Unsupervised Natural Language Parsing

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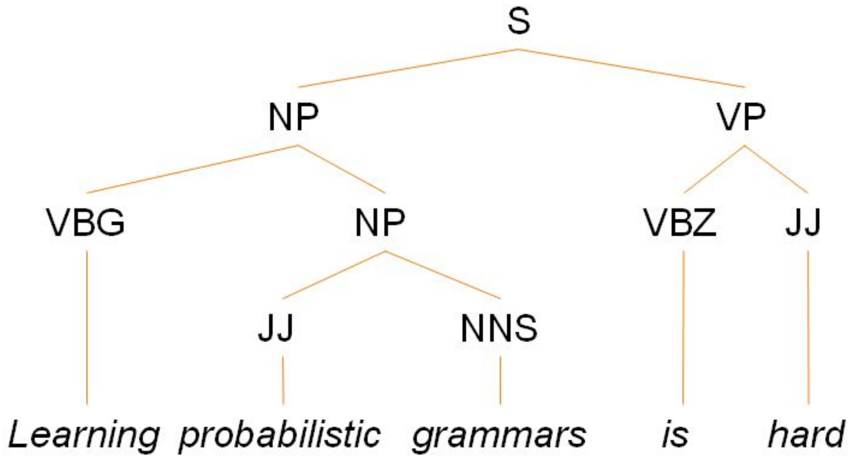
Tutorial Overview

1.	Introduction	(Kewei)
2.	Generative Approaches	(Kewei, Yong)
3.	Discriminative Approaches	(Wenjuan)
4.	Special Topics	(Yanpeng)
5.	Summary	(Kewei)

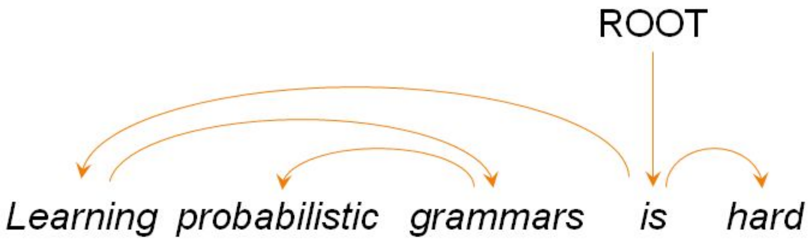
1. Introduction

Syntactic Parsing

- Goal: identifying the syntactic structure of a sentence
    - Typically a tree structure over the sequence of words

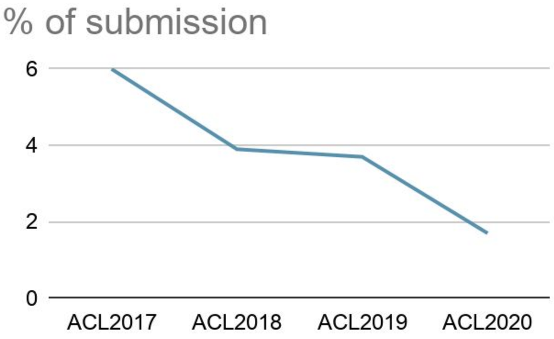


Constituency Parsing



Dependency Parsing

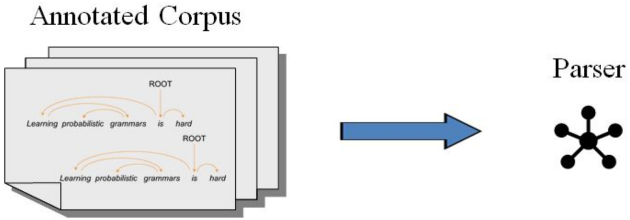
Syntactic Parsing



- In traditional NLP:
  - A key component in the NLU pipeline
- In the era of deep learning:
  - Diminishing importance...
    - Sequential models (+attention) seem to work very well.
  - ...but regains some attention in recent years
    - Ex: useful in some tasks, such as SRL (Strubell et al., 2018)
    - Ex: knowledge distillation from RNNG (a syntactic parser/LM) to BERT (Kuncoro et al., 2020)
- Our thoughts:
  - Linguistic structures are an intrinsic property of natural languages
  - We should utilize them instead of ignoring them

Supervised vs. Unsupervised Parsing

- Supervised parsing: learning a parser from training sentences annotated with parses (treebank)


Annotated Corpus
ROOT
Learning probabilistic grammars is hard
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Learning probabilistic grammars is hard
Parser

Supervised vs. Unsupervised Parsing

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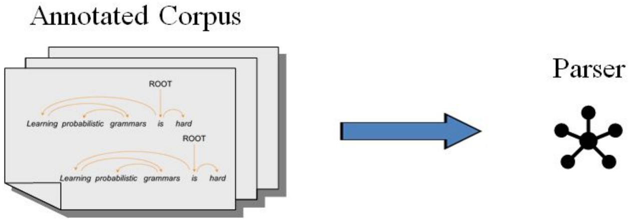
    - Limitation: shortage of high-quality treebanks in low-resource languages or domains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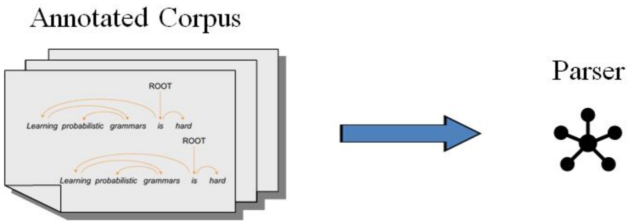
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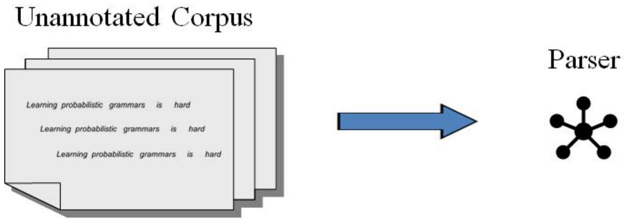
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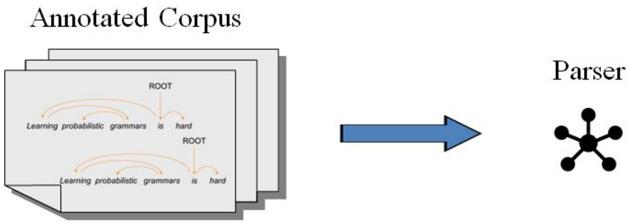
  - Typical setting: learning from unannotated data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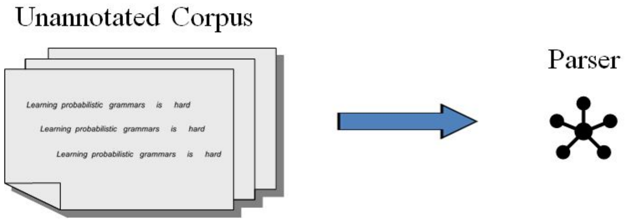
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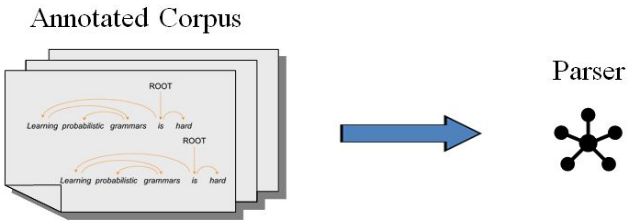
  - Exception exists: no data at all (Søgaard, 2012)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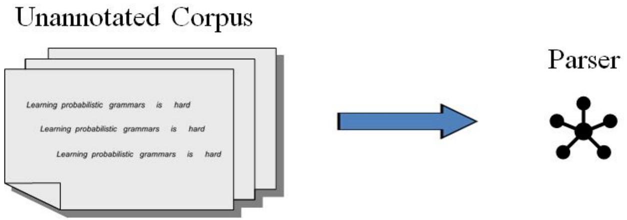
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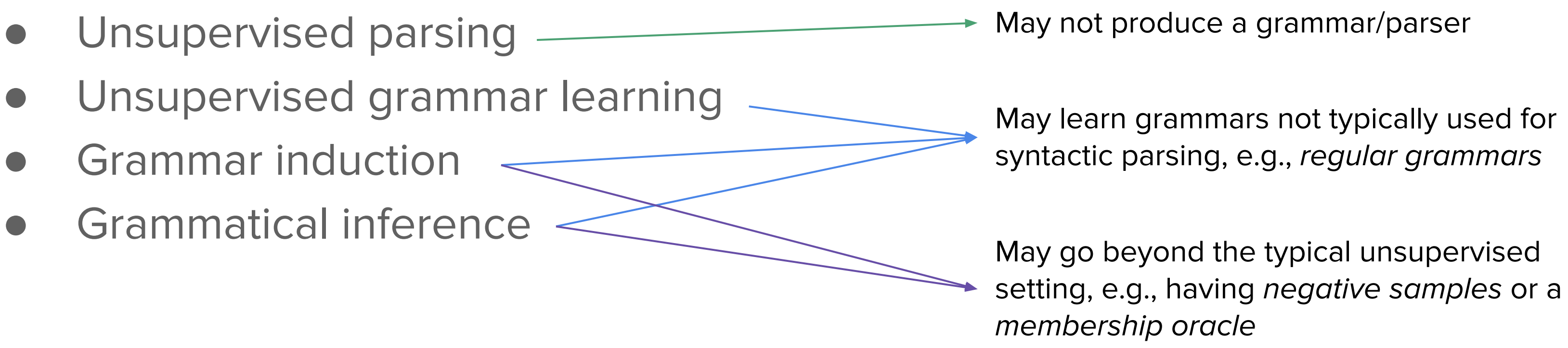
Why Unsupervised?

- It requires no human annotation (good for low-resource settings)
- It can utilize (potentially unlimited) unannotated text data.
- It serves as the basis for semi-supervised, weakly supervised, and transfer learning of syntactic parsers.
    - Ex: CRFAE unsupervised (Cai et al., 2017), semi-supervised (Jia et al., 2020; Zhang & Goldwasser, 2020), cross-lingual transfer (Li & Tu, 2020)
- It is a representative task of unsupervised structured prediction.
- It inspires/verifies cognitive research of human language acquisition.
- It can be extended to data of other modalities without treebanks.
    - Ex: image parsing (Tu et al., 2013), probabilistic modeling (Poon & Domingos, 2011)

Terminology



- Unsupervised parsing
- Unsupervised grammar learning
- Grammar induction
- Grammatical inference

May not produce a grammar/parser

May learn grammars not typically used for syntactic parsing, e.g., *regular grammars*

May go beyond the typical unsupervised setting, e.g., having *negative samples* or a *membership oracle*

History

- A long history
    - Language identification in the limit (Gold, 1967)
    - Inside-outside algorithm (Baker, 1979)
- Recent surge of interest
    - [a plot of #paper over the past 3-5 years?]
    - [a figure of two trends:]
        - a general trend in deep learning towards unsupervised training or pre-training
        - an emerging trend in the NLP community towards finding or modeling linguistic structures in neural models

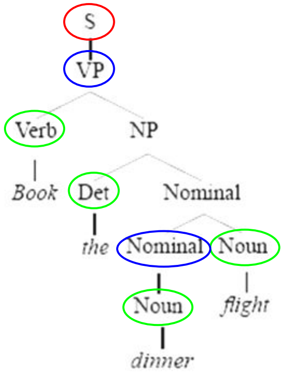
Evaluation -- typical experimental setup

- Availability of POS annotations
  - Exceptions: induced POS tags (Spitkovsky et al., 2011a; He et al., 2018), no POS (Seginer, 2007; Pate & Johnson, 2016)
- Length limit of training sentences
  - Many methods work best with a length limit of 10-15 for English
  - More recent methods are able to learn from longer sentences
- Punctuation removal
  - Punctuation marks can provide info of phrase boundaries; simply treating them as words may hurt learning (Spitkovsky et al., 2011b)

Evaluation -- metrics

Constituency parsing

- F1 score: the harmonic mean of precision & recall of constituents
  - Precision: the percentage of predicted constituents that are correct
  - Recall: the percentage of gold constituents that are predicted
- Removing trivial constituents
  - Single-word spans
  - Whole-sentence spans
  - Duplicate spans



⚠ *Many previous studies follow different practices.*

Evaluation -- metrics

Dependency parsing

- Directed dependency accuracy (DDA)
  - Percentage of correctly predicted dependencies
- Undirected dependency accuracy (UDA)
  - Percentage of correctly predicted dependencies when ignoring their directions
- Neutral edge detection (NED) (Schwartz et al., 2011)
  - Similar to UDA, but allows that the predicted parent of a token is actually the grandparent

Evaluation -- metrics

Micro-average (i.e., corpus-level score)

- Aggregating the predicted and gold constituents/dependencies from all the sentences and then calculating the score

Macro-average (i.e., sentence-level score)

- Calculating the score for each individual sentence and then take an average over all the sentences

⚠ *Many previous studies use different averaging methods.*

Evaluation -- hyperparameter tuning ⚠

- A lot of previous studies perform hyperparameter tuning with evaluation metrics (e.g., F1 or DDA) on a development corpus annotated with parse trees
- Consequences:
  - Learning is no longer purely unsupervised.
  - It calls for comparison with supervised learning on the dev set
    - This has been found to outperform unsupervised parsing (Shi et al., 2020).
- Alternative strategies
  - Perform hyperparameter tuning with metrics not based on gold parses, e.g., perplexity
  - Perform hyperparameter tuning with gold parses on one language, but fix the hyperparameter values during evaluation on other languages

Evaluation -- Are gold parses unique?

- There exist different linguistic theories resulting in different gold parses
    - Ex: Some theories choose determiners as the heads of noun phrases (Abney, 1987).
    - Since unsupervised parsing has no clue what theory it should follow, isn’t it problematic to do evaluation with specific theories embodied by available treebanks?
- Solution?
    - Ultimately, parsing is supposed to provide useful info for downstream tasks.
    - One may use performance on downstream tasks as a surrogate metric.