PSL
UNIVERSITÉ PARIS

Word Embeddings and Translation

WE_HGA

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Plan

I. Supervised setting
    A. “Classical” approach
        1. Theory
        2. Results
    B. Procrustes method
        a. Motivation
        b. Results
II. Unsupervised setting
    A. Unsupervised theory
    B. Results

Supervised Setting - Classical approach

Final objective

“Hello!” ⟶ “Bonjour!”

Words to Vectors

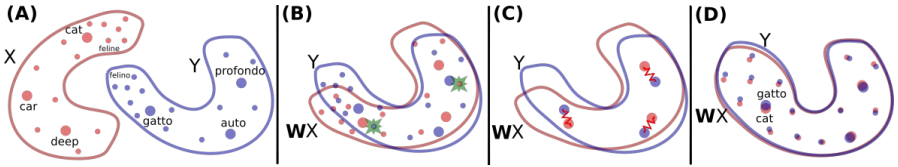
“Hello!” —embedding→ $x_i = \begin{bmatrix} 2{,}3 \\ 3{,}7 \\ \dots \\ 0{,}6 \end{bmatrix} \in \mathbb{R}^d$

Basic idea: similar words are closed in a sentence (Harris, 1954)

Knowing a dictionary of elements $\{x_i, y_i\}$

$$\min_W \sum_i \|Wx_i - y_i\|^2$$

Exploiting Similarities among Languages for Machine Translation, Mikolov et al., 2013



Word Translation Without Parallel Data, Conneau et al., 2017

Supervised Setting - Classical approach

Embedding

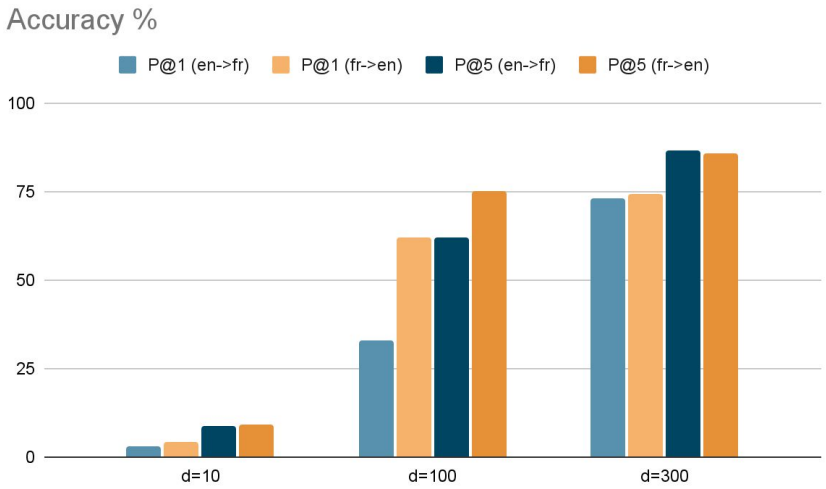
- FastText (from Meta)

Data

- dictionaries from MUSE (Meta)
- Train set : 10k words
- Test set: 1k words

Evaluation

- Cosine distance (not squared loss)
- kNN to find closest words



Supervised Setting - Procrustes method

$$W^\star = \underset{W \in M_d(\mathbb{R})}{\operatorname{argmin}} \|WX - Y\|_{\mathrm{F}}$$

$$W^\star = \underset{W \in O_d(\mathbb{R})}{\operatorname{argmin}} \|WX - Y\|_{\mathrm{F}} = UV^T, \text{with } U\Sigma V^T = \mathrm{SVD}(YX^T)$$

➡ Ensures that the monolingual quality of the embeddings is preserved

See : Chao Xing, Dong Wang, Chao Liu, and Yiye Lin. Normalized word embedding and orthogonal transform for bilingual word translation. Proceedings of NAACL, 2015

Supervised Setting - Procrustes method

	EN-FR P@1	EN-FR P@5	FR-EN P@1	FR-EN P@5	EN-TR P@1	EN-TR P@5	TR-EN P@1	TR-EN P@5
SGD	**73.4**	**86.4**	**75.4**	**85.8**	**75.2**	**86.0**	**83.0**	**93.2**
Procrustes alignement	**79.6**	**90.0**	**81.8**	**88.8**	**86.0**	**93.0**	**92.8**	**96.0**

*Word translation **P@1** and **P@5** for 2 language pairs (using d=300 **fastText** embeddings).*

*We consider **1000 test queries** with **10k target words** for each language pair.*

Generative Adversarial Networks

Two player game

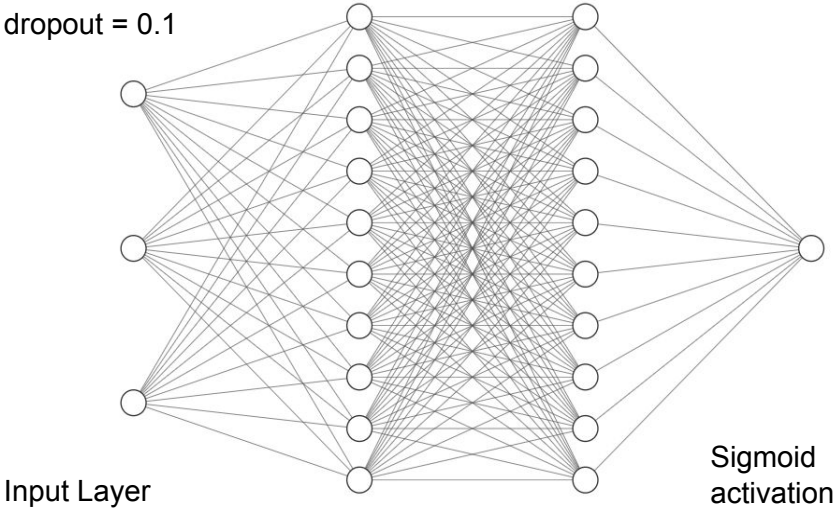
Mapping

$$\mathcal{L}_W(W|\theta_D) = -\frac{1}{n}\sum_{i=1}^{n}\log P_{\theta_D}(\text{source}=0|Wx_i) - \frac{1}{m}\sum_{i=1}^{m}\log P_{\theta_D}(\text{source}=1|y_i)$$

Discriminator

$$\mathcal{L}_D(\theta_D|W) = -\frac{1}{n}\sum_{i=1}^{n}\log P_{\theta_D}(\text{source}=1|Wx_i) - \frac{1}{m}\sum_{i=1}^{m}\log P_{\theta_D}(\text{source}=0|y_i)$$

Discriminator



2 Hidden Layers of size 1028

Generator

$$\begin{pmatrix} \ddots & & & & & \\ & \ddots & & & & \\ & & \ddots & & & \\ & & & \ddots & & \\ & & & & \ddots & \\ & & & & & \ddots \end{pmatrix}$$

Linear mapping W of size 300x300

Optimizer for discriminator/generator : SGD

What should we do next ?

Improve our training method for the GAN