Training and evaluating dependency parsers

(added to the course by popular demand)

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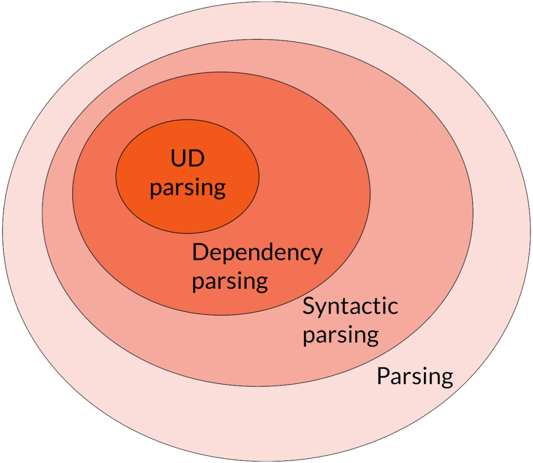
LT2214 Computational Syntax

Today's topic



Parsing

A structured prediction task

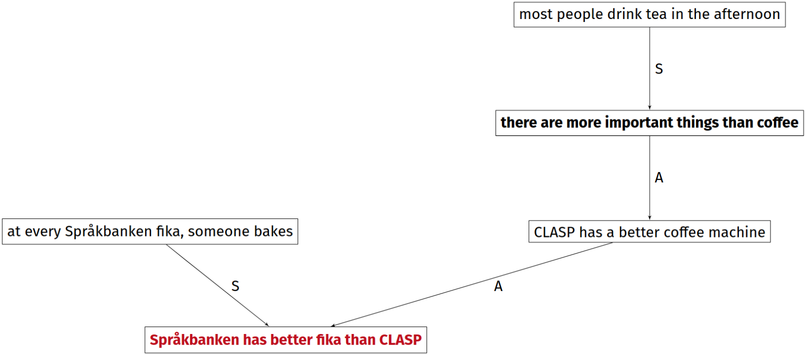
Sequence → structure, e.g.

- natural language sentence → syntax tree
- code → AST
- argumentative essay → argumentative structure
- ...

Example (argmining)

Språkbanken has better fika than CLASP: every fika, someone bakes. Sure, CLASP has a better coffee machine. On the other hand, there are more important things than coffee. In fact, most people drink tea in the afternoon.

Example (argmining)



From "A gentle introduction to argumentation mining" (Lindahl et al., 2022)

Syntactic parsing

From sentence to tree

From chapter 18 of *Speech and Language Processing*, (Jurafsky & Martin, January 2024 draft):

> *Syntactic parsing is the task of assigning a syntactic structure to a sentence*

- the structure is usually a *syntax tree*
- two main classes of approaches:
  - constituency parsing (e.g. GF)
  - dependency parsing (e.g. UD)

Example (GF)

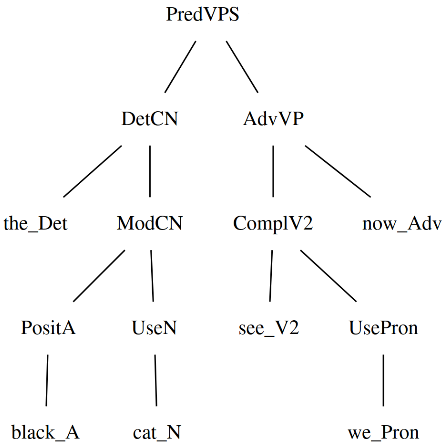
```
MicroLang> i MicroLangEng.gf
linking ... OK

Languages: MicroLangEng
7 msec
MicroLang> p "the black cat sees us now"
PredVPS (DetCN the_Det (AdjCN (PositA black_A)
(UseN cat_N))) (AdvVP (ComplV2 see_V2 (UsePron
we_Pron)) now_Adv)
```

Example (GF)

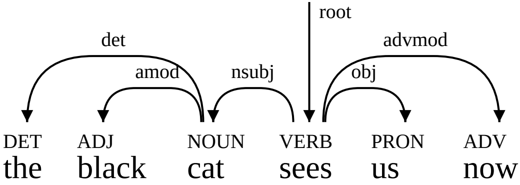
```
PredVPS
    (DetCN
        the_Det
        (AdjCN (PositA black_A) (UseN cat_N))
    )
    (AdvVP
        (ComplV2 see_V2 (UsePron we_Pron))
        now_Adv
    )
```

Example (GF)


PredVPS
DetCN
AdvVP
the_Det
ModCN
ComplV2
now_Adv
PositA
UseN
see_V2
UsePron
black_A
cat_N
we_Pron

Dependency parsing

Example (UD)




```
1	the	_	DET	_	_	3	det	_	_
2	black	_	ADJ	_	_	3	amod	_	_
3	cat	_	NOUN	_	_	4	nsubj	_	_
4	sees	_	VERB	_	_	0	root	_	_
5	us	_	PRON	_	_	4	obj	_	_
6	now	_	ADV	_	_	4	advmod	_	_
```

Two paradigms

- **graph-based algorithms**: find the optimal tree from the set of all possible candidate solutions (or a subset of it)
- **transition-based algorithms**: incrementally build a tree by solving a sequence of classification problems

Graph-based approaches

$$\hat{t} = \underset{t \in T(s)}{argmax}\; score(s, t)$$

- t: candidate tree
- $\hat{t}$: predicted tree
- s: input sentence
- $T(s)$: set of candidate trees for s

Complexity

Depends on:

- choice of T (upper bound: n^{n-1}, where n is the number of words in s)
- scoring function (in the **arc-factor model**, the score of a tree is the sum of the score of each edge, scored individually by a NN)

In practice: $O(n^3)$ complexity

Transition-based approaches

- trees are built through a sequence of steps, called *transitions*
- training requires:
  - a gold-standard treebank (as for graph-based approaches)
  - an *oracle* i.e. an algorithm that converts each tree into a a gold-standard sequence of transitions
- much more efficient: $O(n)$

Evaluation

2 main metrics:

- **UAS** (Unlabelled Attachment Score): what's the fraction of nodes are attached to the correct dependency head?
- **LAS** (Labelled Attachment Score): what's the fraction of nodes are attached to the correct dependency head *with an arc labelled with the correct relation type*[1]?

[1] in UD: the `DEPREL` column

Specifics of UD parsing

Not just parsing per se

UD "parsers" typically do a lot more than dependency parsing:

- sentence segmentation
- tokenization
- lemmatization (`LEMMA` column)
- POS tagging (`UPOS` + `XPOS`)
- morphological tagging (`FEATS`)
- ...

Sometimes, some of these tasks are performed **jointly** to achieve better performance.

Evaluation (UD-specific)

Some more specific metrics:

- **CLAS** (Content-word LAS): LAS limited to content words
- **MLAS** (Morphology-Aware LAS): CLAS that also uses the `FEATS` column
- **BLEX** (Bi-Lexical dependency score): CLAS that also uses the `LEMMA` column

Evaluation script output

```
Metric     | Precision |    Recall |  F1 Score | AligndAcc
-----------+-----------+-----------+-----------+-----------
Tokens     |    100.00 |    100.00 |    100.00 |
Sentences  |    100.00 |    100.00 |    100.00 |
Words      |    100.00 |    100.00 |    100.00 |
UPOS       |     98.36 |     98.36 |     98.36 |     98.36
XPOS       |    100.00 |    100.00 |    100.00 |    100.00
UFeats     |    100.00 |    100.00 |    100.00 |    100.00
AllTags    |     98.36 |     98.36 |     98.36 |     98.36
Lemmas     |    100.00 |    100.00 |    100.00 |    100.00
UAS        |     92.73 |     92.73 |     92.73 |     92.73
LAS        |     90.30 |     90.30 |     90.30 |     90.30
CLAS       |     88.50 |     88.34 |     88.42 |     88.34
MLAS       |     86.72 |     86.56 |     86.64 |     86.56
BLEX       |     88.50 |     88.34 |     88.42 |     88.34
```

Three generations of parsers

(all transition-based)

1. **MaltParser** (Nivre et al. 2006): "classic" transition-based parser, data-driven but not NN-based
2. **UDPipe**: neural parser, personal favorite
   - v1 (Straka et al. 2016): fast, solid software, easy to install and available anywhere
   - v2 (Straka et al. 2018): much better results but slower and only available through an API/via the web GUI
3. **MaChAmp** (van der Goot et al. 2021): transformer-based toolkit for multi-task learning, works on all CoNNL-like data, close to the SOTA, relatively easy to install and train

MaChAmp config example

```
{"compsyn": {
    "train_data_path": "PATH-TO-YOUR-TRAIN-SPLIT",
    "dev_data_path": "PATH-TO-YOUR-DEV-SPLIT",
    "word_idx": 1,
    "tasks": {
        "upos": {
            "task_type": "seq",
            "column_idx": 3
        },
        "dependency": {
            "task_type": "dependency",
            "column_idx": 6}}}}
```

Your task (lab 3)

1. annotate a small treebank for your language of choice (started yesterday)
2. train a parser-tagger on a reference UD treebank (tomorrow, or who knows maybe even today: installation)
3. evaluate it on your treebank

Sources/further reading

Main sources

- chapters 18-19 of the January 2024 draft of *Speech and Language Processing* (Jurafsky & Martin) (full text available **here**)
- unit 3-2 of Johansson & Kuhlmann's course "Deep Learning for Natural Language Processing" (slides and videos available **here**)
- section 10.9.2 on parser evaluation from Aarne's course notes (on Canvas or **here**)

Papers describing the parsers

- *MaltParser: A Data-Driven Parser-Generator for Dependency Parsing* (Nivre et al. 2006) (PDF **here**)
- *UDPipe: Trainable Pipeline for Processing CoNLL-U Files Performing Tokenization, Morphological Analysis, POS Tagging and Parsing* (Straka et al. 2016) (PDF **here**)
- *UDPipe 2.0 Prototype at CoNLL 2018 UD Shared Task* (Straka et al. 2018) (PDF **here**)
- *Massive Choice, Ample Tasks (MACHAMP): A Toolkit for Multi-task Learning in NLP* (van der Goot et al., 2021) (PDF **here**)