Dependency Parsing

COM4513/6513 Natural Language Processing

Nikos Aletras
n.aletras@sheffield.ac.uk

@nikaletras

Computer Science Department

Week 5
Spring 2020

The University Of Sheffield.

In previous lectures...

- **Text Classification:** Given an instance x (e.g. document), predict a label $y \in \mathcal{Y}$
- **Tasks:** sentiment analysis, topic classification, etc.
- **Algorithm:** Logistic Regression

In previous lectures...

- **Sequence labelling:** Given a sequence of words $\mathbf{x} = [x_1, ...x_N]$, predict a sequence of labels $\mathbf{y} \in \mathcal{Y}^{\mathcal{N}}$
- **Tasks:** part of speech tagging, named entity recognition, etc.
- **Algorithms:** Hidden Markov Models, Conditional Random Fields

In this lecture...

- Model richer linguistic representations: **graphs**
- **Dependency parses:** Graphs representing syntactic relations between words in a sentence

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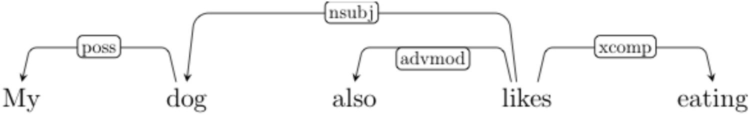
- Model richer linguistic representations: **graphs**
- **Dependency parses:** Graphs representing syntactic relations between words in a sentence
- Two approaches:
  - Graph-based Dependency Parsing
  - Transition-based Dependency Parsing

Dependecny Parsing: Applications

- **Relation extraction**, e.g. identify entity pairs (AM, Arctic Monkeys), (Abbey Road, Beatles), (Different Class, Pulp) with the relation `music_album_by`
- **Question answering**
- **Sentiment analysis**

What is a Dependency Parse?



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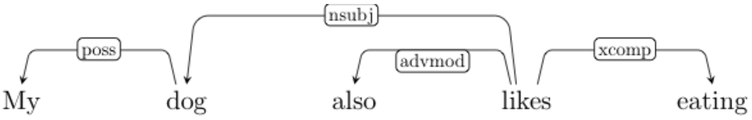

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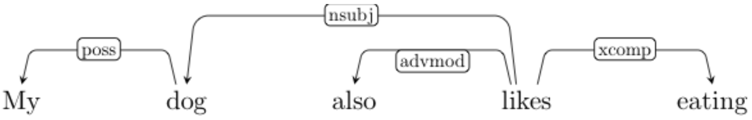

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- **Edges (or arcs):** Syntactic relations between words, e.g. `dog` is the subject (`nsubj`) of `likes` (list of standard dependency relations)
- **Dependency Parsing:** Automatically identify the syntactic relations between words in a sentence

Graph constraints

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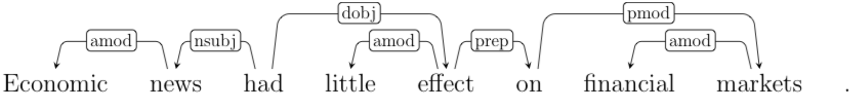
- **Acyclic:** can't re-visit the same word on a directed path
- **Single-Head:** every word can have only one head

Well-formed Dependency Parse?



- Connected?

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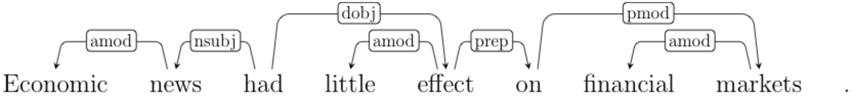

- Connected? NO

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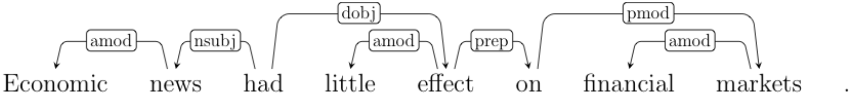

- Connected? NO
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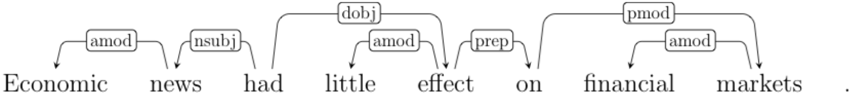

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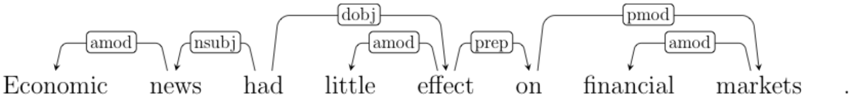

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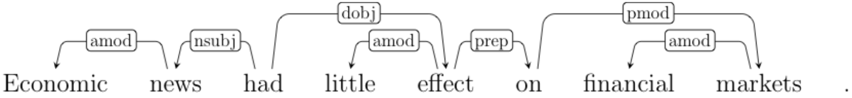
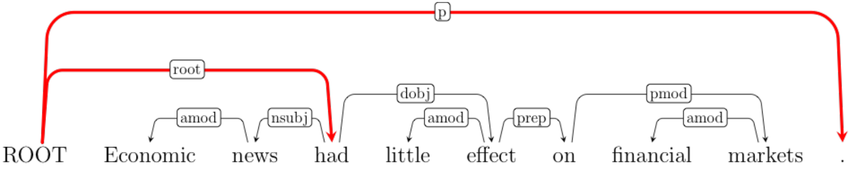


- Connected? NO
- Acyclic? YES
- Single-headed? YES
- Solution?

Well-formed Dependency Parse



Add a **special root node** with edges to any nodes without heads (main verb and punctuation).

Dependency Parsing: Problem setup

Training data is pairs of word sequences (sentences) and dependency trees:

$$
\begin{aligned}
D_{train} &= \{(\mathbf{x}^1, G_x^1)...(\mathbf{x}^M, G_x^M)\} \\
\mathbf{x}^m &= [x_1, ...x_N] \\
graph\ G_{\mathbf{x}} &= (V_{\mathbf{x}}, A_{\mathbf{x}}) \\
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- **How about a classifier that predicts each edge?**

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- **Can we learn it using what we know so far?** Enumeration over all possible graphs will be expensive.
- **How about a classifier that predicts each edge?** Maybe. But predicting an edge makes some edges invalid due to the acyclic and single-head constraints.

Maximum Spanning Tree

- **Spanning Tree:** In graph theory, a spanning tree T of an undirected graph G is a subgraph that includes all of the vertices of G, with the minimum possible number of edges.

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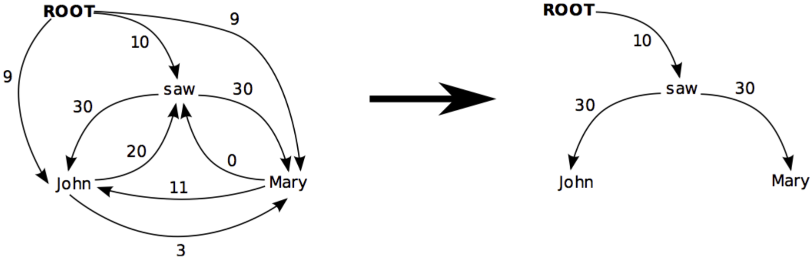
- **Spanning Tree:** In graph theory, a spanning tree T of an undirected graph G is a subgraph that includes all of the vertices of G, with the minimum possible number of edges.
- **Tree:** In computer science, a tree is a widely used data structure (Abstract Data Type) that simulates a hierarchical tree structure, with a root value and subtrees of children with a parent node, represented as a set of linked nodes.

Maximum Spanning Tree

Score all edges, but keep only the max spanning tree using Chu-Liu-Edmonds algorithm, a modification to Kruskal's algorithm for extracting Maximum Spanning Trees.



Exact solution in $O(N^2)$ time using Chu-Liu-Edmonds.

Kruskal's algorithm

Input *scored edges E*

sort E by cost (*opposit of score*)

$G = \{\}$

while *G not spanning* **do:**

    pop the next edge e

    if *connecting different trees* :

        add e to G

Return *G*

Graph-based Dependency Parsing

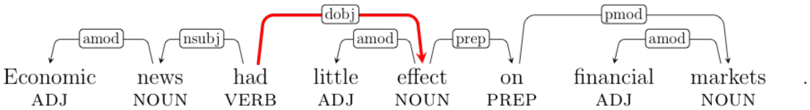
Decompose the graph score into arc scores:

$$\begin{aligned}
\hat{G}_{\mathbf{x}} &= \operatorname*{arg\,max}_{G_{\mathbf{x}} \in \mathcal{G}_{\mathbf{x}}} \mathit{score}(G_{\mathbf{x}}, \mathbf{x}) \\
&= \operatorname*{arg\,max}_{G_{\mathbf{x}} \in \mathcal{G}_{\mathbf{x}}} \mathbf{w} \cdot \Phi(G_{\mathbf{x}}, \mathbf{x}) \quad \text{(linear model)} \\
&= \operatorname*{arg\,max}_{G_{\mathbf{x}} \in \mathcal{G}_{\mathbf{x}}} \sum_{(i,j,l) \in A_x} \mathbf{w} \cdot \phi((i,j,l), \mathbf{x}) \quad \text{(arc-factored)}
\end{aligned}$$

Can learn the weights with a Conditional Random Field!

Feature Representation

What should $\phi((\textit{head}, \textit{dependent}, \textit{label}), \mathbf{x})$ be?



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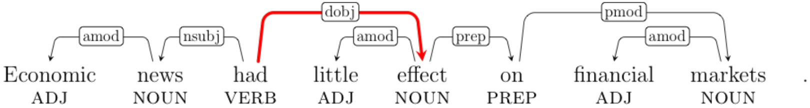

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- **bigram:** head=had & dependent=effect

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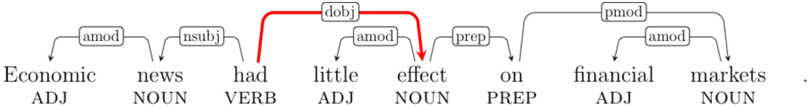

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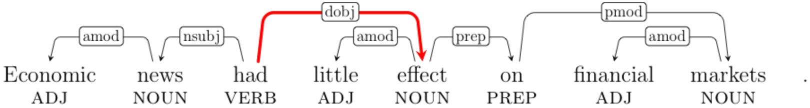

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- head=had & label=dobj & other-label=nsubj

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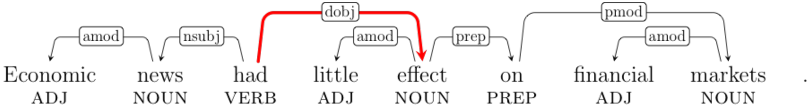

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  NO!!! Breaks the arc-factored scoring

More Global models

- Even though inference and learning are global, features are localised to arcs.
- **Can we have more global features?**

More Global models

- Even though inference and learning are global, features are localised to arcs.
- **Can we have more global features?** Yes we can! Consider subgraphs spanning a few edges. But inference becomes harder, requiring more complex dynamic programs and clever approximations.
- **Is it worth it?** Syntactic parsing has many applications, thus better compromises between speed and accuracy are always welcome!

Transition-based Dependency Parsing

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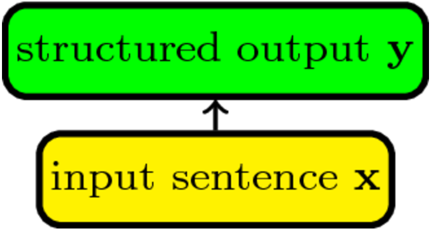
- Graph-based dependency parsing restricts the features to perform joint inference efficiently.
- **Transition-based dependency parsing** trades joint inference for feature flexibility.
- No more argmax over graphs, just use a classifier with any features we want!

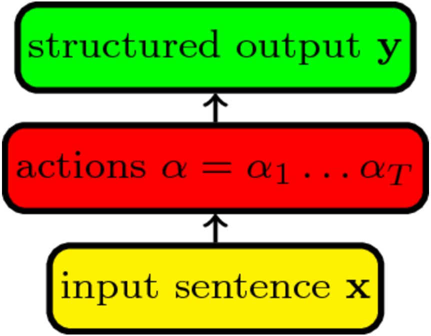
Joint vs incremental prediction

Joint: score (and enumerate) complete outputs (graphs)



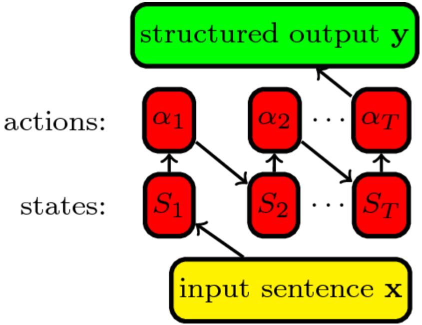
Joint vs incremental prediction

Incremental: predict a sequenceof actions (transitions) constructing the output



Transition system

The **actions** $\mathcal{A}$ the classifier f can predict and their effect on the **state** which tracks the prediction: $S_{t+1} = S_1(\alpha_1 \dots \alpha_t)$



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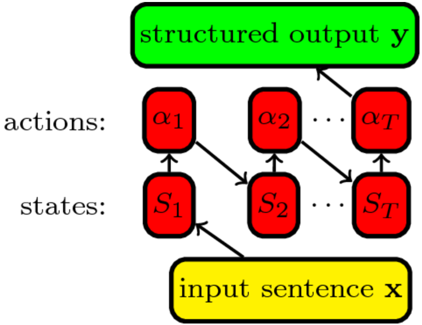

What should the actions (transitions) be for dependency parsing?

Transition system setup

- **Input:** Vertices $V_{\mathbf{x}} = \{0, 1, ..., N\}$ (words sentence $\mathbf{x}$)
- **State** $S = (Stack, B, A)$:
  - Arcs A (dependencies predicted so far)
  - Buffer Buf (words left to process)
  - Stack $Stack$ (last-in, first out memory)
- Initial state: $S_0 = ([], [0, 1, ..., N], \{\})$
- Final state: $S_{final} = (Stack, [], A)$

Transition system

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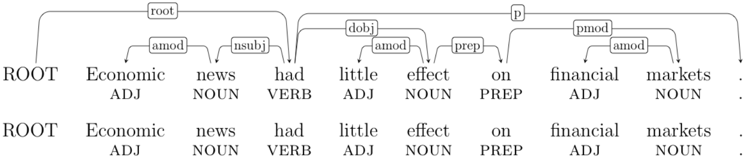
Left-Arc(*label*) $(Stack|i, j|Buf, A) \rightarrow (Stack, j|Buf, A \cup \{(j, i, l)\})$: create edge $(j, i, label)$ and pop i, if i has no head

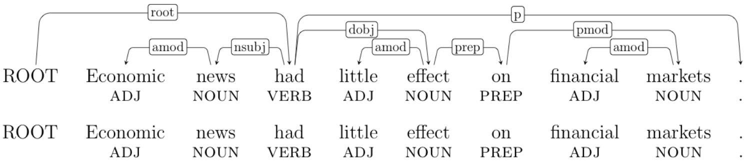
Example



Stack = []
Buffer = [ROOT, Economic, news, had, little, effect, on, financial, markets, .]

Action?

Example



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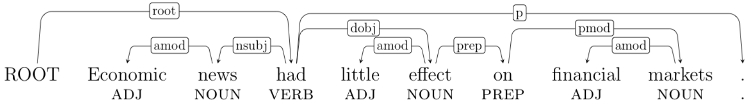

ROOT Economic news had little effect on financial markets .
ADJ NOUN VERB ADJ NOUN PREP ADJ NOUN .

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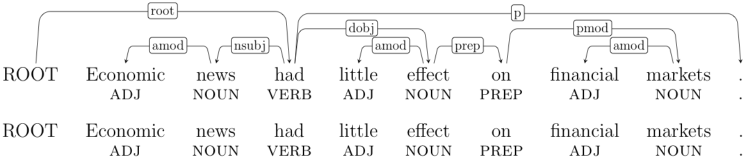

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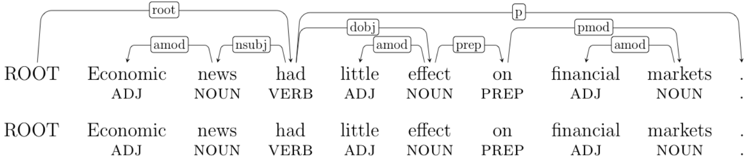

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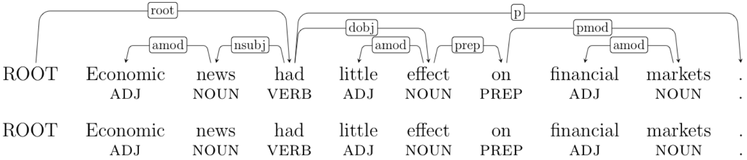

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Action? Left-Arc(*amod*)

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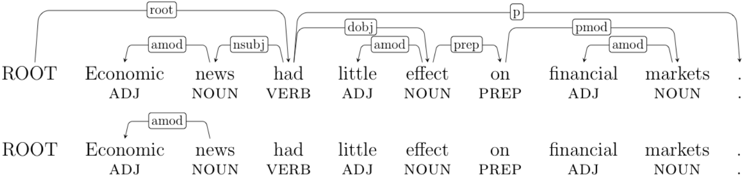

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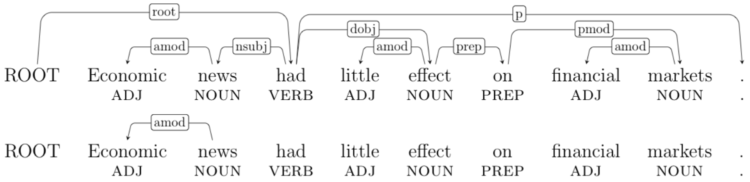

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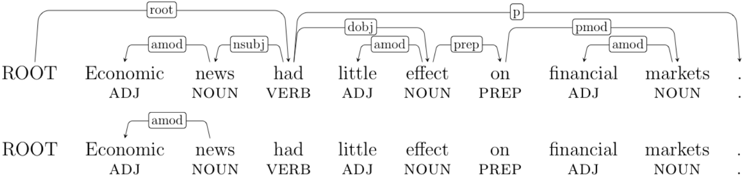

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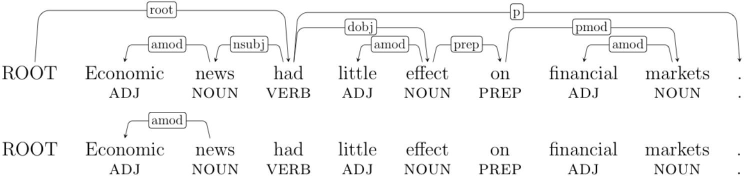

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Action? Left-Arc(*nsubj*)

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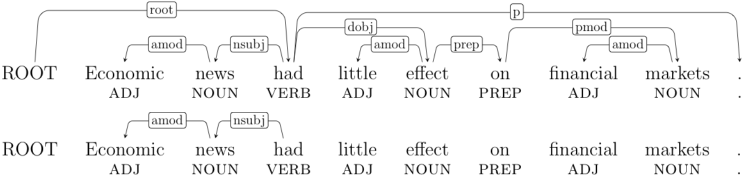

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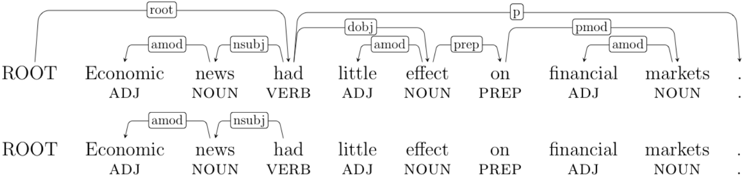

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Action? Right-Arc(*root*)

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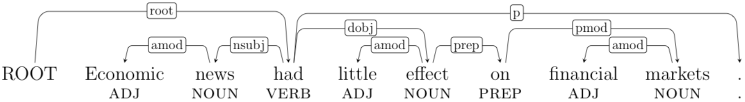

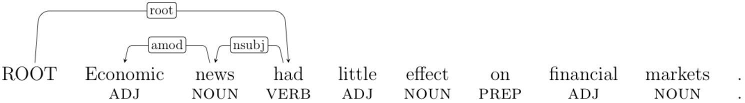

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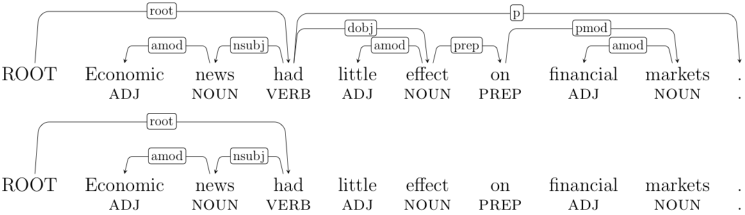

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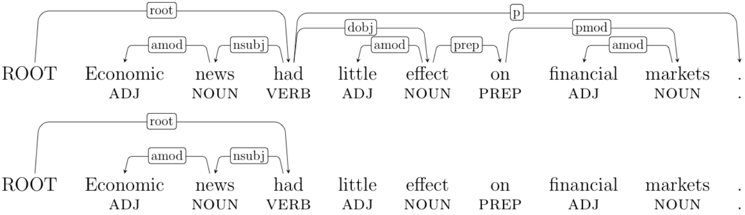

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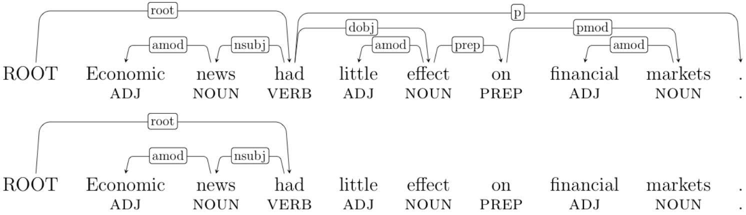

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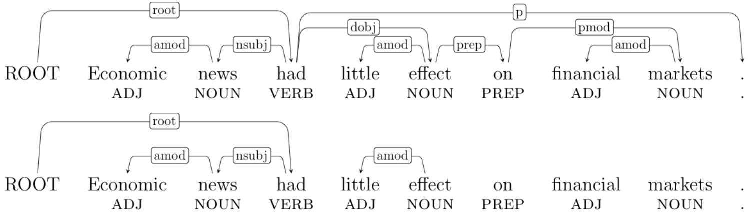
Buffer = [effect, on, financial, markets, .]

Action? Left-Arc(*amod*)

Example



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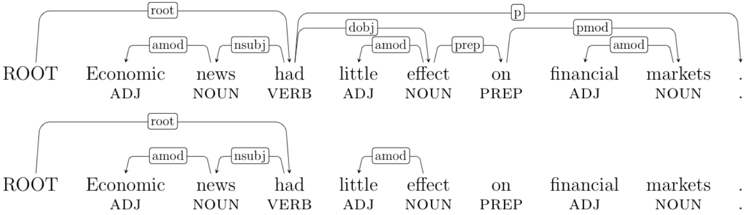
Action?

Example



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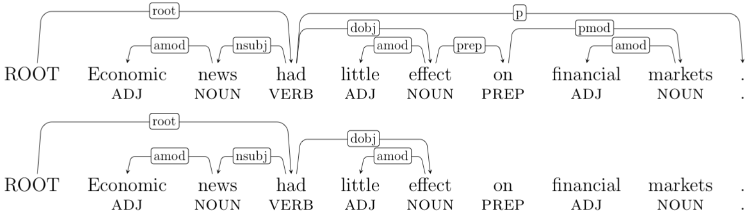
Action? Right-Arc(*dobj*)

Example



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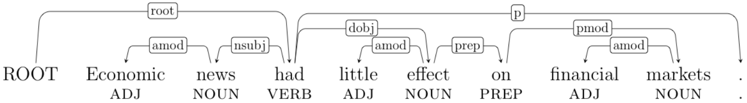

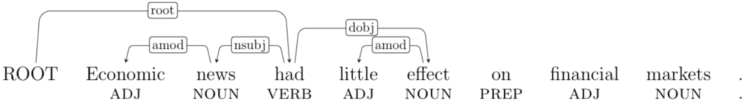

Stack = [ROOT, had, effect]
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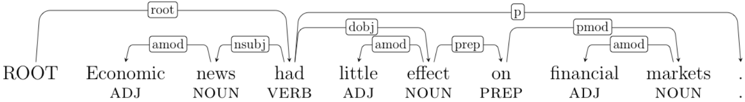
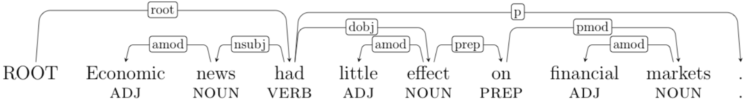
Action? let's fast-forward...

Example

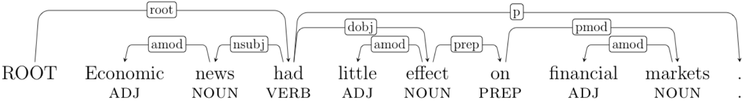


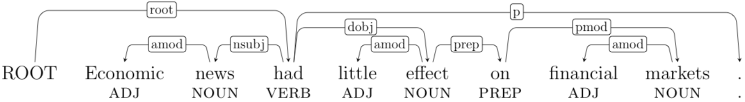


Stack = [ROOT, had, .]
Buffer = []

Empty buffer.

Example





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Empty buffer. DONE!

Other transition systems?

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- This was the arc-eager system. Others:
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- All operate with actions combining:
  - moving words from the buffer to the stack and back (shift/un-shift)
  - popping words from the stack (reduce)
  - creating labeled arcs left and right
- Intuition: Define actions that are easy to learn

Transition-based Dependency Parsing

Input: *sentence* $\mathbf{x}$

state $S_1 = \textit{initialize}(\mathbf{x})$; *timestep* $t = 1$

while S_t not final **do**

 action $\alpha_t = \arg\max_{\alpha \in \mathcal{A}} f(\alpha, S_t)$

 $S_{t+1} = S_t(\alpha_t); t = t + 1$

What is f?

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What do we need to learn it?

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What is f? A multiclass classifier
What do we need to learn it?

- learning algorithm (e.g. logistic regression)
- labelled training data
- feature representation

What are the right actions?

We only have sentences labelled with graphs:
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Ask an oracle to tell us the actions constructing the graph!

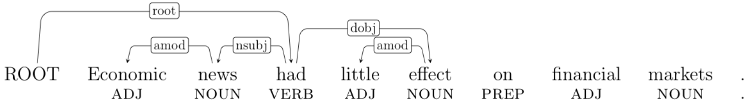
In our case, a set of **rules** comparing the current state $S = (Stack, Buffer, ArcsPredicted)$ with G_x returning the correct action as label

Learning from an oracle

Given a labelled sentence and a transition system, an oracle returns states labelled with the correct actions.

$$
\begin{aligned}
D_{train} &= \{(\mathbf{x}^1, G_x^1)...(\mathbf{x}^M, G_x^M)\} \\
\mathbf{x}^m &= [x_1, ..., x_N] \\
\textit{graph } G_{\mathbf{x}} &= (V_{\mathbf{x}}, A_{\mathbf{x}}) \\
\textit{vertices } V_{\mathbf{x}} &= \{0, 1, ..., N\} \\
\textit{edges } A_{\mathbf{x}} &= \{(i, j, k) | i, j \in V, k \in L(\text{labels})\} \\
\textit{states } \mathbf{S}^m &= [S_1, ..., S_T] \\
\textit{actions } \alpha^m &= [\alpha_1, ..., \alpha_T]
\end{aligned}
$$

Feature Representation



Stack = [ROOT, had, effect]
Buffer = [on, financial, markets, .]

What features would help us predict the correction action Right-Arc(*prep*)?

Feature Representation

- **Words/PoS in stack and buffer:**
  wordS1=effect, wordB1=on, wordS2=had, posS1=NOUN, etc.

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- **Words/PoS in stack and buffer:**
  wordS1=effect, wordB1=on, wordS2=had, posS1=NOUN, etc.
- **Dependencies so far:**
  depS1=dobj, depLeftChildS1=amod, depRightChildS1=NULL, etc.
- **Previous actions:**
  α_{t-1} = Right-Arc(*dobj*), etc.

Transition-based vs Graph-based parsing

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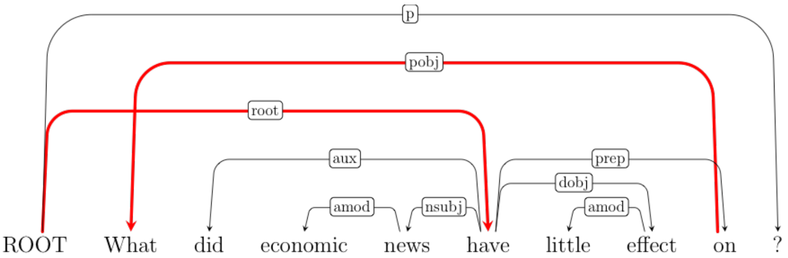
Transition-based vs Graph-based parsing

- Transition-based tends to be better on shorter sentences, graph-based on longer ones
- Graph-based tends to be better on long-range dependencies
- Graph-based lacks the rich structural features
- Transition-based is greedy and suffers from early mistakes
- Actually, can we ameliorate the greedy issue?
  Use Beam Search!

Non-Projectivity



- Arcs are crossing each other
- long-range dependencies
- free word order

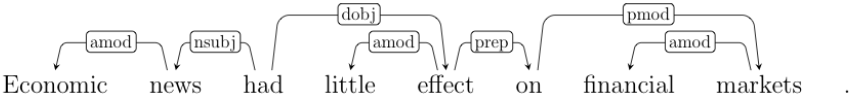
Non-projective Transition-based parsing

- The standard stack-based systems cannot do it.
- But there are extensions:
  - swap actions: word reodering
  - k-planar parsing: use multiple stacks (usually 2)
- Standard graph-based parsing handles non-projectivity.

Incremental Language Processing

- Other problems solved with similar approaches (a.k.a. transition-based, greedy):
  - semantic parsing (converting a natural language utterance to a logical form)
  - coreference resolution
- Whenever you have a problem with a very large space of outputs, worth considering

Evaluation



- **Head-finding word-accuracy:**
  - unlabelled: % of words with the right head
  - labelled: % of words with the right head and label
- **Sentence accuracy:** % of sentences with correct graph

Bibliography

- Chapter 11 from Eisenstein
- Nivre and McDonald's tutorial slides
- Nivre's article on deterministic transition-based dependency parsing
- Nivre and McDonald's paper comparing their approaches

Coming up next week...

- Feed-forward Neural Networks
- Getting ready for Assignment 2!