2A. Dependency Grammar

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Based on slides by Roger Levy, Yuji Matsumoto, Dragomir Radev, Dan Roth, David Smith and Jason Eisner
Word Dependency Parsing

**Raw sentence**
He reckons the current account deficit will narrow to only 1.8 billion in September.

**POS-tagged sentence**
He reckons the current account deficit will narrow to only 1.8 billion in September.

**Word dependency parsed sentence**
He reckons the current account deficit will narrow to only 1.8 billion in September.

slide adapted from Yuji Matsumoto
A dependency structure can be defined as a directed graph $G$, consisting of:
- a set $V$ of nodes,
- a set $E$ of arcs (edges),
- a linear precedence order $<$ on $V$.

Labeled graphs:
- Nodes in $V$ are labeled with word forms (and annotation).
- Arcs in $E$ are labeled with dependency types.

Notational conventions $(i, j \in V)$:
- $i \rightarrow j \equiv (i, j) \in E$
- $i \rightarrow^* j \equiv i = j \lor \exists k : i \rightarrow k, k \rightarrow^* j$
Formal Conditions on Dependency Graphs

- **G** is (weakly) connected:
  - For every node \( i \) there is a node \( j \) such that \( i \rightarrow j \) or \( j \rightarrow i \).

- **G** is acyclic:
  - If \( i \rightarrow j \) then not \( j \rightarrow^* i \).

- **G** obeys the single-head constraint:
  - If \( i \rightarrow j \), then not \( k \rightarrow j \), for any \( k \neq i \).

- **G** is projective:
  - If \( i \rightarrow j \) then \( i \rightarrow^* k \), for any \( k \) such that \( i < k < j \) or \( j < k < i \).
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.

All these conditions will be violated for semantic dependency graphs we will consider later.

Economic news had little effect on financial markets.
Projectivity

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

You can think of it as (related) planarity
Underspecifications of simple typed dependencies

- Flat bracketings
- Non-projective dependency
  
  A woman arrived who was wearing a hat

- Complex word-word dependency constructions:
  - Predicative adjectives
  
  I ate the fish naked/raw

  - Coordination
  
  Pat and Terry sat and laughed

- More generally, semantic roles:
  
  The door opened
  Erin opened the door
  The door opened a crack

- Quantifier scoping, temporal interpretation and so forth
Shift-Reduce Type Algorithms

- Data structures:
  - Stack $[\ldots, w_i]_S$ of partially processed tokens
  - Queue $[w_j, \ldots]_Q$ of remaining input tokens

- Parsing actions built from atomic actions:
  - Adding arcs $(w_i \rightarrow w_j, w_i \leftarrow w_j)$
  - Stack and queue operations

- Left-to-right parsing in $O(n)$ time

- Restricted to projective dependency graphs
Yamada’s Algorithm

- Three parsing actions:

  **Shift**
  \[
  \begin{array}{c}
  [\ldots]s & [w_i, \ldots]Q \\
  [\ldots, w_i]s & [\ldots]Q
  \end{array}
  \]

  **Left**
  \[
  \begin{array}{c}
  [\ldots, w_i, w_j]s & [\ldots]Q \\
  [\ldots, w_i]s & [\ldots]Q
  \end{array}
  \]
  \(w_i \rightarrow w_j\)

  **Right**
  \[
  \begin{array}{c}
  [\ldots, w_i, w_j]s & [\ldots]Q \\
  [\ldots, w_j]s & [\ldots]Q
  \end{array}
  \]
  \(w_i \leftarrow w_j\)

- Algorithm variants:
  - Originally developed for Japanese (strictly head-final) with only the **Shift** and **Right** actions [Kudo and Matsumoto 2002]
  - Adapted for English (with mixed headedness) by adding the **Left** action [Yamada and Matsumoto 2003]
  - Multiple passes over the input give time complexity \(O(n^2)\)
Nivre’s Algorithm

Four parsing actions:

**Shift**  
\[
\begin{array}{c}
\text{[...]}_s \\
\text{[...]}_Q \\
\text{[...]}_s \\
\text{[...]}_Q
\end{array}
\quad
\begin{array}{c}
\text{[...]}_s \\
\text{[...]}_Q
\end{array}
\]

**Reduce**  
\[
\begin{array}{c}
\text{[...]}_s \\
\text{[...]}_Q
\end{array}
\quad
\begin{array}{c}
\text{[...]}_s \\
\text{[...]}_Q
\end{array}
\]

**Left-Arc\(_r\)**  
\[
\begin{array}{c}
\text{[...]}_s \\
\text{[...]}_Q
\end{array}
\quad
\begin{array}{c}
\text{[...]}_s \\
\text{[...]}_Q
\end{array}
\]

**Right-Arc\(_r\)**  
\[
\begin{array}{c}
\text{[...]}_s \\
\text{[...]}_Q
\end{array}
\quad
\begin{array}{c}
\text{[...]}_s \\
\text{[...]}_Q
\end{array}
\]

Characteristics:

- Integrated labeled dependency parsing
- Arc-eager processing of right-dependents
- Two passes over the input gives time complexity \(O(n)\)
Example

[root]$_S$ [Economic news had little effect on financial markets.]$_Q$
Example

Economic news had little effect on financial markets.

[Root Economic]_S [news had little effect on financial markets .]_Q

Shift
Example

Economic news had little effect on financial markets.

Left-Arc_{nmod}
Example

\[
\text{[root Economic news]_S [had little effect on financial markets .]_Q}
\]

Shift
Example

[\textit{root}]_s \quad \text{Economic news} \quad [\text{had little effect on financial markets} .]_Q

Left-Arc_{\textit{subj}}
Example

Economic news had little effect on financial markets.
Example

Economic news had little effect on financial markets.

Shift
Example

Economic news had little effect on financial markets.

Left-Arc<sub>nmod</sub>
Example

\[
\text{Economic news had little effect on financial markets.}
\]

Right-Arc\textsubscript{obj}
Example

Economic news had little effect on financial markets.

Right-Arc_{nmod}
Example

Economic news had little effect on financial markets.

Shift
Example

[Economic news had little effect on financial markets.]"
Example

Economic news had little effect on financial markets.

Right-Arc_{pc}
Example

Reduce
Economic news had little effect on financial markets.
Example

Economic news had little effect on financial markets.

Reduce
Economic news had little effect on financial markets.

Example

```
(root) s
```

```
pred
```

```
nmod
```

```
sbj
```

```
obj
```

```
nmod
```

```
nmod
```

```
pc
```

```
nmod
```

```
[.] Q
```

Reduce
Economic news had little effect on financial markets.

Right-Arc$_p$
Classifier-Based Parsing

- Data-driven deterministic parsing:
  - Deterministic parsing requires an oracle.
  - An oracle can be approximated by a classifier.
  - A classifier can be trained using treebank data.

- Learning methods:
  - Support vector machines (SVM)
  - Memory-based learning (MBL)
    [Nivre et al. 2004, Nivre and Scholz 2004]
  - Maximum entropy modeling (MaxEnt)
    [Cheng et al. 2005]
  - Neural networks
    [you!]
Feature Models

Learning problem:
- Approximate a function from parser states, represented by feature vectors to parser actions, given a training set of gold standard derivations.

Typical features:
- Tokens:
  - Target tokens
  - Linear context (neighbors in $S$ and $Q$)
  - Structural context (parents, children, siblings in $G$)
- Attributes:
  - Word form (and lemma)
  - Part-of-speech (and morpho-syntactic features)
  - Dependency type (if labeled)
  - Distance (between target tokens)
Neural Networks

Neural Networks can be built for different input, output types.

- Outputs can be:
  - Linear, single output (Linear)
  - Linear, multiple outputs (Linear)
  - Single output binary (Logistic)
  - Multi output binary (Logistic)
  - 1 of k Multinomial output (Softmax, categorical)

- Inputs can be:
  - A scalar number
  - Vector of Real numbers
  - Vector of Binary

Goal of training: Given the training data (inputs, targets) and the architecture, determine the model parameters.

Model Parameters for a 3 layer network:
- Weight matrix from input layer to the hidden ($W_{jk}$)
- Weight matrix from hidden layer to the output ($W_{kj}$)
- Bias terms for hidden layer
- Bias terms for output layer

Our strategy will be:
- Compute the error at the output
- Determine the contribution of each parameter to the error by taking the differential of error wrt the parameter
- Update the parameter commensurate with the error it contributed.
Design Choices

• When building a neural network, the designer would choose the following hyper parameters and non linearities based on the application characteristics:
  • Number of hidden layers
  • Number of hidden units in each layer
  • Learning rate
  • Regularization coefft
  • Number of outputs
  • Type of output (linear, logistic, softmax)
  • Choice of Non linearity at the output layer and hidden layer (See next slide)
  • Input representation and dimensionality
Commonly used non-linearities

**Logistic ("sigmoid")**

\[ f(z) = \frac{1}{1 + \exp(-z)} \]

**tanh**

\[ f(z) = \tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \]

**Hard tanh**

\[ \text{HardTanh}(x) = \begin{cases} 
-1 & \text{if } x < -1 \\
0 & \text{if } -1 \leq x \leq 1 \\
1 & \text{if } x > 1 
\end{cases} \]

**Soft sign**

\[ \text{softsign}(z) = \frac{a}{1 + |a|} \]

**Rectified linear (ReLU)**

\[ \text{rect}(z) = \max(z, 0) \]

\[ f'(z) = f(z)(1 - f(z)) \]

\[ f'(z) = 1 - f(z)^2 \]
Objective Functions and gradients

- Linear – Mean squared error
  \[ E(w) = \frac{1}{2N} \sum_{1}^{N} (t_n - y_n)^2 \]

- Logistic with binary classifications: Cross Entropy Error

- Logistic with k outputs: k > 2: Cross Entropy Error

- Softmax: 1 of K "multinomial" classification: Cross Entropy Error, minimize NLL

- In all the above cases we can show that the gradient is: \((y_k - t_k)\) where \(y_k\) is the predicted output for the output unit \(k\) and \(t_k\) is the corresponding target
High Level Backpropagation Algorithm

• Apply the input vector to the network and forward propagate. This will yield the activations for hidden layer(s) and the output layer
  • \( net_j = \sum_i w_{ji} z_i \)
  • \( z_j = h(\text{net}_j) \) where \( h \) is your choice of non linearity. Usually it is sigmoid or tanh. Rectified Linear Unit (ReLU) is also used.

• Evaluate the error \( \delta_k \) for all the output units
  \( \delta_k = o_k - t_k \) where \( o_k \) is the output produced by the model and \( t_k \) is the target provided in the training dataset

• Backpropagate the \( \delta' \)'s to obtain \( \delta_j \) for each hidden unit \( j \)
  \( \delta_j = h'(z_j) \sum_k w_{kj} \delta_k \)

• Evaluate the required derivatives
  \( \frac{\partial E}{\partial W_{ji}} = \delta_j z_i \)