Machine learning: advanced

Language modeling and lexical representation

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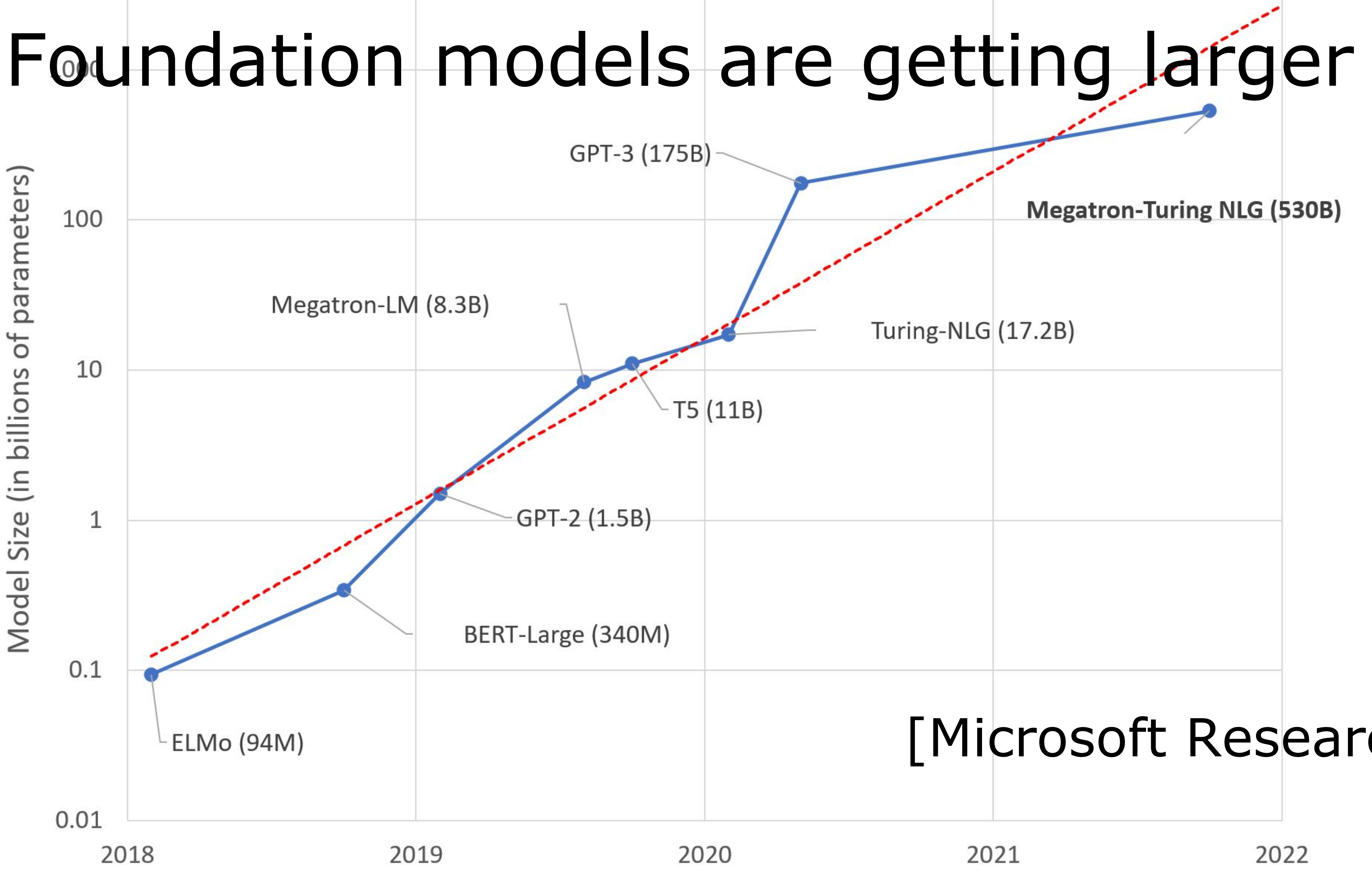
Outline

- Continuous embedding a la matrix factorization
- Word vectors from co-occurence data
- Masked language models, fine-tuning, contextual embeddings
- (Transformer language generation)

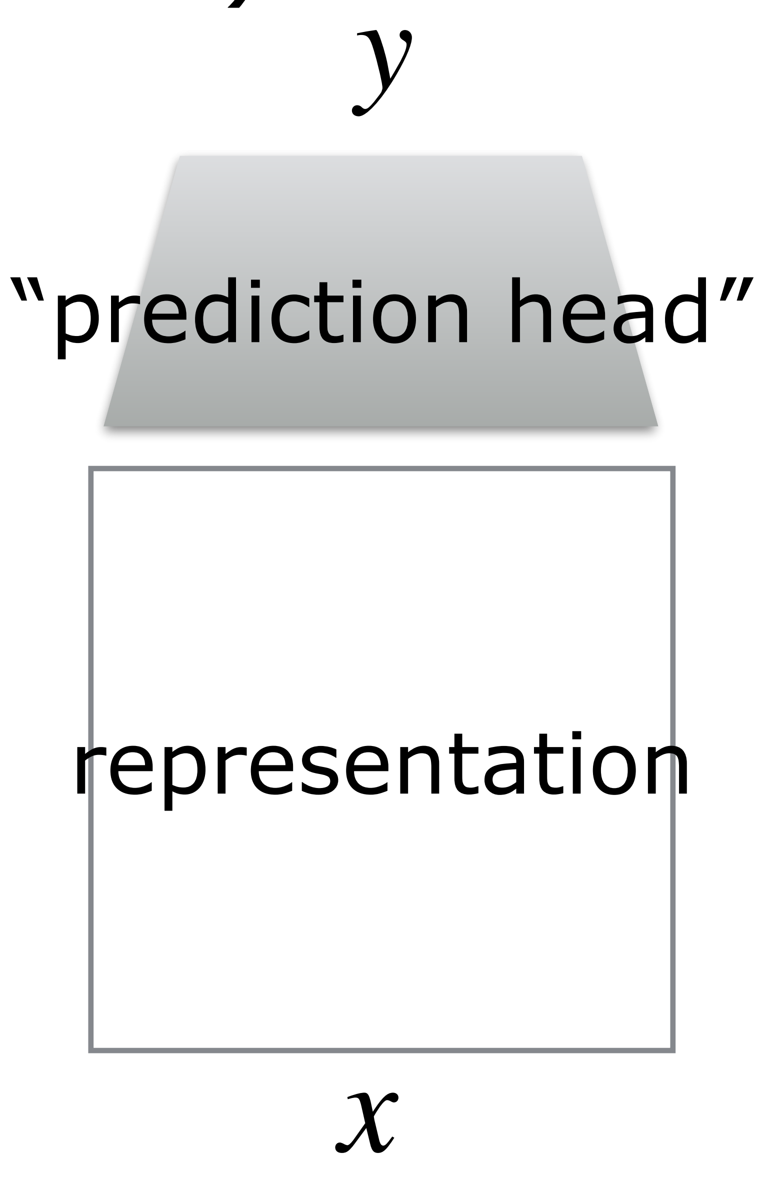
Foundation models

- Foundation models are trained from large amounts of data using auxiliary tasks, then adapted (parts of them reused) for the intended task(s)
- There are many ways to adapt/use these models to new tasks
  - extract useful, broadly useable representations
  - fine-tune (supervised or unsupervised, with or without a new prediction head)
  - use in a few shot prediction (e.g., a few examples available per category)
  - zero shot prediction (no new examples about the intended task; see example later)
- Foundation models are getting larger and larger…



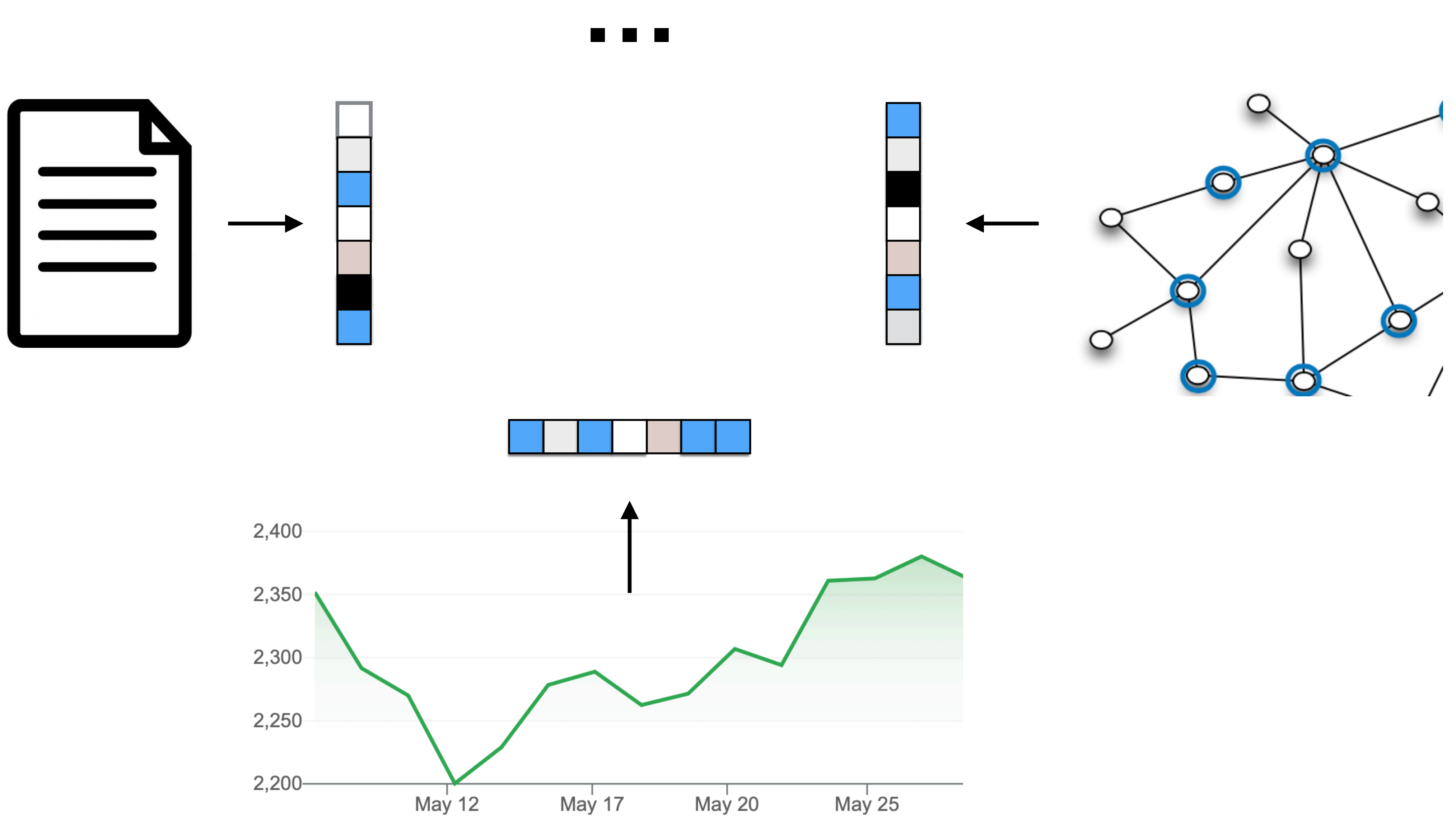
[Microsoft Research Blog 2021]

e.g., fine-tune by training a new prediction head



A step forward: continuous embedding

- We can turn any input into a vector representation (images, text, graphs, time course signals, etc)
- These vector representations can be optimized to preserve relevant information about the objects, often even without any labels!
- One everything is comparable (as vectors), we can easily combine heterogenous data sources, or predict one type from the others
- Some examples
  - users and products (collaborative filtering)
  - words within/across languages
  - images and text (such as captions)
  - service tickets and experts
  - etc.



Recall: matrix factorization

movies/items

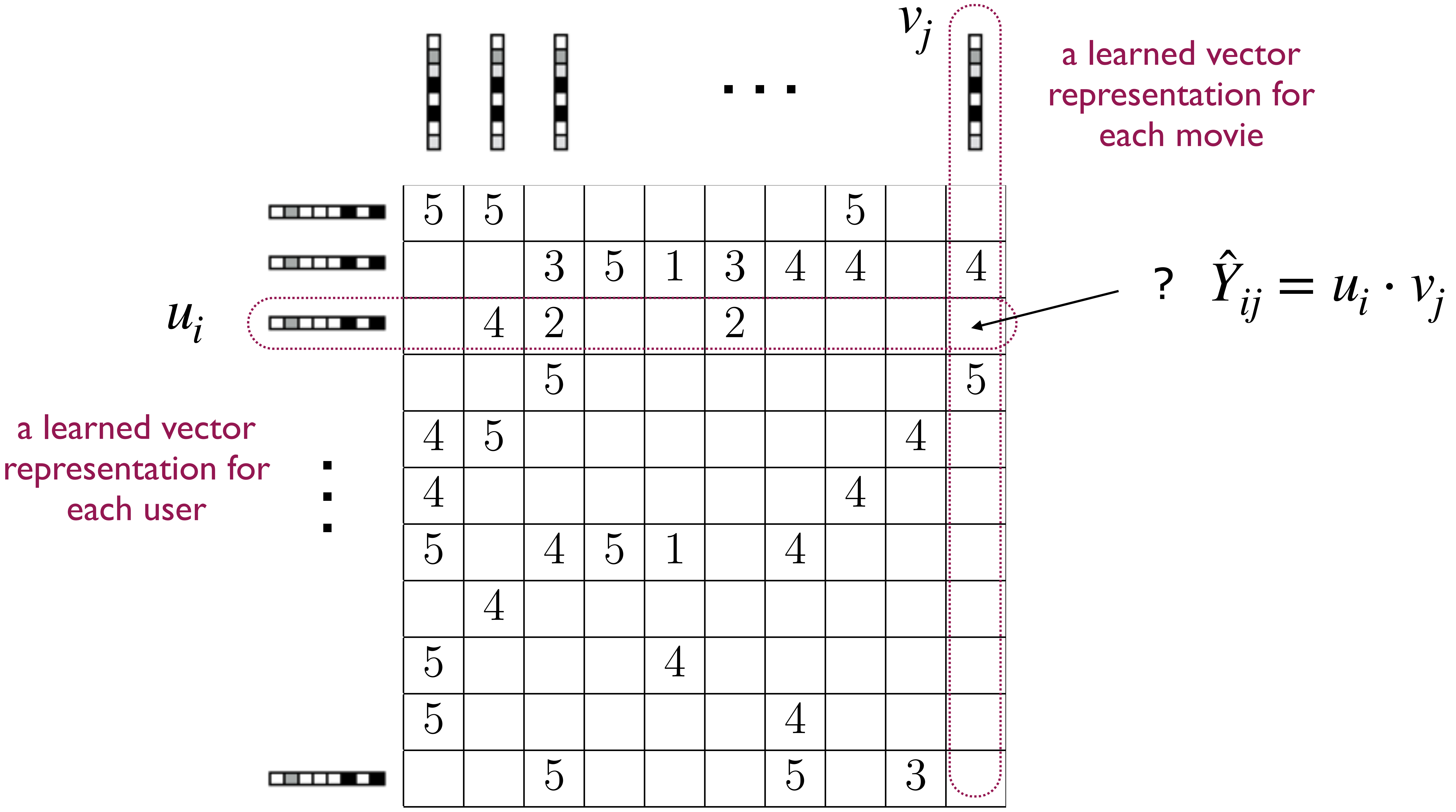
users

5	5						5		
		3	5	1	3	4	4		4
	4	2			2				
		5							5
4	5							4	
4							4		
5		4	5	1		4			
	4								
5				4					
5						4			
		5				5		3	

?

- Vector representations for users and movies are initialized at random, then driven to predict the observed ratings

Recall: matrix factorization



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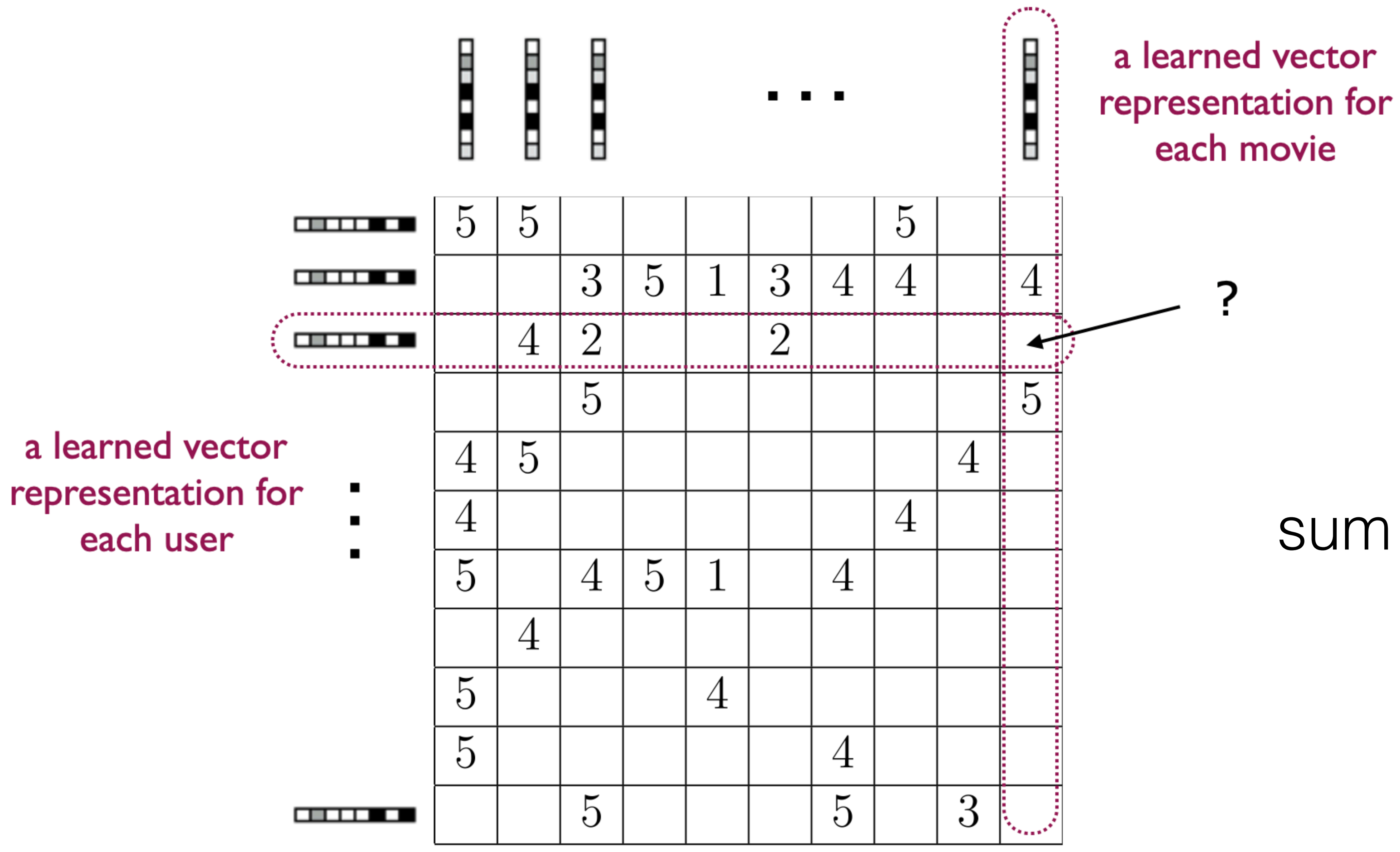
Supervised embedding

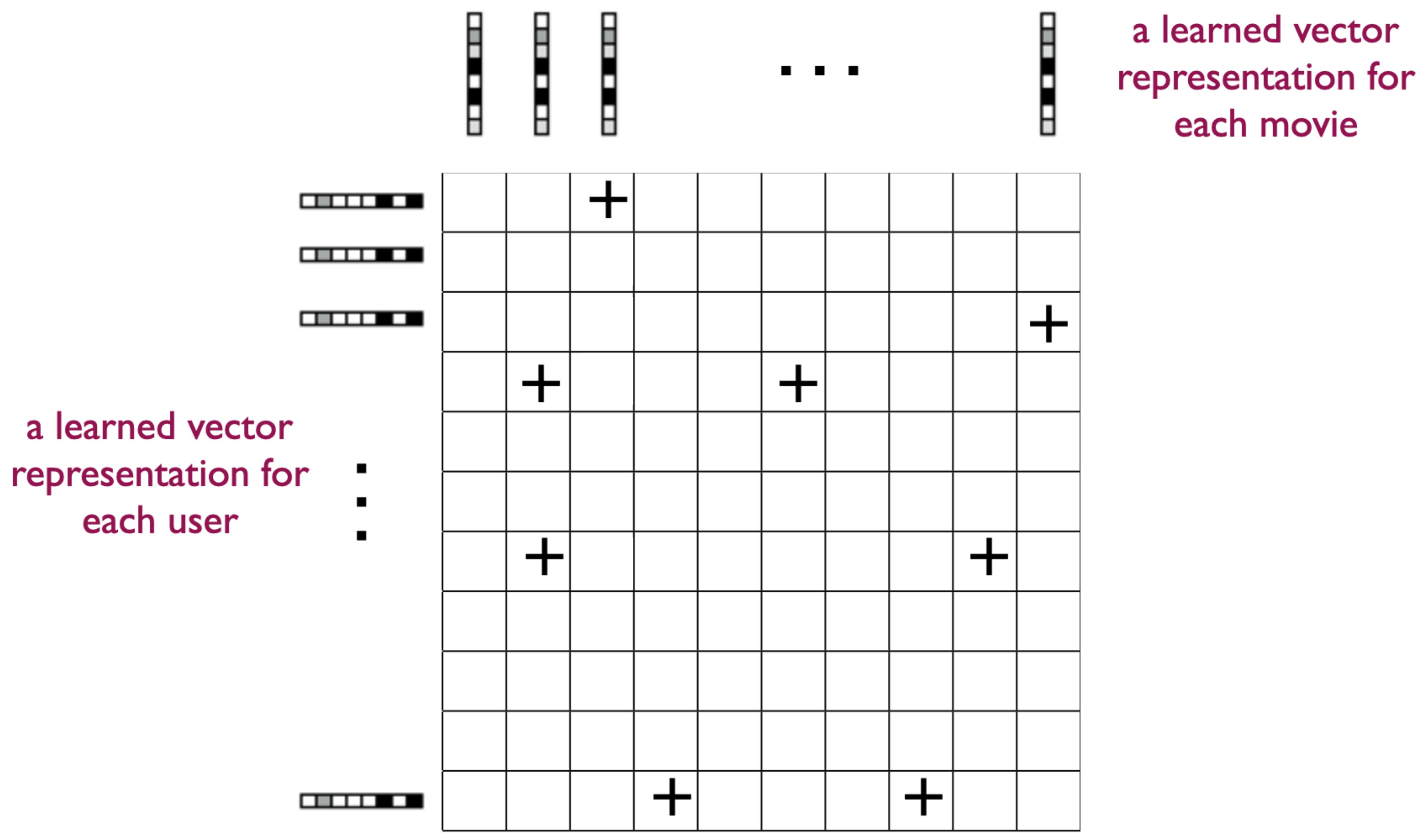


$$\underbrace{\sum_{(i,j)\in D}}_{\text{sum over observations}} (\overset{\text{observed rating}}{Y_{ij}} - u_i \cdot v_j)^2 + \underbrace{\cdots}_{\text{regularization}}$$

- Vector representations for users and movies are initialized at random, then driven to predict the observed ratings

Embedding via co-occurrence

- What if we only have positive “interactions”, not ratings?



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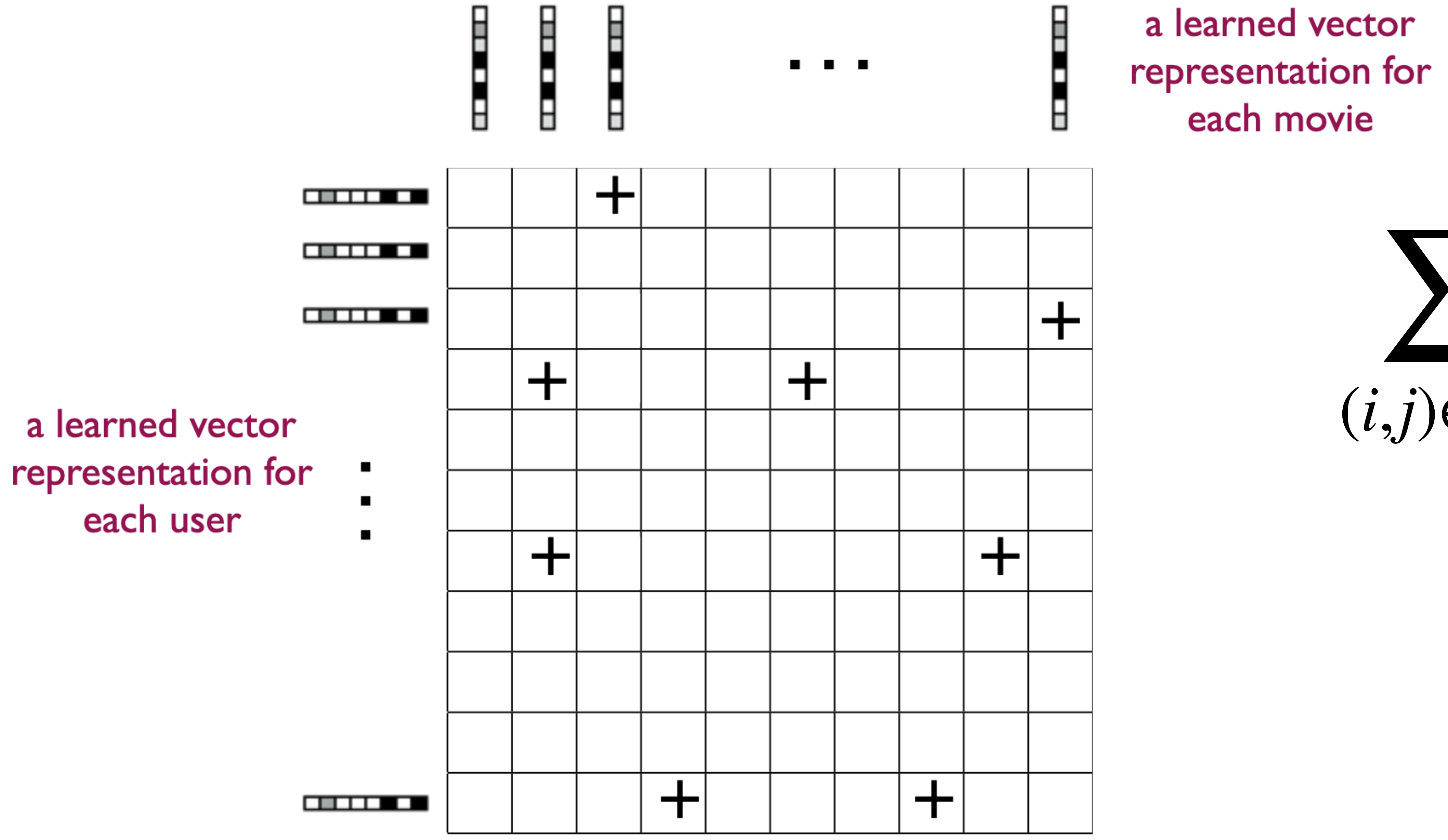

$$\sum_{(i,j)\in D} (1 - u_i \cdot v_j)^2 + \cdots$$

$$\Rightarrow v_i = \vec{1}/\sqrt{d}, \;\; u_j = \vec{1}/\sqrt{d}$$

is a “solution” for all i and j

Embedding via co-occurrence

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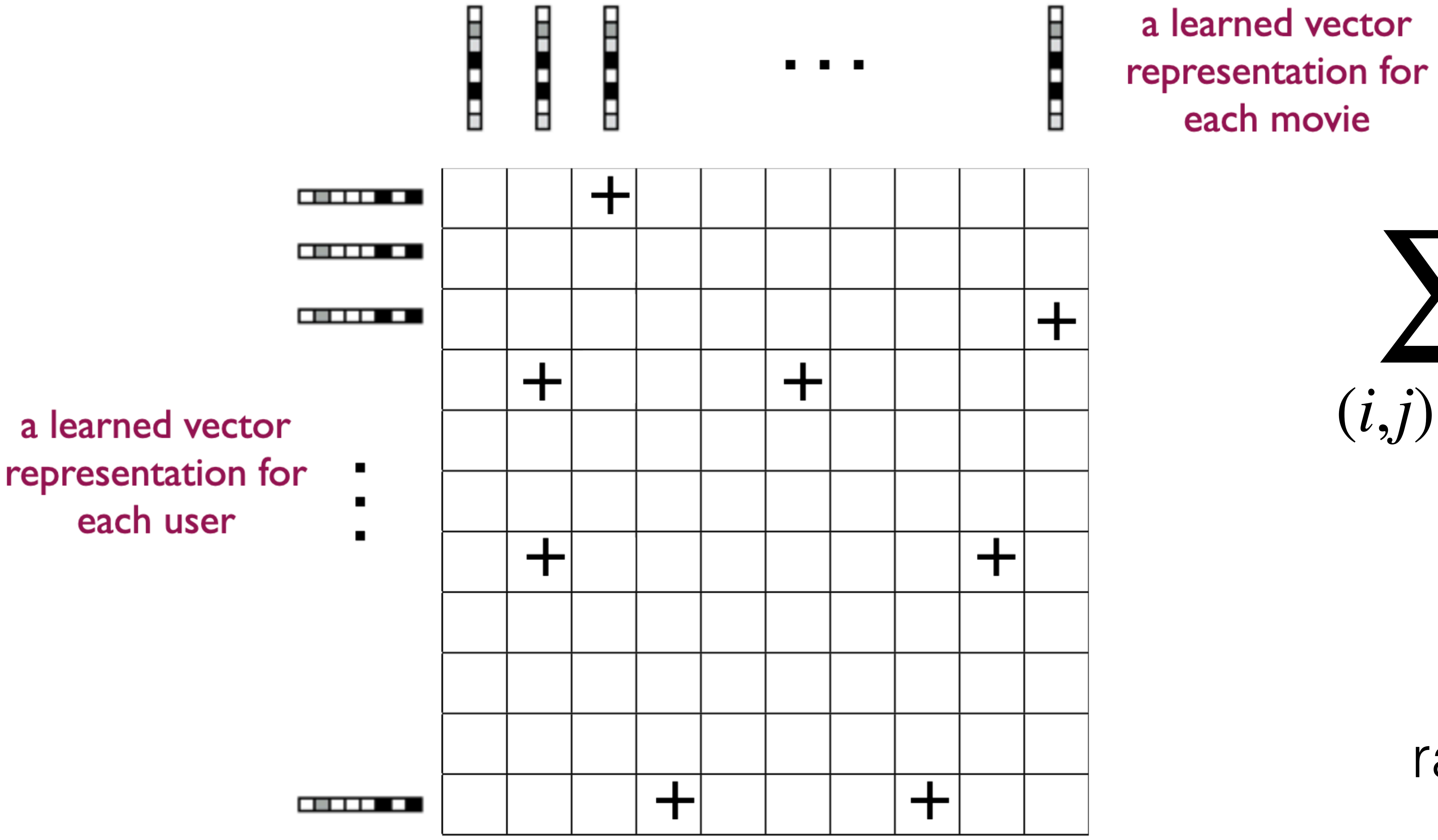

$$\sum_{(i,j)\in D} (1 - u_i \cdot v_j)^2 + \cdots$$

$$+ \sum_{(i,j)\in D^-} (0 - u_i \cdot v_j)^2$$

randomly sampled "negatives"

- As a remedy, we could sample and include a set of negatives out of the unobserved entries, and resample these negatives anew for each (gradient) update of u's and v's (contrastive estimation)

Learning to represent words

- One-hot word vectors are not good enough (do not capture similarity)
- E.g., ‘hotel’ and ‘motel’ should likely have a very similar word representation as they are often interchangeable but as one-hot vectors they are always orthogonal!

$$\phi('hotel') = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ \cdots \\ 0 \end{bmatrix} \qquad \phi('motel') = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ \cdots \\ 0 \end{bmatrix}$$

Learning to represent words

- One-hot word vectors are not good enough (do not capture similarity)
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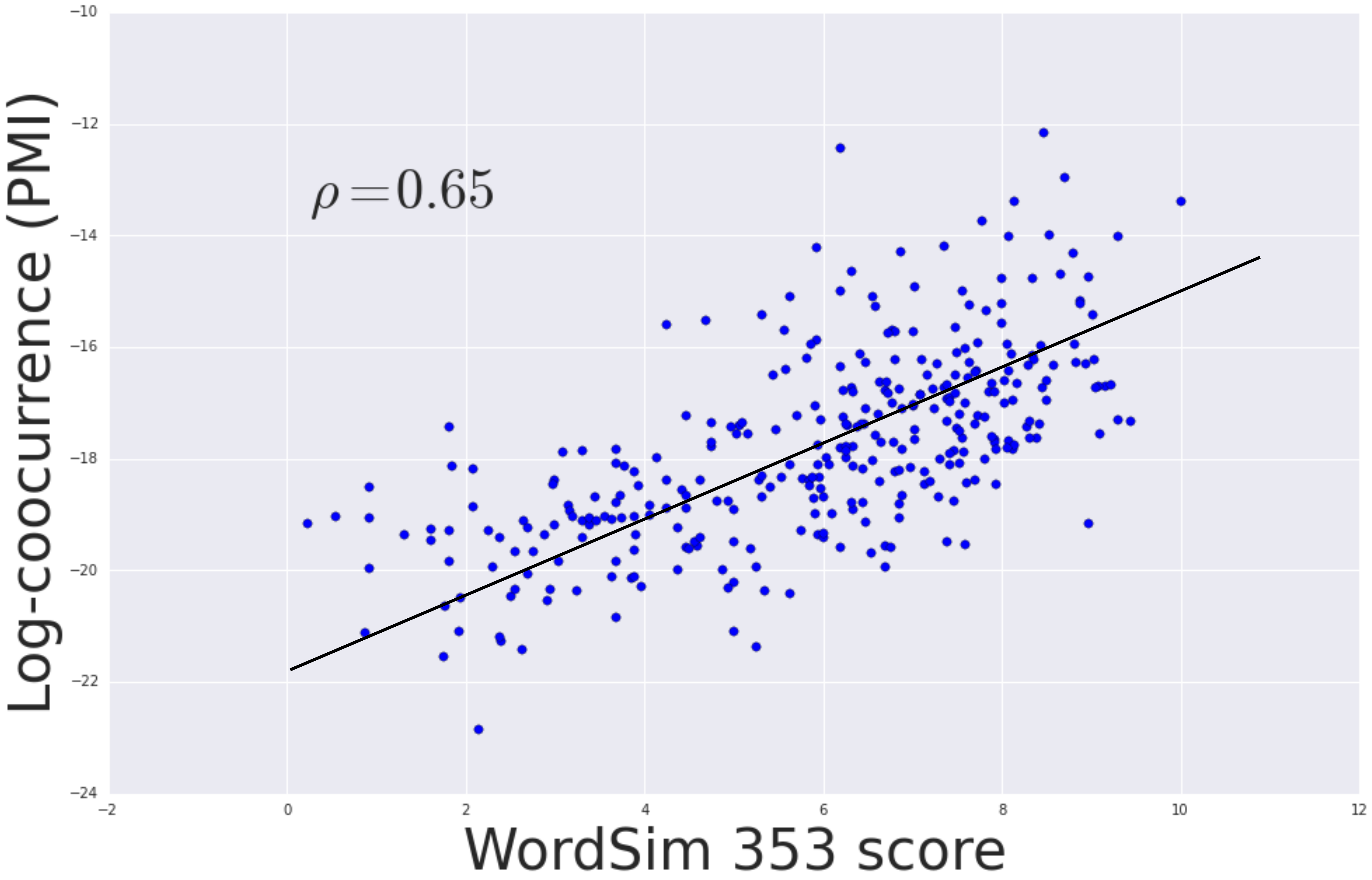
Learning to represent words

- One-hot word vectors are not good enough (do not capture similarity)
- Ideally, we’d find low dimensional vectors for words so that their similarity (e.g., cosine similarity) would capture syntactic/semantic relations
- Co-occurence in sentences across a large corpus provides a sufficient signal to drive these word vector representations to be semantically meaningful

“You shall know a word by the company it keeps”
(Firth, J. R. 1957)

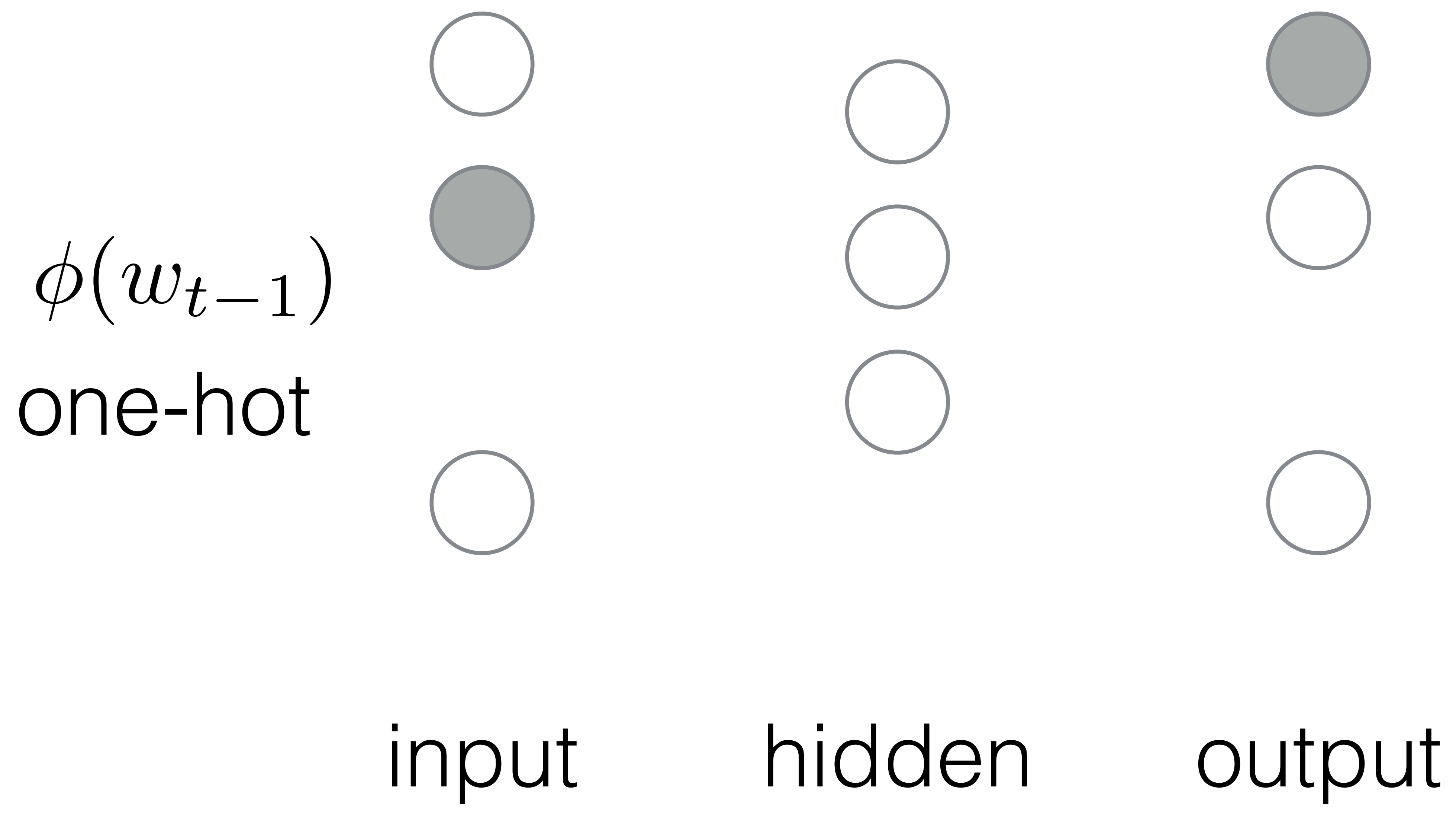
Co-occurence & similarity

- We can obtain semantic similarity assessments between pairs of words from surveys
- Words that co-occur in each other's context in a large corpus tend to be (roughly speaking) semantically similar



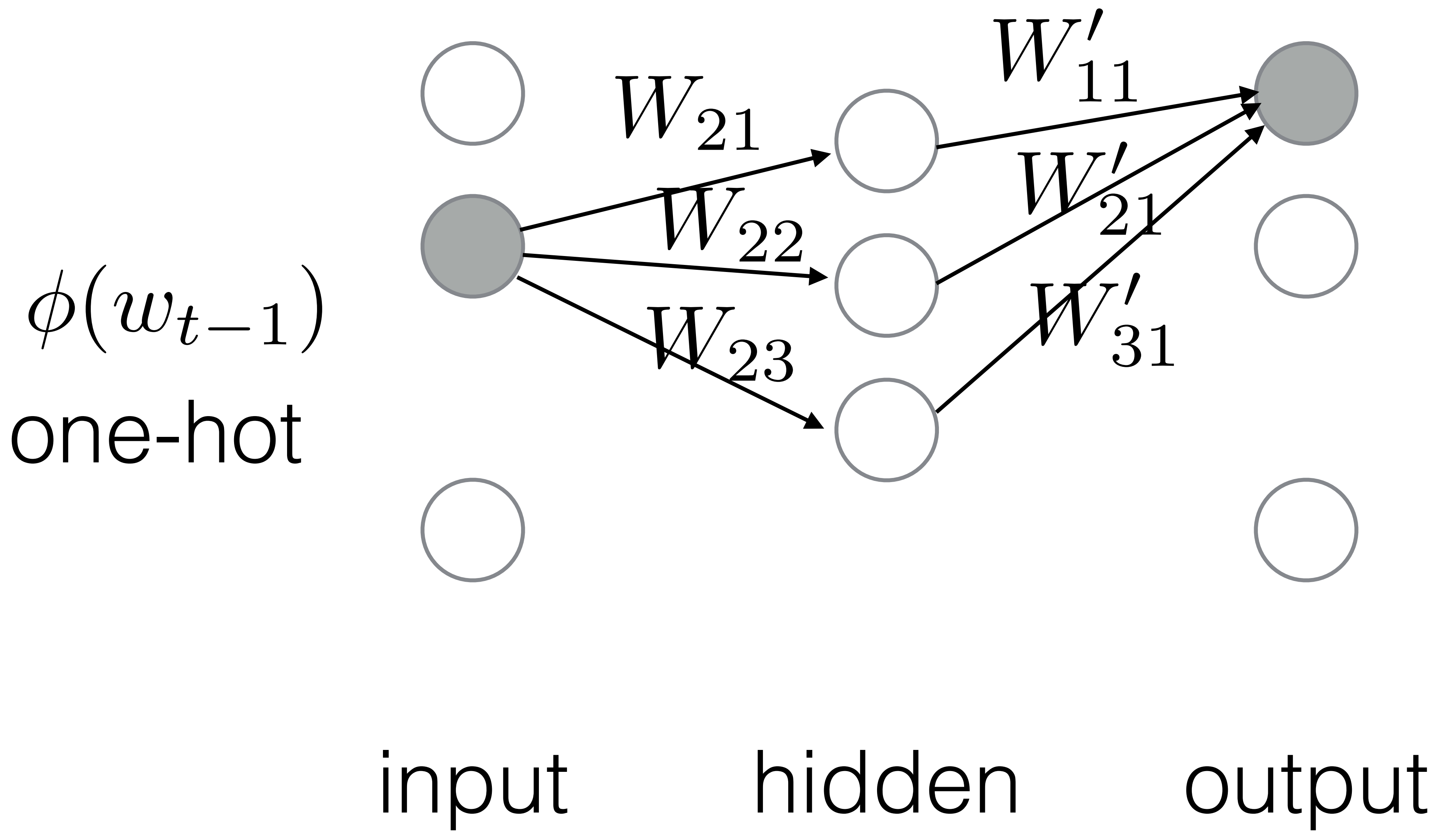
Simple neural bigram model

- Predict each word based on the previous word in the sentence



Word vectors from the model

- Predict each word based on the previous word in the sentence
- This simple model already estimates two different low dimensional dense vectors for each word



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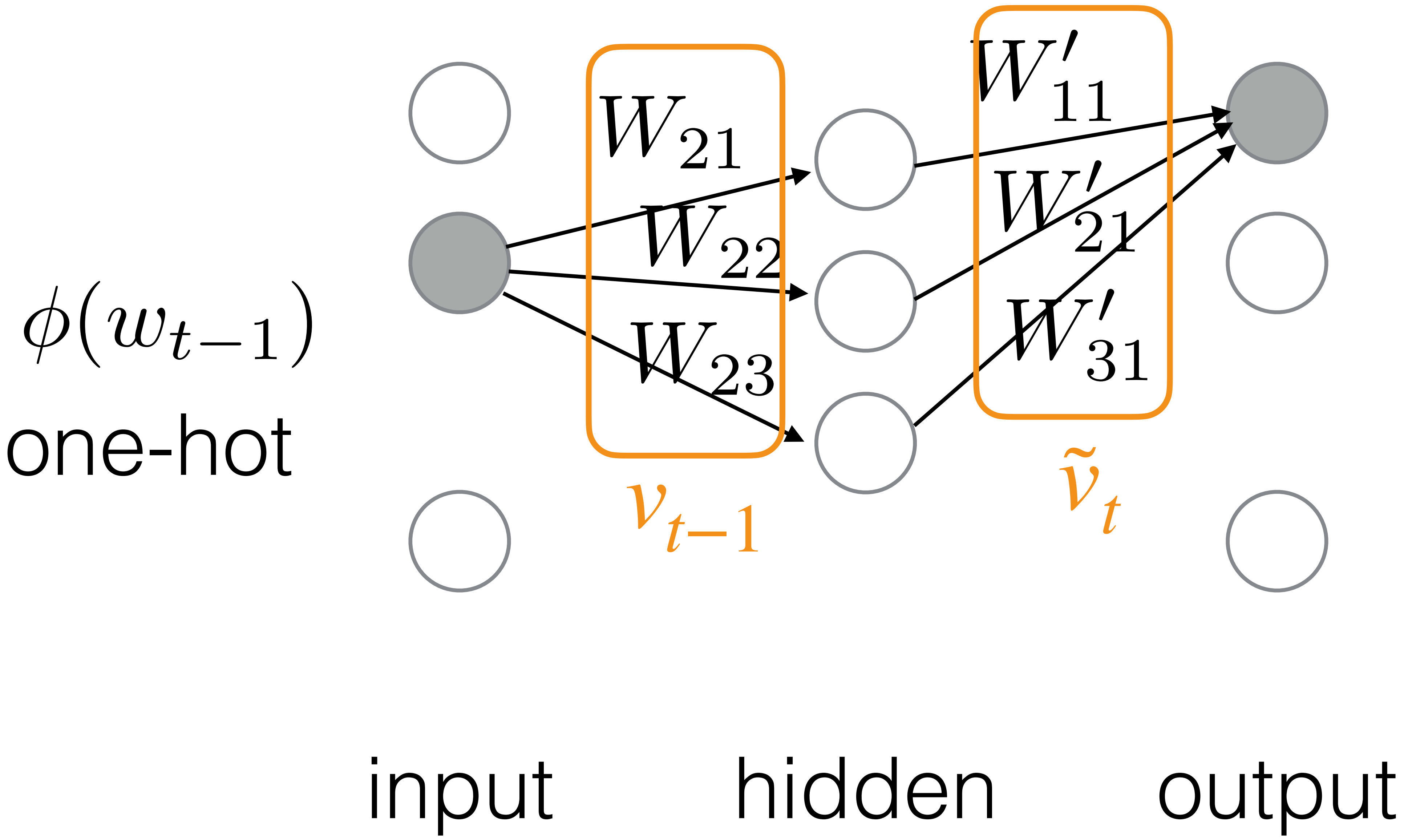
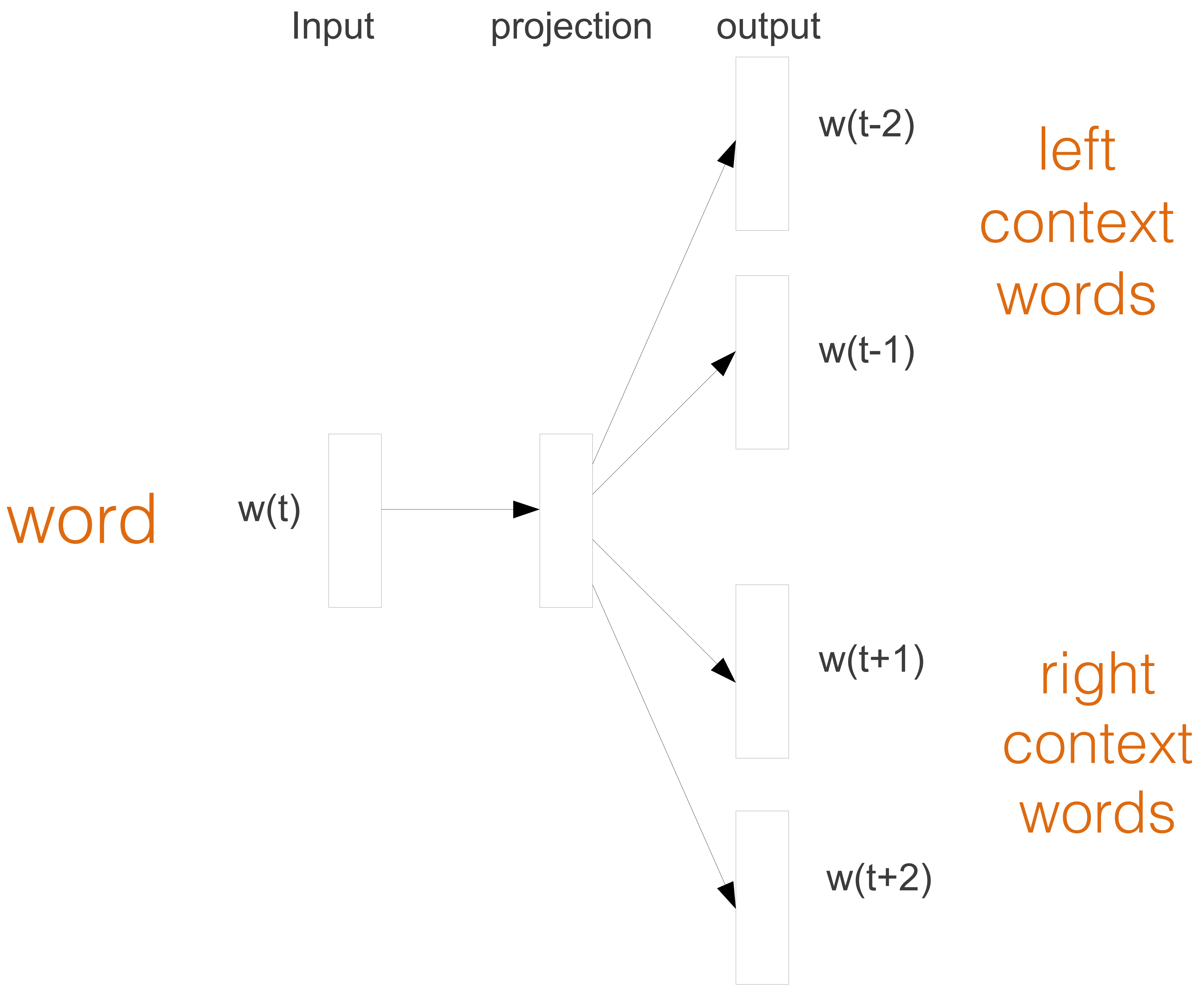
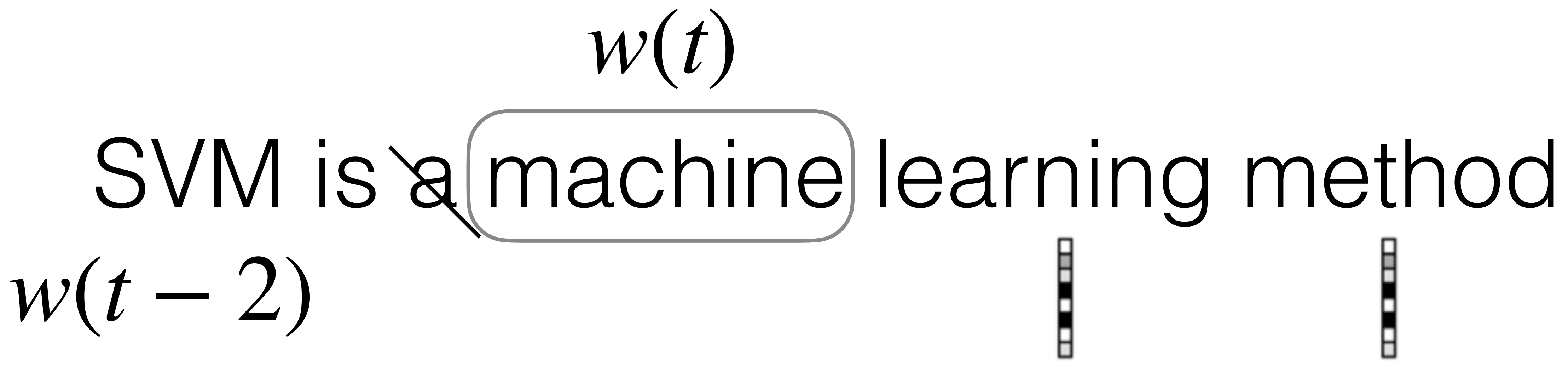


Example: word2vec

- Skip gram model





(Mikolov et al 2013)

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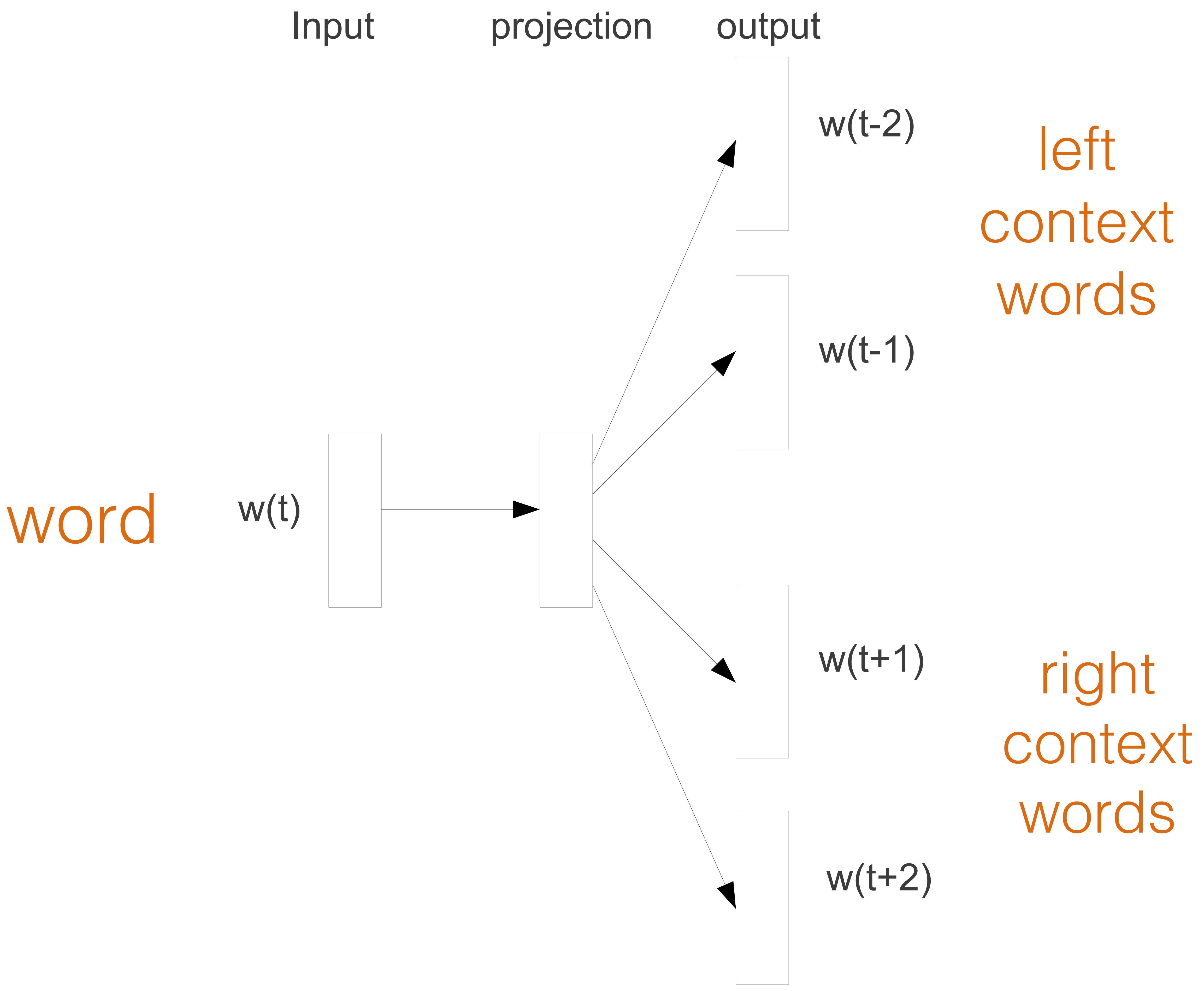

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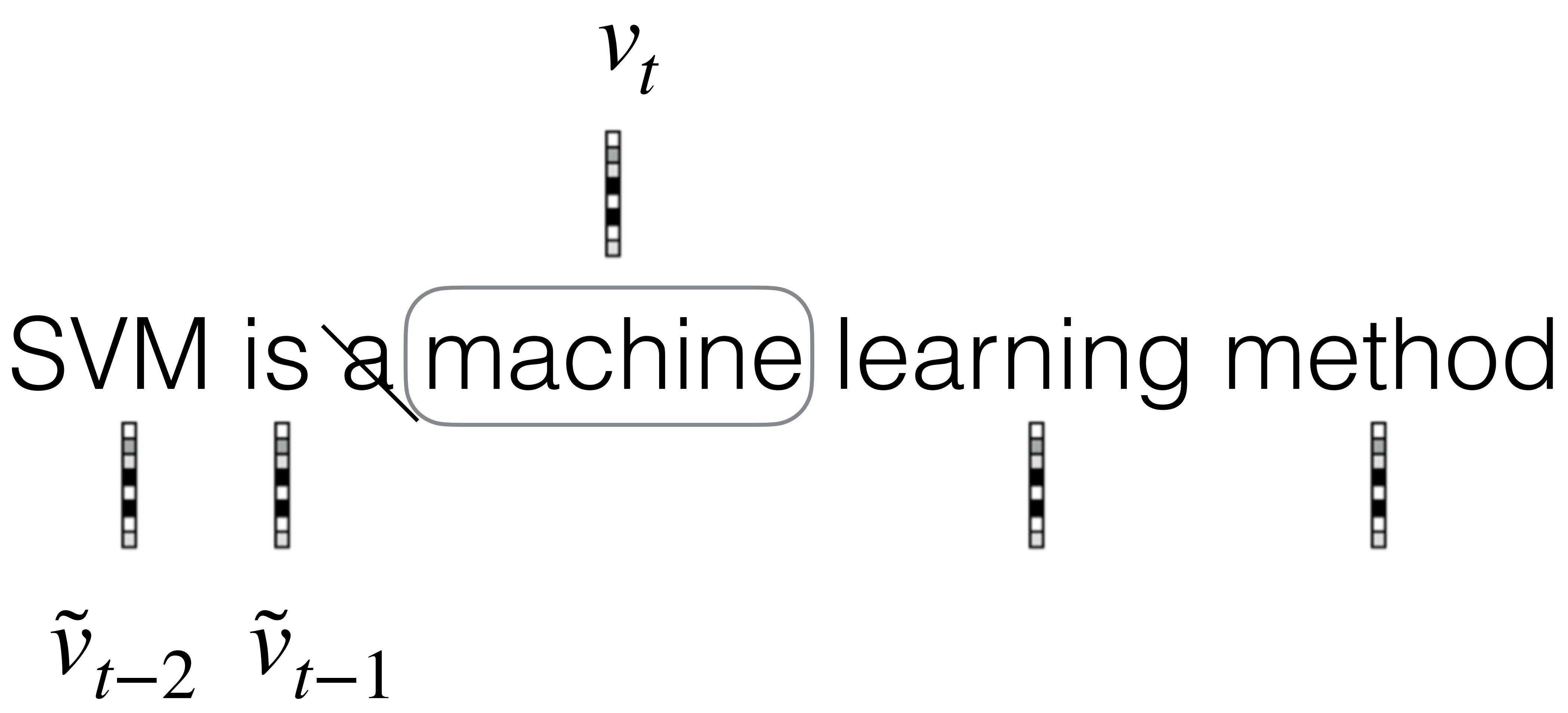

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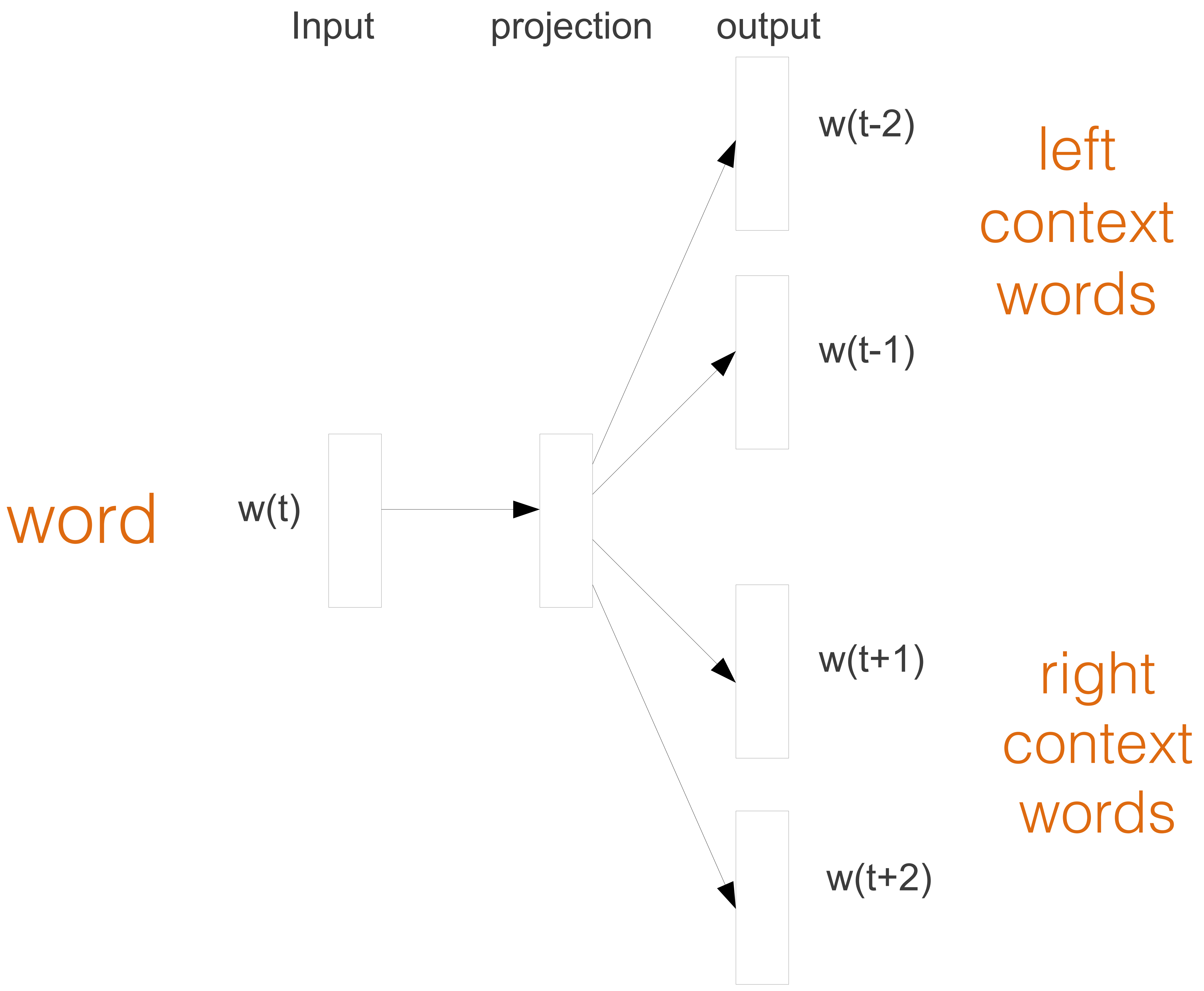
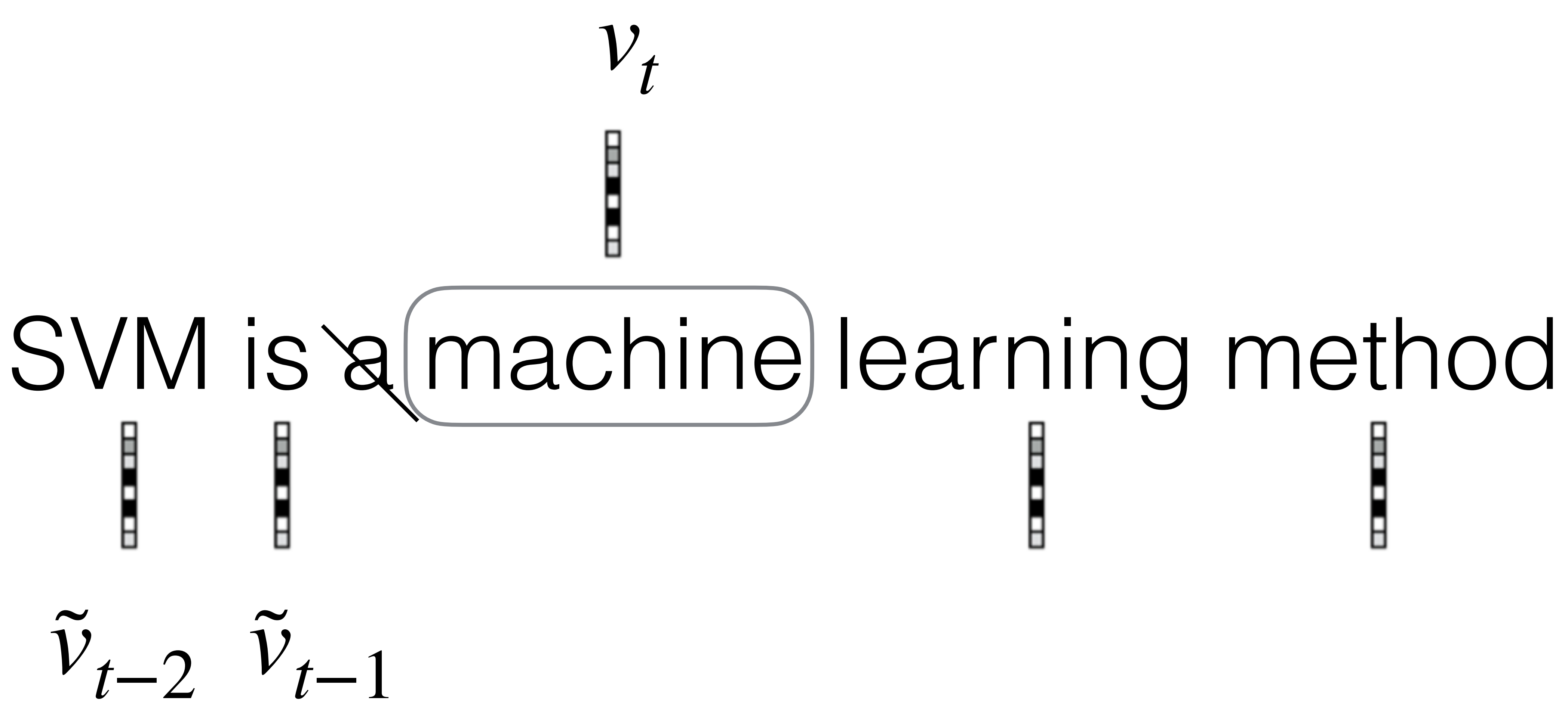




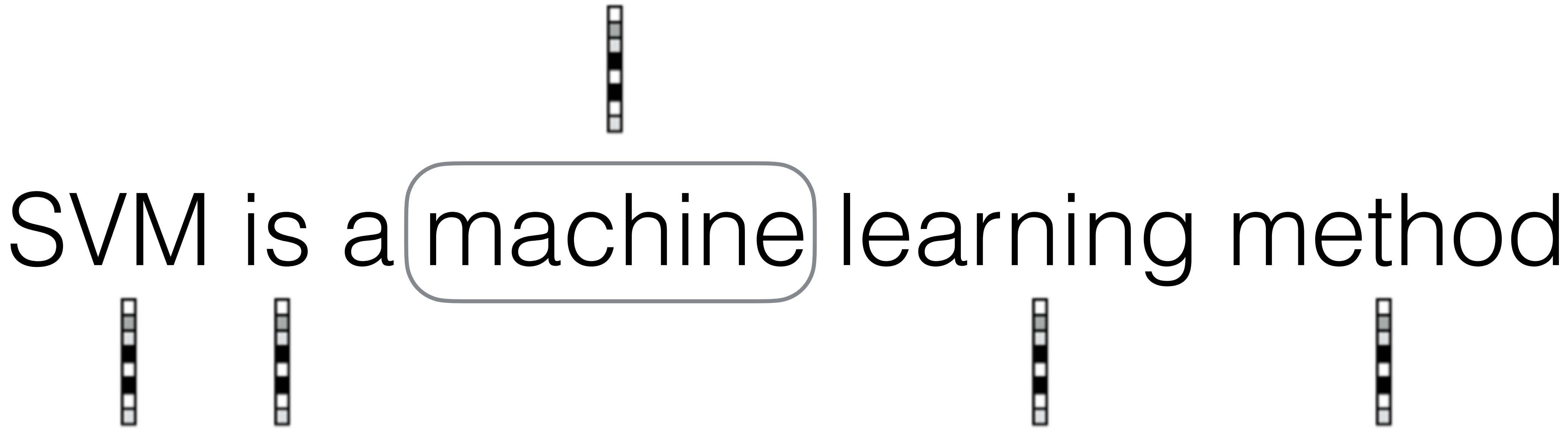
$$P(w(t-2)\,|\,w(t)) = \frac{\exp(v_t \cdot \tilde{v}_{t-2})}{\sum_{\tilde{v}'} \exp(v_t \cdot \tilde{v}')}$$

denominator sums over all the vectors associated with vocab words

(Mikolov et al 2013)

Noise contrastive estimation

- We can also turn the learning problem into a classification task (recognizing words that are in the same context)
- Nearby words are positive examples



- Sampled other K words are negative examples

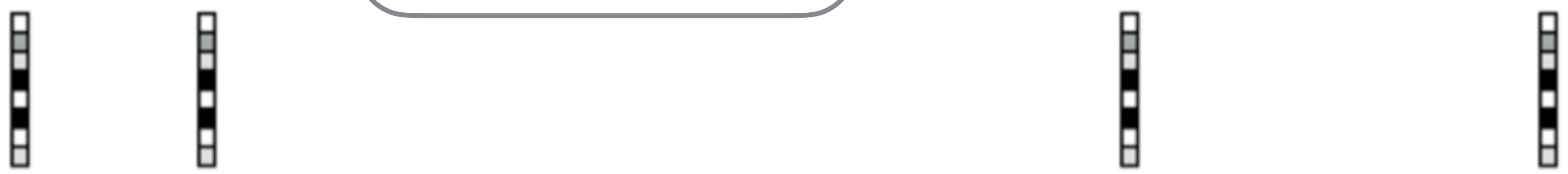
Noise contrastive estimation

- We can also turn the learning problem into a classification task (recognizing words that are in the same context)

$$\sum_i \left[\frac{1}{N(i)} \sum_{j \in N(i)} \log g(v_i \cdot \tilde{v}_j) + \frac{1}{K} \sum_k \log g(-v_i \cdot \tilde{v}_k) \right] \qquad g(z) = \frac{1}{1 + \exp(-z)}$$

- Nearby words are positive examples

SVM is a $\boxed{\text{machine}}$ learning method

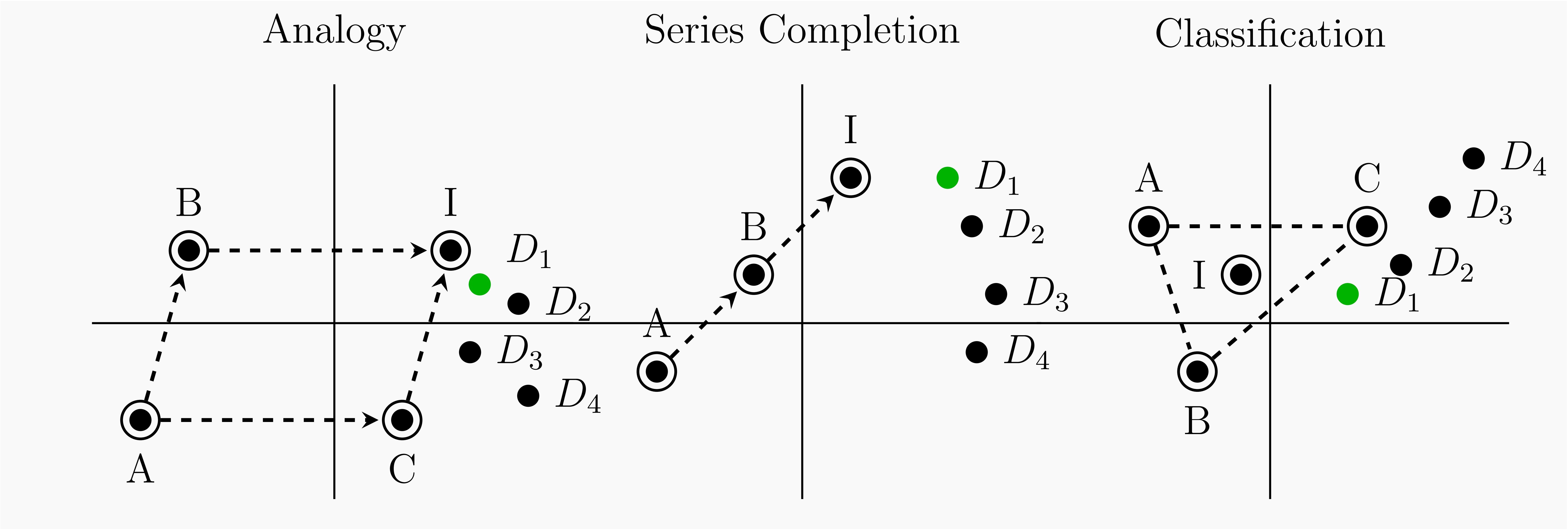


- Sampled other K words are negative examples

Cell biology covers somewhat different material…

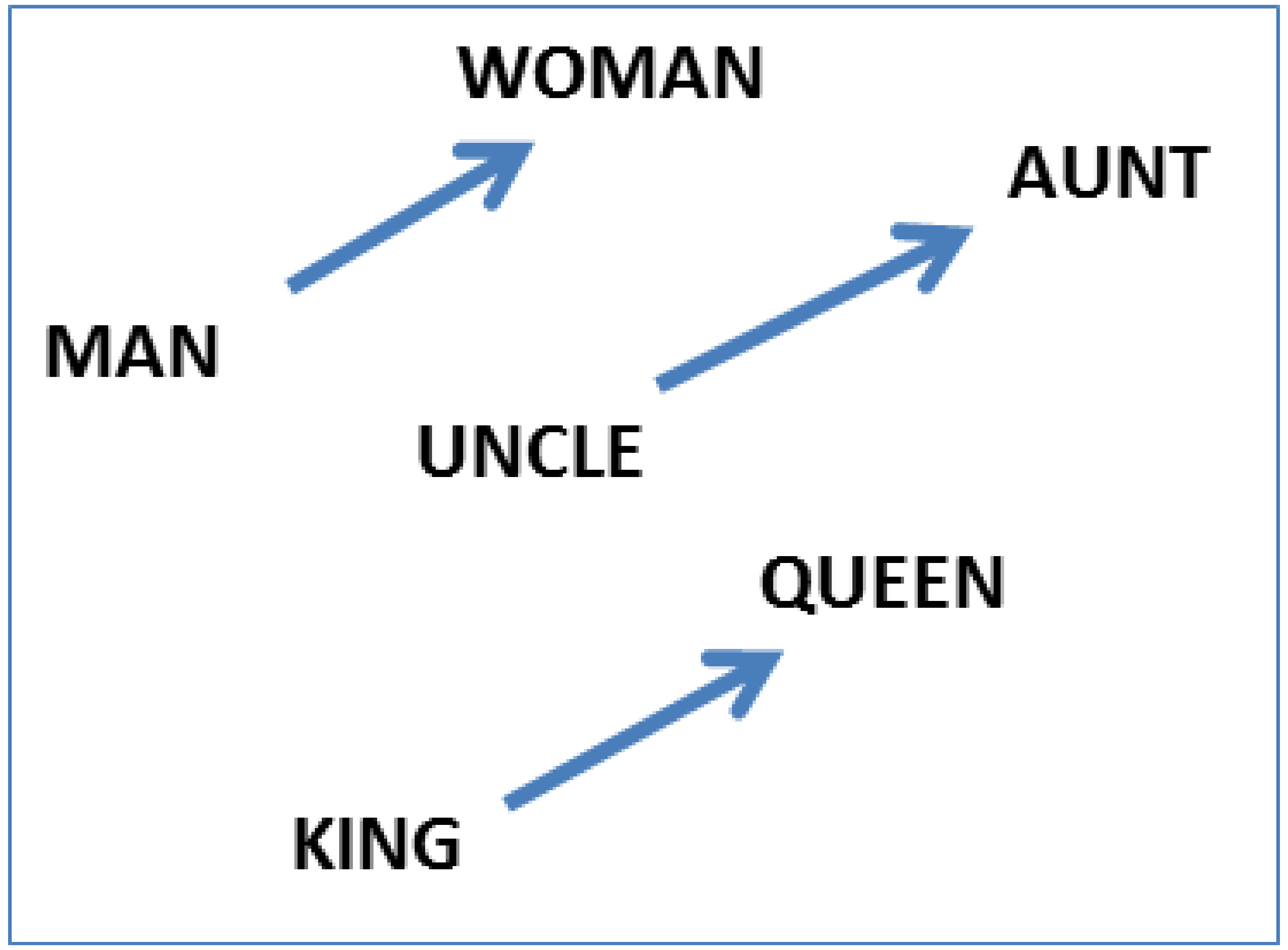
Evaluation: from psychometrics literature

- Word vectors/spaces have long history (e.g., Rumelhart and Abrahamson 73'; Sternberg and Gardner 83')

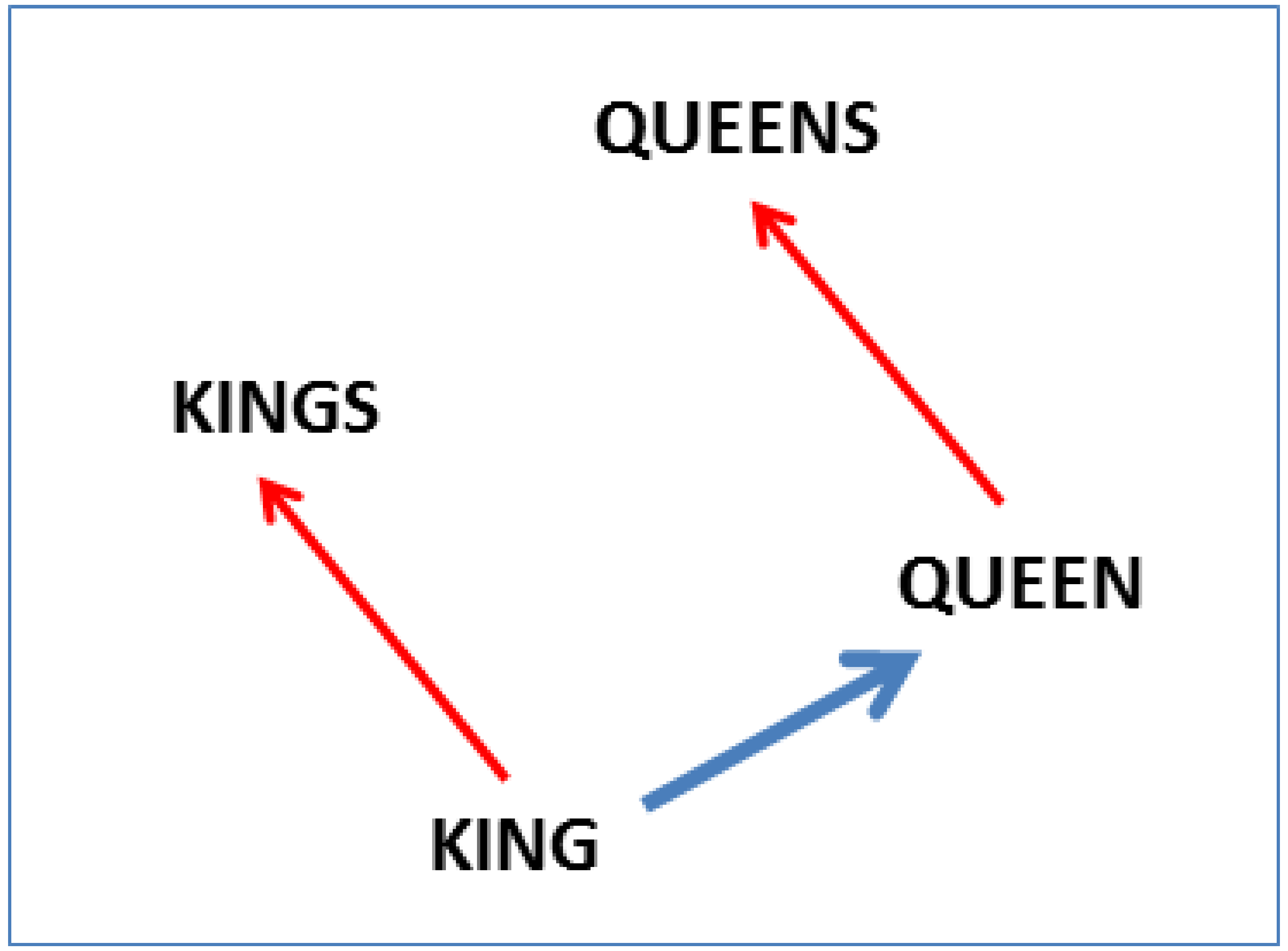


- **analogy**: a king is to man as queen is to ?
- **series completion**: penny, nickel, dime, ?
- **classification**: zebra, giraffe, ? (out of dog, cat, deer)

Testing word vector: analogies



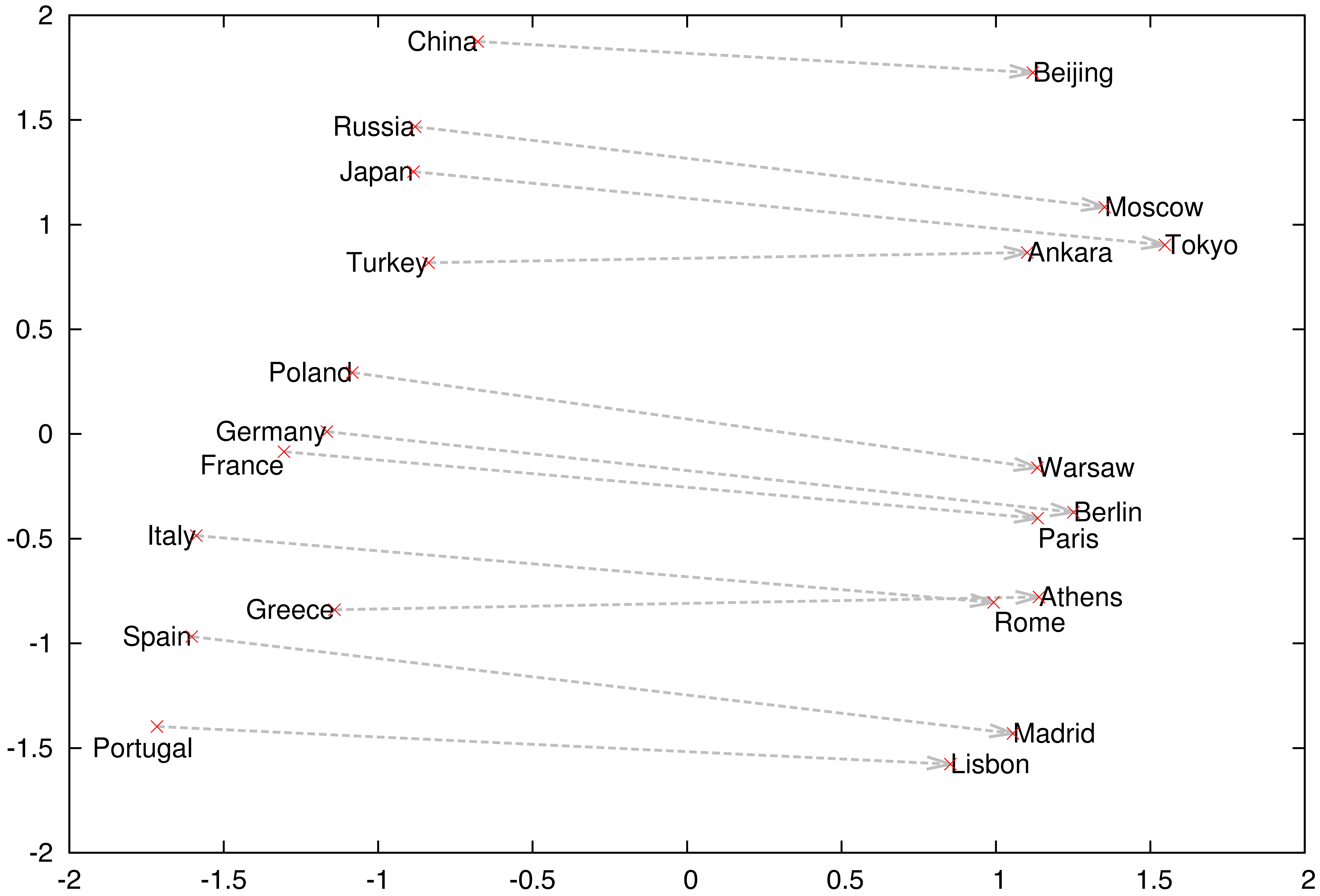
semantic



syntactic

(Mikolov et al., 2013)

Word vector analogies (semantic)



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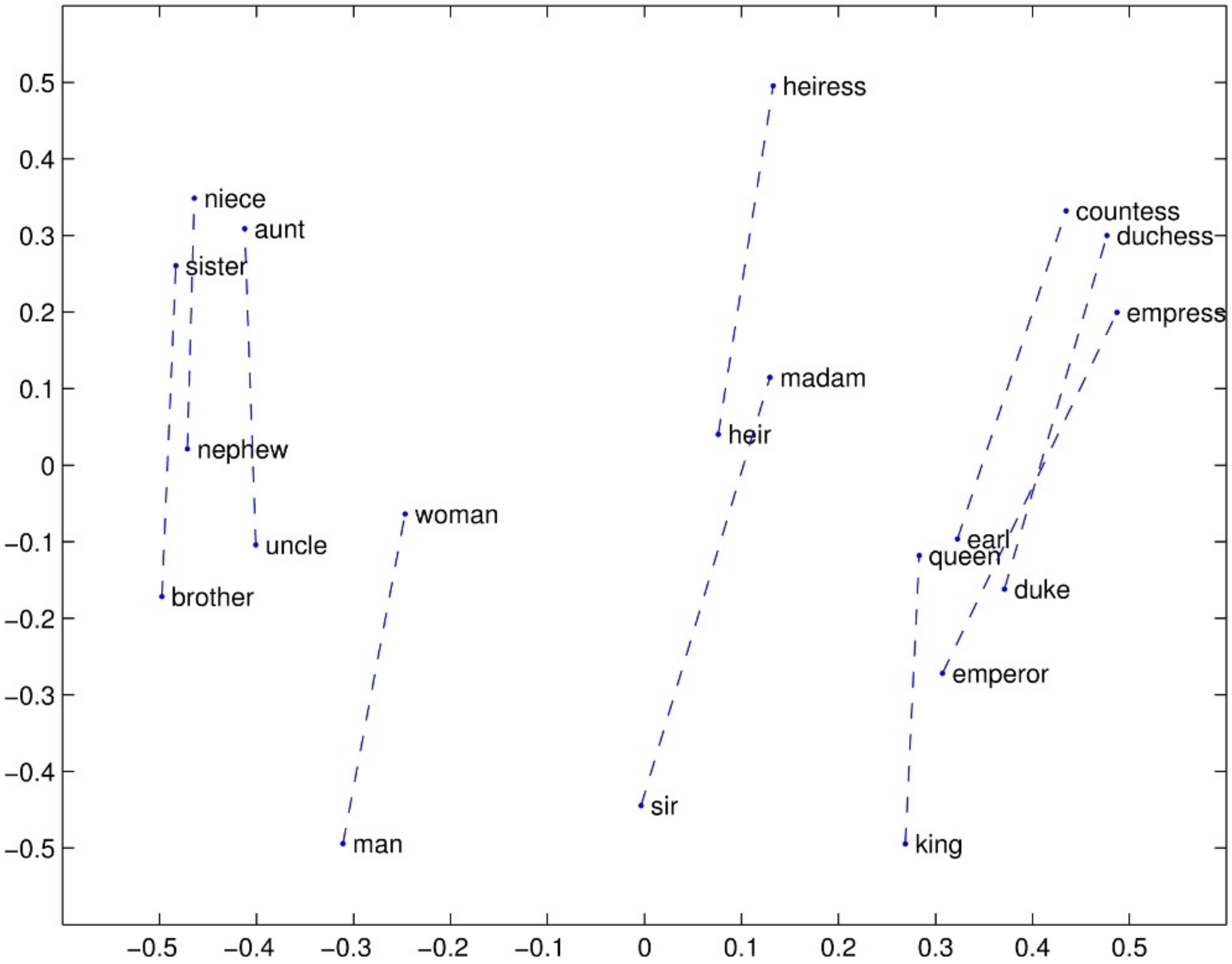
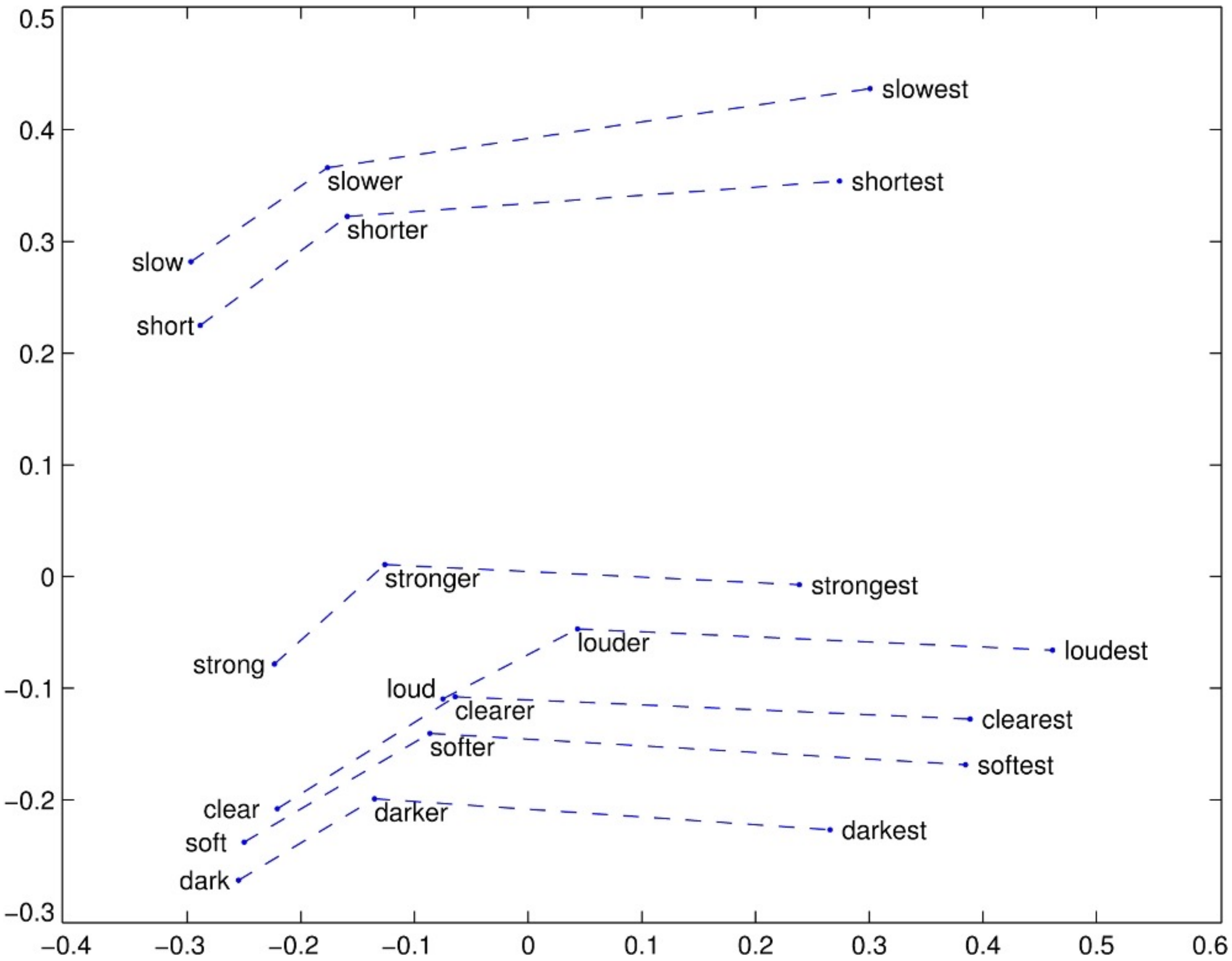
Word vector analogies (semantic)



(Pennington et al., 2014)

Word vector analogies (syntactic)



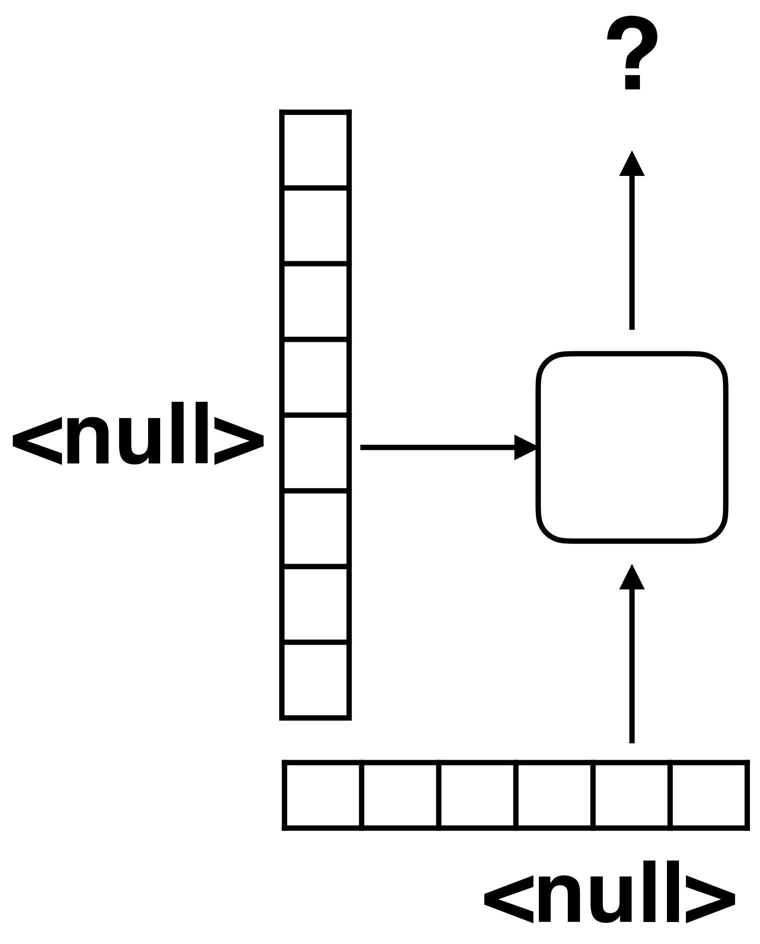
(Pennington et al., 2014)

Beyond bigram/skip gram models

- Autoregressive models for language generate one word at a time, conditioning the generation of each word on the previously generated text

$$P(x_1 \,|\, x_0)$$

E.g., RNN



x_0

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$$P(x_1 \mid x_0)$$

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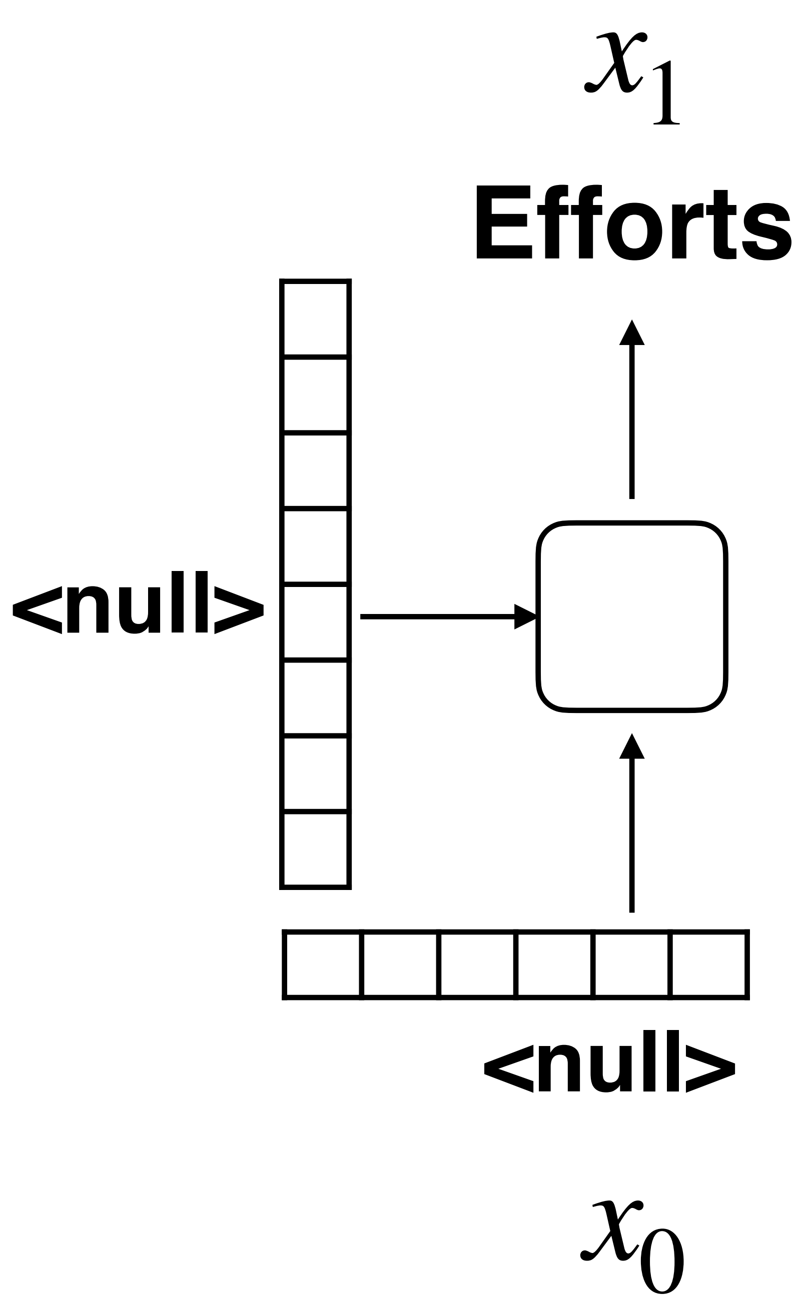

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$$P(x_1 \mid x_0)P(x_2 \mid x_1, x_0)$$

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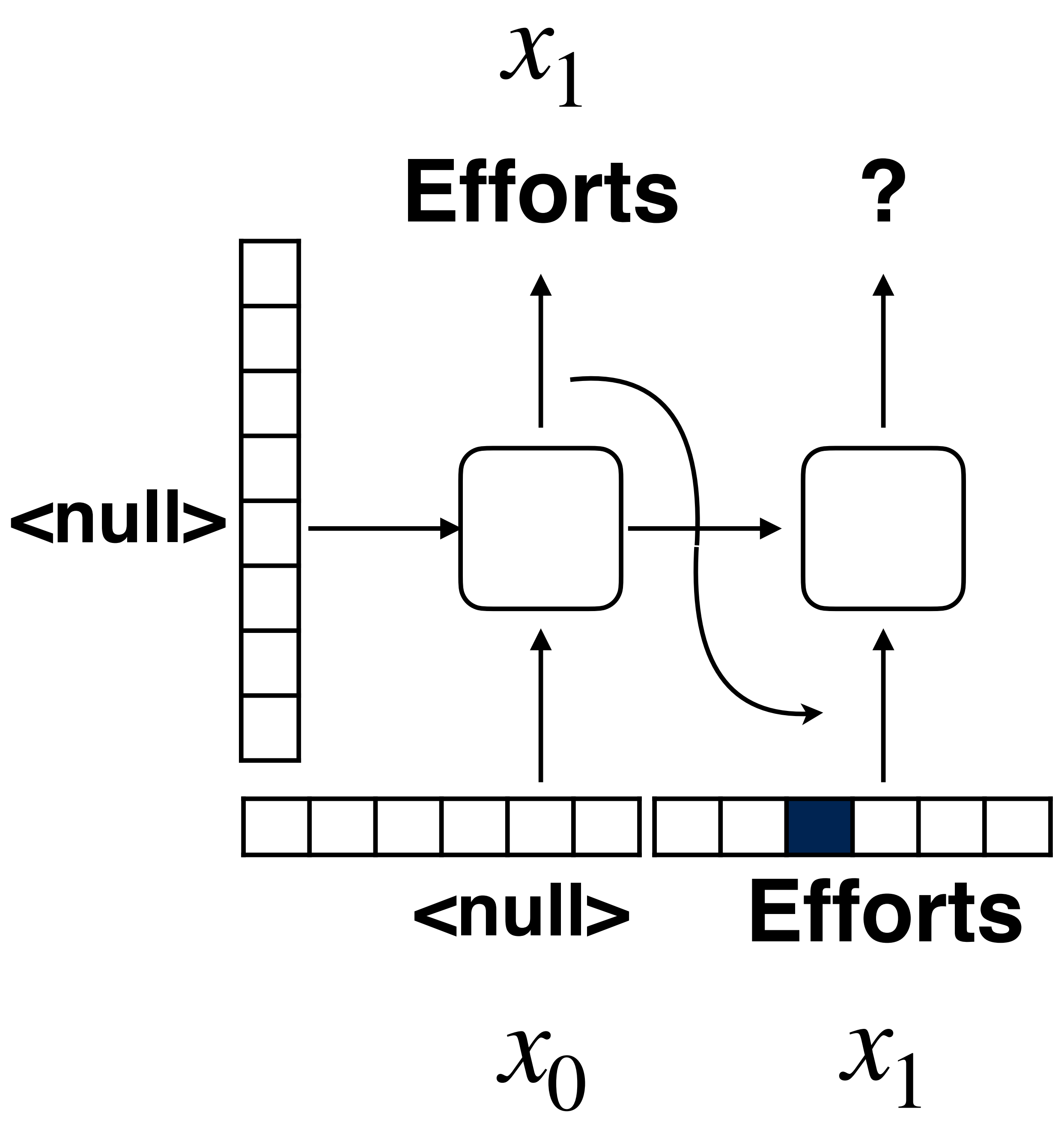

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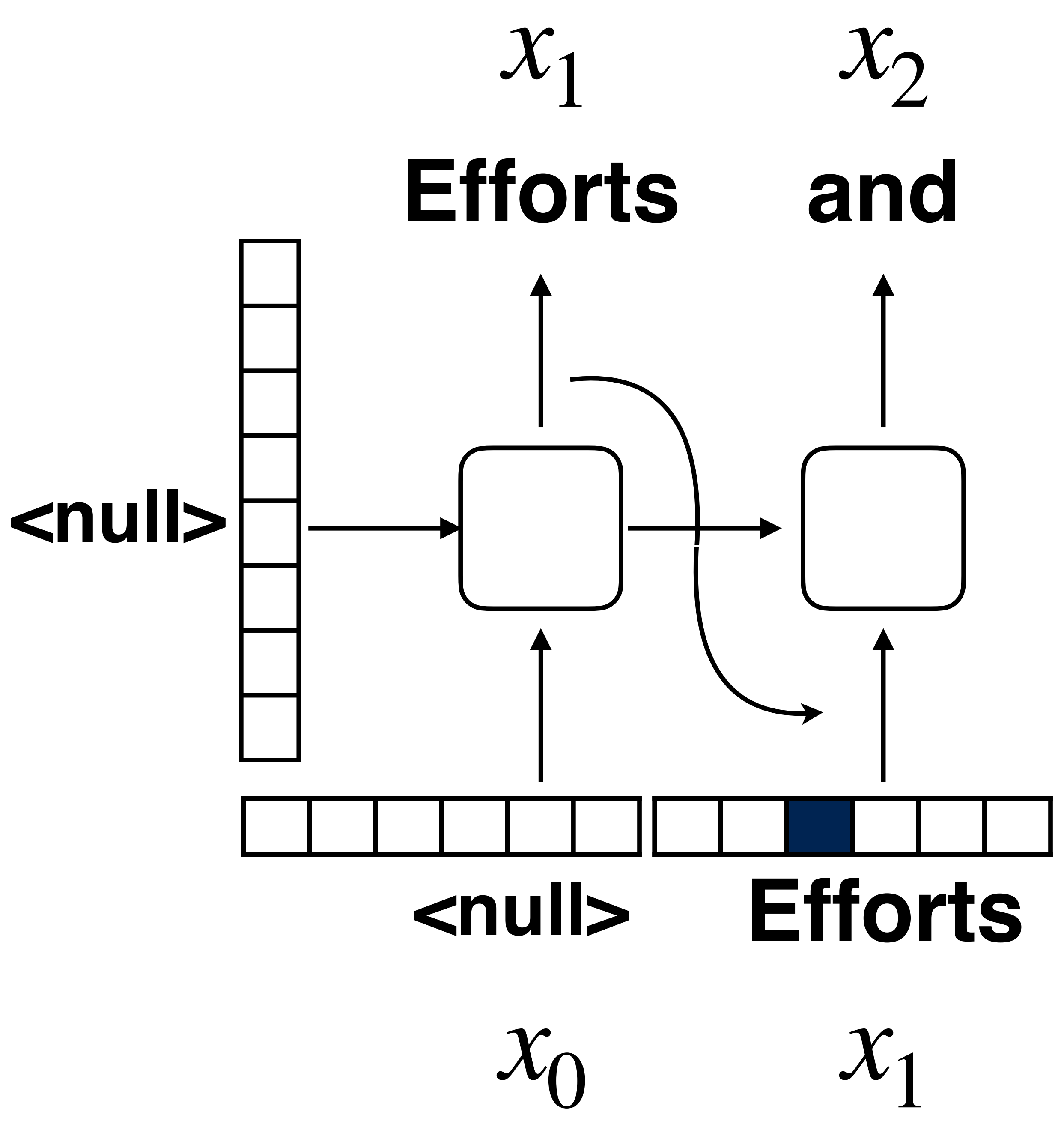

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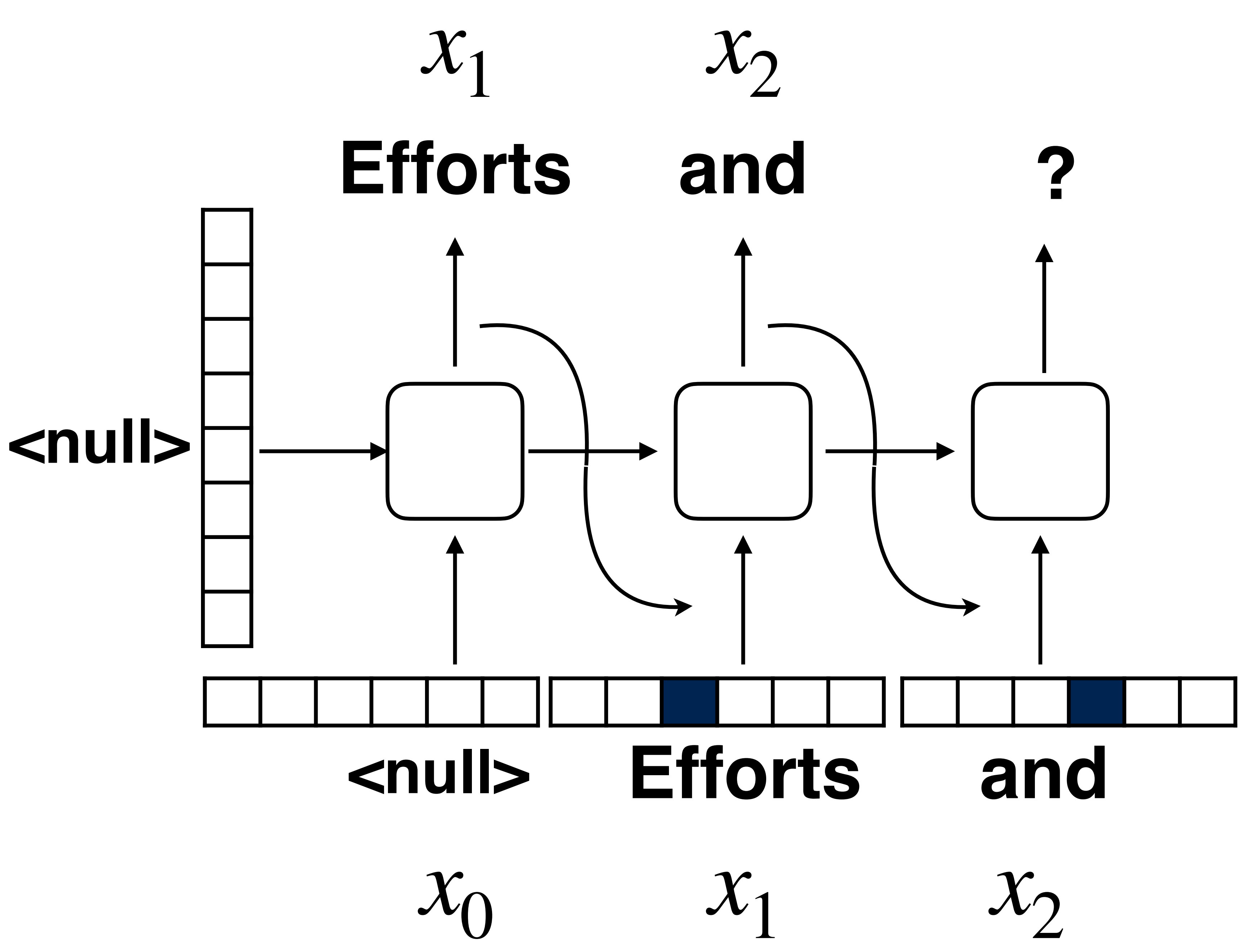

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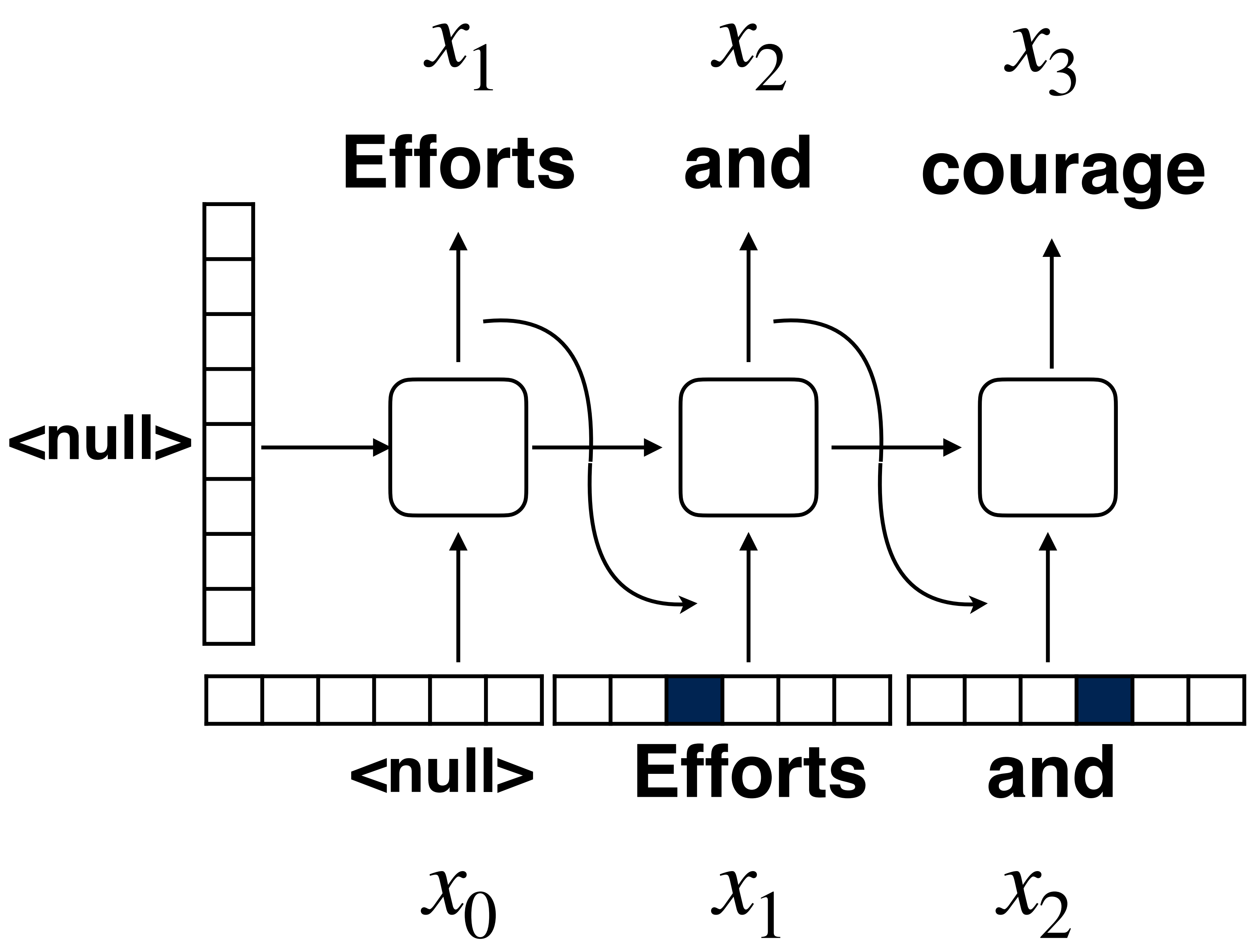

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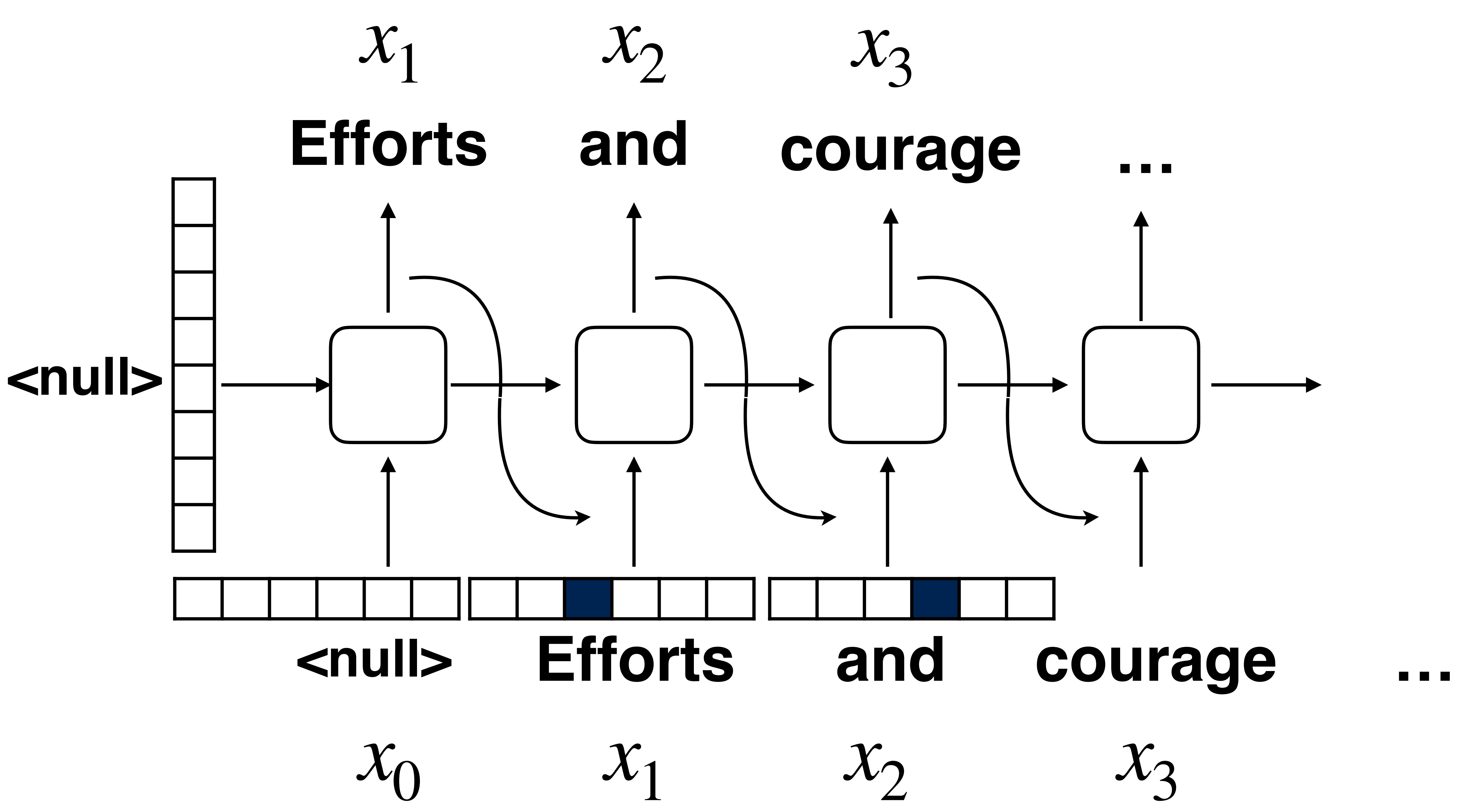

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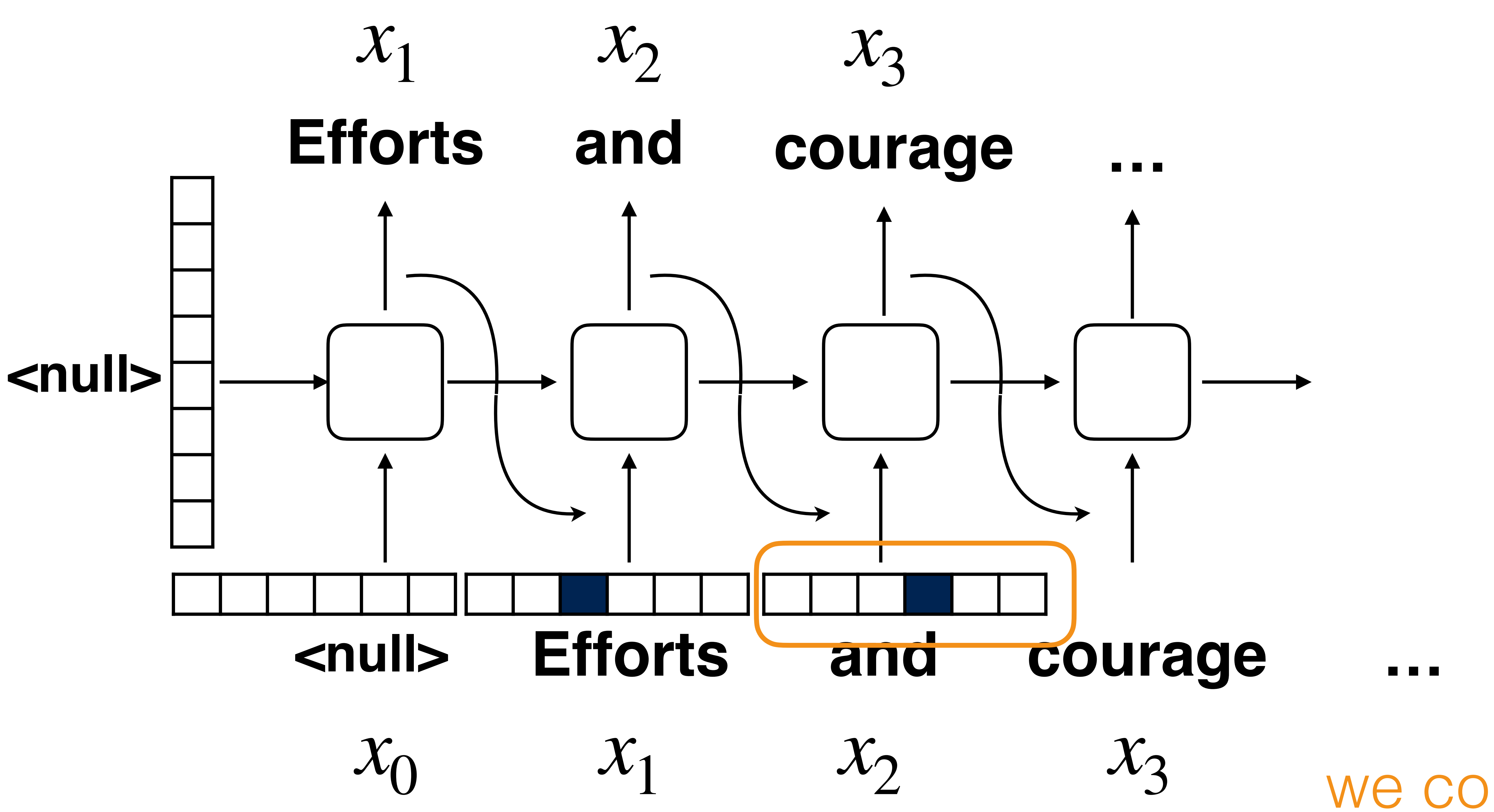
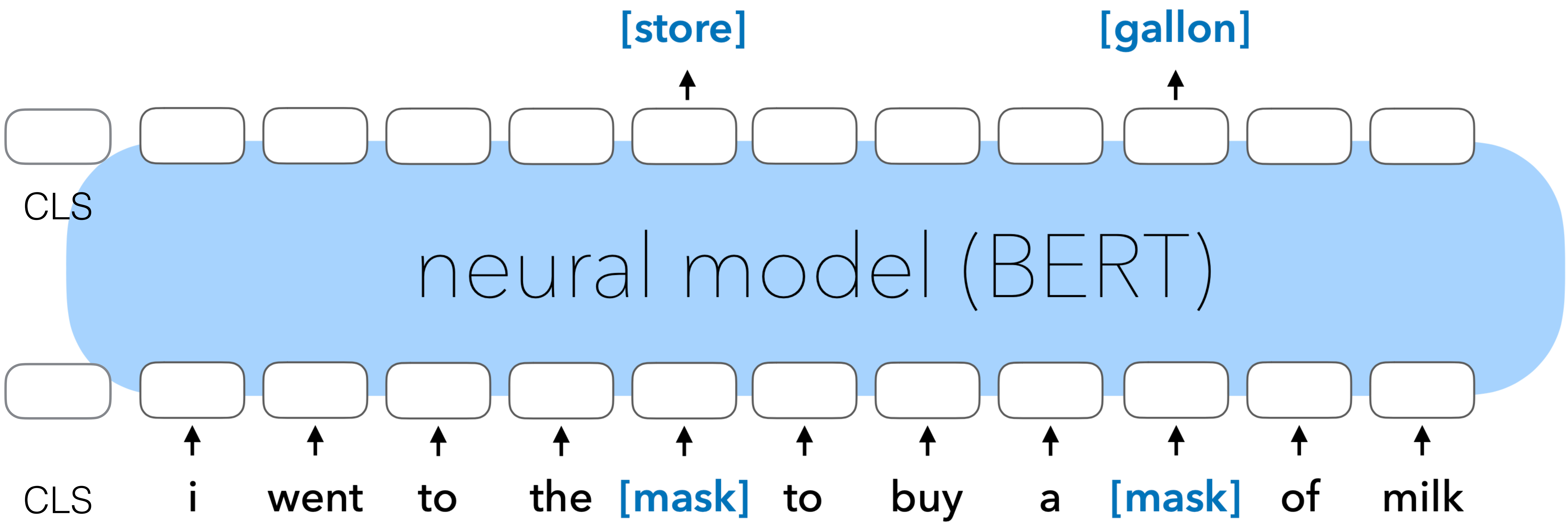


we could use the model
to learn better word embeddings
but this is comp. expensive

Masked Language Models (MLMs)

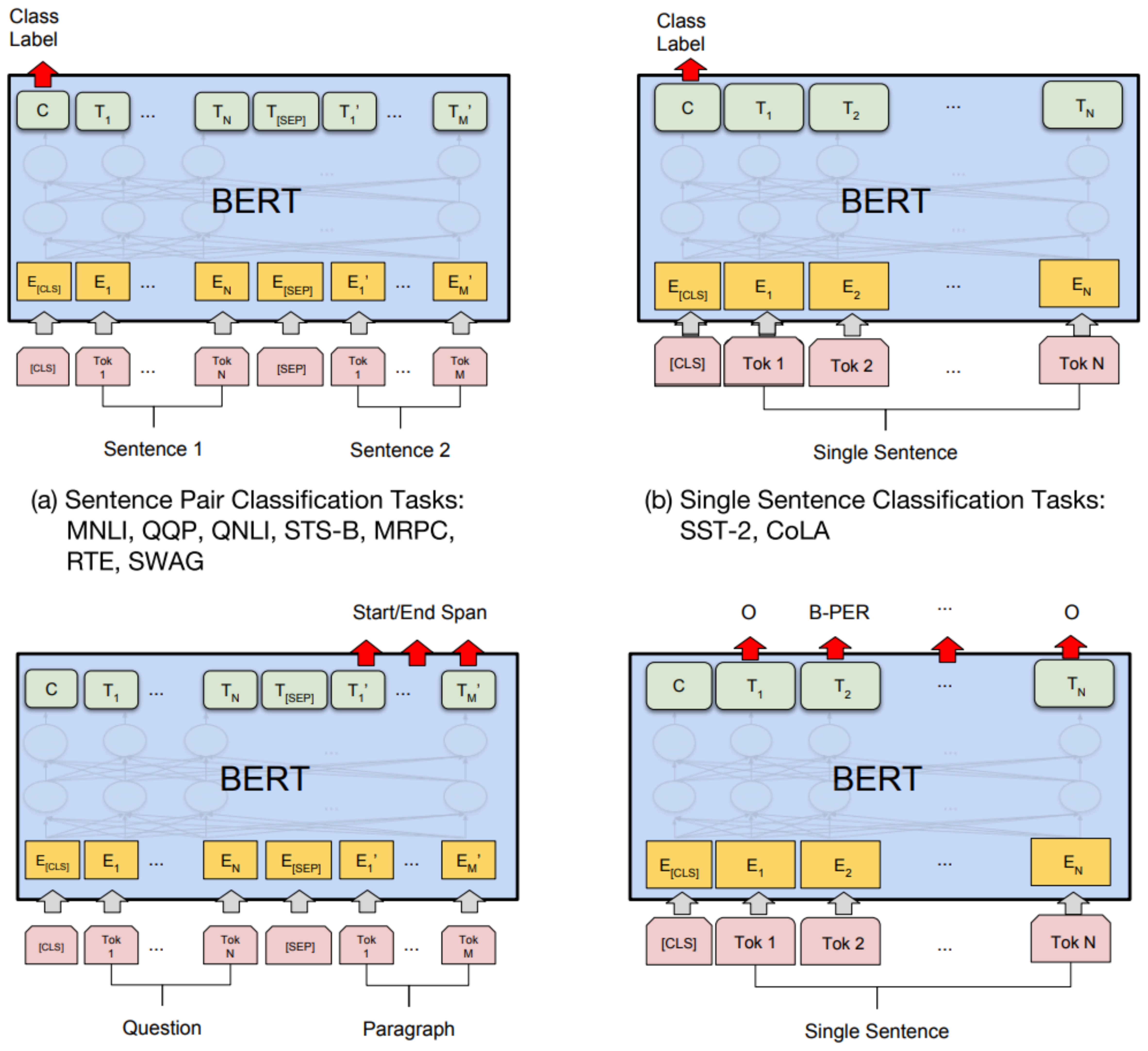
- We can estimate a complex transformer model from large text corpora by setting up a simple self-supervised masking task (masked language model)
- The resulting representation* can substantially help many follow-on tasks
- Some parts, e.g., the output prediction heads, can be stripped before reusing or adapting simple new prediction heads; the rest can be also fine-tuned



Devlin et al., BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, 2019

MLM (Bert) fine tuning tasks

- We can fine-tune a BERT model to a specific downstream task by adopting different prediction heads and input/output arrangements
- E.g.,
  - sentiment classification
  - pair sentence classification
  - sentence tagging
  - question-answering
  - Etc.



(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

(b) Single Sentence Classification Tasks: SST-2, CoLA

(c) Question Answering Tasks: SQuAD v1.1

(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

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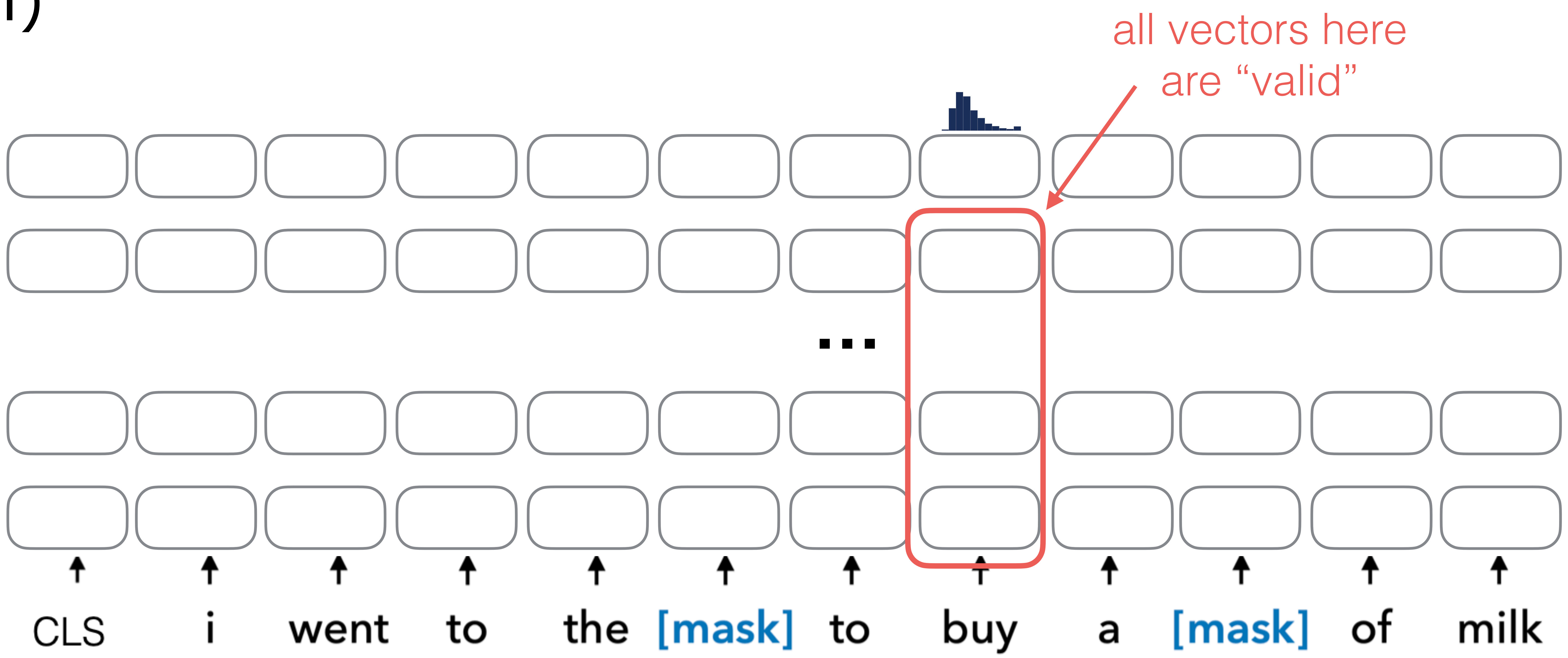
Contextual word vectors from MLM

- We can extract a valid contextually guided word vector from any BERT unit at any layer except the last one (in the original Bert model these vectors were 768 dimensional)



- Note that the input/output layer uses an automatic "word pieces" tokenizer to handle large vocabularies. E.g., you could see 'Teaching' → ['_Teach', 'ing']