Advanced Artificial Intelligence for Data Analytics (**AdArtI**)

2020-1

Word Embeddings and NLP tasks

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https://bit.ly/2rwmvQU

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OUTLINE

- **Representation Learning for Text**
  - SVD
  - Word2Vec
  - Fast Text Embeddings – subword information
  - Document Representations
- NLP tasks and evaluation
  - GLUE, FLUE
  - French Linguistics

Language model

- Goal: determine $P(s = w_1 \dots w_k)$ in some domain of interest

Paris is the capital of France

W

$$\boxed{P(s) = \prod_{i=1}^{k} P\,(w_i \mid w_1 \dots w_{i-1})}$$

c

$\underset{w}{\operatorname{argmax}} \left(P(w \mid c) \right)$

e.g., $P\,(w_1 w_2 w_3) = P\,(w_1)\, P\,(w_2 \mid w_1)\, P\,(w_3 \mid w_1 w_2)$

- Traditional n-gram language model assumption:
  "probability of a word depends only on **context** of $n - 1$ previous words"

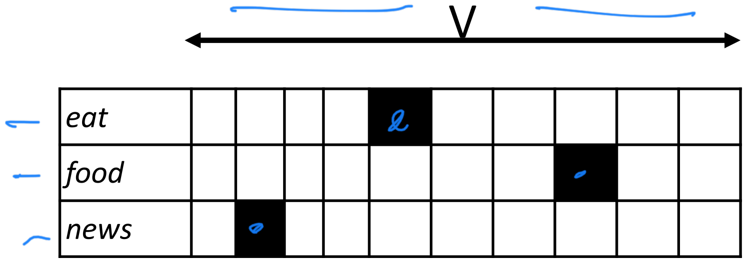
$$\Rightarrow \widehat{P}(s) = \prod_{i=1}^{k} P\,(w_i \mid w_{i-n+1} \dots w_{i-1})$$

- i.e. "Paris is the capital of France located in Ile de ...."

- Typical ML-smoothing learning process (e.g., Katz 1987):
  1. compute $\widehat{P}\,(w_i \mid w_{i-n+1} \dots w_{i-1}) = \dfrac{\# w_{i-n+1} \dots w_{i-1} w_i}{\# w_{i-n+1} \dots w_{i-1}}$ on training corpus
  2. smooth to avoid zero probabilities

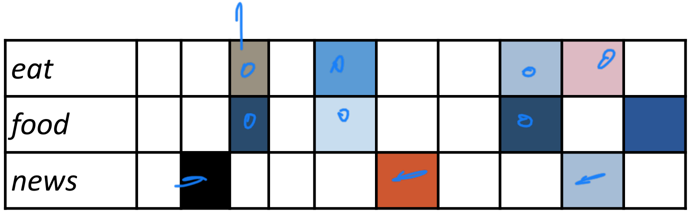
Representing Words

vocabulary



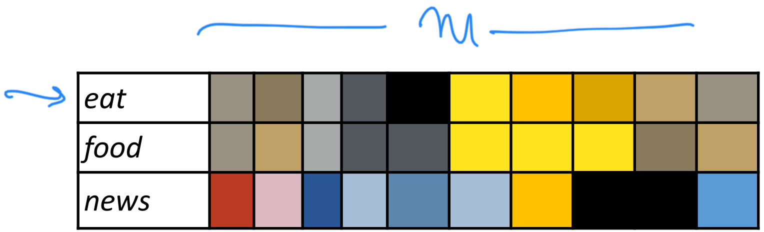
$\overline{eat} \cdot \overline{news} = \phi$

- **One-hot vector**
  - high dimensionality
  - sparse vectors
  - dimensions=|V| (10^6<|V|)
  - unable to capture semantic similarity between words
- **Distributional vector**
  - words that occur in similar contexts, tend to have similar meanings
  - each word vector contains the frequencies of all its neighbors
  - dimensions=|V|
  - computational complexity for ML algorithms



Representing Words

- **Word embeddings**
  - store the same contextual information in a low-dimensional vector
  - **densification** (sparse to dense)
  - **compression**
    - dimensionality reduction
    - dimensions=m
      100<m<500
  - able to capture semantic similarity between words
  - learned vectors (unsupervised)
  - Learning methods
    - SVD
    - word2vec
    - GloVe



Text Similarity

2016

1

- We should assign similar probabilities (discover similarity) to *Obama speaks to the media in Illinois* and the *President addresses the press in Chicago*

2

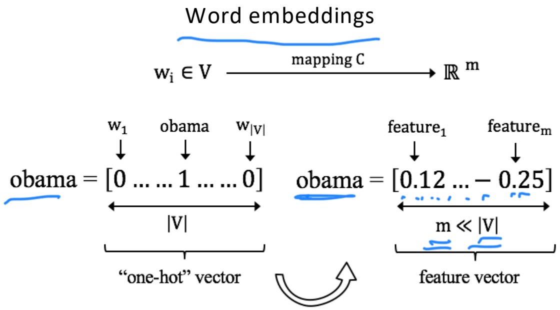
- This does not happen because of the “one-hot” vector space representation

One hot

$$\left.\begin{aligned} obama &= [0\,0\,0\,0\ \dots\ 0\,1\,0\,0] \\ president &= [0\,0\,0\,1\ \dots\ 0\,0\,0\,0] \end{aligned}\right\} \ \overrightarrow{obama}.\overrightarrow{president} = \vec{0}$$

$$\left.\begin{aligned} speaks &= [0\,0\,1\,0\ \dots\ 0\,0\,0\,0] \\ addresses &= [0\,0\,0\,0\ \dots\ 0\,0\,1\,0] \end{aligned}\right\} \ \overrightarrow{speaks}.\overrightarrow{addresses} = \vec{0}$$

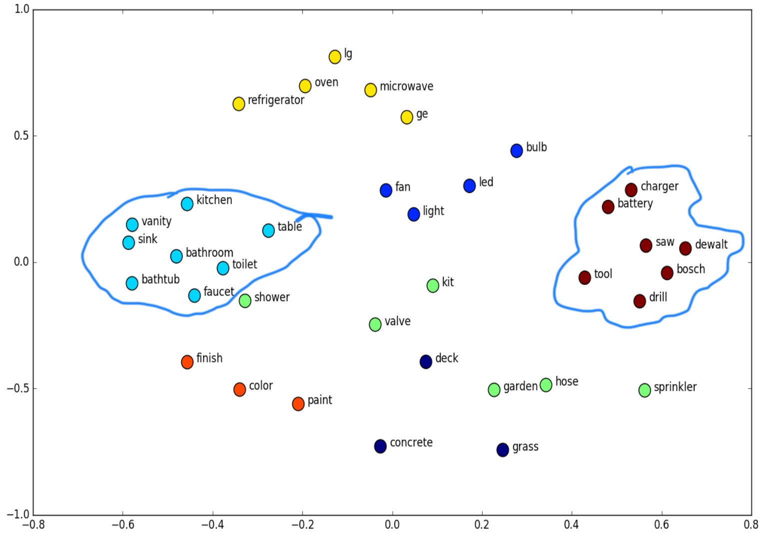
$$\left.\begin{aligned} illinois &= [1\,0\,0\,0\ \dots\ 0\,0\,0\,0] \\ chicago &= [0\,1\,0\,0\ \dots\ 0\,0\,0\,0] \end{aligned}\right\} \ \overrightarrow{illinois}.\overrightarrow{chicago} = \vec{0}$$



Representation Learning for Text

- "a word is defined by "the company it keeps" (Firth, 1957)

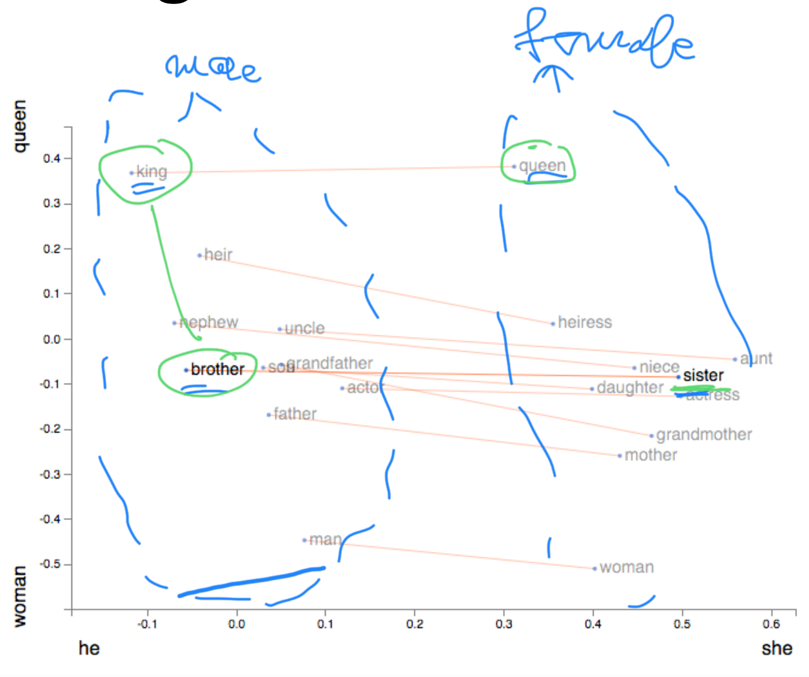
- Word embeddings are a class of algorithms where each word is represented as real-valued vector.
- The learning process of these vectors is either joint with a neural network model on some task or is an unsupervised process.
- Similar words in meaning have similar representation.



Representation Learning for Text

- Words with similar meaning end up close to each other
- Words sharing similar contexts may be analogous
  - Synonyms
  - Antonyms
  - Names
  - Colors
  - Places
  - Interchangeable words

- Vector arithmetics to work with analogies
- i.e. **king - man + woman = queen**



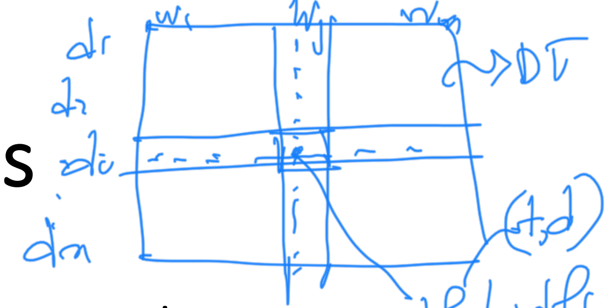
https://lamyiowce.github.io/word2viz/

$\vec{King} - \vec{queen} + \vec{brother} \approx \vec{sister}$

OUTLINE

- Representation Learning for Text
  - **SVD**
  - Word2Vec
  - Fast Text Embeddings – subword information
- Attention based architectures
  - ELMO, BERT. BART
- NLP tasks and evaluation
  - GLUE, FLUE
  - French Linguistics

SVD word embeddings



- Dimensionality reduction on co-occurrence matrix
- Create a $|V| x |V|$ word co-occurrence matrix X
- Apply SVD $X = USV^T$
- Take first k columns of U
- Use the k-dimensional vectors as representations for each word
- Able to capture semantic and syntactic similarity

tf / idf(t)

t in d

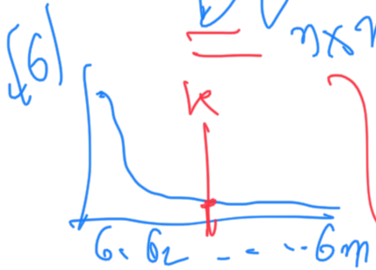
term frequency = $(1 + \log tf(d))$

idf: inverse doc freq(t) = $\log \frac{N}{idf(t)}$

doc count

$D_{n \times m} = U \Sigma V^T \xrightarrow{k} \approx U_k \Sigma_k V_k^T$

$\sum_{i=1}^{k} \sigma_i \geq 85\% \sum_{i=1}^{n} \sigma_i$



$\sigma_1 u_1 v_1^T + \cdots + \sigma_m u_m v_m^T$

LSI – an example

LSI application on a term – document matrix

HCI

C1: Human machine Interface for Lab ABC computer application

C2: A survey of user opinion of computer system response time

C3: The EPS user interface management system

C4: System and human system engineering testing of EPS

C5: Relation of user-perceived response time to error measurements

GM

M1: The generation of random, binary unordered trees

M2: The intersection graph of path in trees

M3: Graph minors IV: Widths of trees and well-quasi-ordering

M4: Graph minors: A survey

- The dataset consists of 2 classes, 1st: “human – computer interaction” (c1-c5) 2nd: related to graph (m1-m4). After feature extraction the titles are represented as follows.

Indexing by Latent Semantic Analysis (1990) Scott Deerwester, Susan T. Dumais, George W. Furnas, Thomas K. Landauer, Richard Harshman, Journal of the American Society of Information Science

LSI – an example

$A=ULV^T$

d

A= df

c1	c2		m1	c5	m1	m2	m3	m4
1	0	0	1	0	0	0	0	0
1	0	1	0	0	0	0	0	0
1	1	0	0	0	0	0	0	0
0	1	1	0	1	0	0	0	0
0	1	1	2	0	0	0	0	0
0	1	0	0	1	0	0	0	0
0	1	0	0	1	0	0	0	0
0	0	1	1	0	0	0	0	0
0	1	0	0	0	0	0	0	1
0	0	0	0	0	1	1	1	0
0	0	0	0	0	0	1	1	1
0	0	0	0	0	0	0	1	1

LSI – an example

SVD

$A=\underline{ULV}^T$

U=

0.22	-0.11	0.29	-0.41	-0.11	-0.34	0.52	-0.06	-0.41	0	0	0
0.20	-0.07	0.14	-0.55	0.28	0.50	-0.07	-0.01	-0.11	0	0	0
0.24	0.04	-0.16	-0.59	-0.11	-0.25	-0.30	0.06	0.49	0	0	0
0.40	0.06	-0.34	0.10	0.33	0.38	0.00	0.00	0.01	0	0	0
0.64	-0.17	0.36	0.33	-0.16	-0.21	-0.17	0.03	0.27	0	0	0
0.27	0.11	-0.43	0.07	0.08	-0.17	0.28	-0.02	-0.05	0	0	0
0.27	0.11	-0.43	0.07	0.08	-0.17	0.28	-0.02	-0.05	0	0	0
0.30	-0.14	0.33	0.19	0.11	0.27	0.03	-0.02	-0.17	0	0	0
0.21	0.27	-0.18	-0.03	-0.54	0.08	-0.47	-0.04	-0.58	0	0	0
0.01	0.49	0.23	0.03	0.59	-0.39	-0.29	0.25	-0.23	0	0	0
0.04	0.62	0.22	0.00	-0.07	0.11	0.16	-0.68	0.23	0	0	0
0.03	0.45	0.14	-0.01	-0.30	0.28	0.34	0.68	0.18	0	0	0

LSI – an example

$A=ULV^T$

L=

3.34	0	0	0	0	0	0	0	0
0	2.54	0	0	0	0	0	0	0
0	0	2.35	0	0	0	0	0	0
0	0	0	1.64	0	0	0	0	0
0	0	0	0	1.50	0	0	0	0
0	0	0	0	0	1.31	0	0	0
0	0	0	0	0	0	0.85	0	0
0	0	0	0	0	0	0	0.56	0
0	0	0	0	0	0	0	0	0.36
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0

LSI – an example

$A = ULV^T$

V=

0.20	-0.06	0.11	-0.95	0.05	-0.08	0.18	-0.01	-0.06
0.61	0.17	-0.50	-0.03	-0.21	-0.26	-0.43	0.05	0.24
0.46	-0.13	0.21	0.04	0.38	0.72	-0.24	0.01	0.02
0.54	-0.23	0.57	0.27	-0.21	-0.37	0.26	-0.02	-0.08
0.28	0.11	-0.51	0.15	0.33	0.03	0.67	-0.06	-0.26
0.00	0.19	0.10	0.02	0.39	-0.30	-0.34	0.45	-0.62
0.01	0.44	0.19	0.02	0.35	-0.21	-0.15	-0.76	0.02
0.02	0.62	0.25	0.01	0.15	0.00	0.25	0.45	0.52
0.08	0.53	0.08	-0.03	-0.60	0.36	0.04	-0.07	-0.45

LSI – an example

Choosing the 2 largest singular values we have

$$U_k = \begin{array}{|c|c|} \hline 0.22 & -0.11 \\ \hline 0.20 & -0.07 \\ \hline 0.24 & 0.04 \\ \hline 0.40 & 0.06 \\ \hline 0.64 & -0.17 \\ \hline 0.27 & 0.11 \\ \hline 0.27 & 0.11 \\ \hline 0.30 & -0.14 \\ \hline 0.21 & 0.27 \\ \hline 0.01 & 0.49 \\ \hline 0.04 & 0.62 \\ \hline 0.03 & 0.45 \\ \hline \end{array}$$

v_1 v_2

$$L_k = \begin{array}{|c|c|} \hline 3.34 \;\sigma_1 & 0 \\ \hline 0 & 2.54 \;\sigma_2 \\ \hline \end{array}$$

$$V_k^T = \begin{array}{c} v_1^T \\ v_2^T \end{array} \begin{array}{|c|c|c|c|c|c|c|c|c|} \hline 0.20 & 0.61 & 0.46 & 0.54 & 0.28 & 0.00 & 0.02 & 0.02 & 0.08 \\ \hline -0.06 & 0.17 & -0.13 & -0.23 & 0.11 & 0.19 & 0.44 & 0.62 & 0.53 \\ \hline \end{array}$$

$A \approx U_k L_k V_k^T$

LSI reconstruction (2 singular values)

$A_k =$

	C1	C2	C3	C4	C5	M1	M2	M3	M4
human	0.16	0.40	0.38	0.47	0.18	-0.05	-0.12	-0.16	-0.09
Interface	0.14	0.37	0.33	0.40	0.16	-0.03	-0.07	-0.10	-0.04
Computer	0.15	0.51	0.36	0.41	0.24	0.02	0.06	0.09	0.12
User	0.26	0.84	0.61	0.70	0.39	0.03	0.08	0.12	0.19
System	0.45	1.23	1.05	1.27	0.56	-0.07	-0.15	-0.21	-0.05
Response	0.16	0.58	0.38	0.42	0.28	0.06	0.13	0.19	0.22
Time	0.16	0.58	0.38	0.42	0.28	0.06	0.13	0.19	0.22
EPS	0.22	0.55	0.51	0.63	0.24	-0.07	-0.14	-0.20	-0.11
Survey	0.10	0.53	0.23	0.21	0.27	0.14	0.31	0.44	0.42
Trees	-0.06	0.23	-0.14	-0.27	0.14	0.24	0.55	0.77	0.66
Graph	-0.06	0.34	-0.15	-0.30	0.20	0.31	0.69	0.98	0.85
Minors	-0.04	0.25	-0.10	-0.21	0.15	0.22	0.50	0.71	0.62

LSI Example

- Query: "human computer interaction" retrieves documents: c_1,c_2, c_4 but *not* c_3 and c_5.
- If we submit the same query (based on the transformation shown before) to the transformed matrix we retrieve (using cosine similarity) all c_1-c_5 even if c_3 and c_5 have no common keyword to the query.
- According to the transformation for the queries we have:

Query transformation

	query
human	1
Interface	0
computer	1
User	0
System	0
Response	0
Time	0
EPS	0
Survey	0
Trees	0
Graph	0
Minors	0

q=

1
0
1
0
0
0
0
0
0
0
0
0

Query transformation

$q^T=$

1	0	1	0	0	0	0	0	0	0	0	0

$U_k=$

0.22	-0.11
0.20	-0.07
0.24	0.04
0.40	0.06
0.64	-0.17
0.27	0.11
0.27	0.11
0.30	-0.14
0.21	0.27
0.01	0.49
0.04	0.62
0.03	0.45

$L_k=$

0.3	0
0	0.39

$q_n=q^TU_kL_k =$

0.138	-0.0273

Query transformation

Map docs to the 2 dim space $V_k L_k =$

0.20	-0.06
0.61	0.17
0.46	-0.13
0.54	-0.23
0.28	0.11
0.00	0.19
0.01	0.44
0.02	0.62
0.08	0.53

3.34	0
0	2.54

=

0.67	-0.15
2.04	0.43
1.54	-0.33
1.80	-0.58
0.94	0.28
0.00	0.48
0.03	1.12
0.07	1.57
0.27	1.35

$q_n L_k =$

0.138	-0.0273

3.34	0
0	2.54

=

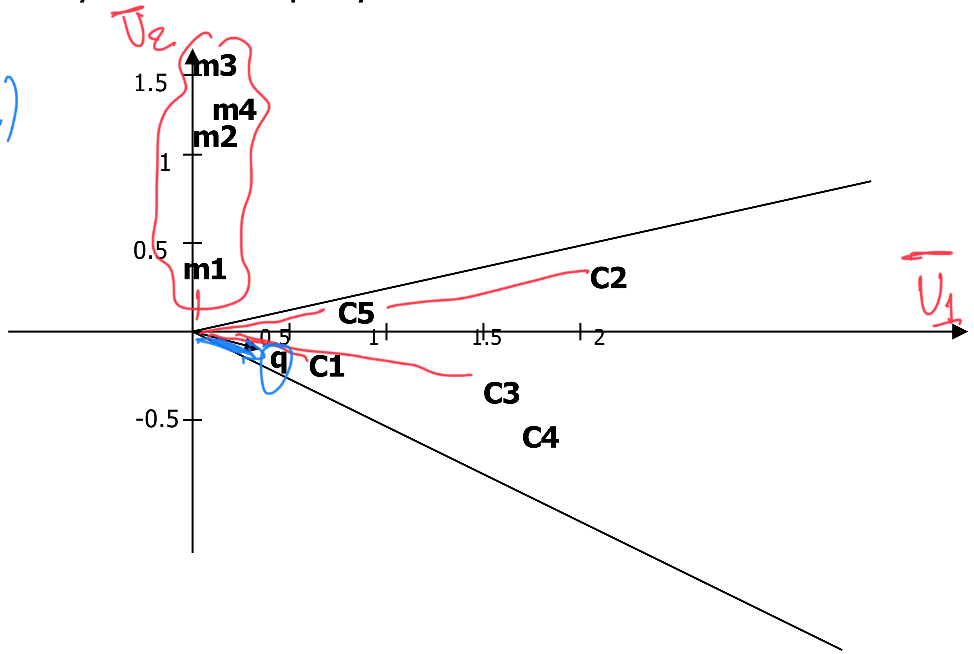
0.46	-0.069

Query transformation

- The cosine similarity matrix of query vector to the documents is:

$\cos(q, d_i)$

	query
C1	0.99
C2	0.94
C3	0.99
C4	0.99
C5	0.90
M1	-0.14
M2	-0.13
M3	-0.11
M4	0.05



SVD problems

1990 (S. Dumais)

- The dimensions of the matrix change when dictionary changes
- The whole decomposition must be re-calculated when we add a word
- Sensitive to the imbalance of word frequency
- Very high dimensional matrix
- Not suitable for large corpora or dictionaries
- Quadratic cost to perform SVD $U \Sigma V^T$ $(\approx O(n^2))$
- Solution: Directly calculate a low-dimensional representation

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  - Document representations
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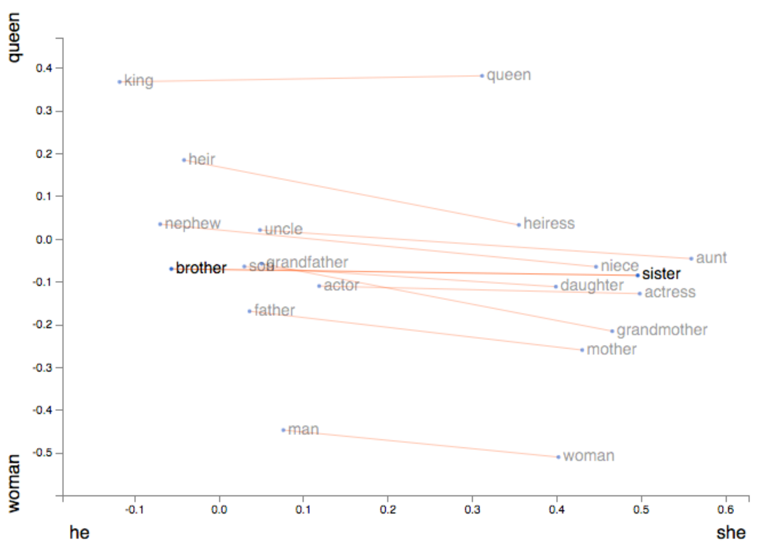
  - GLUE, FLUE
  - French Linguistics

Word analogy

- Words with similar meaning end up close to each other
- Words sharing similar contexts may be analogous
  - Synonyms
  - Antonyms
  - Names
  - Colors
  - Places
  - Interchangeable words

- Vector arithmetics to work with analogies
- i.e. **king - man + woman = queen**



https://lamyiowce.github.io/word2viz/

But why?

- what's an analogy?

$$\frac{p(w'|man)}{p(w'|woman)} \approx \frac{p(w'|king)}{p(w'|queen)}$$

Assume PMI is approximated by a low rank approximation of the co-occurrence matrix.

1. $PMI(w', w) \approx v_w v_{w'}$ *inner product*
2. Isotropic: $E_{w'}[(v_{w'} v_u)]^2 = ||v_u||^2$

Then

3. $argmin_w \ E_{w'}[ln \frac{p(w'|w)}{p(w'|queen)} - ln \frac{p(w'|man)}{p(w'|woman)}]^2$

4. $argmin_w \ E_{w'}[\big(PMI(w'|w) - PMI(w'|queen)\big) - (PMI(w'|man) - PMI(w'|woman))]^2$

5. $argmin_w ||\big(v_w - v_{queen}\big) - (v_{man} - v_{woman})||^2$
6. $v_w \approx v_{queen} - v_{woman} + v_{man}$ which is an analogy!

- *Arora et al (ACL 2016)* shows that if (2) holds then (1) holds as well
- So we need to construct vectors from co-occurrence that satisfy (2)
- d<<|V| in order to have isotropic vectors

A Latent Variable Model Approach to PMI-based Word Embeddings, *Arora et al (ACL 2016)*

Learning Word Vectors

DL: Bengio, LeCun, Hinton
1990s 2018
TURING AWARD

- ➢Corpus containing a sequence of T training words
- ➢Objective: $f(w_t, \ldots, w_{t-n+1}) = \hat{P}(w_t \mid w_{t-n+1} \ldots w_{t-1})$
- ➢Decomposed in two parts:

$$w_i \in V \xrightarrow{\text{mapping C}} \mathbb{R}^m$$

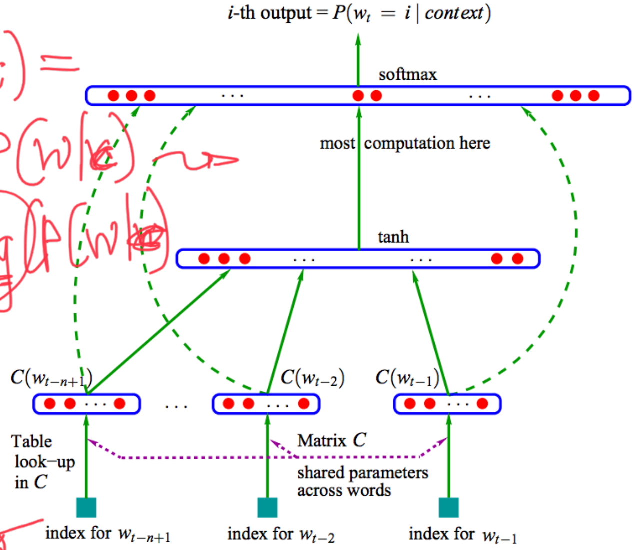
max $P(w|c)$ =
= min $-P(w|c)$ →
→ min $-\log(P(w|c))$

  - ➢ Mapping **C** (1-hotv => lower dimensions)
  - ➢ Mapping any **g** s.t. (estimate prob t+1| t previous)

$$f(w_{t-1},\cdots,w_{t-n+1}) = g(C(w_{t-1}),\cdots,C(w_{t-n+1}))$$

- C(i) is the i-th word feature vector

  (Word embedding)



Bengio, Yoshua, et al. "A neural probabilistic language model." *The Journal of Machine Learning Research* 3 (2003): 1137-1155.

- ➢Objective function: $J = \frac{1}{T}\sum f(w_t, \ldots, w_{t-n+1})$

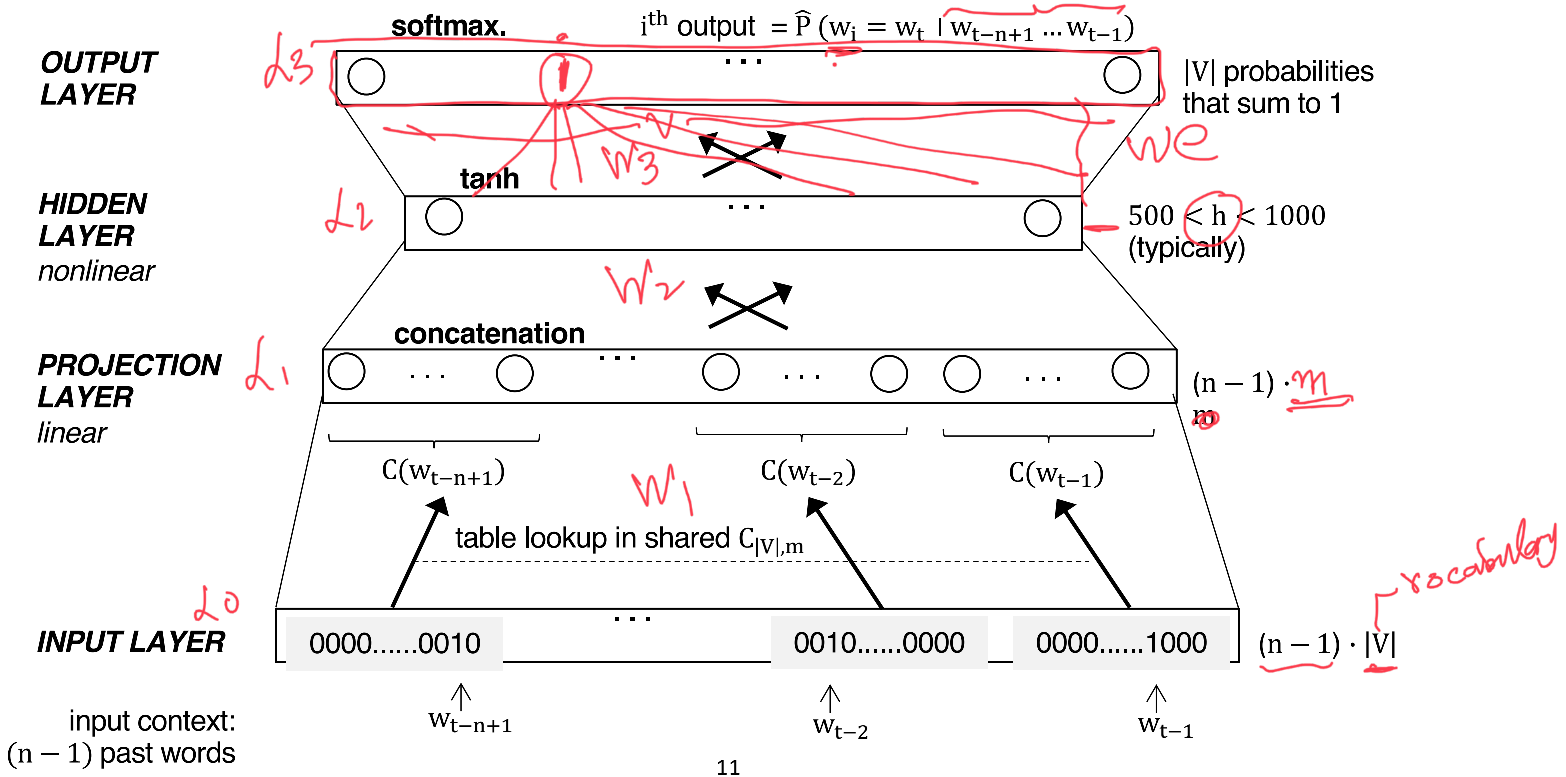
$P(w|c) \simeq \prod_{i=1}^{c} p(w|c_i)$

$p \simeq 10^{-3}$ → $10^{-3}|10$ → 10^{-30}

Neural Net Language Model

For each training sequence: input = (context, target) pair: $(w_{t-n+1} \ldots w_{t-1}, w_t)$

objective: minimize $E = -\log \widehat{P}(w_t \mid w_{t-n+1} \ldots w_{t-1})$



Objective function

- $E = -\log \widehat{P}(w_t \mid w_{t-n+1} \ldots w_{t-1})$
- a probability between 0 and 1.
- On this support, the log is negative => –log term positive.
- makes sense to try to minimize it. ~

  - Probability of word given the context be as high as possible (1 for a perfect prediction).
    - case the error is equal to 0 (global minimum).

p	**log(p)**	**-log(p)**
0,7	-0,15490196	0,15490196
0,2	-0,698970004	0,698970004

NNLM facts

2003, JMLR 2003

- tested on Brown (1.2M words, $|V| \cong 16K$) and AP News (14M words, $|V| \cong 150K$ reduced to 18K) corpuses
- Brown: $h = 100$, $n = 5$, $m = 30$
- AP News: $h = 60$, $n = 6$, $m = 100$, **3 week** training using **40 cores**
- 24% and 8% relative improvement (resp.) over traditional smoothed n-gram LMs
- in terms of test *set perplexity*: geometric average $1/\hat{P}(w_t \mid w_{t-n+1} \dots w_{t-1})$
- Due to **complexity**, NNLM can't be applied to large data sets → poor performance on rare words
- Bengio et al. (2003) initially thought their main contribution was a more accurate LM. They let the interpretation and use of the word vectors as **future work**
- On the opposite, Mikolov et al. (2013) focus on the **word vectors**

Word2Vec

google

- Mikolov et al. in 2013
- Word2vec key idea: achieve better performance not by using a more complex model (i.e., with more layers), but by allowing a **simpler (shallower) model** to be trained on **much larger amounts of data**
- no hidden layer (leads to 1000X speedup)
- projection layer is shared (not just the weight matrix) - C
- context: words from both history & future:
- Two algorithms for learning words vectors:
  - **CBOW**: from context predict target
  - **Skip-gram**: from target predict context

$C = C_1 \cup C_2$

$C \rightarrow W$: CBOW

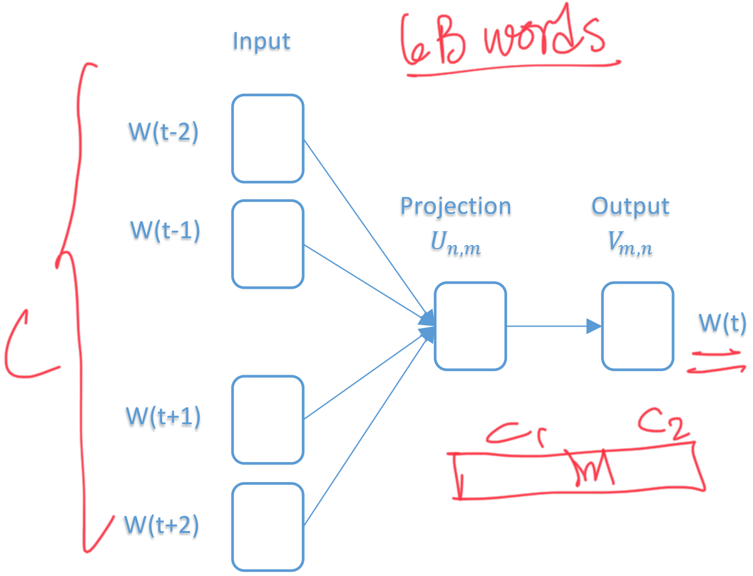
$W \rightarrow C$: Skipgram

W2V: Continuous Bag Of Words – CBOW

- An unsupervised technique to learn word embeddings.
- CBOW learns the embeddings by predicting the target word (the center one) based on the context words (surrounding words).
- i.e. “Paris is the capital of France located in Ile de France”

e

w

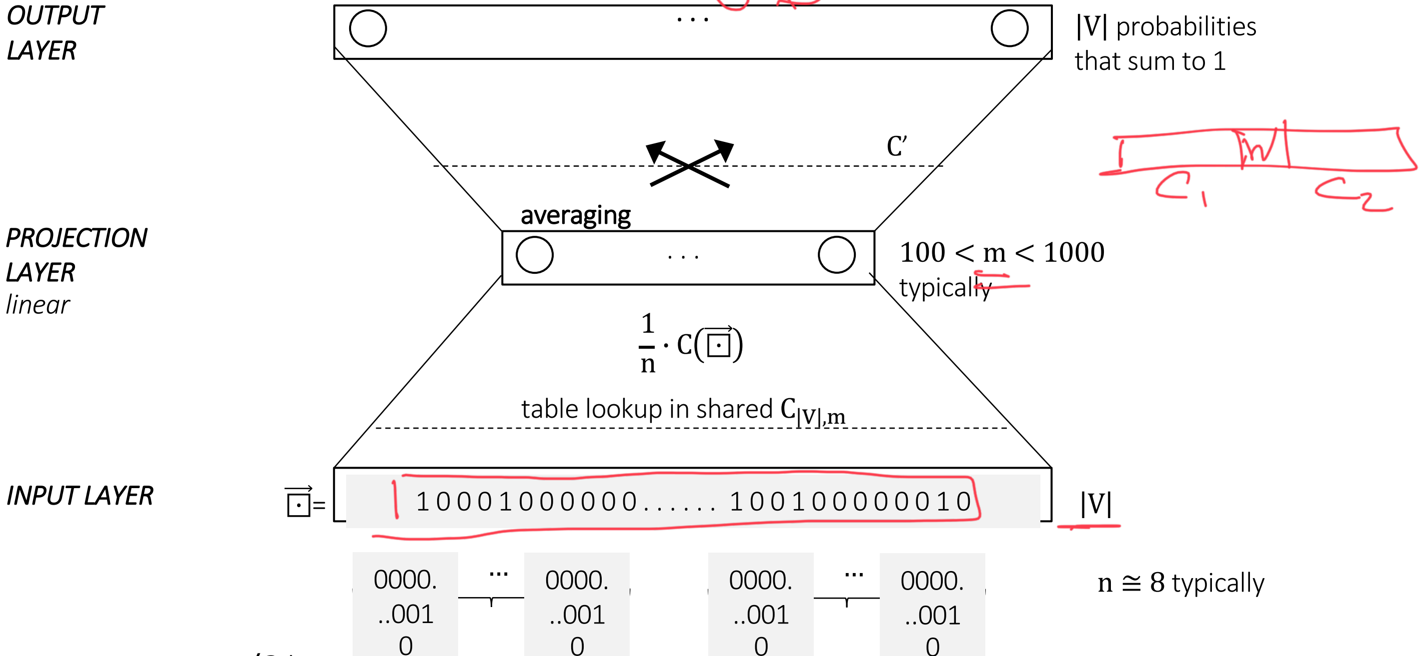


Continuous Bag-of-Words (CBOW)

For each training sequence: input = (context, target) pair: $(w_{t-\frac{n}{2}} \dots w_{t-1} w_{t+1} \dots w_{t+\frac{n}{2}}, w_t)$

objective: minimize $-\log \hat{P}(w_t \mid w_{t-n+1} \dots w_{t-1})$

hierarchical softmax. t^{th} output $= P(w_i = w_t \mid w_{t-n+1} \dots w_{t-1})$



context: $n/2$ history words: $w_{t-\frac{n}{2}} \dots w_{t-1}$ $n/2$ future words: $w_{t+1} + \dots + w_{t+\frac{n}{2}}$

W2V: Continuous Bag Of Words – CBOW : Forward

- Each word **W(t)** is represented by one-hot vector of size **n** (vocabulary size).
- The **w** context words are averaged and forwarded to the projection layer to produce an embedded vector **z** of size **m:**

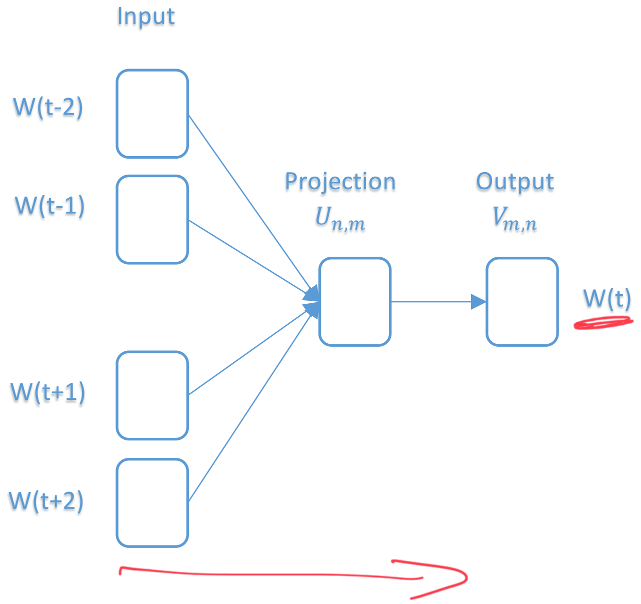
$$z_{1,m} = \frac{1}{w} \sum_{W \epsilon context} W_{1,n} U_{n,m}$$

- The vector **z** is forwarded to an output projection layer that produce the out vector **y** of size **n**.

$$y_{1,n} = z_{1,m} V_{m,n}$$

- Finally, a soft-max activation function is applied to the output to find a vector of probabilities for each word:

$$\sigma(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}}$$



W2V: Continuous Bag Of Words – CBOW : Backward

- To update the weights, first we compute the log loss function (~~cross-entropy~~):

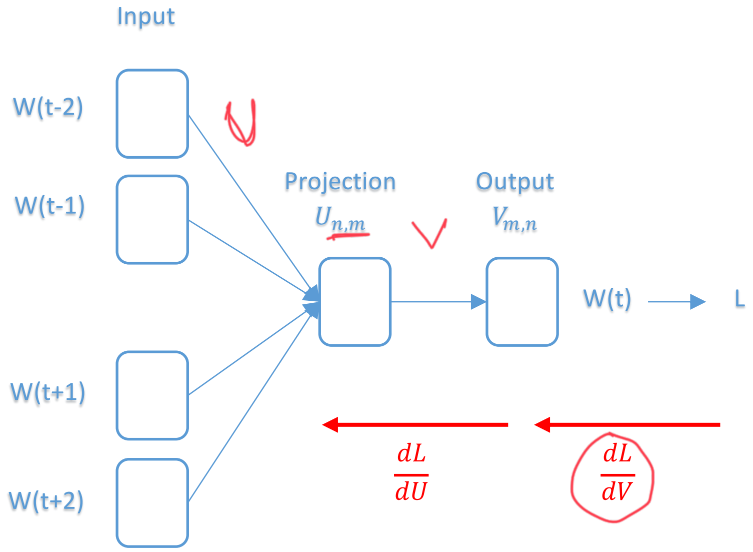
$$L = -\frac{1}{n}\sum_{i=1}^{n} W(t)_i \log(\sigma(y_i))$$

- The weights (matrices U and V) are now updated using gradient descent with learning rate α.

- $V = V - \alpha\frac{dL}{dV}$

- $U = U - \alpha\frac{dL}{dU}$

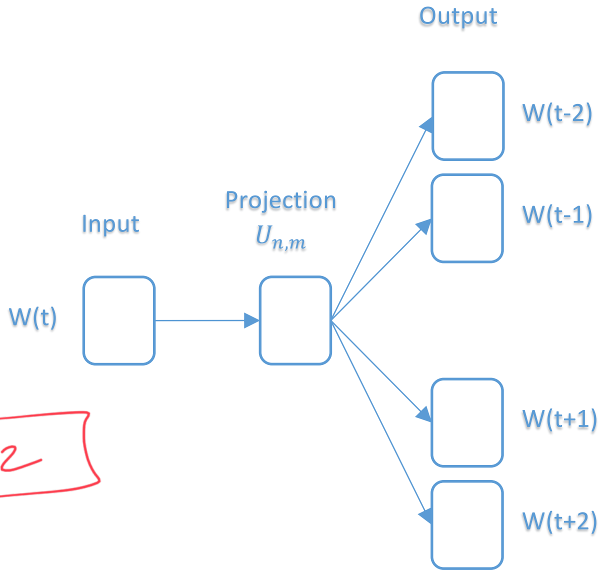
- Finally, after multiple passes through the corpus, **U** is the final **Word Embeddings Matrix** where each row represent a vector of size **m** for a specific word.



W2V: Skip-Gram

- An unsupervised technique to learn word embeddings.
- Skip-gram learn the embeddings by predicting the context of the word.
- The used loss function is cross-entropy as in CBOW.

$\boxed{c_1}\boxed{w}\boxed{c_2}$



Skip-gram

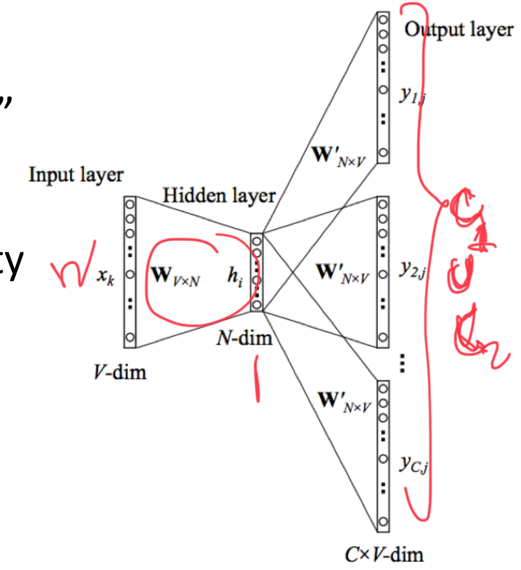
- skip-gram uses the context's center word to predict the surrounding words

C_1 C_2

- i.e. "Paris is the capital of France located in Ile de France"

w

- instead of computing the probability of the target word w_t given its previous words, we calculate the probability of the surrounding word w_{t+j} given w_t
- $p(w_{t+j}|w_t) = \frac{\exp(v_{w_t}^{T} v'_{w_{t+j}})}{\sum_{w \in V} \exp(v_{w_t}^{T} v'_{w_{t+j}})}$
- $v^{T}{}_{wt}$ is a column of W_{VxN} and $v'_{w_{t+j}}$ is a column of W'_{NxV}
- Objective function $J = \frac{1}{T}\sum_{t=1}^{T} \sum_{-n \le j \le n} \log p(w_{t+j}|w_t)$



Word2vec facts

- Complexity is $\mathbf{n} * \mathbf{m} + \mathbf{m} * \mathbf{log}|\mathbf{V}|$ (Mikolov et al. 2013a)
- **n**:size of context window (~10) **nxm**: dimensions of the projection layer, **|V|** size of the vocabulary
- On Google news 6B words training corpus, with $|\mathbf{V}| \sim 10^6$:
  - CBOW with $\mathrm{m} = 1000$ took **2 days** to train on **140 cores**
  - Skip-gram with $\mathrm{m} = 1000$ took **2.5 days** on **125 cores**
  - NNLM (Bengio et al. 2003) took **14 days** on **180 cores**, for $\mathrm{m} = 100$ only!

word2vec training speed ≅ 100K-5M words/s

- Quality of the word vectors:
  - ↗ significantly with **amount of training data** and **dimension of the word vectors** (m)
  - measured in terms of accuracy on 20K semantic and syntactic association tasks.

  e.g., words in **bold** have to be returned:

Capital-Country	Past tense	Superlative	Male-Female	Opposite
Athens: **Greece**	walking: **walked**	easy: **easiest**	brother: **sister**	ethical: **unethical**

- Best NNLM: 12.3% overall accuracy. Word2vec (with Skip-gram): 53.3%
- References: http://www.scribd.com/doc/285890694/NIPS-DeepLearningWorkshop-NNforText#scribd ---- https://code.google.com/p/word2vec/

GloVe

Probability and Ratio	$k = solid$	$k = gas$	$k = water$	$k = fashion$
$P(k\|ice)$	1.9×10^{-4}	6.6×10^{-5}	3.0×10^{-3}	1.7×10^{-5}
$P(k\|steam)$	2.2×10^{-5}	7.8×10^{-4}	2.2×10^{-3}	1.8×10^{-5}
$P(k\|ice)/P(k\|steam)$	8.9	8.5×10^{-2}	1.36	0.96

- Ratio of co-occurrence probabilities best distinguishes relevant words

$$F(w_i, w_j, \tilde{w}_k) = \frac{P_{ik}}{P_{jk}} \quad \Rightarrow \quad w_i^T \tilde{w}_k + b_i + \tilde{b}_k = \log(X_{ik})$$

- *Cast this into a lease square problem:*

$$J = \sum_{i,j=1}^{V} f\left(X_{ij}\right)\left(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij}\right)^2$$

$$f(x) = \begin{cases} (x/x_{\max})^{\alpha} & \text{if } x < x_{\max} \\ 1 & \text{otherwise} \end{cases} .$$

- X co-occurrence matrix
- f weighting function,
- b bias terms
- $w_i = word\ vector$
- $\widetilde{w_j} = context\ vector$

model that utilizes
- count data
- bilinear prediction-based methods like word2vec

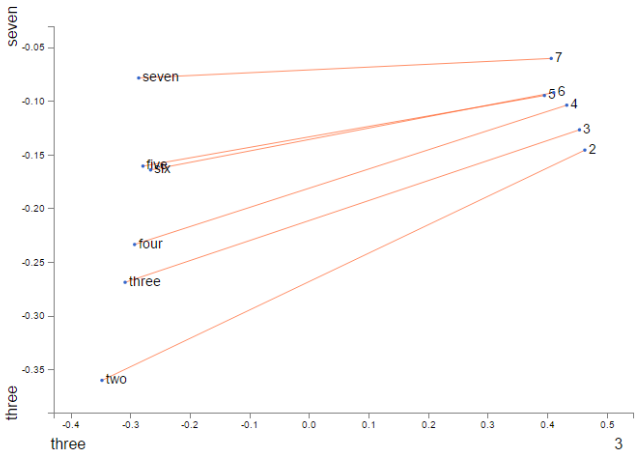
https://nlp.stanford.edu/pubs/glove.pdf

Which is better?

- Open question
- SVD vs word2vec vs GloVe
- All based on co-occurrence
- *Levy, O., Goldberg, Y., & Dagan, I. (2015)*
  - SVD performs best on similarity tasks
  - Word2vec performs best on analogy tasks
  - *No single algorithm consistently outperforms the other methods*
  - *Hyperparameter tuning is important*
  - 3 out of 6 cases, tuning hyperparameters is more beneficial than increasing corpus size
  - word2vec outperforms GloVe on all tasks
  - *CBOW is worse than skip-gram on all tasks*

Applications

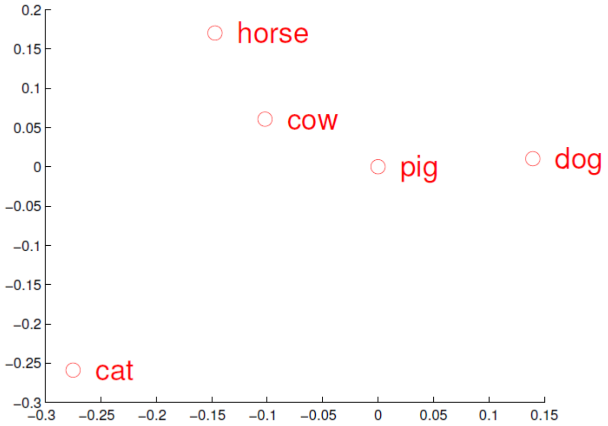
- Word analogies
- Find similar words
  - Semantic similarity
  - Syntactic similarity
- POS tagging
- Similar analogies for different languages
- Document classification

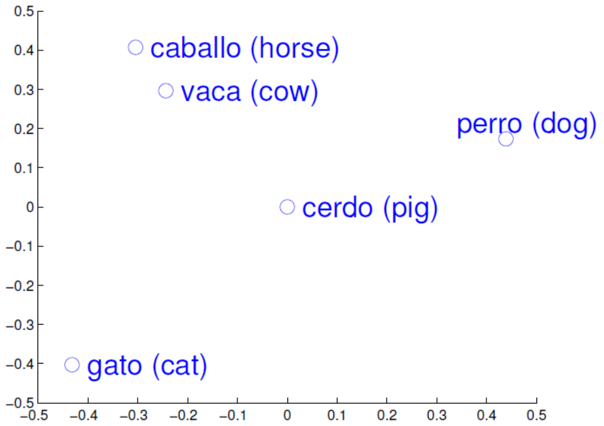


https://lamyiowce.github.io/word2viz/

Applications

- High quality word vectors boost performance of all NLP tasks, including document classification, machine translation, information retrieval…
- Example for English to Spanish machine translation:

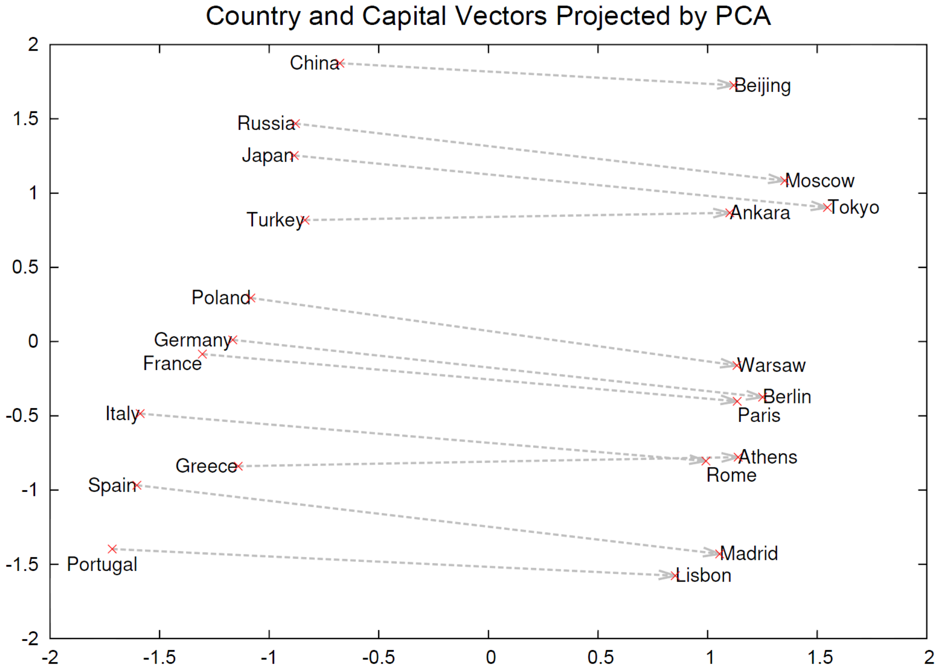




About 90% reported accuracy (Mikolov et al. 2013c)

Mikolov, T., Le, Q. V., & Sutskever, I. (2013). Exploiting similarities among languages for machine translation. *arXiv preprint arXiv:1309.4168.*

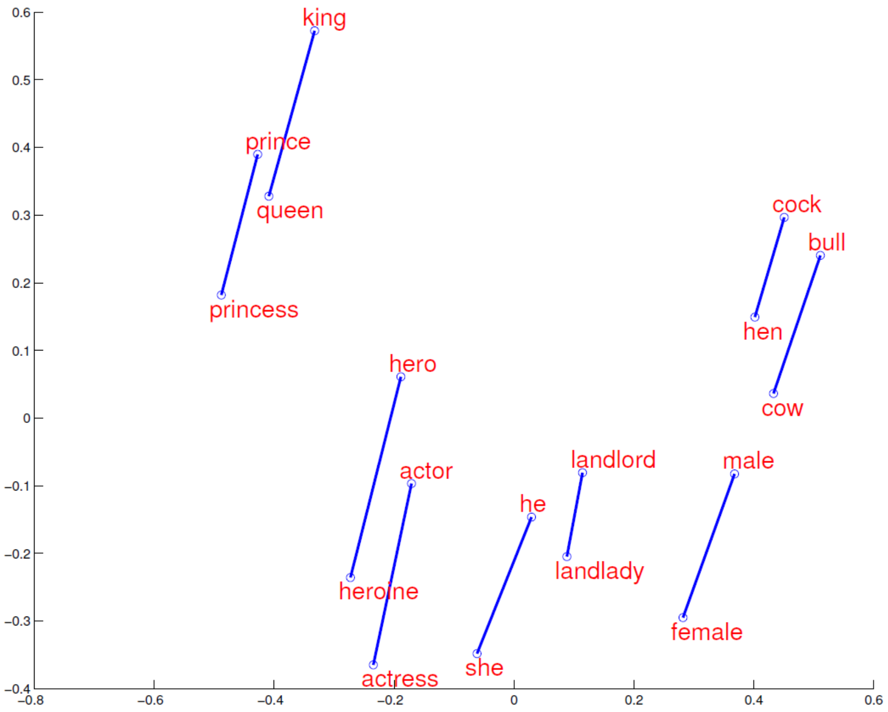
Remarkable properties of word vectors



regularities between words are encoded in the difference vectors
e.g., there is a constant **country-capital** difference vector

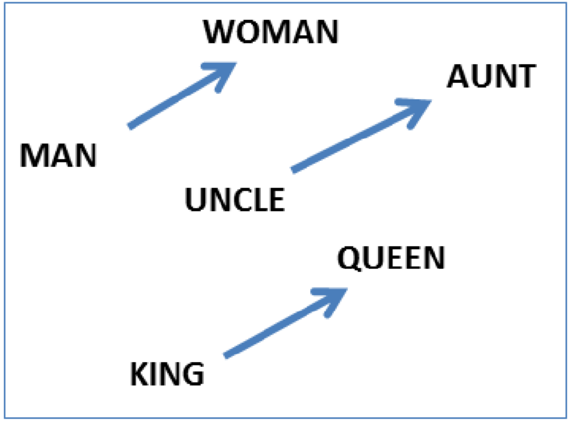
Mikolov et al. (2013b)
Distributed representations of words and phrases and their compositionality

Remarkable properties of word vectors

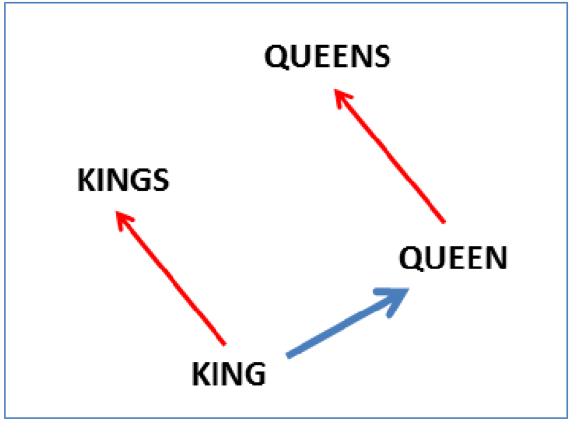


constant **female-male** difference vector

http://www.scribd.com/doc/285890694/NIPS-DeepLearningWorkshop-NNforText#scribd



constant **male-female** difference vector



constant **singular-plural** difference vector

- Vector operations are supported and make intuitive sense:

$$w_{king} - w_{man} + w_{woman} \cong w_{queen}$$

$$w_{einstein} - w_{scientist} + w_{painter} \cong w_{picasso}$$

$$w_{paris} - w_{france} + w_{italy} \cong w_{rome}$$

$$w_{his} - w_{he} + w_{she} \cong w_{her}$$

$$w_{windows} - w_{microsoft} + w_{google} \cong w_{android}$$

$$w_{cu} - w_{copper} + w_{gold} \cong w_{au}$$

- Online demo (scroll down to end of tutorial)

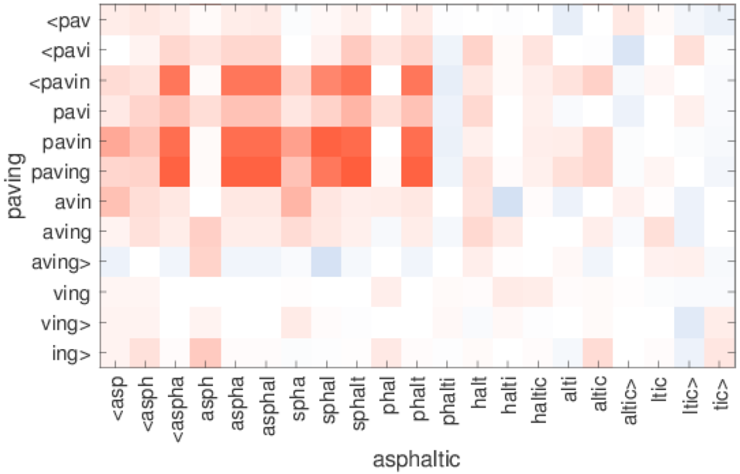
http://rare-technologies.com/word2vec-tutorial/

OUTLINE

- Representation Learning for Text
  - SVD
  - Word2Vec
  - **Fast Text Embeddings – subword information**
  - Document representations
- NLP tasks and evaluation
  - GLUE, FLUE
  - French Linguistics

Enriching Word Vectors with Subword Information

FAIR 2017, 860 cites



X'11-MVA'12

Piotr Bojanowski
Facebook AI Research
Verified email at fb.com - Homepage
Computer Vision Machine Learning

X'9-MVA'10

X'8-MVA'9

Armand Joulin
Research scientist at Facebook
Verified email at fb.com - Homepage
Artificial Intelligence Machine Learning

Tomas Mikolov
Research scientist, Facebook
Verified email at fb.com
Artificial Intelligence Machine Learning

- [*Enriching Word Vectors with Subword Information,*](#) Piotr Bojanowski, Edouard Grave, Armand Joulin and Tomas Mikolov, 2016
- [*Bag of Tricks for Efficient Text Classification,*](#) Armand Joulin, Edouard Grave, Piotr Bojanowski, Tomas Mikolov, 2016

Enriching Word Vectors with Subword Information

Simple problem: word2vec/glove etc. ignore the internal structure of words

E.g., knowledge about *luck* is not used when learning a representation for *unlucky or luckily*

=> parameters are not shared => difficult to learn good vectors for rare words, and impossible for out-of-vocabulary words

Simple solution: learn vectors for character n-grams. Compose word vectors from their n-gram vectors.

Enriching Word Vectors with Subword Information

Quick recap: in skip-gram (Mikolov et al. 2013), the objective is to maximize:

$$\sum_{t=1}^{T} \sum_{c \in \mathcal{C}_t} \log p(w_c \mid w_t)$$

$w_1, \ldots, w_T$: the training corpus
C_t : set of indices of the context words around w_t
In English: the objective is to *predict well the context of a word given this word*

$p(w_c \mid w_t)$ is parameterized by the word vectors through a scoring function ***s***

$$s(w_t, w_c) = \mathbf{u}_{w_t}^{\top} \mathbf{v}_{w_c}$$

u and **v** above are taken from the input and output embedding matrices, resp.

Enriching Word Vectors with Subword Information

Proposed approach:

Each word is represented as a bag of **character n-grams**. E.g., for the word *where* and n=3:

<wh, whe, her, ere, re>

The < and > characters are added at the beginning and end of the word to keep prefix/suffix information.

New scoring function: $$s(w, c) = \sum_{g \in \mathcal{G}_w} \mathbf{z}_g^\top \mathbf{v}_c$$

G_w is the set of character n-grams in word w. z_g is the vector of the g^{th} n-gram
V_c is the vector of the context word c
=> w is represented as the sum of its n-gram vectors

Enriching Word Vectors with Subword Information

Quantitative results: word similarity and word analogy tasks in 7 languages
- similarity: better than original skipgram and CBOW on 6/7 datasets
- analogy: - improves on original skipgram and CBOW for syntactic tasks
  - no improvement for semantic tasks

Qualitative results:

query	tiling	tech-rich	english-born	micromanaging	eateries	dendritic
`sisg`	tile	tech-dominated	british-born	micromanage	restaurants	dendrite
	flooring	tech-heavy	polish-born	micromanaged	eaterie	dendrites
`sg`	bookcases	technology-heavy	most-capped	defang	restaurants	epithelial
	built-ins	.ixic	ex-scotland	internalise	delis	p53

Nearest neighbors of rare words using subword (sisg) and original (sg) skipgram

Enriching Word Vectors with Subword Information

	anarchy	chy	<anar	narchy
	monarchy	monarc	chy	<monar
	kindness	ness>	ness	kind
	politeness	polite	ness>	eness>
EN	unlucky	<un	cky>	nlucky
	lifetime	life	<life	time
	starfish	fish	fish>	star
	submarine	marine	sub	marin
	transform	trans	<trans	form
	finirais	ais>	nir	fini
FR	finissent	ent>	finiss	<finis
	finissions	ions>	finiss	sions>

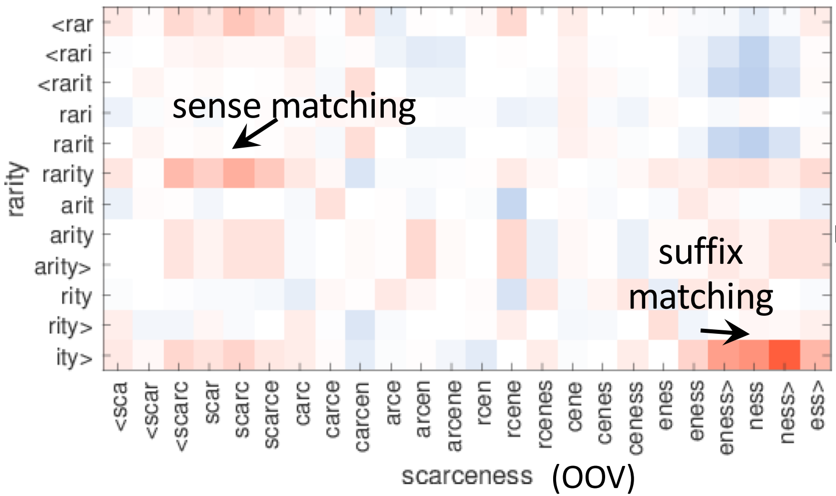
Most important character n-grams for selected words

Observations:

the most important n-grams tend to make sense and match:

- prefixes & suffixes
- morphemes
- verb inflections

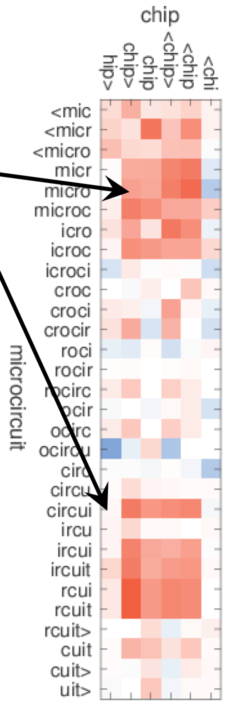
Enriching Word Vectors with Subword Information



(OOV)

The areas corresponding to *micro* and *circuit* match *chip* the most

(OOV)



Similarity between n-grams of in and out of vocabulary words

Observation: matches between n-grams are meaningful.

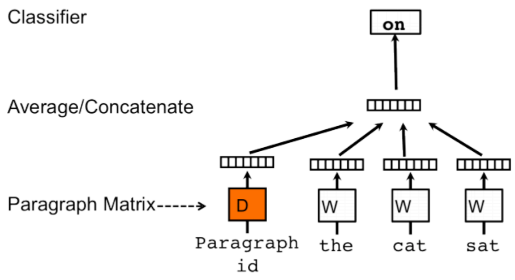
=> high quality vectors can be constructed for the OOV words (by summing the vectors of the n-grams)

OUTLINE

- Representation Learning for Text
  - SVD
  - Word2Vec
  - Fast Text Embeddings – subword information
  - **Document representations**
- NLP tasks and evaluation
  - GLUE, FLUE
  - French Linguistics

Distributed Representations of Sentences and Documents

- **Doc2vec**
- Paragraph or document vectors
- Capable of constructing representations of input sequences of variable length
- Represent each document by a dense vector
- Trained to predict words in the document
- paragraph vector and word vectors are averaged or concatenated to predict the next word in a context
- can be thought of as another word shared across all contexts in document

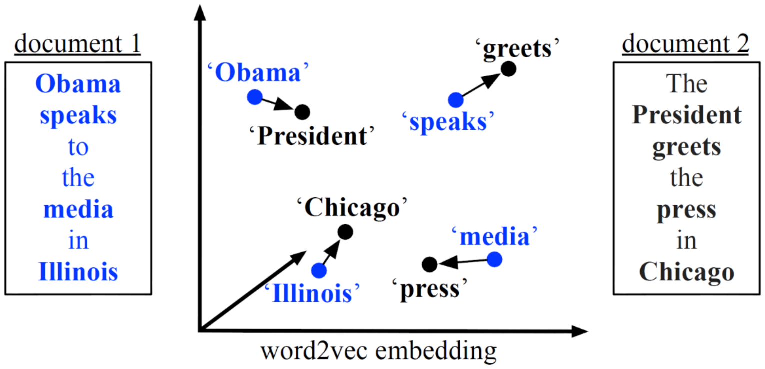


Model	Error rate (Positive/ Negative)	Error rate (Fine-grained)
Naïve Bayes (Socher et al., 2013b)	18.2 %	59.0%
SVMs (Socher et al., 2013b)	20.6%	59.3%
Bigram Naïve Bayes (Socher et al., 2013b)	16.9%	58.1%
Word Vector Averaging (Socher et al., 2013b)	19.9%	67.3%
Recursive Neural Network (Socher et al., 2013b)	17.6%	56.8%
Matrix Vector-RNN (Socher et al., 2013b)	17.1%	55.6%
Recursive Neural Tensor Network (Socher et al., 2013b)	14.6%	54.3%
Paragraph Vector	**12.2%**	**51.3%**

https://cs.stanford.edu/~quocle/**paragraph_vector**.pdf

Word Mover’s distance

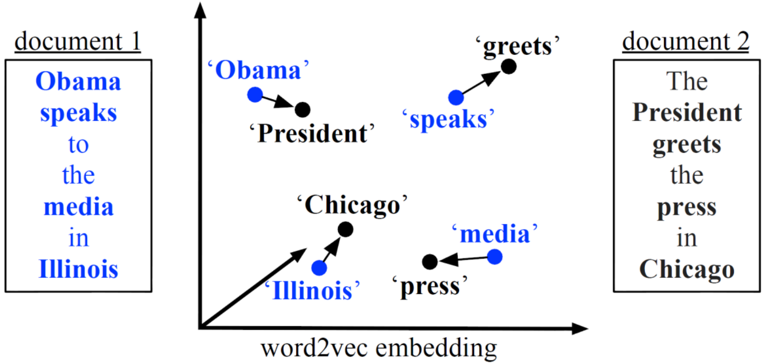
- “Edit” distance of 2 documents
- Based on word embedding representations
- Incorporate semantic similarity between individual word pairs into the document distance metric
- Based on “travel cost” between two words
- Calculates the cost of moving d to d’
- hyper-parameter free
- highly interpretable
- high retrieval accuracy

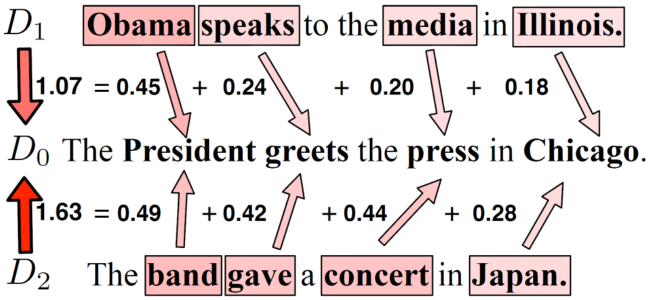


“minimum cumulative distance that all words in document 1 need to travel to exactly match document 2”

Word Mover's distance example

With BOW representation D_1 and D_2 are at equal distance from D_0. Word embeddings allow to capture the fact that D_1 is closer to D_0.





Kusner, M. J., Sun, E. Y., Kolkin, E. N. I., & EDU, W. From Word Embeddings To Document Distances. Proceedings of the 32nd International Conference on Machine Learning, Lille, France, 2015. JMLR: W&CP volume 37.

WMD

$d_i = \frac{c_i}{\sum_{j=1}^{n} c_j}$: Normalized frequency of word $\boldsymbol{i}$

$c(i,j) = \|\mathbf{x}_i - \mathbf{x}_j\|_2$ *word embeddings distance among* $\boldsymbol{i,j}$

- *Assume documents* $\boldsymbol{d, d'}$*.*
- *Assume each word* $\boldsymbol{i}$ *from* $\boldsymbol{d}$ *can be transformed into any word* $\boldsymbol{j}$ *in* $\boldsymbol{d'}$
- $\boldsymbol{T_{ij} \geq 0}$ denotes how much of word $\boldsymbol{i}$ in $\boldsymbol{d}$ travels to word $\boldsymbol{j}$ in $\boldsymbol{d'}$.
- To transform $\boldsymbol{d}$ entirely into $\boldsymbol{d'}$: entire outgoing flow from word $\boldsymbol{i}$ equals $\boldsymbol{d_i}$: .
- Transportation problem:
-

$$\min_{\mathbf{T}\geq 0} \sum_{i,j=1}^{n} \mathbf{T}_{ij} c(i,j)$$

$$\text{subject to: } \sum_{j=1}^{n} \mathbf{T}_{ij} = d_i \quad \forall i \in \{1,\ldots,n\}$$

$$\sum_{i=1}^{n} \mathbf{T}_{ij} = d'_j \quad \forall j \in \{1,\ldots,n\}.$$

$\sum_j \mathbf{T}_{ij} = d_i.$

$\sum_i \mathbf{T}_{ij} = d'_j$

- *Learn parameters* $\boldsymbol{T_{ij}}$ *tl*

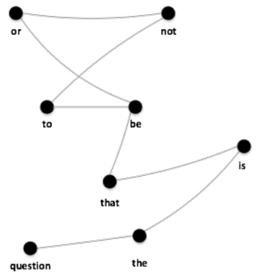
$$\sum_{i,j=1}^{n} \mathbf{T}_{ij} c(i,j)$$

Gaussian Document Representation from Word Embeddings

DASCIM @ EACL 2017

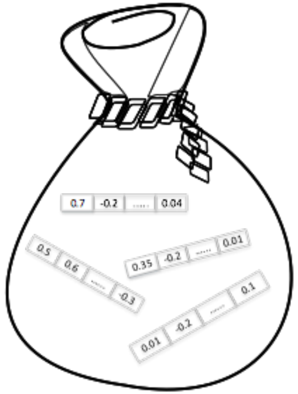
Document representation

- Bag-of-Words
  - Document-term matrix
  - high dimensionality
  - sparse vectors
  - dimensions=|V| |V|>10^6
  - unable to capture semantic similarity
- Graph-of-Words
  - captures co-occurrence
  - graph algorithms and techniques
  - graph kernels



Bag-of-Vectors

- Distributed representations of words
    - store contextual information in a low-dimensional vector
  - dimensionality reduction
  - dimensions=m $100<m<500$
  - able to capture semantic similarity between words
  - many learning methods (word2vec, GloVe, SVD)
- Document is represented by a bag-of-vectors
- Goal: meaningful document representations and distance metrics based on representations of their words



Related work

- Centroid of vectors *[Lebret and Collobert, 2015]*
- Paragraph Vector *[Mikolov, 2014]*
  - vector representations for paragraphs by inserting an additional memory vector in the input layer.
- Word Mover's Distance *[Kusner, 2015]*
  - cumulative edit distance between two documents
- CNN for document classification *[Kim, 2014]*
  - Use the high quality embeddings as input for Convolutional Neural Network

Gaussian Document Representation from Word Embeddings

- Assumption that words w present in a document are i.i.d. samples drawn from a multivariate Gaussian distribution
- Document is represented as a multivariate Gaussian distribution
  - mean vector
  - covariance matrix

$$\boldsymbol{\mu} = \frac{1}{|d|} \sum_{w \in d} \mathbf{w}$$

$$\boldsymbol{\Sigma} = \frac{1}{|d|} \sum_{w \in d} (\mathbf{w} - \boldsymbol{\mu})(\mathbf{w} - \boldsymbol{\mu})^T$$

- Words contained in the ... ed in the embeddings model are randomly initialized

Document Similarity

- centroid similarity

$$sim(\boldsymbol{\mu}_1, \boldsymbol{\mu}_2) = \frac{\boldsymbol{\mu}_1 \cdot \boldsymbol{\mu}_2}{\|\boldsymbol{\mu}_1\| \|\boldsymbol{\mu}_2\|}$$

- covariance similarity

$$sim(\boldsymbol{\Sigma}_1, \boldsymbol{\Sigma}_2) = \frac{\sum \boldsymbol{\Sigma}_1 \circ \boldsymbol{\Sigma}_2}{\|\boldsymbol{\Sigma}_1\|_F \times \|\boldsymbol{\Sigma}_2\|_F}$$

- $(\cdot \circ \cdot)$ is the Hadamard or element-wise product

- similarity between two documents

$$sim(d_1, d_2) = \alpha\big(sim(\boldsymbol{\mu}_1, \boldsymbol{\mu}_2)\big) + (1-\alpha)\big(sim(\boldsymbol{\Sigma}_1, \boldsymbol{\Sigma}_2)\big)$$

$$\alpha \in [0, 1]$$

- valid kernel function

Why Gaussian?

- Each document follows a distribution described by its topic
- Word embeddings capture lexico-semantic regularities
- Words with similar syntactic and semantic properties are found to be close to each other in the embedding space
- Semantically related words are localized in space
- Gaussian distributions capture a notion of centrality in space
- Gaussian parameterization justified
    - analytic convenience
    - Euclidean distances between embeddings correlate with semantic similarity

Experiments

Datasets

Dataset	# training examples	# test examples	# classes	vocabulary size	*word2vec* size
Reuters	5,485	2,189	8	23,585	15,587
Amazon	8,000	CV	4	39,133	30,526
TREC	5,452	500	6	9,513	9,048
Snippets	10,060	2,280	8	29,276	17,067
BBCSport	348	389	5	14,340	13,390
Polarity	10,662	CV	2	18,777	16,416
Subjectivity	10,000	CV	2	21,335	17,896
Twitter	3,115	CV	3	6,266	4,460

Baselines

- BOW-SVM
- NBSVM
- Centroid-SVM
- WMD-KNN
- CNN

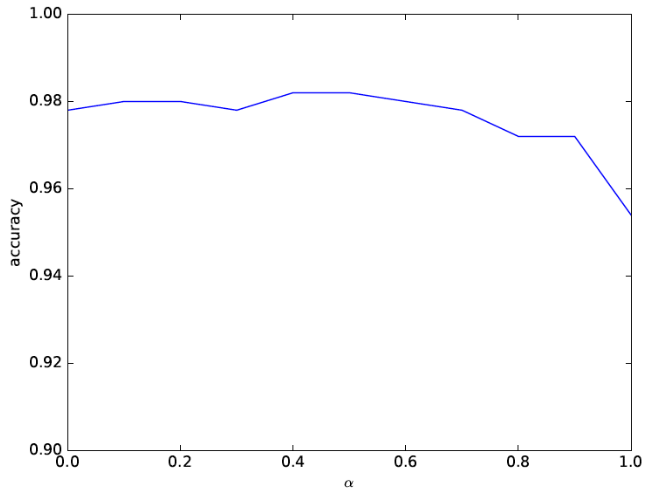
Results

Method \ Dataset	Reuters		Amazon		TREC		Snippets	
	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score
BOW (binary)	0.9571	0.8860	0.9126	0.9127	0.9660	0.9692	0.6171	0.5953
Centroid	0.9676	0.9171	0.9311	0.9312	0.9540	0.9586	0.8123	0.8170
WMD	0.9502	0.8204	0.9200	0.9201	0.9240	0.9336	0.7417	0.7388
NBSVM	**0.9712**	0.9155	0.9486	0.9486	0.9780	0.9805	0.6474	0.6357
CNN	0.9707	0.9297	0.9448	0.9449	0.9800	0.9800	**0.8478**	**0.8466**
Gaussian	**0.9712**	**0.9388**	**0.9498**	**0.9497**	**0.9820**	**0.9841**	0.8224	0.8244

Method \ Dataset	BBCSport		Polarity		Subjectivity		Twitter	
	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score
BOW (binary)	0.9640	0.9690	0.7615	0.7614	0.9004	0.9004	0.7467	0.6205
Centroid	0.9923	0.9915	0.7783	0.7782	0.9100	0.9100	0.7361	0.5727
WMD	0.9871	0.9866	0.6642	0.6639	0.8604	0.8603	0.7031	0.4436
NBSVM	0.9871	0.9892	**0.8698**	**0.8698**	**0.9369**	**0.9368**	**0.7852**	0.6191
CNN	0.9486	0.9461	0.8037	0.8031	0.9315	0.9314	0.7549	0.6137
Gaussian	**0.9974**	**0.9974**	0.8021	0.8020	0.9310	0.9310	0.7534	**0.6443**

Results

- Parameter a sensitivity
- TREC dataset
- Centroid performance drops significantly
- Highest accuracy a=0.5

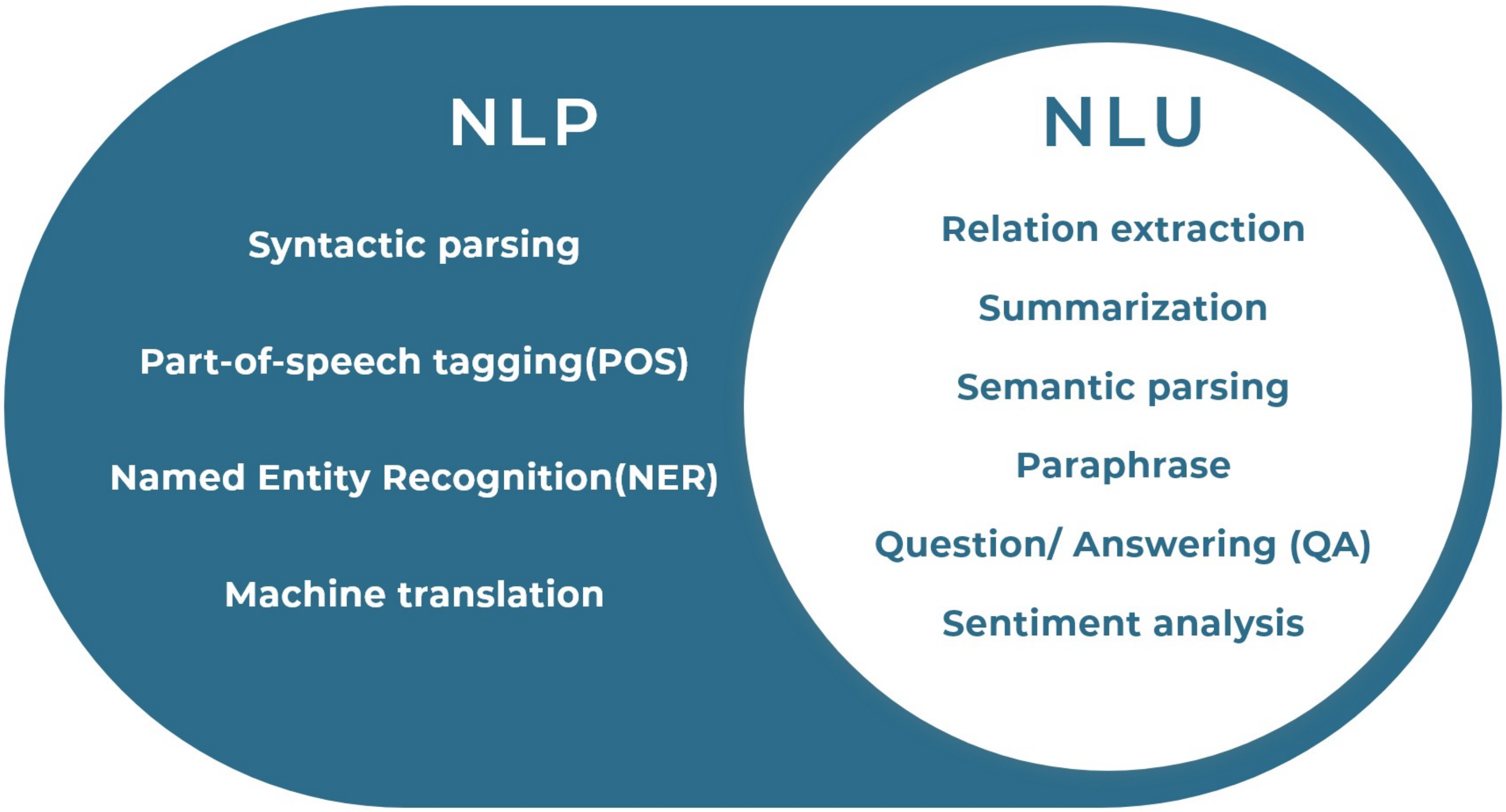


Conclusion

- Model each document as a Gaussian distribution based on the embeddings of its words
- Similarity between two documents based on the similarity of their distributions
- Empirical evaluation demonstrates the effectiveness of the approach across a range of data
- Performance gain is attributed to the high quality of the embeddings and the ability to effectively utilize them

OUTLINE

- Representation Learning for Text
  - SVD
  - Word2Vec
  - Fast Text Embeddings – subword information
  - Document Representations
- **NLP tasks and evaluation**
  - **GLUE, FLUE**
  - French Linguistics


NLP
Syntactic parsing
Part-of-speech tagging(POS)
Named Entity Recognition(NER)
Machine translation
NLU
Relation extraction
Summarization
Semantic parsing
Paraphrase
Question/ Answering (QA)
Sentiment analysis

Motivation

Nowadays, it's critical to develop NLU models with understanding beyond the detection of superficial correspondences between inputs and outputs, and to facilitate this development we need an evaluation test or a **benchmark** to evaluate language models.

GLUE [1] **Flaubert** [2] papers…

[1] https://arxiv.org/abs/1804.07461 [2] https://arxiv.org/abs/1912.05372

G.L.U.E

General Language Understanding Evaluation

- Collection of NLU tasks (Q/A, sentiment analysis, etc…)
- An online platform for model evaluation
- GLUE only considers data sets in English language
- GLUE only considers the ability to make predictions
- Based on 9 data sets that cover different sizes, text genres and difficulties
- In addition it has diagnostic evaluation data set

GLUE: tasks and datasets

Dataset	Description	Data example		Metric
CoLA	Is the sentence grammatical or ungrammatical?	"This building is than that one." = **Ungrammatical**	**acceptability (2 classes)**	Matthews
SST-2	Is the movie review positive, negative, or neutral?	"The movie is funny , smart , visually inventive , and most of all , alive ." = **.93056 (Very Positive)**	**only positive/negative sentiments**	Accuracy
MRPC	Is the sentence B a paraphrase of sentence A?	A) "Yesterday , Taiwan reported 35 new infections , bringing the total number of cases to 418 ." B) "The island reported another 35 probable cases yesterday , taking its total to 418 ." = **A Paraphrase**	**Similarity (2 classes)**	Accuracy / F1
STS-B	How similar are sentences A and B?	A) "Elephants are walking down a trail." B) "A herd of elephants are walking along a trail." = **4.6 (Very Similar)**	**Similarity (regression)**	Pearson / Spearman
QQP	Are the two questions similar?	A) "How can I increase the speed of my internet connection while using a VPN?" B) "How can Internet speed be increased by hacking through DNS?" = **Not Similar**	**Q/A task (2 classes)**	Accuracy / F1
MNLI-mm	Does sentence A entail or contradict sentence B?	A) "Tourist Information offices can be very helpful." B) "Tourist Information offices are never of any help." = **Contradiction**	**Entailment task (3 classes)**	Accuracy
QNLI	Does sentence B contain the answer to the question in sentence A?	A) "What is essential for the mating of the elements that create radio waves?" B) "Antennas are required by any radio receiver or transmitter to couple its electrical connection to the electromagnetic field." = **Answerable**	**Q/A task (3 classes)**	Accuracy
RTE	Does sentence A entail sentence B?	A) "In 2003, Yunus brought the microcredit revolution to the streets of Bangladesh to support more than 50,000 beggars, whom the Grameen Bank respectfully calls Struggling Members." B) "Yunus supported more than 50,000 Struggling Members." = **Entailed**	**Entailement task (2 classes)**	Accuracy
WNLI	Sentence B replaces sentence A's ambiguous pronoun with one of the nouns - is this the correct noun?	A) "Lily spoke to Donna, breaking her concentration." B) "Lily spoke to Donna, breaking Lily's concentration." = **Incorrect Referent**	**Inference task (2 classes)**	Accuracy
Diagnostic	This dataset do not envolve in evaluation but only to address certain phenomena in the language such as	A) I have never seen a hummingbird not flying. B) I have never seen a hummingbird. A-->B : **no entailement.** B-->A : **entailement.**	Inference task (3 classes)	R3 score

	Rank	Name	Model	Score
+	1	PING-AN Omni-Sinitic	ALBERT + DAAF + NAS	90.6
	2	ERNIE Team - Baidu	ERNIE	90.4
+	3	Alibaba DAMO NLP	StructBERT	90.3
	4	T5 Team - Google	T5	90.3
	5	Microsoft D365 AI & MSR AI & GATECH	MT-DNN-SMART	89.9
+	6	ELECTRA Team	ELECTRA-Large + Standard Tricks	89.4
+	7	Huawei Noah's Ark Lab	NEZHA-Large	88.7
+	8	Microsoft D365 AI & UMD	FreeLB-RoBERTa (ensemble)	88.4
	9	Junjie Yang	HIRE-RoBERTa	88.3
	10	Facebook AI	RoBERTa	88.1

F.L.U.E

French Language Understanding Evaluation

- Represents the same idea as GLUE but for the french language
- Contains 6 different datasets with different sizes, tasks and difficulties
- 3 from these datasets are from cross-lingual datasets
- The idea of FLUE came with Flaubert model to compare different french language models such as CamemBert

FLUE: tasks and datasets

Dataset	Domain	Task
CLS	Books/DVD/Music product reviews	Sentiment Analysis (2 classes)
PAWS-X	General domain	Paraphrase/Similarity (2 classes)
XNLI	Diverse Genres	Inference, NLI (3 classes)
French TreeBank	Daily newspaper	POS tag
French SemEval	Diverse Genres	Verb Sense
Noun Sense Disambiguation	Diverse Genres	Noun Sense

Model	Books	DVD	Music
MultiFiT[†]	91.25	89.55	93.40
mBERT[†]	86.15	86.90	86.65
CamemBERT	92.30	93.00	94.85
FlauBERT$_{\text{BASE}}$	93.10	92.45	94.10
FlauBERT$_{\text{LARGE}}$	**95.00**	**94.10**	**95.85**

[†] Results reported in (Eisenschlos et al., 2019).

OUTLINE

- Representation Learning for Text
  - SVD
  - Word2Vec
  - Fast Text Embeddings – subword information
- **NLP tasks and evaluation**
  - GLUE, FLUE
  - **French Linguistics (DaSciM)**

Large Scale French Linguistics Resources (DaSciM)

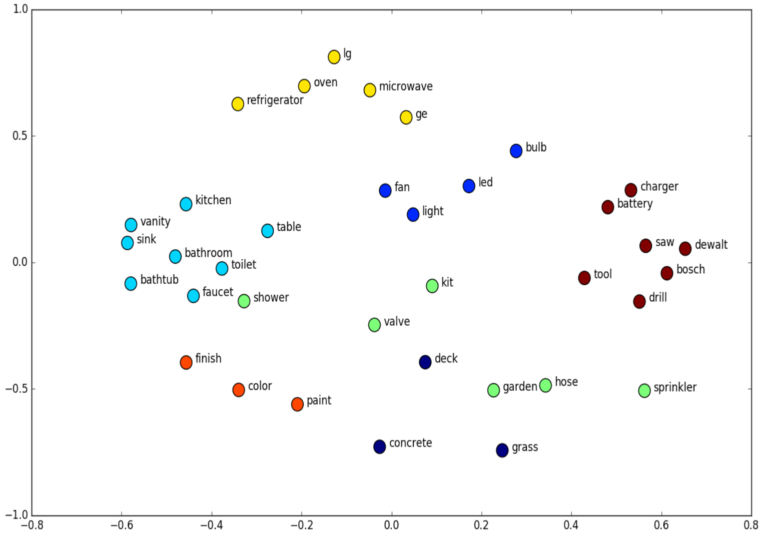
Data Collection

- Crawling more than 1M web pages using Heritrix for **45 days** to get **500GB** of text.
- Using FastText Language detection tool to extract **330GB** of French text.
- Applying deduplication to eliminate redundant data from the corpus which gives us **33GB** of deduplicated French raw text.
- Using Stanford NLP French tokenizer to tokenize the deduplicated text.

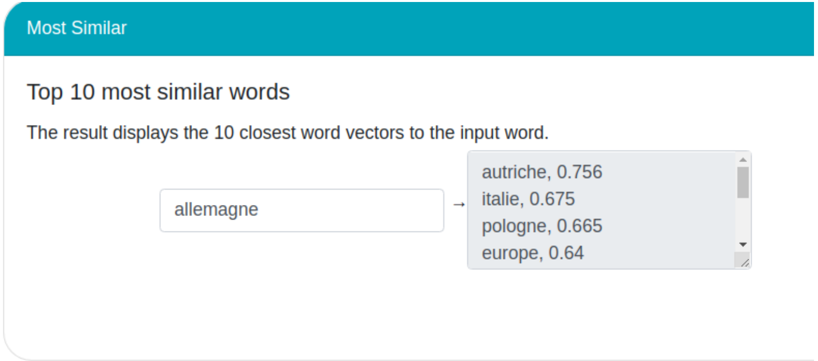
Large Scale French Linguistics Resources (DaSciM)

Word Embeddings

- Word embeddings are a class of algorithms where each word is represented as real-valued vector.
- The learning process of these vectors is either joint with a neural network model on some task or is an unsupervised process.
- Similar words in meaning have similar representation.



Training French Word Vectors



Training on:

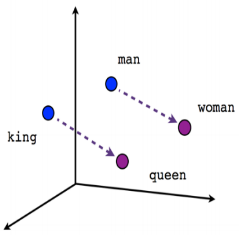
- 33GB French raw text crawled from the French web
- multiple pre-processing: French language detection, deduplication and tokenization.

Embeddings	VOC	Tool	Method	Corpus	Window
Fr_web_w5	0.8M	word2vec	CBOW	Fr_web	5
Fr_web_w20	4.4M	word2vec	CBOW	Fr_web	20
Fr_fl_w5	1M	word2vec	CBOW	Flaubert_data	5
Fr_fl_w20	6M	word2vec	CBOW	Flaubert_data	20

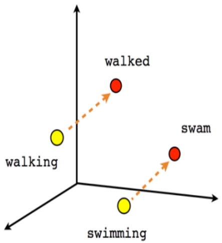
http://master2-bigdata.polytechnique.fr/

Word Analogy

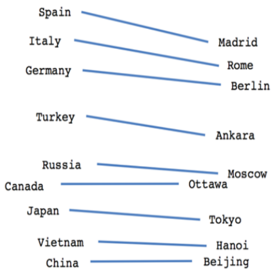
- Word embeddings evaluation method.
- Based on the assumption that a linear relation between word pairs indicates the quality of word embeddings.
- French word analogies dataset that contains **31 688** questions.



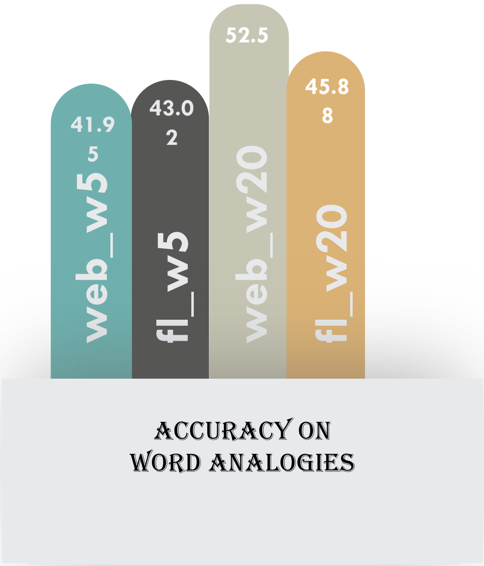
Male-Female



Verb tense



Country-Capital



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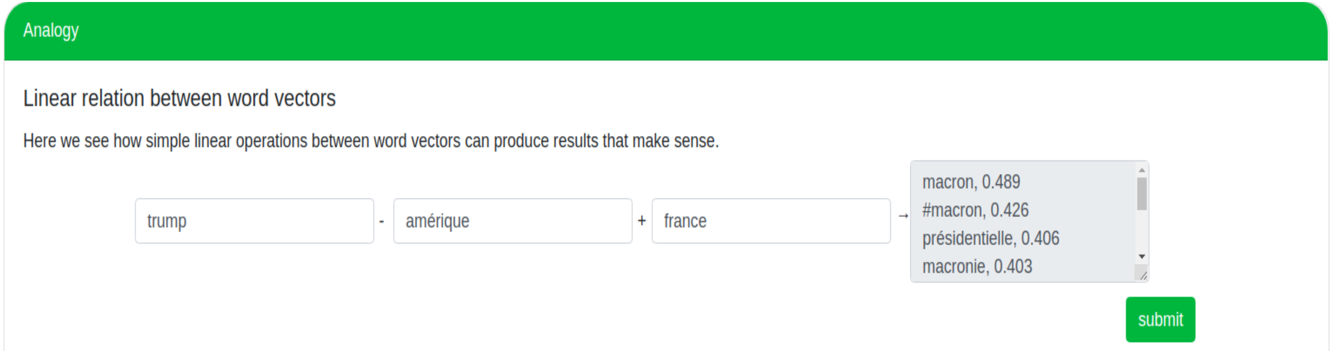
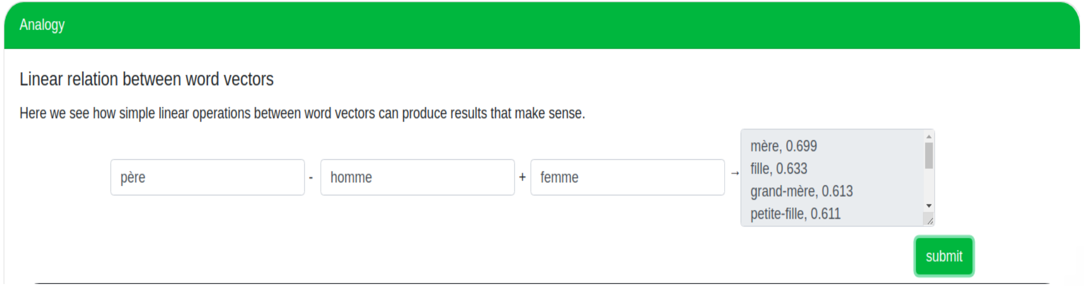
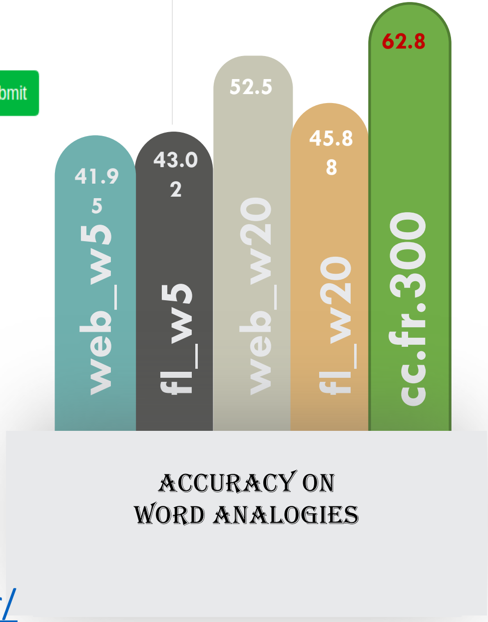
Word Analogy







http://master2-bigdata.polytechnique.fr/

French Language Understating Evaluation - FLUE

- A French language understanding evaluation benchmark.
- It contains many datasets that varies in subject, level of difficulty, size and degree of formality.

Dataset	Domain	Task
CLS	Product reviews	Sentiment analysis (Binary classification)
PAWS-X	General domain	Paraphrasing (Binary classification)
XNLI	Diverse genre	Natural language inference (3 classes)
NSD	Diverse domain	Noun sense

Cross Lingual Sentiment - CLS

- Amazon reviews with rating from 1 to 5 divided into three subsets: books, DVD and music.

- Each subset contains a balanced train and test set that contains around 1000 positive and 1000 negative samples.

PAWS-X - Paraphrasing (Binary classification)

- Binary classification task that aims to identify if there is a semantic relation between a pair of sentences or not.
- Wikipedia

high lexical overlap

Quora

Pair-sentence sample $\xrightarrow{\text{Translation+human judge}}$ PAWS-FR

- Dataset contains 49 401 training samples, 1 992 validation samples and 1 985 test samples.

XNLI - Natural language inference (3 classes)

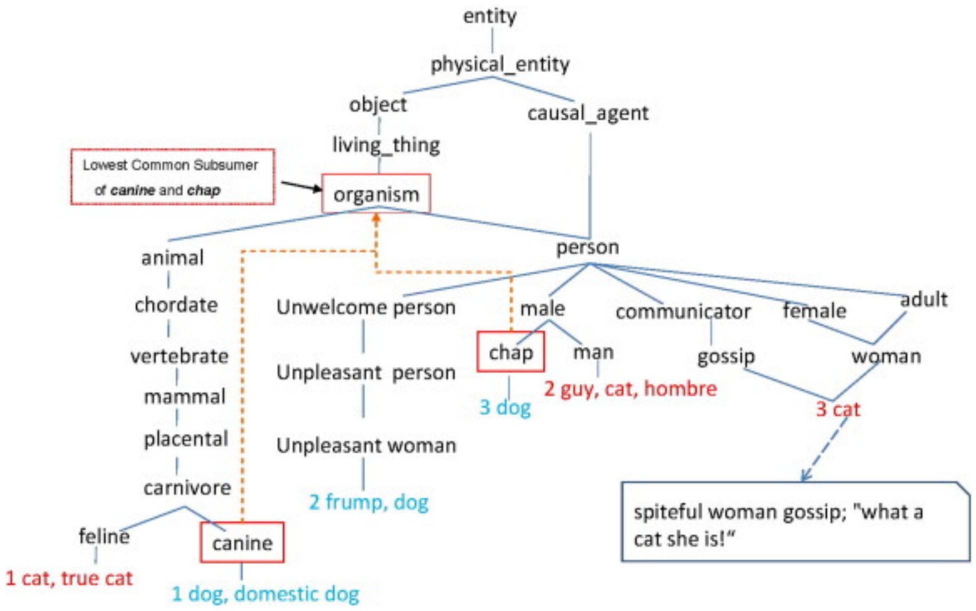
- Task of determining whether a “hypothesis” is true (entailment), false (contradiction), or undetermined (neutral) given a “premise”.
- **premise:** un vaste programme de rénovation devrait être achevé d’ici la fin de 2001.

  hypothesis: le programme de rénovation prendra fin avant le début de l’année 2001.

  label: contradiction.
- The dataset consists of **392 702** training samples, **2 491** validation samples and **5 010** test samples.

NSD - Noun sense

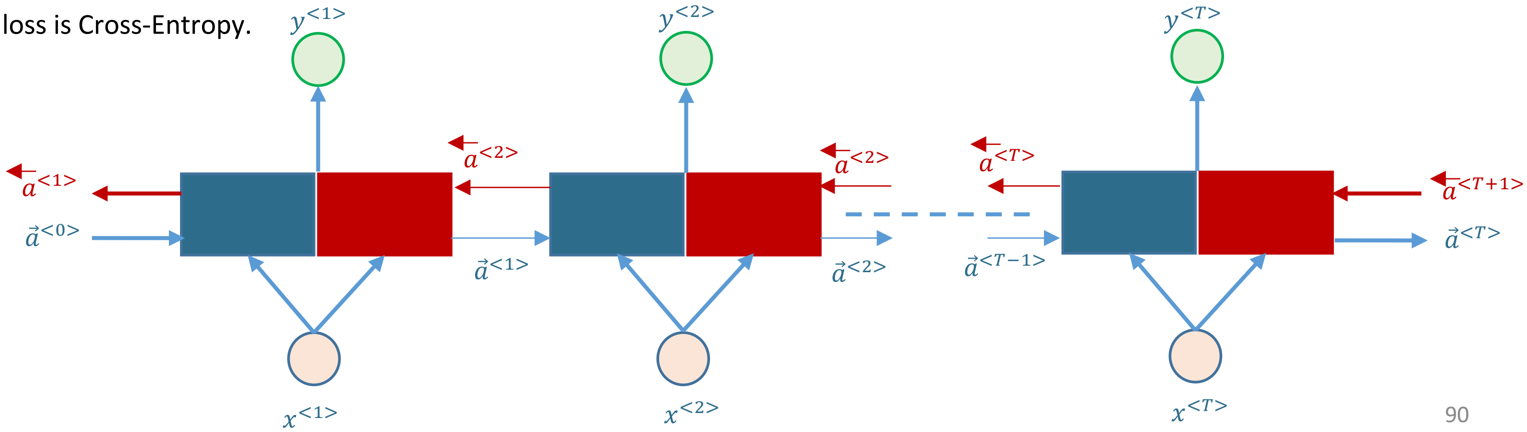
- The evaluation set that is composed of 306 sentences and 1 445 French annotated nouns translated from WordNet.
- The training set is resulted from translating **WordNet Gloss Corpus** to French.



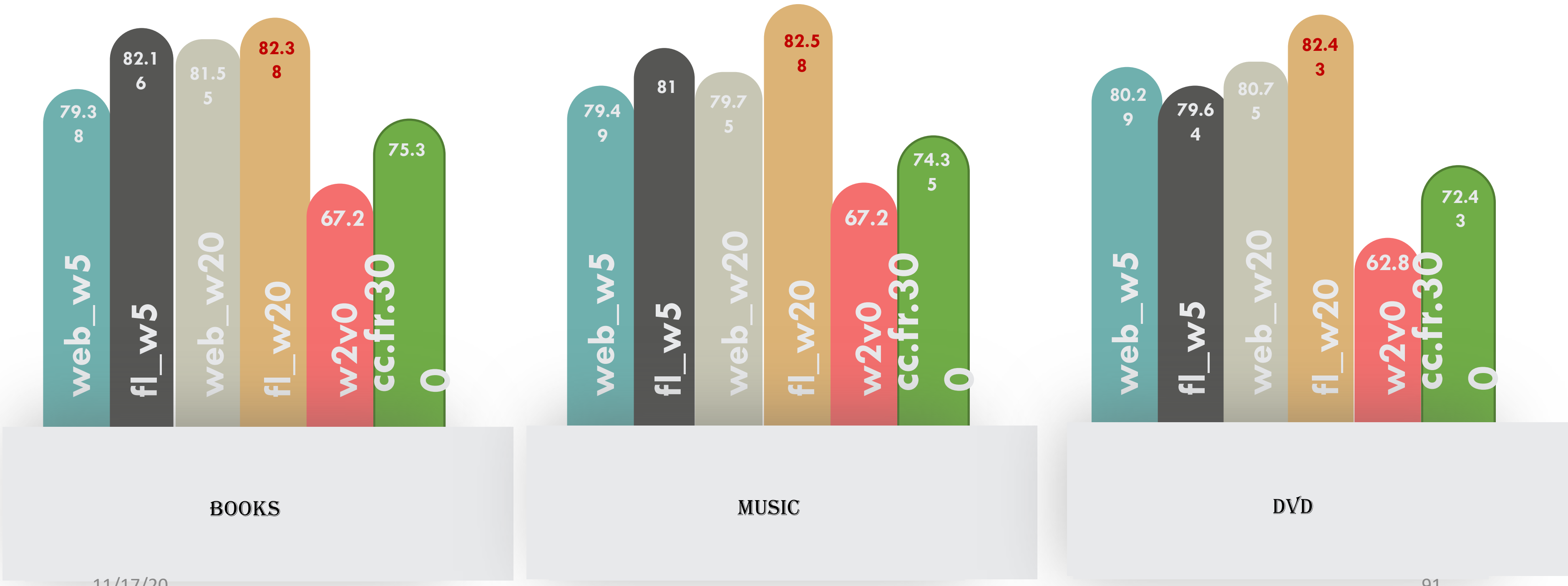
CLS using BiLSTM

BiLSTM/RNN for sentiment classification

- The output of both the previous and next steps are used as input to the current step.
- $\vec{a}^{<t>} = g_1(W_{\vec{a}\vec{a}}\,\vec{a}^{<t-1>} + W_{\vec{a}x}x^{<t>} + b_{\vec{a}}\,)$
- $\overleftarrow{a}^{<t>} = g_1(W_{\overleftarrow{a}\overleftarrow{a}}\,\overleftarrow{a}^{<t+1>} + W_{\overleftarrow{a}x}x^{<t>} + b_{\overleftarrow{a}}\,)$
- $y^{<t>} = g_2(W_{y\overleftarrow{a}}\,\overleftarrow{a}^{<t>} + W_{y\vec{a}}\vec{a}^{<t>} + b_y)$
- The used classification head is formed of: 0.1 dropout, 3000D projection layer, hyperbolic tangent activation, 0.1 dropout, 2D projection layer (classes number) and finally soft-max to find the probability of each class.
- The used loss is Cross-Entropy.

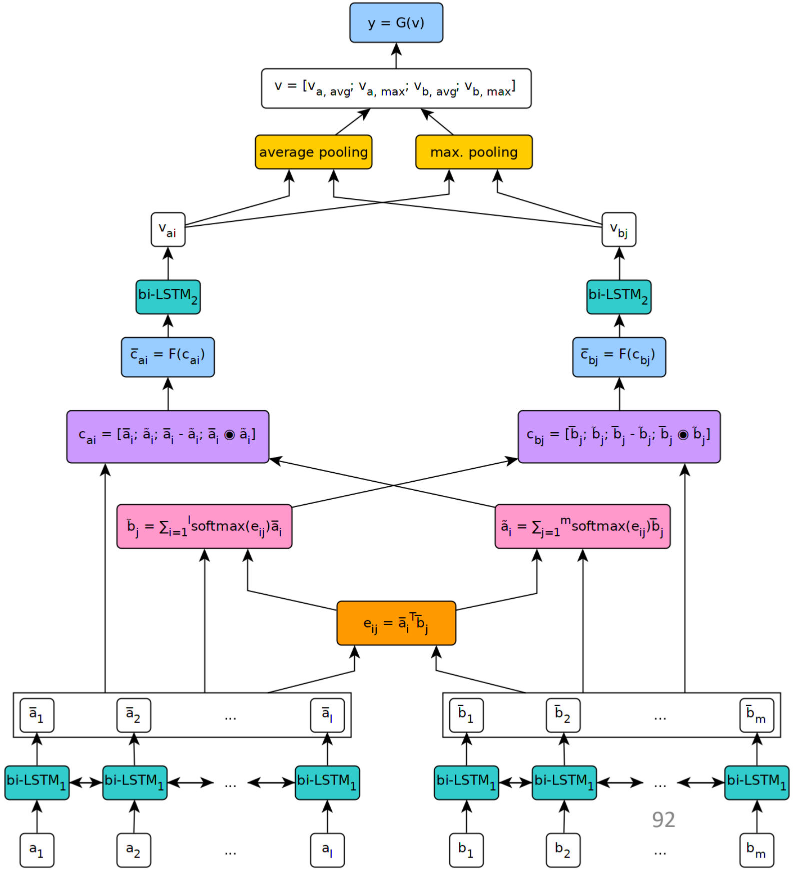


Accuracy On CLS using BiLSTM

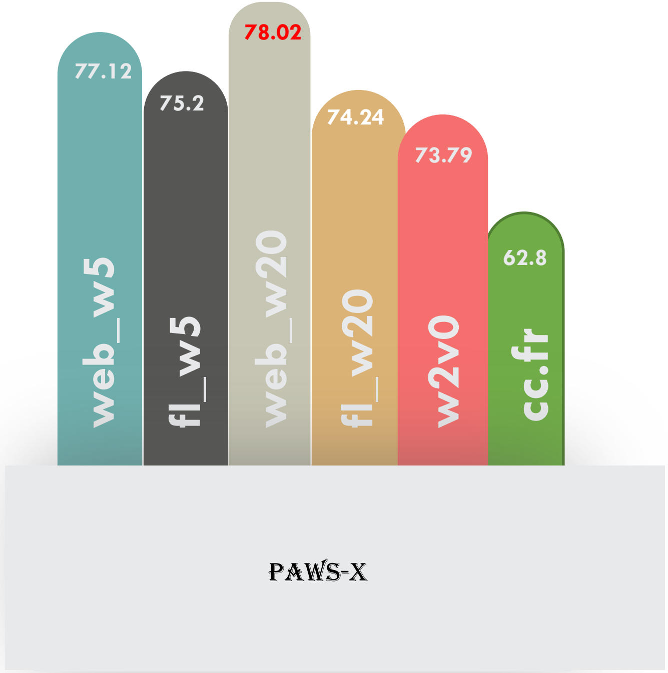


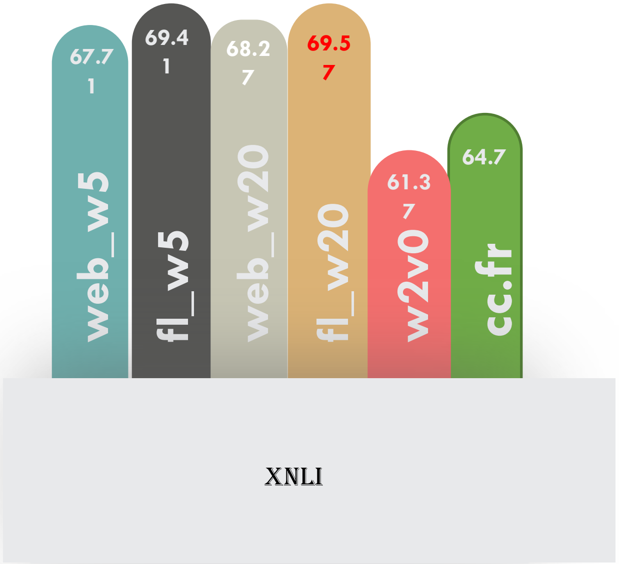
ESIM - Enhanced Sequential Inference Model

- Based on representing each word by its meaning in the first sentence using BiLSTM and by its relation with each word in the second sentence.
- The classification head is the same as sentiment prediction used in CLS dataset.
- The used loss to finetune the model is Cross-Entropy.



Accuracy On PAWS-X ανδ XNLI using ESIM

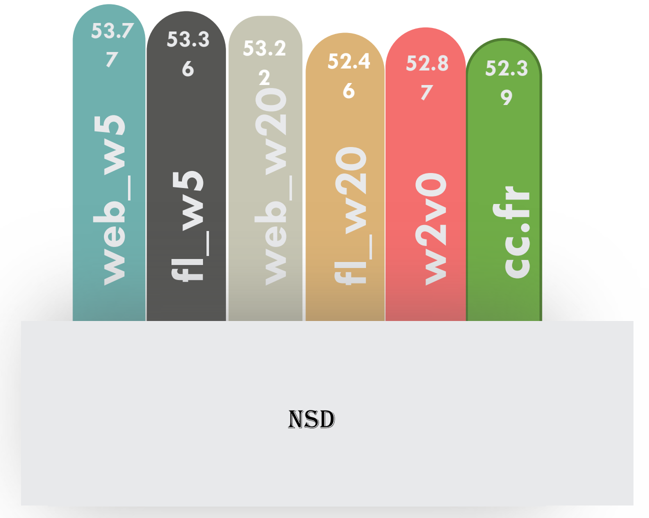




F1 Score (%) on NSD

- To finetune The embeddings on NSD task, we used stack of 6 transformer encoder layers.

- The output is then forwarded to a soft-max layer to choose the meaning of the word with the highest probability.



THANK YOU

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- P. Meladianos: Word embeddings part

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