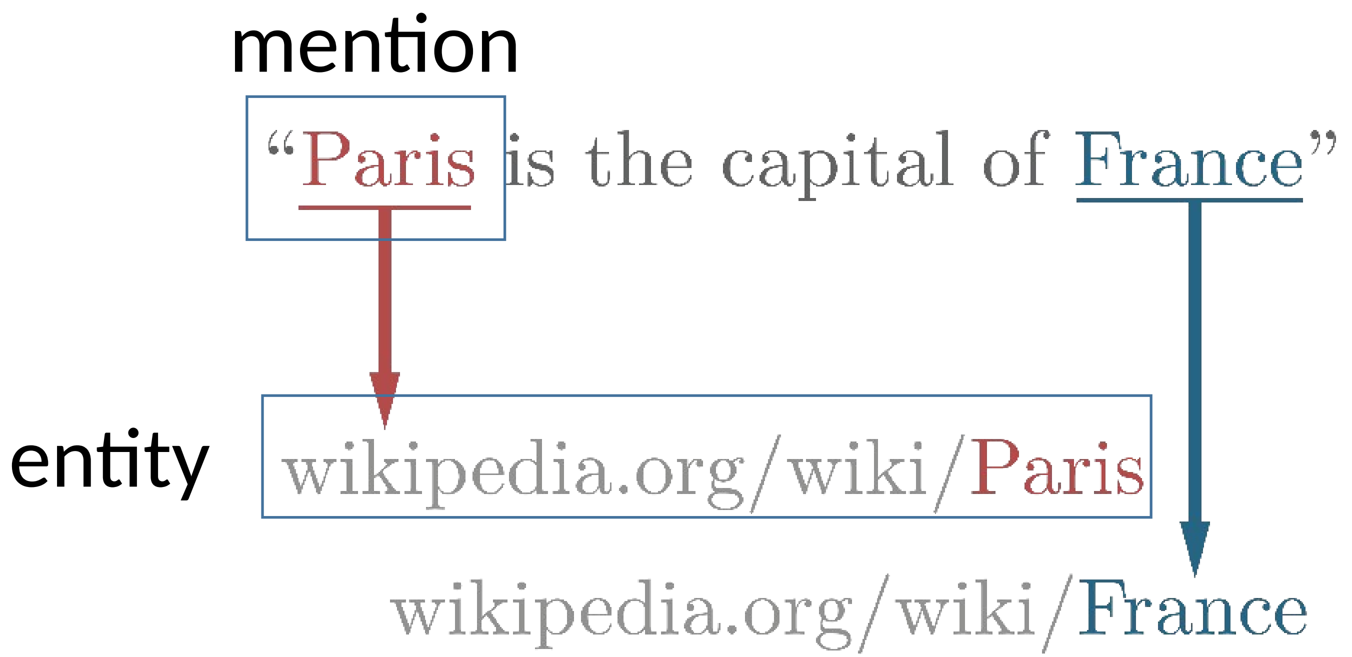
Entity Linking

Entity linking

- Assign a unique identity to entities mentioned in the text
  - Knowledge graph
  - Ontology
  - Dictionary
- Aka
  - named-entity disambiguation
  - named-entity normalization
  - Concept Recognition



Related tasks

- Co-reference resolution
  - understands whether multiple words in a text refer to the same entity

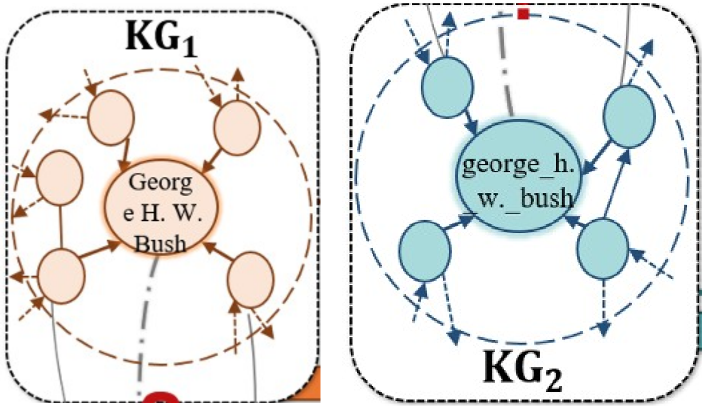
Paris is the capital of France. It is also the largest city in France.

- Entity resolution
  - Record linkage, data matching, data linkage
  - Database

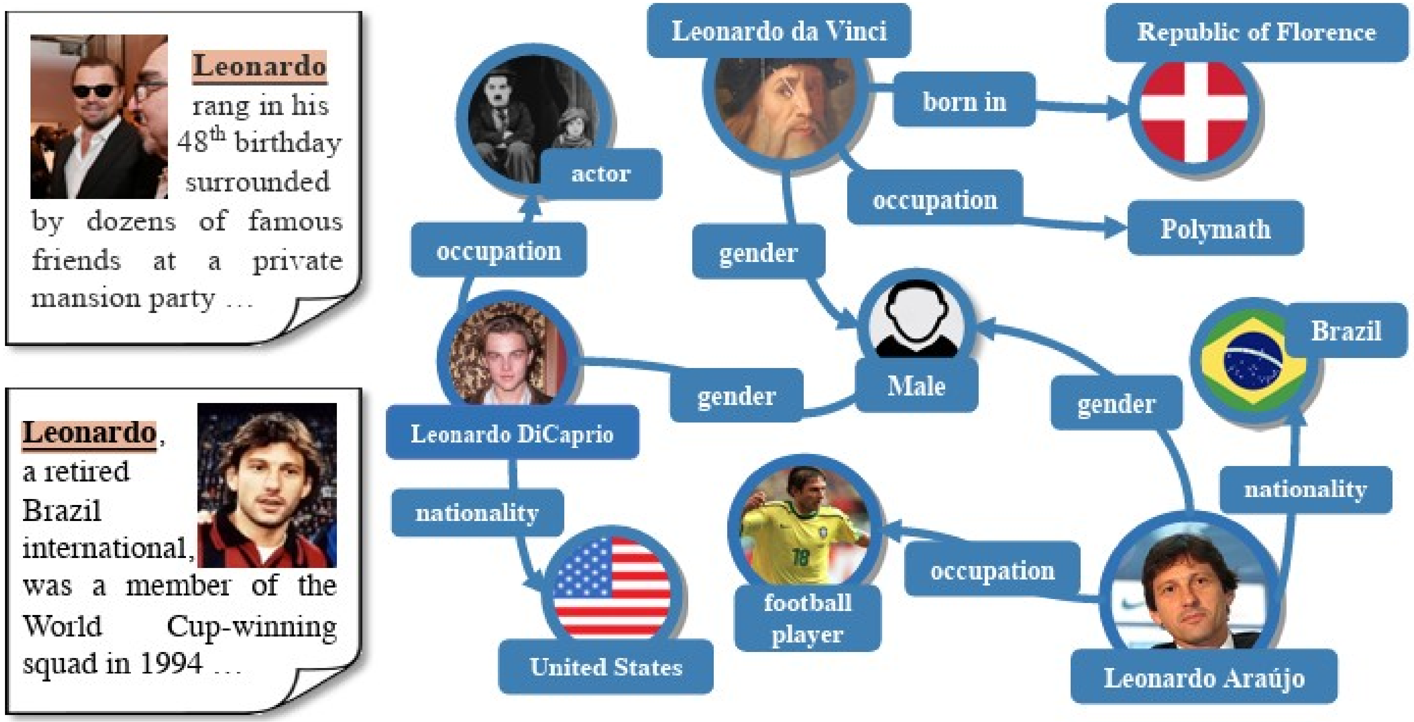
Data set	Name	Date of birth	City of residence
Data set 1	William J. Smith	1/2/73	Berkeley, California
Data set 2	Smith, W. J.	1973.1.2	Berkeley, CA
Data set 3	Bill Smith	Jan 2, 1973	Berkeley, Calif.

Related tasks

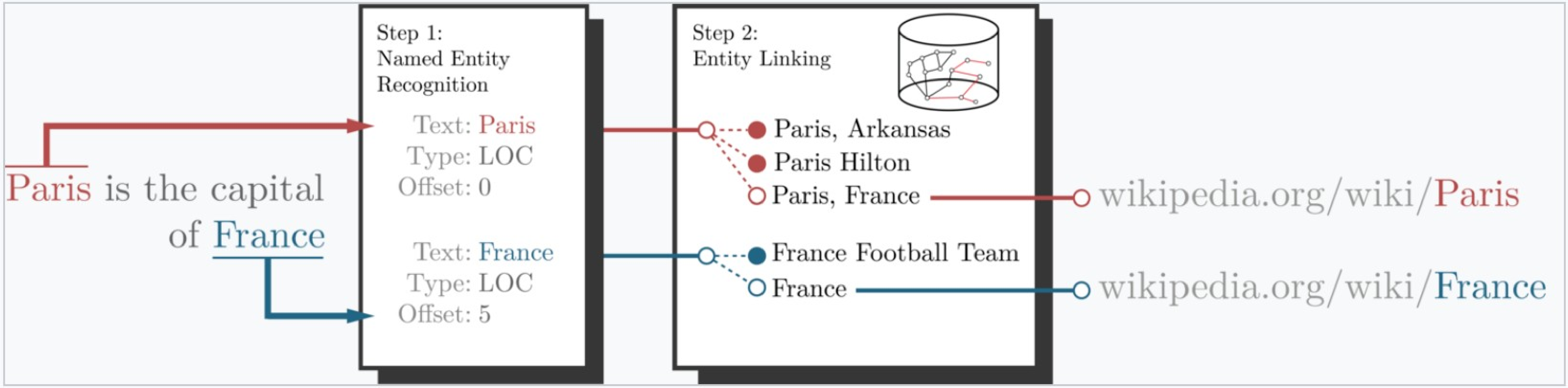
- Entity alignment
  - identifying and linking equivalent entities across different knowledge graphs



- Multi-modal entity linking



Typical steps



Typical entity linking steps. 1. NER - find named entities in the text (here, Paris and France); 2. link found named named entities to corresponding unique identifiers (here, Wikipedia pages). (2) is often done by: 2.1. defining a metric for comparing candidates in the system; 2.2. creating a small set of candidate identifiers for each named entity, and 2.3. Scoring candidates with the metric and choosing one that has the highest score.

https://en.wikipedia.org/wiki/Entity_linking

Typical Modules

- Candidate entity generation
  - Filter out irrelevant entities
  - Retrieve a candidate set
  - Requirement: fast
- Candidate entity ranking (Disambiguation)
  - rank the candidate entities
- Unlinkable mention prediction (NIL)
  - whether the top-ranked entity identified in the Candidate Entity Ranking module is the target entity for mention m.

Applications

- Information Extraction
- Information Retrieval
    - Semantic entity-based search
    - Query disambiguation
- Content Analysis
    - recommendation systems
- Question Answering
- Knowledge Base Population

Heuristic Based Methods (Candidate entity generation)

- acronym that is in parenthesis adjacent to the expansion
  - Iowa State University (ISU)
- identify named entities from the document and if some identified named entity contains the entity mention as a substring
  - Michael I. Jordan = Jordan
- Name Dictionary (Wikipedia)
  - Entity page
  - Redirect pages
  - Disambiguation pages
  - Bold phrases from the first paragraphs (nick names, alias, etc)
  - Hyperlinks in Wikipedia articles

Disambiguation

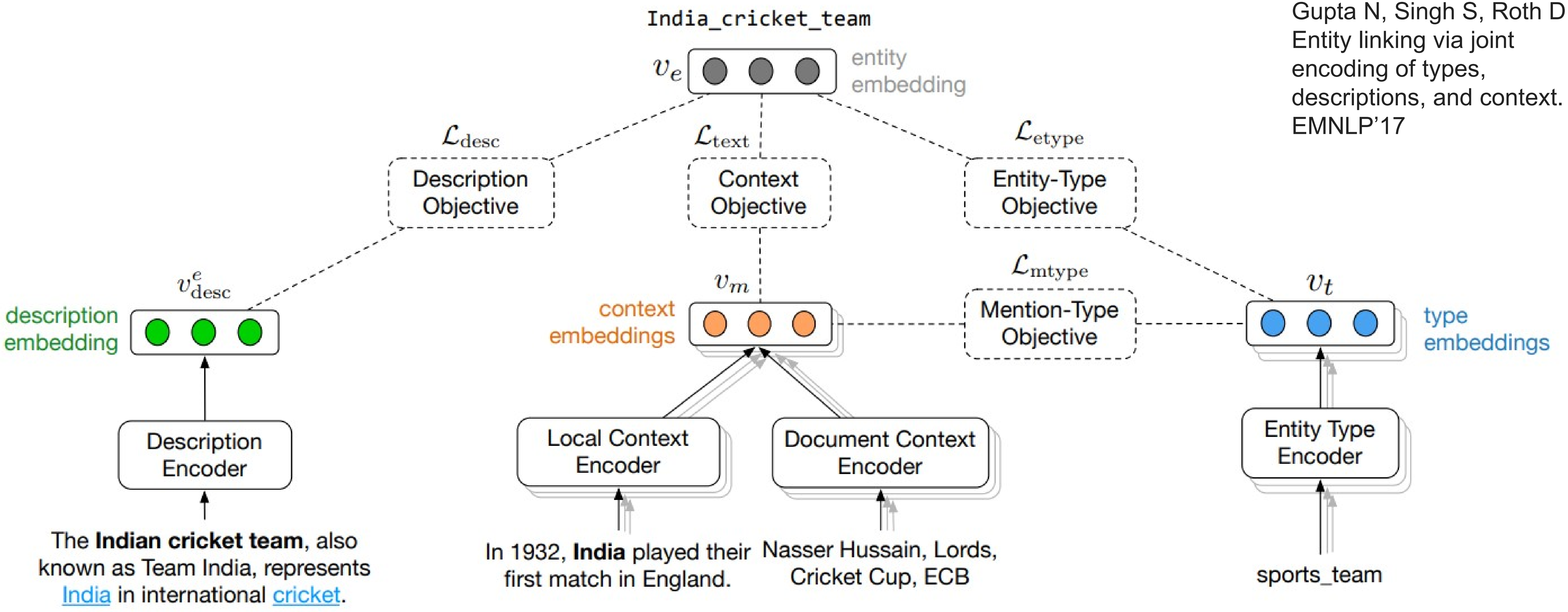
- Features

Disambiguation

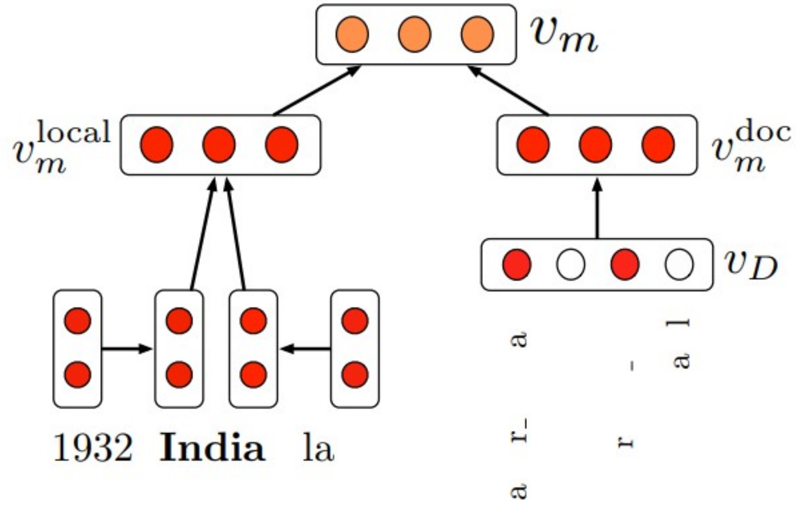
- Features
  - Similarity
    - Lexicon (name string comparison)
    - semantic
  - Anchors statistic (Mention-entity prior)
  - Entity type
  - Context
  - Entity description
  - KG graph

Entity linking via joint encoding of types, descriptions, and context

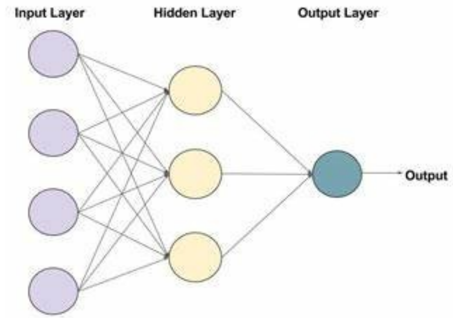
Gupta N, Singh S, Roth D. Entity linking via joint encoding of types, descriptions, and context. EMNLP'17



Mention Context Encoder



- Local-Context Encoder
  - Sentence:
  - Representation
    - FFNN
- Document-Context Encoder
  - , bag-of-mention for all mentions in training data
  - FFNN



- Mention-Context Encoder
  - FFNN
- maximize the probability of predicting the correct entity from the mention-context vector

$$P_{\text{text}}(e|m) = \frac{\exp(v_m \cdot v_e)}{\sum_{c_k \in C_m} \exp(v_m \cdot v_{c_k})} \qquad \mathcal{L}_{\text{text}} = \frac{1}{M} \sum_{i=1}^{M} \log P_{\text{text}}(e_{m^{(i)}} | m^{(i)})$$

- Entity Description Encoder

  - maximize the probability of predicting the correct entity from the entity description vector

- Fine-Grained Types Encoder
  - entity has multiple types
  - : probability of typebeing relevant to entity

$$\mathcal{L}_{\text{etype}} = \frac{1}{|\mathcal{E}|} \sum_{e \in \mathcal{E}} \log \prod_{t \in T_e} P(t|e) \prod_{t' \notin T_e} (1 - P(t'|e))$$

- Type-Aware Context Representation
  - between every and if type belongs to for the entity that refers to.

- Entity Representations

$$\{v_e\}, \Theta = \underset{\{v_e\},\Theta}{\text{argmax}} \, \mathcal{L}_{\text{text}} + \mathcal{L}_{\text{desc}} + \mathcal{L}_{\text{etype}} + \mathcal{L}_{\text{mtype}}$$

$$\begin{aligned} P(e|m) = {} & P_{\text{prior}}(e|m) + P_{\text{text}}(e|m) \\ & - (P_{\text{prior}}(e|m) * P_{\text{text}}(e|m)) \end{aligned}$$

$$\hat{e}_m = \underset{e \in C_m}{\text{argmax}} \; P(e|m)$$

Supervised Ranking Methods

- Binary classification

- Learning to rank
  - Pointwise (regression problem)
    - : predicting the real-value or ordinal score of x
    -
  - **Pairwise**
    - : classification problem for a given pair
    - Usually implemented with a scoring function:

  - Listwise

Training loss

- max-margin loss

$$\mathcal{L} = \max(0, \gamma - \Phi(m, e^+) + \Phi(m, e^-)),$$

ranking score

- Cross-entropy loss

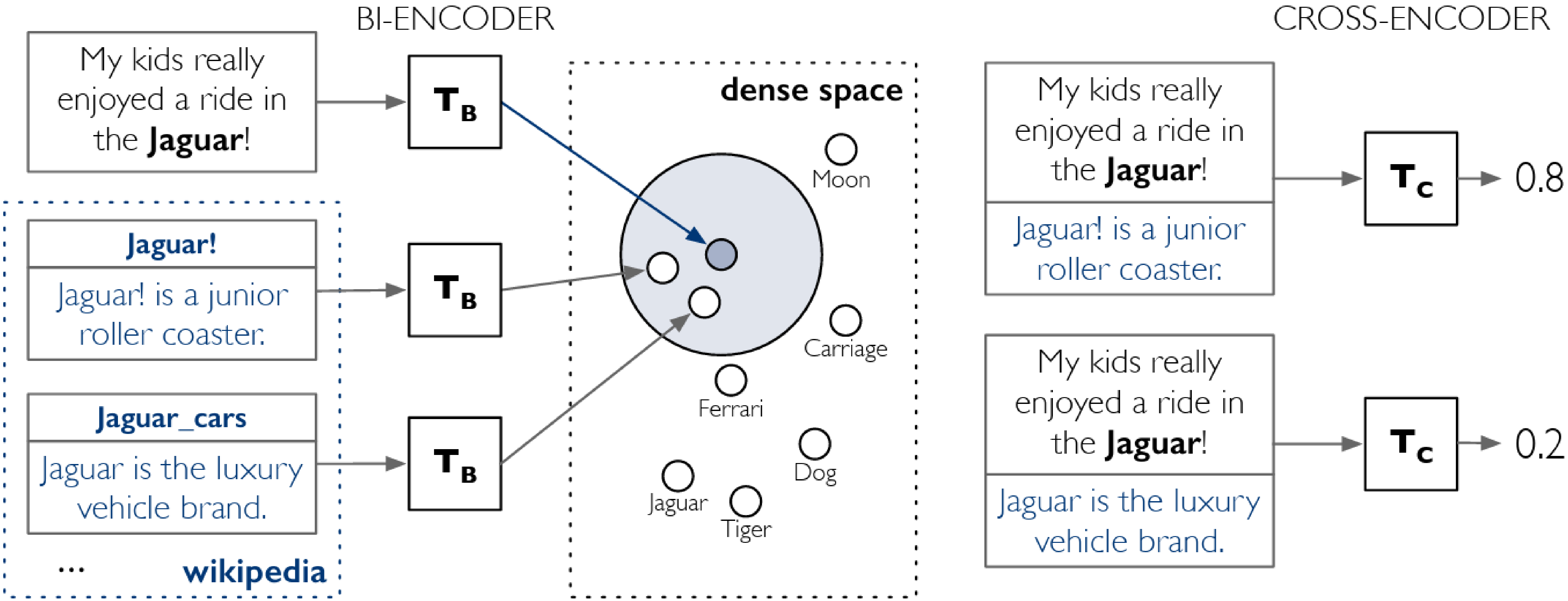
$$\mathcal{L} = -(y\log\Phi(m, e) + (1 - y)\log(1 - \Phi(m, e))),$$

EL Settings

- Zero-shot
  - Train in Domain A
  - Inference in Domain B
  - Unseen mentions & entities
- End-to-End
  - Combine NER with EL
- Multi-modal

BLINK (by Facebook 2020)

- Retrieve and rerank



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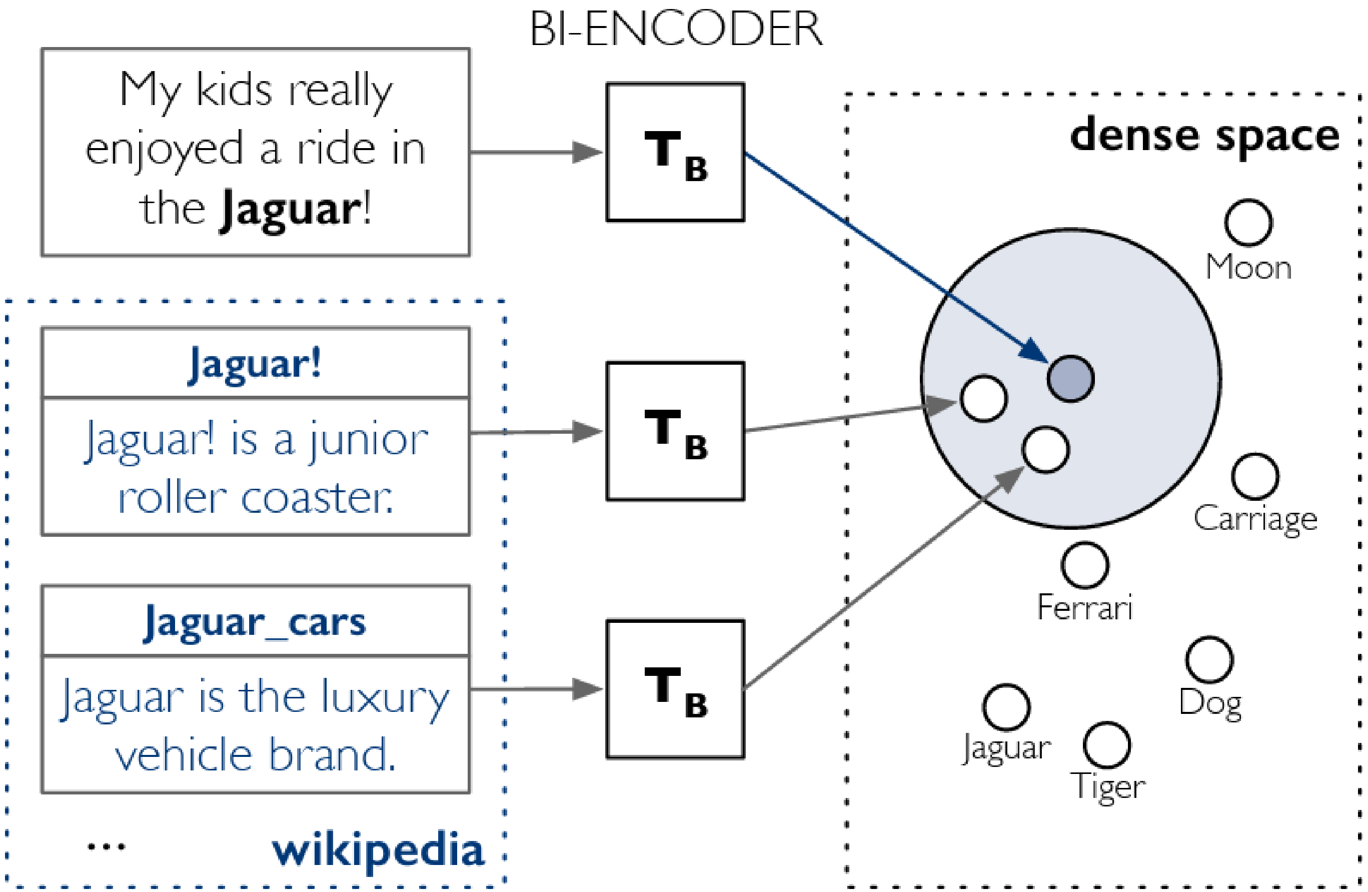


- Mention Encoder

Input

Context [B] Mention [E] Context

Output

Last layer

- Entity Encoder

Input

Entity Title [X] Description

Output

Last layer

Optimize dot-product of the two output

BLINK

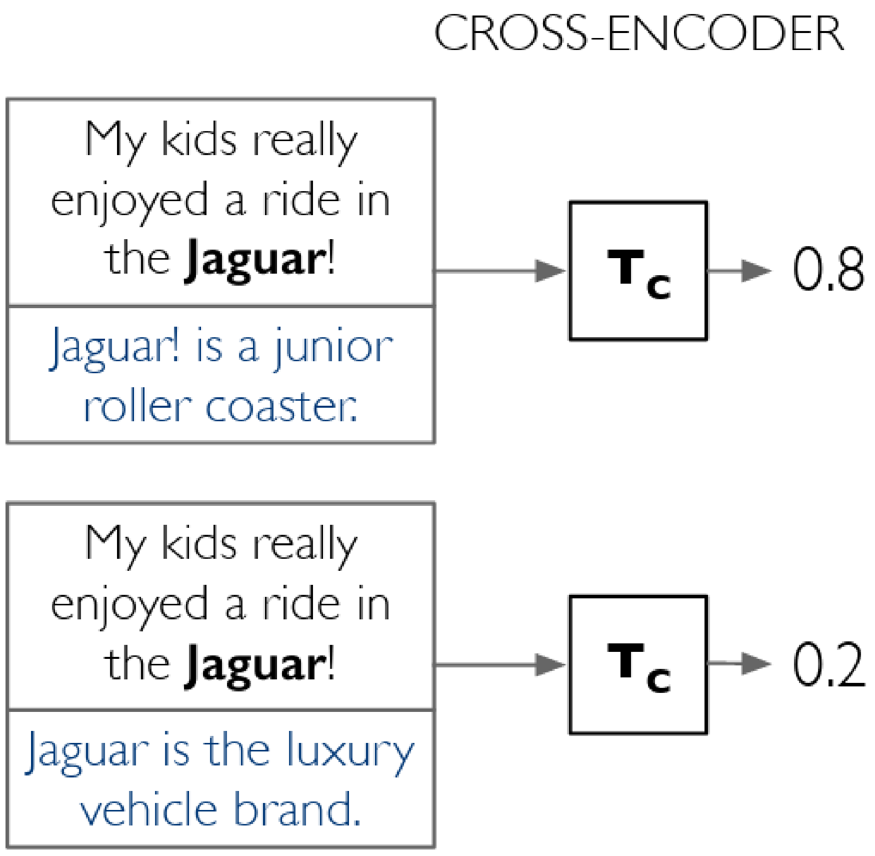
- Cross Encoder

Input

Context [B] Mention [E] Context [S] Entity Title [X] Description

Output

Probability distribution among entity choices



BiEncoder VS CrossEncoder

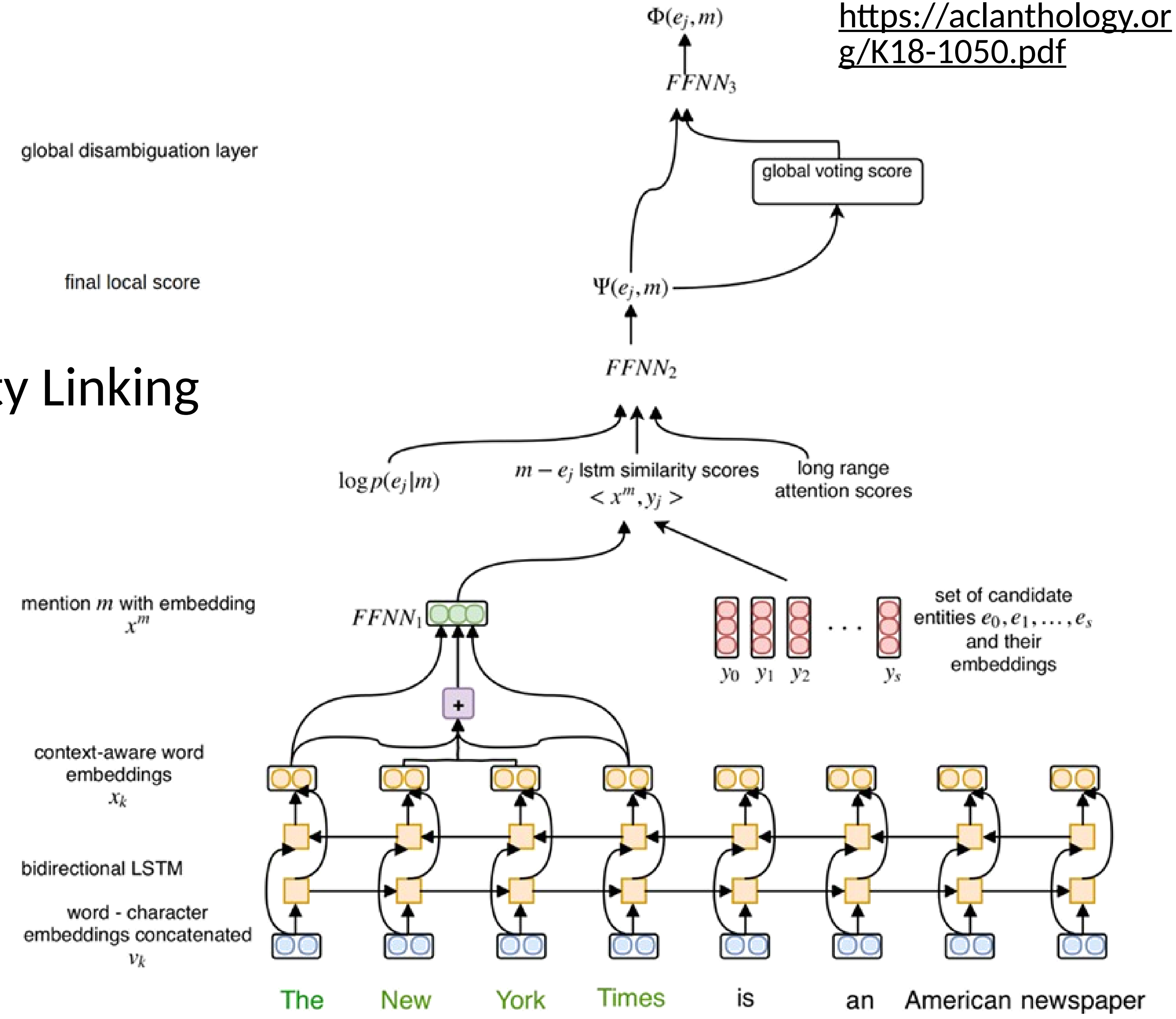
- Bi-Encoder
  - Fast
    - Pre-compute entity representations (off-line)
  - Less accurate comparing to cross-encoder

- Cross-Encoder
  - Accurate
  - Expensive to compute
    - Linear to number of candidates

End-to-End

https://aclanthology.org/K18-1050.pdf

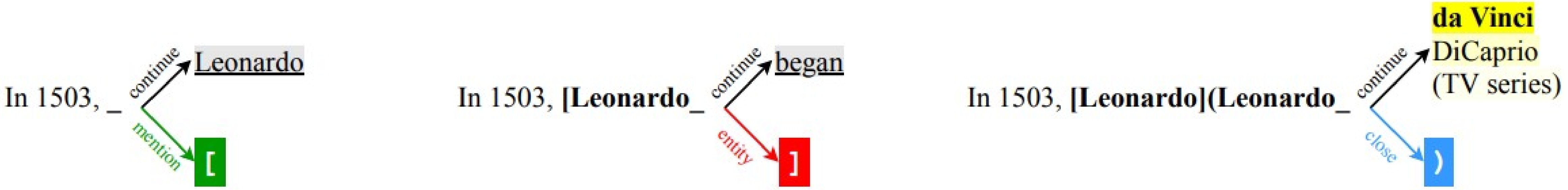
- End-to-End Neural Entity Linking



Kolitsas N, Ganea OE, Hofmann T. End-to-End Neural Entity Linking. InProceedings of the 22nd Conference on Computational Natural Language Learning 2018 Oct (pp. 519-529).

Autoregressive Entity Retrieval

sequence-to-sequence model



(a) Outside: we can either continue to generate the input or start a new mention.

(b) Inside a mention: we can either continue to generate the input or end the current mention.

(c) Inside an entity link: we can either generate from the entities prefix trie or close if the generated prefix is a valid entity.

Figure 2: Example of dynamically constrained *Markup* decoding for entity linking using "*In 1503, Leonardo began painting the Mona Lisa.*" as input. There are 3 cases: when we are outside a mention/entity (a), inside a mention generation step (b), and inside an entity link generation step (c). The model is supposed to output the input source annotating mentions and pointing them to the respective entities: "*In 1503, **[Leonardo]**(Leonardo da Vinci) began painting the **[Mona Lisa]**(Mona Lisa)*".

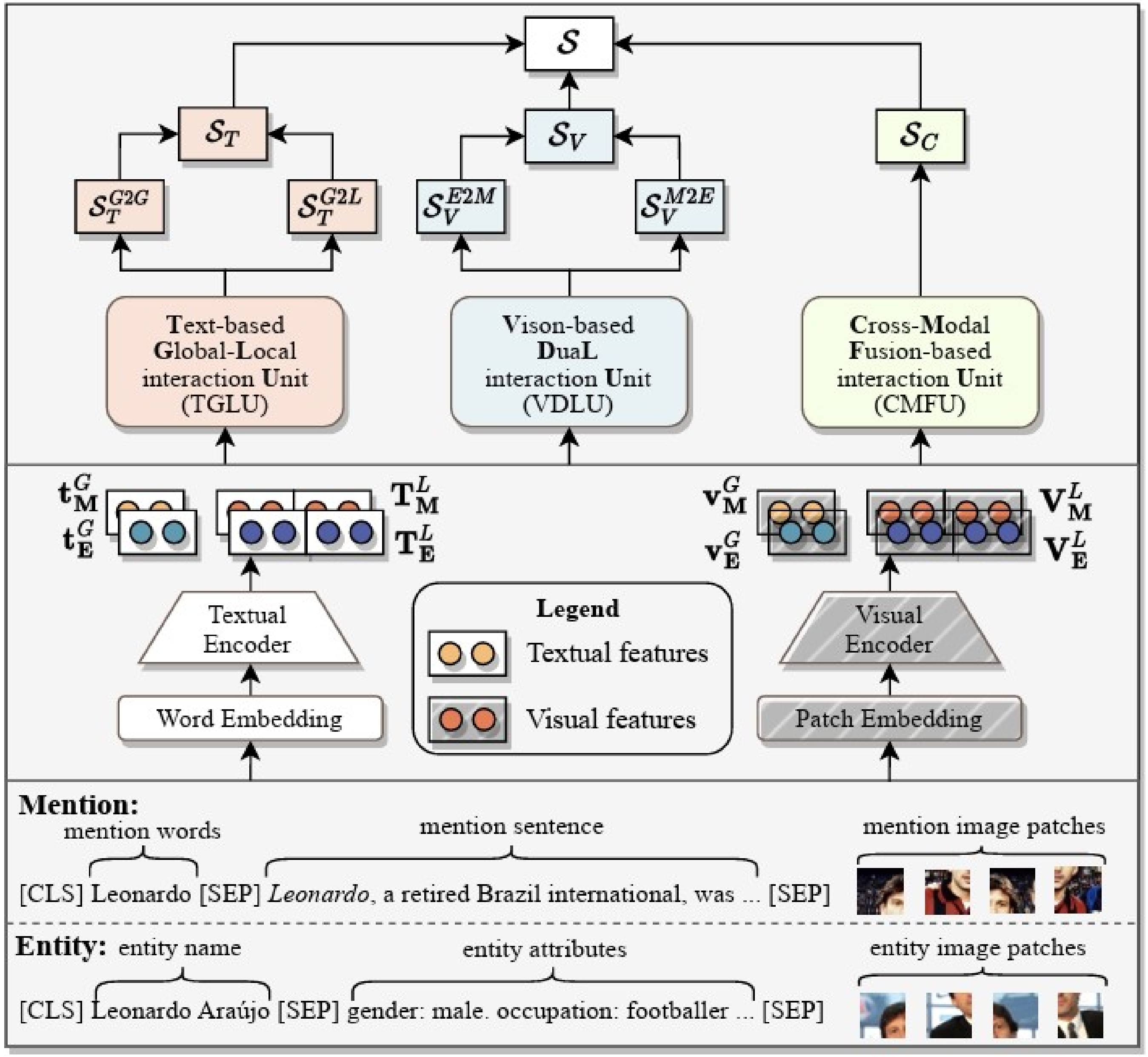
Autoregressive Entity Retrieval

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

- standard seq2seq objective: maximizing the output sequence likelihood
- Inference: constrained Beam search

Multi Modal EL

- Text
- Vision
- Cross modal



Luo, Pengfei, et al. "Multi-grained multimodal interaction network for entity linking." *Proceedings KDD* 2023.