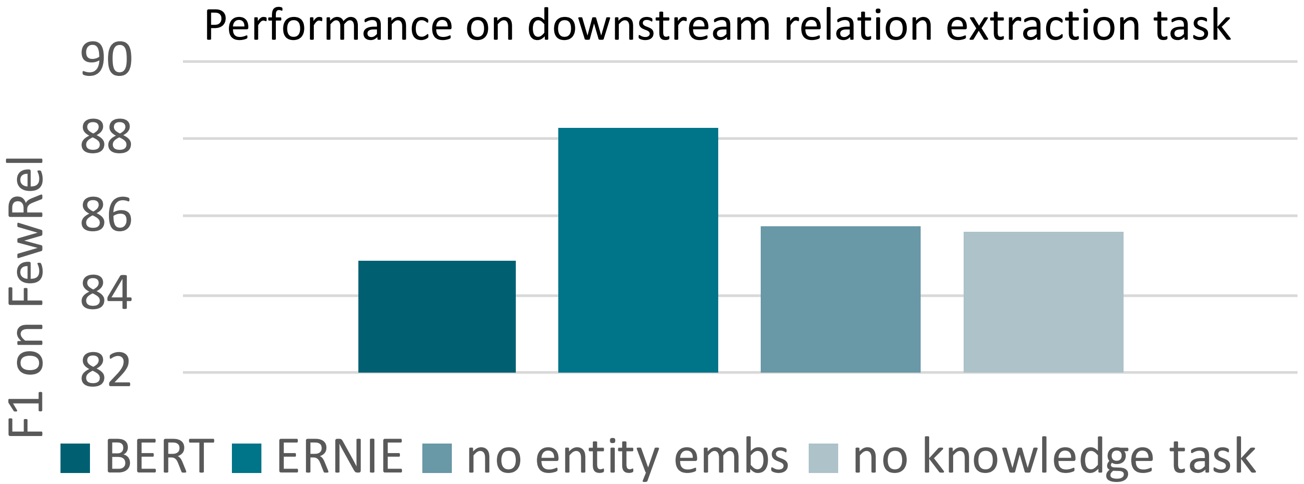
$$\mathcal{L}_{ERNIE} = \mathcal{L}_{MLM} + \mathcal{L}_{NSP} + \mathcal{L}_{dEA}$$

[1] 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

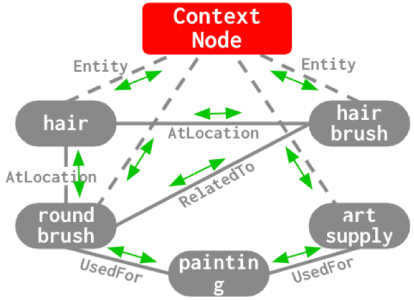
- Limitation:
  - Needs to link each entity mention in input text to knowledge base in advance
    - For instance, "Bob Dylan wrote Blowin' in the Wind" needs entities linked to Wikidata knowledge base
    - It's challenging to get a good entity linker for any domain of text or tasks
    - We will next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

[CTX] If it is not used for hair, a round brush is an example of what? Art supplies.



Text

Local knowledge graph

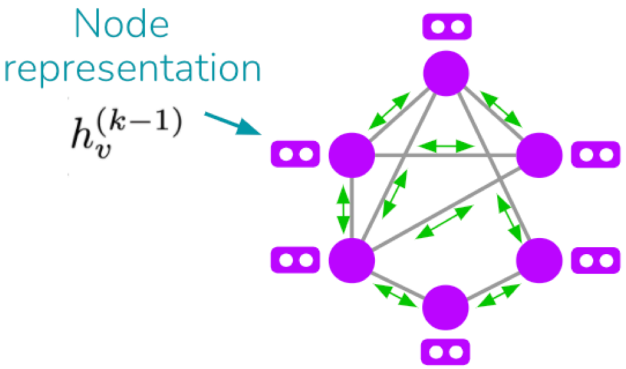
Get all entity candidates and their neighbors in KG to prepare a local KG

- **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/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 a 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.
  - Check out CS224W for more about GNN!

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

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

QAGNN/GreaseLM: Reasoning with Language Model and Knowledge Graph

[Yasunaga et al. NAACL 2021; Zhang et al. ICLR 2022]

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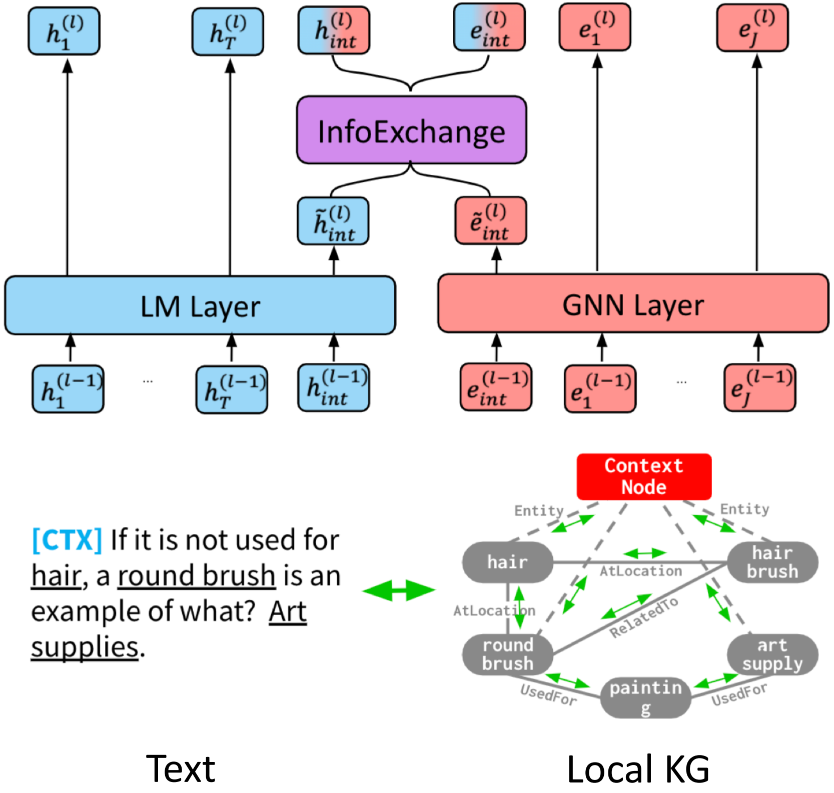


QAGNN/GreaseLM: Reasoning with Language Model and Knowledge Graph

[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

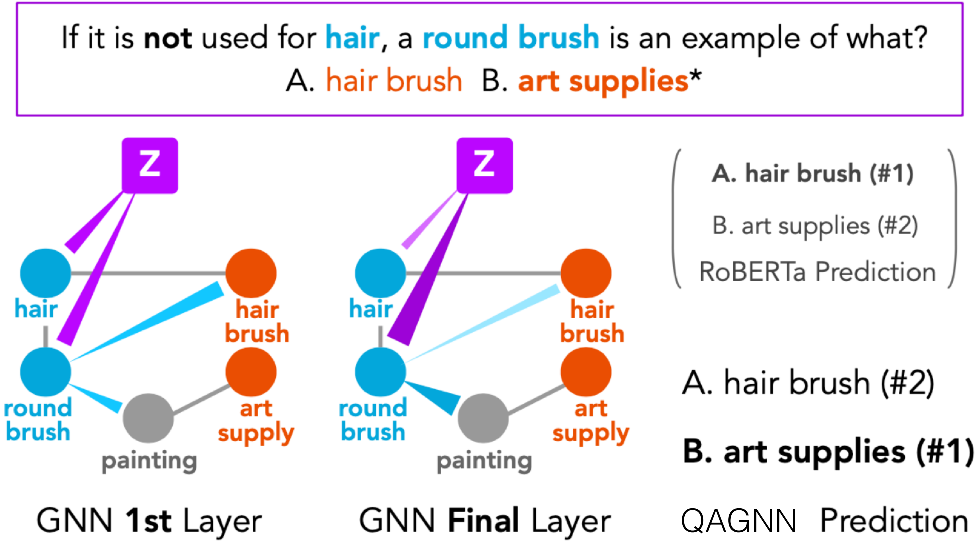
QAGNN/GreaseLM: Reasoning with Language Model and Knowledge Graph

[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)

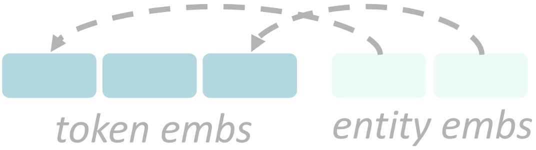
- Vanilla LMs don't handle negation well.. [Kassner et al., ACL 2020]

- New insight on how KG can help LM
  - Provide background knowledge
  - Provide scaffold for reasoning



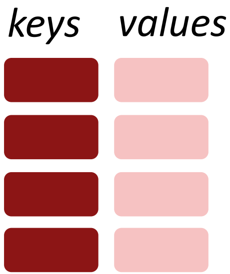
After several layers of fusion,
attention weight from text over **hair** decreases, but attention weight over **round brush** and **painting** increases, adjusting for the negation in text

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 (↔ it's harder to debug model predictions if we use entity embeddings)

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:

$$\mathrm{P}\left(x^{(t+1)} \middle| x^{(t)}, \ldots, x^{(1)}\right), \text{ where } x^{(1)}, \ldots., x^{(t)} \text{ is a sequence of words}$$

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

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

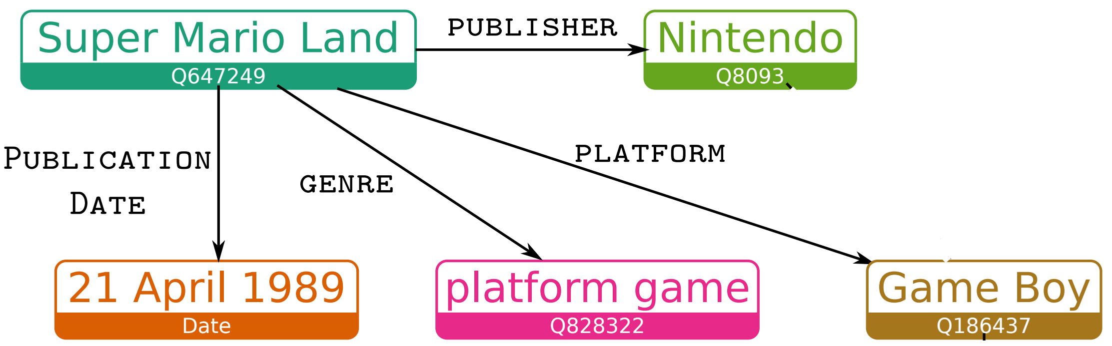
where $\mathcal{E}^{(t)}$ is the set of KG entities mentioned at timestep t

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

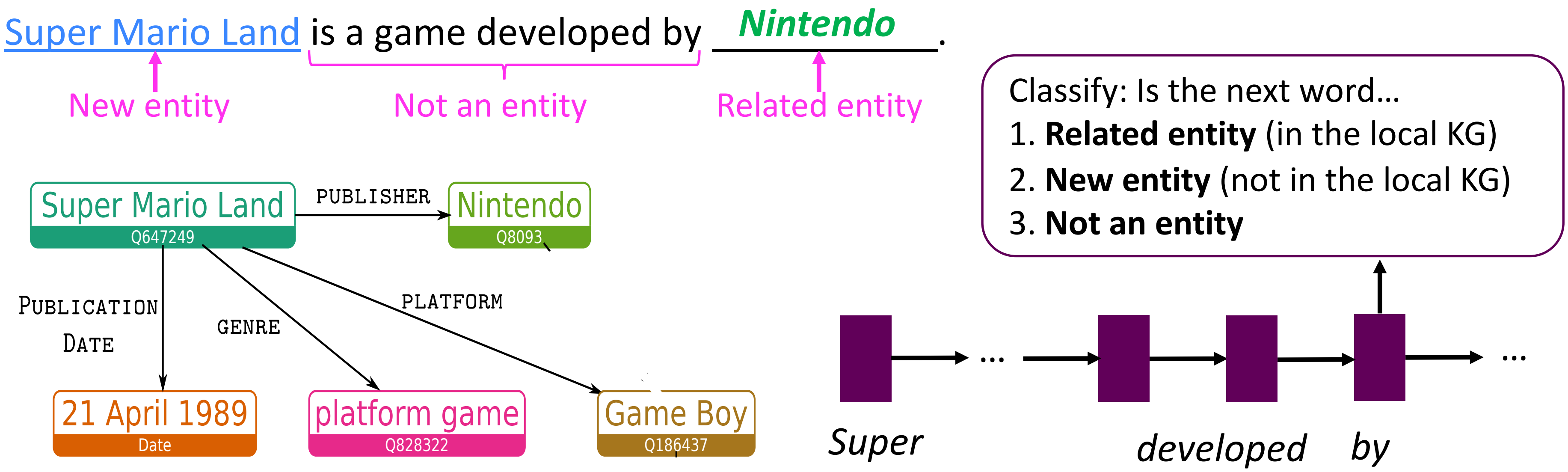
Super Mario Land is a game developed by ___Nintendo___.

Assumes entities are known during training!



  - 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?

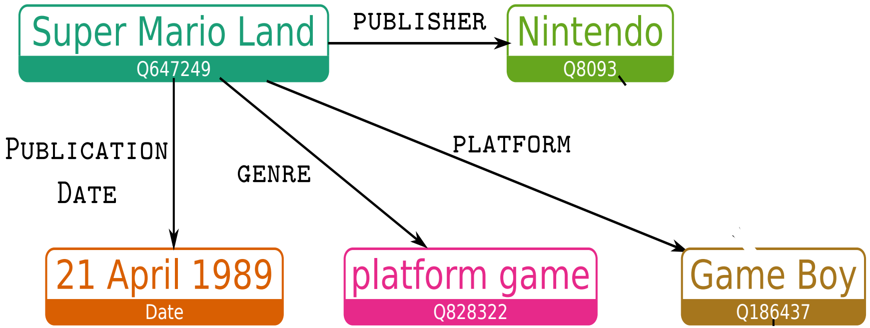
KGLM [Logan et al., ACL 2019]

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]

Super Mario Land is a game developed by Nintendo.

New entity — Not an entity — Related entity

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 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]

Super Mario Land is a game developed by Nintendo.

$\underbrace{\text{is a game developed by}}_{\text{Not an entity}}$

New entity

Not an entity

Related entity

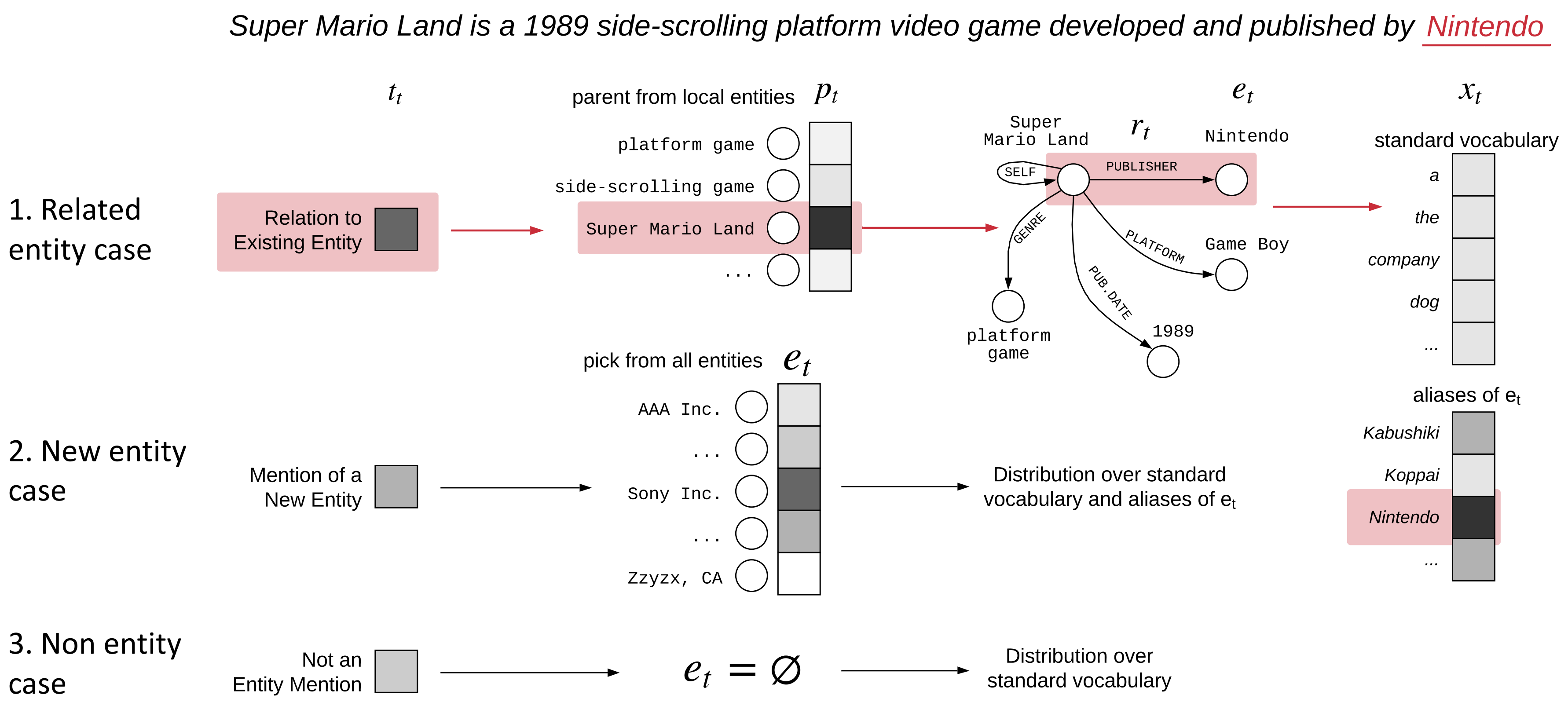
2. New entity case (not in the local KG)

- 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]



KGLM [Logan et al., ACL 2019]

- Outperforms GPT-2 and AWD-LSTM[1] 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

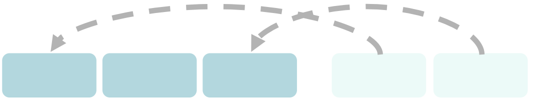
Barack Obama was born on __________.

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!

[1] Merity et al., ICLR 2018

Techniques to add knowledge to LMs



Add pretrained entity embeddings

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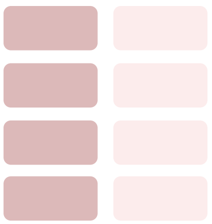

Use an external memory

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Modify the training data

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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]

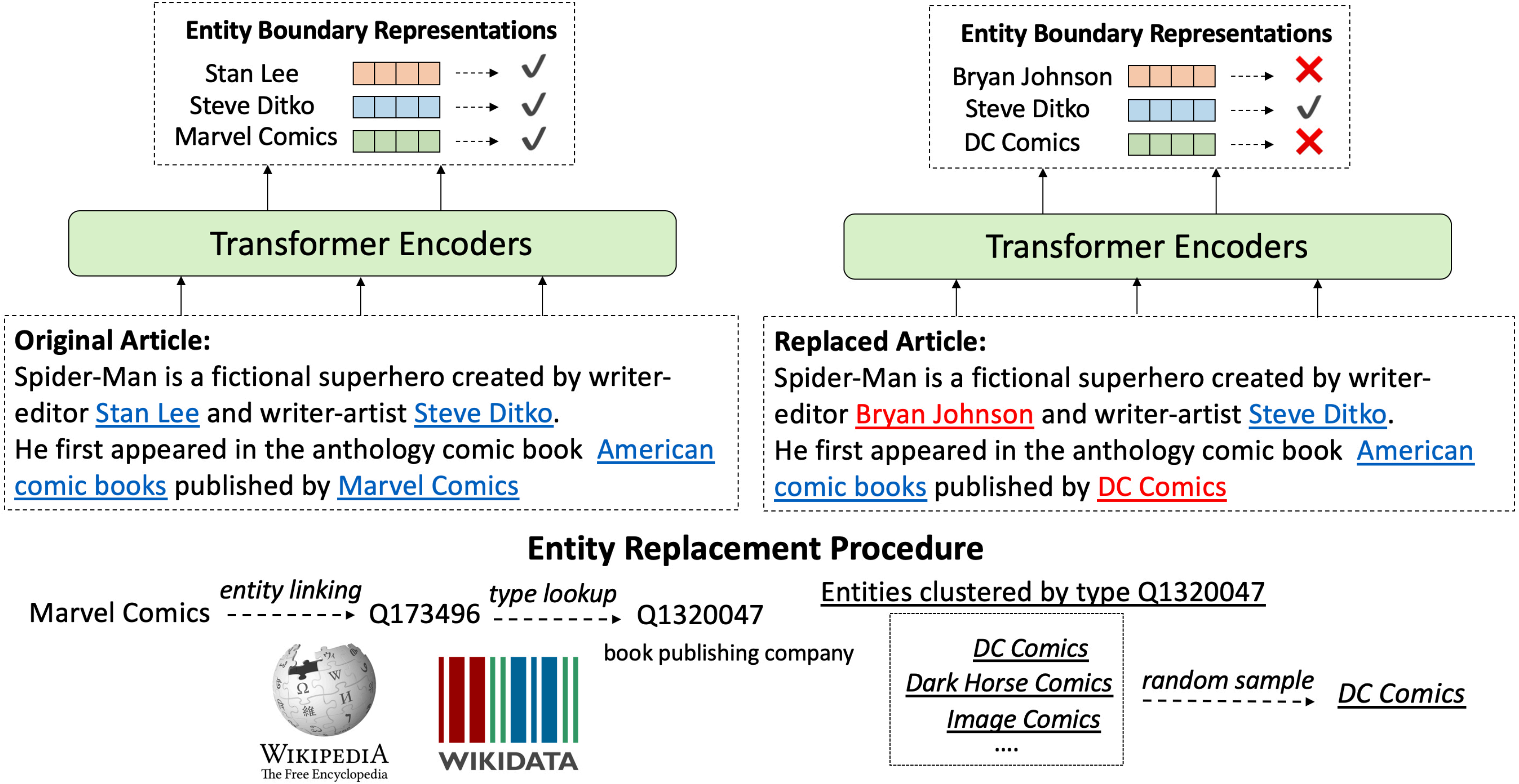
- Key idea: train the model to distinguish between true and false knowledge
- Method: Replace mentions in the text with mentions that refer to different entities of the same type to create negative knowledge statements
  - Make the model predicts whether entity has been replaced or not
  - Need type-constraint 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

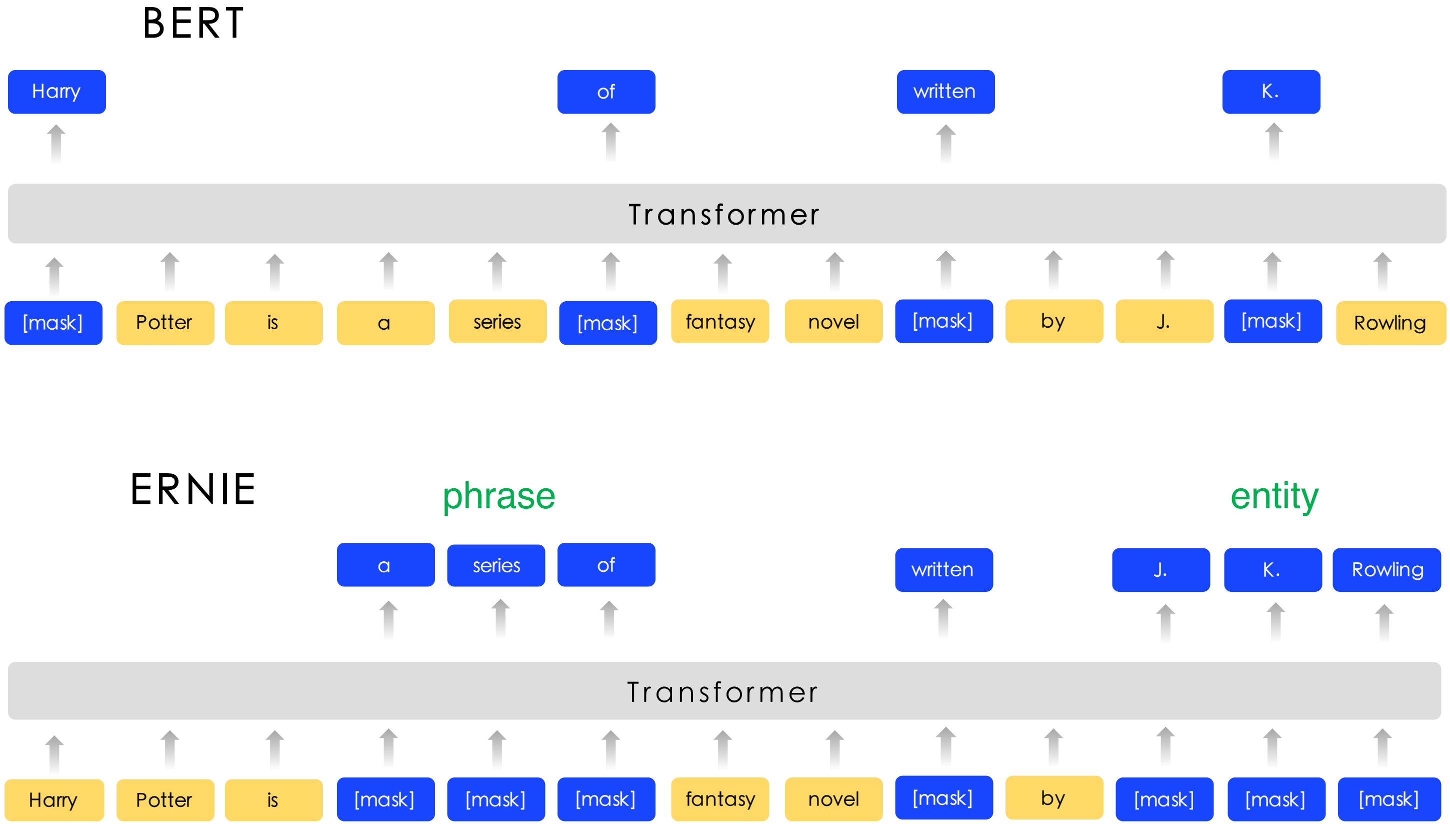
  - How Much Knowledge Can You Pack Into the Parameters of a Language Model?, Roberts et al., EMNLP 2020
    - Uses "salient span masking" (Guu et al., ICML 2020) to mask out salient spans (i.e. named entities and dates)
    - Shows that salient span masking improves T5's performance on QA tasks

[1] Yes, another ERNIE paper!

ERNIE[1]: Enhanced Representation through Knowledge Integration

[Sun et al., arXiv 2019]

[1] Yes, another ERNIE paper!



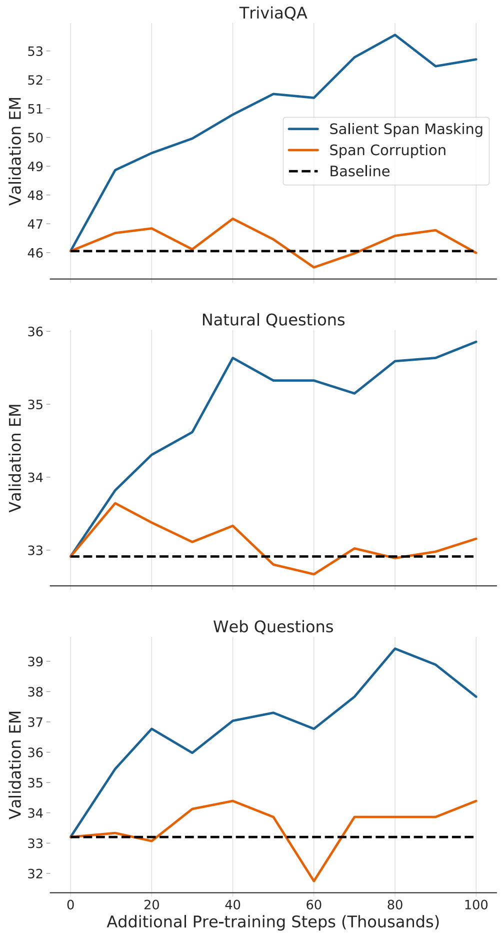
Salient span masking

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

Recap: Techniques to add knowledge to LMs

1. Use pretrained entity embeddings
   - Convenient to apply to existing architectures: just plug in entity features
   - Indirect handle of knowledge (e.g. embedding space instead of direct copy)

2. Add an external memory
   - Can support some updating of factual knowledge and easier to interpret
   - Tend to require more complex implementation and more memory

3. Modify the training data
   - Requires no model architecture changes, no additional computation/memory.
   - Still open question if this is always as effective as model changes

- It is also an active area of research to combine and get the best of those techniques!

Section 3:
Evaluating knowledge in LMs

- Probes
- Downstream tasks

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.

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
```

[1] Example courtesy of the authors at link above.

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., <u>Pope Clement VII</u> has the position of <u>pope</u>)
  - 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

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[1] 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

[1] One mining approach uses dependency parsing to build the template!

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

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

Recap: Evaluating knowledge in LMs

- 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 & what's next?

- Retrieval-augmented language models [More details in Kelvin Guu's lecture!]
  - REALM, Guu et al., ICML 2020
  - RAG, Lewis et al., NeurIPS 2020
  - Retro, Borgeaud et al., 2022
- Modifying knowledge in language models [More details in Eric Mitchell's lecture!]
  - 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

Good luck with your projects!