Learning Latent Trees with Stochastic Perturbations and Differentiable Dynamic Programming

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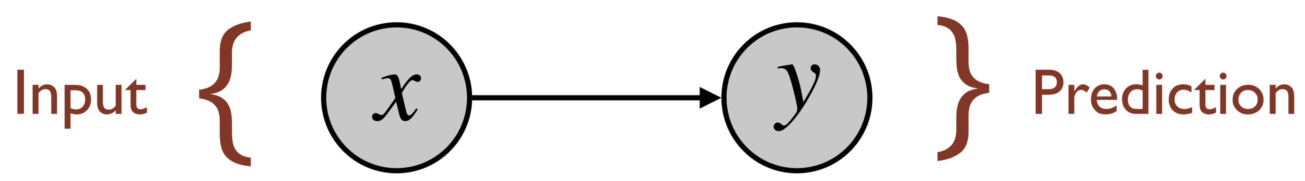
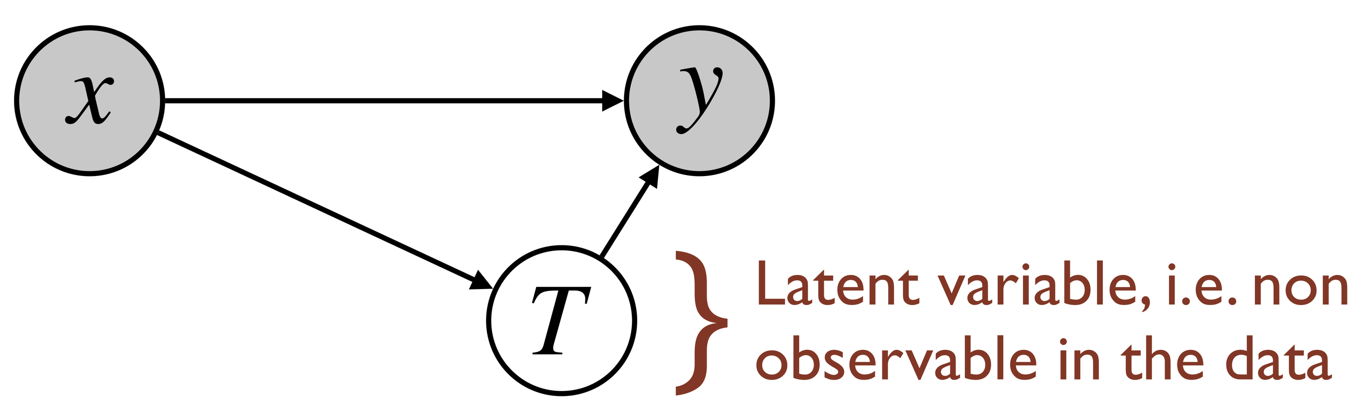
Latent Variable Models

Supervised learning can be understood as inferring the probability distribution corresponding to a directed graphical model.

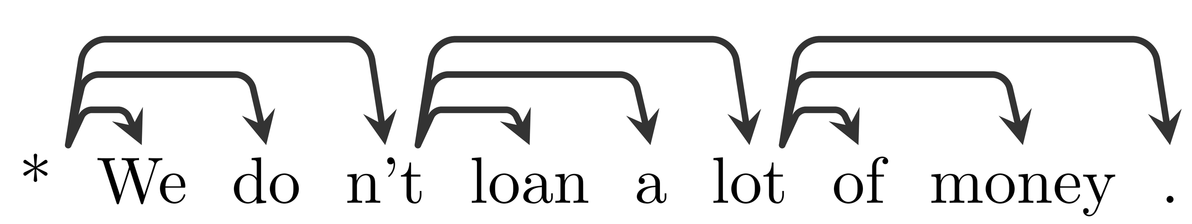


Latent variables can model unobserved inter-dependencies or introduce knowledge about the structure of a given problem.



Projective Dependency Tree

We are interested in **latent projective dependency trees** that implicitly encode hierarchical decomposition of a sentence into spans.



Distribution over Trees

The probability distribution over dependency trees is a log-linear model factored over arc weights.

W : matrix of arc weights computed with a NN

T : boolean adjacency matrix,
i.e $T_{h,m} = 1$ iff arc $x_h \rightarrow x_m$ is in the tree

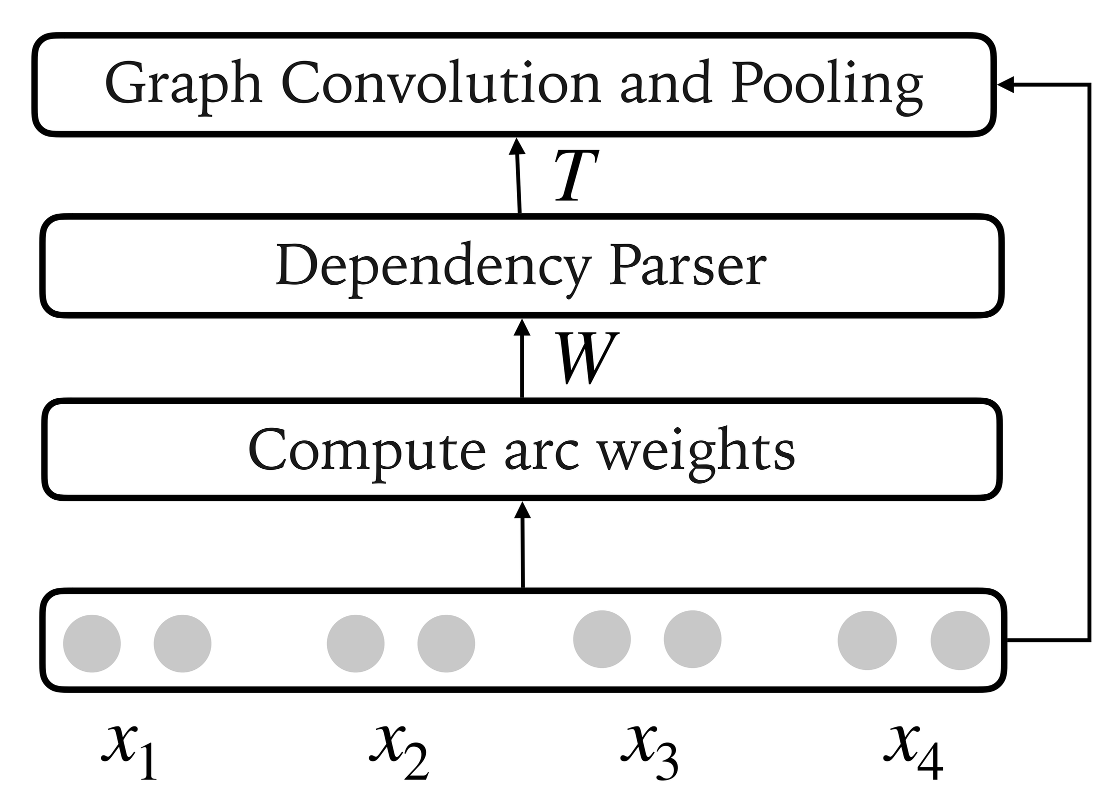
$$p(T|x) = \frac{\sum_{h,m} T_{h,m} \times W_{h,m}}{Z(T,x)}$$

Contributions

1. We show that a **latent tree model** can be estimated by drawing global approximate samples via **Gumbel perturbation and differentiable dynamic programming**
2. We demonstrate that constraining the structures to be projective dependency trees is beneficial
3. We show the effectiveness of our approach on two standard tasks and on a synthetic dataset

Neural Architecture

A **Graph Convolutional Network** [Kipf and Welling, 2017] is used to compute the sentence representation w.r.t. the dependency tree.



Training Loss

We maximise the likelihood of training data via SGD:

$$\max \sum_{x,y} p(y|x) \quad \Big\} \text{ T does not appear here}$$

where:

$$\log\ p(y|x) = \log\ \mathbb{E}_{T\sim p(T|x)}[\ p(y|T,x)\ ]$$

Unfortunately, exact marginalisation is intractable:

$$= \log \sum_{T} p(T|x) \times p(y|T,x)$$

Therefore, we derive a bound using Jensen's inequality:

$$\geq \mathbb{E}_{T\sim p(T|x)}[\ \log\ p(y|T,x)\ ]$$

Which can be approximated via Monte-Carlo method.

Perturb-and-MAP

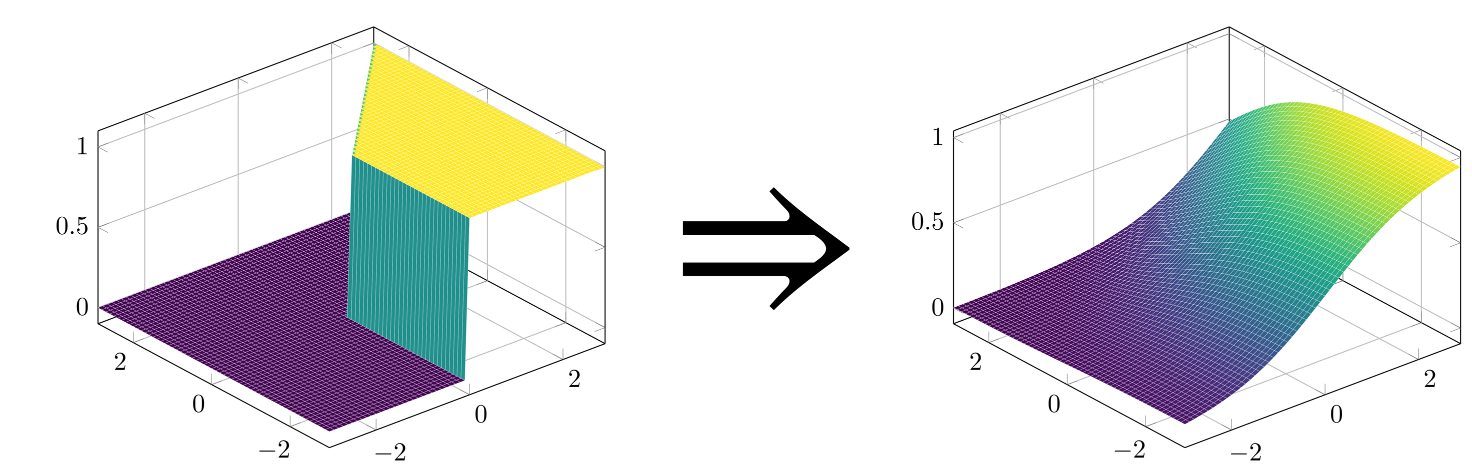
Approximate sampling method for log-linear models:

$$\left.\begin{array}{l} G \sim \mathcal{G}(0,1) \\ \widetilde{W} = W + G \end{array}\right\} \text{Arc weight perturbation with Gumbel noise [Papandreou \& Yuille, 2011]}$$

$$\left.\underset{T\in\mathcal{T}(s)}{argmax} \sum_{h,m} T_{h,m} \times \widetilde{W}_{h,m}\right\} \text{Solved with dynamic programming [Eisner, 1996]}$$

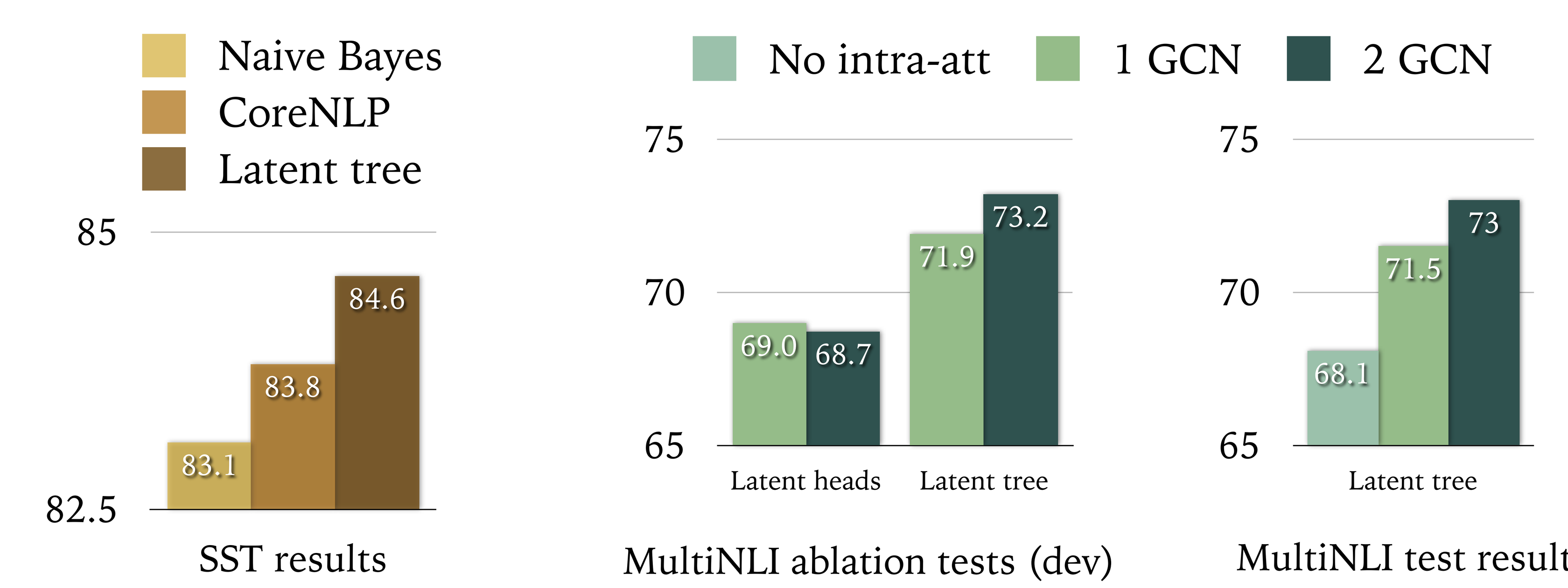
Differentiable Dynamic Programming

The dynamic programming approach for parsing relies on recursive calls to the *one-hot-argmax* op, which introduces ill-defined derivatives during the backward pass. We replace *one-hot-argmax* ops with *softmax* ops to smooth the optimization landscape.



Experimental Results

Experimentally, we observe that our **Latent Tree (LT)** model improves comparable baselines on **sentiment analysis** with syntactic trees predicted by CoreNLP and on **Natural Language Inference** datasets.



Acknowledgments

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