Multilingual Word Embeddings

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April 20, 2023

EUROPEAN UNION
European Structural and Investment Fund
Operational Programme Research,
Development and Education

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Words Are Sparse

- Brown clustering
  - Peter F. Brown, Peter V. de Souza, Robert L. Mercer, Vincent J. Della Pietra, Jenifer C. Lai **(1992):** Class-based n-gram models of natural language. In: *Computational Linguistics* 18 (4)
- Short motivation (Jurafsky and Martin):
  - Never seen bigram *to Shanghai*, estimate its probability
  - Known bigrams *to London, to Beijing, to Denver*
  - Known word *Shanghai* but not in this context
  - Can we figure out that names of cities form one class of words?

Brown Clustering

- Start: each word its own class (cluster)
- Repeat: merge two clusters into one
  - Selection: minimize loss in **mutual information (MI)**
- Stop: if desired number of classes (task-dependent)

- MI: How does event A decrease entropy of event B?
- $MI(A, B) = H(B) - H(B|A) = H(A) - H(A|B)$
  - $H(B|A) = -\sum_{i=1}^{|A|} \sum_{j=1}^{|B|} P(a_i, b_j) \log_2 P(b_j|a_i)$
- For an arbitrary bigram (w_{i-1}, w_i):
  - A: word type of w_{i-1} is **in cluster** a
  - B: word type of w_i is **in cluster** b

Example Clusters (from Brown et al., 1992)

- Friday Monday Thursday Wednesday Tuesday Saturday Sunday weekends Sundays
- June March July April January December October November September August
- people guys folks fellows CEOs chaps doubters commies unfortunates blokes
- down backwards ashore sideways southward northward overboard aloft downwards adrift
- water gas coal liquid acid sand carbon steam shale iron
- great big vast sudden mere sheer gigantic lifelong scant colossal
- man woman boy girl lawyer doctor guy farmer teacher citizen
- American Indian European Japanese German African Catholic Israeli Italian Arab
- pressure temperature permeability density porosity stress velocity viscosity gravity
- mother wife father son husband brother daughter sister boss uncle
- machine device controller processor CPU printer spindle subsystem compiler plotter
- John George James Bob Robert Paul William Jim David Mike
- anyone someone anybody somebody
- feet miles pounds degrees inches barrels tons acres meters bytes
- director chief professor commissioner commander treasurer founder superintendent dean

Example Clusters (Czech PDT dev data)

- než nebo 1993 produkce zhruba 1992 soudu 1994 1991 smlouvu
- a či S miliónů 9. Tento (Tato přičemž anebo
- to tu navíc člověk ta rozpočet vhodné rada nabídka taky
- nám mu mi ho jim svým stal jí existuje dá
- pak dnes stále proto nyní dokonce často tam přitom snad
- však totiž ovšem sice prý jich podařilo poslanec pochopitelně patrně
- již ještě už zde letos stát většinou dále situace firma
- pouze jen asi především právě zejména zcela vůbec přímo něco
- také tedy například zatím vždy opět zájem rovněž skutečně vlastně
- budou bude lze má může mají musí chce mohou nebude
- měl měla mělo mohl měly měli mohla mohly mohli mohlo
- jsme jsem jste bych dlouho divadla americký uvádí ať policisté
- by bychom Aby
- být mít právo moci muset hrát platit hledat pomoci dát
- není byla byl bylo nejsou platí nebyl nebylo podmínky nabízí

Neural Networks and Language Modeling

- Input: **index vectors** ("one-hot vectors"). Vocabulary size $|V|$ is the number of dimensions. The dimension corresponding to the represented word has value 1, all other dimensions have 0.
- **Embedding:** map the index vector into a vector with a lower, fixed number of dimensions (features, latent factors). We get an **embedding matrix:** rows correspond to word types, columns correspond to latent features (dimensions). The values in the cells get updated during training of the network; but we remember the index of the row for each word, so we can locate its updated vector.

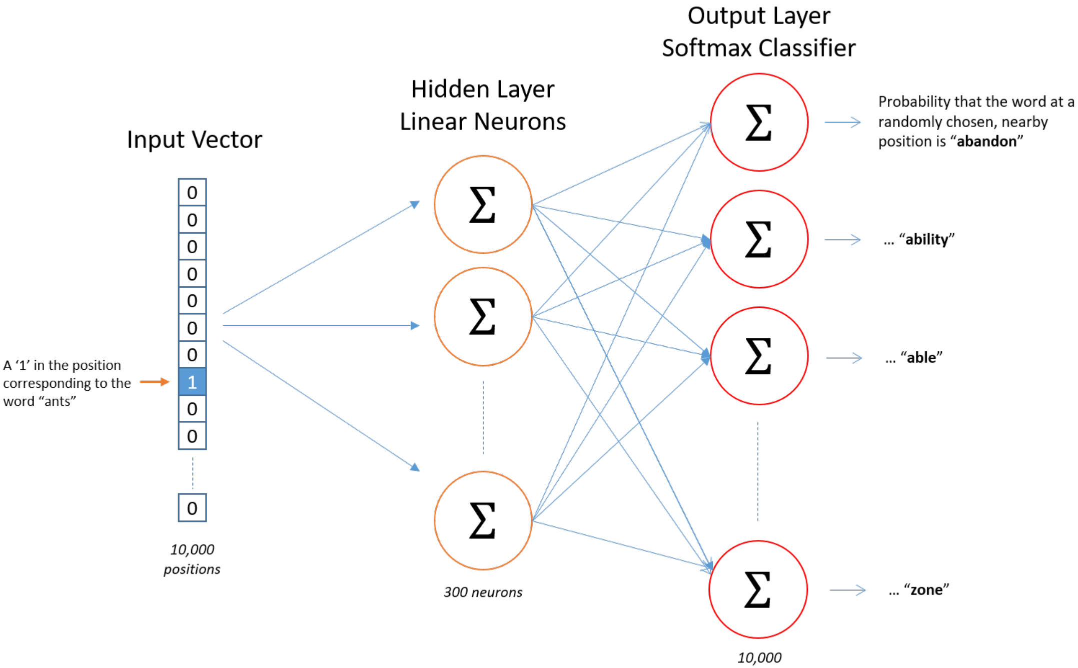
Neural Networks and Language Modeling

- Same goal: probability of a word in the neighborhood
- New setting: 20 years after Brown, neural networks on the rise
  - (Actually, Bengio et al. described a neural LM already in 2003. But it took another decade until a tractable variant appeared: word2vec.)

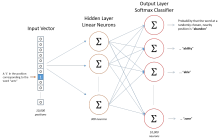
- Tomáš Mikolov, Ilya Sutskever, Kai Chen, Greg Corrado, Jeffrey Dean (2013). *Distributed Representations of Words and Phrases and their Compositionality*

- Skip-gram: probability that word y appears within a window of fixed size around word x

- *Images on following slides credit McCormick, Chris (2016, April 19). Word2Vec Tutorial - The Skip-Gram Model. Retrieved from* `http://www.mccormickml.com`

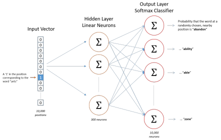

Output Layer
Softmax Classifier
Hidden Layer
Linear Neurons
Input Vector
0
0
0
0
0
0
0
1
0
0
0
A '1' in the position corresponding to the word "ants"
10,000 positions
300 neurons
10,000
Probability that the word at a randomly chosen, nearby position is "**abandon**"
... "**ability**"
... "**able**"
... "**zone**"

Skip-gram Neural Network



- Hidden layer = embedding layer = embedding matrix
- 300 neurons
  - Each neuron has its own set of weights for each input word
  - $\Rightarrow$ huge matrix 300 neurons $\times$ 10,000 words
  - Input word activates its own weight in each neuron

Skip-gram Neural Network



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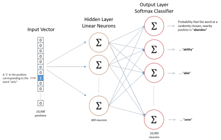
  - Another view:
    - Input word represented as one-hot vector (10,000 dimensions)
    - Embedding matrix 10,000 $\times$ 300 dimensions
    - Multiply input vector with embedding matrix
    - $\Rightarrow$ embedding vector for the word (300 dimensions)

Skip-gram Neural Network



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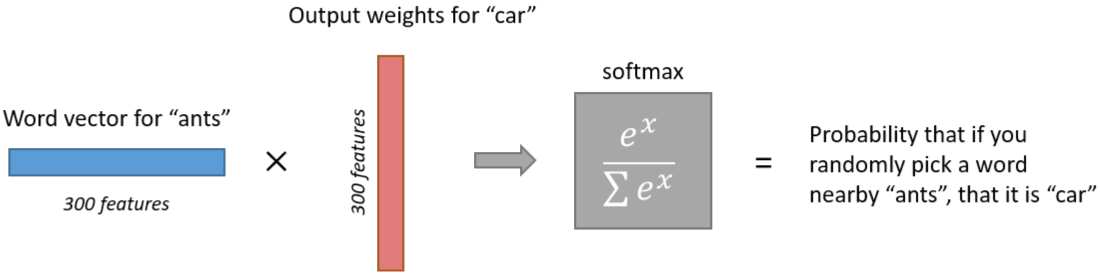
  - Output layer: 10,000 neurons
    - Each has a vector of 300 weights
    - Multiply word embedding vector with the weight vector
    - Normalize using softmax
    - $\Rightarrow$ probability of word y in the window!

Skip-gram Output Layer



The softmax function takes a vector of K real numbers and returns a normalized vector interpretable as a probability distribution:
$\sigma(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$ for $i = 1, \ldots, K$ and $\mathbf{z} = (z_1, \ldots, z_K) \in \mathbb{R}^K$

Skip-gram Training

- Take a word x from the corpus
- Randomly pick a word y from the window around x

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- Compare with the actual output given current weights
- Loss function, gradient descent, back propagation $\Rightarrow$
- $\Rightarrow$ update weights!

Collect Embeddings

- Trained neural network for skip-gram prediction
- Take the embedding layer, discard the rest

- For each word: a vector of 300 dimensions (features)
- **“Similar” words have similar vectors!** (cf. Brown clusters)

Collect Embeddings

- Trained neural network for skip-gram prediction
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- For each word: a vector of 300 dimensions (features)
- **“Similar” words have similar vectors!** (cf. Brown clusters)
- Cosine similarity: angle θ between vectors, regardless their magnitude. Same orientation $\Rightarrow$ similarity 1; orthogonal $\Rightarrow$ similarity 0

Given two vectors of attributes, A and B, the cosine similarity, $\cos()$, is represented using a dot product and magnitude as

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}},$$

where A_i and B_i are components of vector A and B respectively.

Multilingual Word Representations

- Both clusters and embeddings are like partial delexicalization
- Unsupervised – they don't need annotated data!
- They rely on context of other words

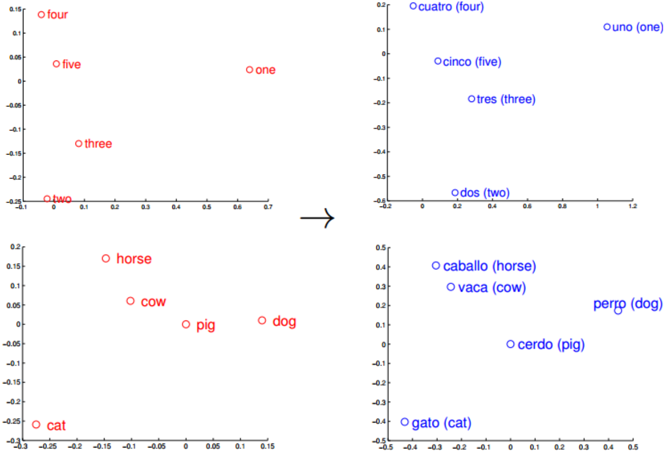
- Unfortunately do not work across languages:
  - You don't see a Czech word surrounded by English very often!

Brown Clusters Trained on Czech and English PUD

- 0000 of through Natural Yves captured comedy globálního independent opinion reduced
- 00010 with about over before around without since record better conquered down
- 001010 is like until began told found brought helps opened sent announced changed
- 0100 his their this her other these North both some New October each South April
- 0101 the its several our European my any your financial natural religious St. bad exact
- 01100 time up people years year city state government world day war own power area
- 10000 aby led včetně followed played pokud prezident aniž directed however
- 10001 že který které ale která co když jak kteří kde což kdy zatímco zda protože proč
- 100111 je byl bylo byla i jsou byly bude má mnoho už není například jsme každý mají
- 10100 roce letech době oblasti případě této druhé důsledku hlavní den jedné roli té
- 10110 na z s ve o k pro za od mezi ze proti pod u de svého nad nové kolem bez několik
- 111100 The In A But Na On During Po After However As At By Avšak With And

Aligning Vector Spaces

- Tomáš Mikolov, Quoc V. Le, Ilya Sutskever (2013). *Exploiting Similarities among Languages for Machine Translation*



Aligning Vector Spaces

- Large monolingual data in two languages
- Train monolingual word embeddings in both languages
- Take a small bilingual dictionary
- Transform (rotate & scale) source vector space to match the target space as closely as possible
  - For known translation pairs (x, z), transformed vector of x should be close to vector of z
  - $\{x_i, z_i\}_{i=1}^{n}$, where $x_i \in \mathbb{R}^{d_1}$, and $z_i \in \mathbb{R}^{d_2}$
  - Find transformation matrix $W \in \mathbb{R}^{d_1 \times d_2}$ such that distance of transformed vectors from their translations is minimal:
$$\min_{W} \sum_{i=1}^{n} ||Wx_i - z_i||^2$$
  - Use neural network (gradient descent) to find the matrix!

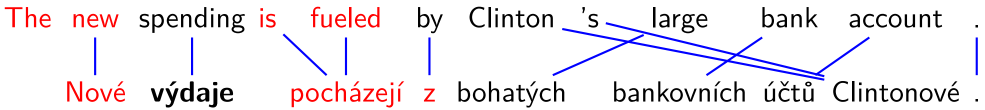
Spanish-English Example Translations

- emociones → **emotions,** emotion, feelings
- protegida → wetland, undevelopable, **protected**
- imperio → dictatorship, imperialism, tyranny (correct: empire)
- determinante → crucial, key, important (correct: determinant)
- preparada → **prepared,** ready, prepare
- millas → kilometers, kilometres, **miles**
- hablamos → talking, talked, **talk**
- destacaron → **highlighted,** emphasized, emphasised

English-Czech Examples of Ambiguities

English	Computed Translation	Dictionary
said	řekl *(said)*	uvedený *(listed)*
will	může *(can)*	vůle *(testament)*
did	udělal *(did)*	ano *(yes)*
hit	zasáhl *(hit)*	hit
must	musí *(must)*	mošt *(cider)*
current	stávající *(current)*	proud *(stream)*
shot	vystřelil *(shot)*	shot
minutes	minut *(minutes)*	zápis *(record)*
latest	nejnovější *(newest)*	poslední *(last)*
blacks	černoši *(black people)*	černá *(black color)*
hub	centrum *(center)*	hub
minus	minus *(minus)*	bez *(without)*
retiring	odejde *(will leave)*	uzavřený *(closed)*
grown	pěstuje *(grows)*	dospělý *(adult)*

Skip-gram across Word Alignment



Skip-gram across Word Alignment

The new spending is fueled by Clinton 's large bank account .

Nové výdaje **pocházejí** z bohatých bankovních účtů Clintonové .

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Nové výdaje pocházejí z bohatých bankovních účtů **Clintonové** .

Artificial Code Switching

At random positions, jump across word alignment to the other language.

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The Nové výdaje is fueled by bohatých bank account Clintonové .

Unsupervised Multilingual Word Embeddings

- Multilingual (as opposed to bilingual)
- Unsupervised: no bilingual dictionary or parallel corpus
- Input: Monolingual embeddings for many languages

- Xilun Chen, Claire Cardie (2018). *Unsupervised Multilingual Word Embeddings*

- Adversarial training
  - Train a network that says whether a vector is likely to come from embeddings of language l_i
  - Train a converter from other languages to an "interlingua" vector space and then to space of l_i
  - Try to make the converter so good that the classifier network cannot recognize converted vectors from domestic ones
- Pseudo-supervised second step:
  - After approximate alignment, we trust translations of high-frequency words
  - $\Rightarrow$ Generate a bilingual dictionary for each language pair
  - $\Rightarrow$ Use it in a "supervised" scenario to align the two languages better