From Parser to Query

Day 1. Introduction to Dependency Queries

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10-11 June 2024

Outline

Practical Information about this workshop

Introduction to Historical Parsed Corpora

From Constituency to Dependency

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Plan of this workshop

- Day 1 : Parsed corpora and gueries
 - 1. Introduction to Historical Parsed Corpora
 - 2. From constituency to dependency
 - 3. Querying UD corpora with Grew Match
- Day 2 : Parsing and guerying your own texts

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- Day 1 : Parsed corpora and queries
 - 1. Introduction to Historical Parsed Corpora
 - 2. From constituency to dependency
 - 3. Querying UD corpora with Grew Match
- Day 2 : Parsing and guerying your own texts
 - 1. Parsing with UD Pipe and HOPS Parser
 - 2. Examining parser results with GREW match

 - 3. Techniques for getting the best results

GitHub repository

https://github.com/ILR-Stuttgart/from-parser-to-query

- step-by-step guides for all exercises using the command-line
- sample data
- these slides

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What is a parsed corpus?

Parsed Corpus (Treebank)

An electronic corpus divided into words and sentences in which the syntactic relations between the words within each sentence are represented.

(1) John gave the book to his father.

- ▶ *John* is a nominal and is the subject of *gave*.
- ▶ *the book* is the object of *gave*, *the* determines *book*.
- ▶ to his father is the indirect object of gave, his determines father [and refers to John]

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From Text to Query

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2. Parse

- 2a. add syntactic annotation
- 2b. verify annotation

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- Annotation scheme and data format
 - Penn format (constituency, generative)
 - Universal Dependencies
- Semi-automated or automated initial parsing
 - if resources available
- Manual annotation and/or error correction
 - resource- and time-intensive

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How are parsed corpora used?

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- specialized corpus query programmes
 - ► CorpusSearch https://corpussearch.sourceforge.net/
 - ► ANNIS https://corpus-tools.org/annis/
 - ► GREW Match, etc... https://match.grew.fr/
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 - ... so train your own from existing data
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From Constituency to Dependency

Historical corpora in dependency and constituency

Constituency (Penn format)

https://www.ling.upenn.edu/hist-corpora/other-corpora.html

- ► Germanic : English, German, Saxon, Icelandic, Faroese
- ► Romance : French, Portuguese
- Japanese
- ▶ Dependency (UD) https://universaldependencies.org/
 - Akkadian, Classical Chinese, French, Gothic, Ancient Greek, Icelandic and Faroese (converted), Irish, Latin, Sanskrit, Old East Slavic, Old Church Slavonic, Turkish

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Sample sentence

Song of Roland, I. 1–2

Carles li reis, nostre emperere magnes, Set anz tuz pleins ad estet en Espaigne. 'Charles the King, our great emperor, has been in Spain for seven full long years'

Penn Format (constituency)

```
( (IP-MAT (NP-SBJ (NPRS Carles)
          (NP-PRN (D li) (NCS reis))
          (PON ,)
          (NP-PRN (DZ nostre)
              (NCS emperere)
              (ADJP (ADJ magnes))))
      (PON ,)
      (NP-MSR (ADJNUM Set)
          (NCPL anz)
          (ADJP (Q tuz) (ADJ pleins)))
      (AJ ad)
      (VPP estet)
      (PP (P en)
          (NP (NPRS Espaigne)))
      (PONFP:))
  (ID 1100-ROLAND-MCVF-V,1.3))
```

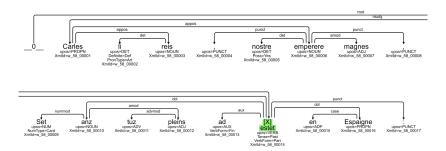
Quelle: Martineau, France, Paul Hirschbühler, Anthony Kroch, and Yves Charles Morin, eds. 2021. MCVF Corpus,

Conllu Format (dependency)

1 Carles	PROPN	NOMpro		14 nsubj	Xmlid=w_58_00001
2 li	_ DET	DETdef	Definite=Def ▶	3 det	XmlId=w 58 00002
3 reis	NOUN	NOMcom		1 appos	SpaceAfter=No Xmlid=w_58_00003
4,	PUNCT	PONfbl		6 punct	Xmlid=w_58_00004
5 nostre	DET	DETpos	Poss=Yes	6 det	XmlId=w_58_00005
6 emperere	NOUN	NOMcom		1 appos	Xmlid=w_58_00006
7 magnes	ADJ	ADJqua		6 amod	SpaceAfter=No XmlId=w_58_00007
8,	PUNCT	PONfbl		6 punct	Xmlid=w_58_00008
9 Set	NUM	DETcar	NumType=C▶	10 nummod	XmlId=w 58 00009
10 anz	NOUN	NOMcom		14 obl	XmlId=w_58_00010
11 tuz	ADV	ADVgen		12 advmod	Xmlid=w_58_00011
12 pleins	ADJ	ADJqua		10 amod	XmlId=w_58_00012
13 ad	AUX	VERcjg	VerbForm=F 	14 aux	XmlId=w_58_00013
14 estet	VERB	VERppe	Tense=Past >	0 root	XmlId=w 58 00014
15 en	ADP	PRE		16 case	XmlId=w_58_00015
16 Espaigne	PROPN	NOMpro		14 obl	XmlId=w_58_00016
17:	PUNCT	PONfbl		14 punct	XmlId=w_58_00017

 $Quelle: \verb"UD_Old_French-Profiterole2.14", \verb"https://gitlab.huma-num.fr/profiterole/srcmf-ud" in the profiterole of the profit$

Graph Format (dependency)



Source: GREW Match https://universal.grew.fr

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- easier to parse, parsers more widely available
 - large community of developers
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