Neuro-Symbolic Representations for IR
2.2 – Neural Text and Graph Representations

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SIGIR

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Opportunities for Query-Specific Entity Representations

Context-aware representations of entities in text based on a query

- Query Understanding
  - Captures both inherent properties of entities
  - Models entity relevance to the query
- Retrieval and Ranking
  - Overcomes limitations of simple keyword matching
  - Uncovers deeper connections between entities, documents, and the query
- Answer Generation
  - Generates more coherent, contextually appropriate responses
  - Tailors output to the specific information need

Slide genrated by chatGPT 3.5

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Lots of magical hand waving. Let's look at that!

Deep Learning Techniques

Demystify some magic :

- Metric Learning as Latent Space Projection
- Clustering, Retrieval = Metric Learning
- Attention = Metric Learning
- Transformers = Graph Neural Networks

Tutorial Timetable

Part 1: Knowledge Graphs and Entities

- 1.1 Welcome & Motivation
- 1.2 Knowledge Graphs and GPT
- 1.3 Entity Linking

Part 2: Neuro-Symbolic Foundations

- 2.1 Ranking Wikipedia Entities / Aspects
- 2.2 Neural Text Representations and Semantic Annotations ←
- 2.3 Infusion of Symbolic Knowledge into Text Representation

Part 3: Reasoning, Robustness, and Relevance

- 3.1 Denoising Dense Representations with Symbols
- 3.2 Reasoning about Relevance
- 3.3 From PRF to Retrieval Enhanced Generation

Part 4: Emerging Topics

- 4.1 Conclusion and Outlook
- 4.2 Panel Discussion

https://github.com/laura-dietz/neurosymbolic-representations-for-IR/SIGIR23/

Outline

1. Metric Learning
2. Text Ranking
3. Document Representation with Transformers
4. Attention Learning in Transformers
5. Transformers
6. Graph Neural Networks
7. Transformers + Graph Neural Nets
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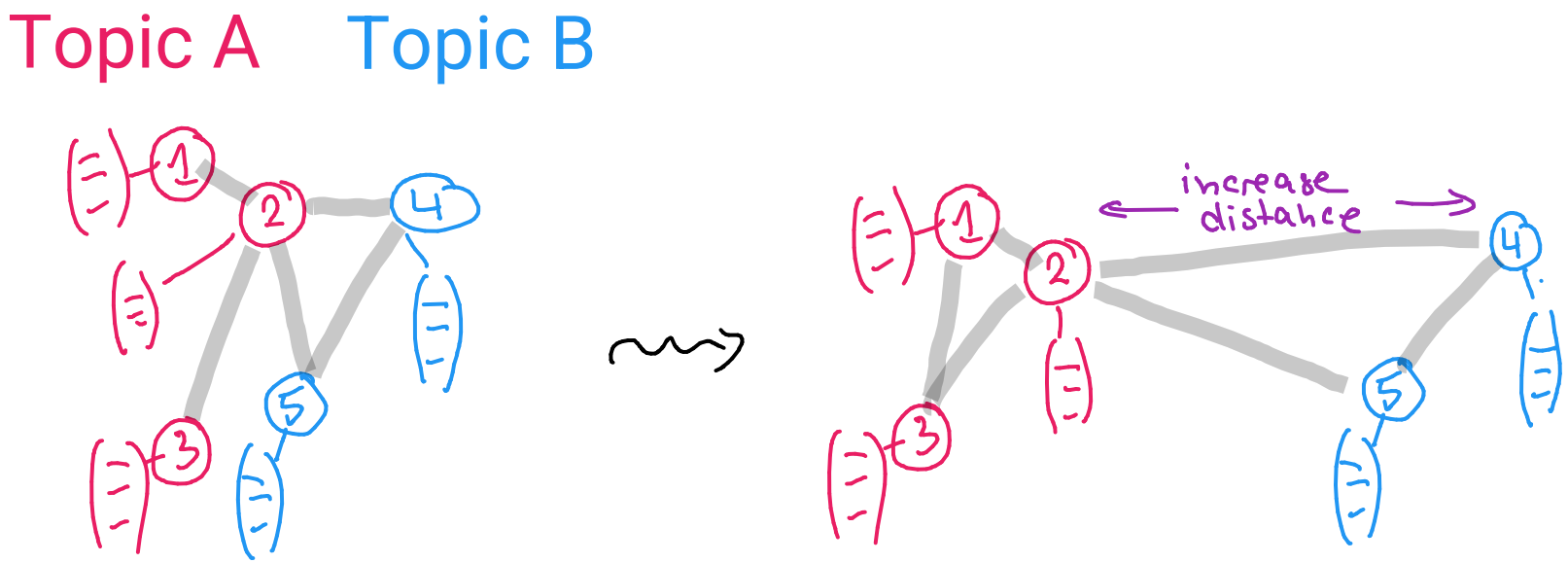
Metric Learning for Topics

Task:

- Given data points (vectors), with true topic labels
- Project into vector space where points with
  - same labels are close
  - different labels are far apart

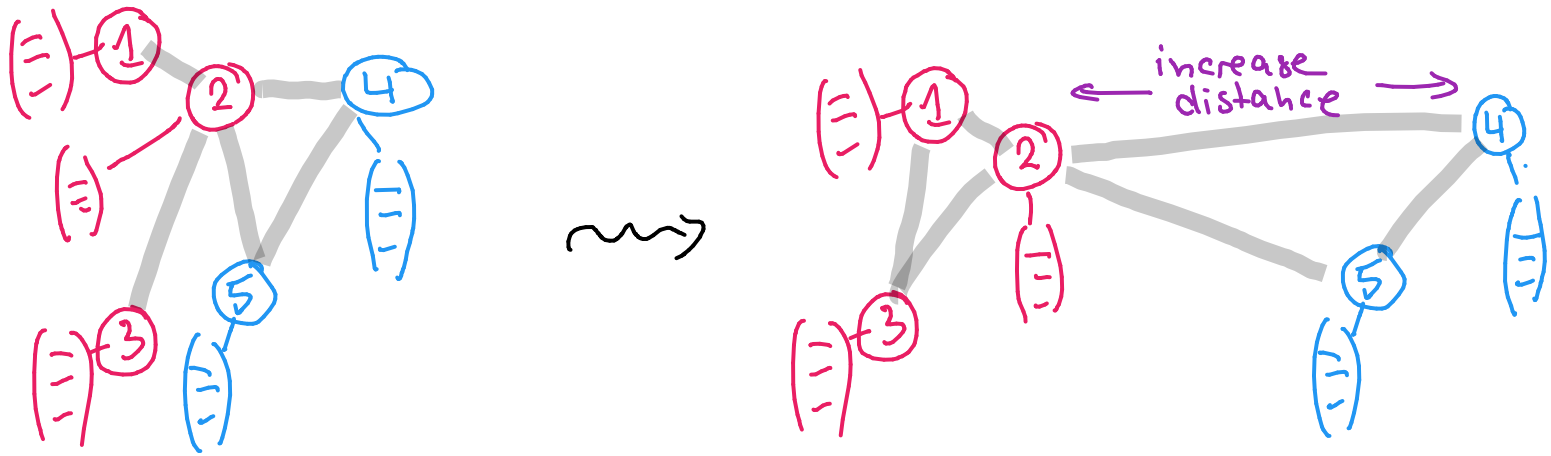


Train: latent space has "useful" representation of proximity.

Metric Learning as Neural Network

- Project each point $\mathbf{x}$ with a function $\texttt{proj}$.
  - $\mathbf{y} = \texttt{proj}(\mathbf{x}) = \mathbf{W}\mathbf{x} + \mathbf{b}$
  - where $\mathbf{W}$ and $\mathbf{b}$ are trainable parameters.

Topic A Topic B



$\mathbf{x}$ $\texttt{proj}(\mathbf{x})$

Learn Projection function so that proximity $\approx$ same/different label

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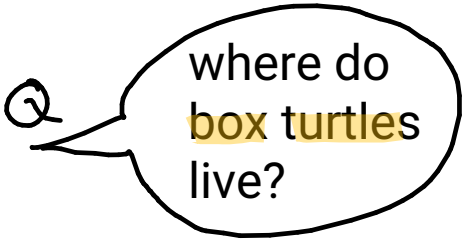
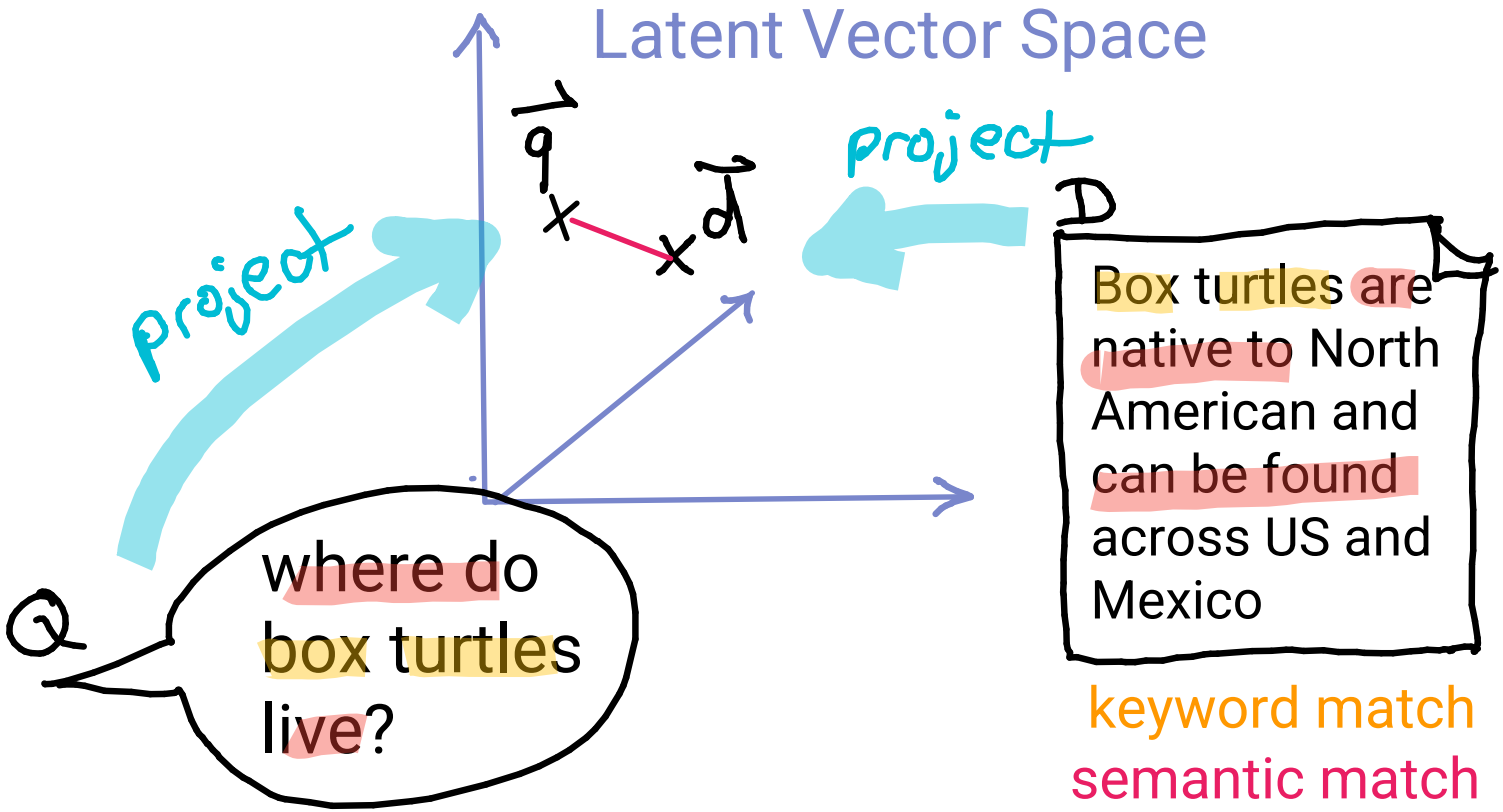
Ad hoc Text Ranking



SOTA: ad hoc Text Ranking

Dense Retrievel Approach:

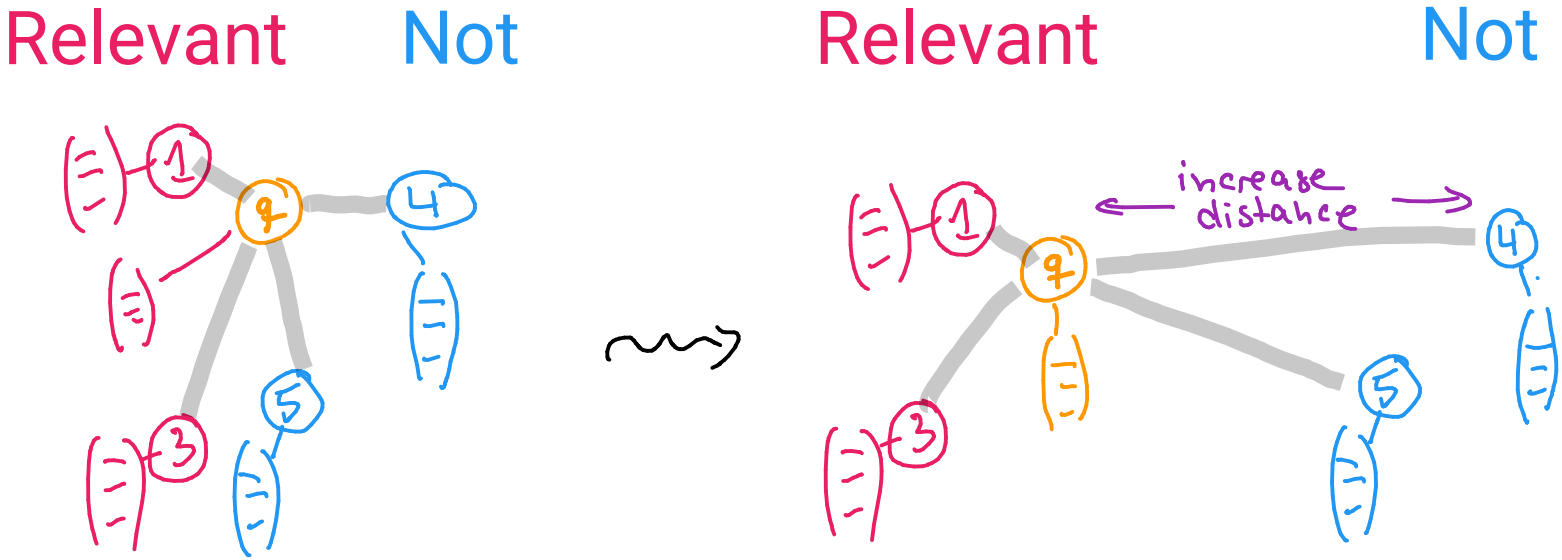


Latent space and projections are trained, so that $\mathbf{q}$ and $\mathbf{d}$ are close whenever documents are relevant for the query.

Ranking as Metric Learning

Task:

- Given query and document points, with relevance labels
- Project into vector space where
  - relevant points close to query
  - not relevant points are far away

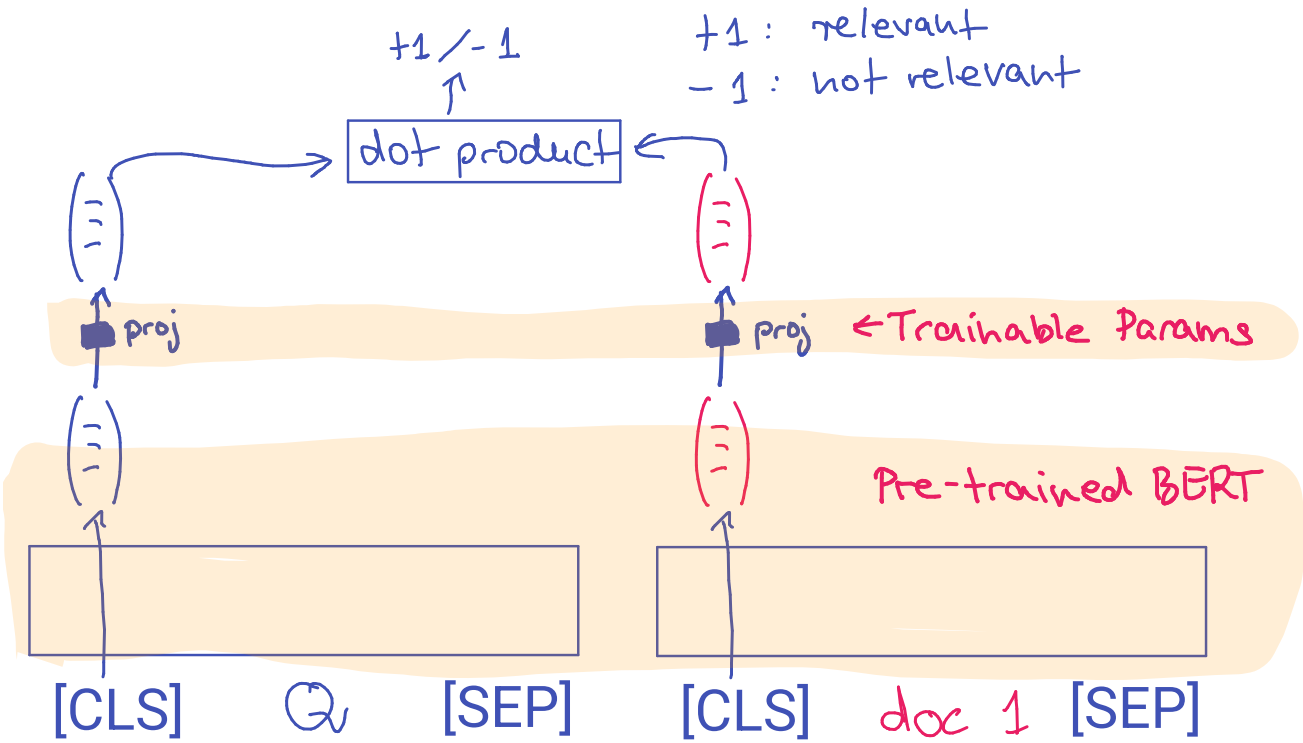


Learn Projection function so that proximity $\approx$ relevance.

$\rightarrow$ Can use Standard K-NN for ranking

Ranking as Neural Network (Bi-encoders)

- Projection layer for training
  - $\texttt{proj}(\mathbf{x}) = \mathbf{W}\mathbf{x} + \mathbf{b}$
  - where $\mathbf{W}$ and $\mathbf{b}$ are trainable parameters.
- (Non-) Linear projection with trainable parameters



- Alternative: Single trainable Transformer layer

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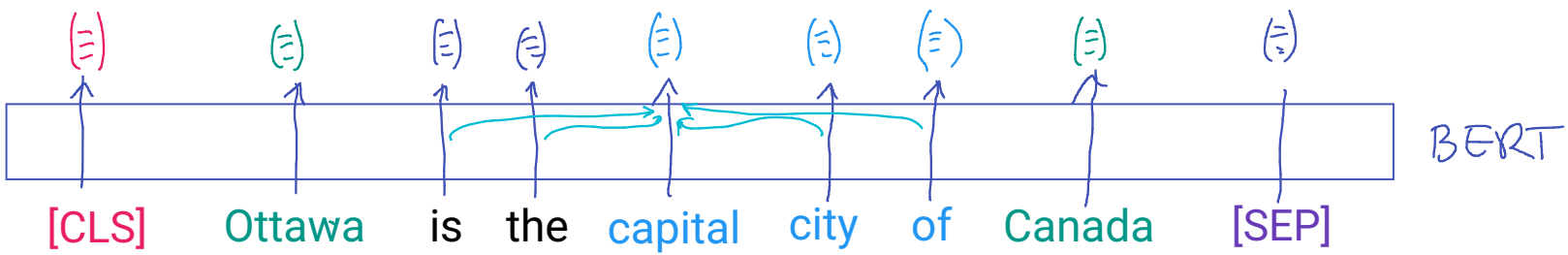
Text Representation with Large Language Models (LLM)

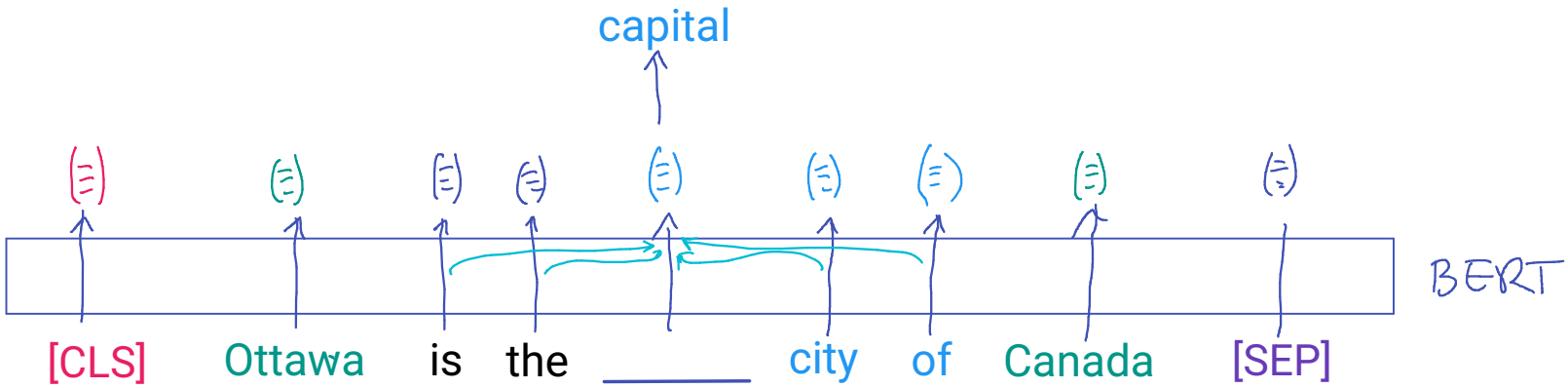
Large Language Models (BERT, T5, GPT, Word2Vec)

- Capture rich contextual information
- Can be fine-tuned for tasks such as entity linking, recognition, or relation extraction
- Represent each word as a vector



Each word vector is aware of neighboring words!
Also: special `[CLS]` and `[SEP]` tokens have vectors

BERT Training with CLOZE "fill the blanks"



Each word vector is aware of neighboring words!

→Contextualized representation

How does this "awareness" work?

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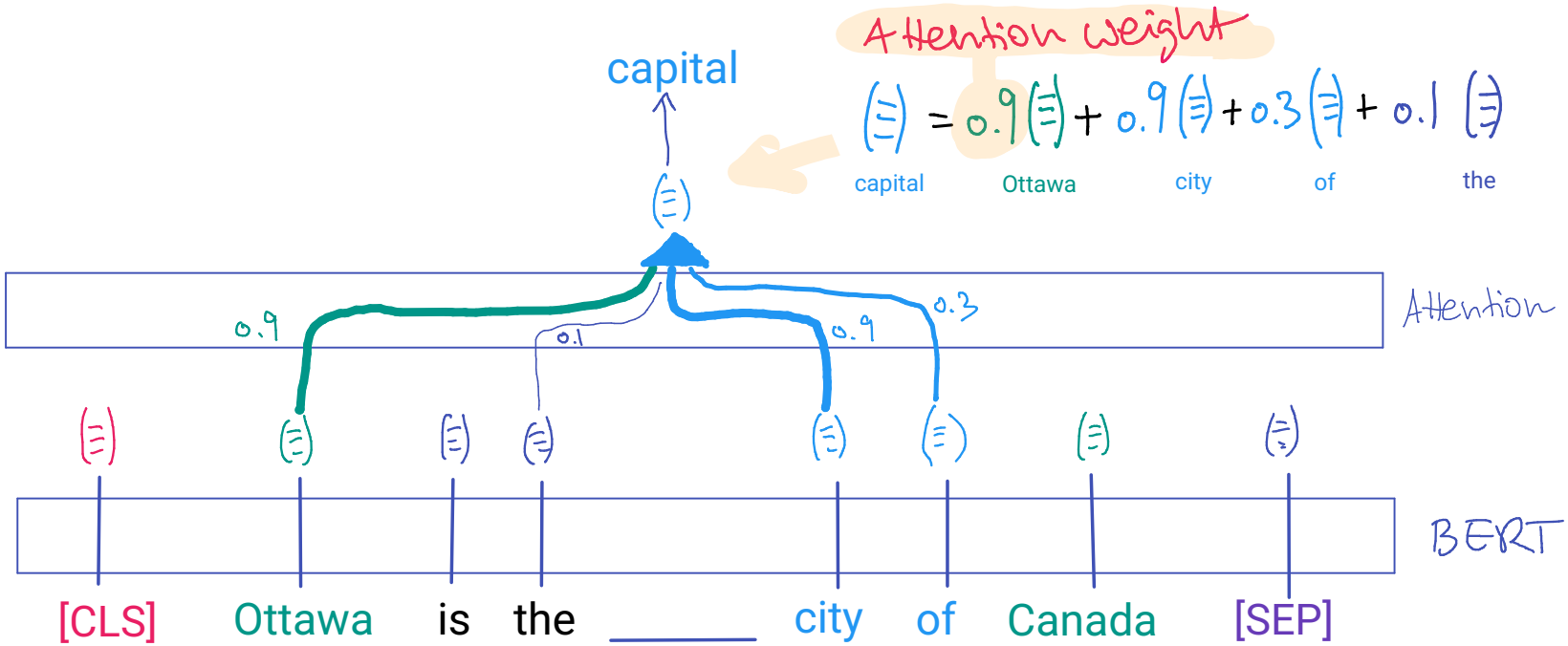
Attention Mechanisms = Adding vectors

- Selectively focuses on relevant parts for each prediction
- Improves the performance especially for long input sequences

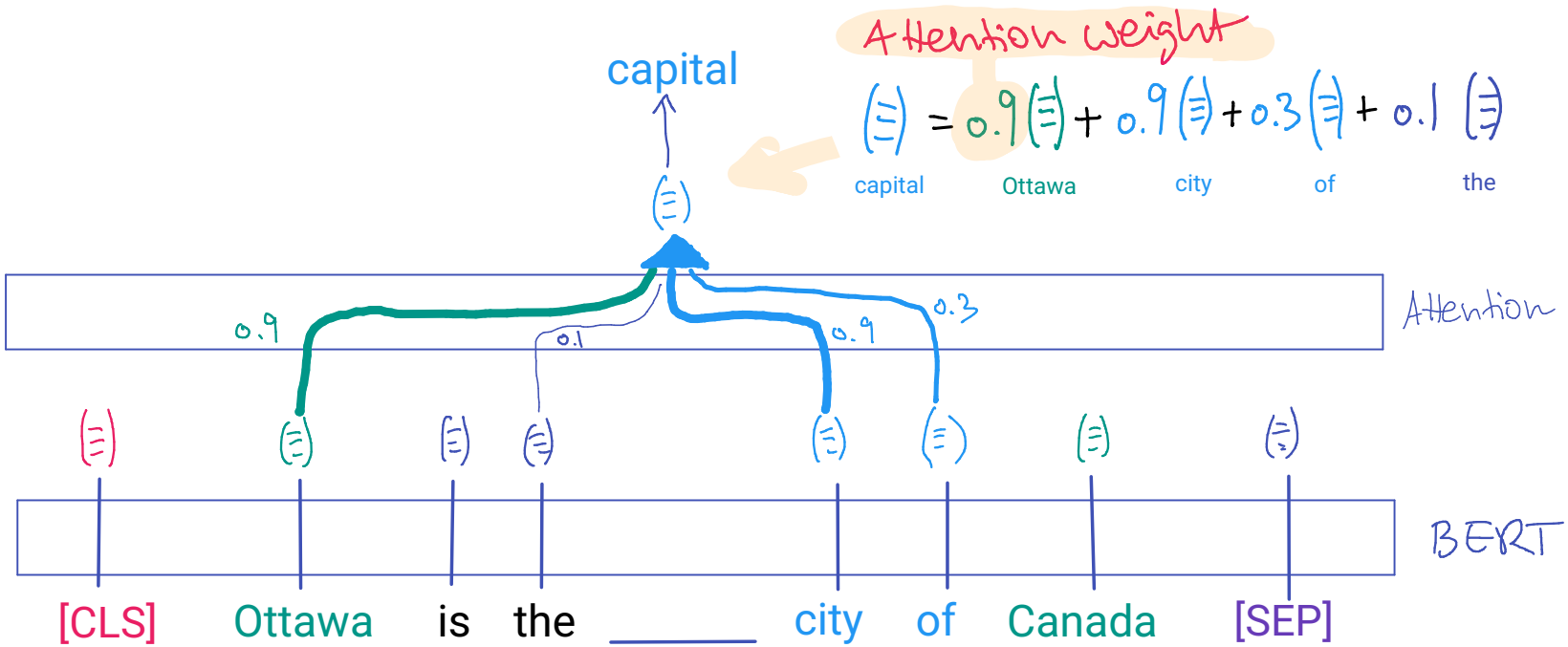


What does "selectively focus" mean?

How Attention is Trained?

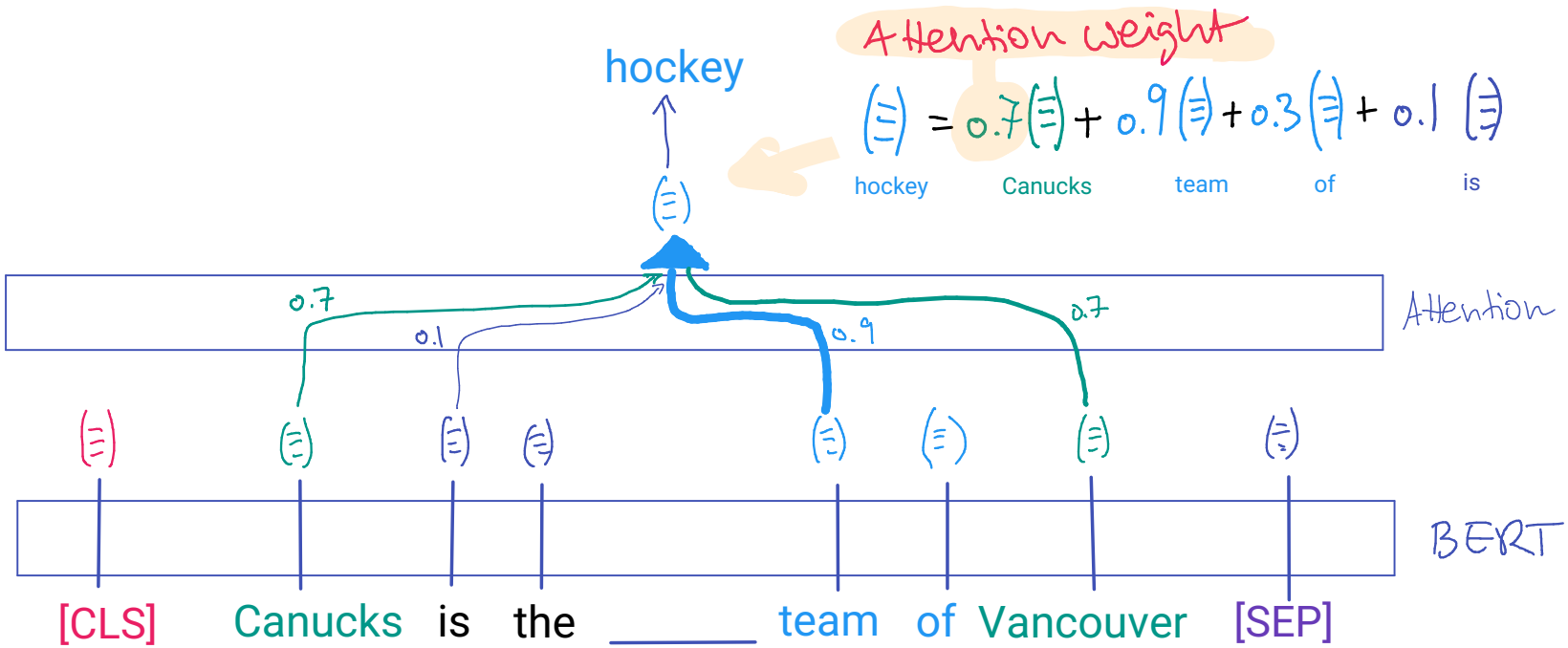
Thought experiment:

- Which tokens should we sum, so we get the best representation?
- Train to assign those tokens a high attention weight!



Generalizing Attention to Unseen Text

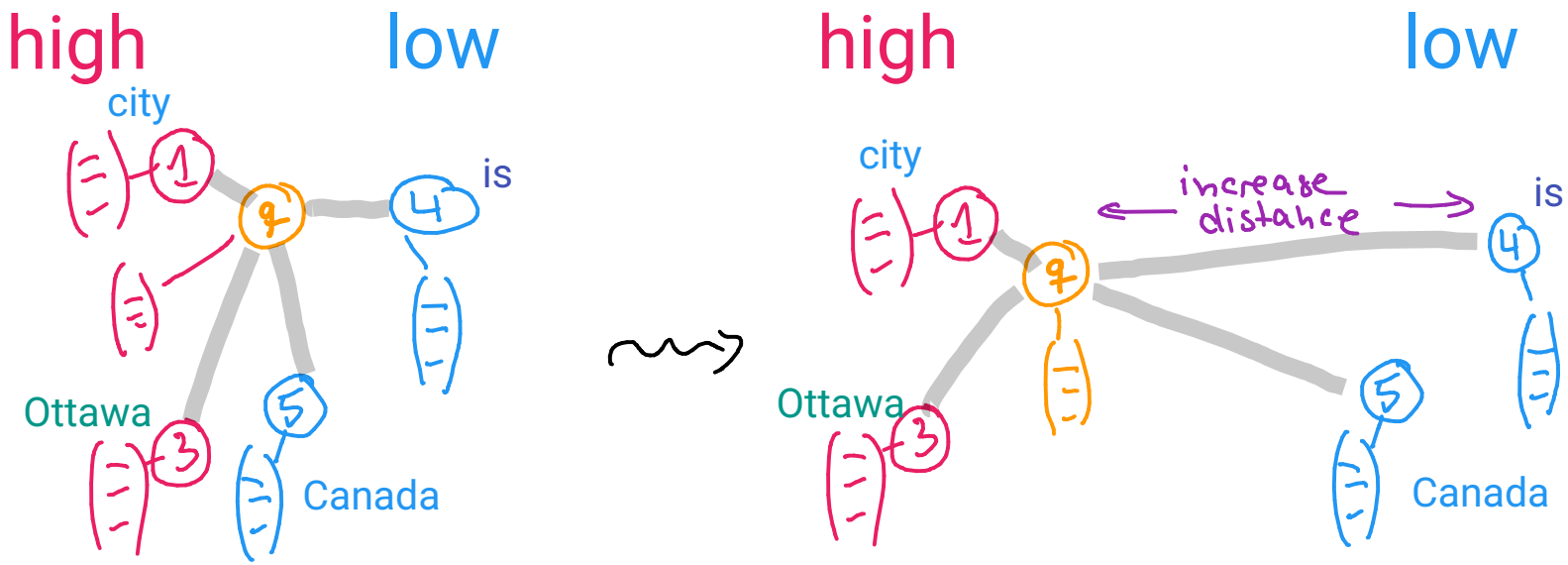
- Need a model to assign these "ideal" attention weights
- .... needs to generalize to unseen text ($\rightarrow$ Delexicalized Space)



Which words should be weighted high in sum?

Attention as Metric Learning on Words

- Project each point $\mathbf{x}$ with a two functions $\texttt{proj}$.
  - Query: $\texttt{proj}(\mathbf{q}) = \mathbf{W}^q\mathbf{q} + \mathbf{b}^q$
  - Key: $\texttt{proj}(\mathbf{k}) = \mathbf{W}^k\mathbf{k} + \mathbf{b}^k$



$\mathbf{q}, \mathbf{k}$ $\qquad$ $\texttt{proj}(\mathbf{q}), \texttt{proj}(\mathbf{k})$

The blank word plays the role of "the query"
High impact words $\approx$ proximity $= \texttt{proj}(\mathbf{q}) \cdot \texttt{proj}(\mathbf{k})$

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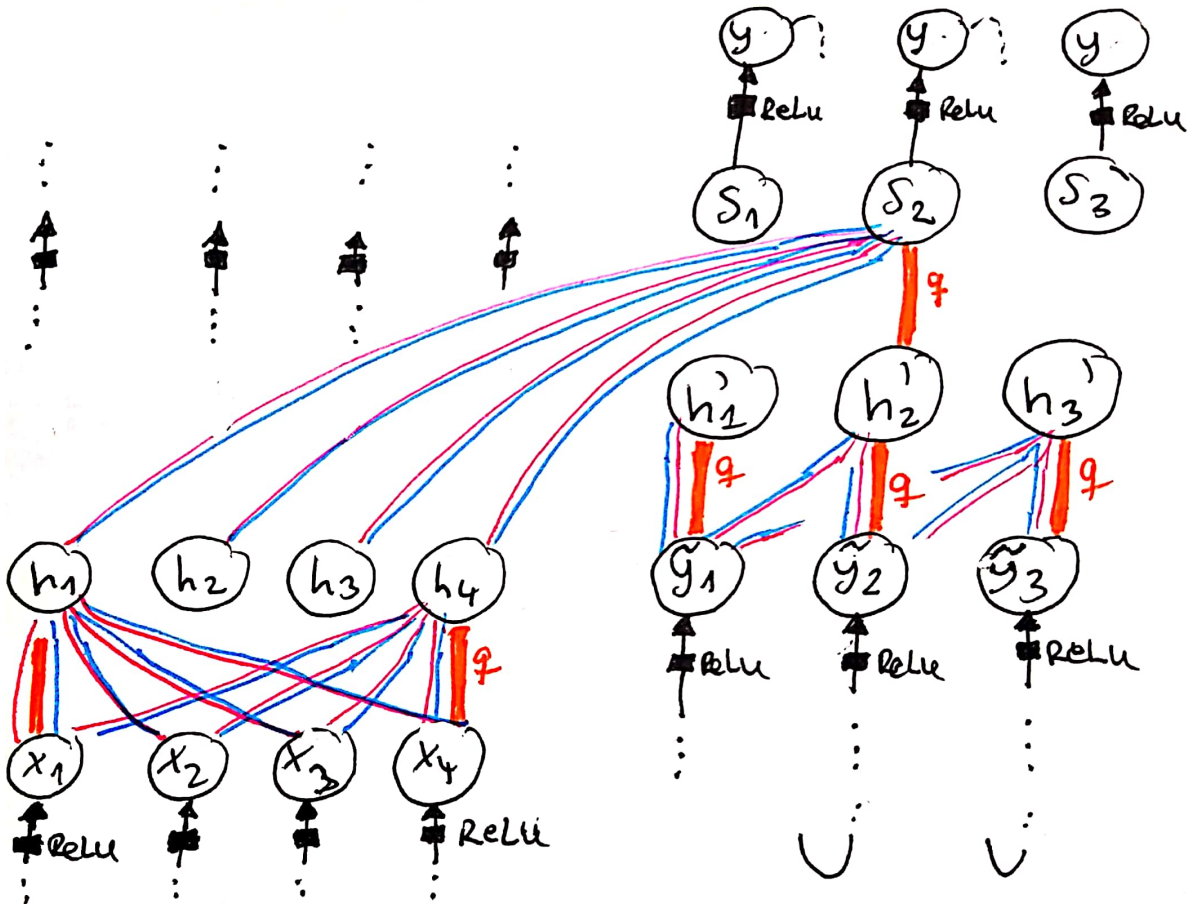
Transformers

- Several layers with attention mechanism = Capture context
- Fine-tuned for specific tasks, such as generation or classification
- Encoder → State → Decoder



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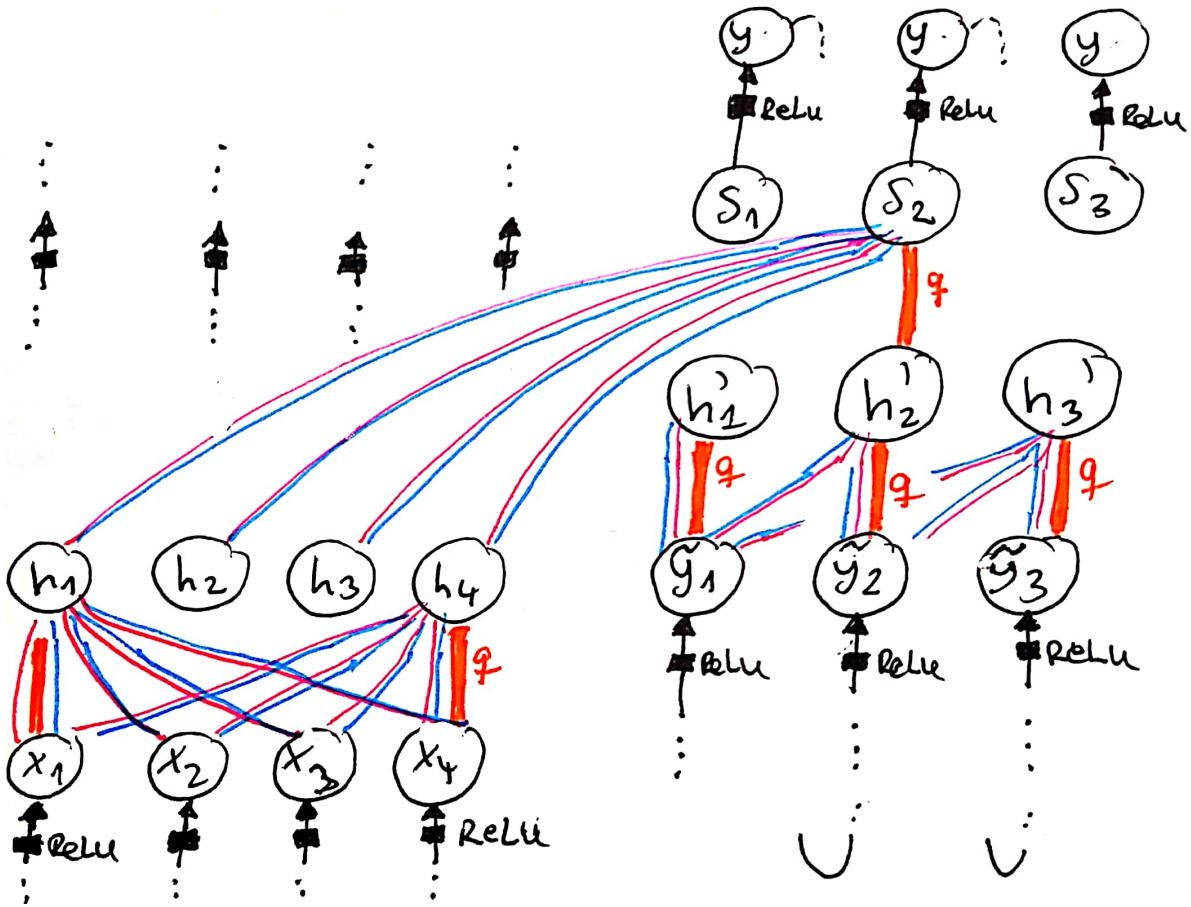
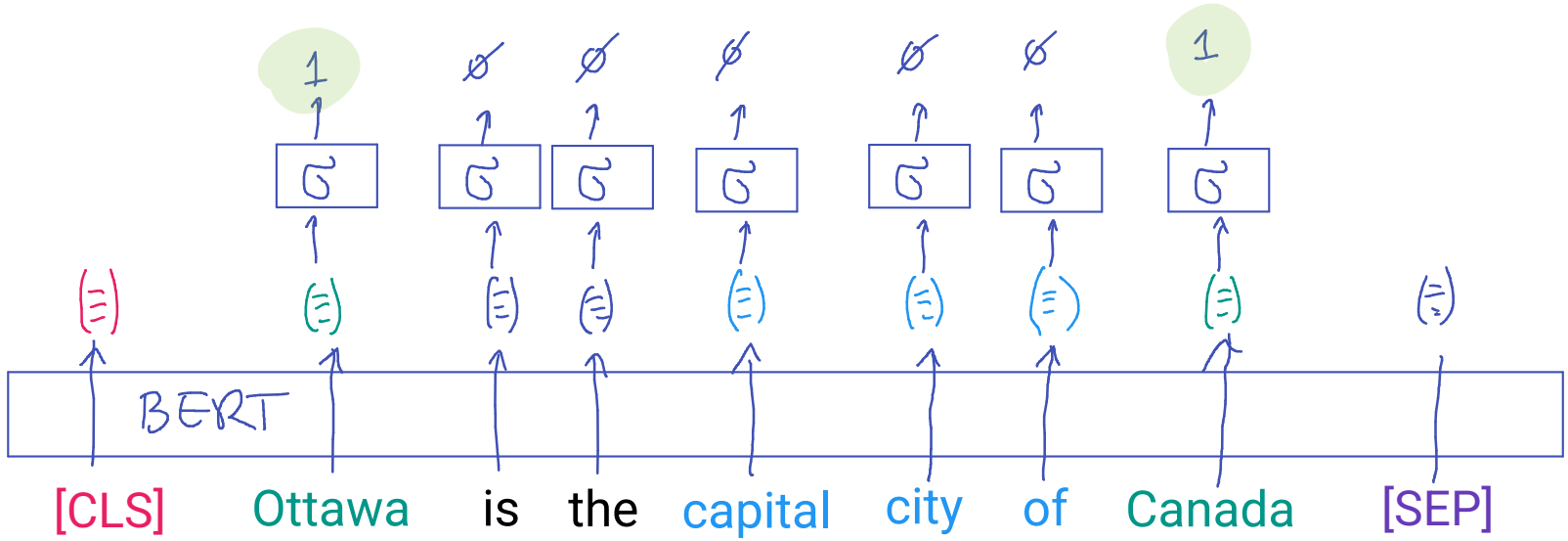


Tagging

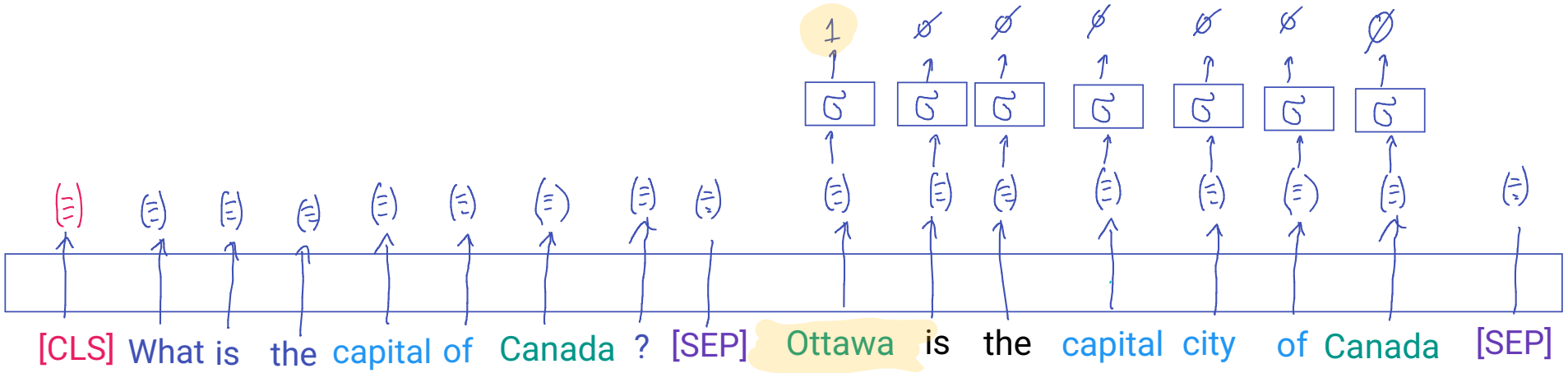
Example: Tag all LOCATION entities in the sentence (green)



- Connect ground truth to vector of words
- Connect to a logistic layer to predict yes/no

Question Answering: Answer Extraction

Example: What is the capital of Canada?
Find the answer in the given passage.



- Connect ground truth to vector of words
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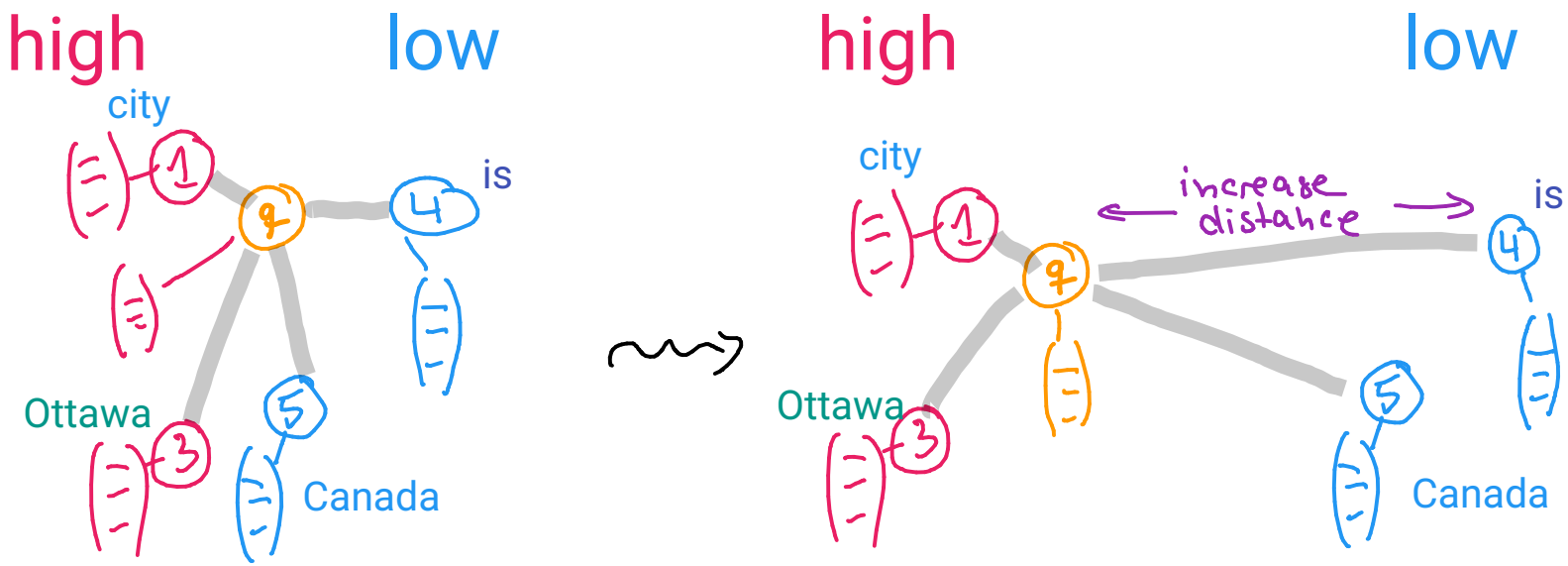
Attention and "long-range dependencies"

- "Attention can model long range dependencies" – How?
- Because: Attention does not consider the sequence
- Add **position encoding** to teach about "neighboring words"



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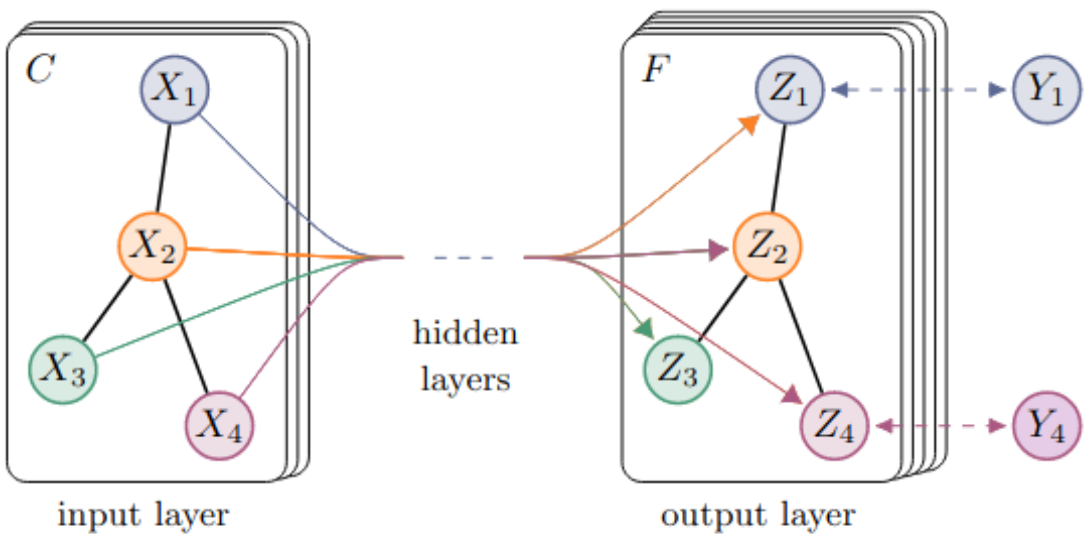
Graph Attention Networks

Given a graph, where

- nodes: entities
- edges: relations

Task:
Which nodes are researchers?

Represent nodes by adding vectors of neighbors

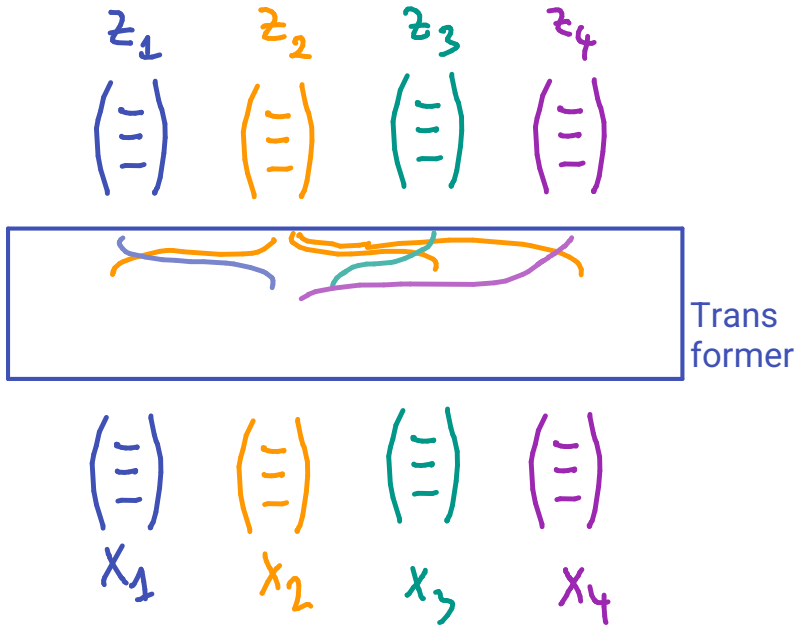


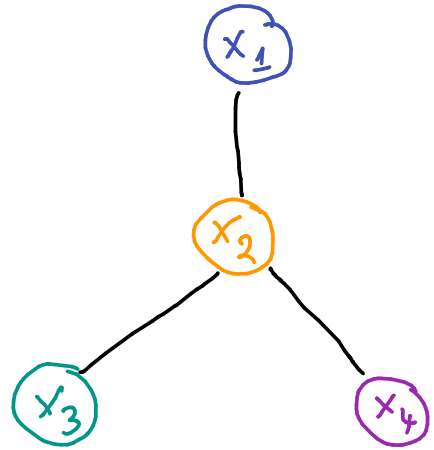
(a) Graph Convolutional Network

(b) Hidden layer activations

Kipf 2017 "Semi-supervised Classification with Graph Concolutional Neural Networks"

Graph Attention = Addition of Neighbors





Attention $\boldsymbol{a}_{qk}$ is restricted to edges (k, q)
Weight in sum is zero when there is no edge

Metric learning on neighbors (stretch edges with low attention)

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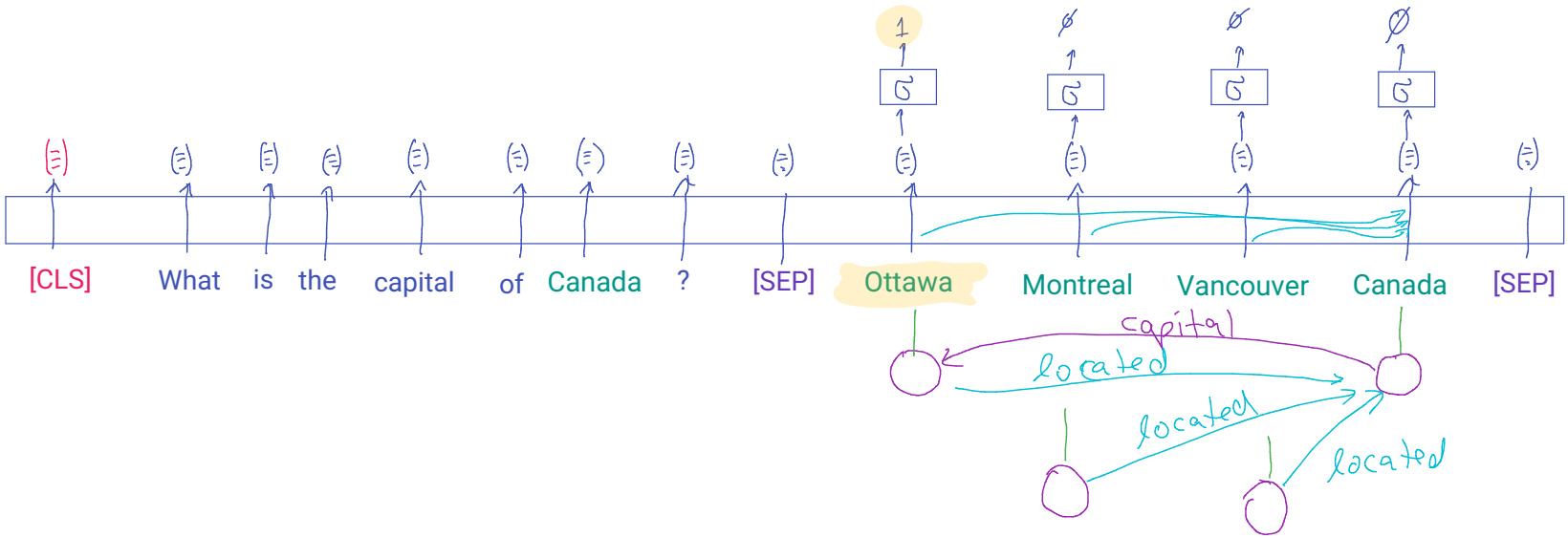
Question Answering with Knowledge Graphs

Example: What is the capital of Canada?
Find the node in the knowledge graph that is the answer.



- Combine sequence and graph data via attention
- Graph Attention Networks to select a node = answer.
- Just works because: Attention does not consider the sequence

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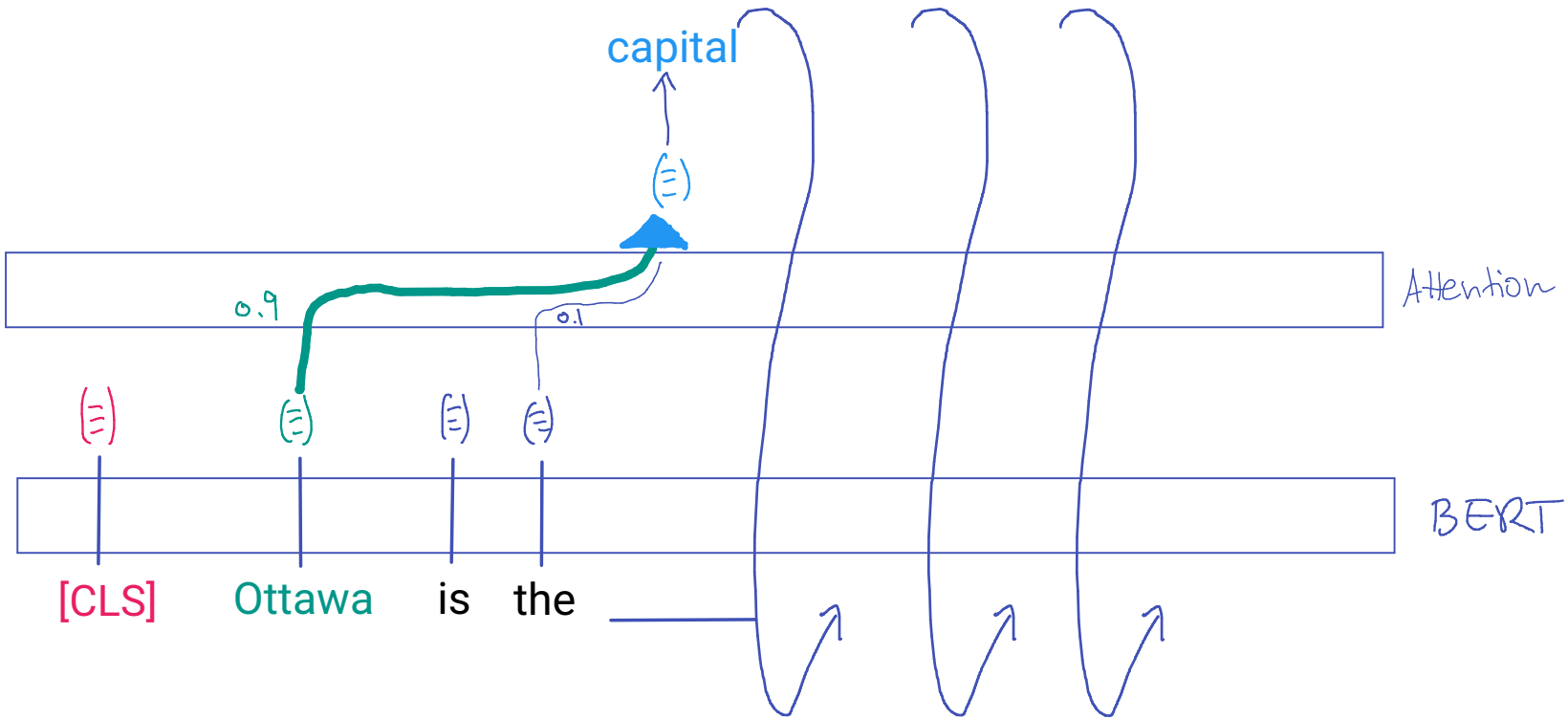
GPT

Input: Sequence of Text
Output: Next Word



Main differences to BERT Transformers:

- Can't access the "future"
- Needs to commit to a word before proceeding

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Representing "Hard" Symbols

In Neuro-symbolic methods we think of

- words as soft
- symbols as hard

Transformers can directly handle both words and symbols.
(because attention has no inate concept of position)

Difference:
Symbols come with additional information (KG, DB, semantics)
...we only need to leverage it!