Target Language-Aware Constrained Inference for Cross-lingual Dependency Parsing

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Overview

Task: Cross-lingual Dependency Parsing

Motivations

- Prior work: focus on capturing *commonalities* between languages.
- Leverage linguistic properties of the target to facilitate the transfer.

Contributions

- We explore *corpus linguistic statistics* derived from WALS features and compile them into *corpus-wise constraints* to guide the inference process during the test time.
- We improve the performances on 17 out of 19 target languages.

Background

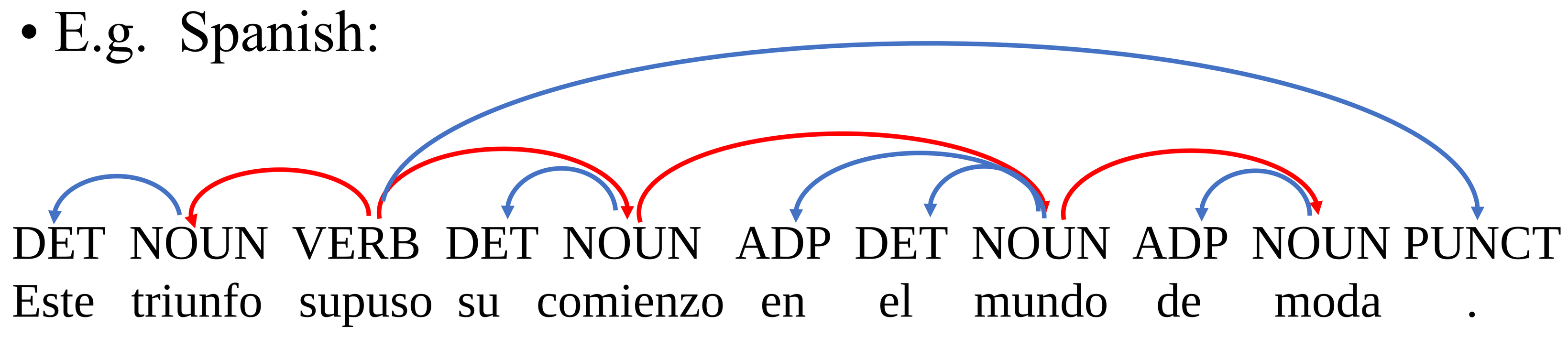
Graph-Based Parser:

- Assigns a score for every word pair and conducts inference to derive a directed spanning tree with the highest accumulated score.
- Integer linear program (ILP) Inference: $\max_{Y\in\mathcal{Y}} \sum_{k,i,j} S_{ij}^{(k)} y_k(i,j)$

Corpus-Statistics Constraints

Unary constraints:

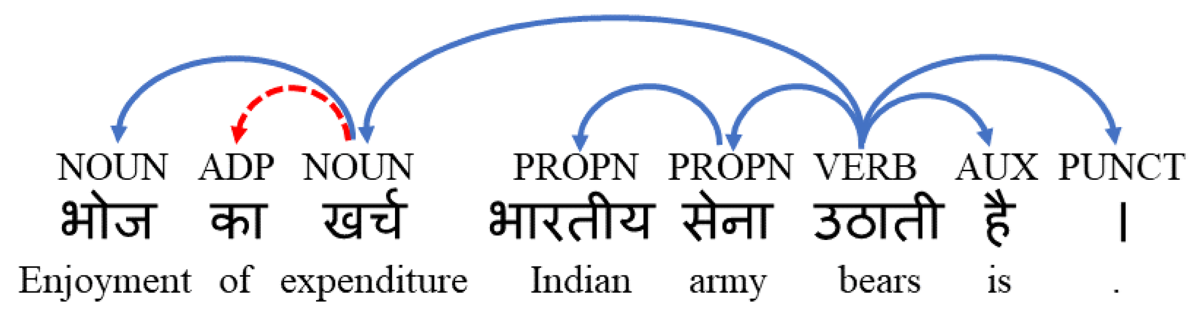
- Statistics regarding a particular POS tag (POS).
- E.g. Spanish:



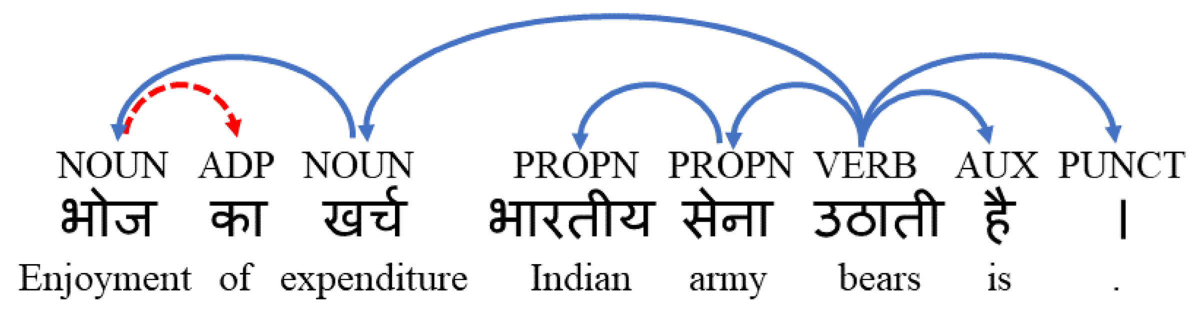
Heads of NOUN appears on the left 82.9% of the time.

Binary constraints:

- Statistics regarding a pair of POS tags (POS_1, POS_2).
- E.g. In Hindi, ADP appears on the right of NOUN in ADP-NOUN arcs 99.9% of the time



Constraint: In an ADP-NOUN arc in Hindi, ADP is more likely to be on the right.



- Given parse trees Y and a constraint C, we define the ratio function $R(C,Y)$.

$$R(C,Y) := \frac{\sum_k \sum_{i,j:(k,i,j)\in C^+} y_k(i,j)}{\sum_k \sum_{i,j:(k,i,j)\in C^+ \cup C^-} y_k(i,j)},$$

- Constraints: statistics of Y consistent with the pre-defined ratio r:

$$r - \theta \le R(C,Y) \le r + \theta. \qquad \theta\text{: pre-defined margin}$$

- WALS features → three types of constraints:

$$WALS_{NOUN} \xrightarrow{LinearRegression} C1 = (NOUN),$$

$$WALS_{85A} \rightarrow C2 = (NOUN, ADP),$$

$$WALS_{87A} \rightarrow C3 = (NOUN, ADJ).$$

- Dominant order → 75% or more.

Inference with Corpus-Statistics Constraints

- **Lagrangian Relaxation (Right).**
  - Constrained inference problem can be formulated as an ILP:
    $\max_{Y\in\mathcal{Y}} \sum_{k,i,j} S_{ij}^{(k)} y_k(i,j)$. s.t. $r_i - \theta_i \le R(C_i, Y) \le r_i + \theta_i,\ i \in [N]$
  - Solve approximately by Lagrangian Relaxation:
    - Lagrangian multipliers $\boldsymbol{\lambda}$ → relax the constraints.
    - Iteratively ($\boldsymbol{\lambda}^{(t)} \xrightarrow{Inference} Y \xrightarrow{Gradient} \boldsymbol{\lambda}^{(t+1)}$)
    - Inference with the trained multipliers $\boldsymbol{\lambda}^{(T)}$.
- **Posterior Regularization (Middle).**
  - Treat the model as a probability model p_θ:

$$p_k(i,j) \propto \exp S_{ij}^{(k)}$$

  - Define the feasible set Q by constraints:

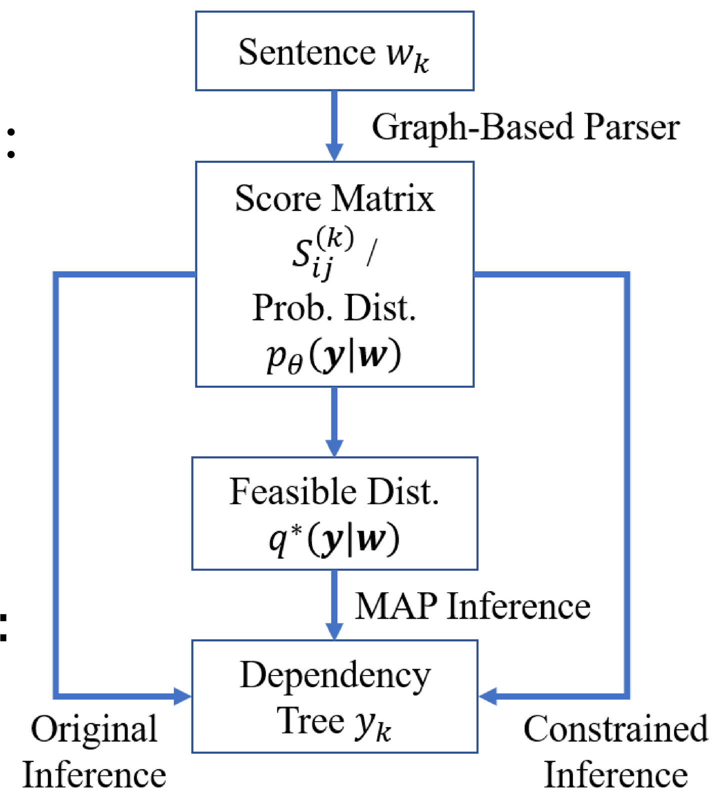
$$r_i - \theta_i \le R(C_i, q) \le r_i + \theta_i, i \in [N]$$

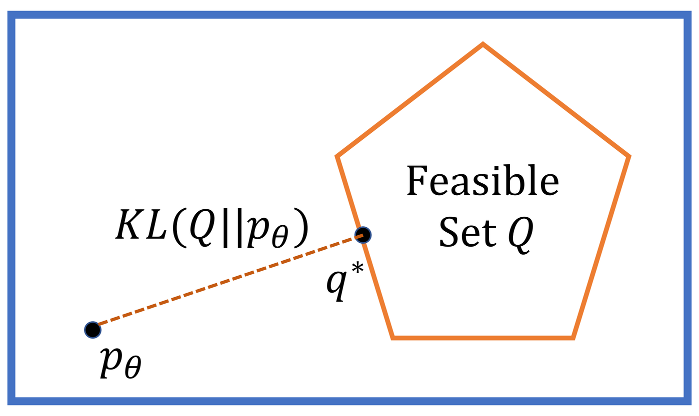
  - Find the closest distribution in Q from p_θ:

$$q^* = \arg\min_{q\in Q} KL(q||p_\theta)$$

  - MAP inference based on the feasible distribution q^*.

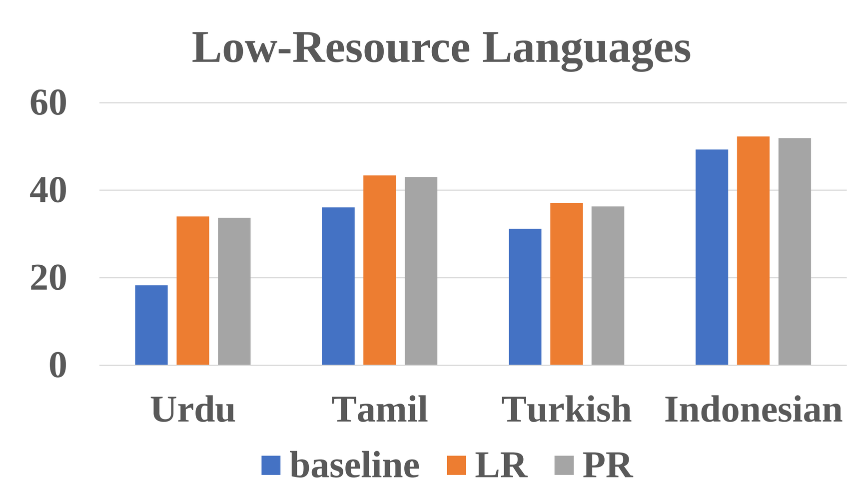
$$Y = \arg\max_{Y\in\mathcal{Y}} q^*(Y) = \arg\max_{Y\in\mathcal{Y}} \prod_{k,i,j} q_k^*(i,j)^{y_k(i,j)}$$

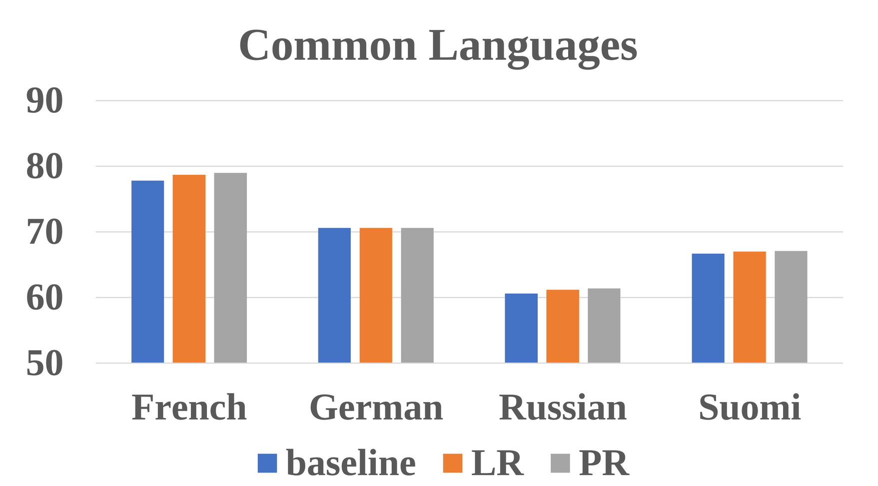




Results

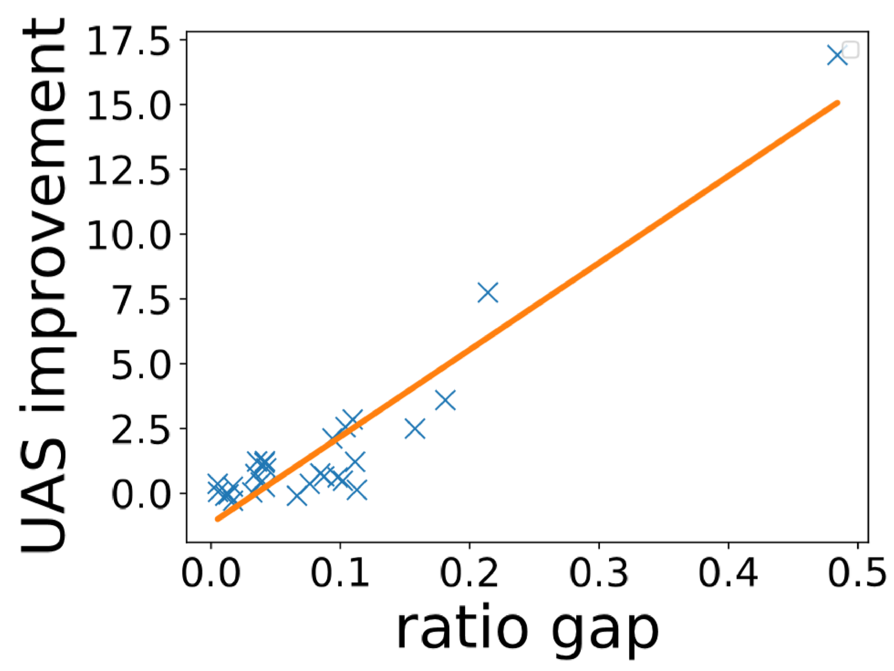
- *Significant improvements* in low-resource languages. Keep or slightly improve the performance in common languages.





- Analysis about individual constraints and the relation between improvements and ratio gap (*Highly related, Pearson 0.938*).

Model	UAS	coverage	Δ
baseline	54.3	N/A	N/A
+Proj.	54.6	N/A	+0.3
+Proj.+C1	57.0	0.24	+2.4
+Proj.+C2	55.7	0.08	+1.1
+Proj.+C3	55.0	0.07	+0.4
oracle	58.4	N/A	+4.1



Conclusion

- Improve *15* and *17* languages out of 19 with LR and PR, respectively.
- Languages with different word order from English improve significantly.
- Lagrangian relaxation has a greater average improvement, while posterior regularization improves more languages.
- Code and models:
  https://github.com/MtSomeThree/CrossLingualDependencyParsing/