Lecture 6: Modeling Syntactico-Semantic Composition

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- Mama have you said, that you first your homework make must.
- When you this ready have, then you can to Julia go.
- Lara, can you me please out the bath a towel bring?

from Knallerfrauen

Lecture 6: Modeling Syntactico-Semantic Composition

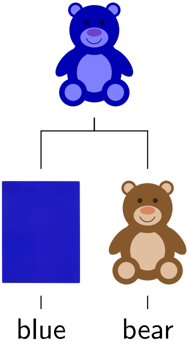
1. Principle of compositionality
2. Composition-based approach to semantic parsing
3. Locality
4. Context-free graph rewriting

Principle of Compositionality

Modeling syntactico-semantic composition

The Principle of Compositionality

> *The meaning of an expression is a function of* **the meanings of its parts** *and of* **the way they are syntactically combined**.
>
> *B. Partee*



Modeling syntactico-semantic composition

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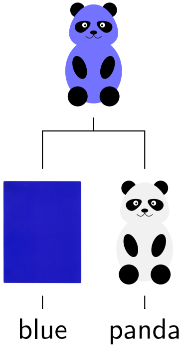

Modeling syntactico-semantic composition

The Principle of Compositionality

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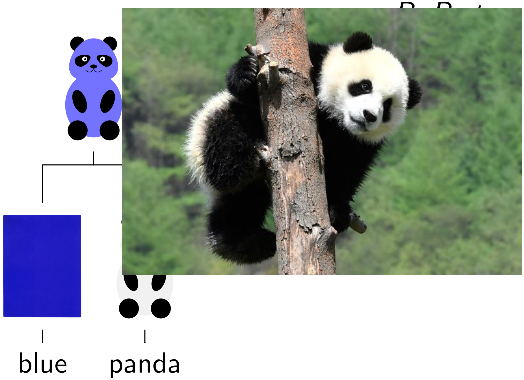
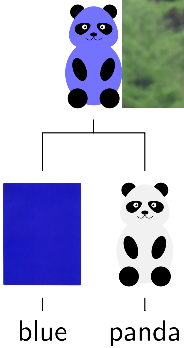


Modeling syntactico-semantic composition

The Principle of Compositionality

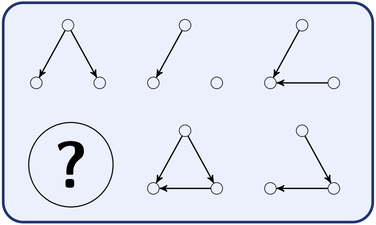
The meaning of an expression is

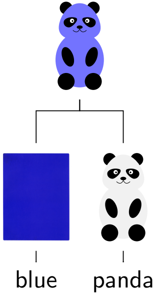
its parts *and of* **the way they are s**



Composition-Based Approach

Representational vs derivational





Modeling syntactico-semantic composition/derivation

- Assume the complicated structure is generated step-by-step.
- And assume that it is relatively easy to make a decision for a single step.
- An internal structure, e.g. tree, is used to represent the process.
- We don't directly evaluate the *goodness* of the target structure, which is the result of a derivation.
- We directly evaluate the *goodness* of the derivation structure, and get the derived structure (for free).
- Parsing and generation share a model, probably like human language processing.

Composition

I want to eat apples

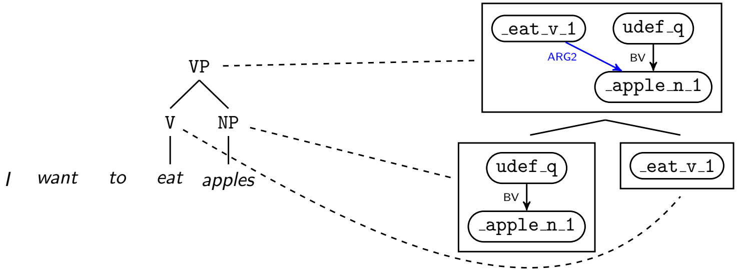
Composition

Compositional Parsing

semantic/meaning representation parsing: mapping a sentence to an MR, such as semantic graph.

step 1: assign semantic interpretations to "words". The elementary MR for *apples* is graph with a single node. We mainly do "word sense disambiguation" in this step.

step 2: combine graphs according to syntactico-semantic rules. We merge the "eat" and "apples" graphs by augmenting VP→V NP. We add the blue edge to link the two graphs. We should view the blue edge as a third graph.



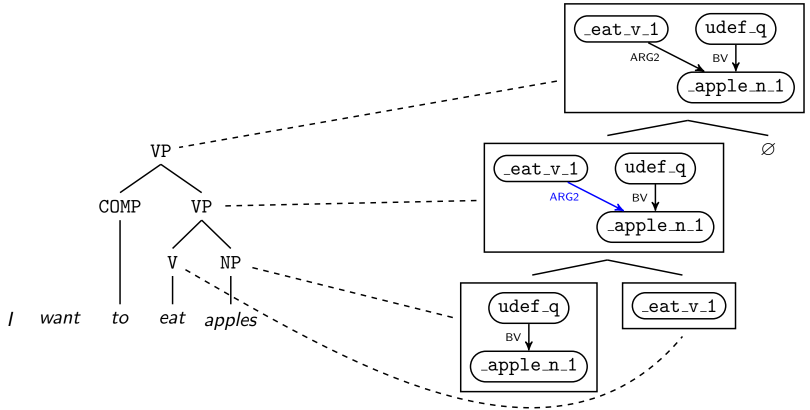
Composition

Compositional Parsing

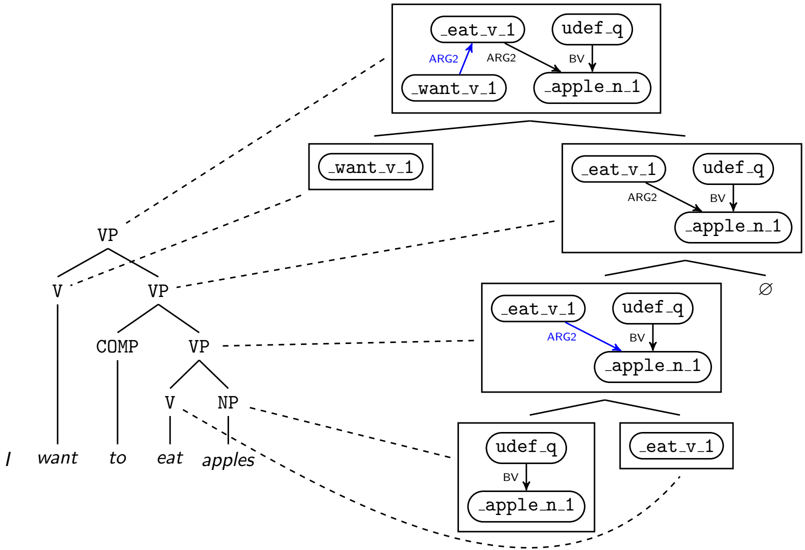
step 1: assign semantic interpretations to "to", which is an empty graph.

step 2: glue the "eat apples" graph together with an empty graph.

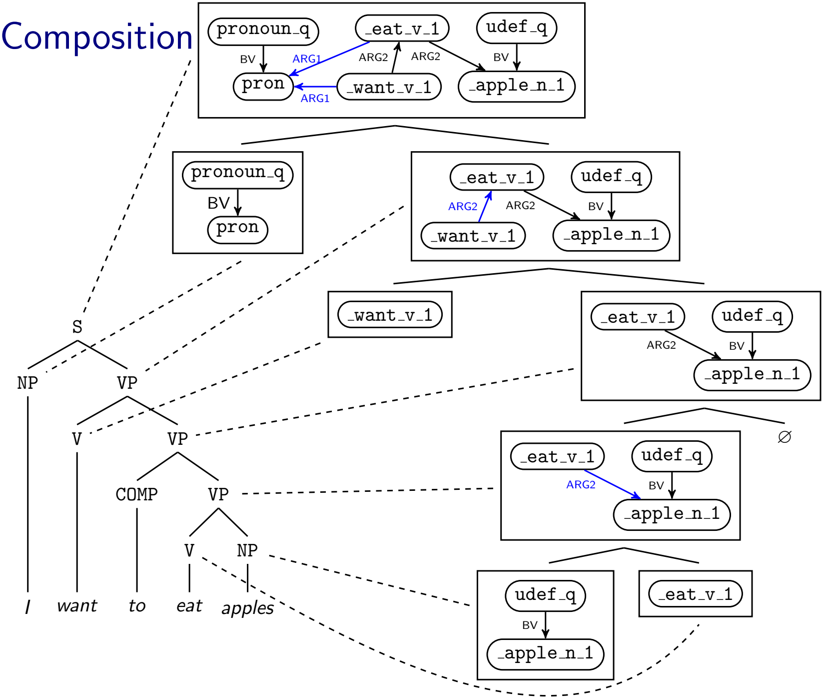
continue: iterate the above process.



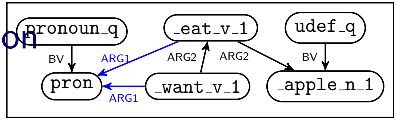
Composition



Composition



Decomposition



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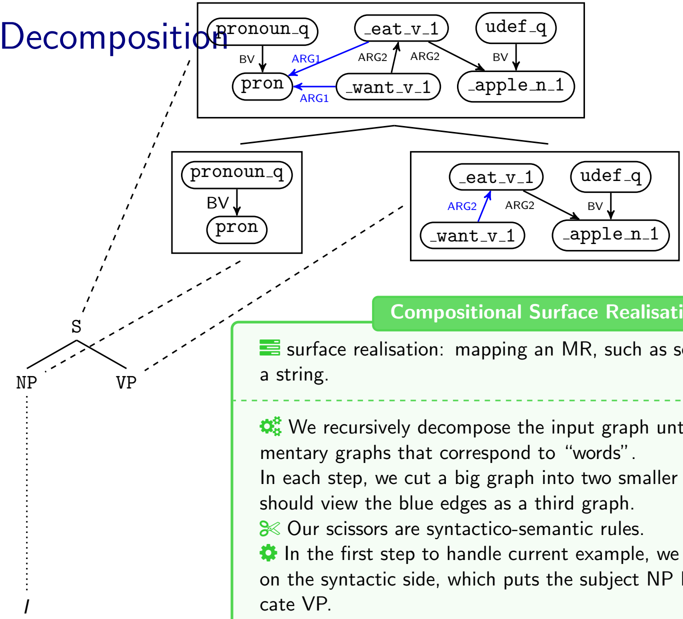
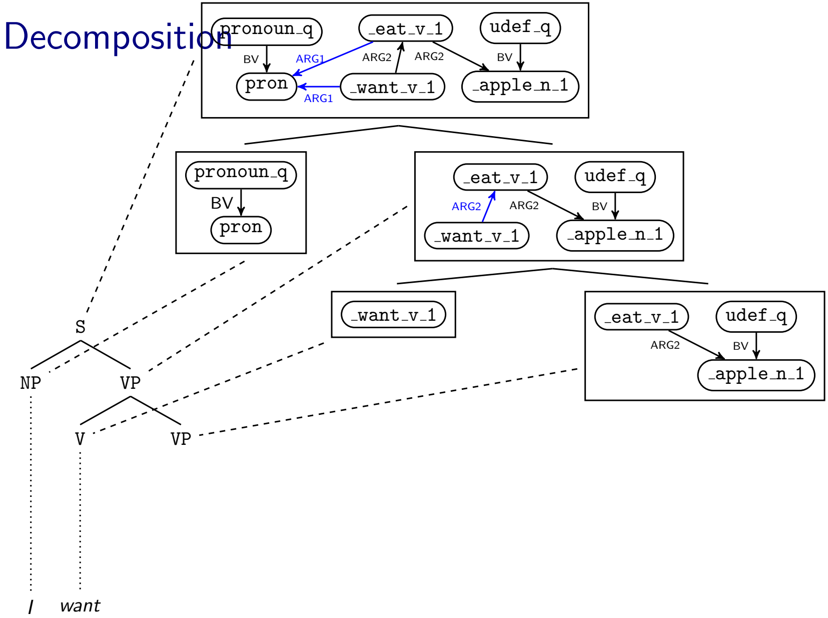


Compositional Surface Realisation

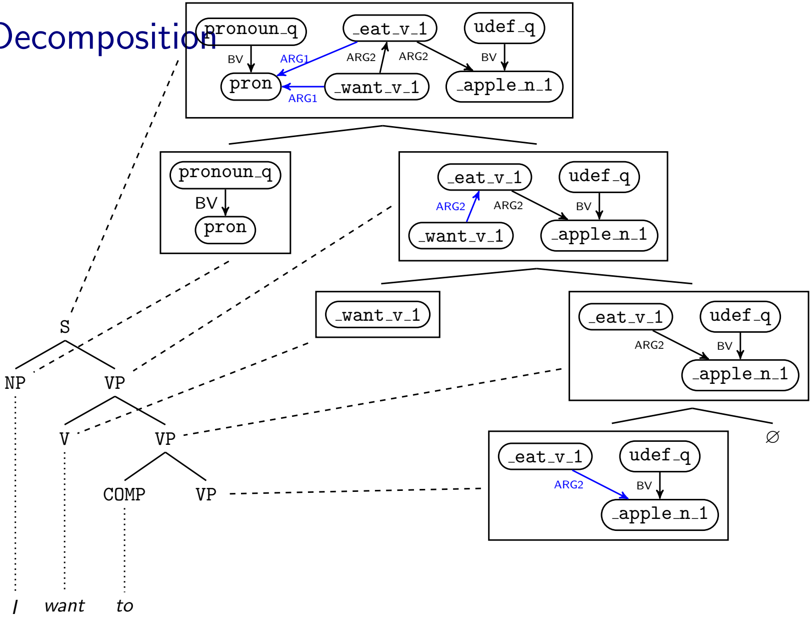
surface realisation: mapping an MR, such as semantic graph, to a string.

We recursively decompose the input graph until we meet elementary graphs that correspond to "words".
In each step, we cut a big graph into two smaller ones. In fact, we should view the blue edges as a third graph.
Our scissors are syntactico-semantic rules.
In the first step to handle current example, we get S→NP VP on the syntactic side, which puts the subject NP before the predicate VP.

Decomposition



Decomposition



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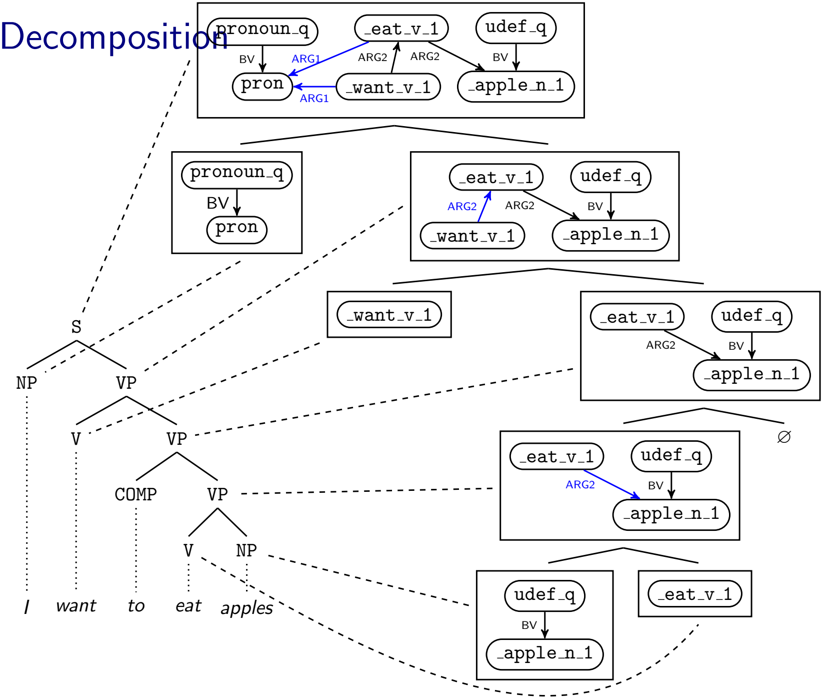
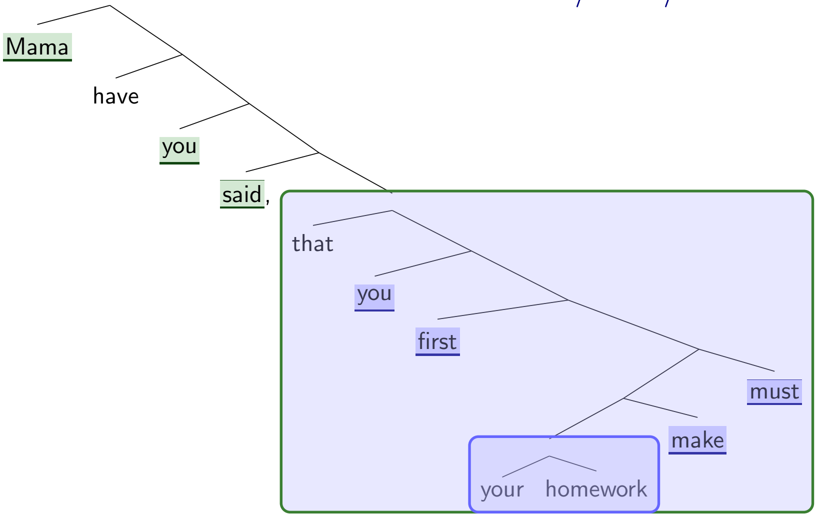


Locality

Idan Landau's lecture note on syntax

> *Syntax is a thankless trade; the man on the street (and some semanticists, for that matter) think it is trivial (at best) or superfluous (at worst).*

I can understand because of the sister/aunt/...relations



- Arguments/adjuncts should **c-command** a target verb.
- A node in a syntactic tree c-commands its sister node and all of its sister's descendants

Can you understand?

- Mama have you said, that you first your homework make must.
- When you this ready have, then you can to Julia go.

(1) Mama first have you said, that you your homework make must.

It is hard for me to understand (1), because it breaks the sister/aunt/... pattern, which is found in a majority of natural languages.

Is the distance between *you* and *make* long?

Mama have you said, that you first your homework, *which you should do but haven't done yet,* make must.

11 words in between; but still local wrt *tree*

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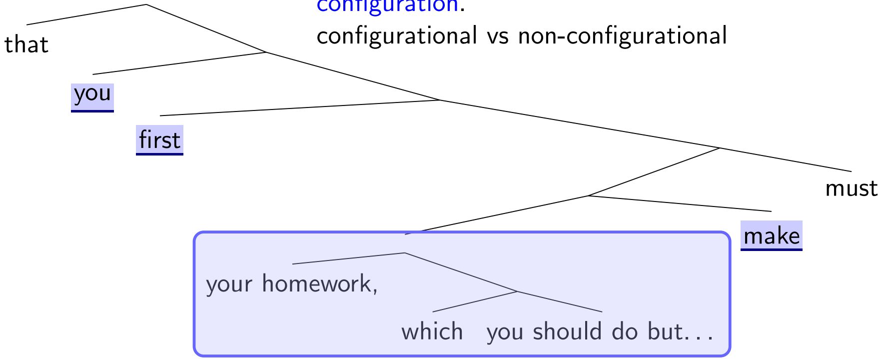
Mama have you said, that you first your homework, *which you should do but haven't done yet,* make must.

11 words in between; but still local wrt *tree*

the calculation of distance is based on the syntactic configuration.

configurational vs non-configurational



Can you understand?

- Mama have you said, that you first your homework make must.

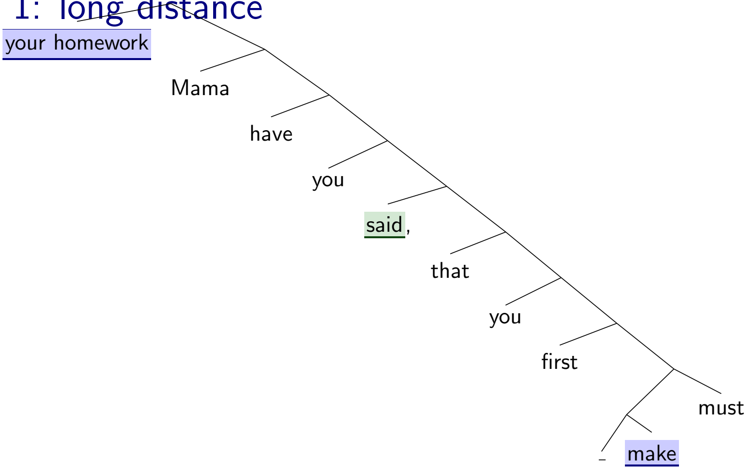
(2) Your homework, Mama have you said, that you first make must.

Topic-prominent vs subject-prominent

- Li and Thompson distinguish topic-prominent languages, such as Mandarin and Japanese, from subject-prominent languages, such as English.
- A topic-prominent language uses morphology/syntax to emphasize the topic-comment structure of the sentence.

I can understand (2) because this is a very frequent phenomenon in Mandarin.

Challenge 1: long distance



Modeling syntactico-semantic composition/derivation

- In each step, the rule should be "local".
- The long-distance dependency is derived by combining all "local" rules.
- We can achieve this by augmenting phrase-structure rules.

Unbounded dependency constructions (UDC)

Topicalisation

(3) a. Kim, Sandy loves.

b. Your homework, Mama have you said, that you first make must.

Wh-movement

(4) a. Who do you think Bob saw?

b. Who do you think Bob said he saw?

c. Who do you think Bob said he imagined that he saw?

- Some sentences exhibit phrases that appear “out of place” based on simple head–argument or head–modifier constraints.
- The distance from the position of the “dislocated” phrase to its “natural home” can be quite far (in the limit, unbounded).

More UDCs

Coindexation

- The "dislocated" phrase is called "trace", denoted as $\_{i}$ or t_i.
- We use subscript, e.g. $_i$, to indicate a discourse referent.

Relative clause

(5) a. This is the man [who$_i$ Sandy loves $\_{i}$]. ▷*Wh*-**relative clause**

b. This is [the man]$_i$ [Sandy loves $\_{i}$]. ▷**Reduced relative clause**

Clefts

(6) a. It is Kim$_i$ [who$_i$ Sandy loves $\_{i}$]. ▷*It*-**clefts**

b. It is Kim$_i$ [Sandy loves $\_{i}$].

(7) [What$_i$ Sandy loves $\_{i}$] is Kim$_i$. ▷**Pseudoclefts**

And more...

A syntactic link is needed

(8) a. Kim_i, Sandy trusts $\_i$.

b. $[\text{On Kim}]_i$, Sandy depends $\_i$.

(9) a. *$[\text{On Kim}]_i$, Sandy trusts $\_i$.

b. *Kim_i, Sandy depends $\_i$.

(10) a. Kim_i, Ada believes Bob knows Sandy trusts $\_i$.

b. $[\text{On Kim}]_i$, Ada believes Bob knows Sandy depends $\_i$.

(11) a. *$[\text{On Kim}]_i$, Ada believes Bob knows Sandy trusts $\_i$.

b. *Kim_i, Ada believes Bob knows Sandy depends $\_i$.

This link has to be established for an unbounded length.

Bounded vs unbounded

(12) a. Sandy$_i$ is hard to love $\_{i}$. ▷ *Tough* **construction**

b. [This question]$_i$ is tough to answer $\_{i}$.

c. Kim$_i$ is easy (for John) to please $\_{i}$.

d. Kim$_i$ is easy to prove that Mary asked Paul to bribe $\_{i}$.

(13) a. Kim seems to love Sandy. ▷**raising**

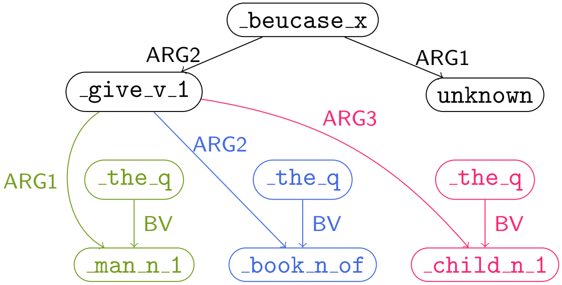
b. Kim wants to prove that. ▷**control**

What is the difference to the raising/control construction?
The corresponding dependencies in the raising/control construction are bounded.

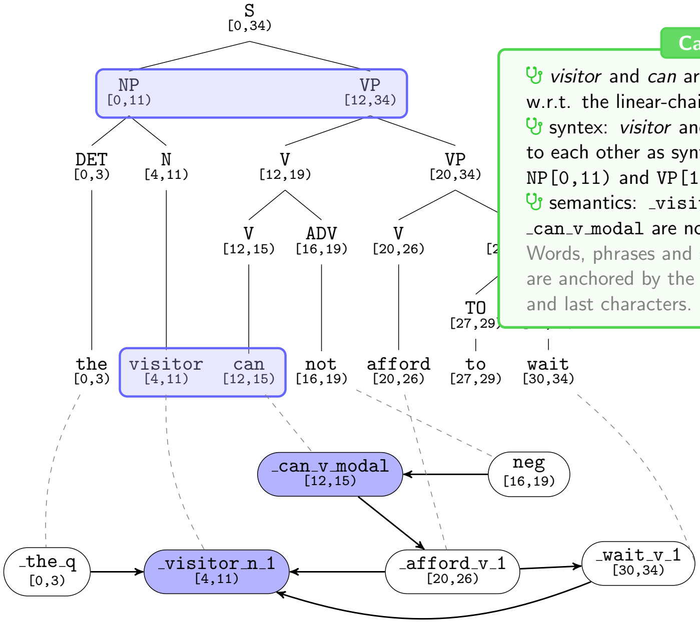
Case and word order in German

because the man gives the book to the child							
weil	*der*	*Mann*	*dem*	*Kind*	*das*	*Buch*	*gibt*
weil	*der*	*Mann*	*das*	*Buch*	*dem*	*Kind*	*gibt*
weil	*das*	*Buch*	*der*	*Mann*	*dem*	*Kind*	*gibt*
weil	*das*	*Buch*	*dem*	*Kind*	*der*	*Mann*	*gibt*
weil	*dem*	*Kind*	*der*	*Mann*	*das*	*Buch*	*gibt*
weil	*dem*	*Kind*	*das*	*Buch*	*der*	*Mann*	*gibt*

from S. Müller's course



Challenge 2: syntax–semantics mismatch?

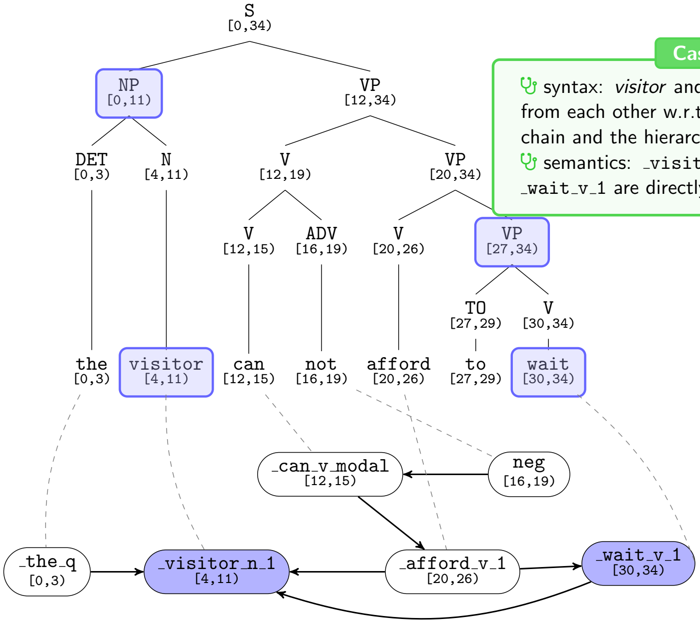


Case 1

- *visitor* and *can* are next to each other w.r.t. the linear-chain structure.
- syntex: *visitor* and *can* are also next to each other as syntactic heads of `NP[0,11)` and `VP[12,34)`.
- semantics: `_visitor_n_1` and `_can_v_modal` are not directly linked.

Words, phrases and semantic predicates are anchored by the positions of their first and last characters.

Challenge 2: syntax–semantics mismatch?



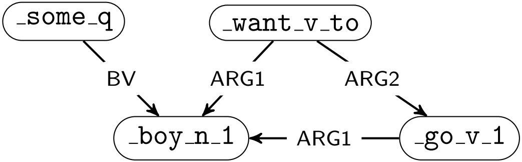
Case 2

syntax: *visitor* and *wait* are distant from each other w.r.t. both the linear-chain and the hierarchical structures.

semantics: _visitor_n_1 and _wait_v_1 are directly linked.

Context-Free Graph Rewriting

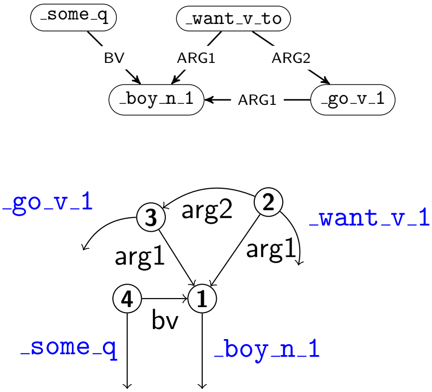
Hypergraph



A graph consists of:

- A set of nodes.
- A set of edges connecting two nodes.

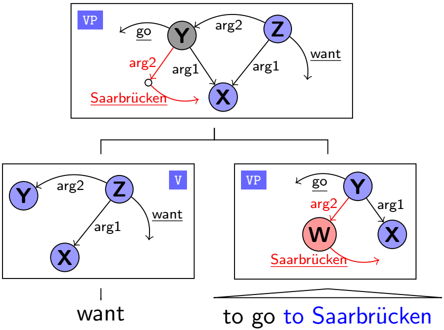
Hypergraph



A hypergraph adds:

- Hyperedges connecting any number of nodes.
- A single node can be treated as an edge.

Hyperedge Replacement Grammar



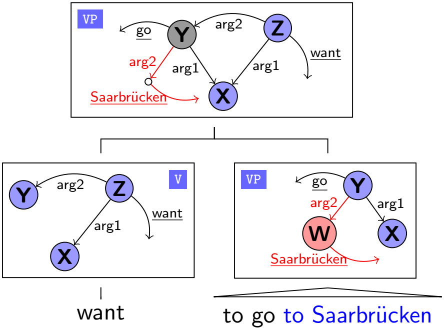
$\lambda \sim$ external node

When we combine two graphs, we don't need they know every detail of each other.

Only very few nodes of each graphs should be accessible. All other nodes are internal; they won't participate in further composition. E.g. the "Saarbrüecken" node is invisible from outside of the phrase "to go to Saarbüecken".

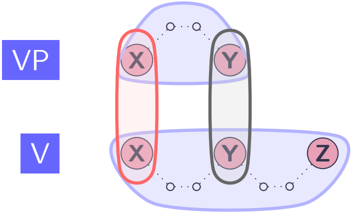
The few accessible nodes are called "external nodes", and they together make up an hyperedge.

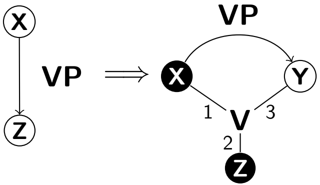
Hyperedge Replacement Grammar



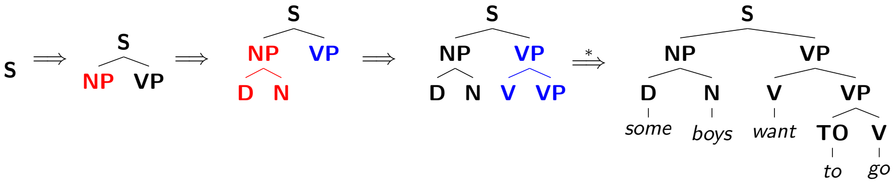
$\lambda \sim$ external node

- Graphs are glued together at their corresponding external nodes.
- After a new bigger graph is created, some nodes no longer participate in further composition; we then "forget" them.





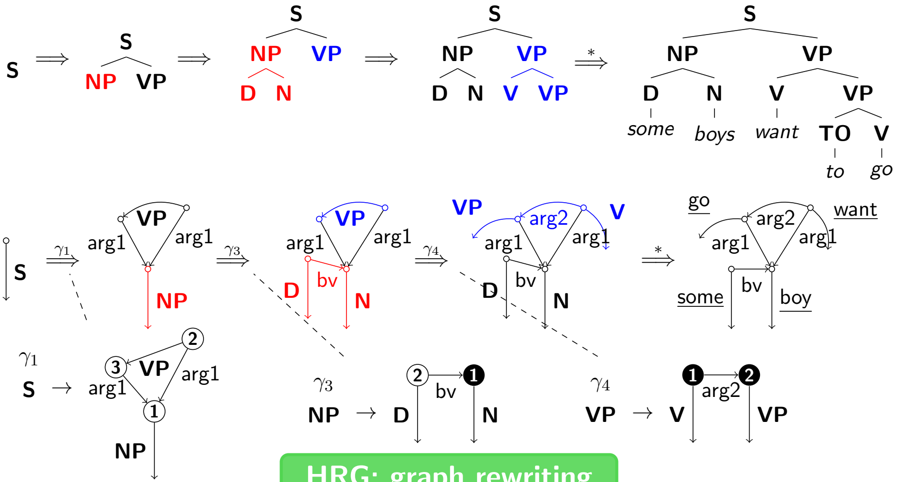
Symbol rewriting and graph rewriting



CFG: symbol rewriting

When we derive according to a CFG, we iteratively rewrite non-terminal symbols. E.g. `S` is rewritten to `NP VP`.

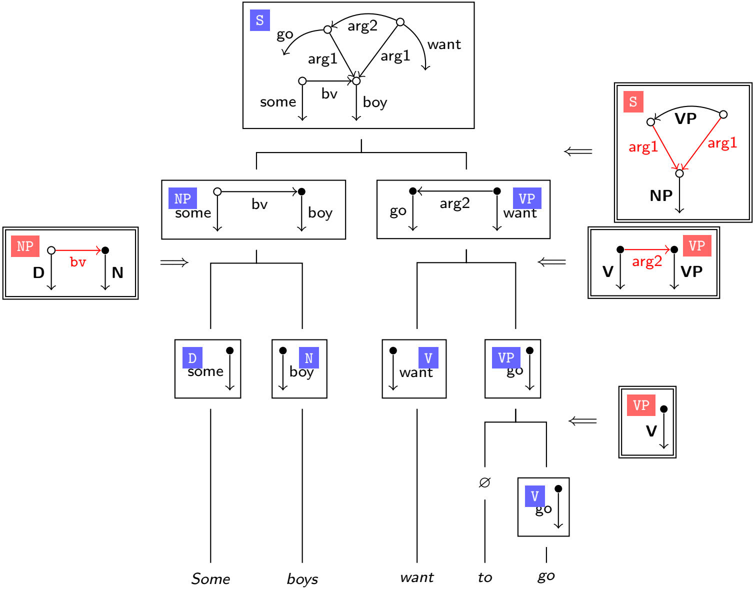
Symbol rewriting and graph rewriting



HRG: graph rewriting

We iteratively rewrite non-terminal hyperedges, i.e. hyperedges with non-terminal labels. Each hyperedge is replaced by a hypergraph. Rules should and could be linguistically-informed. γ_1: control; γ_3: quantification; γ_4: verb–object

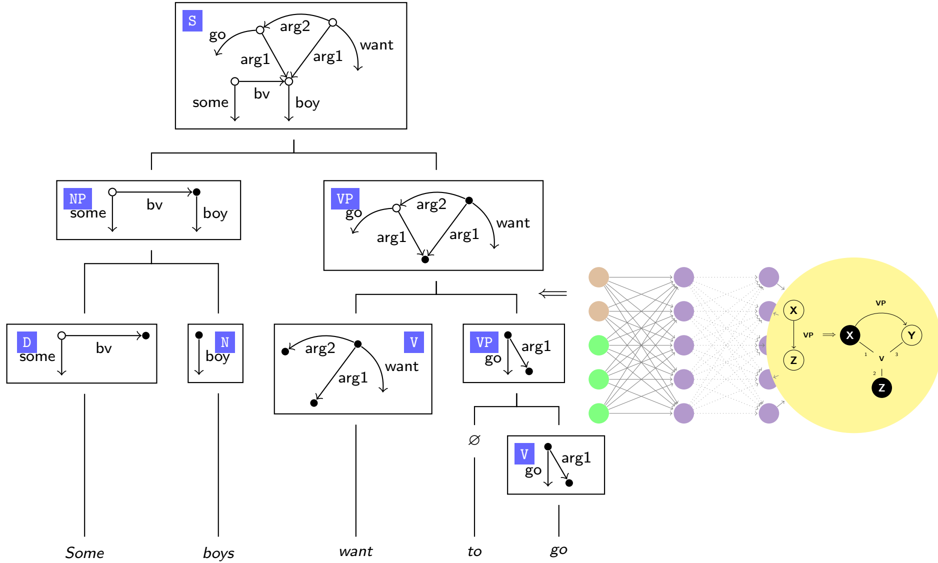
Derivation structure is tree; derived structure is graph



Derivation structure is tree

- The derived structure is a complicated graph, while the derivation structure is a seemingly simpler tree.
- A very general approach for understanding complex structures.
- For programming languages, compilers build abstract syntactic trees.
- For categorial grammars, categories like "S\NP" are merged along with a tree.

Scoring a derivation tree step-by-step



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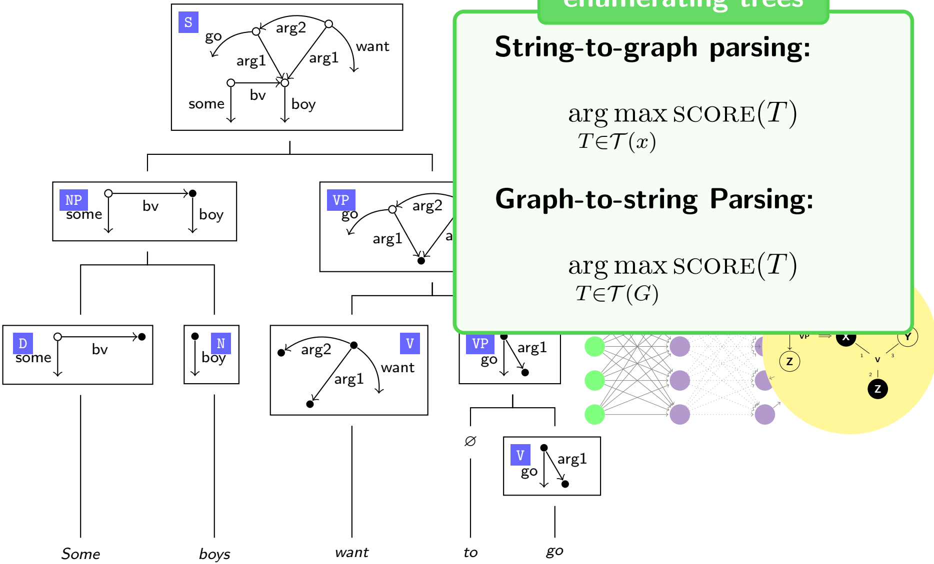


enumerating trees

String-to-graph parsing:

$$\underset{T \in \mathcal{T}(x)}{\arg\max}\, \mathrm{SCORE}(T)$$

Graph-to-string Parsing:

$$\underset{T \in \mathcal{T}(G)}{\arg\max}\, \mathrm{SCORE}(T)$$

Graph parsing and graph parsing

- Task 1: graph parsing (=string-to-graph parsing).
- Task 2: graph parsing (=graph-to-string parsing).
- To solve both tasks, we need to score a derivation tree, and search for the best tree in different spaces.
- It is relatively straightforward to score a tree by summation over all rules applied.

Task 1

The search space is denoted as $\mathcal{T}(x)$, where x is the input string. We enumerate all trees that are compatble to x, or say all trees licensed by our grammar.

$$\arg\max_{T \in \mathcal{T}(x)} \textsc{ScoreTree}(T) = \arg\max_{T \in \mathcal{T}(x)} \sum_{r \in T} \textsc{ScoreRule}(r)$$

Graph parsing and graph parsing

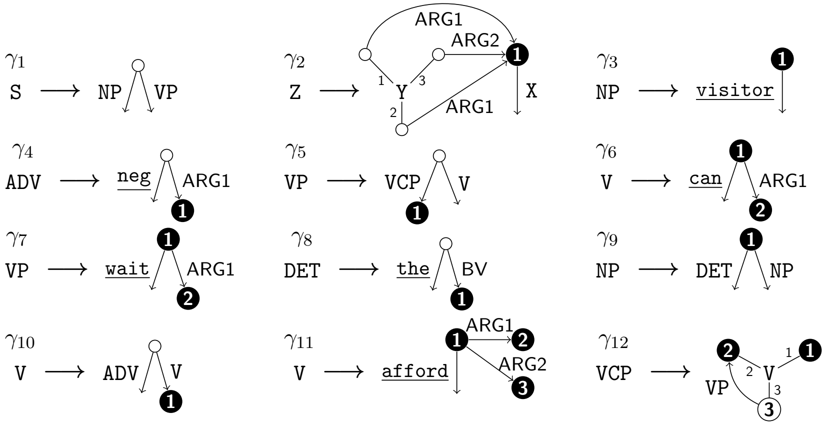
- Task 1: graph parsing (=string-to-graph parsing).
- Task 2: graph parsing (=graph-to-string parsing).
- To solve both tasks, we need to score a derivation tree, and search for the best tree in different spaces.
- It is relatively straightforward to score a tree by summation over all rules applied.

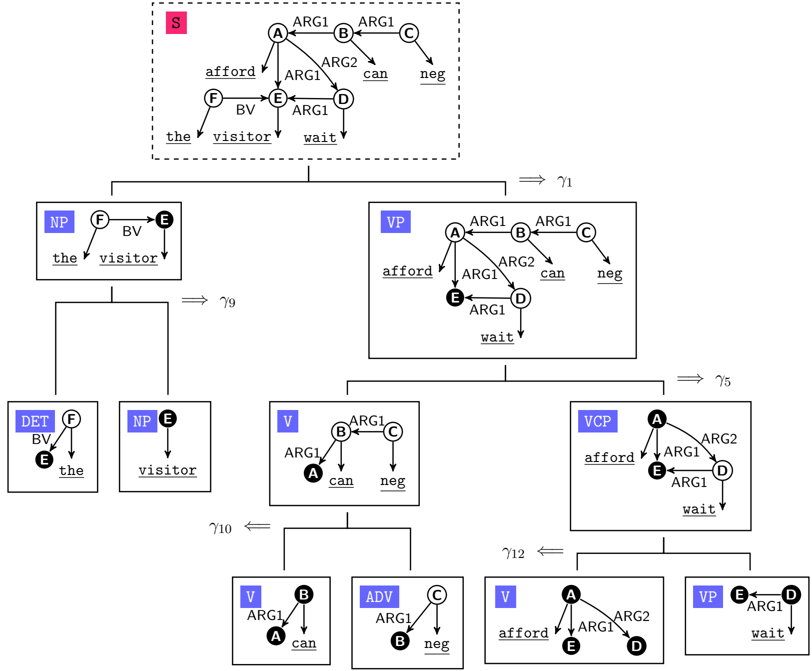
Task 2

The search space is denoted as $\mathcal{T}(G)$, where G is the input meaning representation. We enumerate all trees that are compatble to G, again, according to our grammar.

$$\arg\max_{T \in \mathcal{T}(G)} \textsc{ScoreTree}(T) = \arg\max_{T \in \mathcal{T}(G)} \sum_{r \in T} \textsc{ScoreRule}(r)$$

Example: more rules




S
A
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visitor
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neg
V
A
ARG2
afford
ARG1
E
D
VP
E
D
ARG1
wait

Readings

- Y. Chen and W. Sun. Parsing into Variable-in-situ Logico-Semantic Graphs.
- Y. Ye and W. Sun. Exact yet Efficient Graph Parsing, Bi-directional Locality and the Constructivist Hypothesis.