Multilingual NLP

8. Word Alignment & Label Projection

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Image: Alexander Mikhalchyk

After this lecture, you'll...

- Learn about machine-translation-based cross-lingual transfer
- Understand why MT-based CL transfer is difficult for token-level tasks
- Learn about word alignment (WA) algorithms, symbolic and semantic
- Be aware of „mark-then-translate" as an alternative to WA

Content

- **Translation-Based CL Transfer**
- Word Alignment
  - Symbolic word alignment
  - Semantic word alignment
- Mark-then-Translate

Why Multilingual NLP?

- **Cross-Lingual transfer**: transfer supervised models for concrete NLP tasks
  - Models trained on labeled data in high-resource <u>source</u> language…
  - …make predictions on texts in low-resource <u>target</u> languages with little or no labeled data

Cross-Lingual Transfer: Practical Necessity

- Only a handful of NLP tasks have annotated data in many languages
  - Part-of-speech tagging (Universal Dependencies, UD)
  - Syntactic parsing (UD)
  - Named Entity Recognition (e.g., WikiANN)

- Higher-level semantic tasks often have only English training data
  - Generally more difficult tasks, e.g.:
    - Natural Language Inference (NLI)
    - Semantic Text Similarity (STS)
    - Question Answering (QA)
    - Causal Commonsense Reasoning
    - …

Translation-Based Transfer

- How about we use state-of-the-art **machine translation** to get annotated data in the languages we care about?

- Two common strategies:

1. **Translate train**
   - Automatically translate our training dataset in the source language L_S to the target language L_T
   - We obtain a (noisy) monolingual training dataset in L_T
   - We train a dedicated model M_T for L_T
   - For instances I_T from L_T we make predictions with M_T

Translation-Based Transfer

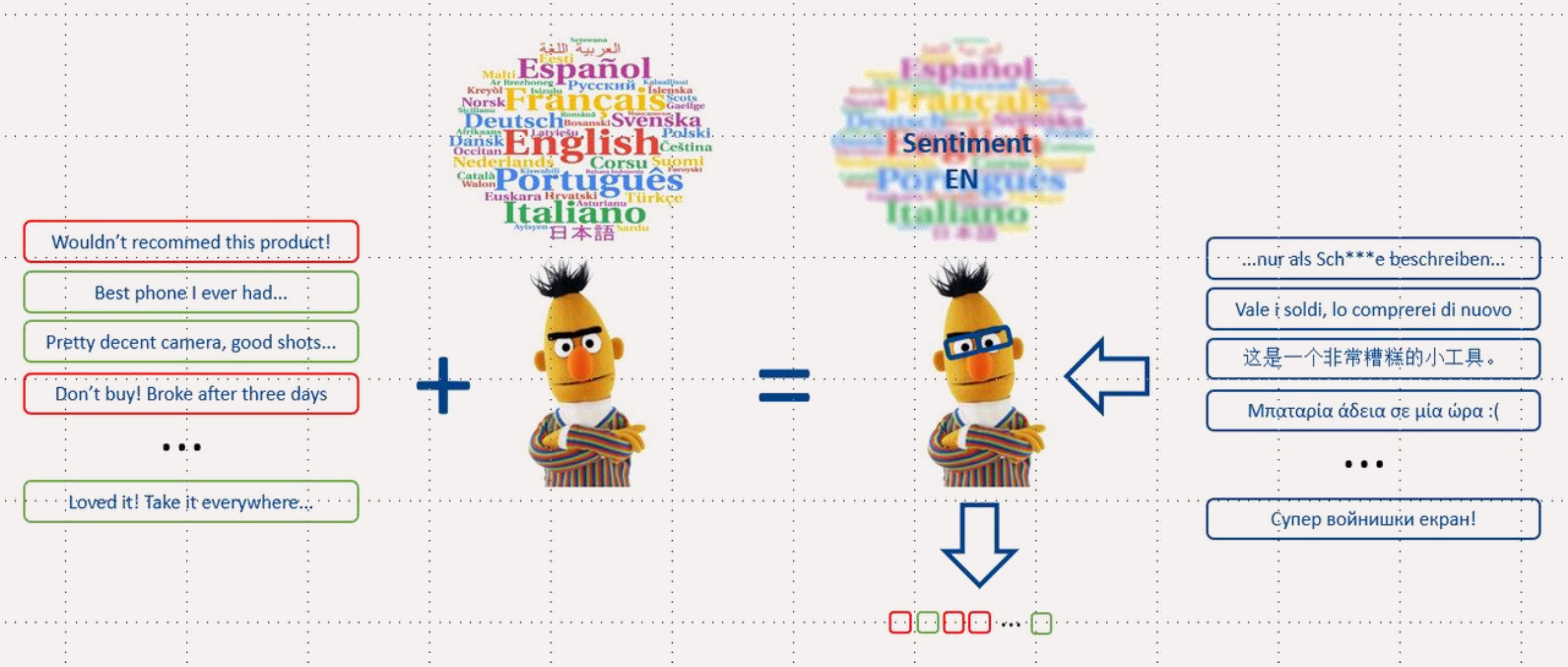
- How about we use state-of-the-art **machine translation** to get annotated data in the languages we care about?

- Two common strategies:

2. **Translate test**
    - Train the model M_S using the clean training data in L_S
    - At inference time, for input I_T in L_T:
        - First translate I_T to the source language L_S
        - Make the prediction with the model M_S on the translation

Zero-Shot CL Transfer

- **Cross-lingual transfer with MMTs** is conceptually trivial
  1. Place a task-specific head on top of the Transformer body
  2. Perform standard fine-tuning using task-specific training data in L_S
  3. Use the Transformer and classifier to make predictions for data in L_T



Translate-Train Transfer

1. Automatically translate our training dataset in the source language L_S to the target language L_T

Training set (EN)		Noisy training set (HR)
Wouldn't recommed this product!		Ne bih preporučila ovaj proizvod…
Best phone I ever had…		Najbolji telefon koji sam ikad imao…
Pretty decent camera, good shots…	MT	Solidna kamera, odlične slike…
Don't buy! Broke after three days		Ne kupujte! Pokvarilo se brzo…
…		…
Loved it! Take it everywhere…		Obožavam ga! Svugdje ga nosim…

Translate-Train Transfer

2. Train (i.e., fine-tune an MMT) on the translated train set
3. Make inference with the obtained model on target language input

Translate-Test Transfer

1. Train (i.e., fine-tune an MMT) on the original training set in L_S

Training set (EN)

Wouldn't recommed this product!

Best phone I ever had...

Pretty decent camera, good shots...

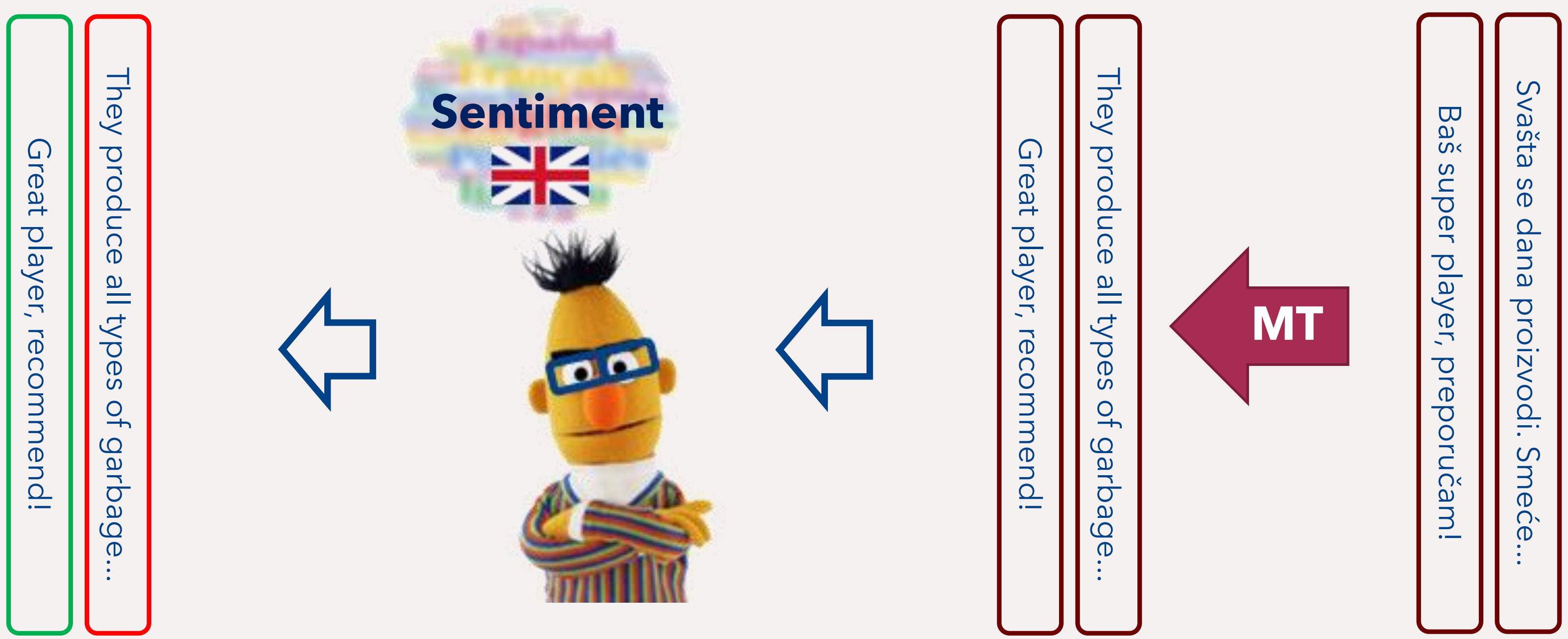
Don't buy! Broke after three days

...

Loved it! Take it everywhere...

Translate-Test Transfer

1. At inference, first translate the input from L_T to L_S
2. Then make prediction with the model trained on L_S data



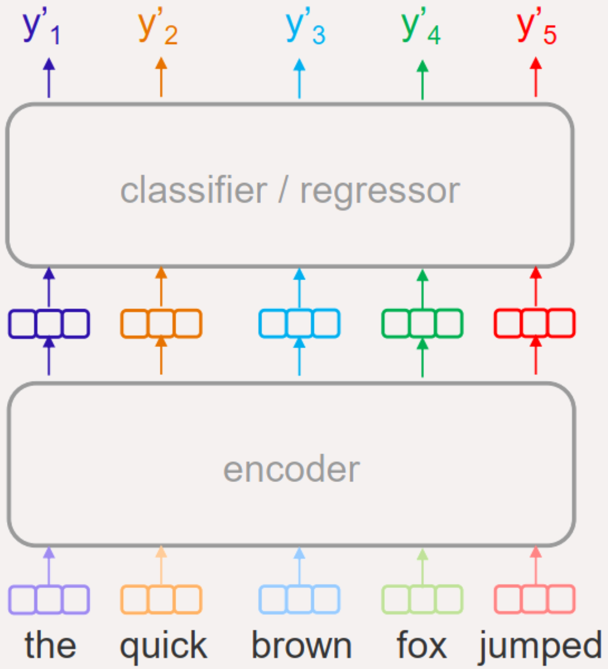
Translation-Based Transfer: Limitations

- Q: Translation-based vs. zero-shot CL transfer?
- Q: Translate-train vs. translate-test?
- Q: Shortcomings of translation-based transfer?
- The quality of translation-based transfer, obviously, depends on the quality of machine translation
- Translation-based CL transfer typically comparable or better than zero-shot CL transfer for higher-resource languages
  - For languages with strong MT models
- Translate-train typically more robust that translate test
  - Especially for higher-level semantic tasks (QA, NLI, ...)
  - Q: Why?

Translation Transfer for Token Classification?

- **Token-level classification** (or regression), also known as sequence labeling, denotes tasks in which a label (class or score) is to be assigned to each input token
- Examples:
  - Part-of-speech tagging
  - Named entity recognition
  - Any of the other IE tasks where we need to extract
  - the span of tokens hat represent a concept instance
- Labels are at the token level
  - Translation-based transfer = need to align:
    - Words from the translation l_T
    - to the tokens of the source input l_S

    as tokens from l_S have labels



Translation Transfer for Token Classification?

- Example: Named Entity Recognition

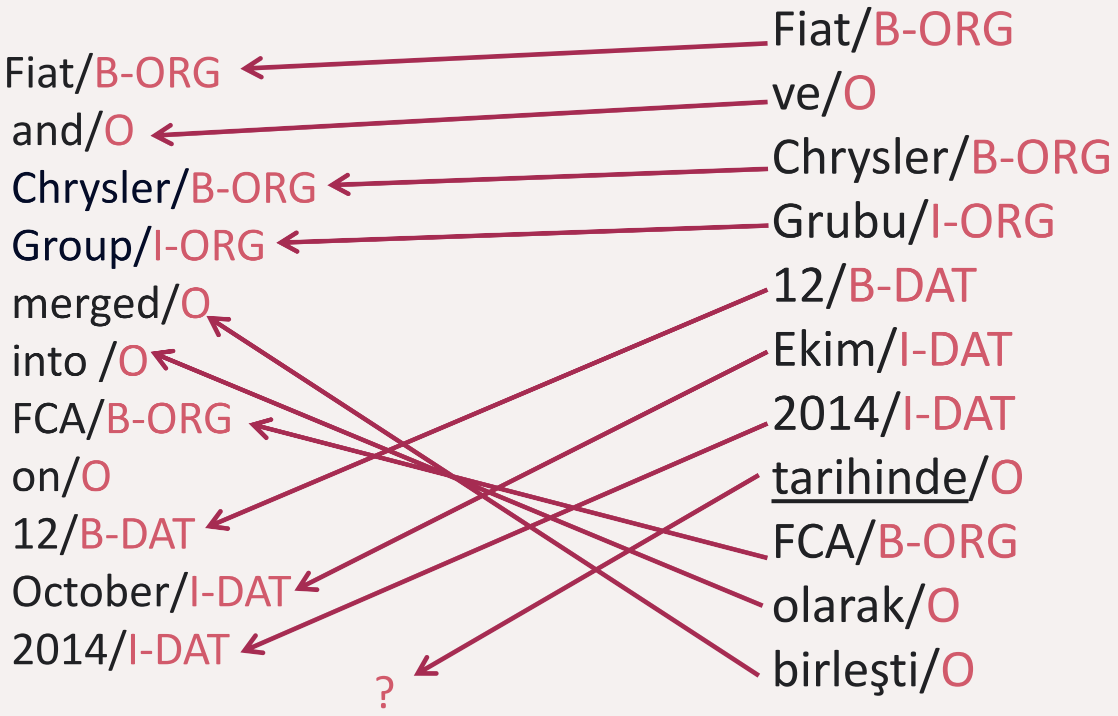
Fiat/B-ORG
and/O
Chrysler/B-ORG
Group/I-ORG
merged/O
into /O
FCA/B-ORG
on/O
12/B-DAT
October/I-DAT
2014/I-DAT

Machine translation EN->TR

Fiat/?
ve/?
Chrysler/?
Grubu/?
12/?
Ekim/?
2014/?
tarihinde/?
FCA/?
olarak/?
birleşti/?

Translation Transfer for Token Classification?

- To be able to transfer labels from l_S to its translation l_T (or vice-versa), we need to establish the **word alignment**
- This method of transfer is called annotation (or label) projection



Content

- Translation-Based CL Transfer
- **Word Alignment**
  - **Symbolic word alignment**
  - Semantic word alignment
- Mark-then-Translate

Word Alignment

- **Word alignment** is a task of finding mutual word translations between parallel texts (aka bitext), typically sentences that are translations of each other

- Word alignment is a „messy" task because:
  - 1-N, N-1, and N-N relations between words
  - Different word orders (and other morphosyntactic differences) between languages

- Word alignment was crucial in **statistical machine translation**
  - WA and SMT itself → two sides of the same coin
  - Shift to <u>NMT</u> reduced the importance of WA
    - Still important for CL transfer for token-level tasks!

Word Alignment

- **Word alignment** is practically (for CL transfer) defined as aligning each token t_i of the target sentence $\boldsymbol{t} = \{t_1, t_2, \ldots, t_m\}$ to a token s_j of the source sentence $\boldsymbol{s} = \{s_1, s_2, \ldots, s_n\}$

- In reality, not all target language tokens have a direct translation in the source sentence → we introduce a special „empty" token s_0
  - $\boldsymbol{s} = \{\underline{s_0}, s_1, s_2, \ldots, s_n\}$

- Multiple tokens from $\boldsymbol{t}$ can be aligned to the same source token s_j

Word Alignment

- **IBM Word Alignment Models**
  - Originally SMT models
  - Later on primarily used as word alignment models

Translation formulation:

- We're going to swap source and target language for a moment
  - Source in the translation formulation is target for alignment
- We're searching for the most likely translation ***s*** for a given input ***t***

$$s^* = \mathrm{argmax}_{\mathbf{s}} P(\mathbf{s}|\mathbf{t}) \quad \text{(which, given Bayes rule)}$$
$$\propto \mathrm{argmax}_{\mathbf{s}} \underbrace{P(\mathbf{t}|\mathbf{s})}_{\text{Translation model}} \; \underbrace{P(\mathbf{s})}_{\text{Language model (of translation target language, } L_S)}$$

Translation model

Language model (of translation target language, L_S)

Word Alignment

- **IBM Models**
  - Translation model: estimates the probabilities P(**t**|**s**)
  - IBM Model 2:
    - Let's assume alignments $a_1, a_2, \ldots, a_m$
    - Alignment $a_k = (i, j)$ – means that t_i is aligned to s_j

$$P(\mathbf{t}|\mathbf{s}) = \prod_{i=1}^{m} q_p(j|i, m, n) * q_w(t_i|s_j)$$

Position alignment score (for positions i and j given lengths m and n)

Word translation scores (regardless of positions of words)

Word Alignment: IBM Model 2

- If we had estimates $q_p(j|i,m,n)$ for all position pairs i and j
- And estimates $q_w(t|s)$ for all word pairs

- We could then easily compute the „optimal" word alignment (according to the IBM Model 2) for any two parallel sentences **t** and **s**

- **Algorithm**
  - For each t_i in ***t***
    - Select s_j in ***s*** for which $q_p(j|i,m,n) * q_w(t_i|s_j)$ is the largest

Word Alignment: IBM Model 2

- Q: How do we obtain position alignment scores q_p and word translation scores q_w?

- We estimate them from the **parallel corpus** using an expectation maximization (EM) algorithm

- Parallel corpus: $\{\mathbf{s}^{(k)}, \mathbf{t}^{(k)}\}_k$

Word Alignment: IBM Model 2

- Q: How do we obtain position alignment scores q_p and word translation scores q_w?
- Parallel corpus: $\{\mathbf{s}^{(k)}, \mathbf{t}^{(k)}\}_k$
- Let's for a moment assume that we also have „gold" word alignments in our training corpus (which in reality, we won't have)
  - We can directly do the maximum likelihood estimation (MLE) of q_w and q_p as follows (function „c" indicates the raw count):

$$q_p(j|i,m,n) = \frac{c(j|i,m,n)}{c(i,m,n)}$$

Number of times (in our training parallel corpus with gold alignments) that the i-th word in $\boldsymbol{t}$ (which is of length m) was aligned with the j-th word in $\mathbf{s}$ (which is of length n)

Word Alignment: IBM Model 2

- Q: How do we obtain position alignment scores q_p and word translation scores q_w?
- Parallel corpus: $\{\mathbf{s}^{(k)}, \mathbf{t}^{(k)}\}_k$
- Let's for a moment assume that we also have „gold" word alignments in our training corpus (which in reality, we won't have)
  - We can directly do the maximum likelihood estimation (MLE) of q_w and q_p as follows (function „c" indicates the raw count):

$$q_w(t|s) = \frac{c(t,s)}{c(s)}$$

Number of times some target word (e.g., *Hund*) was aligned to some source word (e.g., *dog*)

Number of times that source word (e.g., *dog*) appeared in the parallel corpus

Word Alignment: IBM Model 2

- Q: How do we obtain position alignment scores q_p and word translation scores q_w?
- In reality, we won't have word alignments provided on our parallel corpus $\{\mathbf{s}^{(k)}, \mathbf{t}^{(k)}\}_k$
- We cannot really count $c(t|s)$ and $c(j|i,m,n)$
- But words and positions of alignments will tend to appear more often over the sentences of our parallel corpus
- „Learning" algorithm: a variant of **expectation maximization,** iteratively:
  1. Estimate changes to counts $c(t|s)$ and $c(j|i,m,n)$ (expected counts) from current parameter values (q_p and q_w)
  2. Update all parameters (q_p and q_w) based on new expected counts

Word Alignment: IBM Model 2

- Parallel corpus $\{\mathbf{s}^{(k)}, \mathbf{t}^{(k)}\}_k$

- Let's assume some parameter initialization $q_p(j|i, m, n)$, $q_w(t|s)$, e.g., with random values

- The EM algorithm then iterates over each sentence pair $\mathbf{s}^{(k)}$, $\mathbf{t}^{(k)}$ and:
  - Computes the probability of alignment δ(k, i, j) for positions *i* (from $\mathbf{t}^{(k)}$) and *j* (from $\mathbf{s}^{(k)}$) as follows:

$$\delta(k, i, j) = \frac{q_p(j|i, m^k, n^k) * q_w(t_i{}^k | s_j{}^k)}{\sum_{j'=0}^{n} q_p(j'|i, m^k, n^k) * q_w(t_i{}^k | s_{j'}{}^k)}$$

Word Alignment: IBM Model 2

$$\delta(k, i, j) = \frac{q_p(j|i, m^k, n^k) * q_w(t_i{}^k | s_j{}^k)}{\sum_{j'=0}^{n} q_p(j'|i, m^k, n^k) * q_w(t_i{}^k | s_{j'}{}^k)}$$

<u>Alignment algorithm</u>: (initialize all parameters (q_p, q_w), e.g., to random values)

- For step in 1 to S (S iterations of the algorithm):
  - Initialize all counts ($c(j|i,m,n)$ and $c(i,m,n)$, $c(t_i{}^k, s_j{}^k)$, $c(s_j{}^k)$) to **zero**
  - **for each** training pair of sentences $\mathbf{t}^{(k)}$ and $\mathbf{s}^{(k)}$:
    - **for** *i* in 1 to m^k (iterating over all tokens of $\mathbf{t}^{(k)}$):
      - **for** *j* in 0 to n^k (iterating over all tokens of $\mathbf{s}^{(k)}$):
        - Compute δ(k, i, j) according to the above formula
        - Update count expectations:
          - $c(j|i, m^k, n^k) \leftarrow c(j|i, m^k, n^k) + \delta(k, i, j)$
          - $c(i, m^k, n^k) \leftarrow c(i, m^k, n^k) + \delta(k, i, j)$
          - $c(t_i{}^k, s_j{}^k) \leftarrow c(t_i{}^k, s_j{}^k) + \delta(k, i, j)$
          - $c(s_j{}^k) \leftarrow c(s_j{}^k) + \delta(k, i, j)$
  - Update the parameters based on collected (expected) counts
    - $q_p(j|i,m,n) = \frac{c(j|i,m,n)}{c(i,m,n)}$ and $q_w(t|s) = \frac{c(t,s)}{c(s)}$

Word Alignment: IBM Model 2

- Q: Why does this (intuitively) work?
  - Words that are translations of each other will appear in multiple pairs of sentence translations
  - Thus their count accumulation $c(t, s)$ will be larger

- Based on morpho-syntactic similarities/differences between languages a „more informed" initialization of the positional alignments q_p possible
  - E.g., if the languages have same word order → $q_p(j|i, m, n)$ can be set larger for values of i and j that are closer to each other

Word Alignment: FastAlign

Dyer, C., Chahuneau, V., & Smith, N. A. (2013, June). A simple, fast, and effective reparameterization of IBM model 2. In Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (pp. 644-648).

- IBM Model 2 is „sparse" and has very many parameters
  - $q_p(j|i, m, n)$ → i*j parameters for every different combination of lengths of sentences in the training set (every different m-n combination)
  - Likelihood of aligning certain position i and j is probably similar for various sentence lengths m and n
- **FastAlign** is a sparse WA model that reduces the number of parameters
  - Essentially a „reparametrization" of IBM Model 2

Word Alignment: FastAlign

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- **FastAlign** is a sparse WA model that reduces the number of parameters
  - Essentially a „reparametrization" of IBM Model 2
  - Instead of having an (updatable) parameters $q_p(j|i,m,n)$ for each combination (i, j, m, n) combination, we compute it with a function:

$q_p(j|i,m,n)$ = p_0 if $j = 0$ (i.e., p_0 is the probability of no alignment)

$$(1 - p_0) * \frac{\exp(\lambda * h(i,j,m,n))}{\sum_{j'=1}^{n} \exp(\lambda * h(i,j,m,n))}$$ otherwise $(j > 0)$

Word Alignment: FastAlign

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  - Where h is a fixed function of relative positional distance:
    - $h(i, j, m, n) = -|i/m - j/n|$
    - Larger h → lower probability of alignment between positions i (in ***t***) and j (in ***s***)

Word Alignment: FastAlign

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  - λ (≥ 0): decides how strongly we prefer alignments of close positions
    - $\lambda < 1$: scales down the effect of relative distance of i and j
      - Appropriate for syntactically dissimilar languages
    - $\lambda > 1$: emphasizes the effect of relative distance of i and j
      - Appropriate for syntactically similar languages

Word Alignment

- Problems with „symbolic" word alignment methods
  - Same as for any other NLP task/problem

  - Do not capture semantic relations between words
    - Probability/count of alignment q_w(car, Auto) is independent of the probability of alignment q_w(automobile, Auto)

  - Strictly requires parallel data
    - The more the better
    - Hard to find/create large parallel corpora for low-resource langs
    - Not able to align words that are not in the parallel „training" corpus

Content

- Translation-Based CL Transfer
- **Word Alignment**
  - Symbolic word alignment
  - **Semantic word alignment**
- Mark-then-Translate

Semantic Word Alignment

- We assume we have a semantic representation for each t_i from $\boldsymbol{t}$ and each word s_j from $\boldsymbol{s}$
- The representations of words from the target language L_T need to be semantically aligned with the representations of words from the source language L_S
- Q: how can we obtain embeddings that satisfy this?
  1. Cross-lingual word embedding spaces (CLWEs)
  2. Multilingual Transformers (e.g., mBERT)

Semantic Word Alignment

- Let $\mathbf{t}_i \in \mathbb{R}^d$ be an embedding of the token t_i from $\boldsymbol{t}$
- Let $\mathbf{s}_j \in \mathbb{R}^d$ be an embedding of the token s_j from $\boldsymbol{s}$

- Then we can obtain the similarity matrix $S \in \mathbb{R}^{m \times n}$ which contains cosine similarities between all vectors $\mathbf{t}_i$ from $\boldsymbol{t}$ and $\mathbf{s}_j$ from $\boldsymbol{s}$
  - $S_{ij} = \cos(\mathbf{t}_i, \mathbf{s}_j)$
- We use the similarity matrix S to obtain the alignments:
  - Greedy alignment
  - Greedy alignment with removal
  - Optimal alignment (with removal)
- Does <u>not require</u> parallel data

Semantic Word Alignment

- **Greedy alignment**
  - For each word t_i we find the s_j that is semantically most similar to t_i according to cosine similarity between their embeddings: $\cos(\mathbf{t}_i, \mathbf{s}_j)$
  - I.e., in each row S[i:], we find the cell S_{ij} (column j) with max. value
  - The same column j (i.e., same word s_j) may be chosen for multiple rows (i.e., multiple words t_i may be aligned to the same s_j)

Semantic Word Alignment

- **Greedy alignment with removal**
  - Iteratively:

1. Find the most similar pair (**t_i**, **s_j**), i.e., the cell S_{ij} with the maximal value (among the remaining eligible cells) and make the alignment (t_i, s_j)

2. Prevent any further alignments that involve s_j
   - I.e., set all values S[:, j] to -1 (minimal cosine)

Semantic Word Alignment

- **Optimal alignment** (with removal)
  - We are solving the following optimization problem: we're looking for a set of alignments that maximize the sum of pairwise similarities
  - Let A be a binary matrix (values 0 or 1): $A_{ij} = 1$ indicates that an alignment has been established between t_i and s_j
    - Constraint: A can have only one „1" in each row and each column

$$A^* = \mathrm{argmax}_{A \in \{0,1\}^{m \times n}} \sum_{i=1}^{m} \sum_{j=1}^{n} A_{ij} S_{ij}$$

Semantic Word Alignment

- **Optimal alignment** (with removal)

$$A^* = \operatorname{argmax}_{A \in \{0,1\}^{m\times n}} \sum_{i=1}^{m} \sum_{j=1}^{n} A_{ij} S_{ij}$$

- This is a well-known problem called bipartite graph matching
  - Also known as (optimal) alignment problem

- Efficient algorithms exist (solve it in polynomial time)
  - The Hungarian algorithm (Kuhn-Munkres algorithm, from 1955) – solved the problem in $O(n^4)$
  - Later – better algorithms with complexity $O(n^3)$

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- Word Alignment
    - Symbolic word alignment
    - Semantic word alignment
- **Mark-then-Translate**

Mark-then-Translate

- **Simple idea:** put special tags around the tokens, indicating their label and translate with some MT system
  - Used a lot in token-level CL transfer, but empirically tested recently

„<ORG>Fiat</ORG> and <ORG>Chrysler Group</ORG> merged into <ORG>FCA</ORG> on <DAT>12 October 2014</DAT>”

MT
EN→TR

(ideally)

„<ORG>Fiat</ORG> ve <ORG>Chrysler Grubu </ORG> <DAT>12 Ekim 2014 </DAT> tarihinde <ORG>FCA</ORG> olarak birleşti”

Mark-then-Translate

Chen, Y., Jiang, C., Ritter, A., & Xu, W. (2023, July). Frustratingly Easy Label Projection for Cross-lingual Transfer. In Findings of the Association for Computational Linguistics: ACL 2023 (pp. 5775-5796).

- More directly dependent on the quality of MT (i.e., abundance of parallel data between languages)
- Mark-then-Translate gets better as MT models get better
  - Chen et al. (2023) experiment with Google Translate and open-source NLLB („No Language Left Behind", covered in L9)
  - Report MtT better than WA-based label projection for many languages and tasks
    - Though mostly for high- and moderate-resource languages

Image: Alexander Mikhalchyk