Introduction to Word Embeddings (biased towards neural nets)

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Colloquium

Introduction to Neural Nets and Language Technology

25th May 2018

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 Talk 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)

**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

Similar Meanings...

Basketball

Sumo

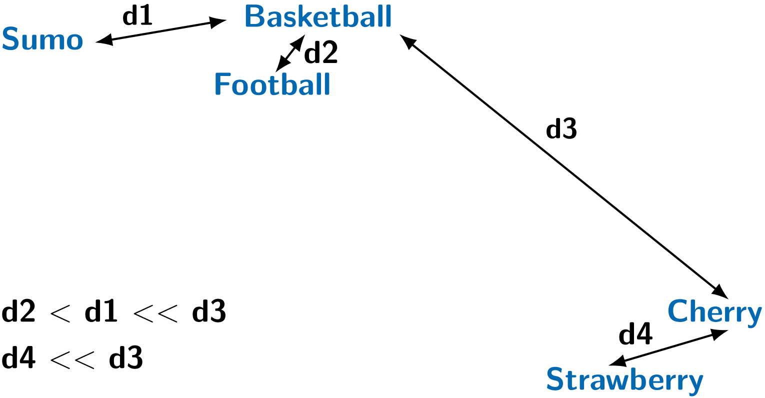
Football

Cherry

Strawberry

Introduction

Similar Meanings...

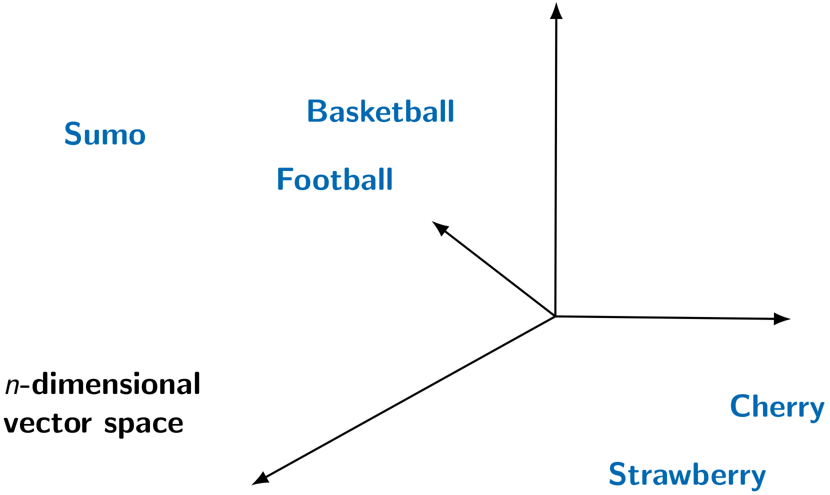


d2 $<$ **d1** $<<$ **d3**

d4 $<<$ **d3**

Introduction

Word Vector Space



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

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

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 $\rightarrow \{0, 0, 0, 1\}$

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

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

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

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

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

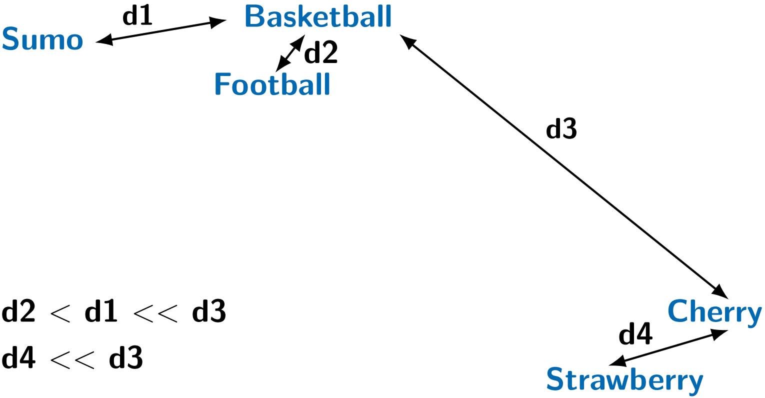
sim(basketball, cherry)=0

sim(sumo, cherry)=0

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

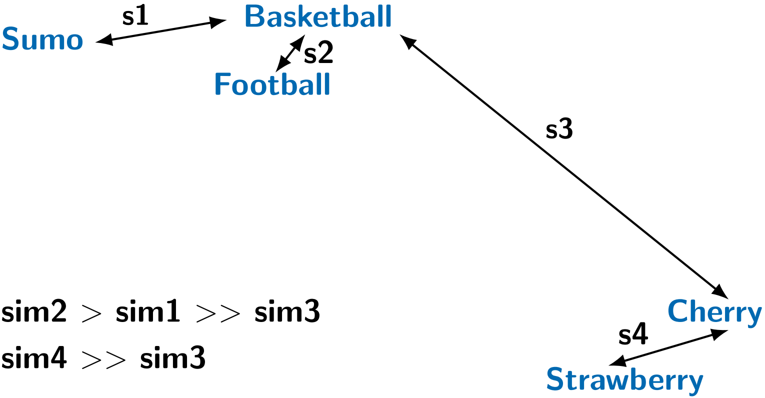
Introduction

Similarity vs. Distance



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

d4 $<<$ **d3**



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

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

Term Frequency

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

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

Inverse Document Frequency

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

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

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.

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.

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

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.

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

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.

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

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.

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

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

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, Extra Slides)

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

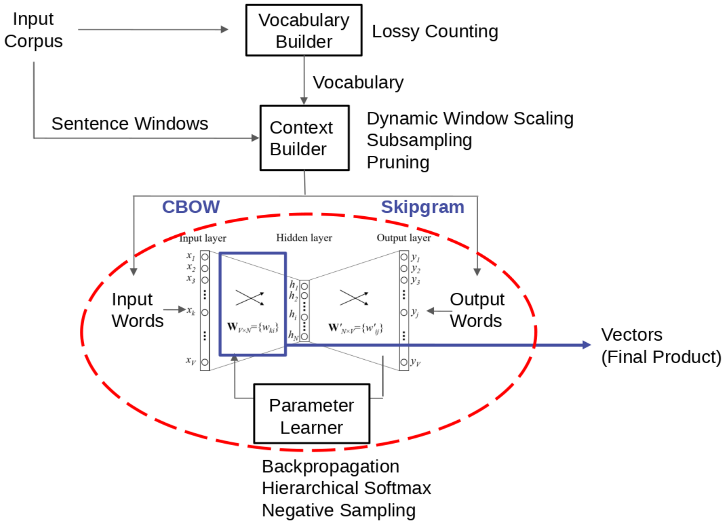
Word Embeddings (word2vec example)

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

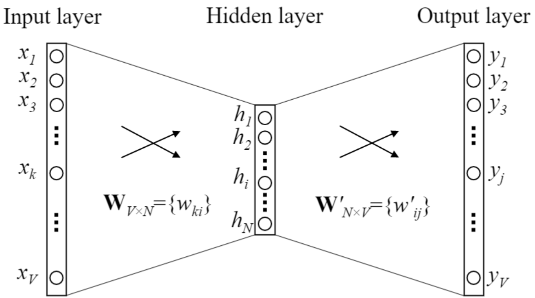
Word Embeddings (word2vec example)



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!

Prediction-based Embeddings

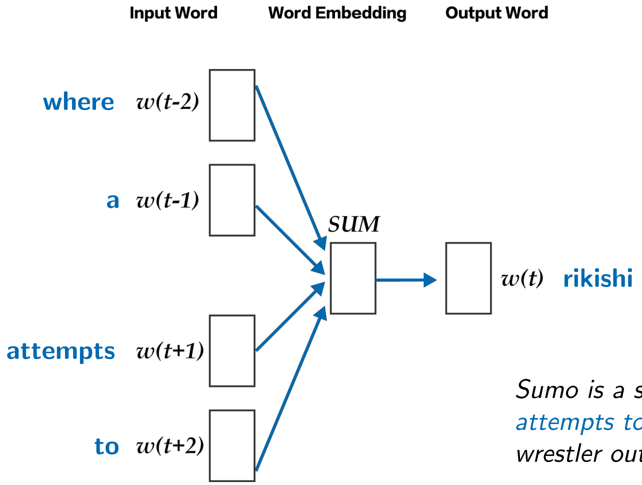
Word Embeddings (word2vec example)

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

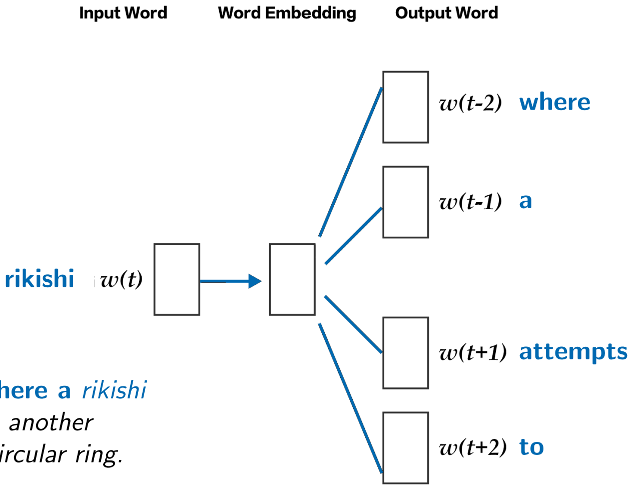
Continuous Bag of Words, CBoW



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

Prediction-based Embeddings

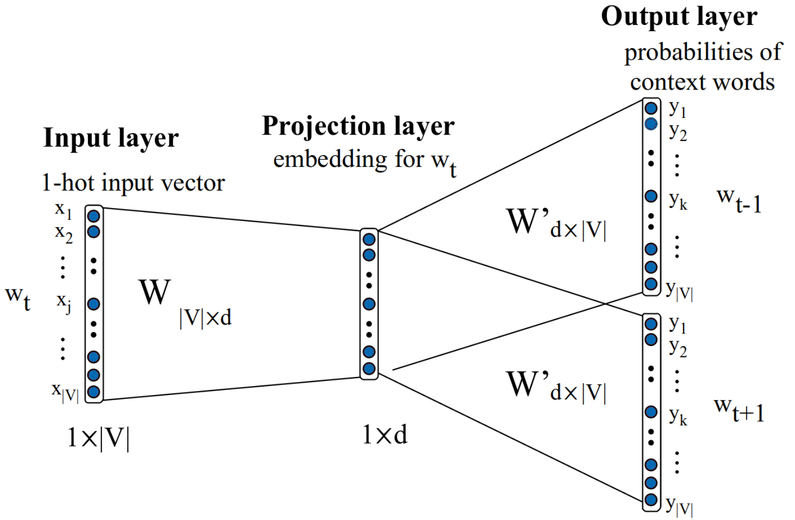
Skip-Gram Model



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)

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

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)

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

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

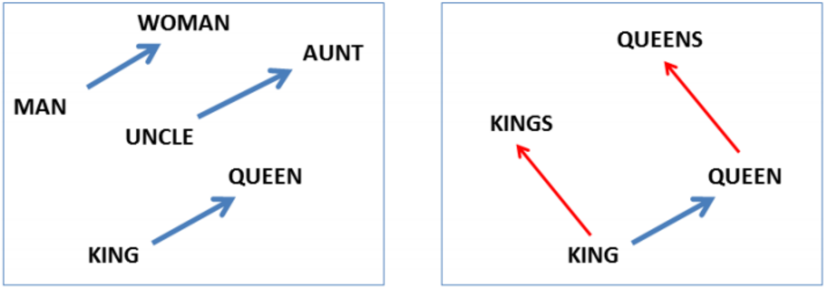
Let's Play!

Word Embedding Visual Inspector, wevi

`https://ronxin.github.io/wevi/`

Nice Properties

King - Man + Woman = Queen

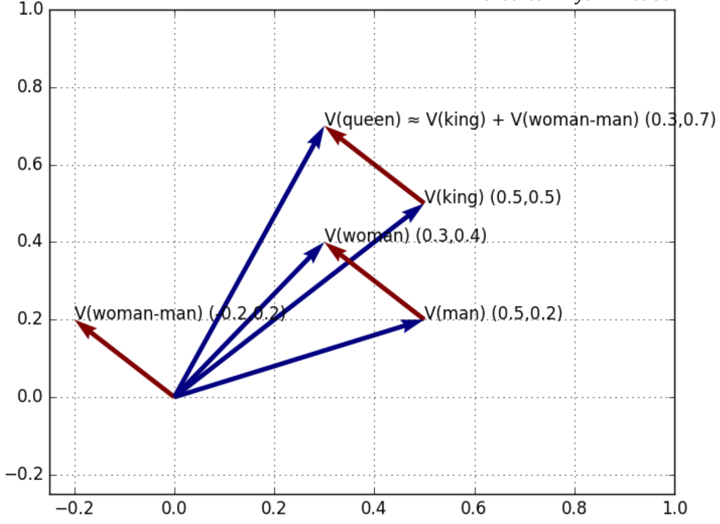


(Mikolov et al., NAACL HLT, 2013)

Prediction-based Embeddings

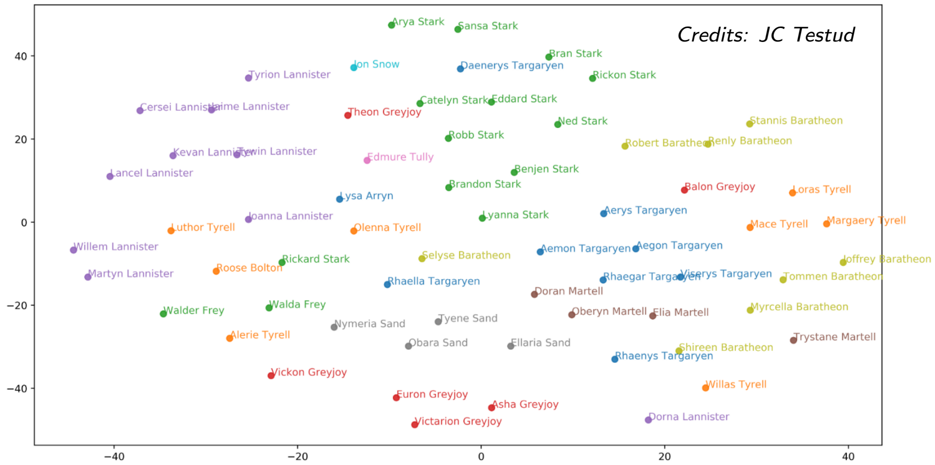
Nice Properties

Credits: Ryan Heuser



Prediction-based Embeddings

Nice Properties

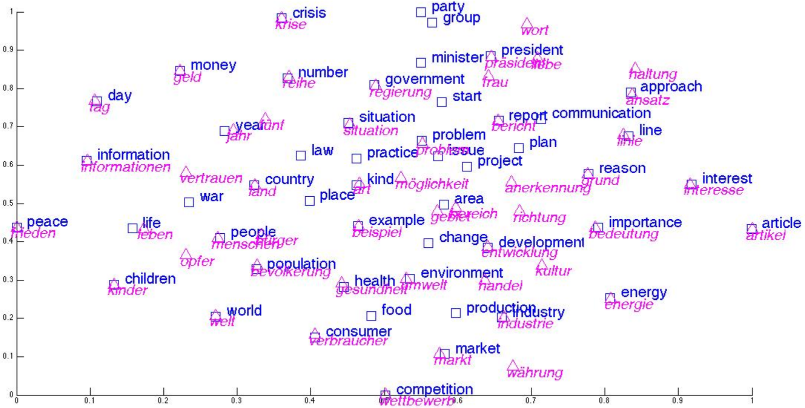


2D tSNE projection of the main characters of Game of thrones colored by House

Prediction-based Embeddings

Nice Properties

(Luong, Pham & Manning, NAACL, 2015)



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

Prediction-based Embeddings

Let's Explore!

Embedding Projector

`http://projector.tensorflow.org/`

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

Is Language Compositional?

Computer Scientist-like Background Yes!

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

Linguist-like Background No!

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

Computer Scientist-like Background Yes!

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

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

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...)

(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	$p_i = v_i(t_1 t_2)$

(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

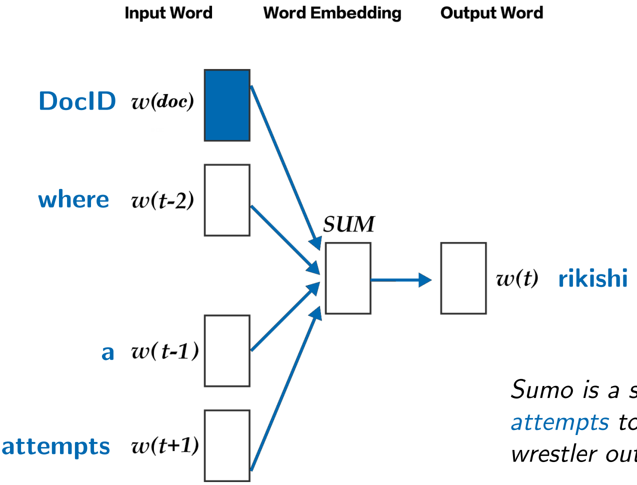
Beyond *Word* Embeddings

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

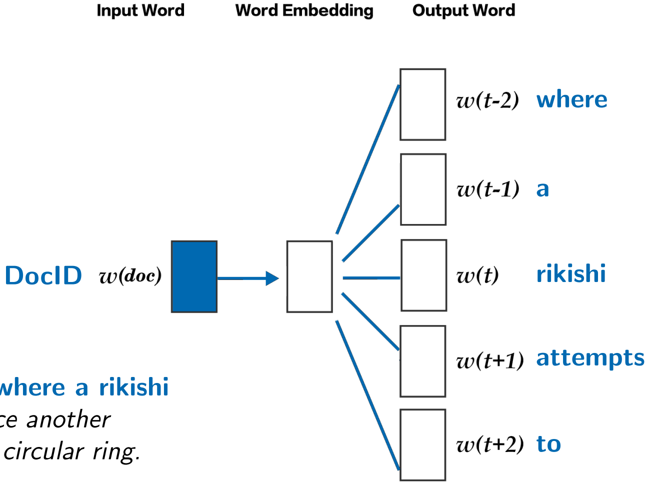
Distributed Memory Model of Paragraph Vectors, PV-DM



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

Beyond *Word* Embeddings

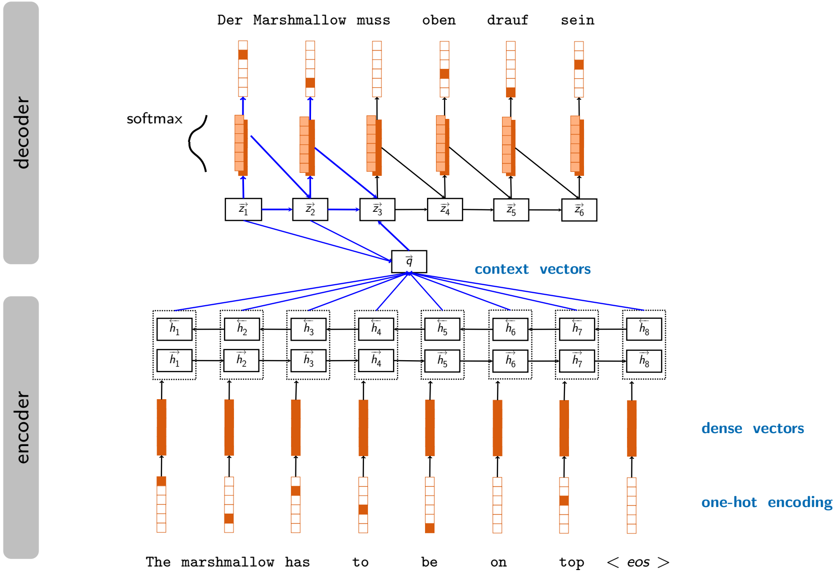
Distributed Bag of Words version of Paragraph Vector



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

Beyond *Word* Embeddings

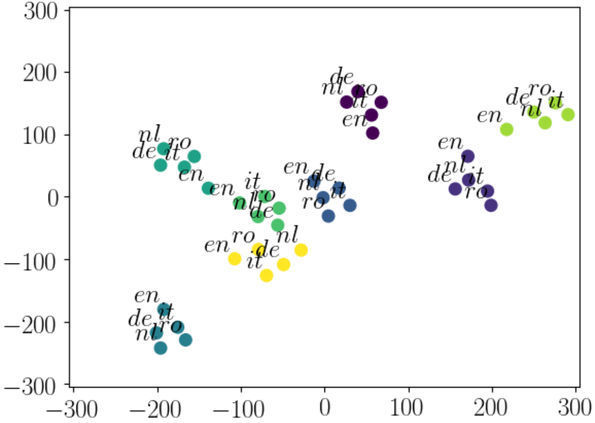
Seq2Seq Internal Representations: (Multilingual) NMT



Beyond *Word* Embeddings

Multilingual Semantic Space for Context Vectors

(España-Bonet & van Genabith, 2018)

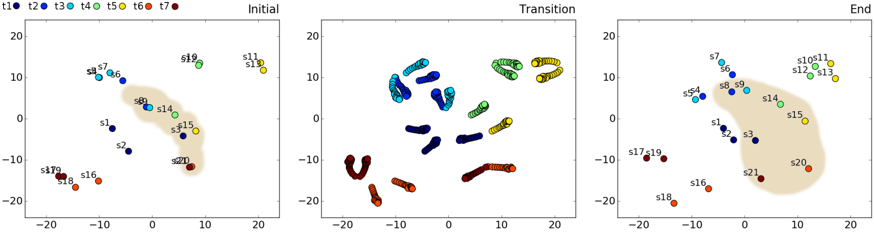


ML-NMT $\{de, en, nl, it, ro\} \rightarrow \{de, en, nl, it, ro\}$ with TED talks

Beyond *Word* Embeddings

Evolution of Context Vectors through Training I

(España-Bonet et al., 2017)



ML-NMT $\{en, es, ar\} \rightarrow \{en, es, ar\}$ with heterogeneous corpora

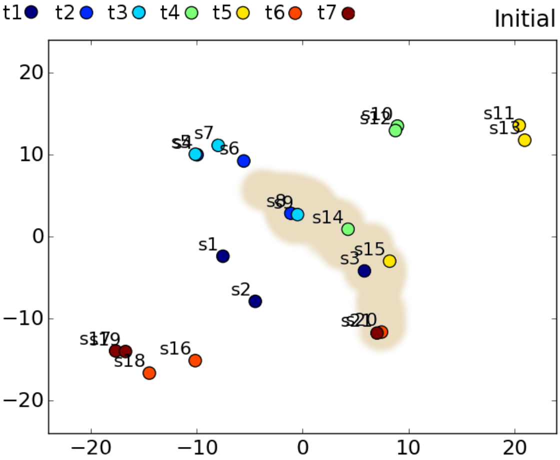
Beyond *Word* Embeddings

Evolution of Context Vectors through Training II

$s1{:}t1$	Spain princess testifies in historic fraud probe
$s2{:}t1$	Princesa de España testifica en juicio histórico de fraude
$s3{:}t1$	أميرة أسبانيا تدلي بشهادتها في قضية احتيال تاريخي.
$s4{:}t2$	You do not need to worry.
$s5{:}t3$	You don’t have to worry.
$s6{:}t2$	No necesitas preocuparte.
$s7{:}t3$	No te tienes por que preocupar.
$s8{:}t2$	لا ينبغي أن تقلق
$s9{:}t3$	لا ينبغي أن تجزع.
$s10{:}t4$	Mandela’s condition has ’improved’
$s11{:}t5$	Mandela’s condition has ’worsened over past 48 hours’
$s12{:}t4$	La salud de Mandela ha ’mejorado’
$s13{:}t5$	La salud de Mandela ’ha empeorado en las últimas 48 horas’
$s14{:}t4$	لقد تحسنّت حالة مانديلا الصحية.
$s15{:}t5$	ساءت الحالة الصحية لمانديلا خلال ال ٨٤ ساعة الماضية.
$s16{:}t6$	Vector space representation results in the loss of the order which the terms are in the document.
$s17{:}t7$	If a term occurs in the document, the value will be non-zero in the vector.
$s18{:}t6$	La representación en el espacio de vecores implica la pérdida del órden en el que los términos ocurren en el documento.
$s19{:}t7$	Si un término ocurre en el document, el valor en el vector será distinto de cero.
$s20{:}t6$	يؤدي تمثيلُ فضاءِ المتجهِ إلى فقد الترتيب الذي تكون عليه المصطلحات في الوثيقة.
$s21{:}t7$	إذا ما ورد مصطلح في الوثيقة، فالقيمة ستكون غيرصفرية المتجه.

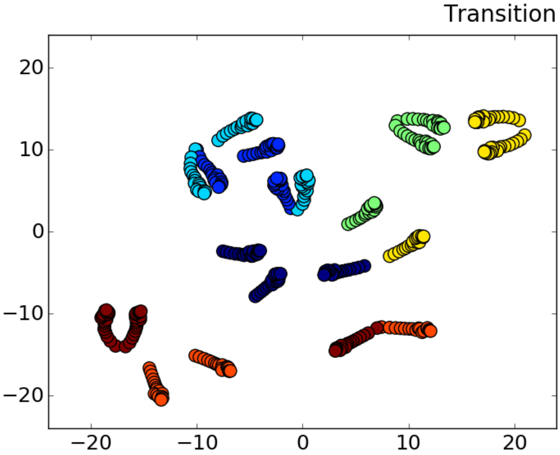
Beyond *Word* Embeddings

Evolution of Context Vectors through Training III



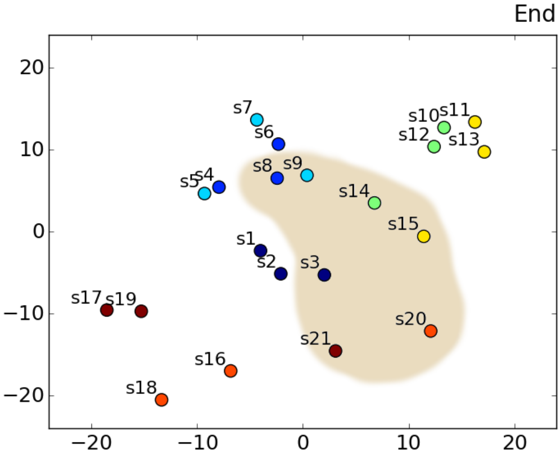
Beyond *Word* Embeddings

Evolution of Context Vectors through Training III



Beyond *Word* Embeddings

Evolution of Context Vectors through Training III



Evolution of Context Vectors through Training IV

Pearson correlation (ρ) on the Semantic Textual Similarity Task

	track1 *ar–ar*	track2 *ar–en*	track3 *es–es*	track4a *es–en*	track5 *en–en*
`WE-d300-nmt`	0.49	0.28	0.55	0.40	0.56
`WE-d1024-nmt`	0.51	0.33	0.59	0.45	0.60

Beyond *Word* Embeddings

Evolution of Context Vectors through Training IV

Pearson correlation (ρ) on the Semantic Textual Similarity Task

	track1 *ar–ar*	track2 *ar–en*	track3 *es–es*	track4a *es–en*	track5 *en–en*
`WE-d300-nmt`	0.49	0.28	0.55	0.40	0.56
`WE-d1024-nmt`	0.51	0.33	0.59	0.45	0.60
`S1-w-0.1Ep`	0.32	0.25	0.55	0.32	0.54
`S1-w-0.5Ep`	0.52	0.36	0.71	0.40	0.68
`S1-w-1.0Ep`	0.57	0.42	0.74	0.44	0.72
`S1-w-2.0Ep`	0.59	0.44	0.78	0.49	0.76

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

Summary

Can you Answer now the Initial Basic Questions?

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)

Summary

Can you Answer now the Initial Basic Questions?

- How can we obtain those numbers?
  - ✓ Co-occurrences in a corpus by either frequency counts or machine learning and dimensionality reduction

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Summary

Can you Answer now the Initial Basic Questions?

- How can we obtain those numbers?
  - ✓ Co-occurrences in a corpus by either frequency counts or machine learning and dimensionality reduction
- What's word2vec?
  - ✓ A framework to learn embeddings using a simple feed-forward network
- Is it the only way to obtain those numbers?
  - ✓ Nope! We have seen that also simple counts work well, but we haven't talk about other models such as GloVe. That's really a hot research topic!

Summary

Can you Answer now the Initial Basic Questions?

- Do the vectors (and components!) have any semantic meaning?
  - ✓ Mmmm... we should talk more about this. For today, let's say they have very nice general semantic properties and are useful for many NLP tasks

Summary

Can you Answer now the Initial Basic Questions?

- Do the vectors (and components!) have any semantic meaning?
  - ✓ Mmmm... we should talk more about this. For today, let's say they have very nice general semantic properties and are useful for many NLP tasks
- Are we crazy by summing or multiplying words to get the meaning of a larger unit?
  - ✓ Yes, probably a bit... But, hey, it also works! We can use them in many NLP tasks while developing better approaches

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/`

Software & References

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- Daniel Jurafsky and James H. Martin. 2017. **Speech and Language Processing.** Chapter 16: Semantics with Dense Vectors.
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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

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Thanks!

Questions?

Introduction to Word Embeddings
(biased towards neural nets)

Cristina España-Bonet

UdS & DFKI, Saarbrücken, Germany

Colloquium

Introduction to Neural Nets and Language Technology

25th May 2018

Extra Slides

Singular-Value Decomposition, SVD

- Linear algebra

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

Singular-Value Decomposition, SVD

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  - ✓ $\mathbf{U}$ is an $m \times m$ orthogonal matrix,

- 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**,
    - $\mathbf{U^T U} = \mathbf{U U^T} = \mathbf{I}$
    - or, equivalently, $\mathbf{U^T} = \mathbf{U}^{-1}$

Extra Slides

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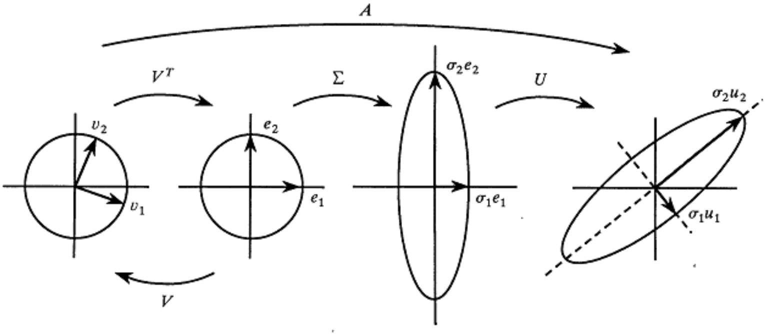
  - ✓ $\mathbf{V^T}$ is the conjugate transpose of an $n \times n$ orthogonal matrix

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`

$$\begin{pmatrix} \\ \\ m \times n \\ \\ \\ \end{pmatrix} = \begin{pmatrix} \\ \\ \quad\quad m \times m \quad\quad \\ \\ \\ \end{pmatrix} \begin{pmatrix} \\ \\ m \times n \\ \\ \\ \end{pmatrix} \begin{pmatrix} \\ n \times n \\ \\ \end{pmatrix}$$

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

$$\mathbf{\Sigma} = \begin{pmatrix} \sigma_1 & & & & \\ & \ddots & & \mathbf{0} & \\ & & \ddots & & \\ & \mathbf{0} & & \sigma_r & \\ & & & & 0 \end{pmatrix};$$

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

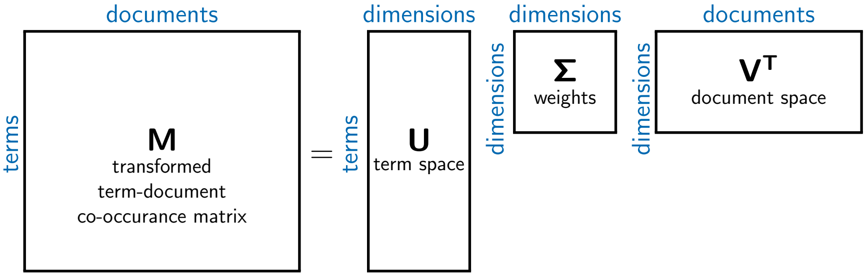
r, rank of $\mathbf{M}$

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

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

r, rank of **M**

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.