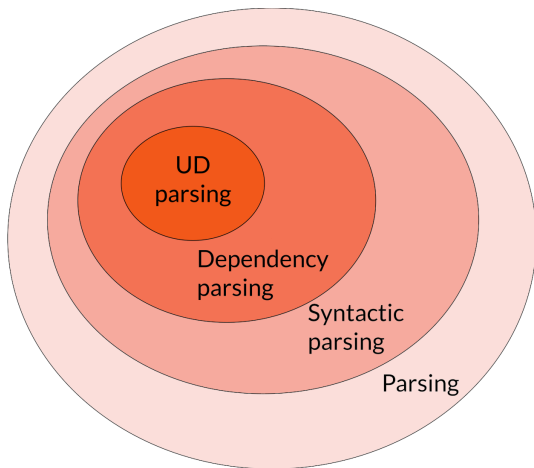


# Training and evaluating dependency parsers

this time using slides so we have time for more examples

Arianna Masciolini  
LT2214 Computational Syntax

# Today's topic



# Parsing

# A structured prediction task



Sequence  $\rightarrow$  data structure, e.g.

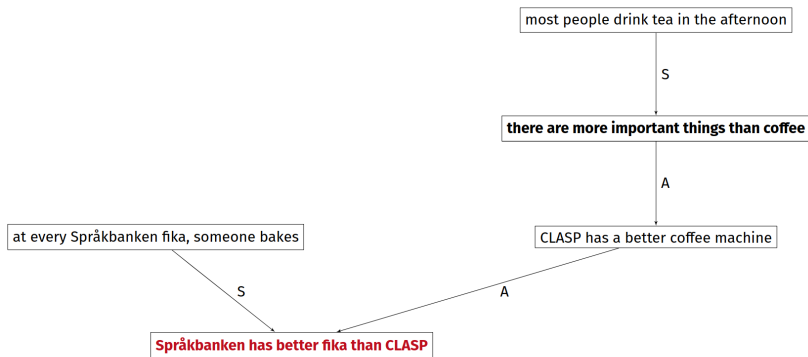
- ❑ natural language sentence  $\rightarrow$  syntax tree
- ❑ argumentative essay  $\rightarrow$  argumentative structure
- ❑ code  $\rightarrow$  AST
- ❑ ...

# 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 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
```

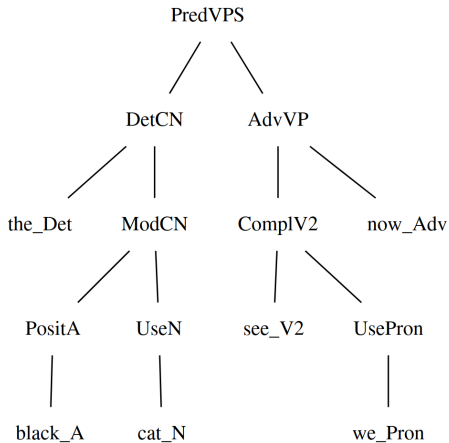
```
MicroLang> p "the black cat sees us now"  
PredVPS (DetCN the_Det (AdjCN (PositA black_A)  
(UseN cat_N))) (AdvVP (ComplV2 see_V2 (UsePron  
we_Pron)) now_Adv)
```

# Example (GF)



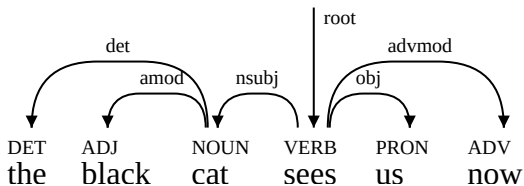
```
PredVPS
  (DetCN
    the_Det
    (AdjCN (PositA black_A) (UseN cat_N))
  )
  (AdvVP
    (ComplV2 see_V2 (UsePron we_Pron))
    now_Adv
  )
```

# Example (GF)



# 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

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

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

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





- ❖ 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 gold-standard sequence of transitions
- ❖ much more efficient:  $O(n)$

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*<sup>1</sup>?

---

<sup>1</sup> in UD: the DEPREL column

# Specifics of UD parsing

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.

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

# To learn more



- ❖ chapters 18-19 of the January 2024 draft of *Speech and Language Processing* (Jurafsky & Martin) (full text available **here**)
- ❖ Richar Johansson **materials for the Machine Learning for Natural Language Processing course at CSE** (lectures 7-8)
- ❖ section 10.9.2 on parser evaluation from Aarne's course notes (on Canvas)

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



1. DIT231 Programming language technology
  - ❖ build a complete compiler
2. DIT301 Compiler construction
  - ❖ the hardcore version of 1.
  - ❖ build another compiler *and optimize it*
3. DIT247 Machine learning for NLP (?)
  - ❖ has a module on dependency parsing similar to the one in “Deep Learning for Natural Language Processing”