Multilingual NLP

5. Cross-Lingual Word Embeddings

(+ Multilingual Resources)

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Image: Alexander Mikhalchyk

After this lecture, you'll...

- Know what cross-lingual word embeddings (CLWEs) are
- Understand methods for inducing CLWEs from scratch
- Understand how to induce CLWEs from monolingual embeddings
- Know the limitations of unsupervised induction of CLWEs
- Be able to evaluate the quality of CLWEs
- Be aware of resources with word/sentence translations

Content

- **Cross-Lingual Word Embeddings**
  - Joint Training (from scratch)
  - Projection-Based CLWEs
  - Unsupervised Induction of CLWEs
- Evaluation of CLWEs

Cross-Lingual Word Embeddings

- A **semantic vector space** in which words with similar meaning have similar vectors
  - Whether they come from the same language or from different languages.

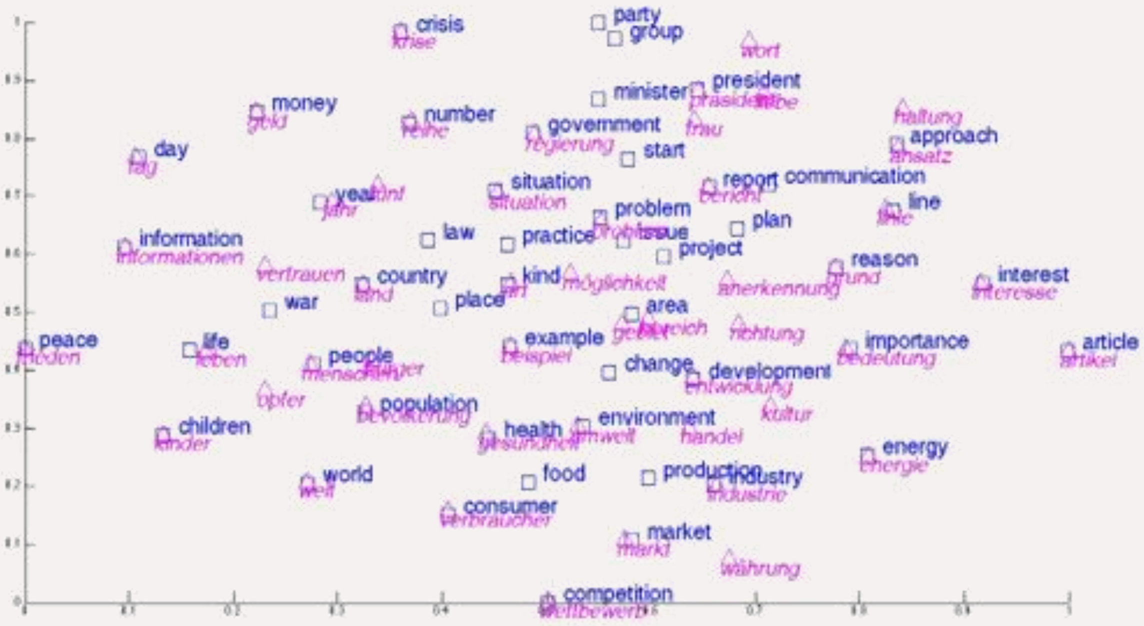

Image from: Luong, M. T., Pham, H., & Manning, C. D. (2015). [Bilingual word representations with monolingual quality in mind](). *Proc. 1st Workshop on vector space modeling for natural language processing* (pp. 151-159).

Cross-Lingual Word Embeddings

Ruder, S., Vulić, I., & Søgaard, A. (2019). A Survey of Cross-Lingual Word Embedding Models. Journal of Artificial Intelligence Research, 65, 569-631.

- Typology of methods for inducing Cross-Lingual Word Embeddings
  - **Type of bilingual / multilingual signal**
    Document-level, sentence-level, word-level, no signal (i.e., unsupervised)
  - **Comparability**
    Parallel texts, comparable texts, not comparable (i.e., randomly aligned)
  - **Point (time) of alignment**
    Joint embedding models vs. *Post-hoc alignment*
  - **Modality**
    Text only vs. using images for alignment

Content

- **Cross-Lingual Word Embeddings**
  - **Joint Training (from Scratch)**
  - Projection-Based CLWEs
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Joint CLWE Models

- Joint Cross-Lingual/Multilingual Word Embedding approaches induce embeddings of words from both/all languages simultaneously

- Using different types of (gold) bilingual signal:
  - Word translations
    - Easier/cheaper to obtain (+)
    - Less reliable signal, words out of context (-)
  - Sentence translations
    - More difficult/expensive to obtain (-)
    - Richer signal for aligning representations between languages (+)

Joint CLWEs with Word Translations

- Input
  - Dictionary of word translations $D = \{(w^k_s, w^k_t)\}_k$
  - Source language corpus C_s and vocabulary V_s
  - Target language corpus C_t and vocabulary V_t
- Q: Where to get D from?
  - Massively multilingual lexico-semantic resources!
  - **BabelNet**, PanLex, …
  - BabelNet covers over 500 languages
    - Caveat: not all languages have same coverage
  - PanLex covers 5,700 languages
    - Caveat: very low coverage for most languages

BabelNet

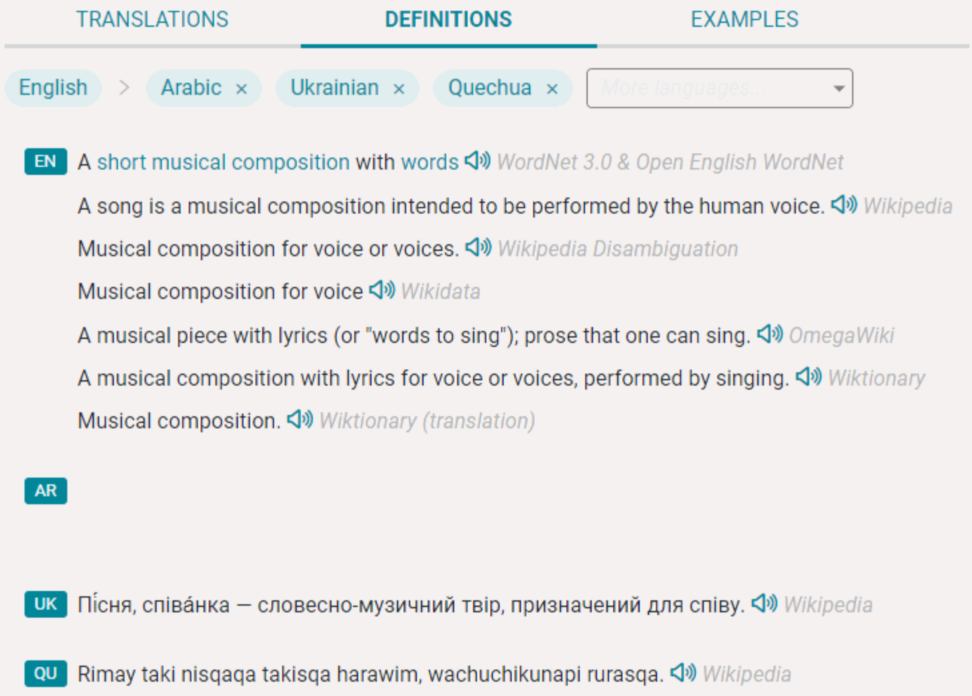
PanLex

BabelNet

- Massively multilingual lexico-semantic network
  - Effectively, a **graph**
  - Nodes are so-called **synonym sets** (synsets)

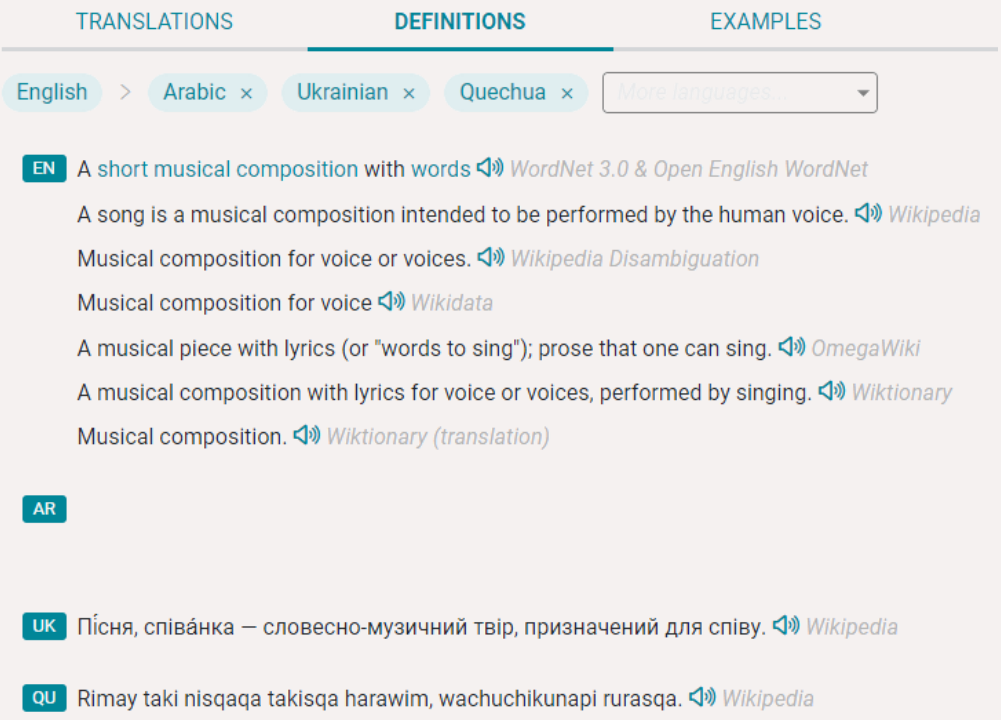
BabelNet

Synset ID



BabelNet

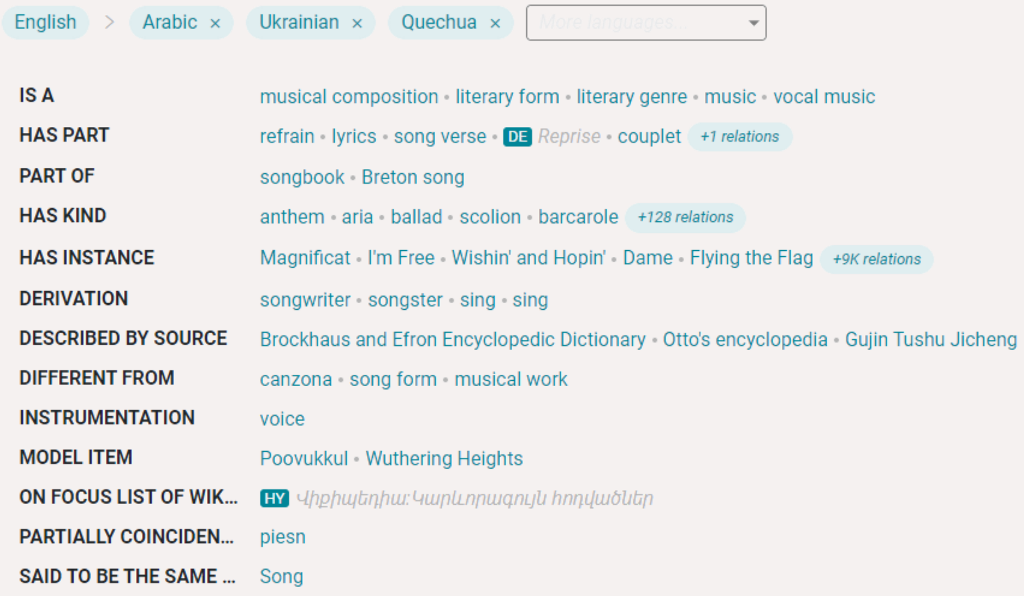
- Massively multilingual lexico-semantic network
  - Effectively, a **graph**
  - Nodes are so-called **synonym sets** (synsets)
    - Multilingual glosses (definitions) available



BabelNet

- Massively multilingual lexico-semantic network
  - Effectively, a **graph** with typed edges
  - Nodes are so-called synonym sets (synsets)
  - Edges are lexico-semantic relations between synsets, e.g.:
    - Hypernymy (is-a)
    - Meronymy (part-of)
    - …

BabelNet



Joint CLWEs with Word Translations

- Word-level alignments: $D = \{(w^k_s, w^k_t)\}_i$
- Source language corpus C_s and vocabulary V_s
- Target language corpus C_t and vocabulary V_t

- Idea: modify the word embedding model (e.g., Skip-Gram) so that words that are mutual translations <u>share the embedding vector</u>
  - I.e., for each pair (w^i_s, w^i_t) from D, enforce $\mathbf{x}^k_s = \mathbf{x}^k_t$

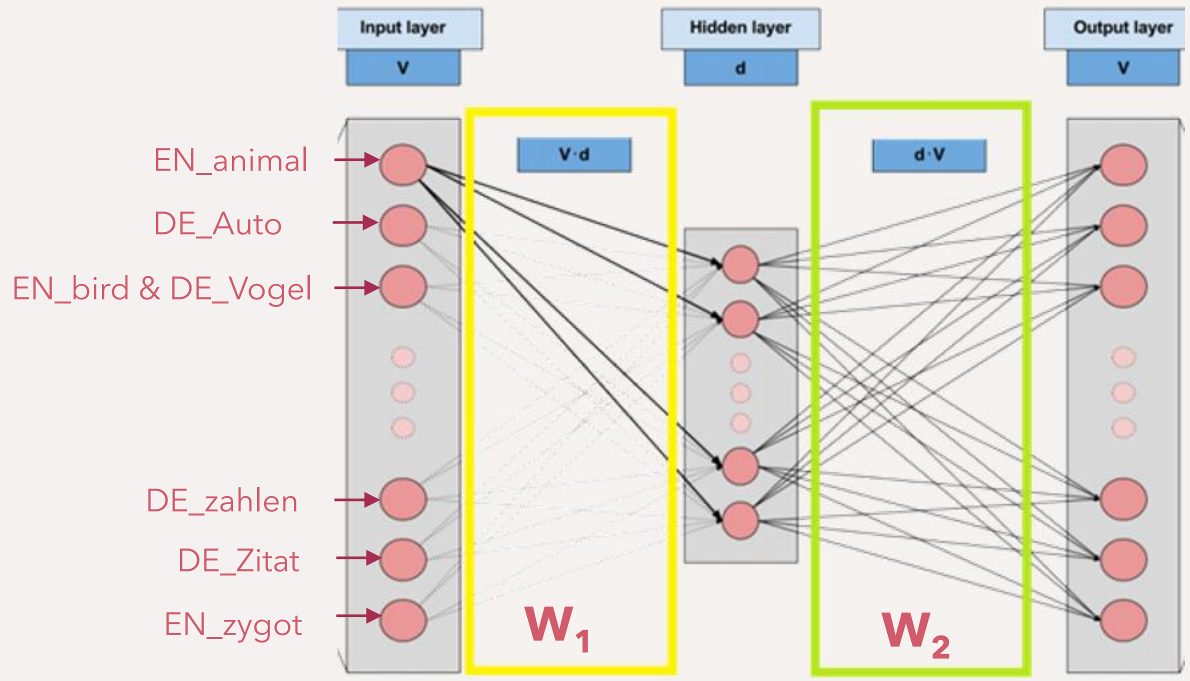
- Joint vocabulary $V = V_s \cup V_T$
  - Corresponding joint embedding matrices: $\mathbf{W}_1 \in \mathbb{R}^{|V| \times d}$ and $\mathbf{W_2} \in \mathbb{R}^{d \times |V|}$
  - Shared embeddings $\mathbf{x}^k_1$ and $\mathbf{x}^k_2$ for mutual translations w^k_s and w^k_t

Joint CLWEs with Word Translations

- Training data: simple <u>concatenation</u> of the corpora in both languages
- Example: EN source, DE target
  - D = {..., (*bird*, *Vogel*), ...}

Context (EN): *blue **bird** flies over the nest...*
Context (DE): *Gesang des roten schönen **Vogels** ...*

  - Tied vectors of word translations <u>drive the representational alignment</u> between languages



Joint CLWEs with Sentence Translations

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- Example: Bilingual Skip-Gram (Bi-Skip-Gram) model of Luong et al.

- Parallel sentences required
  - A model for word alignment also needed
  - We'll cover word alignment in Lecture 8

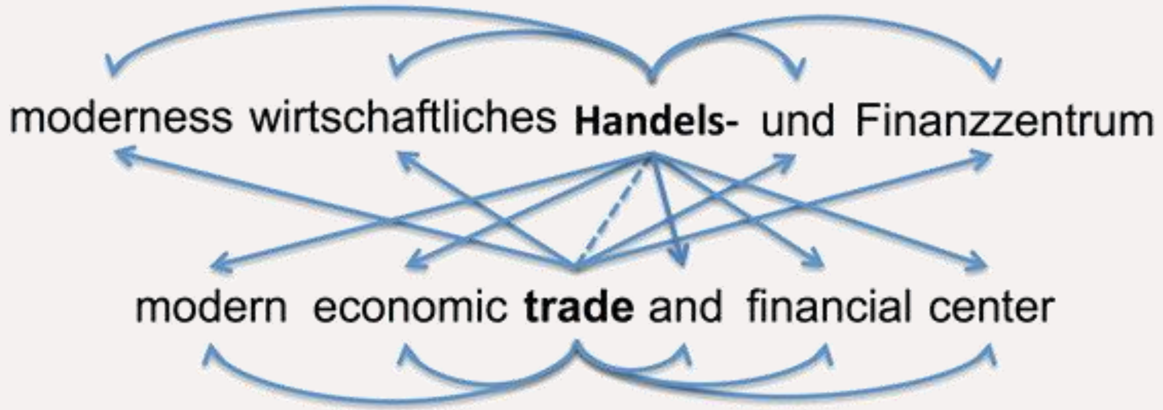

Image from: Luong et al.

Joint CLWEs with Sentence Translations

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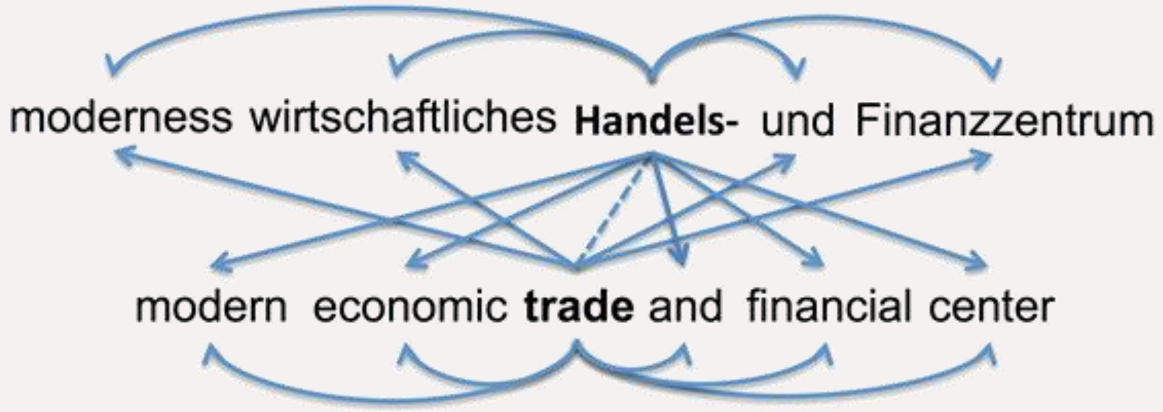
- Example: Bilingual Skip-Gram (Bi-Skip-Gram) model of Luong et al.
- Parallel sentences required

- Monolingual (both languages):
  - *Handels- → moderness*
  - *Handels- → wirtchaftliches*
  - ...
  - *trade → modern*
  - *trade → economic*
  - ...



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- Example: Bilingual Skip-Gram (Bi-Skip-Gram) model of Luong et al.
- Parallel sentences required

- Cross-lingual (both languages):
  - *Handels-* → *modern*
  - *Handels-* → *economic*
  - …
  - *trade* → *moderness*
  - *trade* → *wirtschaftliches*
  - …

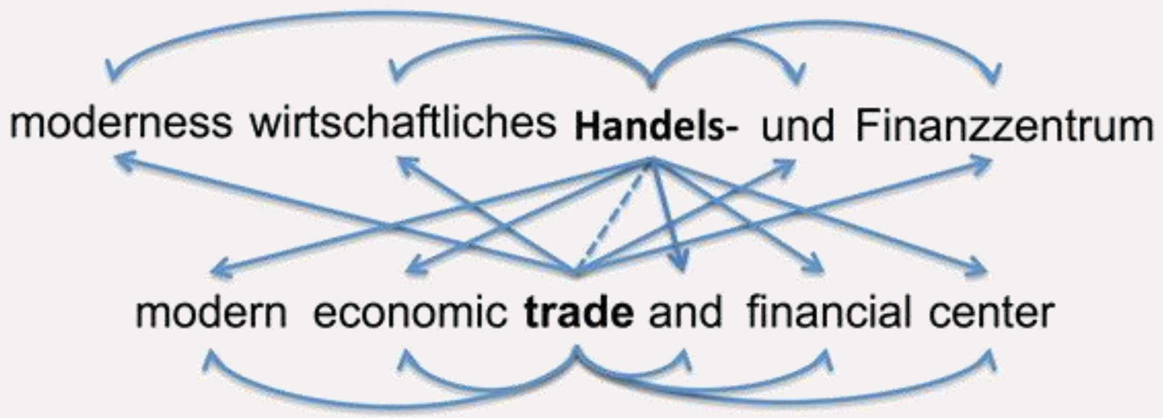

Image from: Luong et al.

Sentence Translations

- Q: Where to get parallel sentences from?
- Parallel corpora is the main training data for **machine translation**
  - Collecting it (manually, automatically, semi-automatically) has therefore been a major focus in MT
  - We will discuss approaches for creating parallel data in Lecture 9
- Some prominent sources of parallel data
  - Opus: Aggregator of all Open-Source parallel corpora
  - WikiMatrix: automatically created from Wikipedia
    - Based on multilingual sentence encoders (Lecture 10)
    - „Quasi-parallel" – not manually curated
    - 85 languages and 1620 language pairs
  - Multi-Bible: Manual Bible translations exist in 1500+ languages
    - Multi-parallel: sentences aligned across many (all) languages

Content

- **Cross-Lingual Word Embeddings**
  - Joint Training (from Scratch)
  - **Projection-Based CLWEs**
  - Unsupervised Induction of CLWEs
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Projection-Based CLWEs

- Q: What could be the main shortcoming of joint CLWE models?
  - Let's say we have N languages
  - And we need words from all N in a joint embedding space

- For each language pair: train a bilingual model from scratch
- For a multilingual space:
  - Let's say we have a pivot language (commonly English)
  - We induce N-1 bilingual spaces EN-L2
  - Q: how to align these N-1 spaces?

  - Q: Multilingual Skip-Gram?
    - We'd need multi-parallel corpora – usually very limited in size

Projection-Based CLWEs

- On the other hand, pretrained monolingual word embeddings exist for very many languages
- Idea: can we (cheaply) align monolingual embedding spaces post-hoc?
- To get a multilingual word embedding space for N languages :
  1. Train N monolingual spaces
  2. Learn N-1 (cheap) alignments (N-1 languages to EN as pivot)
- Let $\mathbf{X}_{L1} \in \mathbb{R}^{|Vs| \times d}$ and $\mathbf{X}_{L2} \in \mathbb{R}^{|Vt| \times d}$ be the independently trained monolingual embeddings of two languages L1 and L2
- **Projection-based CLWEs**: find an „alignment" between $\mathbf{X}_{L1}$ and $\mathbf{X}_{L2}$ such that words with similar meaning (across langs) get similar vectors

Projection-Based CLWEs

- **Post-hoc alignment** of monolingual word embedding spaces

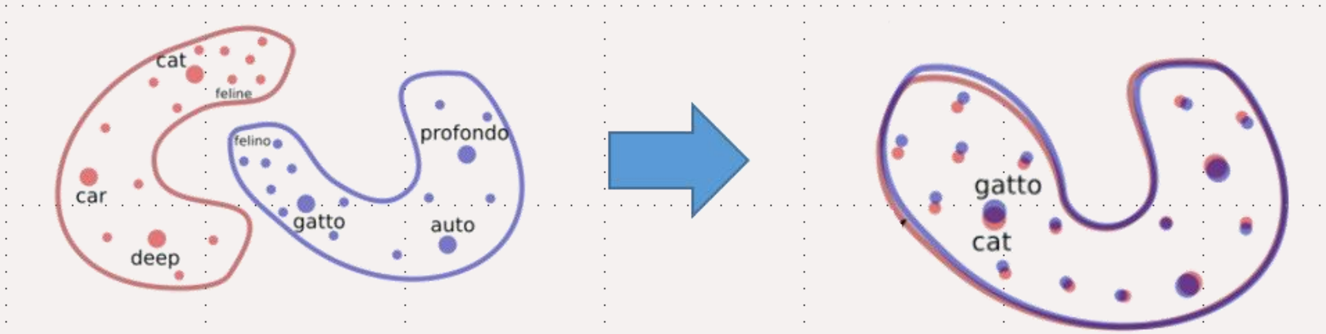
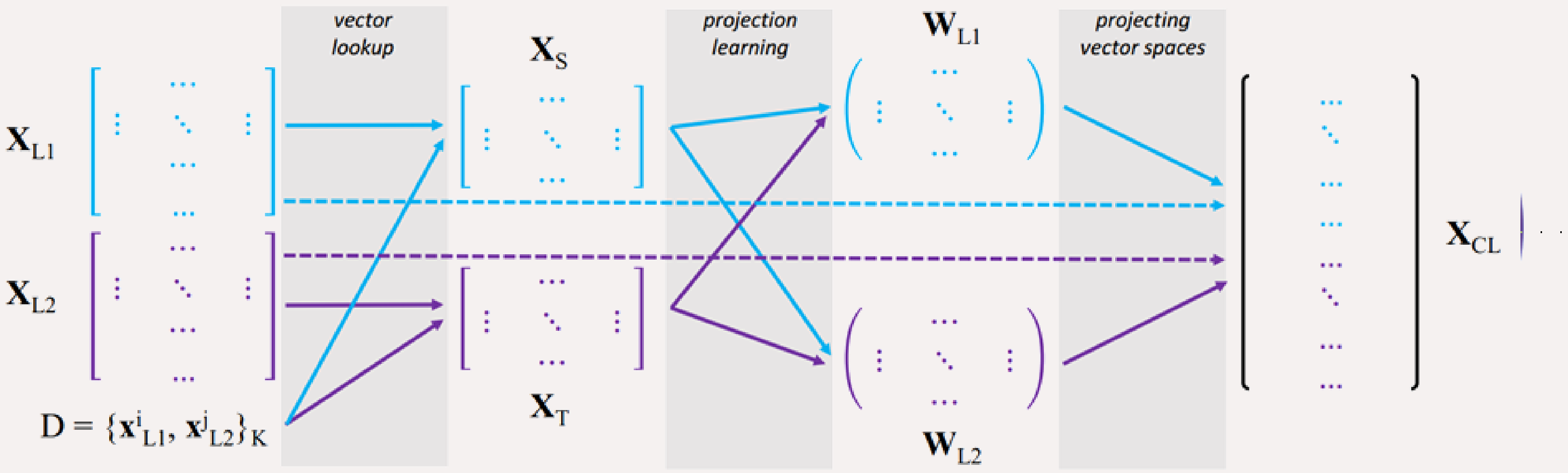


Image from: Lample, G., Conneau, A., Ranzato, M. A., Denoyer, L., & Jégou, H. (2018) [Word translation without parallel data](). In *International Conference on Learning Representations*.

- In general, we are looking for functions f and g that produce a <u>meaningful bilingual embedding space</u> $f(\mathbf{X}_{L1}|\boldsymbol{\theta}_{L1}) \cup g(\mathbf{X}_{L2}|\boldsymbol{\theta}_{L2})$

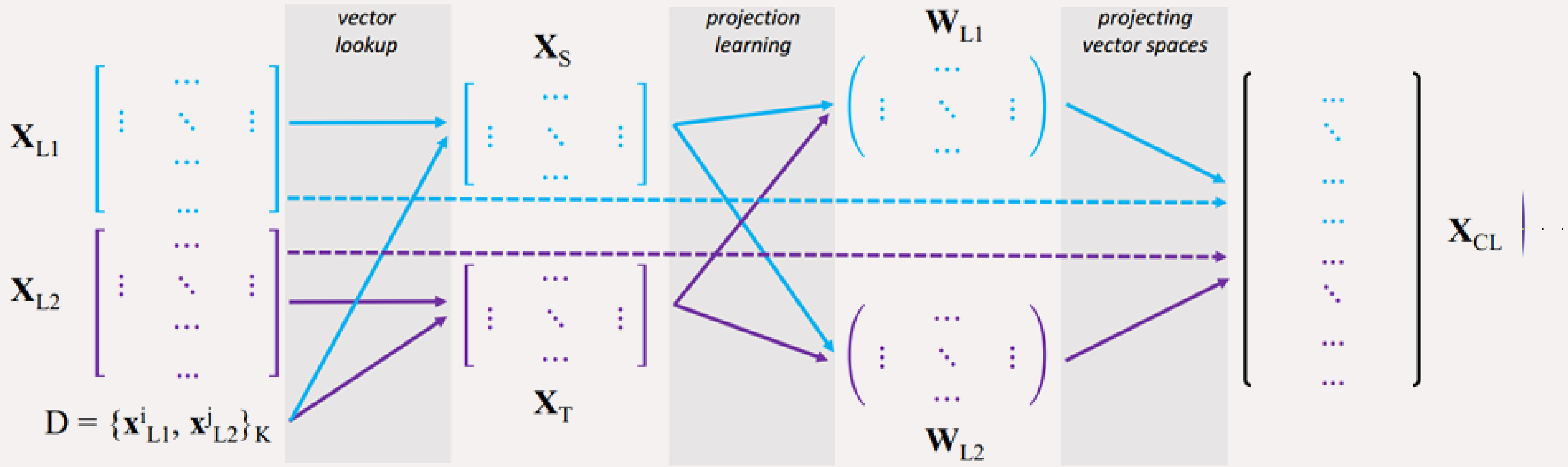
Projection-Based CLWEs

- **Post-hoc alignment** of independently trained monolingual word embedding spaces
  - Alignment based on word translation pairs, **D =** $\{(\mathbf{x}^k_{L1}, \mathbf{x}^k_{L2})\}_k$ is the set of word embedding pairs between the languages corresponding to pairs of mutual translations



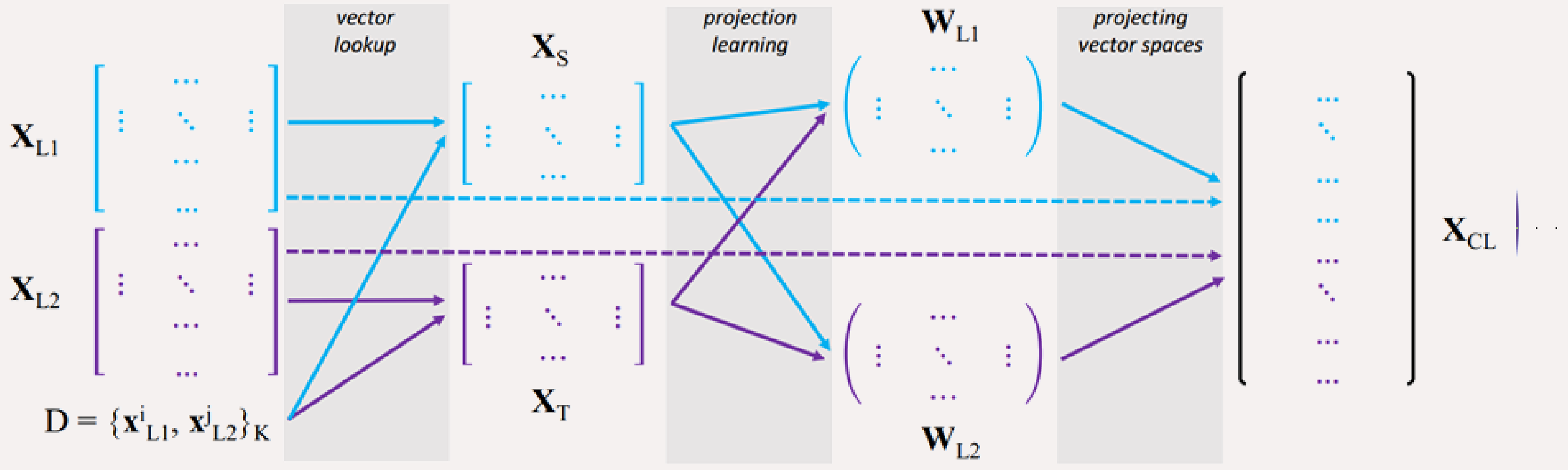
Projection-Based CLWEs

- **Post-hoc alignment** of independently trained monolingual word embedding spaces
  - Alignment based on word translation pairs, $\mathbf{D} = \{(\mathbf{x}^k_{L1}, \mathbf{x}^k_{L2})\}_k$ is the set of word embedding pairs between the languages corresponding to pairs of mutual translations
  - We stack $\{\mathbf{x}^k_{L1}\}_k$ into matrix $\mathbf{X_S} \in \mathbb{R}^{k \times d1}$ and $\{\mathbf{x}^k_{L2}\}_k$ into the matrix $\mathbf{X_T} \in \mathbb{R}^{k \times d2}$



Projection-Based CLWEs

- **Post-hoc alignment** of independently trained monolingual word embedding spaces



- In the general case, we want to find **projection matrices** $\mathbf{W_{L1}} \in \mathbb{R}^{d1 \times d}$ and $\mathbf{W_{L2}} \in \mathbb{R}^{d2 \times d}$ such that $\mathbf{X_S W_{L1} = X_T W_{L2}}$
  - This is a model, in which $\mathbf{W_{L1}}$ and $\mathbf{W_{L2}}$ are parameters
  - Q: What objective function to use?

Projection-Based CLWEs

- Find **projection matrices**
  - $\mathbf{W_{L1}} \in \mathbb{R}^{d1 \times d}$ and $\mathbf{W_{L2}} \in \mathbb{R}^{d2 \times d}$ such that $\mathbf{X_S W_{L1} = X_T W_{L2}}$
  - In practice, the problem is equivalent to learning one parameter matrix $\mathbf{W}$, i.e., $\mathbf{X_S W = X_T}$

$$\begin{array}{r} \text{bird} \\ \text{pretty} \\ \dots \\ \text{eat} \end{array} \overset{\mathbf{X}_{\mathrm{S}}}{\begin{bmatrix} -1.18 & 0.21 & \dots & 0.11 \\ 0.23 & -0.53 & \dots & 0.34 \\ \dots & \dots & \dots & \dots \\ 0.78 & 1.33 & \dots & -0.47 \end{bmatrix}} \mathbf{W} = \overset{\mathbf{X}_{\mathrm{T}}}{\begin{bmatrix} 0.59 & 1.01 & \dots & 0.37 \\ -0.34 & -0.27 & \dots & 0.41 \\ \dots & \dots & \dots & \dots \\ 0.81 & -0.31 & \dots & 0.29 \end{bmatrix}} \begin{array}{l} \text{Vogel} \\ \text{schön} \\ \dots \\ \text{essen} \end{array}$$

Projection-Based CLWEs

$$\begin{array}{r} \\ \text{bird} \\ \text{pretty} \\ \ldots \\ \text{eat} \end{array}\overset{\mathbf{X}_S}{\begin{bmatrix} -1.18 & 0.21 & \ldots & 0.11 \\ 0.23 & -0.53 & \ldots & 0.34 \\ \ldots & \ldots & \ldots & \ldots \\ 0.78 & 1.33 & \ldots & -0.47 \end{bmatrix}} \mathbf{W} = \overset{\mathbf{X}_T}{\begin{bmatrix} 0.59 & 1.01 & \ldots & 0.37 \\ -0.34 & -0.27 & \ldots & 0.41 \\ \ldots & \ldots & \ldots & \ldots \\ 0.81 & -0.31 & \ldots & 0.29 \end{bmatrix}}\begin{array}{l} \text{Vogel} \\ \text{schön} \\ \ldots \\ \text{essen} \end{array}$$

- The corresponding objective is „least squares":

$$\text{argmin}_{\mathbf{W}} \| \mathbf{X}_S \mathbf{W} - \mathbf{X}_T \|_2$$

  - Minimize the Euclidean distance between source language projections and corresponding target language vectors
- If **W** is unconstrained, no unique closed form solution
  - Numeric optimization → minimization with GD

Projection-Based CLWEs

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

- The corresponding objective is least squares:

$$\mathrm{argmin}_{\mathbf{W}} \| \mathbf{X_S} \mathbf{W} - \mathbf{X_T} \|_2$$

  - Mikolov et al. find W via numeric optimization
  - Trains in mini-batches of k word pairs
  - With mini-batch gradient descent

Projection-Based CLWEs

Smith, S. L., Turban, D. H., Hamblin, S., & Hammerla, N. Y. Offline bilingual word vectors, orthogonal transformations and the inverted softmax. In *International Conference on Learning Representations*.

- Turns out that we learn better projections if we constraint **W** to be an orthogonal matrix, i.e., such that its rows and columns are orthonormal

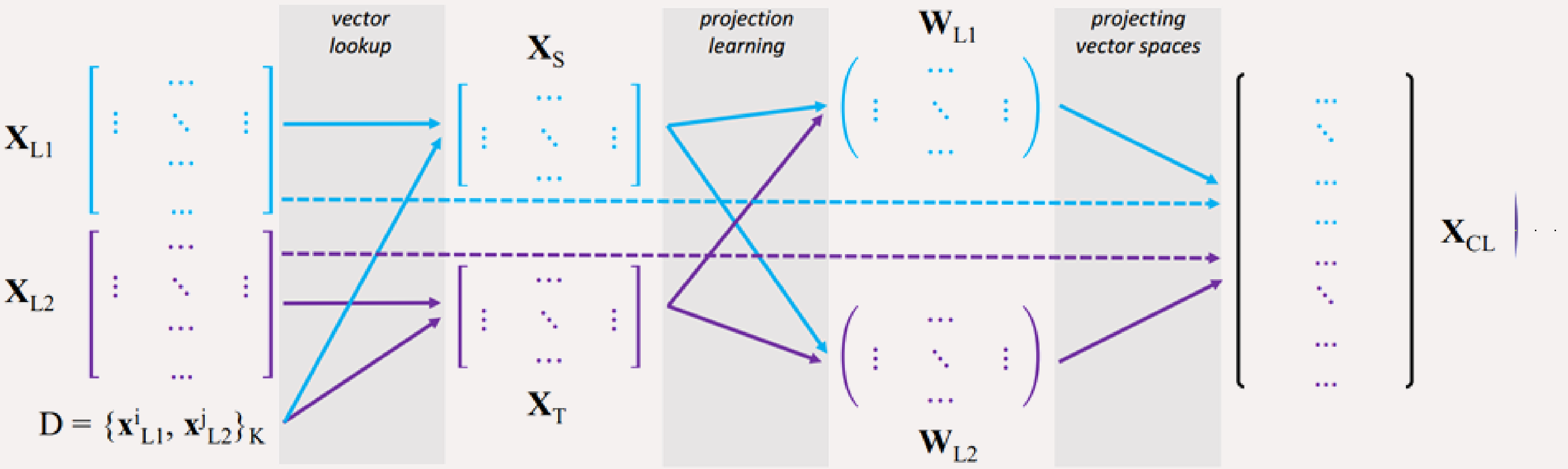
$$\mathrm{argmin}_{W} \| \mathbf{X_S}\, \mathbf{W} - \mathbf{X_T} \|_2, \ \text{s.t. } \mathbf{W}^T \mathbf{W} = \mathbf{I}$$

- This optimization problem is known as the Procrustes problem and has a closed-form solution:

$$\mathbf{W} = \mathbf{U}\mathbf{V}^T \ \text{ where}$$
$$\mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^T = \mathrm{SVD}(\mathbf{X_T}\, \mathbf{X^{-1}_S})$$

- SVD = a matrix factorization method called Singular Value Decomposition

Projection-Based CLWEs



- So, in practice, $\mathbf{W}_{L2} = \mathbf{I}$ and we obtain $\mathbf{W} = \mathbf{W}_{L1}$ by solving the Procrustes problem on $\mathbf{X}_S$ and $\mathbf{X}_T$
- Having „learned" the projection $\mathbf{W}$, we project the whole embedding space of L1 (source) into the embedding space of L2 (target)

$$\mathbf{X}_{\text{biling}} = \mathbf{X}_{L1}\,\mathbf{W} \cup \mathbf{X}_{L2}$$

Projection-Based CLWEs

- Advantage of projection-based CLWE methods over joint induction:
  - Compute: learning an orthogonal projection (i.e., solving Procrustes) is very computationally cheap
  - Flexibility: works regardless of how the monolingual embedding spaces $\mathbf{X}_{L1}$ and $\mathbf{X}_{L2}$ were obtained
    - Even if $\mathbf{X}_{L1}$ and $\mathbf{X}_{L2}$ trained with different methods
  - Performance: the quality of CLWEs induced via projection <u>matches or surpasses</u> that of jointly induced CLWEs

- Q: Where do we get word translations for training the projection $\mathbf{W}$?
- Q: <u>How many</u> word translation pairs do we need to learn a good projection?
  - I.e., what value should we set k in $D = \{(w^k_s, w^k_t)\}_k$ to?

Projection-Based CLWEs

Glavaš, G., Litschko, R., Ruder, S., & Vulić, I. (2019, July). How to (Properly) Evaluate Cross-Lingual Word Embeddings: On Strong Baselines, Comparative Analyses, and Some Misconceptions. In Proceedings of ACL (pp. 710-721).

- Q: How many word translation pairs do we need to learn a good projection?
- Depends on several factors, primarily
  (1) Lexical proximity of languages,
  (2) Quality of monolingual word embeddings (size of pretraining corpora)
- In general, performance saturates with ca. 5K translation pairs
  - Marginal gains with more translation pairs
- Q: why do we stick to a linear model? Why not learn a non-linear model (with more parameters than a single projection matrix)?

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Unsupervised Projection-Based CLWEs

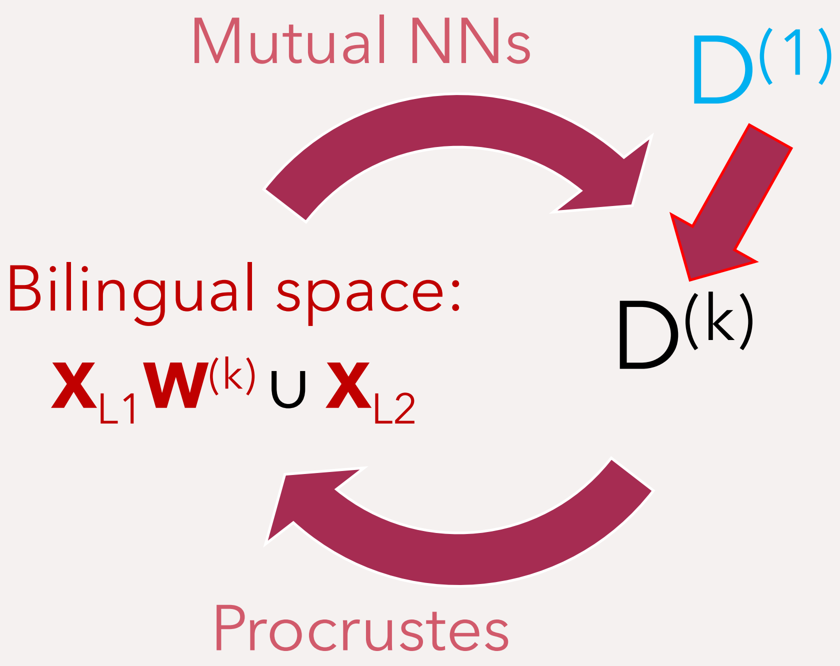
- **Unsupervised CLWEs**: In 2018, a flood of work introducing projection-based CLWE methods that do not require any word translations

- The **same general framework** for all unsupervised CLE models

1. Induce (automatically) initial word alignment dictionary $\mathbf{D}^{(1)}$

Repeat:

2. Learn the projection $\mathbf{W}^{(k)}$ using $\mathbf{D}^{(k)}$
3. Induce new dictionary $\mathbf{D}^{(k+1)}$ from $\mathbf{X}_{L1}\,\mathbf{W}^{(k)} \cup \mathbf{X}_{L2}$

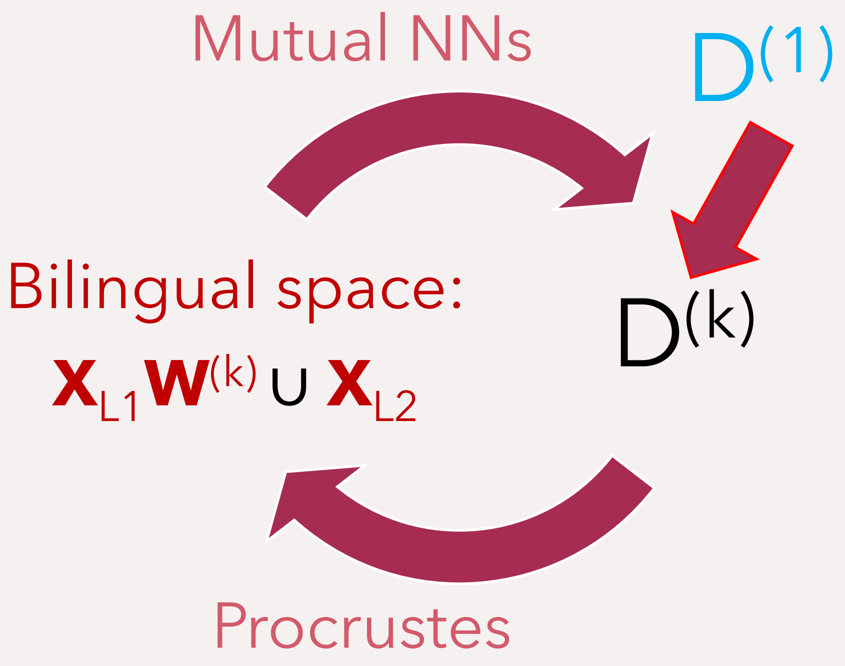


Unsupervised Projection-Based CLWEs

Lample, G., Conneau, A., Ranzato, M. A., Denoyer, L., & Jégou, H. (2018) Word translation without parallel data. In International Conference on Learning Representations.

- **Generative adversarial network** for initial alignment dictionary $D^{(1)}$
  - Generator: the projection matrix $\mathbf{W}$
  - Discriminator: classifier that distinguishes between $\mathbf{x}_{L1}\mathbf{W}$ and $\mathbf{x}_{L2}$, i.e., predicts whether a vector has been obtained by:

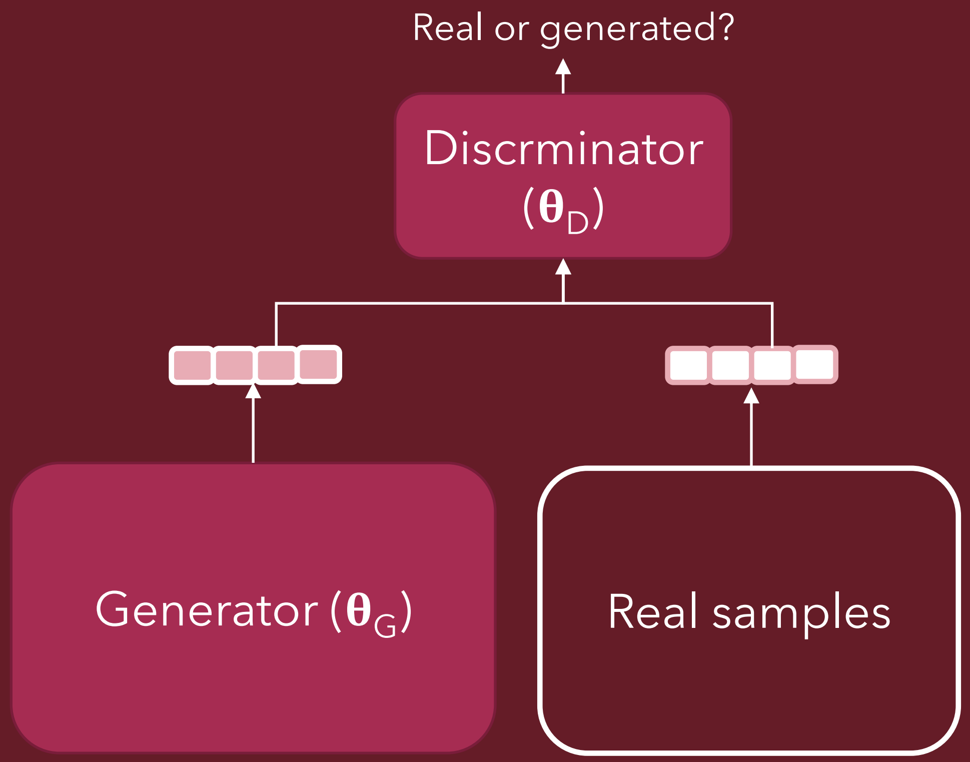
1. Transforming source language vector $\mathbf{x}_{L1}$ with the projection matrix $\mathbf{W}$ (i.e., $\mathbf{x}_{L1}\mathbf{W}$) or
2. if its an original target language vector $\mathbf{x}_{L2}$



Generative Adversarial Networks

Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014, December). Generative Adversarial Nets. In Proceedings of the 27th International Conference on Neural Information Processing Systems-Volume 2 (pp. 2672-2680).

- **Generator**: our core neural model that generates vectors in continous space
  - Images, word embeddings, ...
  - Parameters: $\boldsymbol{\theta}_G$
- **Discriminator**: a binary classifier that predicts whether a vector was
  (1) generated by the generator or
  (2) it is a real/original vector
  - Parameters: $\boldsymbol{\theta}_D$



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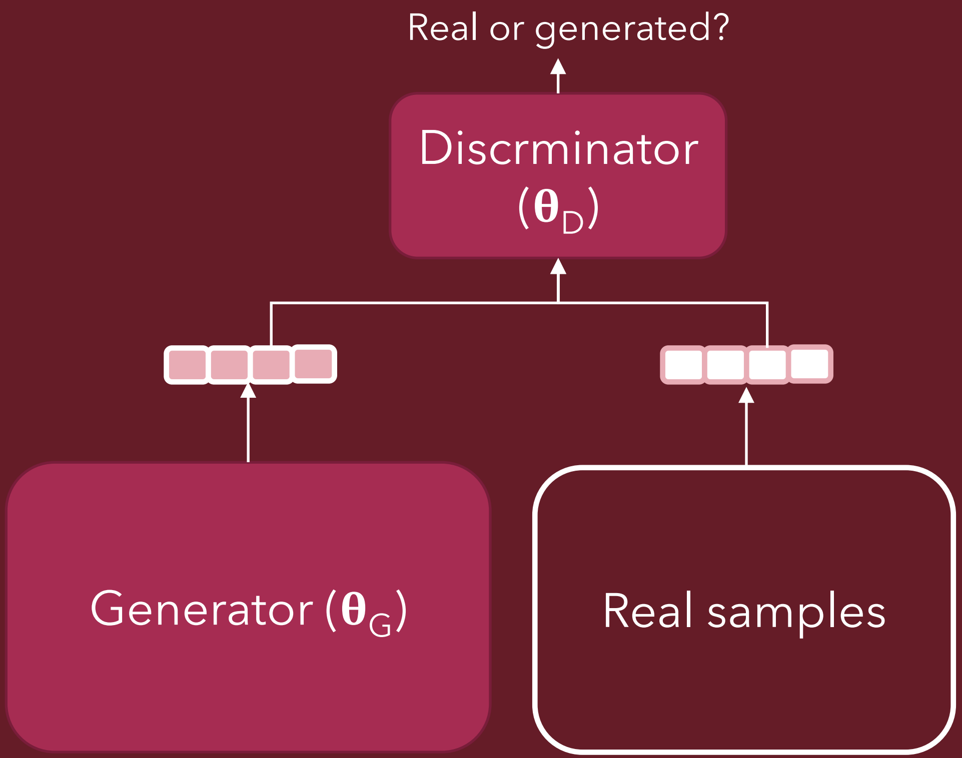
- **Generator**: Gen($\mathbf{x}|\boldsymbol{\theta}_G$)
- **Discriminator**: Disc ($\mathbf{x}|\boldsymbol{\theta}_D$)
- Discriminator's job is to minimize its binary classification loss
- Generator's job is to **fool** the discriminator
    - I.e., maximize the discriminator's loss



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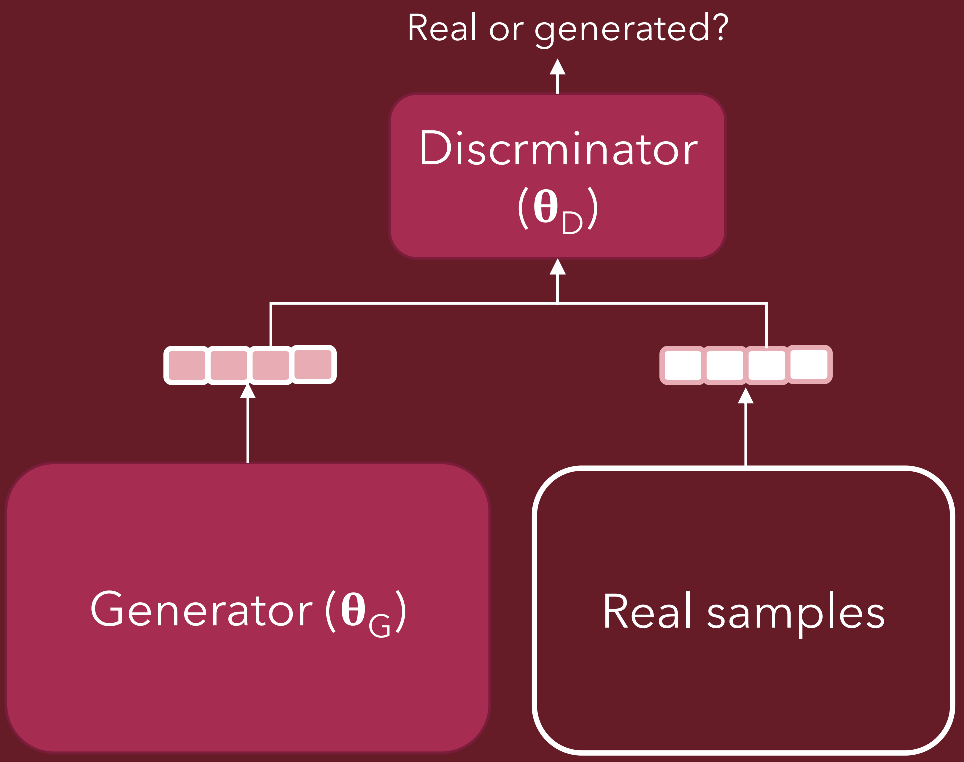
- **Generator**: Gen($\mathbf{x}|\boldsymbol{\theta}_G$)
- **Discriminator**: Disc ($\mathbf{x}|\boldsymbol{\theta}_D$)

- Generator's job is to **fool** the discriminator
  - Generations are better the more they resemble the real examples
  - I.e., generations fit well into the „distribution" of real examples



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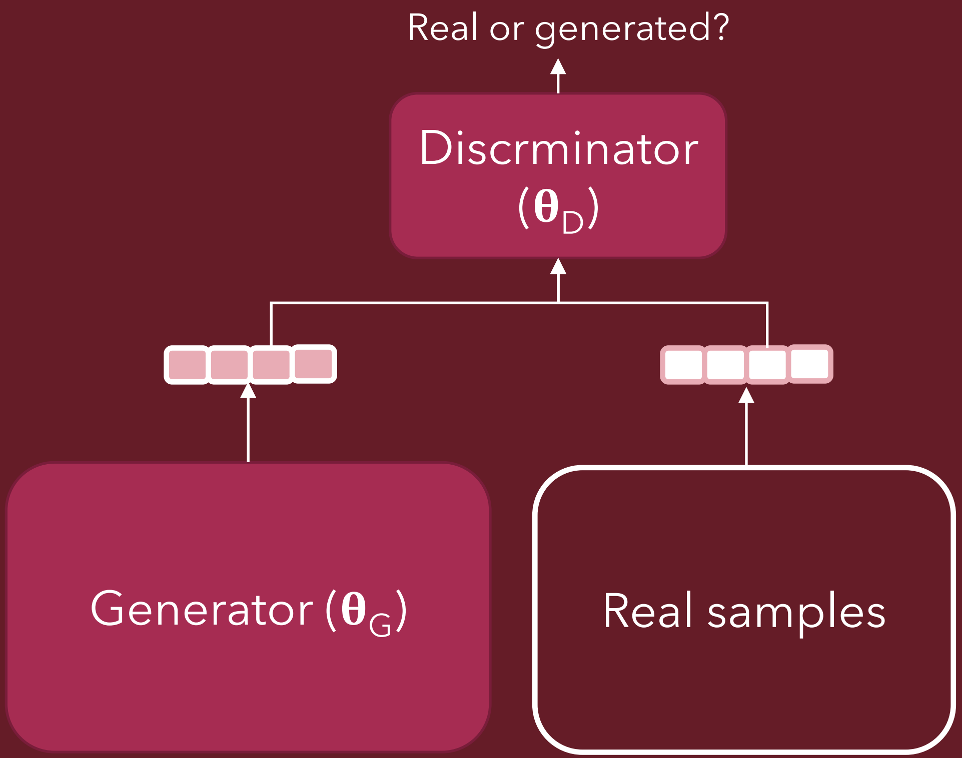
- A competition that iteratively makes both become better
- Iteratively:
  1. Feed into discriminator either (1) $\mathbf{x}$ = Gen(input|$\boldsymbol{\theta}_G$) or a real sample $\mathbf{x}$
  2. Compute the discriminator's loss $L_D(\mathrm{Disc}(\mathbf{x}|\boldsymbol{\theta}_D))$
  3. Minimize discriminator's parameters with GD: $\boldsymbol{\theta}_D^{(k+1)} = \boldsymbol{\theta}_D^{(k+1)} - \eta\nabla_{\boldsymbol{\theta}} L_D$



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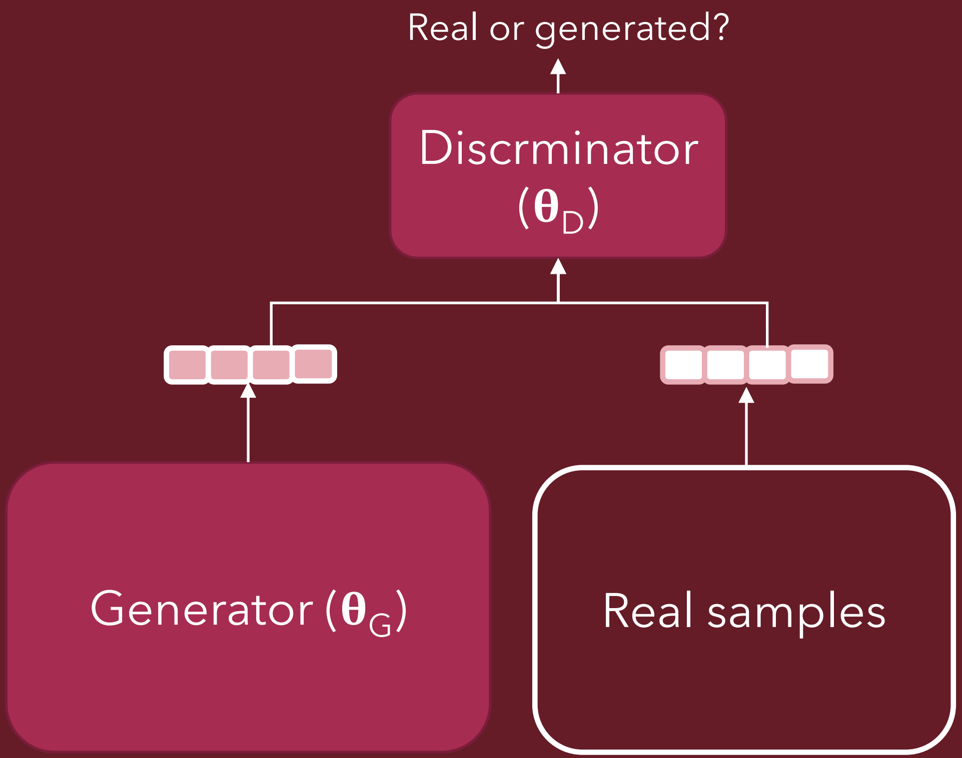
- A competition that iteratively makes both become better
- Iteratively:

…

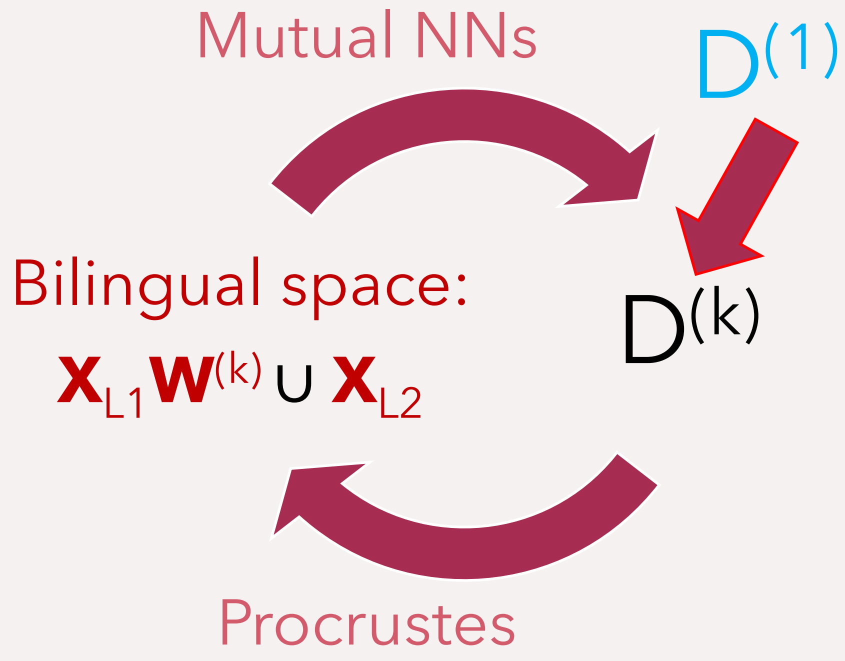
3. Minimize discriminator's parameters (GD):
   $\boldsymbol{\theta}_D^{(k+1)} = \boldsymbol{\theta}_D^{(k+1)} - \eta \nabla_{\boldsymbol{\theta}D} L_D$
4. If $\mathbf{x}$ is a generated sample, $\mathbf{x}$ = Gen(input$|\boldsymbol{\theta}_G$) then update $\boldsymbol{\theta}_G$ to maximize L_D:

   $\boldsymbol{\theta}_G^{(k+1)} + \eta \nabla_{\boldsymbol{\theta}G} L_D$



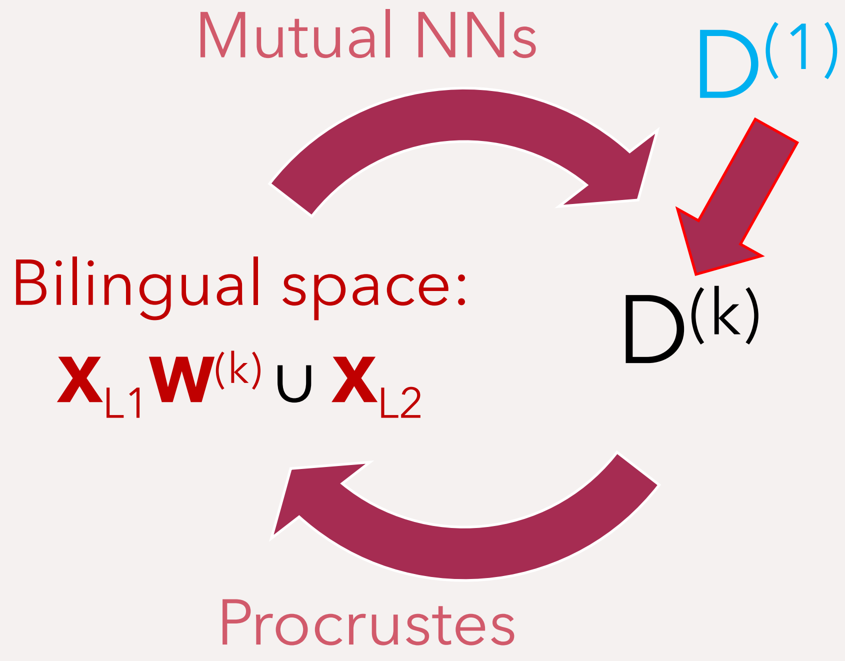
Unsupervised Projection-Based CLWEs

- The dictionary $D^{(k+1)}$ (next iteration):
  - Mutual nearest neighbours in $\mathbf{X}_{L1}\mathbf{W}^{(k)} \cup \mathbf{X}_{L2}$
  - $\mathbf{W}^{(k)}$ induced using dictionary $D^{(k)}$ from the current iteration
- Q: how do we find mutual NNs?
  1. For each $\mathbf{x}^i_{L1}$ in $\mathbf{X}_{L1}\mathbf{W}^{(k)}$ rank all vectors from $\mathbf{x}^j_{L2}$ in $\mathbf{X}_{L2}$
  2. For each $\mathbf{x}^j_{L2}$ in $\mathbf{X}_{L2}$ rank all vectors from $\mathbf{x}^i_{L1}$ in $\mathbf{X}_{L1}\mathbf{W}^{(k)}$
  - Some measure of vector similarity
  - NNs are $\mathbf{x}^i_{L1}$ and $\mathbf{x}^j_{L2}$ that are on top of each other's ranking



Unsupervised Projection-Based CLWEs

- Q: how do we find mutual NNs?
  - Some measure of vector similarity
  - NNs are $\mathbf{x}^{i}_{L1}$ and $\mathbf{x}^{j}_{L2}$ that are on top of each other's ranking
- Similarity measure: cosine similarity
- **Hubness** problem:
  - Vector space: $\mathbf{X} \in \mathbb{R}^{d \times |V|}$
  - If $|V| >> d$, there will be (by chance) vectors in $\mathbf{x} \in \mathbf{X}$ that have high-similarity with many/most other vectors
  - Skewes similarity measures like cosine



Unsupervised Projection-Based CLWEs

Lampele, G., Conneau, A., Ranzato, M. A., Denoyer, L., & Jégou, H. (2018) Word translation without parallel data. In International Conference on Learning Representations.

- Quality of CLWE: accuracy of retrieving translation pair for a given word
  - When w^i_{L1} with vector $\mathbf{x}^i_{L1}$ as „query", we rank all $\mathbf{x} \in \mathbf{X}_{L2}$ based on similarity with $\mathbf{x}^i_{L1}$: where in the ranking is the vector $\mathbf{x}^j_{L2}$ of the actual word translation w^j_{L2}
- **Hubness** problem in CLWEs:
  - A **hub** vector $\mathbf{x}^i_{L1} \in \mathbf{X}_{L1}\mathbf{W}$: high similarity with many vectors in $\mathbf{X}_{L2}$ (and vice versa)
- Cross-Domain Similarity Local Scaling
  - Cosine similarity adjusted for the hubness of both vectors

$$\mathrm{CSLS}(\mathbf{x}_{L1} \in \mathbf{X}_{L1}\mathbf{W}, \mathbf{x}_{L2} \in \mathbf{X}_{L2}) = 2*\cos(\mathbf{x}_{L1}, \mathbf{x}_{L2}) - r_{L2}(\mathbf{x}_{L1}) - r_{L1}(\mathbf{x}_{L2})$$

Unsupervised Projection-Based CLWEs

Lample, G., Conneau, A., Ranzato, M. A., Denoyer, L., & Jégou, H. (2018) Word translation without parallel data. In International Conference on Learning Representations.

- Cross-Domain Similarity Local Scaling
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$$\text{CSLS}(\mathbf{x}_{L1} \in \mathbf{X}_{L1}\mathbf{W}, \mathbf{x}_{L2} \in \mathbf{X}_{L2}) = 2*\cos(\mathbf{x}_{L1}, \mathbf{x}_{L2}) - r_{L2}(\mathbf{x}_{L1}) - r_{L1}(\mathbf{x}_{L2})$$

  - $r_{L2}(\mathbf{x}_{L1})$ is the average cosine similarity that $\mathbf{x}_{L1}$ has with K most similar vectors $\mathbf{x}_{L2} \in \mathbf{X}_{L2}$
  - $r_{L1}(\mathbf{x}_{L2})$ is the average cosine similarity that $\mathbf{x}_{L2}$ has with K most similar vectors $\mathbf{x}_{L1} \in \mathbf{X}_{L1}\mathbf{W}$

Unsupervised CLWEs: Criticism

Vulić, I., Glavaš, G., Reichart, R., & Korhonen, A. (2019). Do We Really Need Fully Unsupervised Cross-Lingual Embeddings? In Proceedings of the EMNLP (pp. 4407-4418).

- **Motivation**
  - „No bilingual signal required"
  - Thus applicable to „under-resourced languages"
- But: Supervised models don't need many word pairs (e.g., 1-5K)
  - Trivial to obtain for any language pair from resources like: BabelNet, PanLex
  - If a few thousand word translation pairs cannot be obtained
    - Then a language is so low-resource that we likely don't have reliable monolingual embeddings due to too small corpora in that language

Unsupervised CLWEs: Criticism

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- **Performance**: „Unsupervised CLE outperforms supervised CLE"
  - *„Without using any character information, our model even outperforms existing supervised methods on cross-lingual tasks for some language pairs"*
  - *„Our method succeeds in all tested scenarios and obtains the best published results in standard datasets, even surpassing previous supervised systems"*
  - *„...our method achieves better performance than recent state-of-the-art deep adversarial approaches and is competitive with the supervised baseline"*
- **Unintuitive**: unsupervised CLE models all solve Procrustes problem in the final step, only on the less reliable (automatically induced) **D**

Content

- **Cross-Lingual Word Embeddings**
  - Joint Training (from Scratch)
  - Projection-Based CLWEs
  - Unsupervised Induction of CLWEs
- **Evaluation of CLWEs**

Evaluation of CLWEs

Glavaš, G., Litschko, R., Ruder, S., & Vulić, I. (2019, July). How to (Properly) Evaluate Cross-Lingual Word Embeddings: On Strong Baselines, Comparative Analyses, and Some Misconceptions. In Proceedings of ACL (pp. 710-721).

- **Intrinsic evaluation**
  - Bilingual Lexicon Induction (BLI)
  - Cross-Lingual Word Similarity (XL-SIM)
- **Extrinsic evaluation**:
  - Cross-lingual transfer in downstream NLP tasks (e.g., text classification)
  - More in Lecture 6 ☺

Evaluation of CLWEs

- **Bilingual Lexicon Induction**
  - Essentially the same task as in „training": word translation
  - Given a test dictionary $D_{test} = \{(w^k_{L1}, w^k_{L1})\}_k$ and a bilingual embedding space $\mathbf{X}_{L1,L2}$ (for projection-based CLWEs $\mathbf{X}_{L1,L2} = \mathbf{X}_{L1}\mathbf{W} \cup \mathbf{X}_{L2}$)
  - For w^k_{L1} with vector $\mathbf{x}_{L1}$ as „query", we rank all $\mathbf{x} \in \mathbf{X}_{L2}$ based on similarity with $\mathbf{x}_{L1}$: let r be the rank at which we find the vector $\mathbf{x}^j_{L2}$ of the translation w^j_{L2}
  - Two common performance measures:
    - Precision@1 (P@1): percentage of pairs (out of k) for which $r = 1$
    - Mean reciprocal rank (MRR): average of $1/r$ (across all k pairs)

Evaluation of CLWEs

Vulić, I., Baker, S., Ponti, E. M., Petti, U., Leviant, I., Wing, K., ... & Korhonen, A. (2020). Multi-simlex: A large-scale evaluation of multilingual and cross-lingual lexical semantic similarity. Computational Linguistics, 46(4), 847-897.

- **Cross-Lingual Word Similarity**
  - Evaluate CLWEs the same way we evaluate monolingual word embeddings
  - Given two words, w_{L1}, w_{L2} measure the similarity of their vectors
    - E.g., CSLS($\mathbf{x}_{L1}$, $\mathbf{x}_{L2}$)
  - Compare embedding similarities against human judgments of semantic similarity for pairs of words
    - Performance measure: Spearman correlation (of two sets of scores)
  - XL-SIM: pairs of words from different languages
    - Need bilingual human annotators
    - Subjective task: need multiple annotators (average their scores)

Unsupervised CLWEs: Revisited

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- **Unintuitive**: unsupervised CLWE models all solve Procrustes problem in the final step, only on the less reliable (automatically induced) **D**
- Performance of unsupervised CLWE models* depends on the extent to which the monolingual embedding spaces $\mathbf{X}_{L1}$ and $\mathbf{X}_{L2}$ have the „same shape" (isomorphism)
  - Good between close and high-resource languages
  - E.g., EN-DE, EN-ES, EN-IT, …
  - Q: What about low-resource and distant languages?

Unsupervised CLWEs: Revisited

Vulić, I., Glavaš, G., Reichart, R., & Korhonen, A. (2019). Do We Really Need Fully Unsupervised Cross-Lingual Embeddings? In Proceedings of the EMNLP (pp. 4407-4418).

- Wider evaluation:
  - 15 languages (210 BLI evaluations)

Language	Family	Type	ISO 639-1
Bulgarian	IE: Slavic	fusional	BG
Catalan	IE: Romance	fusional	CA
Esperanto	– (constructed)	agglutinative	EO
Estonian	Uralic	agglutinative	ET
Basque	– (isolate)	agglutinative	EU
Finnish	Uralic	agglutinative	FI
Hebrew	Afro-Asiatic	introflexive	HE
Hungarian	Uralic	agglutinative	HU
Indonesian	Austronesian	isolating	ID
Georgian	Kartvelian	agglutinative	KA
Korean	Koreanic	agglutinative	KO
Lithuanian	IE: Baltic	fusional	LT
Bokmål	IE: Germanic	fusional	NO
Thai	Kra-Dai	isolating	TH
Turkish	Turkic	agglutinative	TR

Unsupervised CLWEs: Revisited

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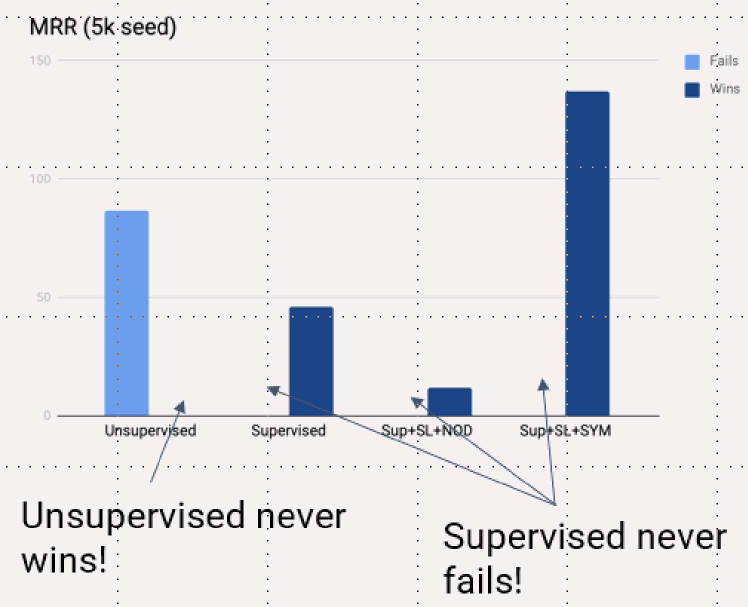

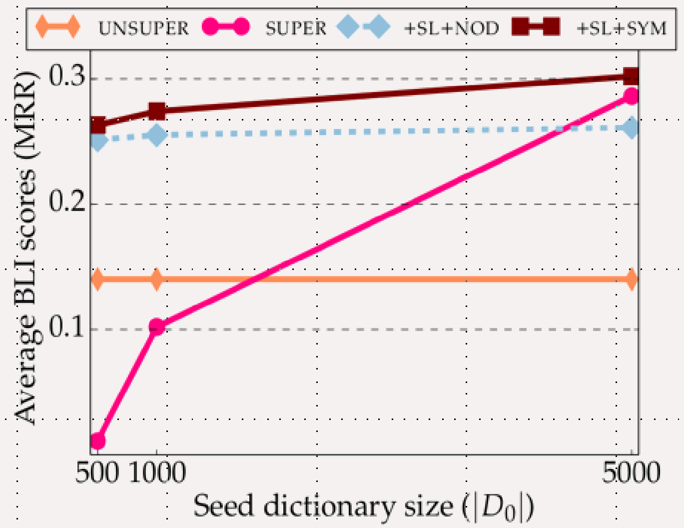

The End

Image: Alexander Mikhalchyk