Naïve Introduction to Word Embeddings

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A word embedding is...

... a numerical representation of a word

- Allow arithmetic operations on text

  Ex: time + flies

A word embedding is...

... a numerical representation of a word

- Allow arithmetic operations on text

  Ex: time + flies

- Several names
  - Semantic Representations of Words
  - Word Vector Representations
  - Word Embeddings

A word embedding is...

time = (1.844012, 0.590383, 1.003636, -0.577031, 1.515419, 1.097797, 1.812856, 0.933615, -2.396581,
-0.931116, -0.719396, -0.376134, -1.204231, 0.045771, -0.287482, 1.084627, 4.399265, 1.516829, -0.838133,
-1.881685, 0.108117, 2.345857, -1.292667, -2.286168, 3.419926, 4.260052, -1.016988, 3.140229, -3.161504,
-0.800707, -1.433775, 2.290546, 1.932333, 0.714649, -3.033084, -0.958289, -1.704687, -1.597345, 1.525060,
3.337017, -2.787743, 1.479353, 3.452092, -3.242210, 0.532302, -0.551804, 2.344314, -0.919049, -1.872516,
0.080137, 1.208913, -2.136555, -2.218254, 0.206410, 0.133225, -1.521032, 1.735609, 2.885288, -2.048691,
2.375038, 0.316599, -0.254595, 2.159168, 1.118603, -0.775468, 0.933521, -0.351797, 2.193516, 2.499064,
2.818742, -0.213898, 0.446962, 1.767461, 1.342941, 1.117215, -0.042004, 4.199081, 3.041796, -1.770649,
-0.528354, -2.067354, 0.283046, -0.099049, -0.105402, 2.823484, -2.583724, -2.906962, 0.592174, -3.029664,
-0.170582, 0.406366, 1.963008, -3.229250, -3.499467, -0.136623, -1.551140, 0.348241, -1.597526, 0.703598,
3.122618, 0.466473, -0.113320, -2.119155, 1.092863, -0.908410, 0.253259, -1.082862, 4.408773, 2.419691,
2.343239, 0.703793, 1.270707, 0.410221, -1.293057, -0.799147, 2.214563, -0.212623, 1.206766, -0.731273,
2.308388, -1.029362, -2.080709, 0.749148, -1.412619, 1.073051, -2.498955, -0.520858, 1.391912, -1.181121,
1.523457, -1.245448, -0.290742, -2.589719, -0.366162, 3.586508, 0.908829, -1.125176, -0.937035, -1.163619,
1.759209, 3.678231, 0.019263, -0.395732, 1.142848, -0.500150, -3.005232, 2.287069, -0.524648, -0.944902,
0.038368, -1.093538, -0.697787, 0.767664, 2.399855, 2.425945, 1.563581, -1.086811, 0.372100, 1.400303,
-2.278863, 0.643208, -0.459837, 1.756295, 2.057359, 3.140241, -1.740582, 1.386243, -1.822378, 1.528883,
-1.984250, 1.214508, -1.336822, -0.321478, -0.162113, 0.272326, -2.673072, 0.612675, -0.657483, -0.557969,
-3.358420, -2.559981, -1.683046, -1.314229, -2.425110, -2.506184, -1.606668, 1.332781, -2.760878, -2.400824,
-1.830618, -2.406664,-1.169146, -1.838281, 0.588559, 2.285466, -0.401462, 1.632473, -0.510084, -2.072332,
-2.627897, 2.531830, -2.524195, 2.035469, 1.906113, -1.257332, -4.039220, -0.467614, -2.275054, -3.409202,
-0.014383, 0.445576, 1.461529, -1.318478, 0.061049, 0.280523, 2.173227, -0.027133, 2.791830, -0.728346,
-1.804815, 1.245291, 0.970318, 2.646388, 0.246842, -1.823608, 1.888760, 0.265116, -2.027269, -0.089802,
0.389976, -0.654499, 2.565478, -2.647825, 2.658914, 1.385568, 2.306623, 0.476923, -0.869644, -0.170338,
0.495097, -2.604649, 0.610231, 0.739677, 0.322778, -2.042915, -1.353154, 0.177016, 1.840185, -0.271689,
-0.401560, -0.421108, -0.185526, 1.041765, -4.599578, -0.829409, 0.076258, -0.503421, 1.891007, -0.931777,
0.434825, -0.467926, -1.417658, -0.320597, -4.084039, -3.899607, 0.977403, 0.774670, 3.269479, -1.031264,
-0.433907, -2.30576 0, 0.811788, 2.347483, -1.254061, -0.861366, 0.080974, -3.666142, -0.363376, -2.384475,
-4.290071, -0.924723, 1.257435, 1.223927, 0.276726, 1.541471, 1.274240, 1.883040, -1.987514, -0.809325,
1.252716, 1.812783, -0.511801, -1.657522, 1.196169, 0.804855, -1.861488, -2.113367, 0.429888, -0.920844,
0.377247)

A word embedding is...

flies = (0.101159, 0.550446, 0.543801, -0.973852, -0.680835, 0.417193, -0.247181, 0.209725, -1.136055, -0.059531, -0.401640, 0.171540, 0.925121, -0.143815, 0.781714, -1.482425, 0.347008, -0.112342, 0.442418, -1.020457, -0.071752, 1.873548, -0.222886, -0.729569, -0.830224, -0.868407, 0.203496, 0.469911, -0.191363, 0.565102, 0.687738, 0.480823, 0.842358, -0.173656, -0.265585, 0.685740, 0.488047, -0.359772, -0.576064, -0.802884, 0.081554, 0.046882, -0.861532, -0.461855, 0.613098, -1.534642, -0.884534, 0.207728, 1.396512, -0.242900, -0.383959, 0.570844, -0.703350, -1.368813, -1.008194, 1.534660, 0.171693, 0.640925, -0.233116, 0.324685, 0.483171, 0.337947, -0.963290, -0.400558, 0.830977, 0.913474, 0.251693, -0.589420, -0.299622, 1.047515, -0.266679, -1.247186, 1.087610, -0.549028, 1.600710, -1.538516, -1.703301, -1.393499, -0.894448, 0.717204, 0.105767, -0.189234, -0.615609, -0.658315, 0.051877, 0.014180, -0.791282, 0.150424, 1.343751, -0.464859, 0.871426, 1.542864, -1.202150, -0.767113, -1.734738, 0.073633, -1.012583, 0.747787, 0.476070, -0.454807, 0.642685, -0.854152, -0.071798, 0.233724, 0.712329, -0.097752, -0.531132, 0.323271, -0.447342, 0.657913, 1.199492, -0.107360, -0.154234, -1.131168, 1.354793, 1.721385, -0.240023, 0.655765, -0.217006, -0.801722, 0.553369, 0.213377, 0.323267, -1.516051, 2.106244, -0.134282, 0.742155, 0.426344, 0.197991, -0.806768, 0.372546, -0.160200, -1.552847, -0.286178, -0.707796, 0.527352, -0.259658, 0.230387, 0.105294, -0.194481, 0.301772, -1.022163, 0.557191, 1.096709, 0.058422, -1.036384, 0.353412, -0.623097, -0.689515, 0.091472, 0.783885, 0.184088, -0.367950, 0.952462, 0.183704, 0.677562, 0.293917, -0.214309, -0.487794, 0.934296, 0.311513, 0.286514, -0.085511, 0.777691, 1.232603, -0.309367, -0.225086, 0.005091, -0.099195, -0.293117, 1.305563, 0.595816, 0.950316, 0.568706, -0.561446, 0.911634, -0.383941, 0.758054, -0.197820, 0.506777, -0.290767, -0.356727, 1.229474, -0.156489, -0.782741, -0.210163, -0.029169, 0.602664, 0.418375, 0.148975, -0.761796, 1.322690, -0.173410, 0.204111, -1.344531, 1.081905, -0.660543, -0.225615, -0.444753, -0.929671, 0.054136, 0.052031, -0.164926, 0.159312, -1.316333, 0.837011, -1.290353, 0.958403, 1.247478, 0.442009, 0.455497, -1.856268, -0.358823, -0.230839, -0.206271, 0.227012, -0.454163, 0.747798, -1.252855, 1.436849, -0.427915, -0.810428, -0.628144, -0.288458, 0.087355, 0.356739, 0.153036, 0.516594, -0.504978, 0.814432, 1.052940, 1.094526, -0.219595, 0.722178, 0.267325, -0.087458, -1.270262, -0.039461, 0.991926, -0.112005, -0.009605, 0.149920, 0.164717, 0.280475, 0.966384, 0.327598, 0.189590, -0.208946, 0.838261, 0.051847, -0.277932, -0.788527, -0.768702, -1.688721, 0.388215, 0.170153, -0.555723, -0.529565, -0.528982, -0.659930, 0.588041, -0.368195, -0.850188, -0.004996, 0.925476, 1.046587, -0.731761, 0.519435, 0.193188, -0.709557, 0.123329, -0.454316, 1.885830, -0.201841, -0.728933, -0.953455, -0.205837, -0.724068, 0.120158, 1.765389, -0.192159, 1.062490, -0.002634, 0.125790, -0.846565, 0.548899, -1.062821, -2.146826, 0.134681, 0.570950, 0.851783, 0.436544, 0.688986, 1.229008, 1.435449, 0.118766, -0.132411, 2.527890, 0.778142, 0.269093)

The Purpose of the First Day is...

...to answer several questions:

- How can we obtain those numbers?
- What's word2vec?
- Is it the only way to obtain those numbers?
- Do the vectors (and components!) have any semantic meaning?
- Are we crazy by summing or multiplying words?

Outline

Never ask for the meaning of a word in isolation, but only in the context of a sentence
(Frege, 1884)

Introduction

Distributional Hypothesis, Contextuality

Never ask for the meaning of a word in isolation, but only in the context of a sentence
(Frege, 1884)

For a large class of cases... the meaning of a word is its use in the language
(Wittgenstein, 1953)

You shall know a word by the company it keeps
(Firth, 1957)

Distributional Hypothesis, Contextuality

Words that occur in similar contexts tend to have similar meaning

(Harris, 1954)

Introduction

Similar Meanings...

- ...need for a concept of **distance** to be defined.
- **Geometry** is the branch of mathematics
  that deals with distances
- **Vector spaces** and linear algebra are our tools

Introduction

Similar Meanings...

Basketball

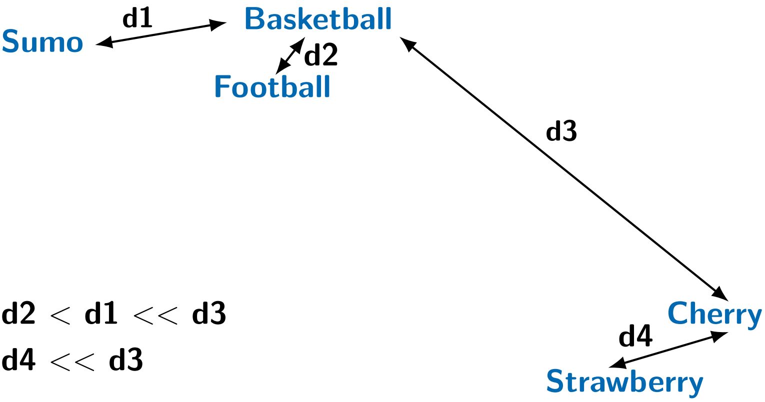
Sumo

Football

Cherry

Strawberry

Similar Meanings...

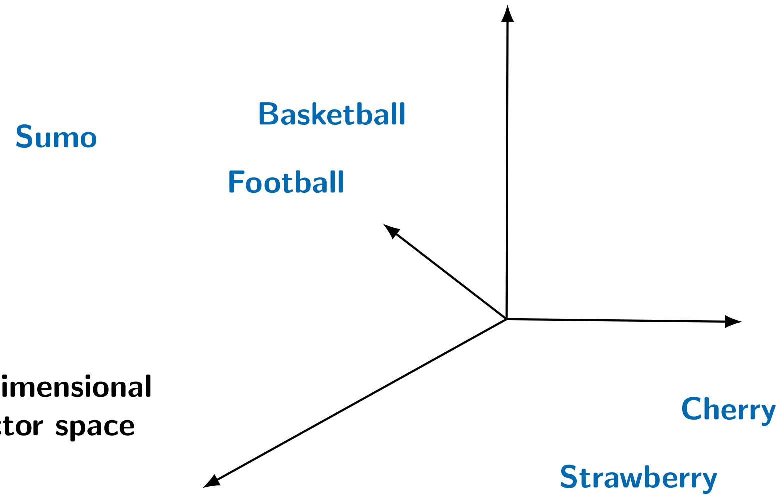


$$\mathbf{d2} < \mathbf{d1} << \mathbf{d3}$$

$$\mathbf{d4} << \mathbf{d3}$$

Introduction

Word Vector Space



n-dimensional vector space

How to Obtain a Vector for a Word?

Naïve example: **term frequencies** in a corpus

- The basis in our vector space is the vocabulary of the corpus
- Consider the document in which a word occurs its context
- Each word is characterised as the number of times it appears in each document

Example: Toy Corpus

S1: We like to play some sport in the afternoon, I like basketball but John likes sumo more.

S2: Sumo is a sport where a rikishi attempts to force another wrestler out of a circular ring.

S3: Messi scored 4 goals yesterday and kept the ball as a memory of this fantastic sports afternoon!

S4: I ate too many cherries yesterday.

Vocabulary:{*like, play, sport, afternoon, basketball, John, ball, sumo, rikishi, attempt, force, werstler, circular, ring, Messi, score, goal, yesterday, keep, memory, fantastic, eat, cherry*}

Introduction

Example: Occurrence Matrix

	like	play	sport	afternoon	basketball	John	ball	sumo	rikishi	attempt	force	werstler	circular	ring	Messi	score	goal	yesterday	keep	memory	fantastic	eat	cherry
S1	2	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S2	0	0	1	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
S3	0	0	1	1	0	0	1	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0
S4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1

Introduction

Example: Occurrence Matrix

	like	play	sport	afternoon	basketball	John	ball	sumo	rikishi	attempt	force	werstler	circular	ring	Messi	score	goal	yesterday	keep	memory	fantastic	eat	cherry
S1	2	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S2	0	0	1	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
S3	0	0	1	1	0	0	1	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0
S4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1

document vector

Example: Occurrence Matrix

	like	play	sport	afternoon	basketball	John	ball	sumo	rikishi	attempt	force	werstler	circular	ring	Messi	score	goal	yesterday	keep	memory	fantastic	eat	cherry
S1	2	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S2	0	0	1	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
S3	0	0	1	1	0	0	1	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0
S4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1

word vector

Introduction

Example: Text Similarity

Euclidean distance $\mathrm{d}(\overrightarrow{x}, \overrightarrow{y}) = \sqrt{\sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{x_i} - \mathrm{y_i})^2}$

basketball $\rightarrow$ {1, 0, 0, 0}
sumo $\rightarrow$ {1, 1, 0, 0}
cherry $\rightarrow$ {0, 0, 0, 1}

$\mathrm{d(basketball,\ sumo)} = \sqrt{(1-1)^2 + (0-1)^2 + (0-0)^2 + (0-0)^2} = 1$

$\mathrm{d(basketball,\ cherry)} = \sqrt{(1-0)^2 + (0-1)^2 + (0-0)^2 + (0-0)^2} = \sqrt{2}$

$\mathrm{d(sumo,\ cherry)} = \sqrt{(1-0)^2 + (1-0)^2 + (0-0)^2 + (0-1)^2} = \sqrt{3}$

$\mathrm{d(basketball,\ sumo)} < \mathrm{d(basketball,\ cherry)} < \mathrm{d(sumo,\ cherry)}$

Introduction

Example: Text Similarity

Cosine similarity $\mathrm{sim}(\overrightarrow{x}, \overrightarrow{y}) = \frac{\sum_{i=1}^{n} x_i y_i}{|\overrightarrow{x}||\overrightarrow{y}|}$

basketball $\rightarrow$ {1, 0, 0, 0}
sumo $\rightarrow$ {1, 1, 0, 0}
cherry $\rightarrow$ {0, 0, 0, 1}

sim(basketball, sumo)=1

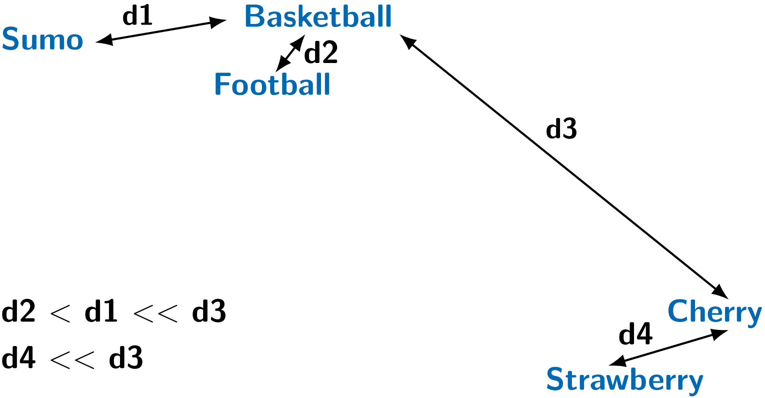
sim(basketball, cherry)=0

sim(sumo, cherry)=0

sim(basketball,sumo)>sim(basketball,cherry)=sim(sumo,cherry)

Introduction

Similarity vs. Distance

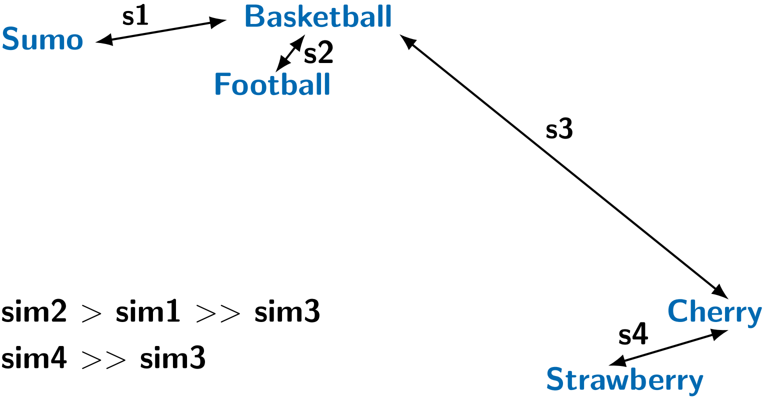


d2 $<$ **d1** $<<$ **d3**

d4 $<<$ **d3**

Introduction

Similarity vs. Distance



sim2 $>$ **sim1** $>>$ **sim3**

sim4 $>>$ **sim3**

Frequency-based Embeddings

Frequency-based Embeddings

Frequency-based Embeddings

- *Term frequency word vectors*
- TF-IDF word vectors
- Co-occurrence word vectors

Frequency-based Embeddings

Term Frequency-Inverse Document Frequency, TF-IDF

Term Frequency

How frequently a term occurs in a document d normalised to account for d length

$$\text{TF}(t, d) = \frac{\text{Number of times term } t \text{ appears in a document } d}{\text{Total number of terms in } d}$$

Frequency-based Embeddings

Term Frequency-Inverse Document Frequency, TF-IDF

Term Frequency

How frequently a term occurs in a document d normalised to account for d length

$$\mathrm{TF}(t, d) = \frac{\text{Number of times term } t \text{ appears in a document } d}{\text{Total number of terms in } d}$$

Inverse Document Frequency

Measures how important a term is (low weight for stop words)

$$\mathrm{IDF}(t, D) = \log_e\left(\frac{\text{Total number of documents } D}{\text{Number of documents with term } t \text{ in it}}\right)$$

Frequency-based Embeddings

Term Frequency-Inverse Document Frequency, TF-IDF

Trivially...

$$\text{TF-IDF}(t, d, D) = \text{TF}(t, d) \times \text{IDF}(t, D)$$

Frequency-based Embeddings

Example: Toy Corpus

d1: We like to play some sport in the afternoon, I like basketball but John likes sumo more.

d2: Sumo is a sport where a rikishi attempts to force another wrestler out of a circular ring.

d3: Messi scored 4 goals yesterday and kept the **ball** as a memory of this fantastic sports afternoon!

d4: I ate too many cherries yesterday.

$$\textbf{TF(ball)} = \left(0, 0, \frac{1}{17}, 0\right);$$

Frequency-based Embeddings

Example: Toy Corpus

d1: We like to play some sport in the afternoon, I like basketball but John likes sumo more.

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d3: Messi scored 4 goals yesterday and kept the **ball** as a memory of this fantastic sports afternoon!

d4: I ate too many cherries yesterday.

$$\textbf{TF(ball)} = \left(0, 0, \frac{1}{17}, 0\right); \qquad \textbf{IDF(ball)} = \log_e \left(\frac{4}{1}\right);$$

Frequency-based Embeddings

Example: Toy Corpus

d1: We like to play some sport in the afternoon, I like basketball but John likes sumo more.

d2: Sumo is a sport where a rikishi attempts to force another wrestler out of a circular ring.

d3: Messi scored 4 goals yesterday and kept the **ball** as a memory of this fantastic sports afternoon!

d4: I ate too many cherries yesterday.

$$\textbf{TF(ball)} = \left(0, 0, \frac{1}{17}, 0\right); \qquad \textbf{IDF(ball)} = \log_e \left(\frac{4}{1}\right);$$

$$\textbf{TF-IDF(ball)}_3 = \frac{1}{17} \times \log_e (4) = 0.08$$

Frequency-based Embeddings

Example: Toy Corpus

d1: We like to play some sport in the afternoon, I like basketball but John likes sumo more.

d2: Sumo is **a** sport where **a** rikishi attempts to force another wrestler out of **a** circular ring.

d3: Messi scored 4 goals yesterday and kept the ball as **a** memory of this fantastic sports afternoon!

d4: I ate too many cherries yesterday.

$$\mathbf{TF(a)} = \left(0, \frac{3}{17}, \frac{1}{17}, 0\right);$$

Frequency-based Embeddings

Example: Toy Corpus

d1: We like to play some sport in the afternoon, I like basketball but John likes sumo more.

d2: Sumo is **a** sport where **a** rikishi attempts to force another wrestler out of **a** circular ring.

d3: Messi scored 4 goals yesterday and kept the ball as **a** memory of this fantastic sports afternoon!

d4: I ate too many cherries yesterday.

$$\mathbf{TF(a)} = \left(0, \frac{3}{17}, \frac{1}{17}, 0\right); \qquad \mathbf{IDF(a)} = \log_e \left(\frac{4}{2}\right);$$

Frequency-based Embeddings

Example: Toy Corpus

d1: We like to play some sport in the afternoon, I like basketball but John likes sumo more.

d2: Sumo is **a** sport where **a** rikishi attempts to force another wrestler out of **a** circular ring.

d3: Messi scored 4 goals yesterday and kept the ball as **a** memory of this fantastic sports afternoon!

d4: I ate too many cherries yesterday.

$$\textbf{TF(a)} = \left(0, \frac{3}{17}, \frac{1}{17}, 0\right); \qquad \textbf{IDF(a)} = \log_e \left(\frac{4}{2}\right);$$

$$\textbf{TF-IDF(a)}_2 = \frac{3}{17} \times \log_e(2) = 0.12; \qquad \textbf{TF-IDF(a)}_3 = 0.04$$

Frequency-based Embeddings

Term Frequency-Inverse Document Frequency, TF-IDF

- Word vectors of D dimensions
- Distances between words as before:
  - Euclidean distance
  - Cosine similarity
  - ...

Frequency-based Embeddings

Co-Occurence Matrix, Count Vectors

- Words co-occurrence statistics describes how words occur together
- Counts how two or more words occur together in a given corpus

Frequency-based Embeddings

Example: Toy Corpus

d1: We like to play some sport in the afternoon, I like basketball but John likes sumo more.

d2: Sumo is a sport where a rikishi attempts to force another wrestler out of a circular ring.

d3: Messi scored 4 goals yesterday and kept the ball as a memory of this fantastic sports afternoon!

d4: I ate too many cherries yesterday.

Frequency-based Embeddings

Example: Toy Corpus

d1: We **like** to play some sport in the afternoon, **I like** basketball but John likes sumo more.

d2: Sumo is **a** sport where **a** rikishi **attempts** to force another wrestler out of **a** circular ring.

d3: **Messi** scored 4 goals yesterday and kept the **ball** as **a** memory of this fantastic sports afternoon!

d4: **I** ate too many cherries yesterday.

Frequency-based Embeddings

Example: Co-Occurrence Matrix

	like	*to*	*sport*	*afternoon*	*basketball*	*John*	*ball*	*a*	*rikishi*	*attempt*	*force*	*werstler*	*circular*	*as*	*Messi*	*score*	*goal*	*yesterday*	*keep*	*memory*
like	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
attempt	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Messi	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
a	0	0	1	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1
ball	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
...																				

Frequency-based Embeddings

Co-occurence matrix, count vectors

- Simple bigram frequencies of all possible word-pairs need a size $N \times N$ matrix to represent N words in a corpus
- Real models use context windows, not only bigrams
- Counts are converted into probabilities
- In general, one has sparse matrices
- Dimensionality reduction (SVD, see next session)

Frequency-based Embeddings

Aside Comment: One-Hot Encodings

	like	to	sport	afternoon	basketball	John	ball	a	rikishi	attempt	force	werstler	circular	as	Messi	score	goal	yesterday	keep	memory
like	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
attempt	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Messi	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
a	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
...																				

One-hot encoding for *like* with this vocabulary:
like $= (1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0)$

Frequency-based Embeddings

Aside Comment: One-Hot Encodings

	like	to	sport	afternoon	basketball	John	ball	a	rikishi	attempt	force	werstler	circular	as	Messi	score	goal	yesterday	keep	memory
like	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
attempt	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Messi	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
a	0	0	1	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1
...																				

Co-occurence word vector for *like* with this vocabulary in the previous corpus:

like = (0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0)

Prediction-based Embeddings

Prediction-based Embeddings

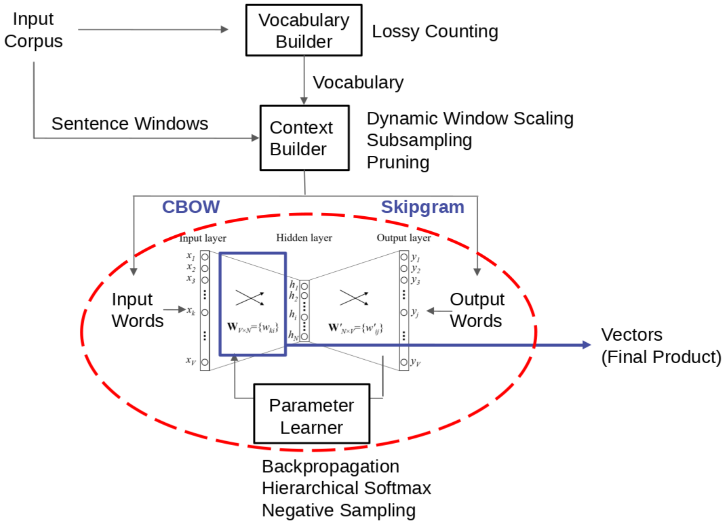
Word Embeddings (word2vec example)

Word vectors learned by a neural network in two tasks:

1. predict the probability of a **word given a context** (CBoW)
2. predict the **context given a word** (skip-gram)

Prediction-based Embeddings

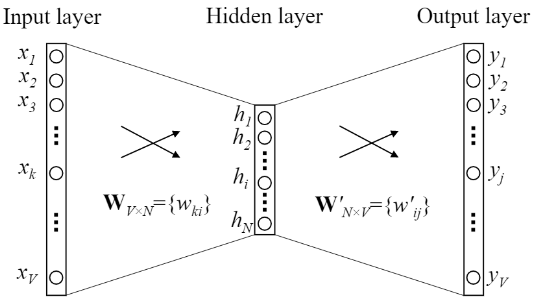
Word Embeddings (word2vec example)



Credits: Xin Rong

Prediction-based Embeddings

Word Embeddings (word2vec example)



Look at the network: simple feed-forward network learned by backpropagation with cross-entropy loss

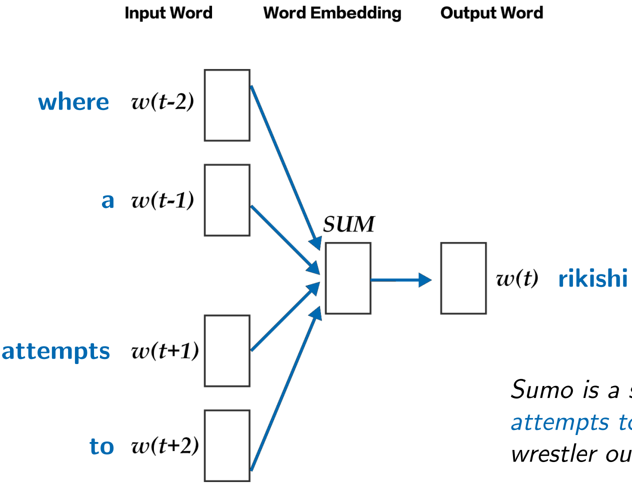
No deep learning at all!

Comments:

- A hidden layer in a NN interprets the input in his own way to optimise his work in the concrete task
- The size of the hidden layer gives you the dimension of the word embeddings
- Too few neurons could not have enough capacity to learn everything needed
- Too many neurons would need a very large corpus to be meaningful

Prediction-based Embeddings

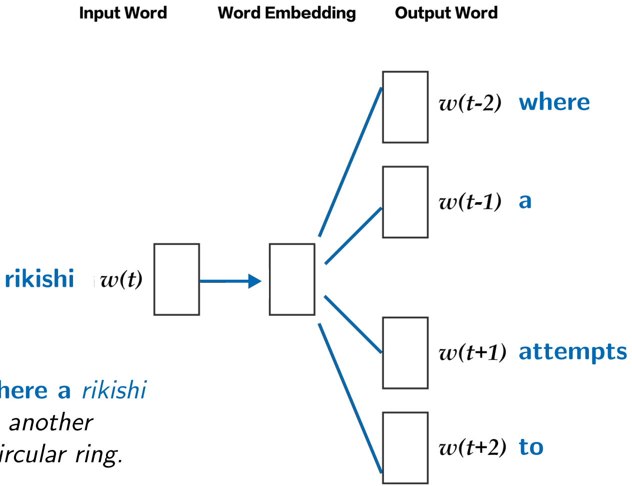
Continuous Bag of Words, CBoW



Sumo is a sport where a **rikishi** *attempts to force another wrestler out of a circular ring.*

Prediction-based Embeddings

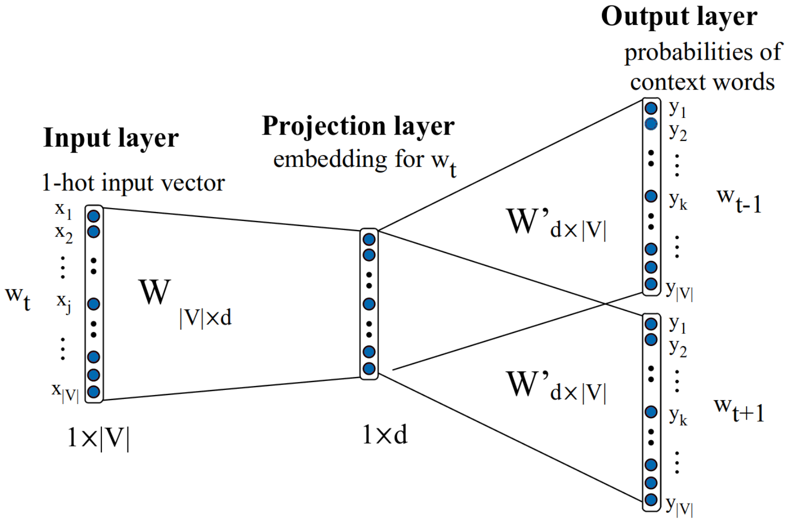
Skip-Gram Model



Sumo is a sport ***where a*** *rikishi* ***attempts to*** *force another wrestler out of a circular ring.*

Prediction-based Embeddings

More Detailed Architecture (skip-gram)



Credits: Xin Rong

Prediction-based Embeddings

More Detailed Architecture (schematic matrix visualisation)

$$\begin{array}{ccccc}
\begin{pmatrix} \\ \\ V \\ \\ \\ \end{pmatrix} & \begin{pmatrix} & & \\ & & \\ & V \times d & \\ & & \\ & & \end{pmatrix} & \begin{pmatrix} d \end{pmatrix} & \begin{pmatrix} & d \times V & \end{pmatrix} & \begin{pmatrix} \\ \\ V \\ \\ \\ \end{pmatrix} \\
\mathbf{x} & \mathbf{W} & \mathbf{h} & \mathbf{W}' & \mathbf{y}
\end{array}$$

Input Embedding

The row *i* of the input matrix W is the $1 \times \mathrm{d}$ for word *i* in the vocabulary

Prediction-based Embeddings

More Detailed Architecture (schematic matrix visualisation)

$$\underset{\mathbf{x}}{\begin{pmatrix} \\ V \\ \\ \end{pmatrix}} \underset{\mathbf{W}}{\begin{pmatrix} \\ V \times d \\ \\ \end{pmatrix}} \underset{\mathbf{h}}{\begin{pmatrix} d \end{pmatrix}} \underset{\mathbf{W'}}{\begin{pmatrix} d \times V \end{pmatrix}} \underset{\mathbf{y}}{\begin{pmatrix} \\ V \\ \\ \end{pmatrix}}$$

Output Embedding

The column *j* of the output matrix W' is the $\mathrm{d} \times 1$ for word *j* in the vocabulary

Prediction-based Embeddings

Observations (Tensorflow Tutorial)

CBoW

- Smoothes over a lot of the distributional information by treating an entire context as one observation. This turns out to be a useful thing for **smaller datasets**

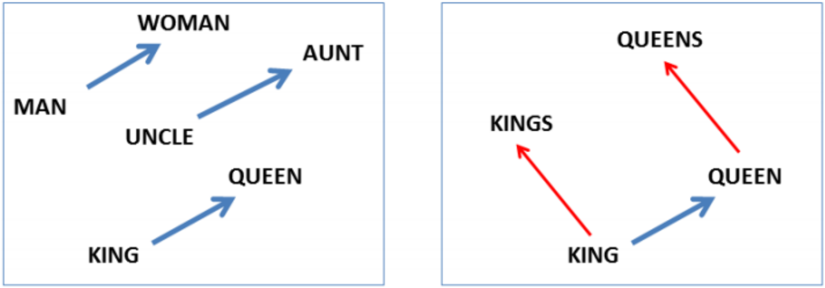
Skip-gram

- Treats each context-target pair as a new observation, and this tends to do better when we have **larger datasets**

Prediction-based Embeddings

Nice Properties

King - Man + Woman = Queen

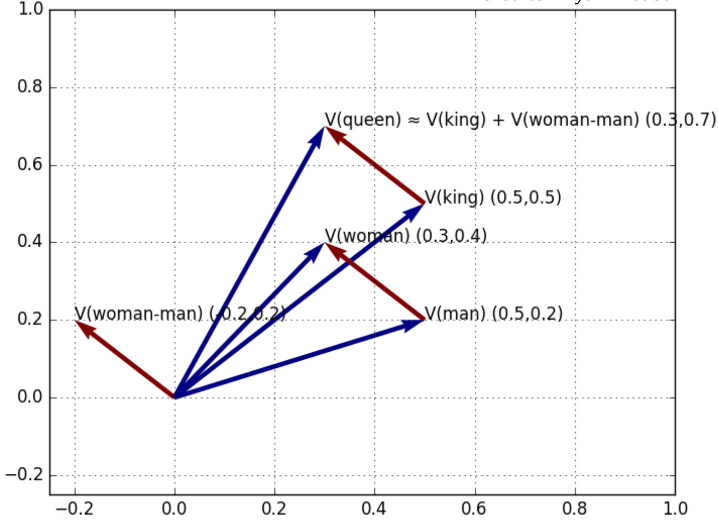


(Mikolov et al., NAACL HLT, 2013)

Prediction-based Embeddings

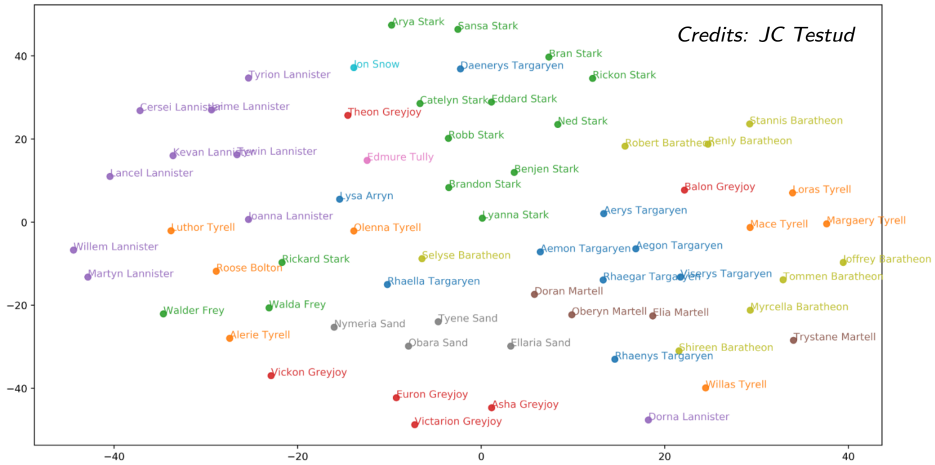
Nice Properties

Credits: Ryan Heuser



Prediction-based Embeddings

Nice Properties

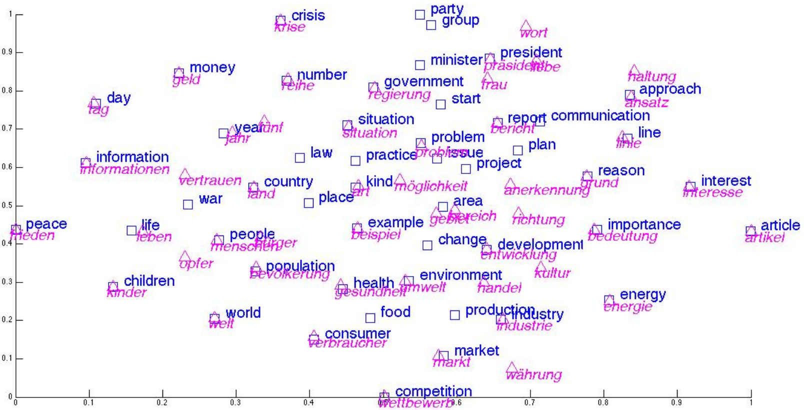


2D tSNE projection of the main characters of Game of thrones colored by House

Prediction-based Embeddings

Nice Properties

(Luong, Pham & Manning, NAACL, 2015)



Barnes-Hut-SNE visualisation of bilingual embeddings German/English

The meaning of a compound expression is a function of the meanings of its parts and of the way they are syntactically combined.

(Partee, 1984)

Beyond *Word* Embeddings

Is Language Compositional?

Computer Scientist-like Background Yes!

$$\texttt{meaning}(\text{Eat the icecream}) = \texttt{meaning}(\text{Eat}) + \texttt{meaning}(\text{the}) + \texttt{meaning}(\text{icecream})$$

Beyond *Word* Embeddings

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Linguist-like Background No!

$$\texttt{meaning}(\text{Break the ice}) \neq \texttt{meaning}(\text{Break}) + \texttt{meaning}(\text{the}) + \texttt{meaning}(\text{ice})$$

Beyond *Word* Embeddings

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Beyond *Word* Embeddings

Representations for Phrases, Sentences or Paragraphs

- **Composition** of word embeddings using operations $(+, \times)$ on vectors and matrices
- **Latent paragraph vectors** in word2vec-like NNs
- Internal representations in **seq2seq** architectures or auto-encoders (NMT context vectors, skip-thought vectors...)
- **Contextual** word vectors (LM by-products for instance)

Beyond *Word* Embeddings

Composition I

(Mitchell & Lapata, 2010)

Table 5
Composition functions considered in our experiments

Model	Function
Additive	$p_i = u_i + v_i$
Kintsch	$p_i = u_i + v_i + n_i$
Multiplicative	$p_i = u_i \cdot v_i$
Tensor product	$p_{i,j} = u_i \cdot v_j$
Circular convolution	$p_i = \sum_j u_j \cdot v_{i-j}$
Weighted additive	$p_i = \alpha v_i + \beta u_i$
Dilation	$p_i = v_i \sum_j u_j u_j + (\lambda - 1) u_i \sum_j u_j v_j$
Head only	$p_i = v_i$
Target unit	$p_i = v_i(t_1 t_2)$

Beyond *Word* Embeddings

Composition II

(Mitchell & Lapata, 2010)

Table 6
Correlation coefficients of model predictions with subject similarity ratings (Spearman's ρ) using a simple semantic space

Model	Adjective–Noun	Noun–Noun	Verb–Object
Additive	.36	.39	.30
Kintsch	.32	.22	.29
Multiplicative	.46	.49	.37
Tensor product	.41	.36	.33
Convolution	.09	.05	.10
Weighted additive	.44	.41	.34
Dilation	.44	.41	.38
Target unit	.43	.34	.29
Head only	.43	.17	.24
Humans	.52	.49	.55

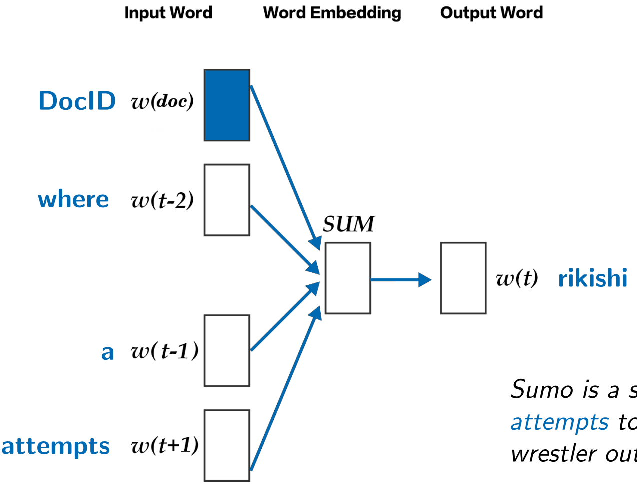
Beyond *Word* Embeddings

Distributed Representations of Sentences and Documents

- word2vec-like architecture where a **document vector** is added to word vectors and learned simultaneously (PV-DM)
- **Generation** of words from a document from its document vector (skip-gram-like architecture!) (PV-DBoW)

Beyond *Word* Embeddings

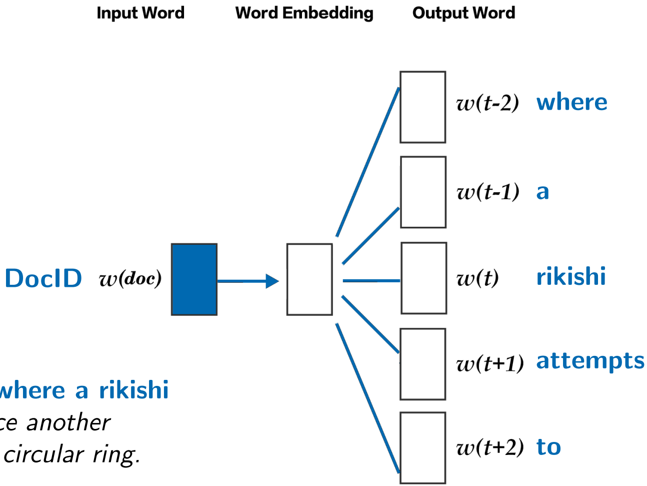
Distributed Memory Model of Paragraph Vectors, PV-DM



Sumo is a sport where a ***rikishi*** *attempts to force another wrestler out of a circular ring.*

Beyond *Word* Embeddings

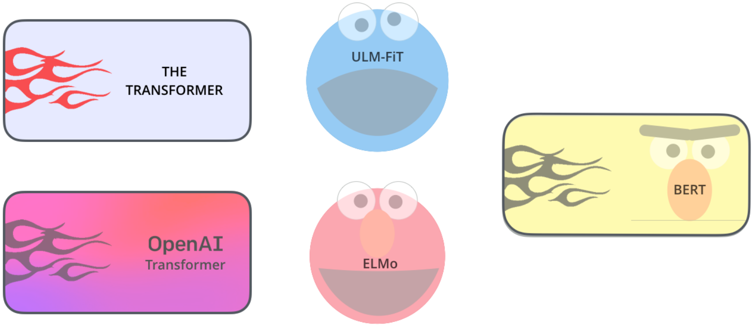
Distributed Bag of Words version of Paragraph Vector



Sumo is a sport **where a rikishi attempts to** *force another wrestler out of a circular ring.*

Beyond *Word* Embeddings

Language Model as Complementary Task for Contextual Vectors



http://jalammar.github.io/illustrated-bert/

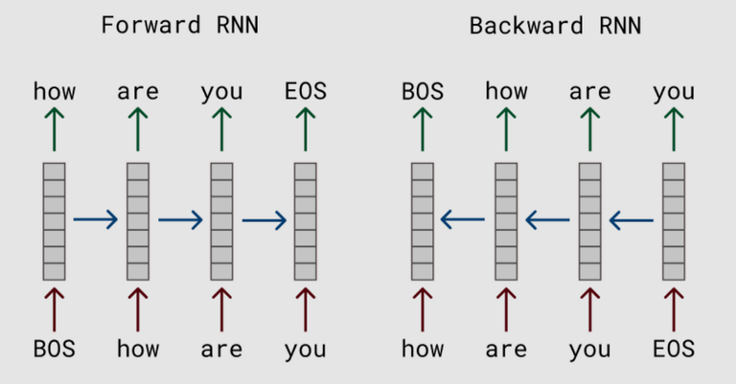
Beyond *Word* Embeddings

Language Model as Complementary Task for Contextual Vectors

- Deep **contextualised** word representations
- Mainly based on LSTMs or transformer architectures
- Example: ELMo, Embeddings from Language Models
- **Bidirectional language models** with LSTMs

Beyond *Word* Embeddings

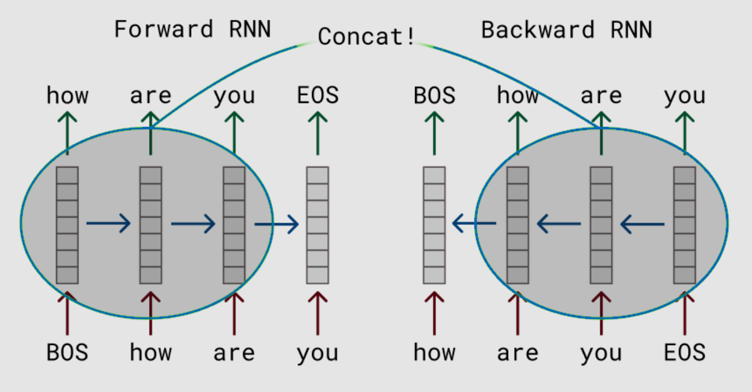
Language Model as Complementary Task for Contextual Vectors



https://medium.com/@plusepsilon/the-bidirectional-language-model-1f3961d1fb27

Beyond *Word* Embeddings

Language Model as Complementary Task for Contextual Vectors



https://medium.com/@plusepsilon/the-bidirectional-language-model-1f3961d1fb27

Beyond *Word* Embeddings

Language Model as Complementary Task for Contextual Vectors

Word vectors and contextual word vectors are used differently:

- **Word vectors**: dictionary look-up of words and their corresponding vectors, they are static entities
  - Good to initialise input word embeddings in several NLP tasks

Beyond *Word* Embeddings

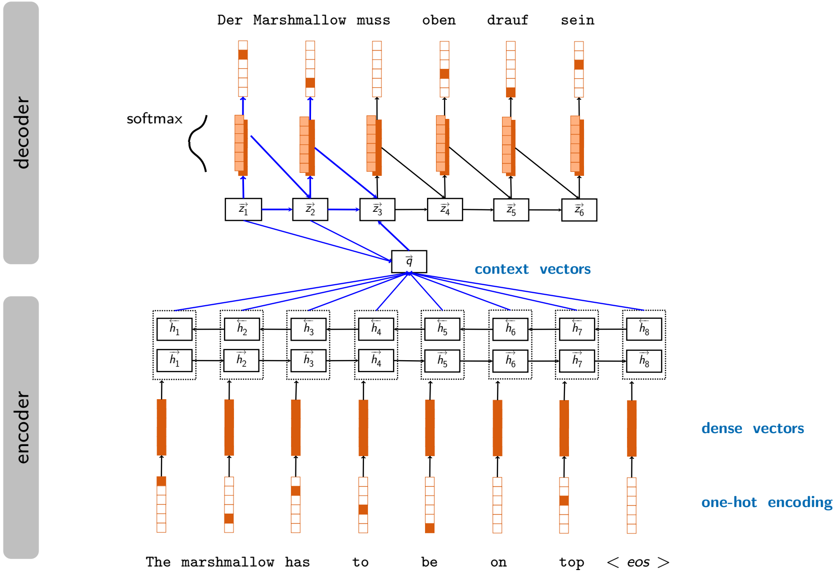
Language Model as Complementary Task for Contextual Vectors

Word vectors and contextual word vectors are used differently:

- **Word vectors**: dictionary look-up of words and their corresponding vectors, they are static entities
  - Good to initialise input word embeddings in several NLP tasks
- **Contextual word vectors**: vectors on-the-fly by passing text through a deep learning model, they would only be static if we could generate all sentences in a language!
  - Good for transfer learning into several NLP tasks (SotA in lots of tasks!)

Beyond *Word* Embeddings

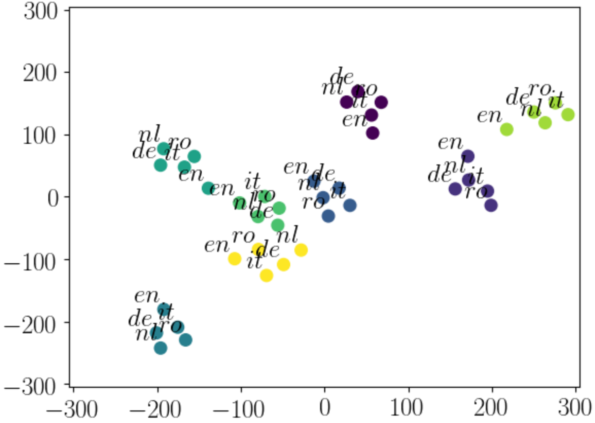
Seq2Seq Internal Representations: (Multilingual) NMT



Beyond *Word* Embeddings

Multilingual Semantic Space for NMT Context Vectors

(España-Bonet & van Genabith, 2018)



ML-NMT $\{de, en, nl, it, ro\} \rightarrow \{de, en, nl, it, ro\}$ with TED talks

Summary

Summary

Assuming Contextuality Holds...

- A word can be represented by a vector that describes it with respect to the context it is usually used
- This vector can be estimated by **counts** in a corpus
- This vector can be **learned** by examples in a corpus
- In fact, skipgram and co-occurence matrix factorisation are equivalent under certain conditions
- They are very useful to characterise text, but we haven't talked about **ambiguity** problems for instance

Summary

Assuming Compositionality Holds...

- A sentence can be decomposed into the vectors of its constituents
- Simple operations such as **sum** and **product** work surprisingly well
- Sentence/Document vectors can also be **learned** in more general tasks such as translation
- They are very useful to characterise text, but we haven't talked about **idioms** or **negation** problems for instance

Software & References

Libraries & Packages

- **word2vec**
  `https://github.com/dav/word2vec`
- **fastText**
  `https://github.com/facebookresearch/fastText`
- **Gensim**
  `https://radimrehurek.com/gensim/models/word2vec.html`
- **GloVe**
  `https://nlp.stanford.edu/projects/glove/`

Libraries & Packages

- **ELMo**
  https://github.com/allenai/allennlp/blob/master/allennlp/modules/elmo.py
- **Open AI**
  https://github.com/openai/gpt-2
- **BERT**
  https://github.com/google-research/bert
- **InferSent**
  https://github.com/facebookresearch/InferSent

Software & References

Basic References

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- Jeff Mitchell and Mirella Lapata. 2010. **Composition in distributional models of semantics**. *Cognitive Science, 34(8)*. Pages 1388–1429.
- Daniel Jurafsky and James H. Martin. 2017. **Speech and Language Processing.** Chapter 16: Semantics with Dense Vectors.
- Xin Rong. 2015. **word2vec Parameter Learning Explained**. *eprint arXiv:1411.2738*.

Software & References

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- Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. **GloVe: Global Vectors for Word Representation**. *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Pages 1532–1543

- Quoc V. Le and Tomas Mikolov. 2014. **Distributed Representations of Sentences and Documents**. *Proceedings of the 31st International Conference on Machine Learning (ICML)*, in PMLR 32(2). Pages 1188–1196

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- Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, Luke Zettlemoyer. 2018. **Deep contextualized word representations**. *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. Pages 2227–2237.

- Jacob Devlin, Ming-Wei Chang, Kenton Lee, Kristina Toutanova. 2018. **BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding**. *https://arxiv.org/abs/1810.04805*.

- Alan Akbik, Duncan Blythe, Roland Vollgraf. 2018. **Contextual String Embeddings for Sequence Labeling**. *Proceedings of the 27th International Conference on Computational Linguistic)*. Pages 1638–1649.

Everything clear? Too much information?

Questions?

Naïve Introduction to Word Embeddings

Cristina España-Bonet

UdS & DFKI, Saarbrücken, Germany

Summer Semester Seminar

17th April 2019

- Linear algebra

Extra Slides

Singular-Value Decomposition, SVD

- Linear algebra
- **Factorisation** of a matrix $\mathbf{M}$ as $\mathbf{M} = \mathbf{U\Sigma V^T}$

Extra Slides

Singular-Value Decomposition, SVD

- Linear algebra
- **Factorisation** of a matrix $\mathbf{M}$ as $\mathbf{M} = \mathbf{U\Sigma V^T}$
  - ✓ $\mathbf{U}$ is an $m \times m$ orthogonal matrix,

Extra Slides

Singular-Value Decomposition, SVD

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- **Factorisation** of a matrix $\mathbf{M}$ as $\mathbf{M} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^\mathsf{T}$
  - ✓ $\mathbf{U}$ is an $m \times m$ **orthogonal matrix**,
    - $\mathbf{U}^\mathsf{T}\mathbf{U} = \mathbf{U}\mathbf{U}^\mathsf{T} = \mathbf{I}$
    - or, equivalently, $\mathbf{U}^\mathsf{T} = \mathbf{U}^{-1}$

Singular-Value Decomposition, SVD

- Linear algebra
- **Factorisation** of a matrix $\mathbf{M}$ as $\mathbf{M} = \mathbf{U\Sigma V^T}$
  - ✓ $\mathbf{U}$ is an $m \times m$ orthogonal matrix,
  - ✓ $\mathbf{\Sigma}$ is a diagonal $m \times n$ matrix with non-negative real numbers,

Singular-Value Decomposition, SVD

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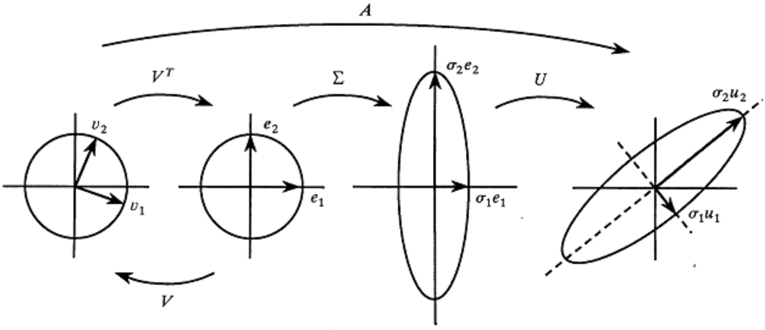
  - ✓ $\mathbf{U}$ is an $m \times m$ orthogonal matrix,
  - ✓ $\mathbf{\Sigma}$ is a diagonal $m \times n$ matrix with non-negative real numbers,
  - ✓ $\mathbf{V^T}$ is the conjugate transpose of an $n \times n$ orthogonal matrix

Extra Slides

SVD: 2 × 2 Geometric Interpretation



a linear transformation is a rotation or reflection, followed by a scaling, followed by another rotation or reflection

`https://blogs.sas.com`

Extra Slides

Singular-Value Decomposition, SVD

$$
\left(\quad m \times n \quad \right) = \left(\quad m \times m \quad \right) \left(\quad m \times n \quad \right) \left(\; n \times n \; \right)
$$

$$
\mathbf{M} \quad = \quad \mathbf{U} \quad \boldsymbol{\Sigma} \quad \mathbf{V}^{\mathsf{T}}
$$

Extra Slides

SVD: Singular Values

$$\boldsymbol{\Sigma} = \begin{pmatrix} \sigma_1 & & & & \\ & \ddots & & \text{\Large 0} & \\ & & \ddots & & \\ & \text{\Large 0} & & \sigma_r & \\ & & & & 0 \end{pmatrix};$$

σ_1 ... σ_r, singular values of $\mathbf{M}$ (in decreasing order)

r, rank of $\mathbf{M}$

SVD: Singular Values

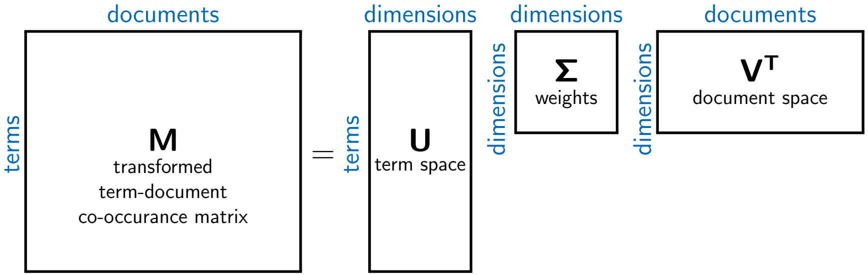
$$\mathbf{\Sigma} = \begin{pmatrix} \sigma_1 & & & & \\ & \ddots & & \mathbf{0} & \\ & & \ddots & & \\ & \mathbf{0} & & \sigma_r & \\ & & & & 0 \end{pmatrix}; \qquad \mathbf{M_r} = \sum_{i=1}^{r} \sigma_i \overrightarrow{u}_i \overrightarrow{v}_i^T$$

σ_1 ... σ_r, singular values of **M** (in decreasing order)

r, rank of **M**

Extra Slides

SVD: Application, Latent Semantic Analysis



$$\Sigma_r \Longrightarrow \mathbf{M}_r$$

https://nlp.stanford.edu/IR-book/pdf/18lsi.pdf

Christopher D. Manning, Prabhakar Raghavan, and Hinrich Schütze. 2008. **Introduction to Information Retrieval**. Cambridge University Press, New York, NY, USA.