ISO 29990:2010

NATIONAL INFOCOMM COMPETENCY FRAMEWORK

NUS National University of Singapore

ISS INSTITUTE OF SYSTEMS SCIENCE

Text Processing using Machine Learning

Word Embeddings

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03 Dec 2019

OVER **5,500** GRADUATE ALUMNI

OFFERING OVER **120** ENTERPRISE IT, INNOVATION & LEADERSHIP PROGRAMMES

TRAINING OVER **120,000** DIGITAL LEADERS & PROFESSIONALS

Overview

- **Word Embeddings**
  - SVD to Word2Vec
  - PyTorch Data Preparation
  - Word2Vec from Scratch

Word Embeddings

Word Embeddings

"You shall know a word by the company it keeps…"
– John R. Firth (1957)

"We propose a unified NN architecture by trying to avoid task-specific engineering therefore disregarding a lot of prior knowledge"
– Collobert and Weston (2011)

"Context-predicting models known as embeddings are the new kids on the distributional semantics block… The result, to our own surprise, show that the buzz is fully justified."
– Baroni et al. (2014)

Classic NLP: Feature Engineering

- **Count-based vectors are**
  - e.g. TF-IDF, PPMI
  - long (|V| > 100,000)
  - sparse (lots of zero)

- **Vector compression** (aka ***dimensionality reduction***)
  - shorter vectors easier to use as features in machine learning
  - ***compression*** use to make vectors short and dense, e.g. Singular Value Decomposition (SVD), Non-negative Matrix Factorization (NMF)

Term Frequency – Inverse Document Frequency

```
sent0 = "The quick brown fox jumps over the lazy brown dog ."

sent1 = "Mr brown jumps over the lazy fox ."
```

	brown	dog	fox	jumps	lazy	mr	over	quick	the
sent0	0.500	0.351	0.250	0.250	0.250	0.000	0.250	0.351	0.500
sent1	0.354	0.000	0.354	0.354	0.354	0.497	0.354	0.000	0.354

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v('dog')

Pointwise Mutual Information

		$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$
		mr	brown	jumps	over	fox
$i = 1$	mr	0	1	1	0	0
$i = 2$	brown	0	0	1	1	2
$i = 3$	jumps	1	0	0	2	1
$i = 4$	over	2	1	0	0	1
$i = 5$	fox	0	0	1	0	0

Matrix F with
- W rows (words)
- C columns (context)

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- W rows (words)
- C columns (context)

Dimensionality Reduction (SVD)

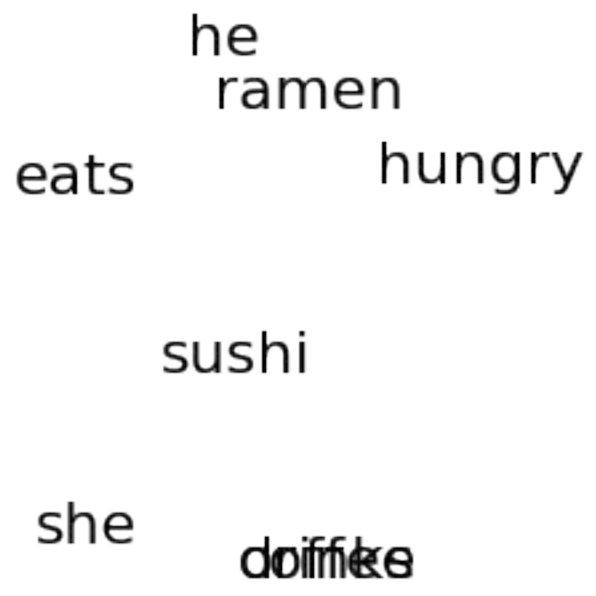
```python
corpus = ['he eats ramen', 'she eats sushi',
          'he hungry', 'she drinks coffee']

# Get the standard term-doc matrix
count_model = CountVectorizer(ngram_range=(1,1))
X = count_model.fit_transform(corpus)
# Multiplying the term-doc matrix with itself
# produces the co-occurence matrix.
X_cooc = (X.T * X)
X_cooc.setdiag(0)   # set co-occurence with self to 0.

U, s, Vh = np.linalg.svd(X_cooc.todense(),
                         full_matrices=False)

words = sorted(count_model.vocabulary_,
               key=count_model.vocabulary_.get)

# Plot pretty words.
for i in range(len(words)):
    plt.text(U[i,0], U[i,1], words[i], fontsize=22)
plt.axis('off')
plt.show()
```



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words = sorted(count_model.vocabulary_,
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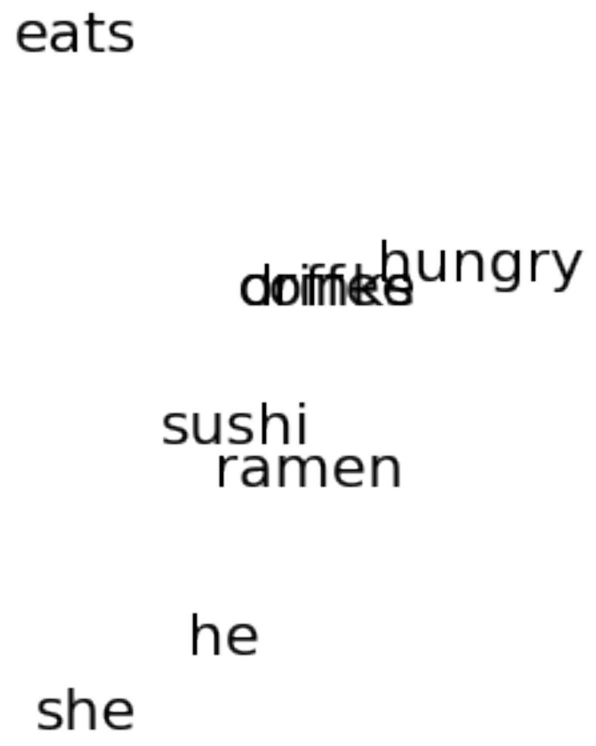
# Plot pretty words.
for i in range(len(words)):
    plt.text(U[i,0], U[i,2], words[i], fontsize=22)
plt.axis('off')
plt.show()
```



Single Value Decomposition (SVD)

- Computational cost scales quadratically,
- O(mn^2) for n x m matrix
  - Even if we can flip the n/m easily, if we have lots of words/documents, it won't help much.
- If there's new words or documents, SVD has to be re-computed from scratch.

Count-based Vectors

tokenization
annotation
tagging
parsing
feature selection
⋮ cluster texts by date/author/discourse context/...
↓ ↙

Matrix type		Weighting		Dimensionality reduction		Vector comparison
word × document		probabilities		LSA		Euclidean
word × word		length normalization		PLSA		Cosine
word × search proximity	×	TF-IDF	×	LDA	×	Dice
adj. × modified noun		PMI		PCA		Jaccard
word × dependency rel.		Positive PMI		IS		KL
verb × arguments		PPMI with discounting		DCA		KL with skew
⋮		⋮		⋮		⋮

(Nearly the full cross-product to explore; only a handful of the combinations are ruled out mathematically, and the literature contains relatively little guidance.)

Potts (2013)

Don’t Count, Predict!

	rg	ws	wss	wsr	men	toefl	ap	esslli	battig	up	mcrae	an	ansyn	ansem
						best setup on each task								
cnt	74	62	70	59	72	76	66	84	98	41	27	49	43	60
pre	84	75	**80**	**70**	**80**	91	75	86	**99**	41	28	**68**	**71**	**66**
						best setup across tasks								
cnt	70	62	70	57	72	76	64	84	98	37	27	43	41	44
pre	83	73	78	68	**80**	86	71	77	98	41	26	67	69	64
						worst setup across tasks								
cnt	11	16	23	4	21	49	24	43	38	-6	-10	1	0	1
pre	74	60	73	48	68	71	65	82	88	33	20	27	40	10
						best setup on rg								
cnt	(74)	59	66	52	71	64	64	84	98	37	20	35	42	26
pre	(84)	71	76	64	79	85	72	84	98	39	25	66	70	61
						other models								
soa	**86**	**81**	77	62	76	**100**	**79**	**91**	96	**60**	**32**	61	64	61
dm	82	35	60	13	42	77	76	84	94	51	29	NA	NA	NA
cw	48	48	61	38	57	56	58	61	70	28	15	11	12	9

Table 2: Performance of count (cnt), predict (pre), dm and cw models on all tasks. See Section 3 and Table 1 for figures of merit and state-of-the-art results (soa). Since dm has very low coverage of the an* data sets, we do not report its performance there.

Baroni et al. (2014)

Word Embeddings: Not New, but Different

- Learning representations by back-propagating errors (Rumelhart et al. 1986)

- Neural Probabilistic Language Model (Bengio et al. 2003)

- NLP (almost) from Scratch (Collobert and Weston, 2008)

- Word2Vec (Mikolov et al., 2013)

One-Hot Encoding (Sparse Representation)

	he	she	eats	drinks	sushi	ramen	hungry	coffee
he	1	0	0	0	0	0	0	0
she	0	1	0	0	0	0	0	0
eats	0	0	1	0	0	0	0	0
drinks	0	0	0	1	0	0	0	0
sushi	0	0	0	0	1	0	0	0
ramen	0	0	0	0	0	1	0	0
hungry	0	0	0	0	0	0	1	0
coffee	0	0	0	0	0	0	0	1

v('drinks')

Word Embeddings (Dense Representation)

	he	she	eats	drinks	sushi	ramen	hungry	coffee
0	0.1	0.2	-0.4	0.9	0.8	0.1	0.8	-0.8
1	0.2	0.1	-0.3	0.9	0.7	0.2	0.3	-2.1
2	0.2	-1.4	0.3	-0.1	0.1	0.5	0.9	-0.5
3	0.3	-2.0	0.5	-0.5	0.2	0.4	0.1	-0.1
4	0.2	-1.1	0.3	-0.7	-0.6	-0.5	0.3	0.4
5	0.3	-1.2	0.4	-0.9	-0.3	-0.4	-0.6	-0.4

v('drinks')

Lookup Function

0
0
0
1
0
0
0
0

X

0.1	0.2	-0.4	0.9	0.8	0.1	0.8	-0.8
0.2	0.1	-0.3	0.9	0.7	0.2	0.3	-2.1
0.2	-1.4	0.3	-0.1	0.1	0.5	0.9	-0.5
0.3	-2.0	0.5	-0.5	0.2	0.4	0.1	-0.1
0.2	-1.1	0.3	-0.7	-0.6	-0.5	0.3	0.4
0.3	-1.2	0.4	-0.9	-0.3	-0.4	-0.6	-0.4

0.9
0.9
-0.1
-0.5
-0.7
-0.9

One-Hot Encoding

1 x |V|

Word Embeddings

|V| x d

Input

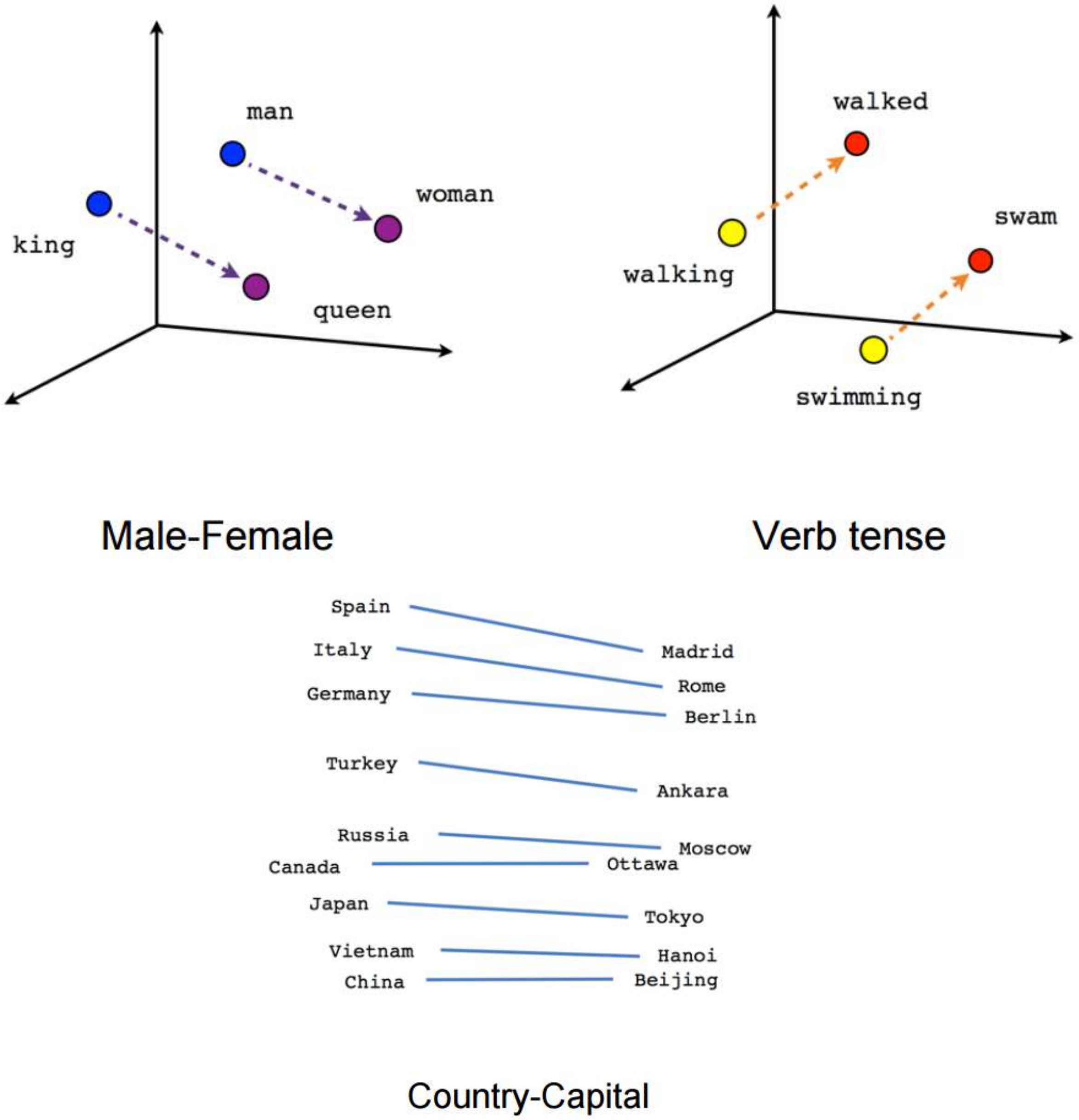
1 x d

Deep NLP: Featurize and Predict

- **Deep learning can create vectors that are**
  - short (often fixed-sized <2000, decided empirically)
  - dense (most are non-zeros)

- **How might we ”featurize” the vectors through some tasks and update the vectors based on gradient descent?**

Word2Vec



Ingredients

Corpus of text	As large as possible
Annotations	0
Initialize weights (aka Embeddings)	1x per word
Deep Learning Model	1x
Cost Function	Appropriately
GPU	Lotsa of it

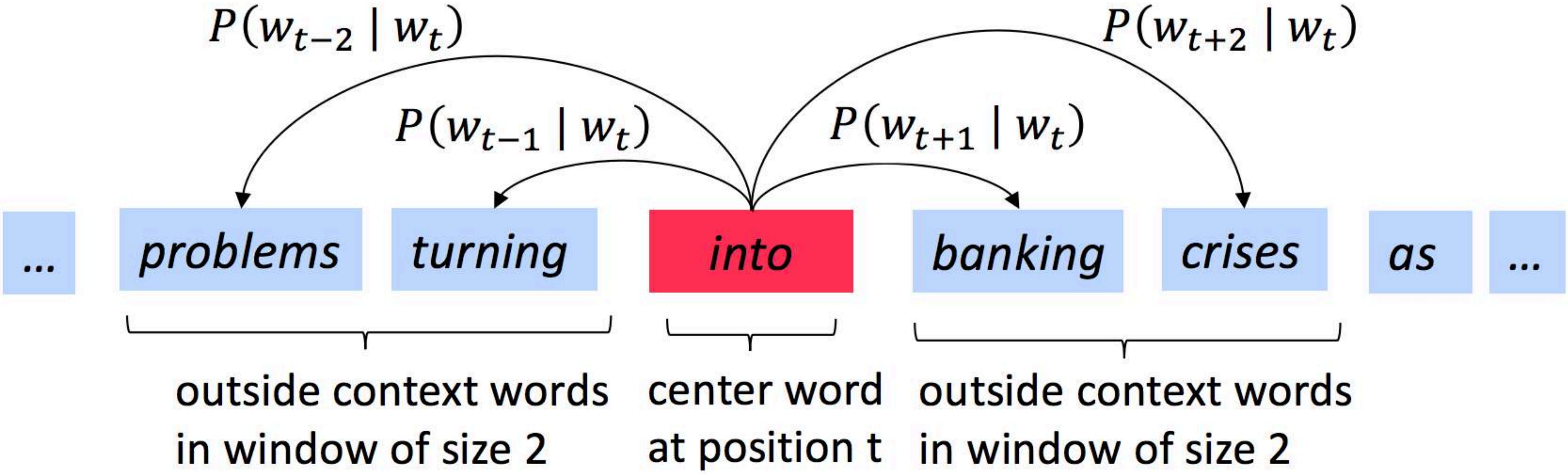
Word2Vec

Steps

1. Define task that we want to predict
2. Go through each sentence and create the task's in-/outputs
3. Iterate through task's I/O, put the inputs through the embeddings and models to create predictions
4. Measure cost of the predicted and expected output
5. Update embedding weights accordingly (*backprop)
6. Repeat Step 3-5 until desired.

Word2Vec (CBOW)

Task: Iterate through each word with a given window; for each word predict the context words within the window



(E.g. from Manning (2018) Stanford cs224n course)

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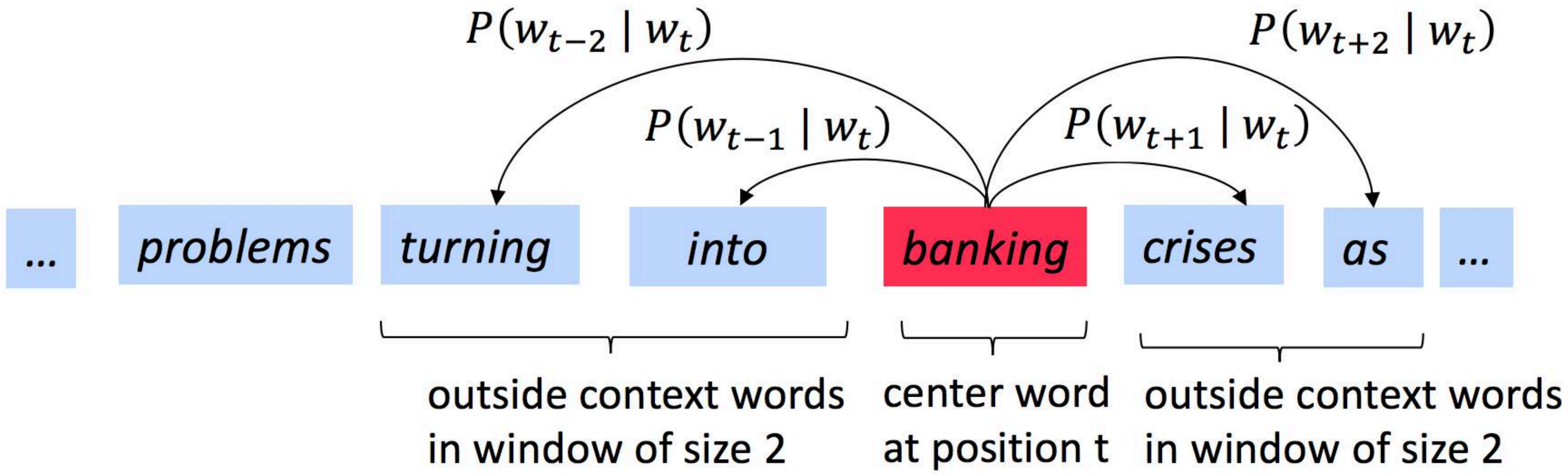

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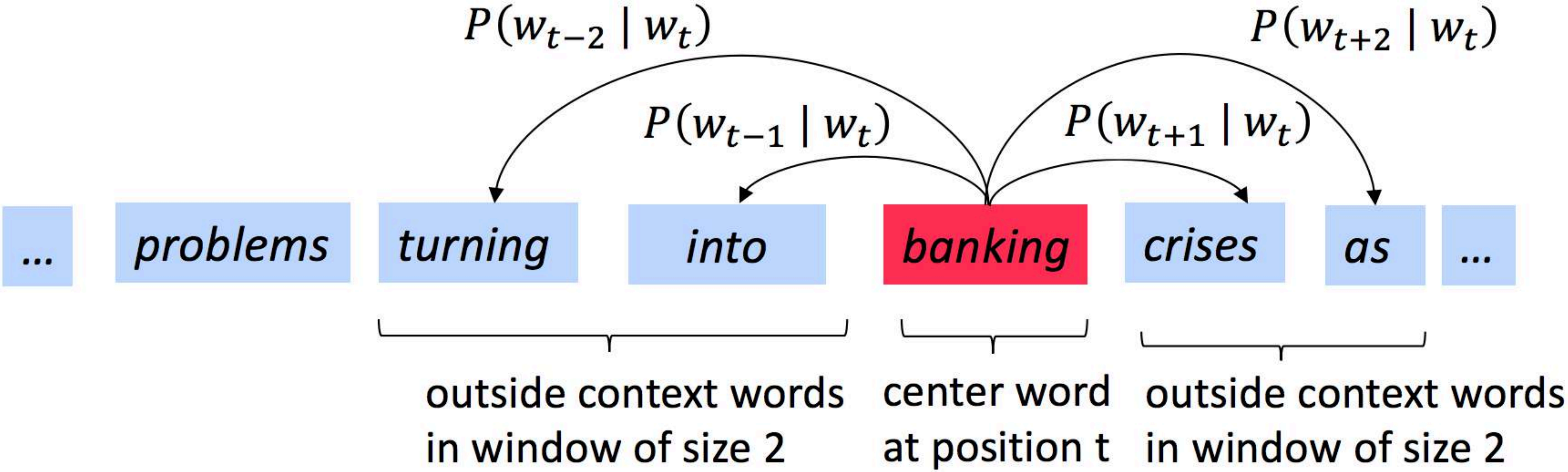

(E.g. from Manning (2018) Stanford cs224n course)

Word2Vec (CBOW)

For each position $t = 1, \ldots, T$, predict context words within a window of fixed size m, given center word w_j.

$$\text{Likelihood} = L(\theta) = \prod_{t=1}^{T} \prod_{\substack{-m \leq j \leq m \\ j \neq 0}} P(w_{t+j} \mid w_t; \theta)$$

θ is all variables to be optimized

sometimes called *cost* or *loss* function

The objective function $J(\theta)$ is the (average) negative log likelihood:

$$J(\theta) = -\frac{1}{T} \log L(\theta) = -\frac{1}{T} \sum_{t=1}^{T} \sum_{\substack{-m \leq j \leq m \\ j \neq 0}} \log P(w_{t+j} \mid w_t; \theta)$$

Minimizing objective function $\Leftrightarrow$ Maximizing predictive accuracy

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Minimizing objective function ⟺ Maximizing predictive accuracy

Word2Vec (CBOW)

We want to minimize the objective function:

$$J(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{\substack{-m\le j\le m \\ j\neq 0}} \log P\left(w_{t+j} \mid w_t; \theta\right)$$

<u>Question:</u> How to calculate $P\left(w_{t+j} \mid w_t; \theta\right)$?

<u>Answer:</u> We will *use two* vectors per word *w*:

- v_w when *w* is a center word
- u_w when *w* is a context word

Then for a center word *c* and a context word *o*:

$$P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w\in V}\exp(u_w^T v_c)}$$

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Word2Vec (CBOW)

Exponentiation makes anything positive

$$P(o|c) = \frac{\exp(\boxed{u_o^T v_c})}{\boxed{\sum_{w \in V} \exp(u_w^T v_c)}}$$

Dot product compares similarity of *o* and *c*.
$u^T v = u.v = \sum_{i=1}^{n} u_i v_i$
Larger dot product = larger probability

Normalize over entire vocabulary
to give probability distribution

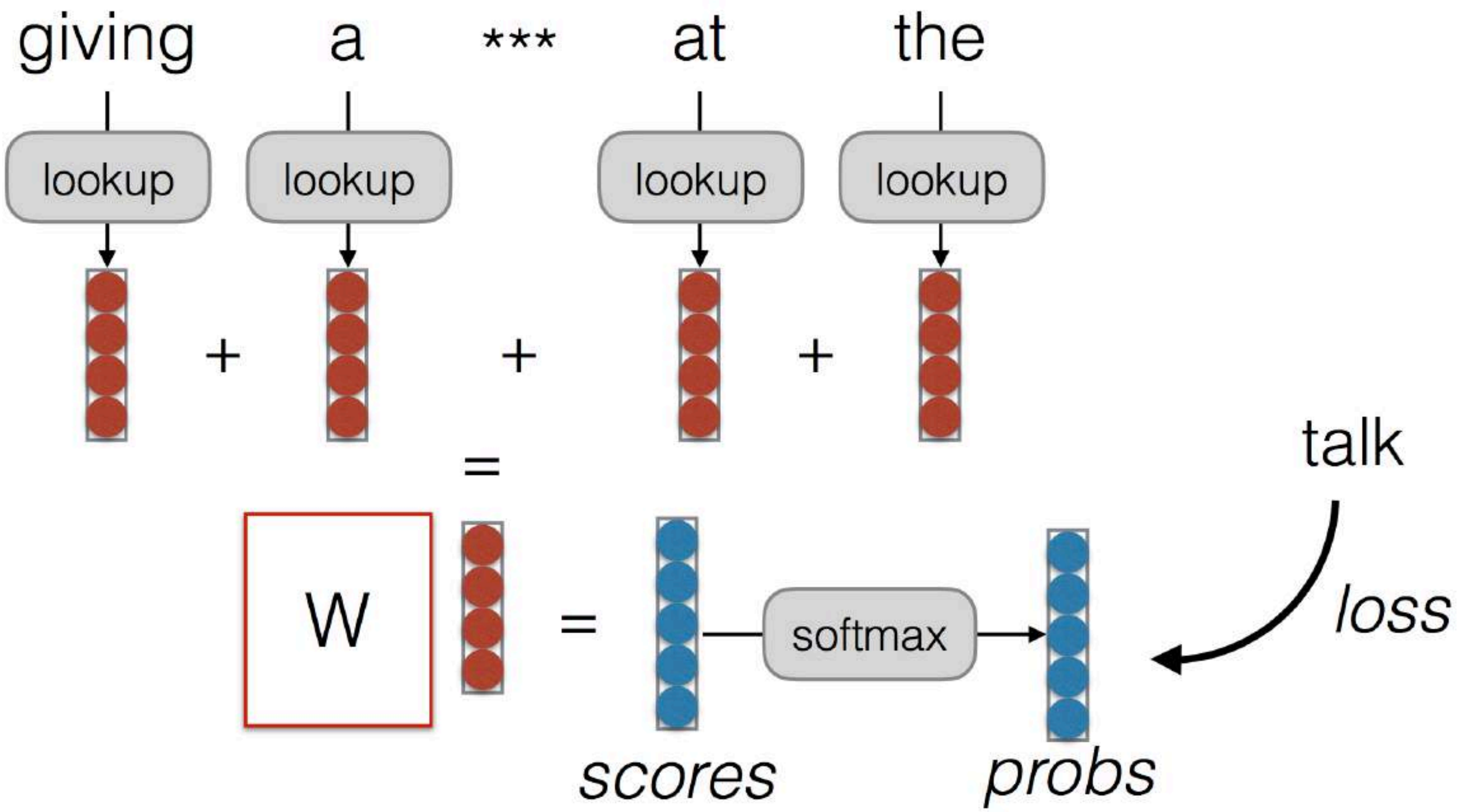
- This is an example of the **softmax function** $\mathbb{R}^n \rightarrow \mathbb{R}^n$

$$\text{softmax}(x_i) = \frac{\exp(x_i)}{\sum_{j=1}^{n} \exp(x_j)} = p_i$$

- The softmax function maps arbitrary values x_i to a probability distribution p_i
  - "max" because amplifies probability of largest x_i
  - "soft" because still assigns some probability to smaller x_i
  - Frequently used in Deep Learning

Word2Vec (CBOW)

Task: Iterate through every word with a given window; learn W such the models can predict what's the word given only the context words as inputs.



(E.g. from Neubig (2018) CMU nn4nlp course)

Word2Vec (CBOW)

Sentence: the bulk of linguistic questions concern the dis- tinction between a and m. a linguistic account of phenomenon …

of	the bulk ______ linguistic questions
linguistic	bulk of ______ questions concern
questions	of linguistic ______ concern the
concern	linguistic questions ______ the dis-
the	questions concern ______ dis- tinction
dis-	concern the ______ tinction between
tinction	the dis- ______ between a
between	dis- tinction ______ a and
a	tinction between ______ and m.
and	between a ______ m. a
m.	a and ______ a linguistic
a	and m. ______ linguistic account
linguistic	m. a ______ account of
account	a linguistic ______ of a
of	linguistic account ______ a phenomenon
a	account of ______ phenomenon gen-
phenomenon	of a ______ gen- erally

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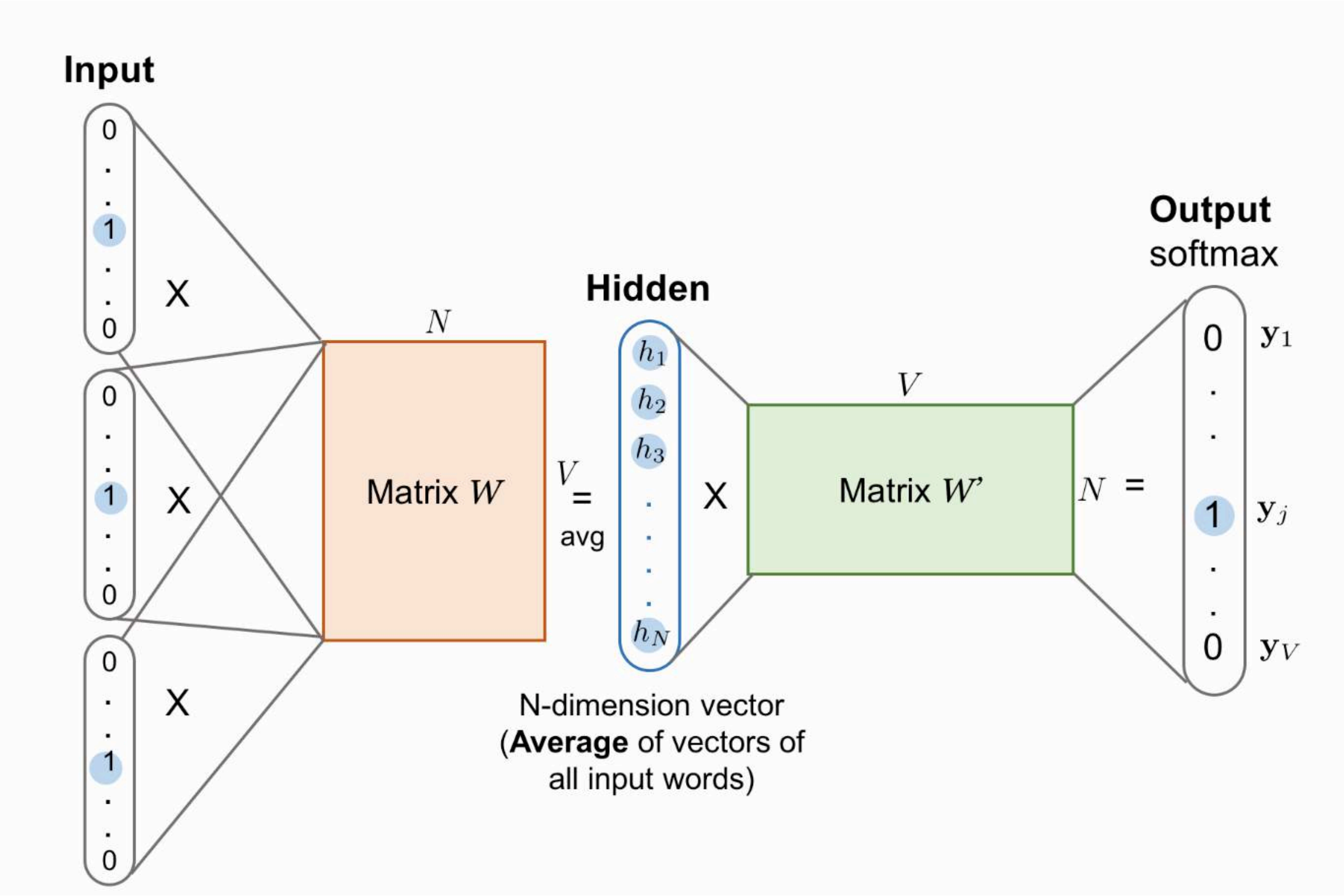
between	dis- tinction ______ a and
a	tinction between ______ and m.
and	between a ______ m. a
m.	a and ______ a linguistic
a	and m. ______ linguistic account
linguistic	m. a ______ account of
account	a linguistic ______ of a
of	linguistic account ______ a phenomenon
a	account of ______ phenomenon gen-
phenomenon	of a ______ gen- erally

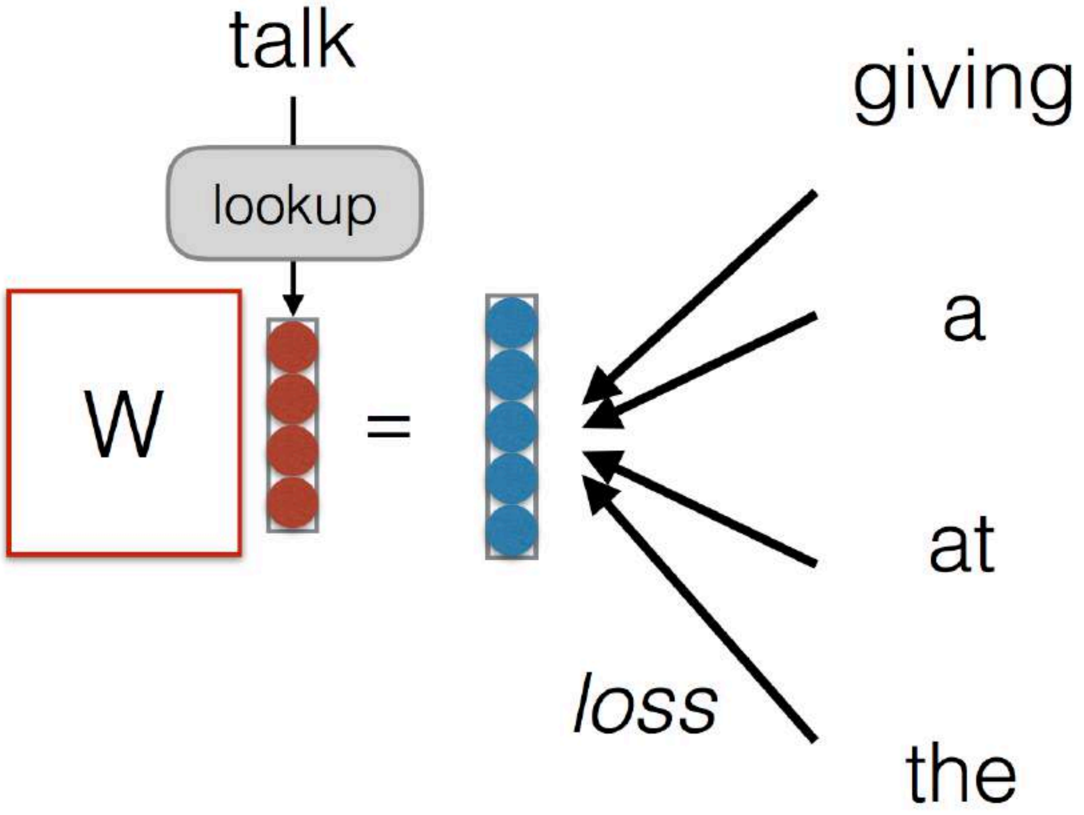
Word2Vec (CBOW)



(Image from https://lilianweng.github.io/lil-log/2017/10/15/learning-word-embedding.html)

Word2Vec (Skipgram)

Task: Iterate through every word with a given window; learn W such the models predicts 1.0 when the model is given (i) embeddings of the focus words and (ii) embedding of any word in the context and the models predicts 0.0 otherwise



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Word2Vec (Skipgram)

Sentence: language users never choose words randomly , and language is essentially non-random .

In-/Outputs:

```
[(['language', 'users', 'choose', 'words'], 'never'),
(['users', 'never', 'words', 'randomly'], 'choose'),
(['never', 'choose', 'randomly', ','], 'words'),
(['choose', 'words', ',', 'and'], 'randomly’),
(['words', 'randomly', 'and', 'language'], ',’),
(['randomly', ',', 'language', 'is'], 'and’),
([',', 'and', 'is', 'essentially'], 'language’),
(['and', 'language', 'essentially', 'non-random'], 'is’),
(['language', 'is', 'non-random', '.'], 'essentially')]
```

Word2Vec (Skipgram)

Sentence: `language users never choose words randomly , and language is essentially non-random .`

Windows:

```
['language', 'users', 'never', 'choose', 'words']

('never', 'language', 1),
('never', 'users', 1),
('never', 'choose', 1),
('never', 'words', 1),
('never', ',', 0),
('never', 'non-random', 0),
('never', 'is', 0),
('never', 'is', 0)
```

aka. negative sampling

How to Choose Context?

- **Different contexts lead to different embeddings**

- **Small context window:** more syntax related

- **Large context window:** more semantics related

How Good are my Embeddings?

Intrinsic Evaluation of Embeddings

- **Relatedness:** Measures correlations between embedding cosine similarity and human evaluation of similarity

- **Analogy:** "a is to b, as x is to ____"

- **Categorization:** Measure purity of clusters based on embeddings

- **Selectional Preference**: "tall" vs "high" man/building

Extrinsic Evaluation of Embeddings

- Load the pretrained embeddings
- Embed the input words as use the embeddings as input to models
- Evaluate which pre-trained embeddings are better for task X

When to use pre-trained embeddings?

- Generally, when you don't have much training/annotated data

- **Very Useful:** Use as inputs to model for classification task, e.g. tagging, parsing, textcat

- **Less Useful:** Machine Translation / Sequence generating tasks

- **Not Useful:** Generic Language Modeling, for those, we have sentence embedings…

Limitations

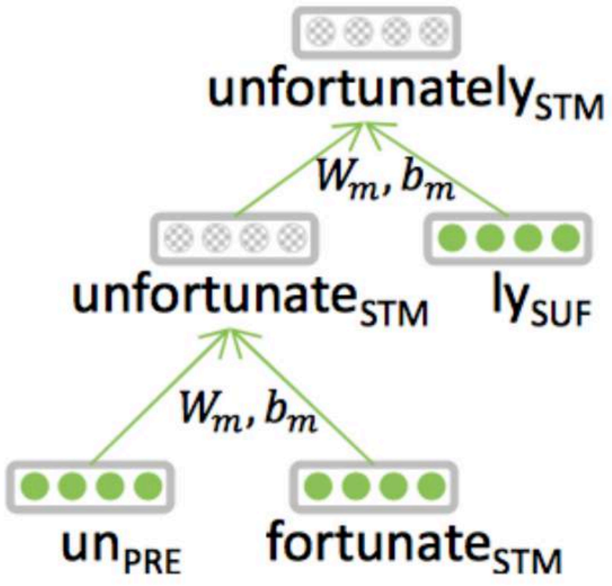
- **Sensitive to "tokens"** (cat vs cats)
- **Insensitive to polysemy** (Industrial *plant* vs "*I'm Groot*")
- **Inconsistent across space**, embeddings for the same words trained with different data are different
- **Can encode bias** (stereotypical gender roles, racial bias)
- **Not interpretable**

How to make Embeddings Better?

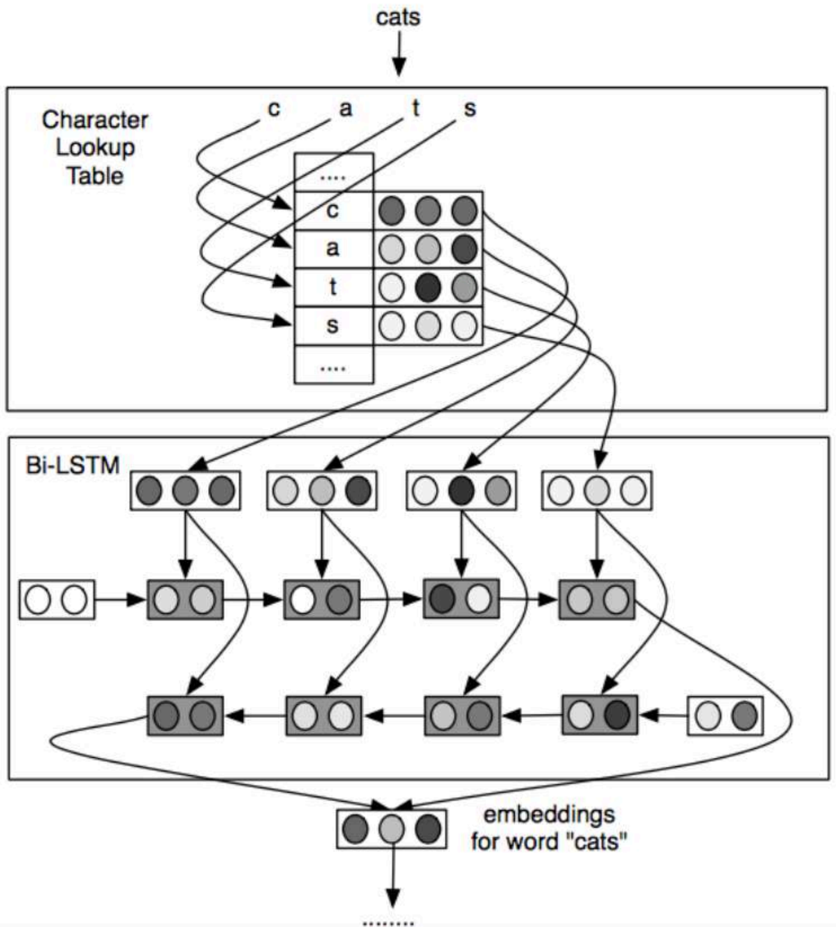
Non-Tokens Embeddings

- Can capture sub-word regularities

Morpheme-based
(Luong et al. 2013)



Character-based
(Ling et al. 2015)



Non-Tokens Embeddings

- **Bag of Characters Ngrams** (Bojanowski et al. 2016)
- `”where” -> [“<where>”, “<wh”, “her”, “ere”, “re>”]`
- Each word is the sum of all parts
- Embedding(“where”) = sum(Embedding(_ng) for _ng in [“<where>”, “<wh”, “her”, “ere”, “re>”])

Embedding Bias

$$\overrightarrow{\text{man}} - \overrightarrow{\text{woman}} \approx \overrightarrow{\text{king}} - \overrightarrow{\text{queen}}$$

$$\overrightarrow{\text{man}} - \overrightarrow{\text{woman}} \approx \overrightarrow{\text{computer programmer}} - \overrightarrow{\text{homemaker}}.$$

	"He" Occupations	"She" Occupations
Cosine Similarity	*["retired", "doctor", "teacher", "student", "miller", "assistant", "lawyer", "baker", "judge", "governor", "butler"]*	*["doctor", "**teacher**", "**nurse**", "actress", "student", "miller", "reporter", "retired", "lawyer", "actor", "artist"]*
Inner Product Similarity	*["cleric", "photographer", "**skipper**", "chaplain", "accountant", "inspector", "rector", "investigator", "psychologist", "treasurer", "supervisor"]*	*["**librarian**", "**housekeeper**", "**nanny**", "accountant", "sheriff", "envoy", "tutor", "salesman", "butler", "footballer", "solicitor"]*

De-biasing Embeddings

Extreme *she*	Extreme *he*
1. homemaker	1. maestro
2. nurse	2. skipper
3. receptionist	3. protege
4. librarian	4. philosopher
5. socialite	5. captain
6. hairdresser	6. architect
7. nanny	7. financier
8. bookkeeper	8. warrior
9. stylist	9. broadcaster
10. housekeeper	10. magician

	Gender stereotype *she-he* analogies	
sewing-carpentry	registered nurse-physician	housewife-shopkeeper
nurse-surgeon	interior designer-architect	softball-baseball
blond-burly	feminism-conservatism	cosmetics-pharmaceuticals
giggle-chuckle	vocalist-guitarist	petite-lanky
sassy-snappy	diva-superstar	charming-affable
volleyball-football	cupcakes-pizzas	lovely-brilliant
	Gender appropriate *she-he* analogies	
queen-king	sister-brother	mother-father
waitress-waiter	ovarian cancer-prostate cancer	convent-monastery

(Bolukbasi et al. 2016)

Word2Vec from Scratch

Sort of *"from scratch"*...

Environment Setup

Open Anaconda Navigator.

Go to the PyTorch installation page, copy the command as per configuration: https://pytorch.org/get-started/locally/

Fire up the terminal in Anaconda Navigator.

Start a Jupyter Notebook.

Download http://bit.ly/ANLP-Session3-Completed

Import the .ipynb to the Jupyter Notebook

Summary

Embedding Checklist

- What is a Word2Vec model
- How to define CBOW and Skipgram task
- How to define CBOW and Skipgram models

PyTorch Checklist

- How to write a model and know what's going on behind loss.backward() and optimizer.step()
- How to declare your own torch.utils.data.Dataset object
- How to save/load a model
- How to overwrite weights and use pretrained embeddings
- Fine-tune/Unfreeze pre-trained embeddings

Fin

3.0.1 Vocabulary

Given a text, the first thing to do is to build a vocabulary (i.e. a dictionary of unique words) and assign an index to each unique word.

```
import random
from itertools import chain

from tqdm import tqdm
from nltk import sent_tokenize, word_tokenize
from gensim.corpora import Dictionary

import torch
from torch import nn, optim, tensor, autograd
from torch.nn import functional as F
```

```
text = """Language users never choose words randomly, and language is essentially
non-random. Statistical hypothesis testing uses a null hypothesis, which
posits randomness. Hence, when we look at linguistic phenomena in corpora,
the null hypothesis will never be true. Moreover, where there is enough
data, we shall (almost) always be able to establish that it is not true. In
corpus studies, we frequently do have enough data, so the fact that a relation
between two phenomena is demonstrably non-random, does not support the inference
that it is not arbitrary. We present experimental evidence
of how arbitrary associations between word frequencies and corpora are
systematically non-random. We review literature in which hypothesis testing
has been used, and show how it has often led to unhelpful or misleading results.""".lower()

tokenized_text = [word_tokenize(sent) for sent in sent_tokenize(text)]

uniq_tokens = set(chain(*tokenized_text))

vocab = {}   # Assign indices to every word.
idx2tok = {} # Also keep an dict of index to words.
for i, token in enumerate(uniq_tokens):
    vocab[token] = i
    idx2tok[i] = token
```

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non-random. Statistical hypothesis testing uses a null hypothesis, which
posits randomness. Hence, when we look at linguistic phenomena in corpora,
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    vocab[token] = i
    idx2tok[i] = token
```

Using `gensim`, I would have written the above as such:

```python
from gensim.corpora.dictionary import Dictionary
vocab = Dictionary(tokenized_text)
```

```python
# Note the key-value order is different of gensim from the native Python's
dict(vocab.items())
```

```
 67: 'evidence',
 68: 'experimental',
 69: 'frequencies',
 70: 'how',
 71: 'of',
 72: 'present',
 73: 'systematically',
 74: 'word',
 75: 'been',
 76: 'has',
 77: 'led',
 78: 'literature',
 79: 'misleading',
 80: 'often',
 81: 'or',
 82: 'results',
 83: 'review',
 84: 'show',
 85: 'unhelpful',
 86: 'used'}
```

```python
vocab.token2id['corpora']
```

```
23
```

```python
vocab.doc2idx(sent0)
```

```
[6, 10, 7, 3, 11, 9, 0, 2, 6, 5, 4, 8, 1]
```

The "indexed form" of the tokens in the sentence forms the ***vectorized*** input to the `nn.Embedding` layer in PyTorch.

3.0.2 Dataset

Lets try creating a `torch.utils.data.Dataset` object.

```
from torch.utils.data import Dataset, DataLoader

class Text(Dataset):
    def __init__(self, tokenized_texts):
        """
        :param tokenized_texts: Tokenized text.
        :type tokenized_texts: list(list(str))
        """
        self.sents = tokenized_texts
        self.vocab = Dictionary(tokenized_text)

    def __getitem__(self, index):
        """
        The primary entry point for PyTorch datasets.
        This is were you access the specific data row you want.

        :param index: Index to the data point.
        :type index: int
        """
        return self.vectorize(self.sents[0])

    def vectorize(self, tokens):
        """
        :param tokens: Tokens that should be vectorized.
        :type tokens: list(str)
        """
        # See https://radimrehurek.com/gensim/corpora/dictionary.html#gensim.corpora.dictionary.Dictionary.doc2idx
        return {'x': self.vocab.doc2idx(tokens)}

    def unvectorize(self, indices):
        """
        :param indices: Converts the indices back to tokens.
        :type tokens: list(int)
        """
        return [self.vocab[i] for i in indices]
```

```
text_dataset = Text(tokenized_text)
```

```
text_dataset[0] # First sentence.
```

```
{'x': [6, 10, 7, 3, 11, 9, 0, 2, 6, 5, 4, 8, 1]}
```

```
from torch.utils.data import Dataset, DataLoader

class Text(Dataset):
    def __init__(self, tokenized_texts):
        """
        :param tokenized_texts: Tokenized text.
        :type tokenized_texts: list(list(str))
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        """
        return self.vectorize(self.sents[0])

    def vectorize(self, tokens):
        """
        :param tokens: Tokens that should be vectorized.
        :type tokens: list(str)
        """
        # See https://radimrehurek.com/gensim/corpora/dictionary.html#gen
        return {'x': self.vocab.doc2idx(tokens)}

    def unvectorize(self, indices):
        """
        :param indices: Converts the indices back to tokens.
        :type tokens: list(int)
        """
        return [self.vocab[i] for i in indices]
```

Required function to access the data from Dataset object

```python
from torch.utils.data import Dataset, DataLoader

class LabeledText(Dataset):
    def __init__(self, tokenized_texts, labels):
        """
        :param tokenized_texts: Tokenized text.
        :type tokenized_texts: list(list(str))
        """
        self.sents = tokenized_texts
        self.labels = labels # Sentence level labels.
        self.vocab = Dictionary(self.sents)


    def __getitem__(self, index):
        """
        The primary entry point for PyTorch datasets.
        This is were you access the specific data row you want.

        :param index: Index to the data point.
        :type index: int
        """
        return {'X': self.vectorize(self.sents[index]), 'Y': self.labels[index]}

    def vectorize(self, tokens):
        """
        :param tokens: Tokens that should be vectorized.
        :type tokens: list(str)
        """
        # See https://radimrehurek.com/gensim/corpora/dictionary.html#gensim.corpora.
        return self.vocab.doc2idx(tokens)

    def unvectorize(self, indices):
        """
        :param indices: Converts the indices back to tokens.
        :type tokens: list(int)
        """
        return [self.vocab[i] for i in indices]
```

Overload the arguments and return the respective labels from the __getitem__()

3.1.1. CBOW

CBOW windows through the sentence and picks out the center word as the `Y` and the surrounding context words as the inputs `X`.

```
def per_window(sequence, n=1):
    """
    From http://stackoverflow.com/q/42220614/610569
        >>> list(per_window([1,2,3,4], n=2))
        [(1, 2), (2, 3), (3, 4)]
        >>> list(per_window([1,2,3,4], n=3))
        [(1, 2, 3), (2, 3, 4)]
    """
    start, stop = 0, n
    seq = list(sequence)
    while stop <= len(seq):
        yield seq[start:stop]
        start += 1
        stop += 1

def cbow_iterator(tokens, window_size):
    n = window_size * 2 + 1
    for window in per_window(tokens, n):
        target = window.pop(window_size)
        yield window, target   # X = window ; Y = target.
```

Context words

```
sent0 = ['language', 'users', 'never', 'choose', 'words', 'randomly', ',',
         'and', 'language', 'is', 'essentially', 'non-random', '.']
```

```
list(cbow_iterator(sent0, 2))
```

```
[(['language', 'users', 'choose', 'words'], 'never'),
 (['users', 'never', 'words', 'randomly'], 'choose'),
 (['never', 'choose', 'randomly', ','], 'words'),
 (['choose', 'words', ',', 'and'], 'randomly'),
 (['words', 'randomly', 'and', 'language'], ','),
 (['randomly', ',', 'language', 'is'], 'and'),
 ([',', 'and', 'is', 'essentially'], 'language'),
 (['and', 'language', 'essentially', 'non-random'], 'is'),
 (['language', 'is', 'non-random', '.'], 'essentially')]
```

Focus words

```
list(cbow_iterator(sent0, 3))
```

```
[(['language', 'users', 'never', 'words', 'randomly', ','], 'choose'),
 (['users', 'never', 'choose', 'randomly', ',', 'and'], 'words'),
 (['never', 'choose', 'words', ',', 'and', 'language'], 'randomly'),
 (['choose', 'words', 'randomly', 'and', 'language', 'is'], ','),
 (['words', 'randomly', ',', 'language', 'is', 'essentially'], 'and'),
 (['randomly', ',', 'and', 'is', 'essentially', 'non-random'], 'language'),
 ([',', 'and', 'language', 'essentially', 'non-random', '.'], 'is')]
```

Fin