recherche appliquée en linguistique informatique

Université de Montréal

Neuro-Symbolic Representations for IR

Part 2.3
Infusion of Symbolic Knowledge into Text Representation

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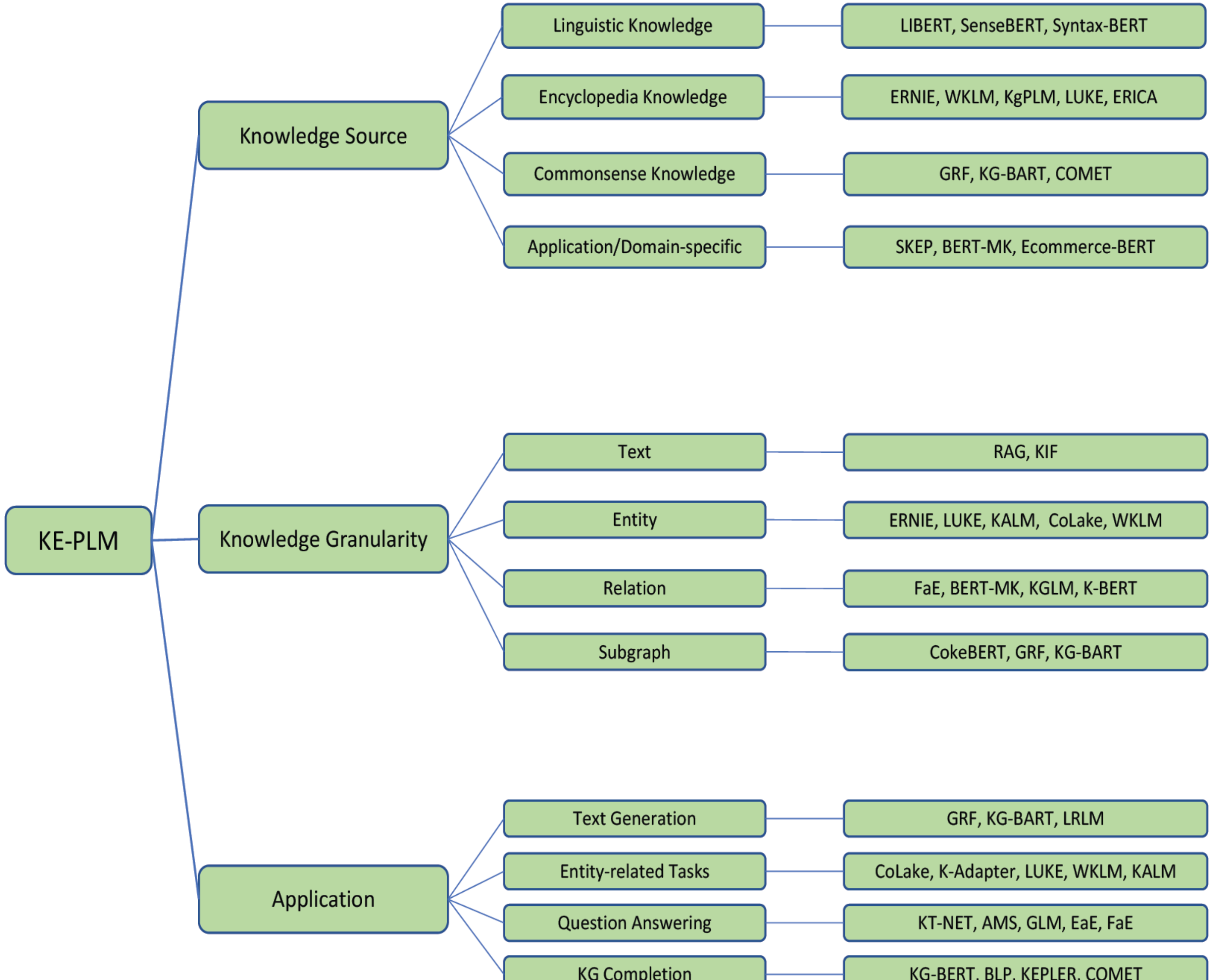
Outline

1. Part 1: Knowledge Graphs and Entities
   1. Welcome & Motivation (Dietz)
   2. Knowledge Graphs and GPT (Bast)
   3. Entity Linking (Bast)
2. Part 2: Neuro-Symbolic Foundations
   1. Ranking Wikipedia Entities / Aspects (Chatterjee)
   2. Neural Text Representations and Semantic Annotations (Dietz)
   3. Infusion of Symbolic Knowledge into Text Representation (Nie) ← We are here
3. Part 3: Reasoning, Robustness, and Relevance
   1. Denoising Dense Representations with Symbols (Nogueira)
   2. Reasoning about Relevance (Dalton)
   3. From PRF to Retrieval Enhanced Generation (Dietz)
4. Part 4: Emerging Topics
   1. Conclusion and Outlook
   2. Panel Discussion

Motivation to infuse knowledge into LM

- Texts contain much world knowledge useful for applications
- But can be limited
  - A piece of knowledge may be infrequent in text
  - Much of our common knowledge is not stated in texts
    - E.g. A father is a male person
- Much of the knowledge implicitly captured by LM may be noise
  - True knowledge vs spurious knowledge is hard to distinguish
- Knowledge graph: Another form of structured knowledge often crafted by experts
  - From expert’s domain knowledge
  - Synthetic knowledge
- Goal: Build better representations of texts for end tasks
  - Enhance true knowledge (conformity)
  - Extend the representation by what the knowledge implies

A taxonomy of knowledge-enhanced LM



Credit: Wei et al. Knowledge Enhanced Pretrained Language Models: A Compreshensive Survey, 2021

Text and knowledge graph: How to integrate?

- Naive approaches
  - Text → representation
  - Knowledge graph → representation
  - E.g. Jeong et al. A Context-Aware Citation Recommendation Model with BERT and Graph Convolutional Networks. arXiv:1903.06464 (2019)

Fusion (concatenation) of representations

- More sophisticated approaches
  1. Interactions between text and knowledge graph representations
  2. Joint objective: LM + knowledge graph objectives
  3. Enriching raw text with knowledge

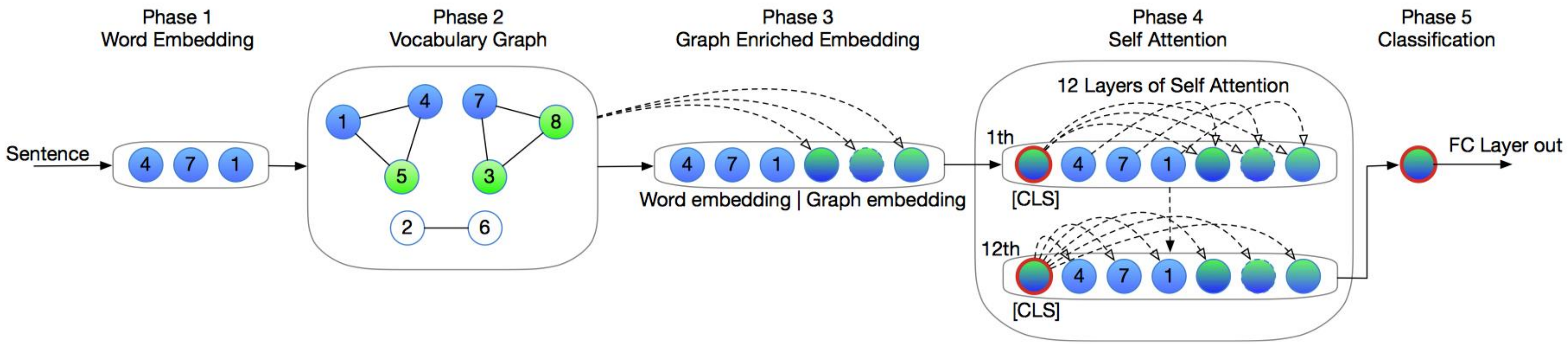
1. Interactions between text and graph representations

- Early work based on word embedding
  - Knowledge (relations/triples) as constraint to build word embeddings
    - Retrofitting (Faruqui et al. 2015): modify word embeddings to make embeddings of related words closer
    - Relation as part of the loss (Yu and Dredze, 2015)
    - Application to medical IR (Liu, Nie and Sordoni, 2016)
- More recent work
  - BERT representation of text
  - Graph representation

Interact to create richer representations

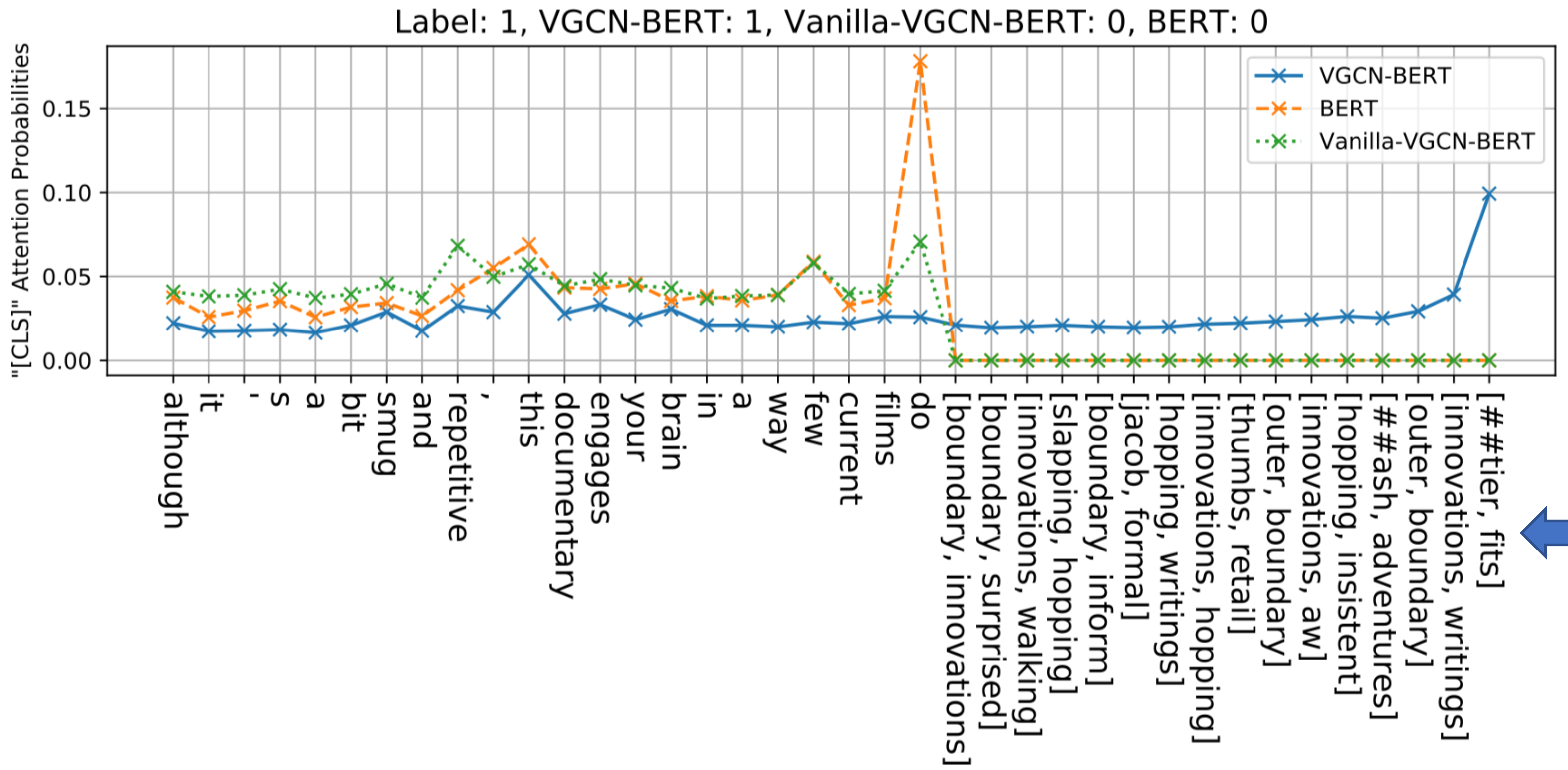
VGCN-BERT: Combining GCN and BERT (Lu et al. ECIR 2020)

- BERT encodes local information from a text
- Knowledge graph: global information encoded by GCN on vocabulary graph
- Attention mechanism on joint representations



Visualization for sentiment classification

- ❖ "Although it's a bit smug and repetitive, this documentary engages your brain a way few current films do. " (movie review SST-2)
  - Negative by BERT
- ❖ "a way few current films do" in general language -> "innovation" positive



Meaning of graph embedding dimensions

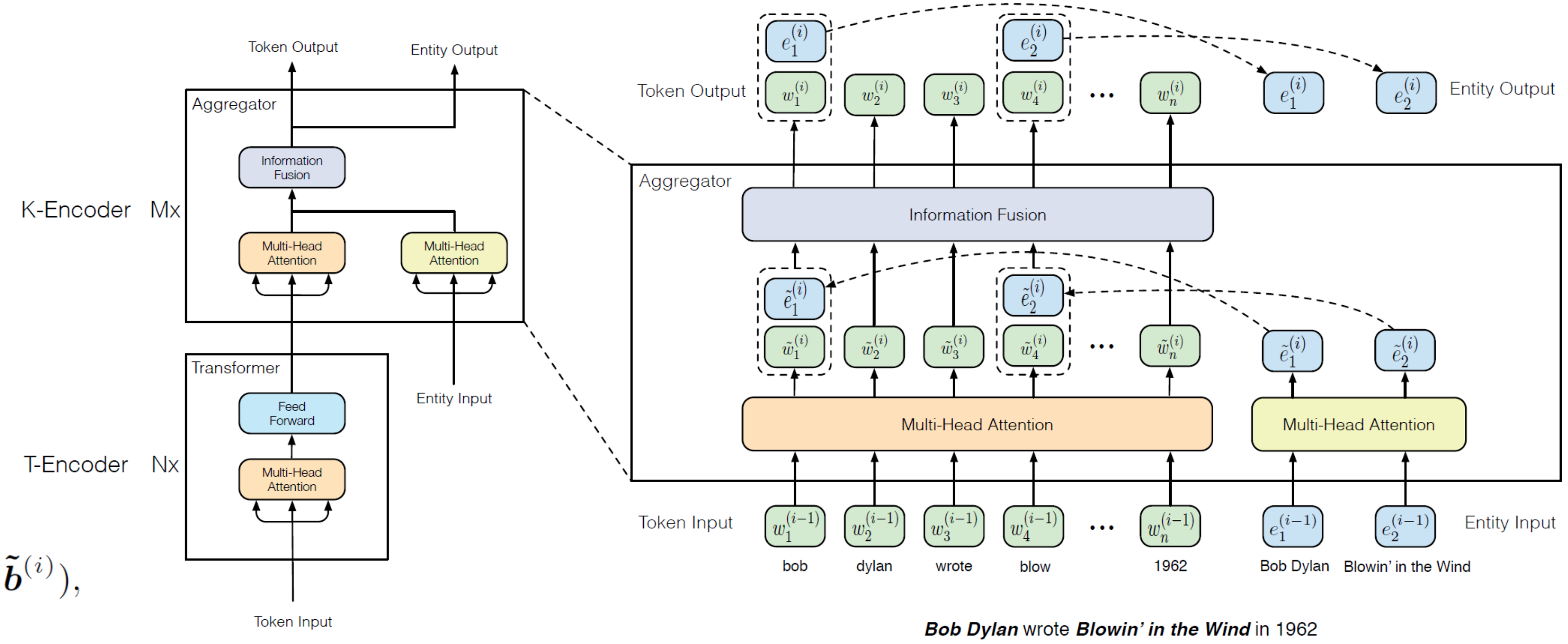
Importing entity embedding into text

- Knowledge graph embedding:
  - Incorporating information of neighbor nodes
- Text embedding:
  - Incorporate information from context words
- Inject entity embedding of graph into text
- ERNIE (Zhang et al. 2019)
  - Linking entities in text to entity nodes in graph
  - Aggregate entity embedding with token embedding

ERNIE

- Text embedding
- Entity embedding
  - TransE (minimize $|e_h + e_r - e_t|$)
- Aggregation:

$$\boldsymbol{h}_j = \sigma(\tilde{\boldsymbol{W}}_t^{(i)}\tilde{\boldsymbol{w}}_j^{(i)} + \tilde{\boldsymbol{W}}_e^{(i)}\tilde{\boldsymbol{e}}_k^{(i)} + \tilde{\boldsymbol{b}}^{(i)}),$$
$$\boldsymbol{w}_j^{(i)} = \sigma(\boldsymbol{W}_t^{(i)}\boldsymbol{h}_j + \boldsymbol{b}_t^{(i)}),$$
$$\boldsymbol{e}_k^{(i)} = \sigma(\boldsymbol{W}_e^{(i)}\boldsymbol{h}_j + \boldsymbol{b}_e^{(i)}).$$



(a) Model Achitecture

(b) Aggregator

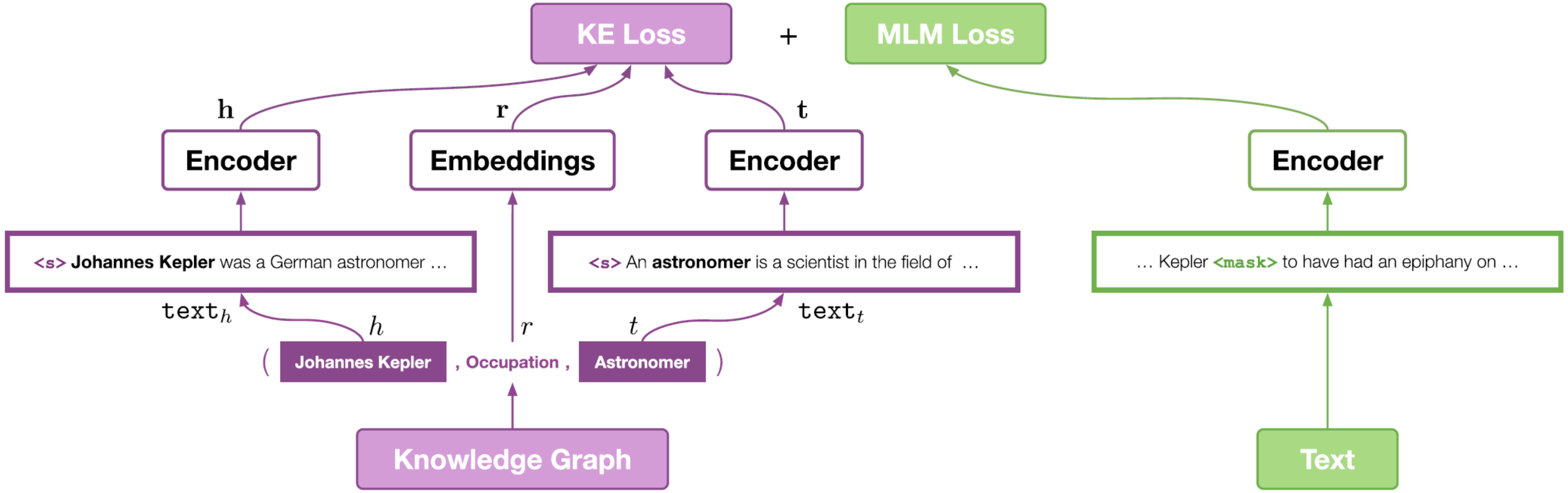
2. Knowledge infusion by multi-task learning

- Language modeling objective
  - Masked Language Modeling: predict the masked token
  - Auto regressive: predict the next token
- Knowledge objective
  - Related entity: head + relation → tail (e.g. TransE)
  - Relation between entities (Relation classification)
  - Linguistic knowledge: dependency
  - Sense: predict the super sense of a token (SenseBERT)
- Combine multiple objectives in multi-task learning

KEPLER: joint training of MLM and TransE

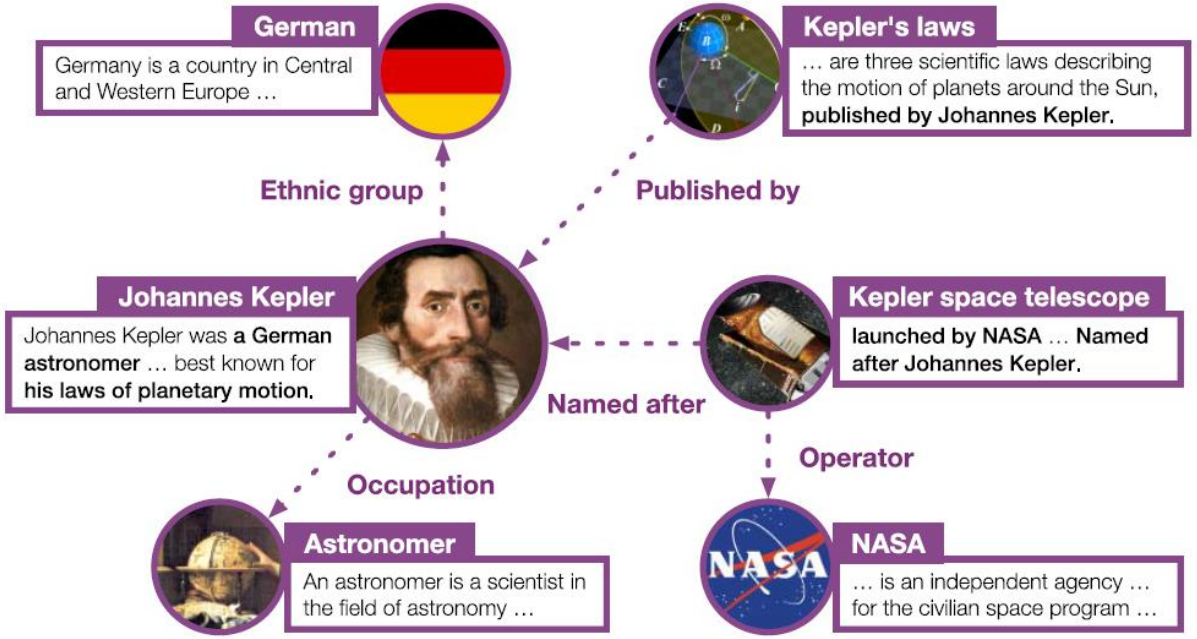
(Wang et al., KEPLER, Trans. ACL, 2021)

- Optimize a joint objective of text encoding (MLM) and graph encoding (TransE): $\mathcal{L} = \mathcal{L}_{\mathrm{KE}} + \mathcal{L}_{\mathrm{MLM}},$
- Architecture of KEPLER



KEPLER

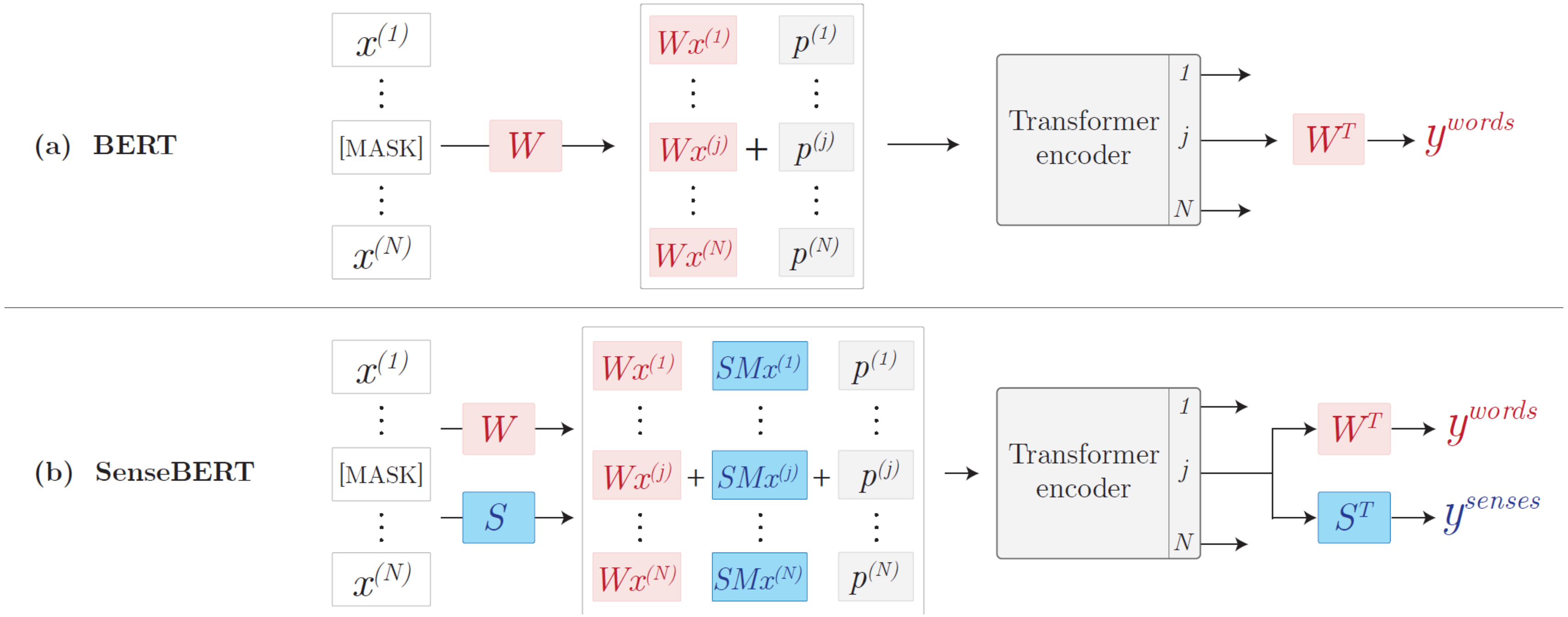
- Use description of entities and relations to create better embedding for entities and relations



SenseBERT: LM + sense

- Sense = higher synset in WordNet
- LM objective + Sense prediction objective

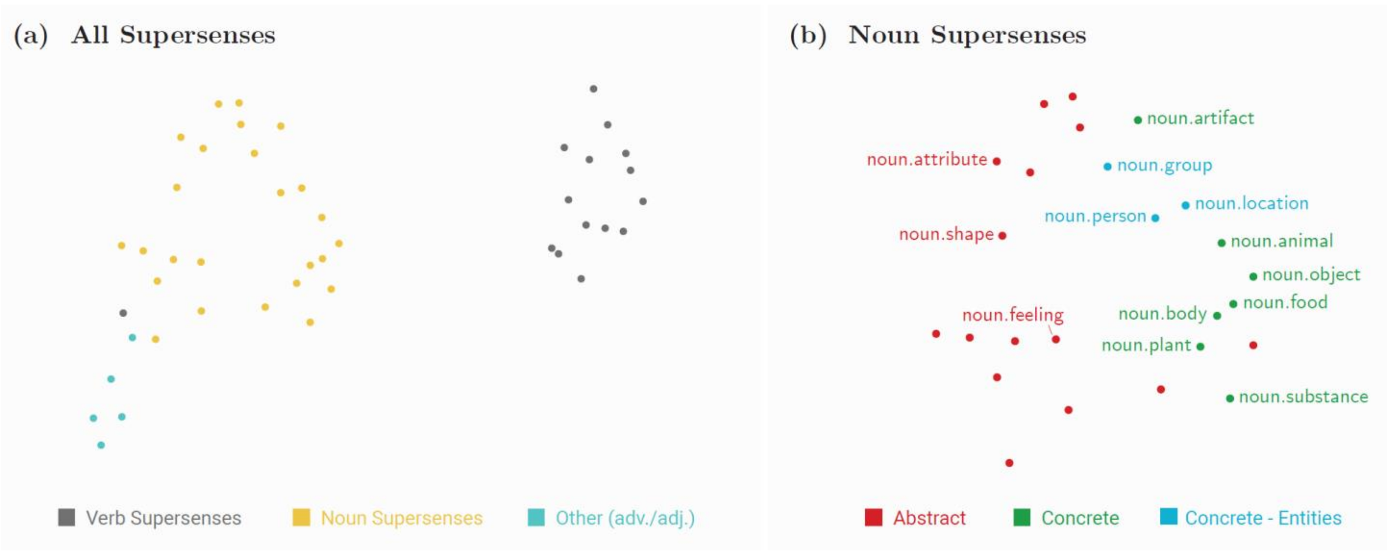
1. "This **bass** is delicious"
   (supersenses: noun.food, noun.artifact, *etc.*)
2. "This **chocolate** is delicious"
   (supersenses: noun.food, noun.attribute, *etc.*)
3. "This **pickle** is delicious"
   (supersenses: noun.food, noun.state, *etc.*)



Credit: Levine et al. SenseBERT, ACL 2020

Effect of SenseBERT

- The model has a better capability to project tokens of the same super-sense closer

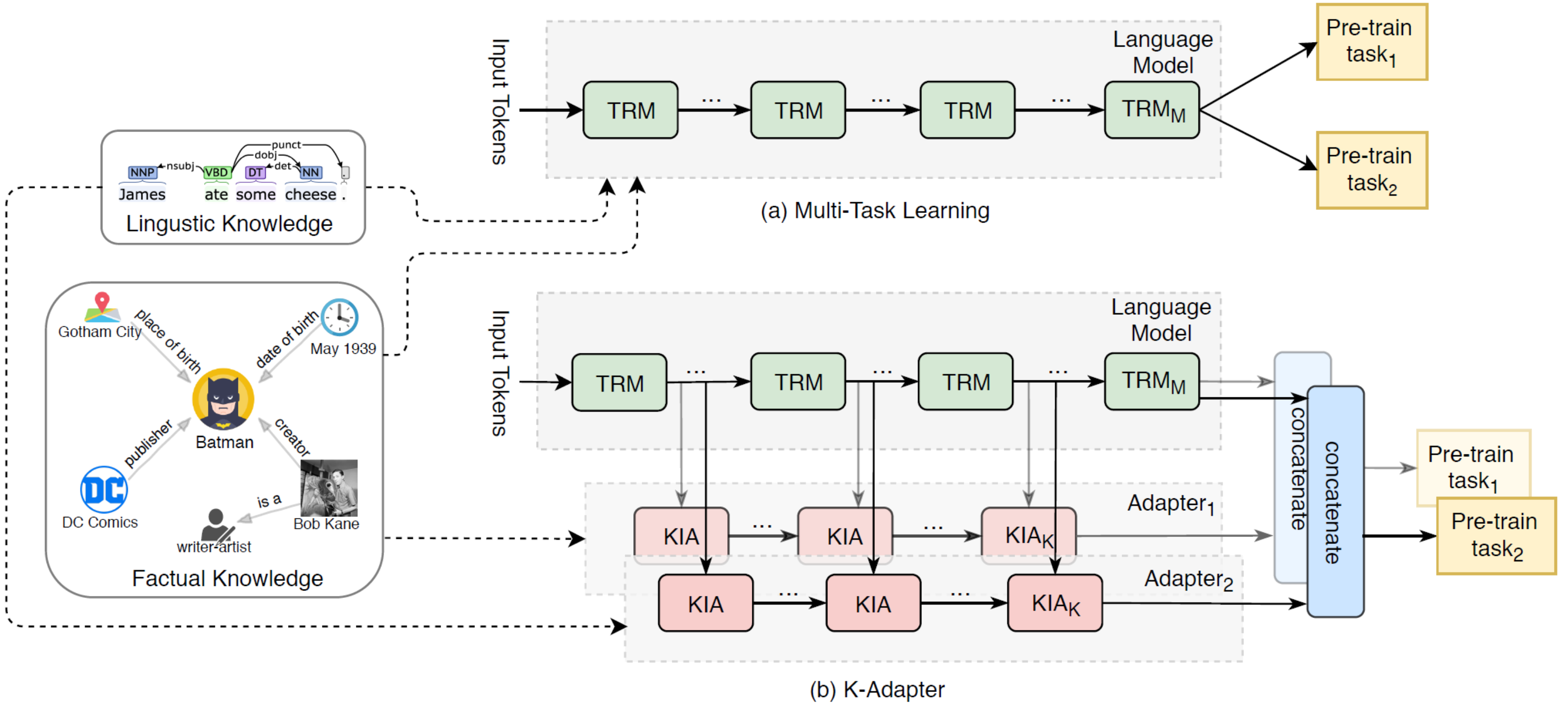


		BERT	SenseBERT
(a) SemEval-SS	The team used a **battery** of the newly developed "gene probes"	*noun.artifact*	*noun.group*
	Ten shirt-sleeved ringers stand in a circle, one **foot** ahead of the other in a prize-fighter's stance	*noun.quantity*	*noun.body*

	Sent. A:	Sent. B:	BERT	SenseBERT
(b) WiC	The **kick** must be synchronized with the arm movements.	A sidecar is a smooth drink but it has a powerful **kick**.	*Same*	*Different*
	Plant bugs in the dissident's apartment.	**Plant** a spy in Moscow.	*Different*	*Same*

K-ADAPTER: adding an adapter aside

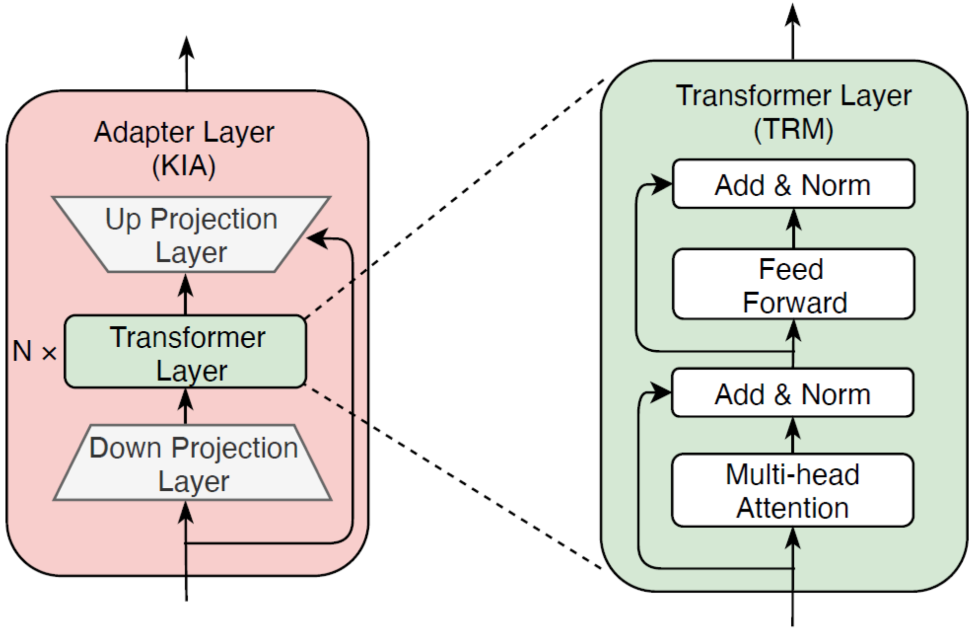
- Idea:
  - Injecting knowledge into a language model may lead to catastrophic forgetting
  - Using adapter instead
- Adapter: a small model that complements a large LM
- Concatenate the outputs of transformer and adapter



Credit: Wang et al. K-ADAPTER, ACL-IJCNLP 2021

K-ADAPTER

- Adapter Architecture
  - Several layers of transformer
  - + projections



K-ADAPTER: Some results

Model	OpenEntity			FIGER		
	P	R	Mi-F_1	Acc	Ma-F_1	Mi-F_1
NFGEC (Shimaoka et al., 2016)	68.80	53.30	60.10	55.60	75.15	71.73
BERT-base (Zhang et al., 2019)	76.37	70.96	73.56	52.04	75.16	71.63
ERNIE (Zhang et al., 2019)	78.42	72.90	75.56	57.19	75.61	73.39
KnowBERT (Peters et al., 2019)	78.60	73.70	76.10	-	-	-
KEPLER (Wang et al., 2021)	77.20	74.20	75.70	-	-	-
WKLM (Xiong et al., 2020)	-	-	-	60.21	81.99	77.00
RoBERTa	77.55	74.95	76.23	56.31	82.43	77.83
RoBERTa + multitask	77.96	76.00	76.97	59.86	84.45	78.84
K-ADAPTER (w/o knowledge)	74.47	74.91	76.17	56.93	82.56	77.90
K-ADAPTER (F)	79.30	75.84	77.53	59.50	84.52	80.42
K-ADAPTER (L)	80.01	74.00	76.89	61.10	83.61	79.18
K-ADAPTER (F+L)	78.99	76.27	**77.61**	61.81	84.87	**80.54**

Table 2: Results on two entity typing datasets OpenEntity and FIGER.

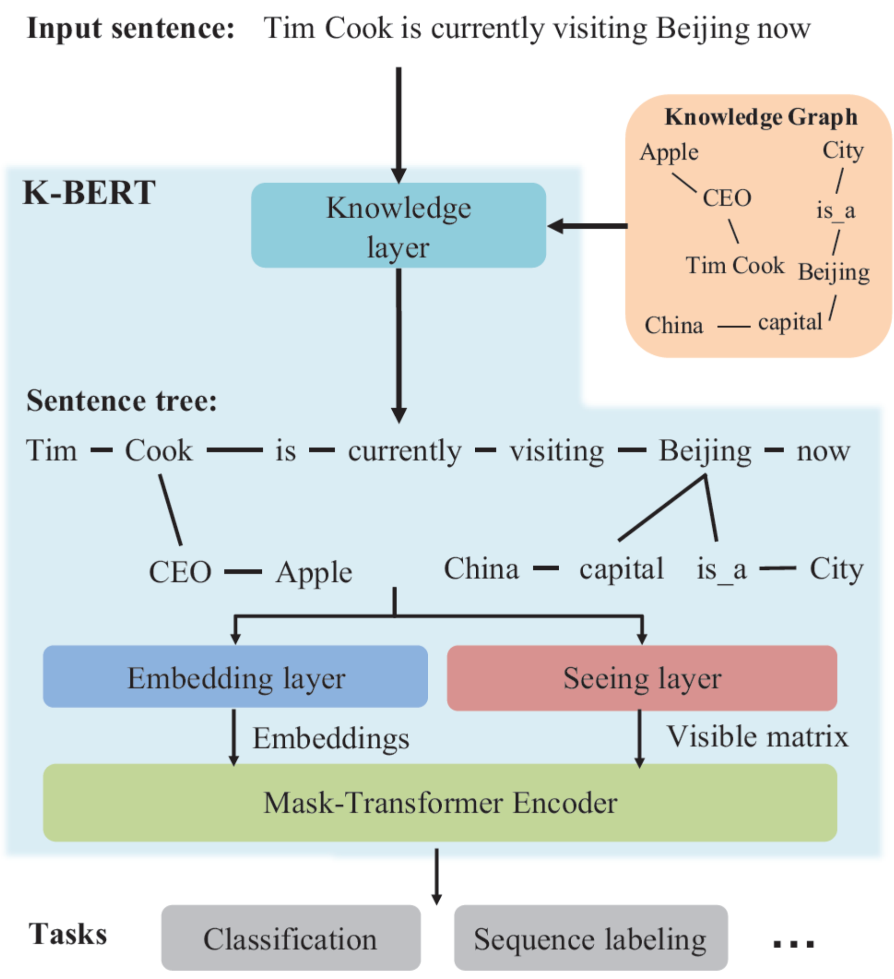
Model	SearchQA		Quasar-T		CosmosQA
	EM	F_1	EM	F_1	Accuracy
BiDAF (Seo et al., 2017)	28.60	34.60	25.90	28.50	-
AQA (Buck et al., 2018)	40.50	47.40	-	-	-
R^3 (Wang et al., 2018a)	49.00	55.30	35.30	41.70	-
DSQA (Lin et al., 2018)	49.00	55.30	42.30	49.30	-
Evidence Agg. (Wang et al., 2018b)	57.00	63.20	42.30	49.60	-
BERT (Xiong et al., 2020)	57.10	61.90	40.40	46.10	-
WKLM (Xiong et al., 2020)	58.70	63.30	43.70	49.90	-
WKLM + Ranking (Xiong et al., 2020)	61.70	66.70	45.80	52.20	-
BERT-FT$_{RACE+SWAG}$ (Huang et al., 2019)	-	-	-	-	68.70
RoBERTa	59.01	65.62	40.83	48.84	80.59
RoBERTa + multitask	59.92	66.67	44.62	51.17	81.19
K-ADAPTER (F)	61.85	67.17	46.20	52.86	80.93
K-ADAPTER (L)	61.15	66.82	45.66	52.39	80.76
K-ADAPTER (F+L)	**61.96**	**67.31**	**46.32**	**53.00**	**81.83**

Table 3: Results on question answering datasets including: CosmosQA, SearchQA and Quasar-T.

3. Enriching raw text by knowledge (K-BERT)

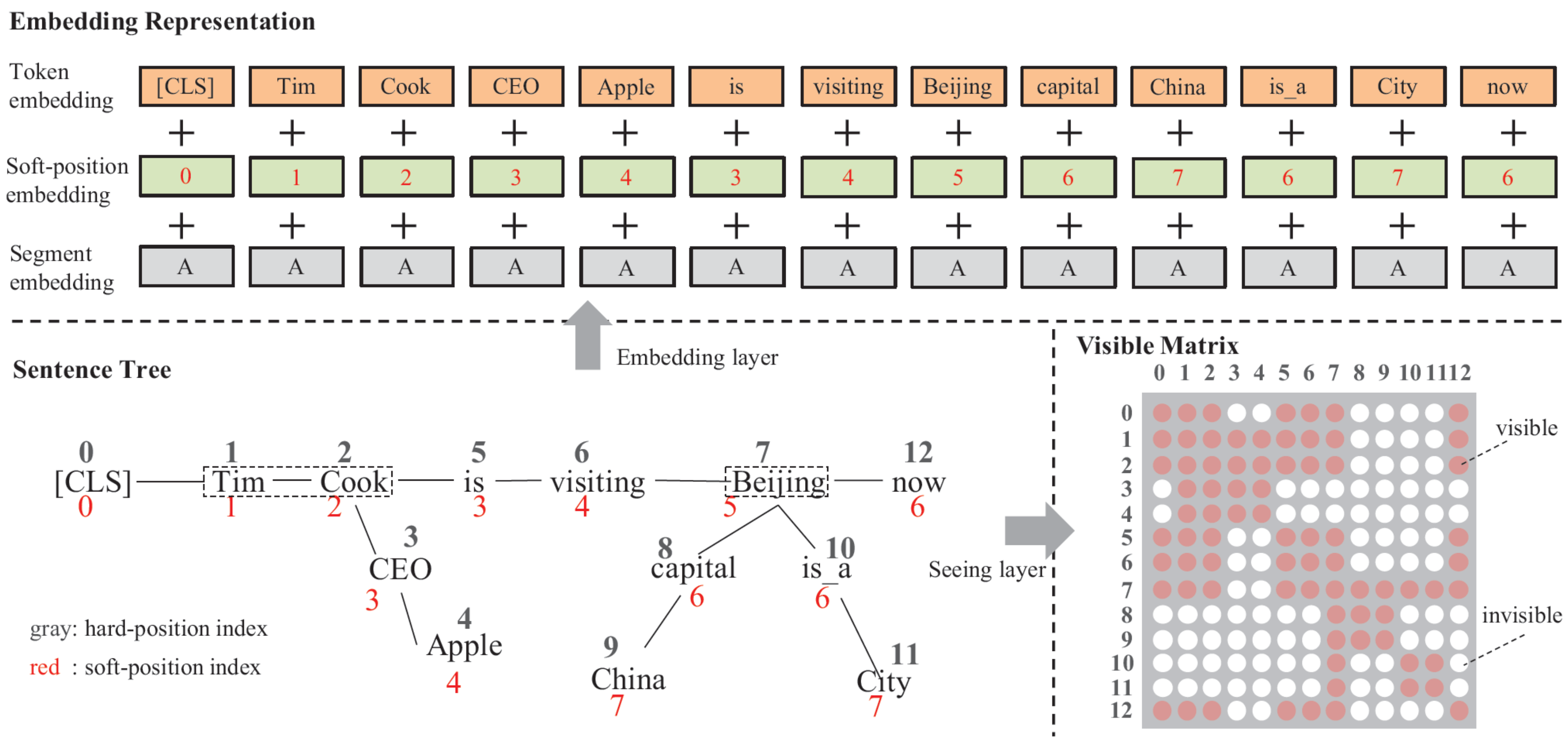
- Input text → mapping to entities of KG
- Infusion: Add links to these tokens
- Visible matrix: what tokens can be seen – a way to define paths
- Embedding training: masking as in BERT

➔ a way to exploit BERT training



Credit: Liu et al. K-BERT: Enabling Language Representation with Knowledge Graph, AAAI 2020

K-BERT: Infusing triples into text



Relevance of knowledge:
What pieces of knowledge to use?

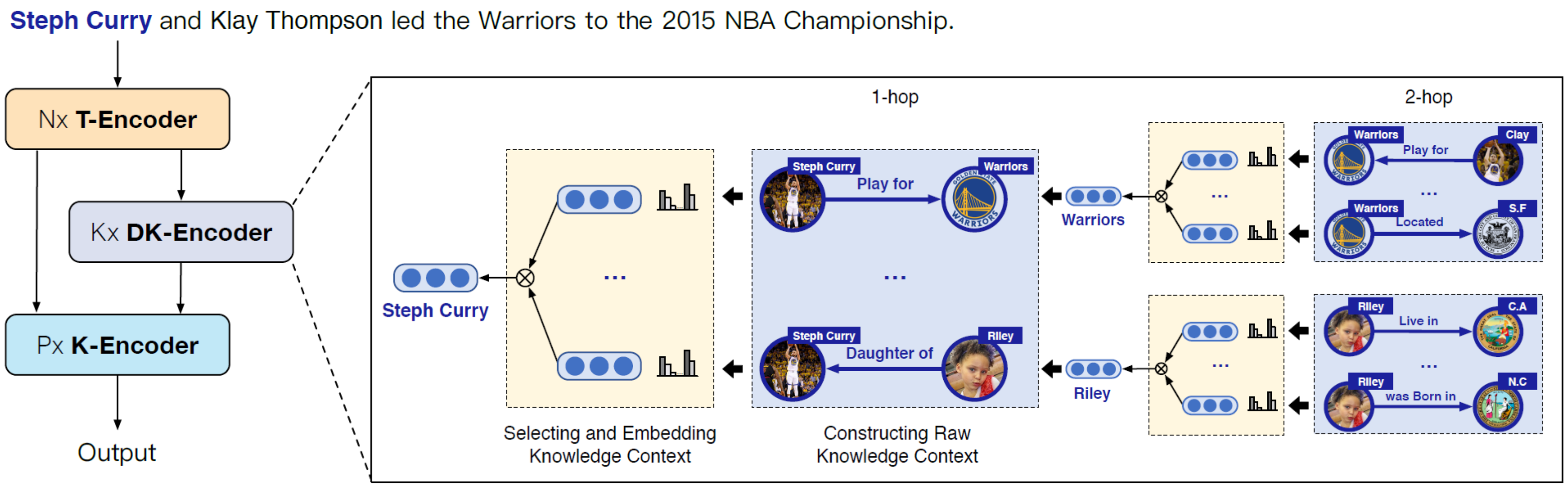
- Usually rely on entity linking: entities in text → related triples/1-hop subgraph
- Knowledge selection is key
  - A wrong piece of knowledge will lead to wrong inference direction
  - A useless (irrelevant) piece of knowledge will add noise
- E.g. Obama visited Japan and met with the Primary minister.

  Obama – function → president of US √

  Obama – spouse → Michele X
- Knowledge selection by attention/relevance

Coke-BERT: Selecting sub-graph with context (Su et al. 2020)

- Text encoding: Using BERT to encode input text
- Knowledge selection: Attention of text context to neighbors of entity
  - Neighbor entities are aggregated according to their attention weights
- Fusion: concatenate text embedding and knowledge embedding as in ERNIE



Selecting knowledge according to usefulness (Zhu, Nie et al. SIGIR 2021)

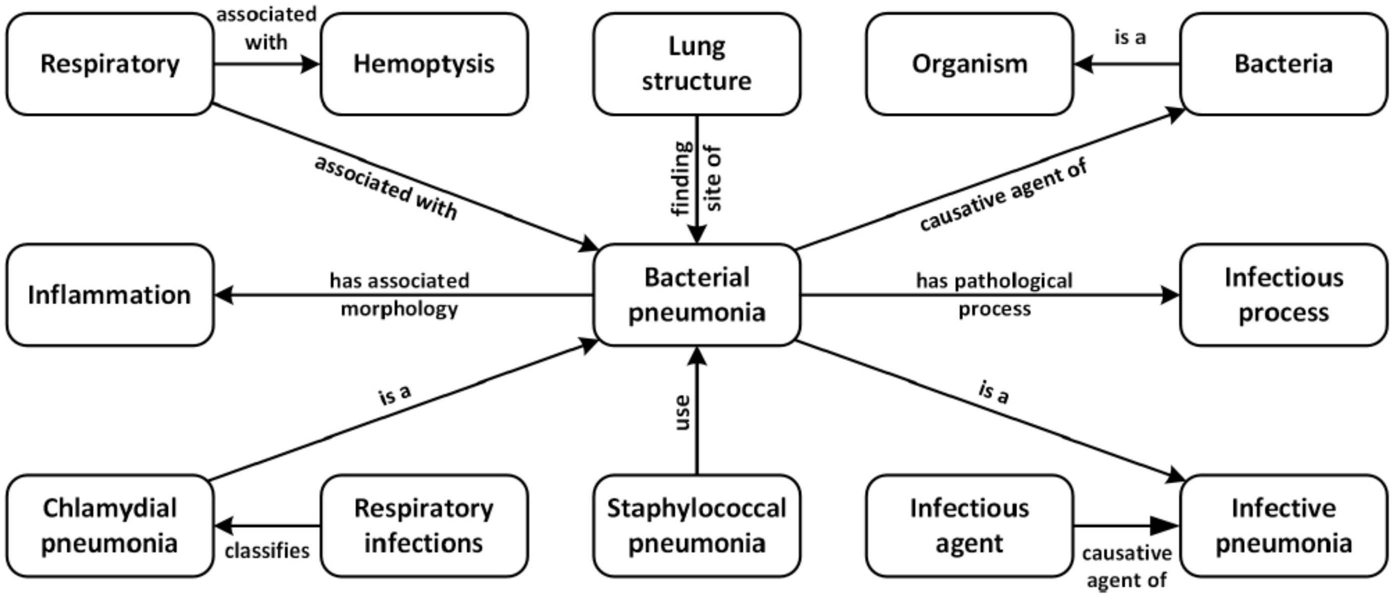
- Given a context (in dialogue), should a piece of knowledge (triple) be used?
- Attention ~ similarity (implicit in end-to-end training)

➔ More explicit learning of usefulness/relevance of a piece of knowledge
➔ Use a piece of knowledge only when it fits the context – useful for the task

- Problem: No annotated data about usefulness/relevance of knowledge
- Pseudo labeling:
  - Raw training data = (context, response)
  - Testing if a triple is useful to connect context to response? → usefulness label
  - Extended training data = (context, response, knowledge)
- Train an explicit knowledge selection network using extended training data
  - Better than implicit selection by attention

Application in medical domain: a special case

- Medical domain is rich of expert knowledge
- Much of such knowledge cannot be extracted from texts



Applications in medical domain

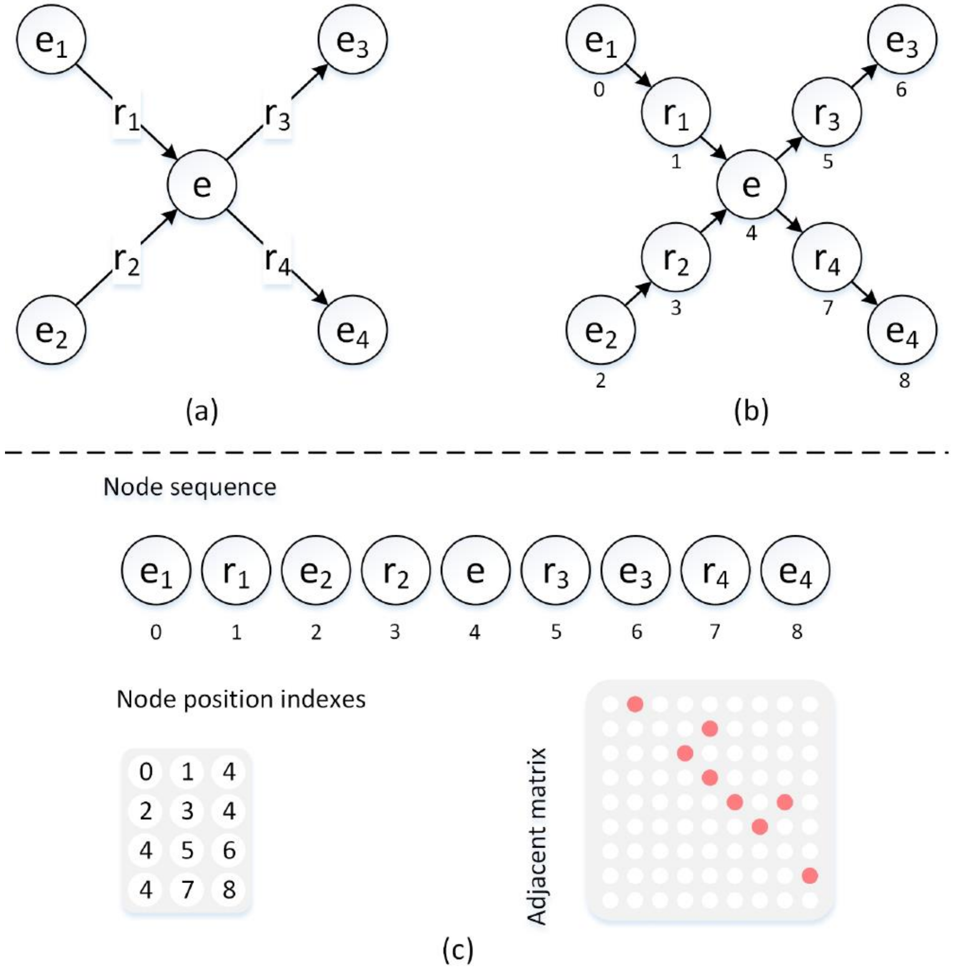
- Rich medical domain knowledge
  - The International Classification of Diseases (ICD)
  - Medical Subject Headings (MeSH)
  - The Systematized Nomenclature of Medicine-Clinical Terms (SNOMED-CT)
  - The Unified Medical Language System (UMLS)
  - …
- Tasks
  - Semantic Annotation of Medical Texts
    - Entities/concepts in the document
    - Relationships (implicit or explicit) between entities
    - Relationship between an entity and a document
  - Medical IR

Applications to medical IR

- Main approaches: query expansion using knowledge graph
  - Add related terms/concepts into query
- Neural representations
  - Specifically trained medical LM: BioBERT, ClinicalBERT
  - Doc2vec: creating an embedding for a medical text
  - Extending word embedding by medical knowledge
    - Liu et al. 2016: Adjusting word embedding to fit medical knowledge, improced medical IR
- Some limited approaches to infuse medical knowledge

BERT-MK: Applying medical knowledge graph

- Extract subgraph from entities in a text (1-hop)
- Converting the subgraph to sequence (special position index)
- BERT encoding



Credit: He et al. BERT-MK: Integrating Graph Contextualized Knowledge into Pre-trained Language Models, EMNLP 2020

BERT-MK: training process

- Train knowledge subgraph encoding to restore the relations

$$\mathcal{L} = \sum_{\mathbf{t}\in\mathbf{T}} \mathtt{max}\{d(\mathbf{t}) - d(f(\mathbf{t})) + \gamma, 0\}$$

- Maximize the distance between *d*(t) – TransE distance of a valid triple

  and *f*(t) – TransE distance of an invalid triple (tail entity replaced)

- Integration with LM: Similar to ERNIE – concatenating text embedding and graph embedding of entities

BERT-MK: experiments

- Knowledge graph: subset of UMLS

Table 1: Statistics of UMLS.

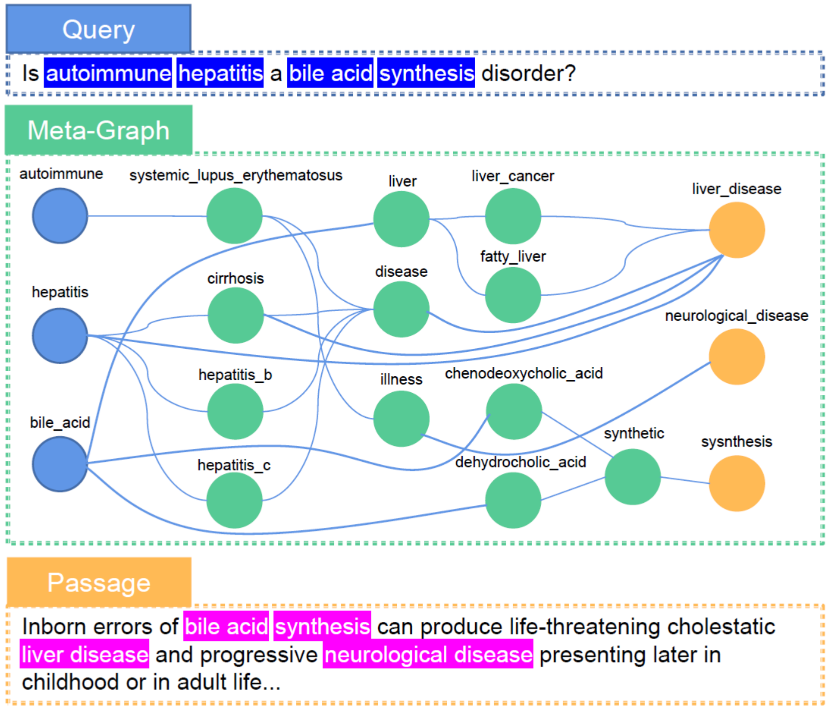
# Entities	**# Relations**	**# Triples**
2,842,735	874	13,555,037
In-degree	**Out-degree**	**Median degree**
5.05	5.05	4

- Results on entity typing and relation classification

Task	**Dataset**	**Metrics**	**E-SVM**	**CNN-M**	**BERT-Base**	**BioBERT**	**SCIBERT**	**BERT-MK**
Entity Typing	2010 i2b2/VA	Acc	-	-	96.76	97.43	**97.74**	97.70
	JNLPBA	Acc	-	-	94.12	94.37	**94.60**	94.55
	BC5CDR	Acc	-	-	98.78	99.27	99.38	**99.54**
Relation Classification	2010 i2b2/VA	P	-	73.1	72.6	76.1	74.8	**77.6**
		R	-	66.7	65.7	71.3	71.6	**72.0**
		F	-	69.7	69.2	73.6	73.1	**74.7**
	GAD	P	79.21	-	74.28	76.43	77.47	**81.67**
		R	89.25	-	85.11	87.65	85.94	**92.79**
		F	83.93	-	79.33	81.66	81.45	**86.87**
	EU-ADR	P	-	-	75.45	81.05	78.42	**84.43**
		R	-	-	**96.55**	93.90	90.09	91.17
		F	-	-	84.71	87.00	85.51	**87.49**

KERM (Dong et al. SIGIR 2022)

- Selecting meta-graph that connects query entities to document entities



KERM

- Knowledge aggregation

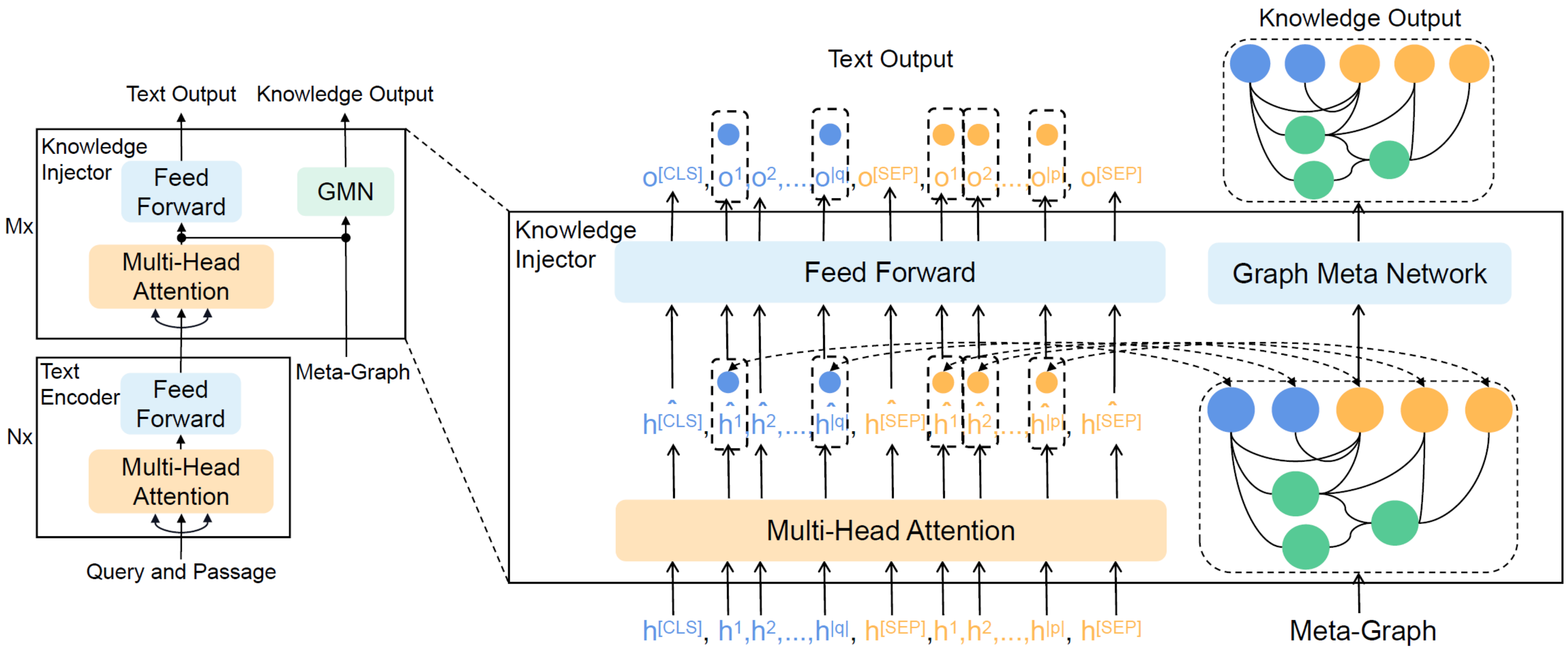


Figure 4: The architecture of KERM.

KERM on medical IR

- Subset of MS MARCO and OHSUMED

	MARCO Dev Queries		Ohsumed Queries	
	General	Bio-Medical		
	MRR@10	MRR@10	MRR@10	MAP@10
BM25	19.2	16.4	69.6	9.5
ERNIE	38.5	30.5	79.7	10.1
KERM	39.7	32.1	81.2	11.0

Remaining questions

- Improvements mainly on entity and relation classification, also on IR
- More experimental evidence of knowledge infusion for IR to be made
- Main observations:
  - Knowledge infusion can improve text representation for tasks requiring knowledge
  - No standard way yet for knowledge infusion
- Key question: What knowledge to use
  - Relying on entity linking
  - Related entities/triples/subgraph?
  - Relatedness by Attention / usefulness?

Slides available at

https://github.com/laura-dietz/neurosymbolic-representations-for-IR/