Cross-lingual POS Tagging
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POS Tags Projection across Parallel Corpora

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  - Target languages: 🇫🇷 French, 🇨🇳 Chinese
  • In Proceedings of the Second Meeting of the North American Association for Computational Linguistics (NAACL-2001), pp. 200–207, Pittsburgh, PA, USA
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    • 1:N English-target word alignment
    • or 0:1 or 1:0 for unaligned words
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- Tag the English side with an existing tagger (e.g., Brill, 1995)
- Direct projection across alignment
  - *Laws* → *Les lois*
  - *NNS* → *NNS*, *NNS*
Training on Noisy Data

• Train a tagger on the target side
• Problem: lot of noise!
• Core tags only: first letter, i.e.:
  • N ... noun
  • J ... adjective
  • V ... verb
  • R ... adverb
  • I ... preposition or subordinating conjunction (?)
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- Aggressive smoothing towards two most frequent core tags of each word
  - \( \hat{P}(t(2)|w) = \lambda_1 P(t(2)|w) \) where \( \lambda_1 < 1.0 \)
  - \( \hat{P}(t(1)|w) = 1 - \hat{P}(t(2)|w) \)
  - \( \hat{P}(t(c)|w) = 0 \) for all \( c > 2 \)
Training on Noisy Data

• Recursively apply the smoothing to subtags
  • E.g. distribute the prob. mass of N to the two most probable subtags, NN and NNS
Training on Noisy Data

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  - E.g. distribute the prob. mass of \( N \) to the two most probable subtags, \textbf{NN} and \textbf{NNS}
- Linear interpolation of model obtained from 1:1 alignments, and of model obtained from 1:N alignments: 
  \[
P(t|w) = \lambda_2 P_{1:1}(t|w) + (1 - \lambda_2)P_{1:N}(t|w)
\]
- \( \lambda_2 \) is some weight from \((0; 1)\)
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- Estimate tag sequence model on filtered, high-confidence alignment data. There are fewer parameters, therefore we can afford it.
  - Alignment confidence score provided by Model 3
  - Sentences where directly projected tags are compatible with the estimated lexical prior probability for each word – penalize less compatible sentences by pseudo-divergence weighting:
    - sentence length \( k \) \Rightarrow weight = \frac{1}{k} \sum_{i=1}^{k} \log \hat{P}(projected\_tag_i|w_i)
  • Differences from Yarowsky and Ngai (2001):
    • Graph-based projection
    • Projected labels are features in an unsupervised model
• Željko Agić, Dirk Hovy, Anders Søgaard (2015). If all you have is a bit of the Bible: Learning POS taggers for truly low-resource languages. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Short Papers), pp. 268–272, Beijing, China.
Projection Graph

- English vertices = word types
- Foreign vertices = word trigram types
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- English vertices are connected to foreign vertices

Cross-lingual POS Tagging
Projection Graph

- English vertices = word types
- Foreign vertices = word trigram types
- English vertices are connected to foreign vertices
- Foreign vertices are connected to other foreign vertices
Training

- Parallel English-foreign corpus, word-aligned
  - English side labeled by a supervised English tagger
- Monolingual foreign corpus, unlabeled
  - Used to compute target edge weights (similarity)
  - ⇒ We will propagate tags across edges
Monolingual Similarity of Foreign Trigrams

- Trigram type $x_2x_3x_4$ in a sequence $x_1x_2x_3x_4x_5$

- Features:
  - Trigram + Context: $x_1x_2x_3x_4x_5$
  - Trigram: $x_2x_3x_4$
  - Left Context: $x_1x_2$
  - Right Context: $x_4x_5$
  - Center Word: $x_3$
  - Trigram – Center Word: $x_2x_4$
  - Left Word + Right Context: $x_2x_4x_5$
  - Left Context + Right Word: $x_1x_2x_4$
  - Suffix: HasSuffix($x_3$)
• Pruthwik Mishra, Vandan Mujadia, Dipti Misra Sharma (2017). POS Tagging for Resource Poor Indian Languages through Feature Projection
  • In Proceedings of ICON 2017, Jadavpur, India
  • Source language: Hindi
  • Target languages:
    • Urdu, Punjabi, Gujarati, Marathi, Konkani, Bengali (Indo-Aryan, i.e., related to Hindi)
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  • Parallel corpora: “Health” and “Tourism” (250 to 500K tokens each; not publicly available)
  • Align words using GIZA++
Source Feature Extraction

- Hindi Treebank (450K tokens)
- Prefix features
  - 1 to 7 prefix characters
- Suffix features
  - 1 to 4 suffix characters
- Length of the word
- Previous word
- Current word
- Next word
Features in Hindi – Example

- पत्रकारों *patrakārom* "journalists"

| Prefix(1) | प pa |
| Prefix(2) | पत pata |
| Prefix(3) | पत् pat |
| Prefix(4) | पत्र patra |
| Prefix(5) | पत्रक patraka |
| Prefix(6) | पत्रका patrakā |
| Prefix(7) | पत्रकार patrakāra |
| Suffix(1) | ◌ं mì |
| Suffix(2) | ◌ों omì |
| Suffix(3) | ◌ों romì |
| Suffix(4) | ◌ारों āromì |
| Length | 9 |
| Current | पत्रकारों patrakārom |
| Previous, Next | context dependent |
Parallel Features in Hindi and Punjabi

- विवाहितَ vivāhita “married”
- पिह विहा viāhutā “married”

| Prefix(1) | व va | → | व va |
|-----------|------|→ | व vi |
| Prefix(2) | ब्व vi | → | ब्व vi |
| Prefix(3) | व्व viva | → | व्व viā |
| Prefix(4) | व्वा vivā | → | व्वा viāha |
| Prefix(5) | व्वाह vivāha | → | व्वाह viāhu |
| Prefix(6) | व्वाहित vivāhi | → | पिह विहा viāhuta |
| Prefix(7) | व्वाहित विवाहित vivāhita | → | पिह विहा viāhutā |
| Suffix(1) | त ta | → | ता ā |
| Suffix(2) | ित ita | → | ित tā |
| Suffix(3) | िहित hita | → | िहित utā |
| Suffix(4) | ाहित āhita | → | ाहित hutā |
| Length | 7 | → | 7 |
| Current | विवाहित विवाहित vivāhita | → | पिह विहा viāhutā |
Feature Mapping

- Source features obtained from the Hindi Treebank.
- Projected through word alignment.
- Only the eleven affix features are projected.
- Unclear: what is the rest good for?

"If the same source feature maps to multiple target features, the most probable target feature is selected."

11 mapping files, 1 for each feature type

Previous slide: just one aligned pair of words

Hindi word occurred multiple times, different targets?

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  • Or just the count of this correspondence?
• Known source feature, but no projection available?
Feature Mapping

- Known source feature, but no projection available?
- Back-off model $\Rightarrow$ shorter feature.
  - Unclear:
    - Map the long source feature to the short target feature?
    - Or simply omit the long feature from the tagging model?
Tagging Model

• POS tags from the Hindi Treebank
• Each Hindi word gets target features
  • ⇒ its Hindi features projected to target language
• Similar to word-by-word translation of the training corpus

• Train a model that looks at the target features and predicts a POS tag
• Such model can be applied to the target language
• Features can be obtained directly there

• Method in the paper: CRF++ (Conditional Random Fields)