Neural Probabilistic Language Models (NPLM)

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Language Model (LM)

- A model to quantify the co-occurrence of sequence of words in text.
- Ex. assign a score (usually a probability) to the word sequence: "This is a class presentation".

- By assigning scores or probabilities to sequences of words (sentences), a LM provides a method to distinguish between probable and improbable sentences.
- Many applications: semantic role labeling, sentiment analysis, named entity recognition, language translation, text parsing, and so on.

Probabilistic Language Model (PLM) (aka Statistical Language Model)

- A LM that uses a probability distribution to quantify word co-occurrence.
- Ex. n-grams models.

Neural Probabilistic Language Model (NPLM)

- A PLM that uses a neural network to obtain the probability of each word sequence.
- Ex. multilayer perceptron (feedforward network).

n-grams

- n-gram: a sequence of n consecutive words. Depending on the value of n, we have: bigrams, trigrams, 4-grams, 5-grams, etc.
- Goal is to access: $P(w_t, w_{t-1}, w_{t-2}, ..., w_{t-n+1})$.
- Problem: longer n-grams require more training data, why?
- Markov assumption limits the relevant history. Ex. for a horizont of n previous words, $P(w_t|w_{t-1:1}) = P(w_t|w_{t-1:t-n+1})$.
- Using Markov assumption and chain rule, we can obtain the prob. of sentences of any length, how? or any marginal like $P(w_t|w_{t-1}, w_{t-2}, ..., w_{t-n+1})$, how?
- Usually, n-gram models can be trained by using frequency counts on large text corpus (multinomial models).

n-grams

Pros

- Simple.
- Reasonable performance.

Cons

- Data sparsity is a big problem to estimate probs. World of n-grams is sparse: Zipfian.
- Also, number of parameters grows exponentially with context size (n-grams length).
- The use of a discrete representation can't generalize properly to unseen instances, i.e., rare or less frequent n-grams.

Discrete representations

- An n-gram model estimates a world model using a discrete distribution (multinomial).
- A main problem of discrete distributions is that all discrete values are equally similar (or dissimilar), there is not a notion of neighborhood.
- As a consequence, there is no simple way to do smoothing based on input similarity. Words like "Restaurant" and "Coffe-Shop" are just "concepts", but not "closely related concepts".
- There are previous works on n-gram smoothing, but so far they do not offer a sound solution.

Continuous representations

- Continuous representations provide a notion of neighborhood and similarity.
- In particular, NPLM models use a continuous vector representation for each word in the vocabulary.
- A NPLM can use training instances such as:

  "I will go to play soccer"

  to obtain information about semantically similar, but less frequent training instances, such as:

  "I will go to play handball"

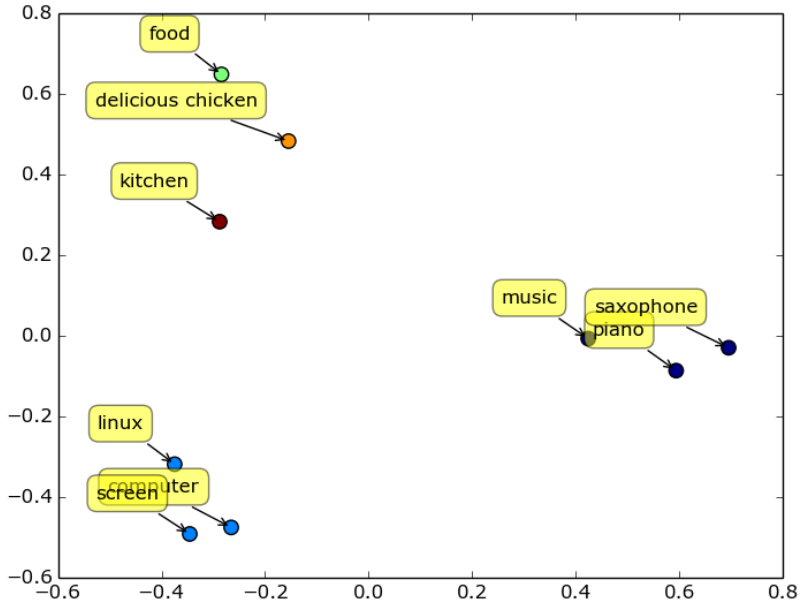
Guiding idea is the "(Semantic) Distributional Hypothesis" (Harris, 1954):

Words in similar contexts have similar meanings.

Distributed Representations

Distributed Representations

As a consequence, words in similar contexts will have similar representation, i.e., a similar (close) vector embedding.



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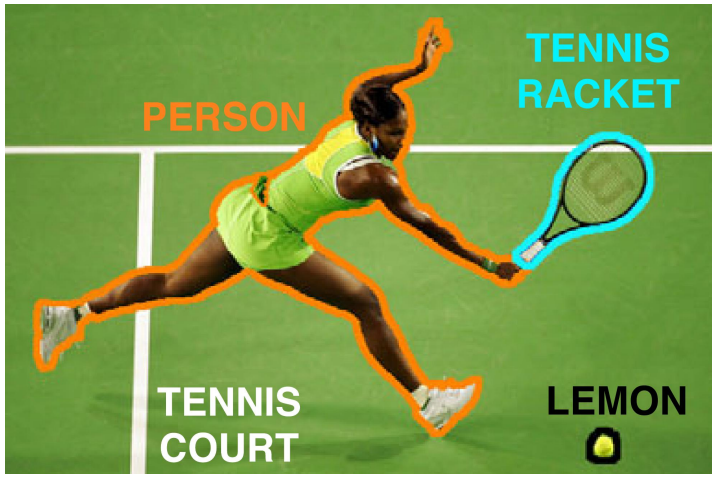
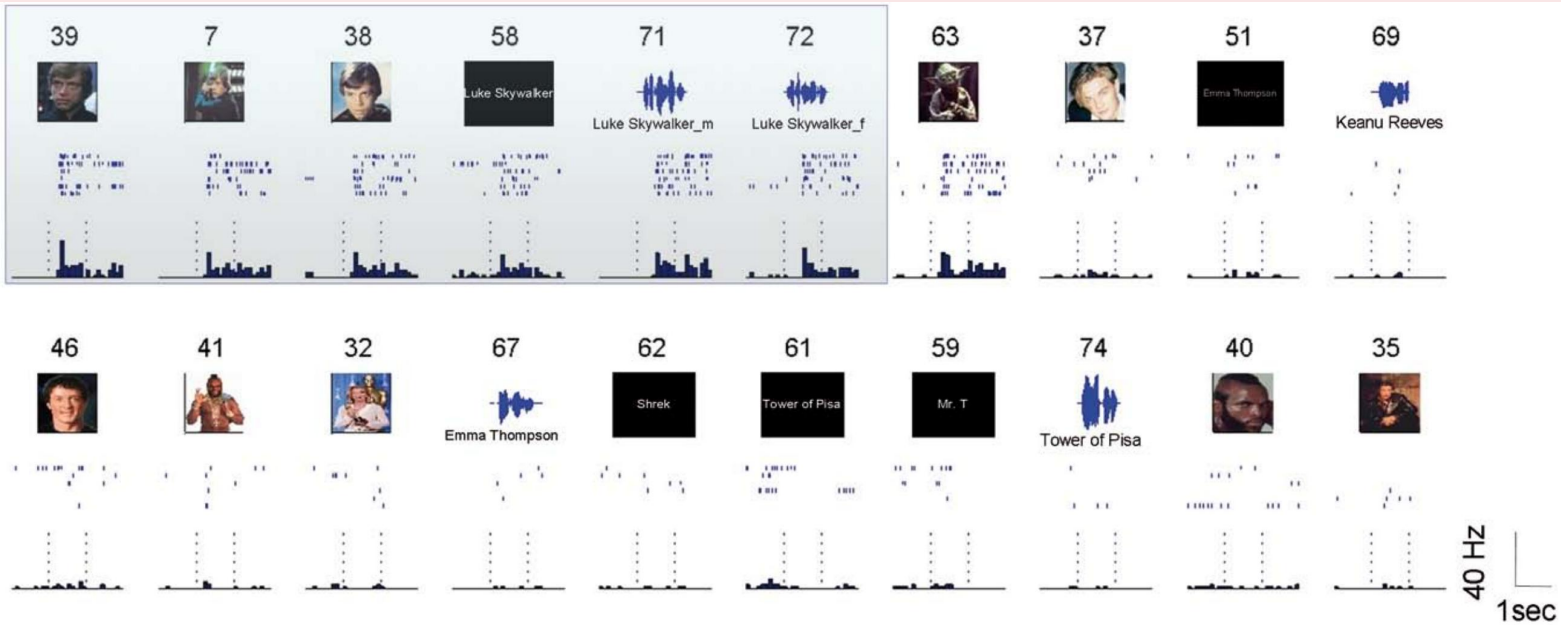
Same principle can be applied to several situations:



Key idea: contextual information determine meaning.

Welcome to one of the secret of most (not all) human intelligence:



Neural Probabilistic Language Model (NPLM)

- Y. Bengio et al. (NIPS, 2000 and JMLR, 2003) propose one of the first NPLM.
- They use a feedforward NN to model the word predicted probability: $P(w_t|w_{t-1}, w_{t-2}, ..., w_{t-n+1})$, i.e., the probability of the last word given the (n-1) previous ones, where n is a parameter.

Key Idea 1: by using word-to-context relations, this approach is able to use supervised machine learning techniques to solve an unsupervised problem.

Key Advantage 1: learning can take advantage of huge amounts of public documents, which can produce impressive results.

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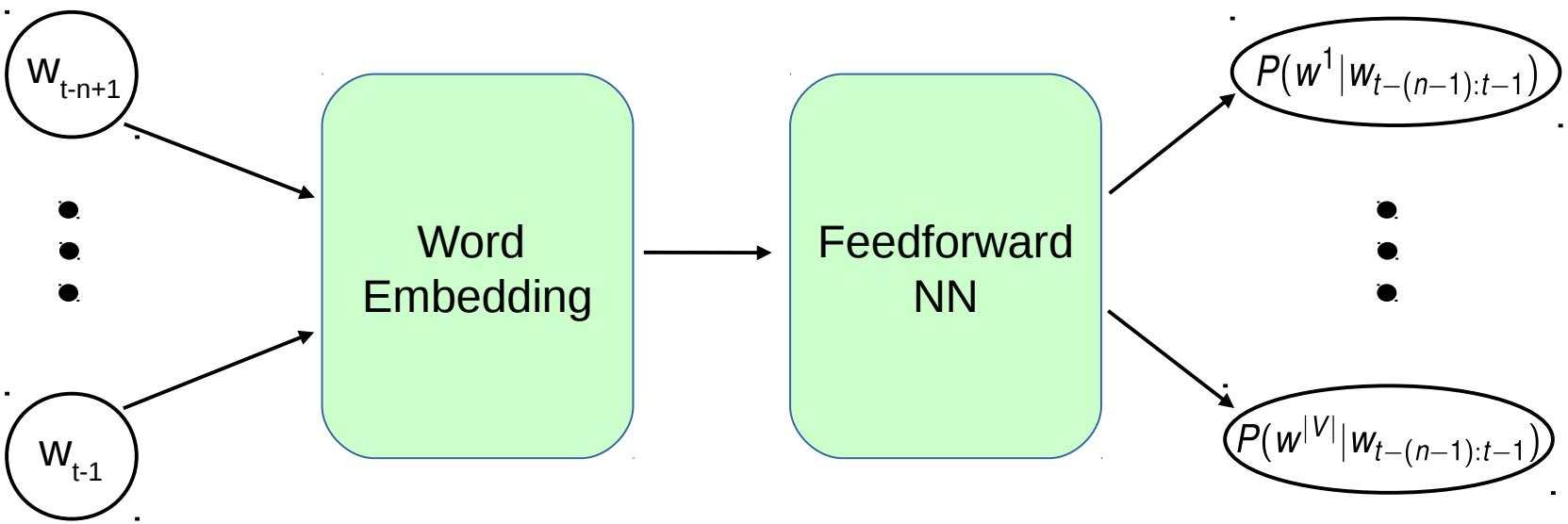
Key Idea 2: by using a continuous representation, the model can learn local similarity relations.

Key Advantage 2: parts of the target space that are highly represented in the training data (frequent patterns) can transfer knowledge to poorly represented areas (long tail).

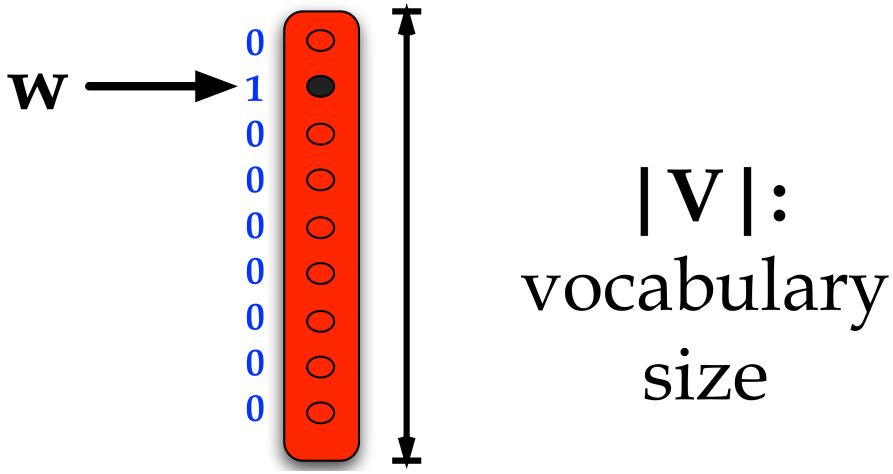
NPLM: Two main goals

- Goal1: Learn a continuous representation for each word w in the vocabulary, i.e., learn a word embedding.
- Goal 2: Learn a model to predict a word w given its context h(w), i.e., learn P(w|h(w)).

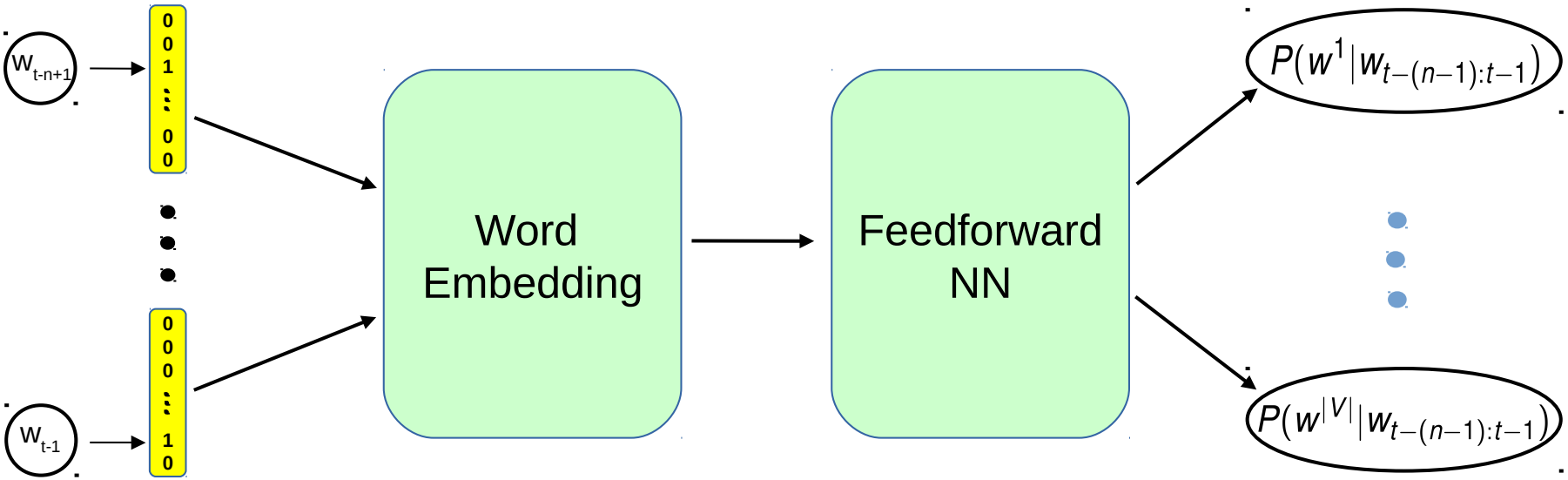
A NPLM learns both goals simultaneously.



- Typically, input words are encoded by a 1-of-$|V|$ representation (aka one-hot representation).



NPLM in a Nutshell



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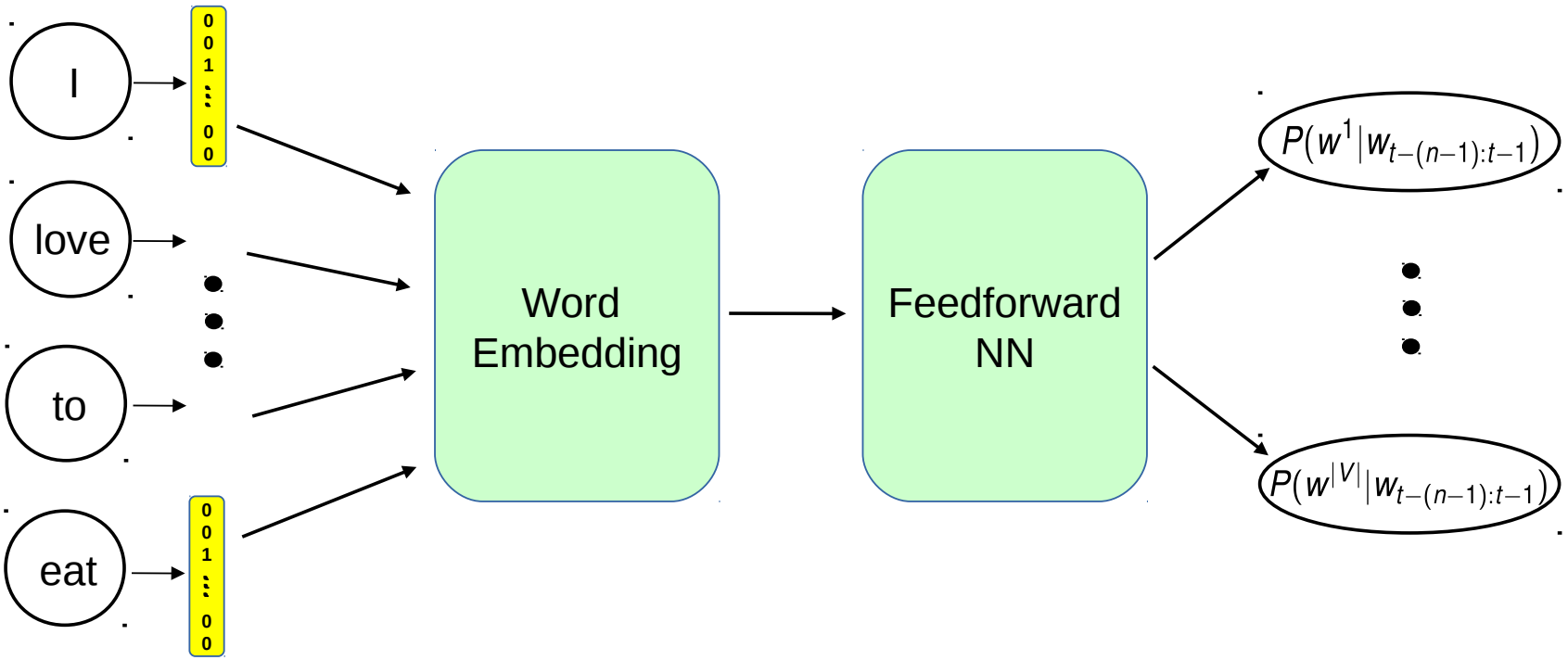
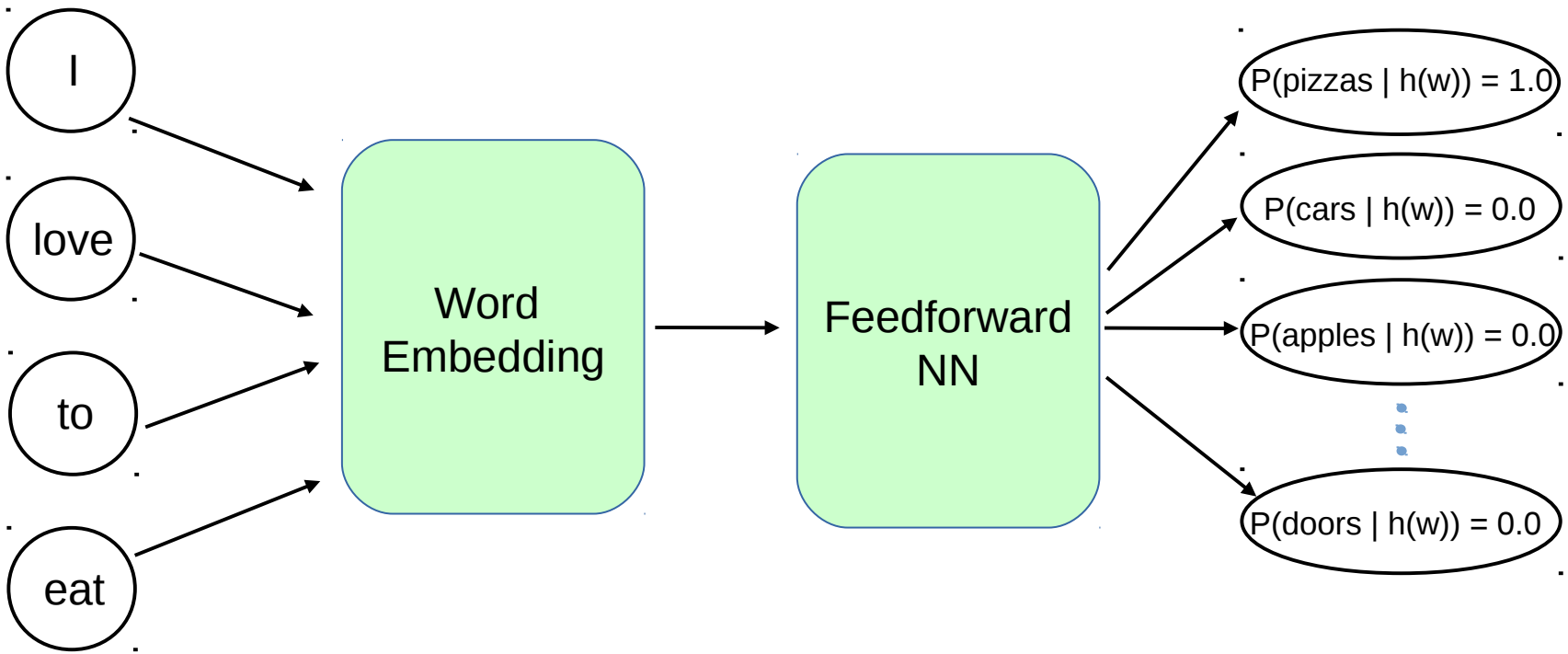


Labeled training instance (x,y):

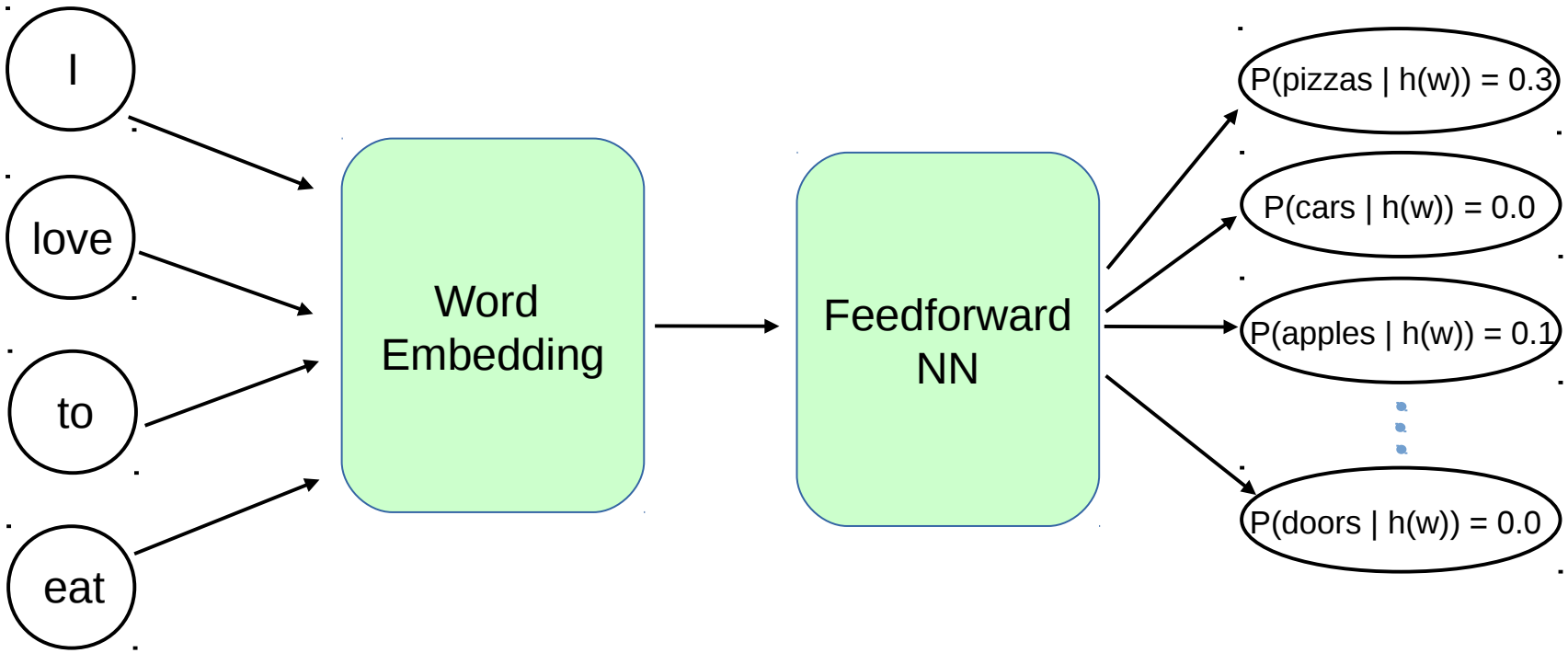
x: I love to eat
y: Pizzas



At training time, model maximizes log-likelihood of the word sequences, $w_{t:t-n+1}$, in the training data: $ML(\theta) = \arg\max_{\theta} \sum_{w_{t:t-n+1}} \log P(w_t | w_{t-1:t-n+1}; \theta)$

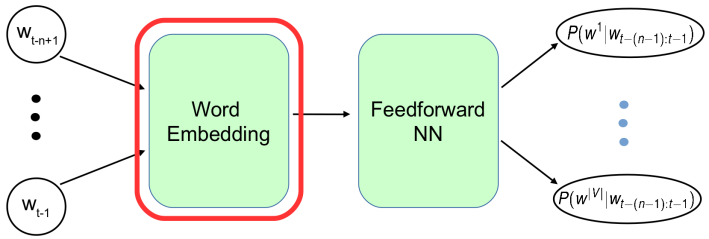
Test instance (x,y):

x: I love to eat
y: ?



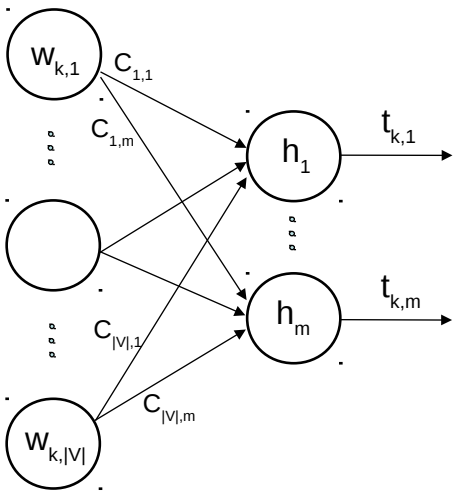
At test time, the model predicts the probability of the next word in the sequence, i.e., $P(w_t|w_{t-1:t-n+1};\theta)$.

Goal 1: Learn word embedding



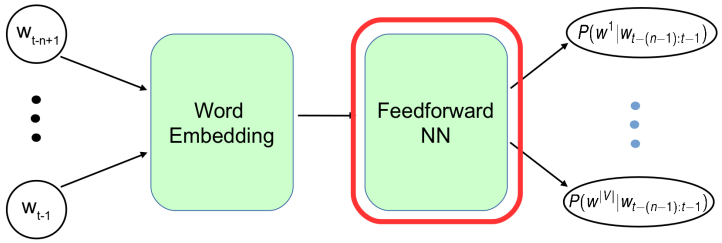
Learn Projection Matrix

$\mathbf{C} \in R^{|V|xm}$

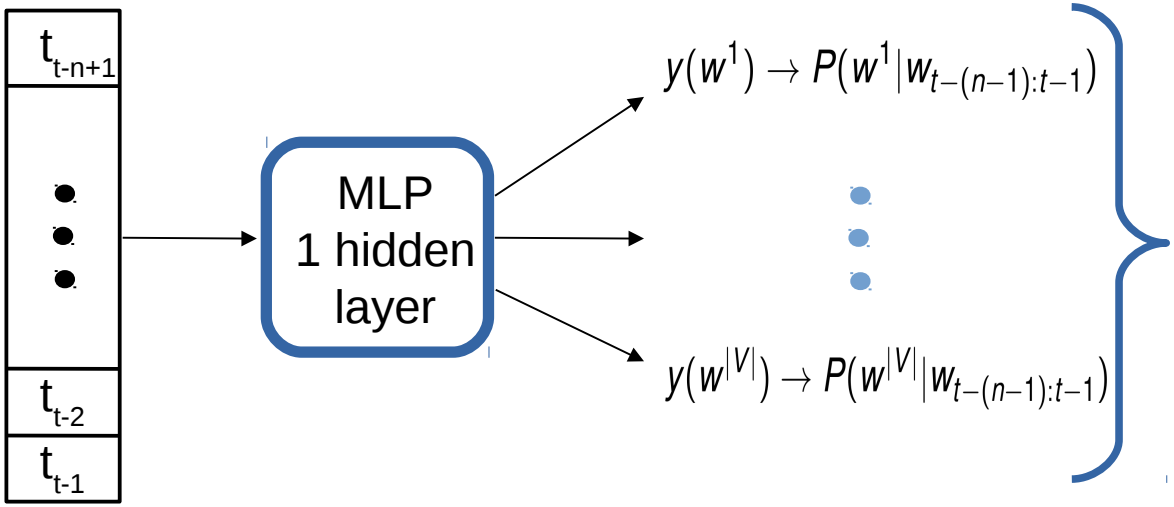


Projection matrix C embeds a word W_k to a vector $t_k \in \mathbb{R}^m$

Goal 2: Learn to Predict Words



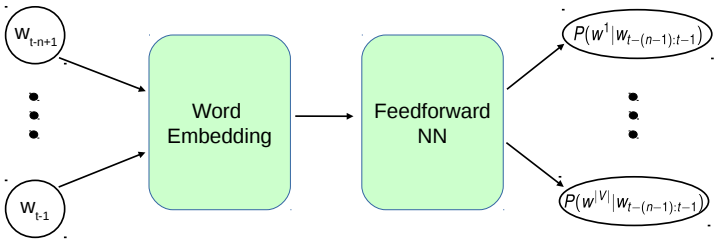
Learn weights for Feedforward NN

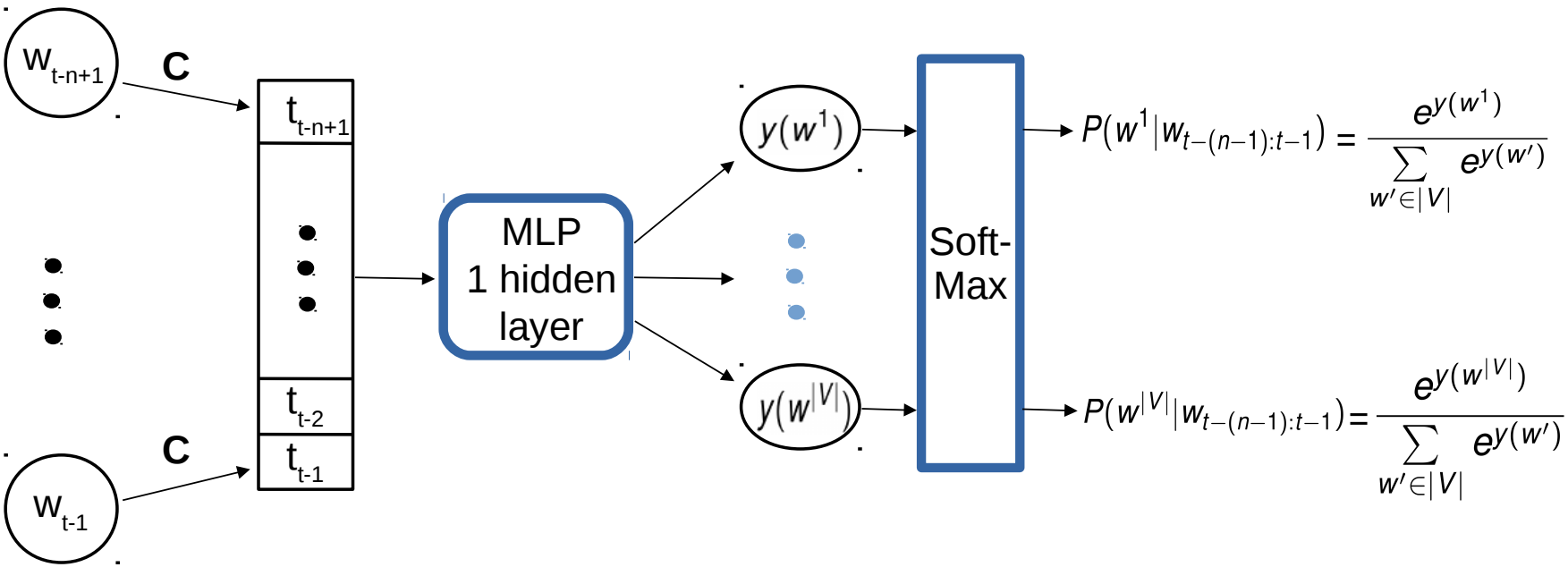


Soft-Max outputs:

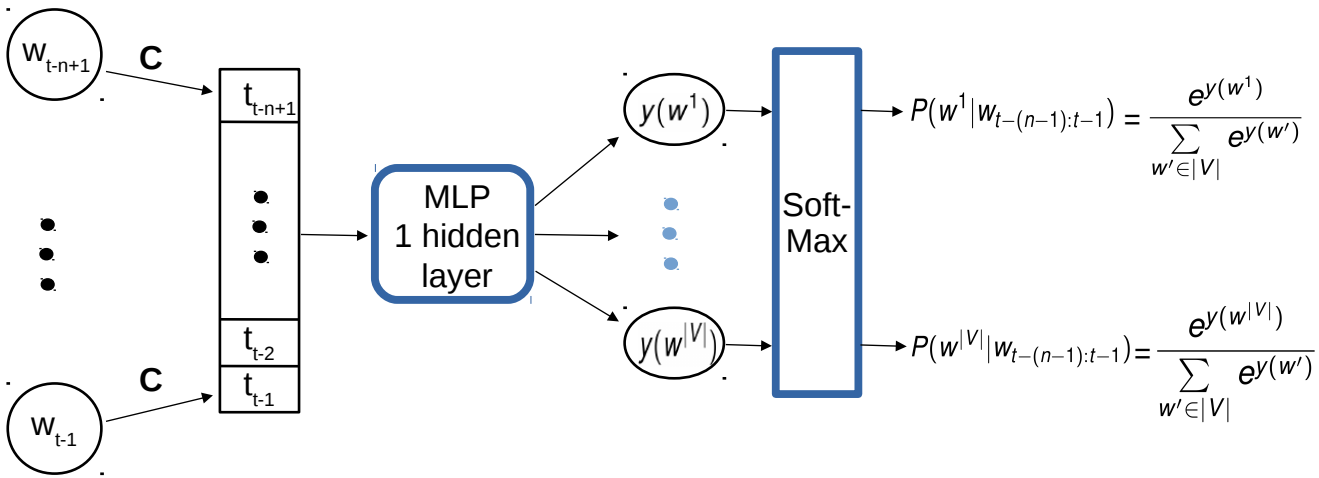
$$P(w^k|w_{t-(n-1):t-1}) = \frac{e^{y(w^k)}}{\sum_{w' \in |V|} e^{y(w')}}$$

Both steps together





Resulting Network Structure



- Matrix $C \in \mathbb{R}^{m \times |V|}$ corresponds to a bilinear transformation.
- This transformation is shared by all words.
- Given the 1-out-of-$|V|$ input representation, embedding of dictionary word w_k is equivalent to column k of C (why?). So it reduces to a linear transformation with complexity $O(m)$.
- As a consequence, embedding C is usually implemented using a lookup table.

Results

Brown corpus

- Stream of 1.181.041 words from a large variety of English texts and books.
- Training set 800.000 words. Validation set 200.000 words (model selection, weight decay, early stopping). Test set 181.041 words.
- $|V| = 47.578$. Rare words with frequency ≤ 3 are merged into a single symbol, reducing the vocabulary size to $|V| = 16.383$.

Associated Press (AP) News

- Training set 13.994.528 words. Validation set 963.138 words. Test set 963.071 words.
- $|V| = 148.721$, reduced to $|V| = 17964$ by keeping only the most frequent words (and keeping punctuation), mapping upper case to lower case, mapping numeric forms to special symbols, mapping rare words to a special symbol, and mapping proper nouns to another special symbol.

Results

Main result in Bengio et al., 2003

- Proposed NPLM significantly outperforms n-grams models.
- Test perplexity difference of about 24% on Brown and about 8% on AP News, when taking the MLP versus the n-gram that worked best on the validation set (a 5-grams approach).
- Training time: 5 epochs for AP News (14M words) take over 3 weeks using 40 CPUs (2002).

Perplexity (PP)

- Measure average level of uncertainty about next word.
- Lower perplexity is better.

NPLMs and Word Embeddings

NPLMs and word feature learning

Word feature learning

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- Learning a suitable vector representation for words is indeed a highly relevant goal. This task can be cast as feature learning, where the resulting features can be used (transfer) to feed several relevant NLP applications.

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- Idea: simpler model can scale to bigger datasets. Algorithmic design should trade model's complexity for efficiency.

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   - Continuous Bag-of-Words Model (CBoW).
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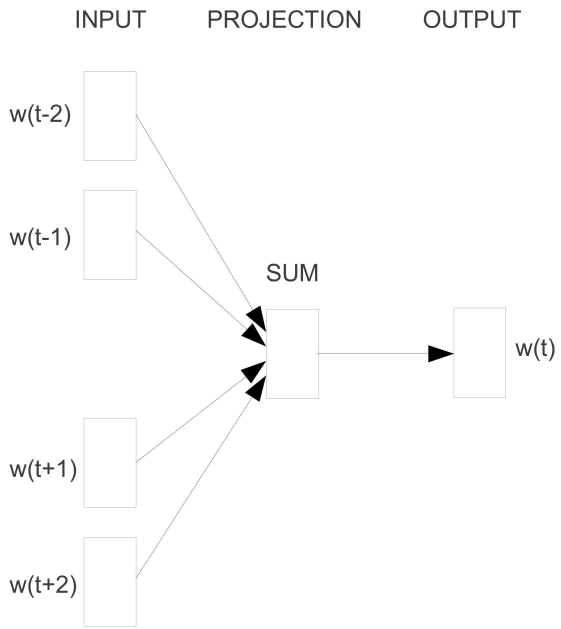
2. Replace the costly soft-max step by simpler schemes, such as, hierarchical soft-max (HSMax) or NCE.

Continuous Bag-of-Words Model (CBoW)



- CBoW sums the projected vector representations of the context words.

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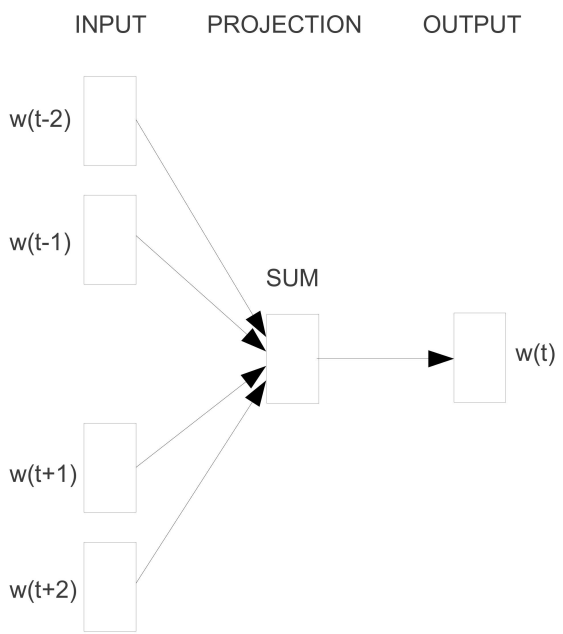

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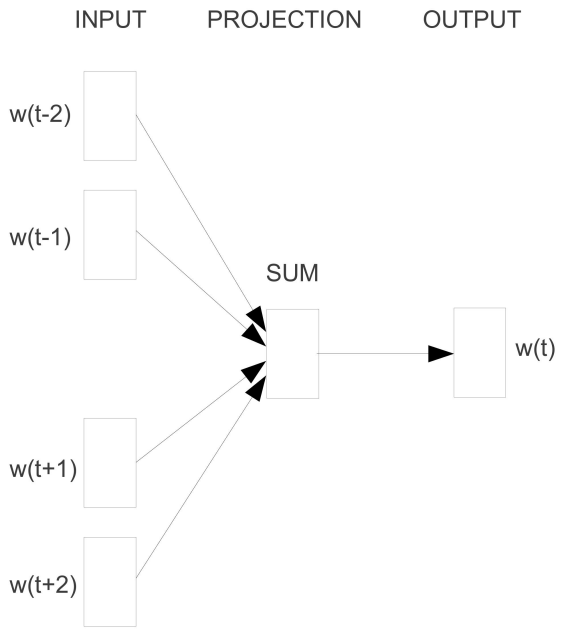

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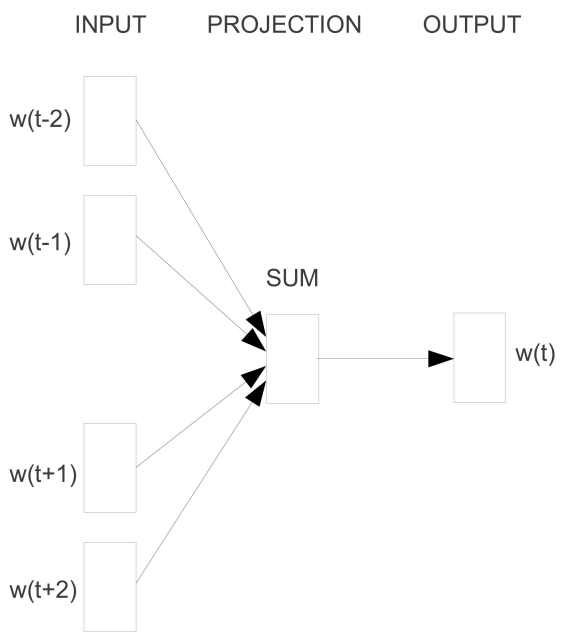

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- The CBoW output vector w(t) is connected through a single proyection or layer to the soft-max output nodes.

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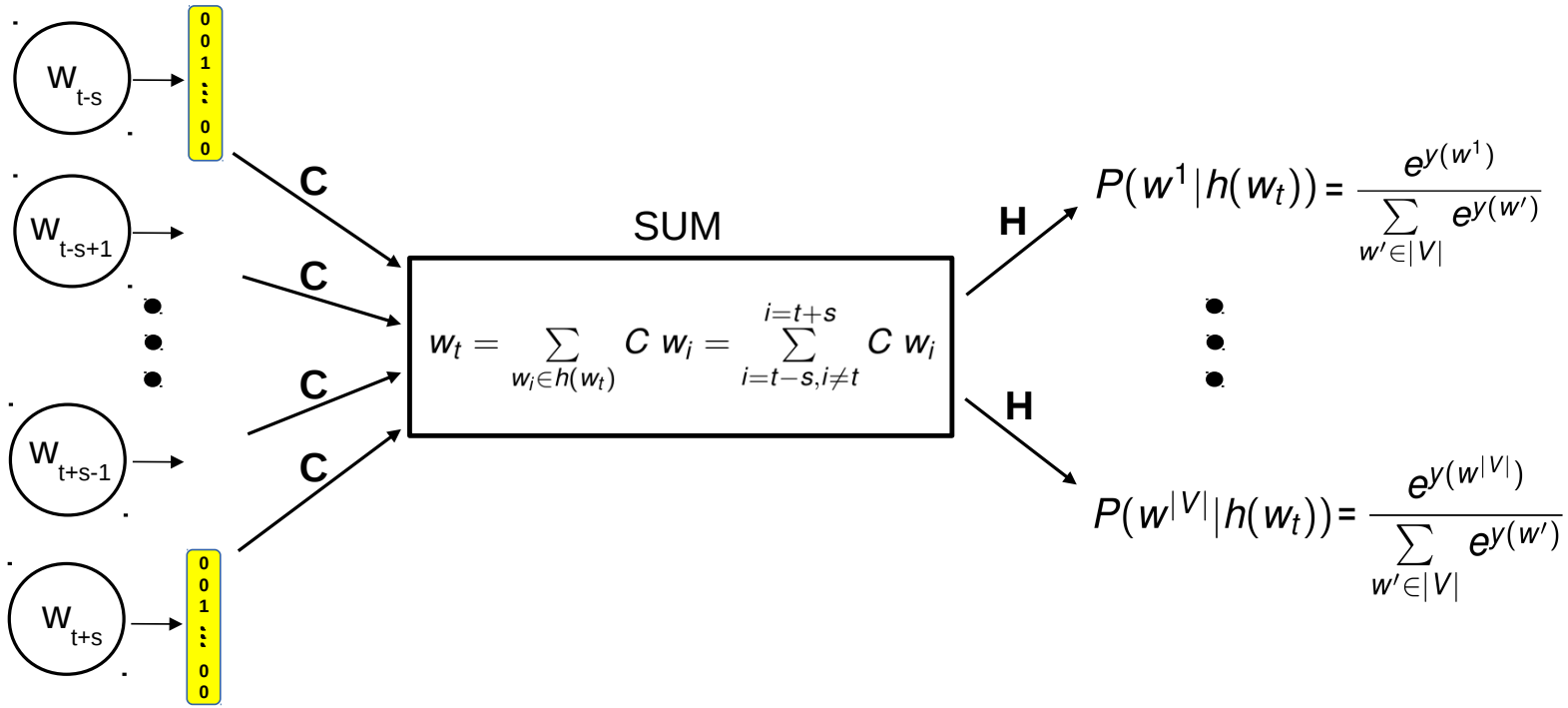

$$C \in \mathbb{R}^{|V| x m}, H \in \mathbb{R}^{m x |V|}$$

- The goal of the training step is to learn weight matrices C and H.

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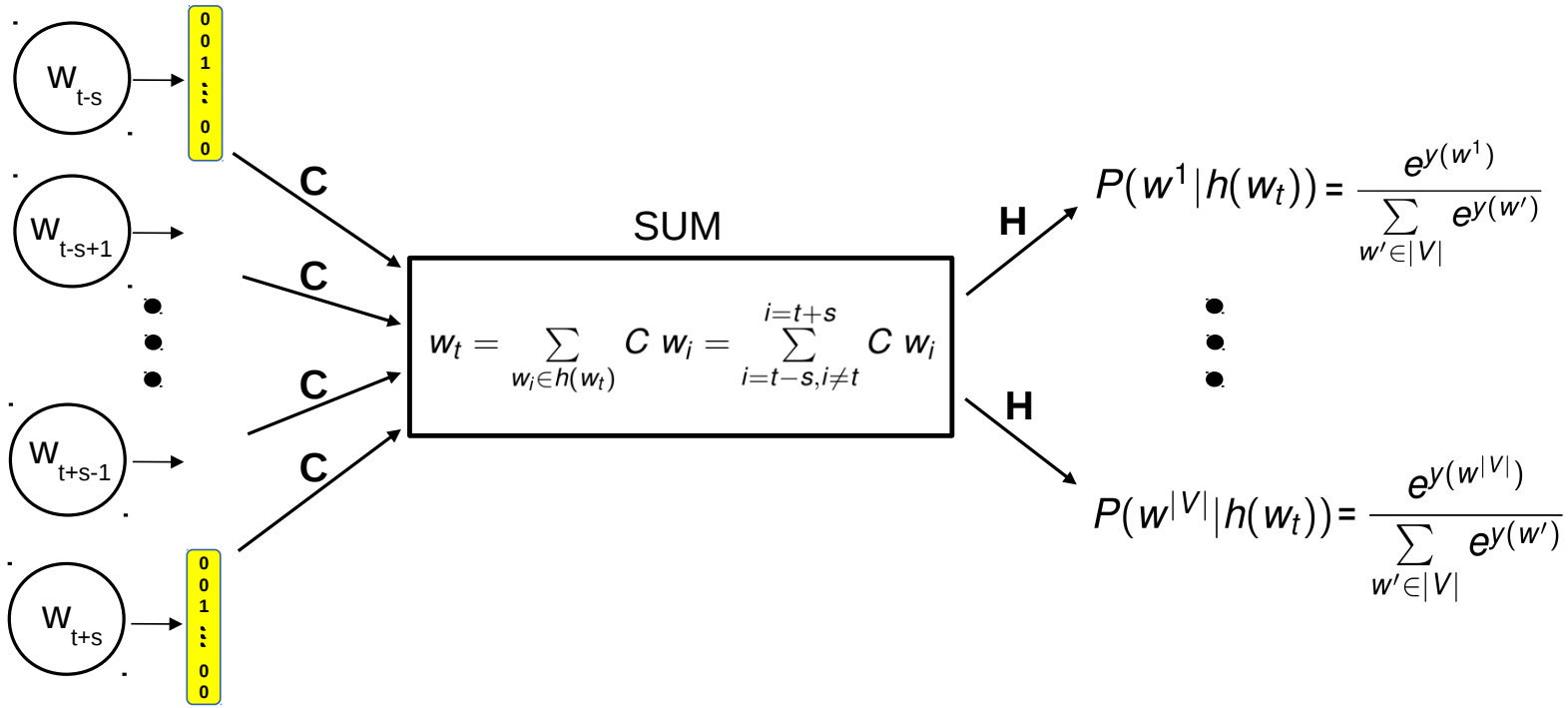

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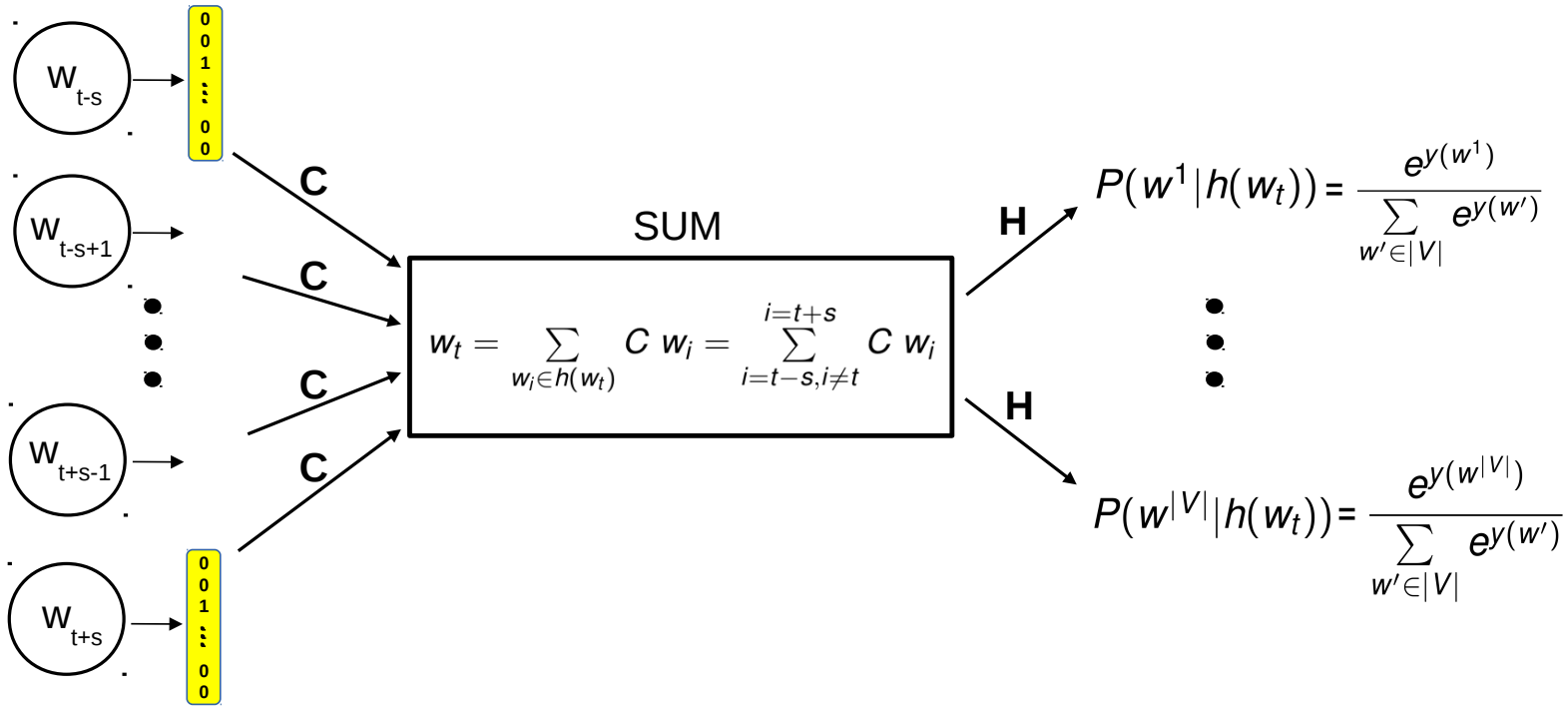

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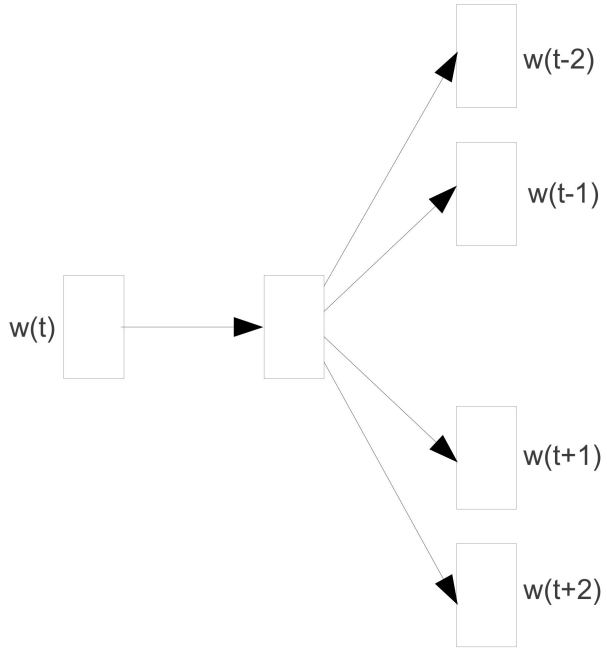
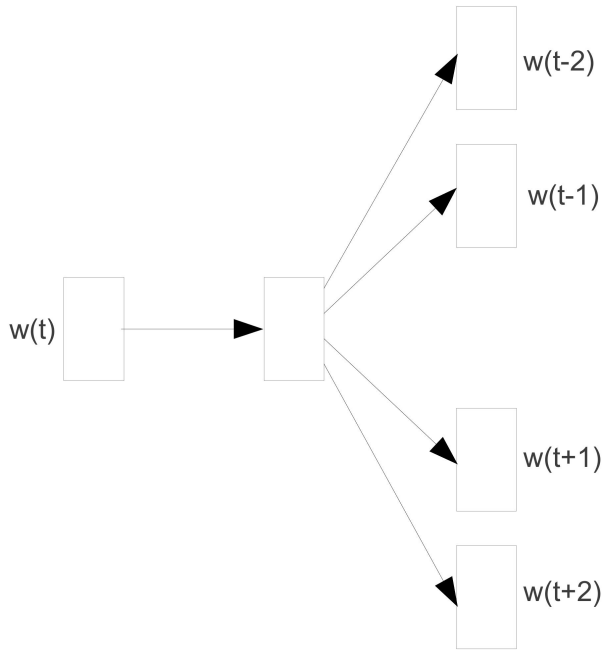
- Notice that there is not a hidden layer, but a direct bilinear connection H between the projection layer and softmax outputs.

Continuous Skip-gram Model



- Given a target word w (usually the center word), the Skip-gram model predicts possible context words within a certain range surrounding word w.

Continuous Skip-gram Model



- Given a target word w (usually the center word), the Skip-gram model predicts possible context words within a certain range surrounding word w.
- More distance words are usually less related to the central one. The Skip-gram model takes account of this fact by sampling less from these words, so they have less relevance in the parameter estimation.

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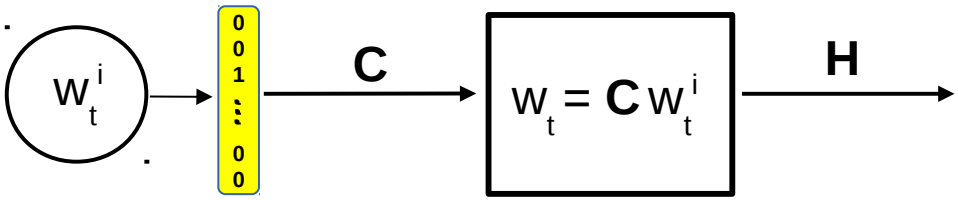

$$P(w^{k \in h(w_t)} | w_t) = \frac{e^{s(w_k, w_t)}}{\sum_{w'_k \in |V|} e^{s(w'_k, w_t)}}$$

where $s(w_k, w_t) = w_k^T w_t$. $C \in \mathbb{R}^{|V| x m}$, $H \in \mathbb{R}^{m x |V|}$

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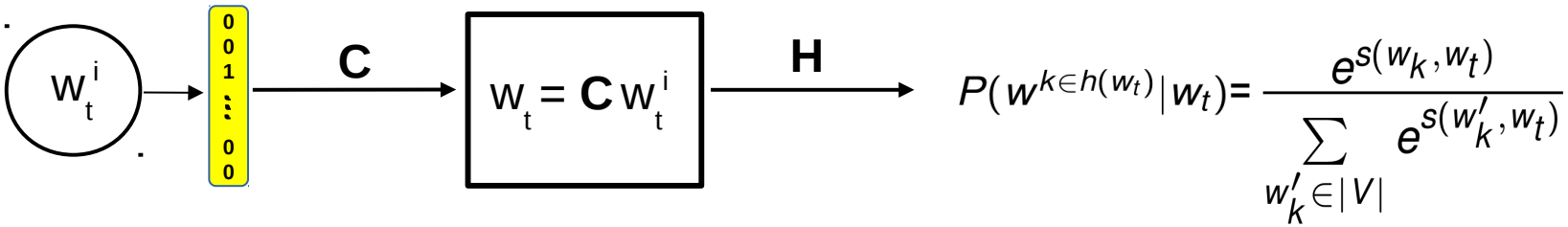

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- Notice that there is not a hidden layer, but a direct linear connection H between the projection layer and softmax outputs.

CBoW and Skip-gram models: Learning

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Results

Type of relationship	Word Pair 1		Word Pair 2	
Common capital city	Athens	Greece	Oslo	Norway
All capital cities	Astana	Kazakhstan	Harare	Zimbabwe
Currency	Angola	kwanza	Iran	rial
City-in-state	Chicago	Illinois	Stockton	California
Man-Woman	brother	sister	grandson	granddaughter
Adjective to adverb	apparent	apparently	rapid	rapidly
Opposite	possibly	impossibly	ethical	unethical
Comparative	great	greater	tough	tougher
Superlative	easy	easiest	lucky	luckiest
Present Participle	think	thinking	read	reading
Nationality adjective	Switzerland	Swiss	Cambodia	Cambodian
Past tense	walking	walked	swimming	swam
Plural nouns	mouse	mice	dollar	dollars
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- Synonyms are thus counted as mistakes. This could be improved in the future using some more elaborated language information.

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Model	Vector Dimensionality	Training words	Accuracy [%]		
			Semantic	Syntactic	Total
Collobert-Weston NNLM	50	660M	9.3	12.3	11.0
Turian NNLM	50	37M	1.4	2.6	2.1
Turian NNLM	200	37M	1.4	2.2	1.8
Mnih NNLM	50	37M	1.8	9.1	5.8
Mnih NNLM	100	37M	3.3	13.2	8.8
Mikolov RNNLM	80	320M	4.9	18.4	12.7
Mikolov RNNLM	640	320M	8.6	36.5	24.6
Huang NNLM	50	990M	13.3	11.6	12.3
Our NNLM	20	6B	12.9	26.4	20.3
Our NNLM	50	6B	27.9	55.8	43.2
Our NNLM	100	6B	34.2	**64.5**	50.8
CBOW	300	783M	15.5	53.1	36.1
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- Note that training of NNLM with 1000-dimensional vectors would take too long to complete.

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- Element-wise vector additions provide Additive Compositionality of semantic concepts. Following table shows some examples:

Czech + currency	Vietnam + capital	German + airlines	Russian + river	French + actress
koruna	Hanoi	airline Lufthansa	Moscow	Juliette Binoche
Check crown	Ho Chi Minh City	carrier Lufthansa	Volga River	Vanessa Paradis
Polish zolty	Viet Nam	flag carrier Lufthansa	upriver	Charlotte Gainsbourg
CTK	Vietnamese	Lufthansa	Russia	Cecile De

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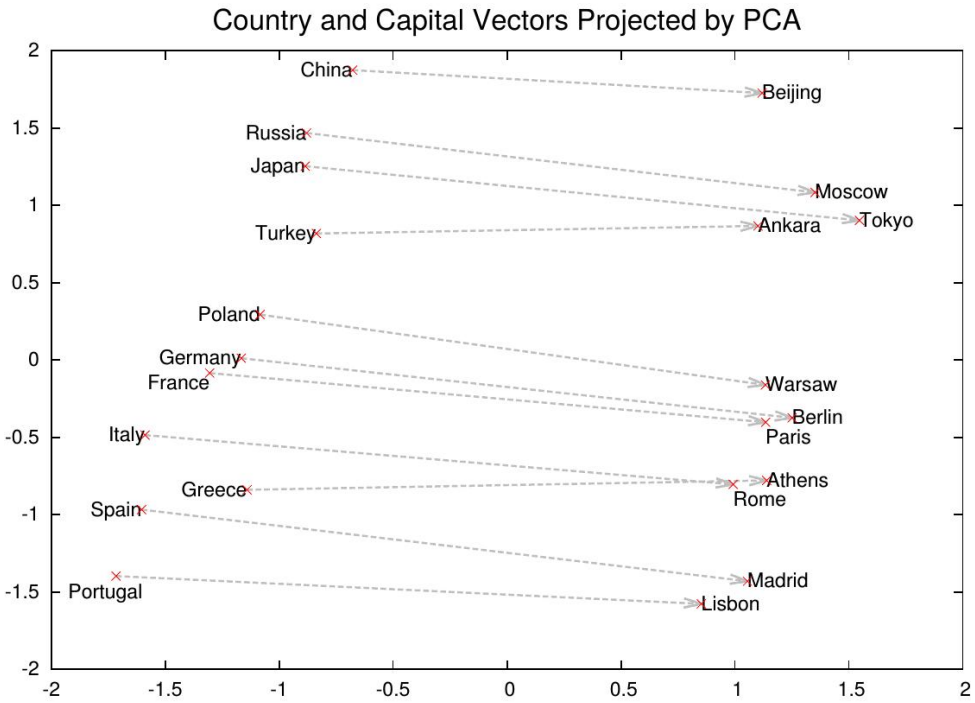
- Any intuition of why we obtain this behavior?.



The amazing power of word vectors

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- "Visual Word2Vec (vis-w2v): Learning Visually Grounded Word Embeddings Using Abstract Scenes", Kottur et. al, 2015.
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- "Item2Vec: Neural Item Embedding for Collaborative Filtering", Barkan et. al, 2016