IN2110: Methods in Language Technology Dependency Parsing

Stephan Oepen

Language Technology Group (LTG)

April 23, 2019





- ► Short recap:
 - ► (Local) Ambiguity in natural languages
 - ► Chart parsing: The Cocke–Kasami–Younger algorithm



- ► Short recap:
 - ► (Local) Ambiguity in natural languages
 - ► Chart parsing: The Cocke–Kasami–Younger algorithm
- Granular evaluation of statistical parsers



- ► Short recap:
 - ► (Local) Ambiguity in natural languages
 - ► Chart parsing: The Cocke—Kasami—Younger algorithm
- Granular evaluation of statistical parsers
- Move on to dependency syntax
 - ► Typological motivation
 - Contrast to constituent syntax
 - ► Properties of dependency graphs



- ► Short recap:
 - ► (Local) Ambiguity in natural languages
 - ► Chart parsing: The Cocke–Kasami–Younger algorithm
- Granular evaluation of statistical parsers
- ► Move on to dependency syntax
 - Typological motivation
 - ► Contrast to constituent syntax
 - Properties of dependency graphs
- Data-driven dependency parsing
 - ► Variations on shift—reduce parsing
 - ► The arc-eager transition system
 - ► Thorough walk-through example



- ► Short recap:
 - ► (Local) Ambiguity in natural languages
 - ► Chart parsing: The Cocke–Kasami–Younger algorithm
- ► Granular evaluation of statistical parsers
- ► Move on to dependency syntax
 - ► Typological motivation
 - ► Contrast to constituent syntax
 - ► Properties of dependency graphs
- ▶ Data-driven dependency parsing
 - ► Variations on shift-reduce parsing
 - ► The arc-eager transition system
 - ► Thorough walk-through example
- ► Sample exam questions

Exercise (1): Natural Language Ambiguity

Assume the following 'toy' grammar of English:

```
\begin{array}{c} \mathsf{S} \to \mathsf{NP} \\ \mathsf{NP} \to \mathsf{Det} \; \mathsf{N} \\ \mathsf{N} \to \mathsf{N} \; \mathsf{N} \\ \\ \mathsf{Det} \to \mathit{the} \\ \mathsf{N} \to \mathit{kitchen} \; | \; \mathit{table} \; | \; \mathit{towel} \; | \; \mathit{rack} \end{array}
```

Exercise (1): Natural Language Ambiguity

Assume the following 'toy' grammar of English:

$$S
ightarrow NP \ NP
ightarrow Det N \ N
ightarrow N N \ Det
ightarrow the \ N
ightarrow kitchen | table | towel | rack$$

(1) How many different syntactic analyses, if any, does the grammar assign to the following strings?

(a) the kitchen towel rack(b) the kitchen table towel rack

Exercise (2): CKY Parsing

Assume the following grammar and CKY parse table:

$S \to NP \; VP$
$VP \to V \; NP$
$VP \rightarrow VP PP$
$NP \rightarrow NP PP$
$PP \to P \; NP$

	1	2	3	4	5
0	NP		S		S
1		V	VP		VP
2			NP		NP
3				Р	PP
4					NP

Exercise (2): CKY Parsing

Assume the following grammar and CKY parse table:

	1	2	3	4	5
$S \to NP \; VP$	0 NP		S		S
$VP \rightarrow V NP$ $VP \rightarrow VP PP$ $NP \rightarrow NP PP$ $PP \rightarrow P NP$	1	V	VP		VP
	2		NP		NP
	3			Р	PP
	4				NP

(2) Which pair(s) of 'input' cells and which production(s) give rise to the derivation of category S in 'target' cell $\langle 0,5\rangle$?

- ► A statistical parser (e.g. using a PCFG) will inevitably make 'mistakes'.
- ► The parser output (most probable derivation) differs from gold standard.
- ► How to measure parser quality? Suggestions for an evaluation metric?

- ► A statistical parser (e.g. using a PCFG) will inevitably make 'mistakes'.
- ► The parser output (most probable derivation) differs from gold standard.
- ► How to measure parser quality? Suggestions for an evaluation metric?
- ► Sentence accuracy ('exact match') easy to interpret. Any deficiencies?

- ► A statistical parser (e.g. using a PCFG) will inevitably make 'mistakes'.
- ► The parser output (most probable derivation) differs from gold standard.
- ► How to measure parser quality? Suggestions for an evaluation metric?
- ► Sentence accuracy ('exact match') easy to interpret. Any deficiencies?
- ▶ The ParsEval metric (Black et al., 1991) measures constituent overlap.
- ightharpoonup Precision, recall, and F_1 for labeled brackets ightarrow allow partial credit.

- ► A statistical parser (e.g. using a PCFG) will inevitably make 'mistakes'.
- ► The parser output (most probable derivation) differs from gold standard.
- ► How to measure parser quality? Suggestions for an evaluation metric?
- ► Sentence accuracy ('exact match') easy to interpret. Any deficiencies?
- ▶ The ParsEval metric (Black et al., 1991) measures constituent overlap.
- ▶ Precision, recall, and F_1 for labeled brackets \rightarrow allow partial credit.
- ▶ De-facto standard for 25 years (combined with crossing brackets count).

```
Gold Standard

(NP (DT a)

(ADVP (RB pretty)

(JJ big))

(NOM (NN dog)

(POS 's)

(NN house)))
```

```
Gold Standard

(NP (DT a)

(ADVP (RB pretty)

(JJ big))

(NOM (NN dog)

(POS 's)

(NN house)))
```

```
(NP (DT a)
(JJ pretty)
(NOM (JJ big)
(NOM (NN dog)
(POS 's)
(NN house))))
```

System Output

0,6 NP

0,6 NP 0.1 DT

```
Gold Standard

(NP (DT a)

(ADVP (RB pretty)

(JJ big))

(NOM (NN dog)

(POS 's)

(NN house)))
```

0,6 NP 0,1 DT 1,3 ADVP

```
Gold Standard

(NP (DT a)

(ADVP (RB pretty)

(JJ big))

(NOM (NN dog)

(POS 's)

(NN house)))
```

```
Gold Standard

(NP (DT a)

(ADVP (RB pretty)

(JJ big))

(NOM (NN dog)

(POS 's)

(NN house)))
```

0,6 NP 1,2 RB

0,1 DT 1,3 ADVP

Gold Standard (NP (DT a) (ADVP (RB pretty) (JJ big)) (NOM (NN dog) (POS 's) (NN house)))

0,1 DT 2,3 JJ

1.3 ADVP

Gold Standard (NP (DT a) (ADVP (RB pretty) (JJ big)) (NOM (NN dog) (POS 's) (NN house))

```
0,6 NP 1,2 RB
0,1 DT 2,3 JJ
1,3 ADVP 3,6 NOM
```

System Output

```
(NP (DT a)
(JJ pretty)
(NOM (JJ big)
(NOM (NN dog)
(POS 's)
(NN house))))
```

Gold Standard

```
(NP (DT a)
   (ADVP (RB pretty)
         (JJ big)
   (NOM (NN dog)
         (POS's)
         (NN house)))
 0,6 NP 1,2 RB 3,4 NN
 0,1 DT 2,3 JJ
 1,3 ADVP 3,6 NOM
```

```
Gold Standard

(NP (DT a)

(ADVP (RB pretty)

(JJ big))

(NOM (NN dog)

(POS 's)

(NN house)))
```

```
0,6 NP 1,2 RB 3,4 NN 0,1 DT 2,3 JJ 4,5 POS 1,3 ADVP 3,6 NOM
```

System Output

```
Gold Standard

(NP (DT a)

(ADVP (RB pretty)

(JJ big))

(NOM (NN dog)

(POS 's)

(NN house)))
```

```
0,6 NP 1,2 RB 3,4 NN 0,1 DT 2,3 JJ 4,5 POS 1,3 ADVP 3,6 NOM 5,6 NN
```

System Output

```
(NP (DT a)
(JJ pretty)
(NOM (JJ big)
(NOM (NN dog)
(POS 's)
(NN house))))
```

```
Gold Standard
(NP (DT a)
   (ADVP (RB pretty)
         (JJ big)
   (NOM (NN dog)
         (POS's)
         (NN house)))
 0,6 NP 1,2 RB 3,4 NN
 0,1 DT 2,3 JJ 4,5 POS
 1,3 ADVP 3,6 NOM 5,6 NN
```

System Output

```
(NP (DT a)
(JJ pretty)
(NOM (JJ big)
(NOM (NN dog)
(POS 's)
(NN house))))
```

0,6 NP 2,6 NOM 3,4 NN 0,1 DT 2,3 JJ 4,5 POS 1,2 JJ 3,6 NOM 5,6 NN

```
Gold Standard
                             System Output
(NP (DT a)
                             (NP (DT a)
   (ADVP (RB pretty)
                                 (JJ pretty)
         (JJ big)
                                 (NOM (JJ big)
   (NOM (NN dog)
                                      (NOM (NN dog)
          (POS's)
                                             (POS 's)
          (NN house)))
                                             (NN house))))
                                  0,6 NP 2,6 NOM 3,4 NN
 0,6 NP 1,2 RB 3,4 NN
                                  0.1 DT 2.3 JJ 4.5 POS
 0,1 DT 2,3 JJ 4,5 POS
                                  1,2 JJ 3,6 NOM 5,6 NN
 1,3 ADVP 3,6 NOM 5,6 NN
```

Correct: 7

```
Gold Standard
                                  System Output
(NP (DT a)
                                 (NP (DT a)
    (ADVP (RB pretty)
                                      (JJ pretty)
           (JJ big))
                                      (NOM (JJ big)
    (NOM (NN dog)
                                            (NOM (NN dog)
           (POS's)
                                                    (POS 's)
           (NN house)))
                                                    (NN house))))
                                       0,6 NP 2,6 NOM 3,4 NN
 0,6 NP 1,2 RB 3,4 NN
                                       0,1 DT 2,3 JJ 4,5 POS
 0,1 DT 2,3 JJ 4,5 POS
                                       1.2 JJ 3.6 NOM 5.6 NN
 1,3 ADVP 3,6 NOM 5,6 NN
 Recall: \frac{Correct}{Cold} = \frac{7}{9}
                         Precision: \frac{Correct}{Sustem} = \frac{7}{9}
```

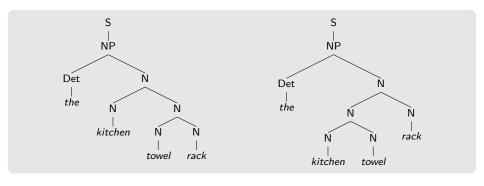
```
Gold Standard
                                   System Output
(NP (DT a)
                                   (NP (DT a)
    (ADVP (RB pretty)
                                       (JJ pretty)
           (JJ big))
                                       (NOM (JJ big)
    (NOM (NN dog)
                                              (NOM (NN dog)
            (POS's)
                                                      (POS's)
            (NN house)))
                                                      (NN house))))
                                         0,6 NP 2,6 NOM 3,4 NN
 0,6 NP 1,2 RB 3,4 NN
                                         0,1 DT 2,3 JJ 4,5 POS
 0,1 DT 2,3 JJ 4,5 POS
                                         1.2 JJ 3.6 NOM 5.6 NN
 1.3 ADVP 3,6 NOM 5,6 NN
                          Precision: \frac{Correct}{System} = \frac{7}{9} F<sub>1</sub> score: \frac{7}{9}
 Recall: \frac{Correct}{Cold} = \frac{7}{9}
```

```
Gold Standard
                                   System Output
(NP (DT a)
                                   (NP (DT a)
    (ADVP (RB pretty)
                                       (JJ pretty)
          (JJ big))
                                       (NOM (JJ big)
    (NOM (NN dog)
                                              (NOM (NN dog)
            (POS 's)
                                                      (POS 's)
            (NN house)))
                                                      (NN house))))
                                         0.6 NP 2.6 NOM 3.4 NN
 0.6 NP 1.2 RB 3.4 NN
                                         0,1 DT 2,3 JJ 4,5 POS
 0.1 DT 2,3 JJ 4,5 POS
                                         1,2 JJ 3,6 NOM 5,6 NN
 1,3 ADVP 3,6 NOM 5,6 NN
 Recall: \frac{Correct}{Gold} = \frac{2}{3} Precision: \frac{Correct}{Sustem} = \frac{2}{3} F<sub>1</sub> score: \frac{2}{3}
```

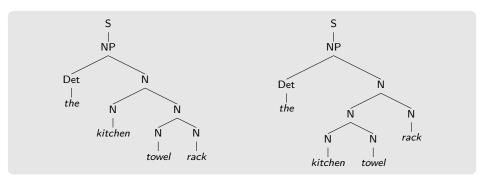
Crossing Brackets: 1

```
Gold Standard
                                   System Output
(NP (DT a)
                                   (NP (DT a)
                                       (JJ pretty)
    (ADVP (RB pretty)
          (JJ big))
                                       (NOM (JJ big)
    (NOM (NN dog)
                                              (NOM (NN dog)
            (POS 's)
                                                      (POS 's)
            (NN house)))
                                                      (NN house))))
                                         0.6 NP 2.6 NOM 3.4 NN
 0.6 NP 1,2 RB 3,4 NN
                                         0,1 DT 2,3 JJ 4,5 POS
 0.1 DT 2,3 JJ 4,5 POS
                                         1,2 JJ 3,6 NOM 5,6 NN
 1,3 ADVP 3,6 NOM 5,6 NN
 Recall: \frac{Correct}{Gold} = \frac{2}{3} Precision: \frac{Correct}{Sustem} = \frac{2}{3} F<sub>1</sub> score: \frac{2}{3}
```

Exercise (3): Parser Evaluation



Exercise (3): Parser Evaluation



(3) What are the ParsEval precision and recall scores for this pair of trees (gold on the left; system on the right)?

- Phrase structure grammar works well for configurational languages.
- ► For example English: rigid word order; subject typically before verb.
- ► Grammatical functions (implicitly) defined as structural relations.

- ► Phrase structure grammar works well for configurational languages.
- ► For example English: rigid word order; subject typically before verb.
- ► Grammatical functions (implicitly) defined as structural relations.
- ► Alternatively, use these relations as primary, explict building blocks.
- ▶ Dependency syntax in terms of directed relations between words.

- Phrase structure grammar works well for configurational languages.
- ► For example English: rigid word order; subject typically before verb.
- ► Grammatical functions (implicitly) defined as structural relations.
- ► Alternatively, use these relations as primary, explict building blocks.
- ▶ Dependency syntax in terms of directed relations between words.
- ► More forgiving to word order variation, e.g. Slavic or German:

```
(weil) [die Frau]_{\rm NOM} [dem Kind]_{\rm DAT} [ein Buch]_{\rm ACC} gab. (weil) [die Frau]_{\rm NOM} [ein Buch]_{\rm ACC} [dem Kind]_{\rm DAT} gab. (weil) [dem Kind]_{\rm DAT} [die Frau]_{\rm NOM} [ein Buch]_{\rm ACC} gab. (weil) [ein Buch]_{\rm ACC} [dem Kind]_{\rm DAT} [die Frau]_{\rm NOM} gab.
```

- ► Phrase structure grammar works well for configurational languages.
- ► For example English: rigid word order; subject typically before verb.
- ► Grammatical functions (implicitly) defined as structural relations.
- ► Alternatively, use these relations as primary, explict building blocks.
- ▶ Dependency syntax in terms of directed relations between words.
- ► More forgiving to word order variation, e.g. Slavic or German:

```
(weil) [die Frau]_{\rm NOM} [dem Kind]_{\rm DAT} [ein Buch]_{\rm ACC} gab. (weil) [die Frau]_{\rm NOM} [ein Buch]_{\rm ACC} [dem Kind]_{\rm DAT} gab. (weil) [dem Kind]_{\rm DAT} [die Frau]_{\rm NOM} [ein Buch]_{\rm ACC} gab. (weil) [ein Buch]_{\rm ACC} [dem Kind]_{\rm DAT} [die Frau]_{\rm NOM} gab.
```

• • •

► Arguably dominant approach to syntactic structure in NLP today.

Recent Advances in Dependency Parsing

Tutorial, EACL, April 27th, 2014

Ryan McDonald¹ Joakim Nivre²

¹Google Inc., USA/UK E-mail: ryanmcd@google.com

²Uppsala University, Sweden E-mail: joakim.nivre@lingfil.uu.se

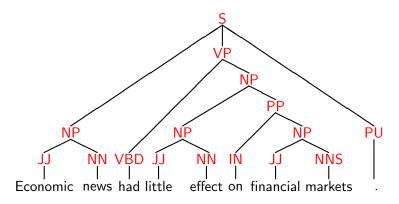
Dependency Syntax

- The basic idea:
 - Syntactic structure consists of lexical items, linked by binary asymmetric relations called dependencies.
- ▶ In the words of Lucien Tesnière [Tesnière 1959]:
 - ▶ La phrase est un ensemble organisé dont les éléments constituants sont les mots. [1.2] Tout mot qui fait partie d'une phrase cesse par lui-même d'être isolé comme dans le dictionnaire. Entre lui et ses voisins, l'esprit aperçoit des connexions, dont l'ensemble forme la charpente de la phrase. [1.3] Les connexions structurales établissent entre les mots des rapports de dépendance. Chaque connexion unit en principe un terme supérieur à un terme inférieur. [2.1] Le terme supérieur reçoit le nom de régissant. Le terme inférieur reçoit le nom de subordonné. Ainsi dans la phrase Alfred parle [...], parle est le régissant et Alfred le subordonné. [2.2]

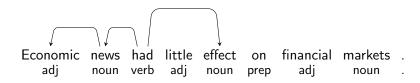
Dependency Syntax

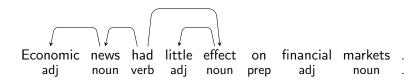
- The basic idea:
 - Syntactic structure consists of lexical items, linked by binary asymmetric relations called dependencies.
- ▶ In the words of Lucien Tesnière [Tesnière 1959]:
 - The sentence is an *organized whole*, the constituent elements of which are *words*. [1.2] Every word that belongs to a sentence ceases by itself to be isolated as in the dictionary. Between the word and its neighbors, the mind perceives *connections*, the totality of which forms the structure of the sentence. [1.3] The structural connections establish *dependency* relations between the words. Each connection in principle unites a *superior* term and an *inferior* term. [2.1] The superior term receives the name *governor*. The inferior term receives the name *subordinate*. Thus, in the sentence *Alfred parle* [...], *parle* is the governor and *Alfred* the subordinate. [2.2]

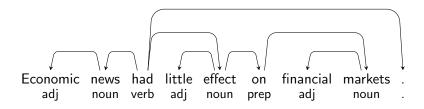
Phrase Structure

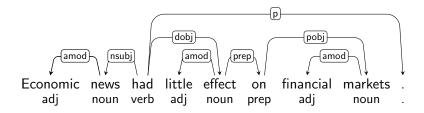


```
Economic news had little effect on financial markets . adj noun verb adj noun prep adj noun .
```









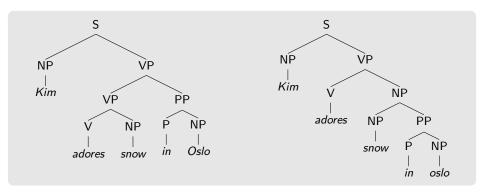
Terminology

Superior	Inferior
Head	Dependent
Governor	Modifier
Regent	Subordinate
:	<u>:</u>

Comparison

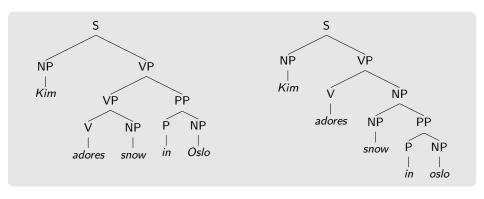
- Dependency structures explicitly represent
 - head-dependent relations (directed arcs),
 - functional categories (arc labels),
 - possibly some structural categories (parts-of-speech).
- Phrase structures explicitly represent
 - phrases (nonterminal nodes),
 - structural categories (nonterminal labels),
 - possibly some functional categories (grammatical functions).
- Hybrid representations may combine all elements.

Exercise (4): Dependency Syntaxx



9

Exercise (4): Dependency Syntaxx



(4) Draw the dependency trees for the two readings. Where does the attachment ambiguity manifest itself?

9

Dependency Graphs

- ► A dependency structure can be defined as a directed graph *G*, consisting of
 - ▶ a set V of nodes (vertices),
 - ▶ a set A of arcs (directed edges),
 - ▶ a linear precedence order < on V (word order).</p>
- ► Labeled graphs:
 - Nodes in V are labeled with word forms (and annotation).
 - Arcs in A are labeled with dependency types:
 - ▶ $L = \{l_1, ..., l_{|L|}\}$ is the set of permissible arc labels.
 - ▶ Every arc in A is a triple (i, j, k), representing a dependency from w_i to w_j with label I_k .

Dependency Graph Notation

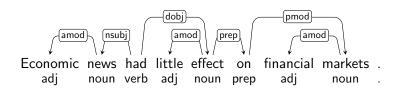
- For a dependency graph G = (V, A)
- With label set $L = \{l_1, \ldots, l_{|L|}\}$
 - $i \rightarrow j \equiv \exists k : (i, j, k) \in A$
 - $\triangleright i \leftrightarrow j \equiv i \rightarrow j \lor j \rightarrow i$

Formal Conditions on Dependency Graphs

- ► *G* is (weakly) connected:
 - ▶ If $i, j \in V$, $i \leftrightarrow^* j$.
- ► *G* is acyclic:
 - ▶ If $i \rightarrow j$, then not $j \rightarrow^* i$.
- ► G obeys the single-head constraint:
 - ▶ If $i \rightarrow j$, then not $i' \rightarrow j$, for any $i' \neq i$.
- G is projective:
 - ▶ If $i \rightarrow j$, then $i \rightarrow^* i'$, for any i' such that i < i' < j or j < i' < i.

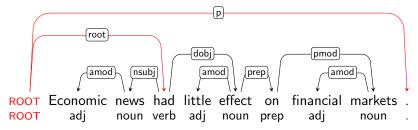
Connectedness, Acyclicity and Single-Head

- Intuitions:
 - Syntactic structure is complete (Connectedness).
 - Syntactic structure is hierarchical (Acyclicity).
 - Every word has at most one syntactic head (Single-Head).
- ► Connectedness can be enforced by adding a special root node.



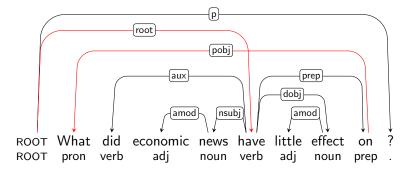
Connectedness, Acyclicity and Single-Head

- Intuitions:
 - Syntactic structure is complete (Connectedness).
 - Syntactic structure is hierarchical (Acyclicity).
 - Every word has at most one syntactic head (Single-Head).
- ► Connectedness can be enforced by adding a special root node.



Projectivity

- Most theoretical frameworks do not assume projectivity.
- ▶ Non-projective structures are needed to account for
 - ▶ long-distance dependencies,
 - free word order.



- ► Constituent tree with head information can be automatically converted.
- ▶ Dependency types based on structural relations (and parts of speech).

- Constituent tree with head information can be automatically converted.
- ▶ Dependency types based on structural relations (and parts of speech).
- ► Much dependency parsing using conversions of constituency treebanks.
- ▶ Including, of course, the venerable Penn Treebank (PTB) for English.
- ► Notable exceptions, e.g. PDT (Czech), NeGra and TiGer (German).

- Constituent tree with head information can be automatically converted.
- ▶ Dependency types based on structural relations (and parts of speech).
- ► Much dependency parsing using conversions of constituency treebanks.
- ▶ Including, of course, the venerable Penn Treebank (PTB) for English.
- ► Notable exceptions, e.g. PDT (Czech), NeGra and TiGer (German).
- ► Recently, greatly increased interest in dependency syntax 'world-wide'.
- ▶ New annotation initiatives now more often 'natively' in dependencies.

- Constituent tree with head information can be automatically converted.
- ▶ Dependency types based on structural relations (and parts of speech).
- ► Much dependency parsing using conversions of constituency treebanks.
- ▶ Including, of course, the venerable Penn Treebank (PTB) for English.
- ► Notable exceptions, e.g. PDT (Czech), NeGra and TiGer (German).
- ► Recently, greatly increased interest in dependency syntax 'world-wide'.
- ▶ New annotation initiatives now more often 'natively' in dependencies.
- ► Many languages have their own linguistic traditions and terminology.
- ► Ongoing cross-linguistic harmonization: Universal Dependencies (UD).
- ► 'Mainstream': treebanks for 70⁺ languages (including NOB & NNO).

Universal Dependencies



Universal Dependencies

Universal Dependencies (UD) is a framework for cross-linguistically consistent grammatical annotation and an open community effort with over 200 contributors producing more than 100 treebanks in over 70 languages.

- Short introduction to UD
- UD annotation guidelines
- · More information on UD:
 - How to contribute to UD
 - How to contribute to ou
 - Tools for working with UD
 - Discussion on UD
 - UD-related events
- · Query UD treebanks online:
 - o SETS treebank search maintained by the University of Turku
 - o PML Tree Query maintained by the Charles University in Prague
 - o Kontext maintained by the Charles University in Prague
 - o Grew-match maintained by Inria in Nancy
 - o INESS maintained by the University of Bergen
- Download UD treebanks

If you want to receive news about Universal Dependencies, you can subscribe to the <u>UD mailing list</u>. If you want to discuss individual annotation

Outlook

Next Week

- ► Statistical dependency parsing: The arc-eager transition system
- ► Supervised machine learning: The transition 'oracle'
- ► Feature functions for transition-based parsing
- Common evaluation metrics for dependency parsing
- ► Variations on syntactico-semantic dependency parsing