Learning Sentence Planning Rules with Bayesian Methods

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Natural Language Generation

How do we transform **non-linguistic input**...

name	price	cuisine
Due Fratelli	\$\$	Italian
Andalucia	\$\$\$	Spanish, Seafood

...into a **natural language text**?

Due Fratelli is an Italian restaurant, while Andalucia is a Spanish seafood restaurant. However, Due Fratelli's price is average, while Andalucia's price is more expensive.

Templates and traditional approaches to NLG

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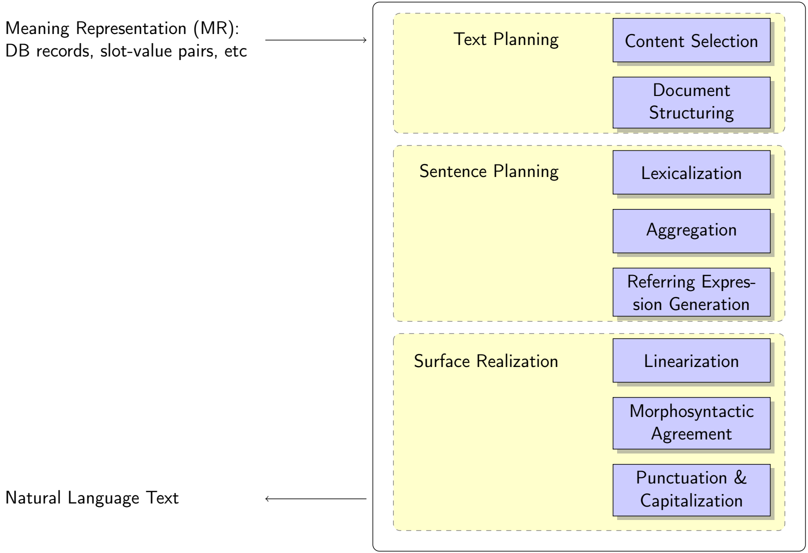
- Factor out language-general elements

'The' NLG Pipeline



More reusable components, but still requires a lot of human attention.

End-to-end machine learning approaches to NLG

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Problem: shallow representations and relative opacity

Can we have the best of both worlds?

From the rule-based approach:

- existing resources for NLG;
- richer semantic & syntactic structure;
- inspectability; and
- modularity where it's helpful.

From the ML approach:

- reduced development effort

Let's find out!

Narrowing our focus:

- assume text planning already done
- **learn sentence planning rules**
- use existing systems for surface realization

Text Plans with Discourse Structure

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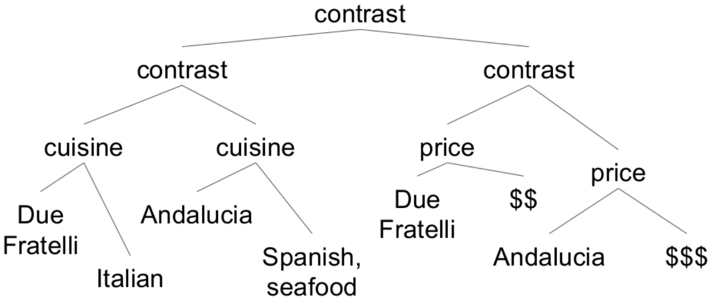

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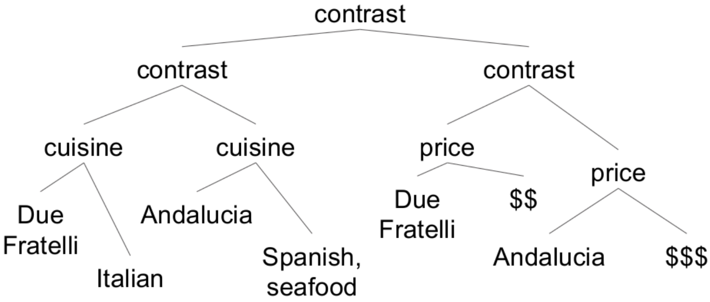

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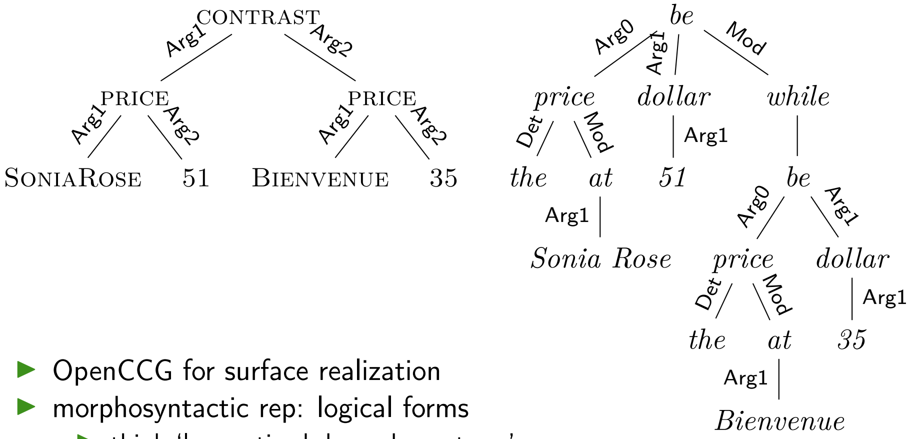
Morphosyntactic Reps for Surface Realization

Text Plan

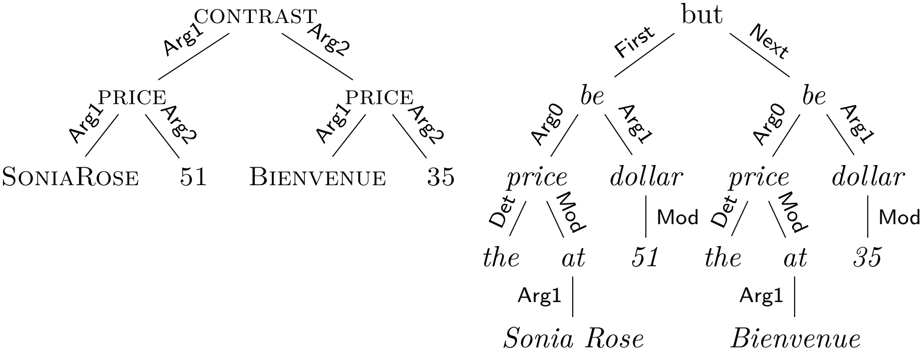
'Logical Form'

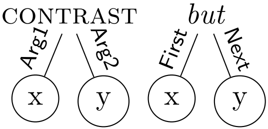


- OpenCCG for surface realization
- morphosyntactic rep: logical forms
  - think 'lemmatized dependency trees'
- based on CCGbank (Hockenmaier 2006) $\Longrightarrow$ WSJ coverage

How to represent tree-to-tree mappings?

Synchronous Tree Substitution Grammars





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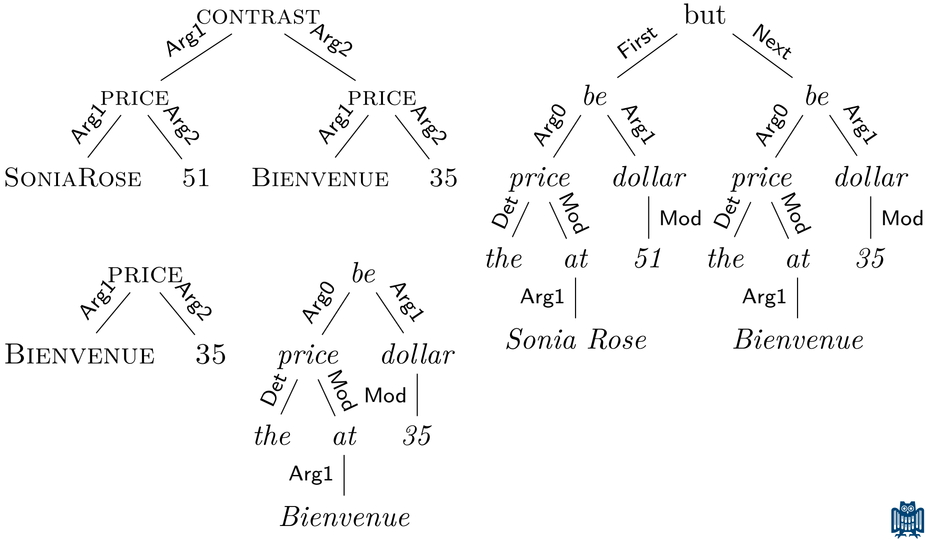

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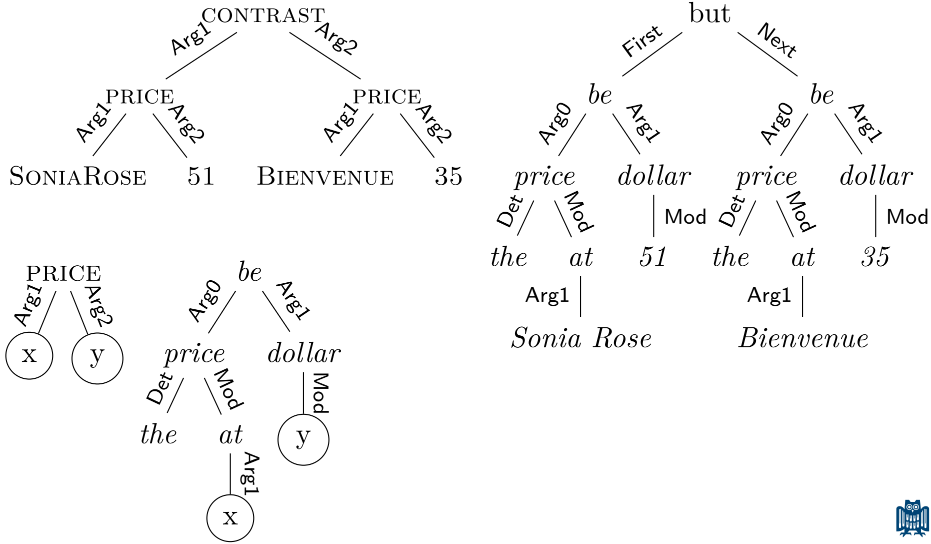
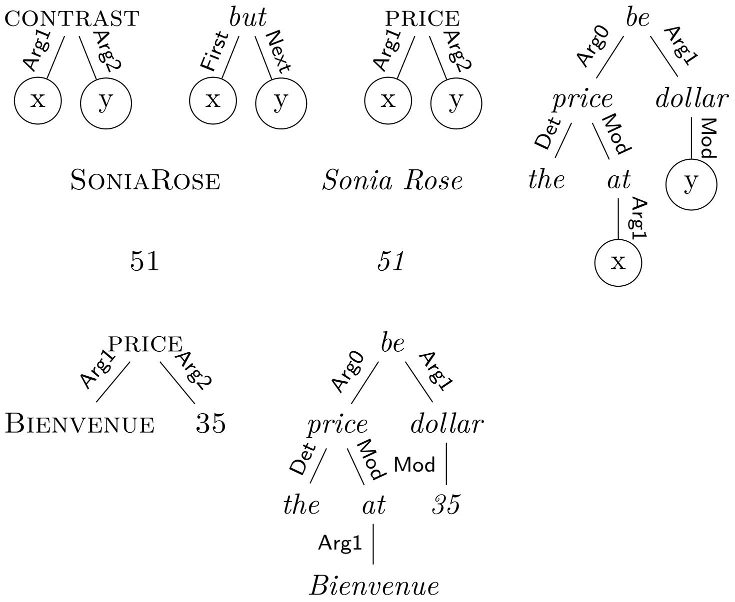


Synchronous Derivation with TSGs



How to learn tree-to-tree mappings?

Hierarchical Dirichlet Processes

- prior biases towards small, reusable trees
- observations provide evidence for larger trees

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Chinese Restaurant Process

$$P(e) = \frac{freq(e)}{\#obs + \alpha} + \frac{\alpha}{\#obs + \alpha} P_{prior}(e), \tag{1}$$

where α is the concentration parameter, $freq(e)$ is the number of times we have observed the elementary tree e, $\#obs$ is the total number of observations, and P_{prior} is our prior.

Statistical Model for sTSGs for SP

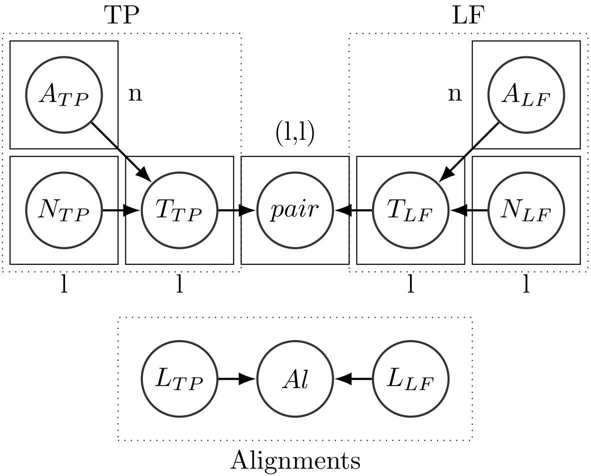

Figure: Dependencies in our statistical model, omitting parameters for clarity. Each node represents a Dirichlet process over base distributions with $\alpha = 1$. n here indexes node labels, while l similarly represents tree locations.

Some example texts

1. Chanpen Thai has the best overall quality among the selected restaurants. Its price is 24 dollars and it has good service. **This Thai restaurant** has good food quality, with decent decor.
2. **Since** Komodo's price is 29 dollars and it has good decor, it has the best overall quality among the selected restaurants.
3. Azuri Cafe, **which** is a **Vegetarian** restaurant has very good food quality. Its price is 14 dollars. It has the best overall quality among the selected restaurants.
4. Komodo has very good service. It has **food food quality, with very good food quality, it has very good food quality** and its price is 29 dollars.

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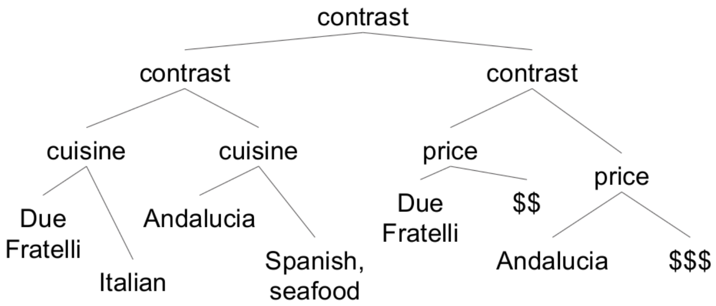

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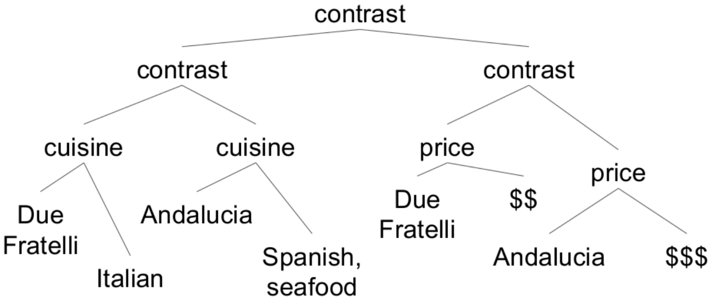

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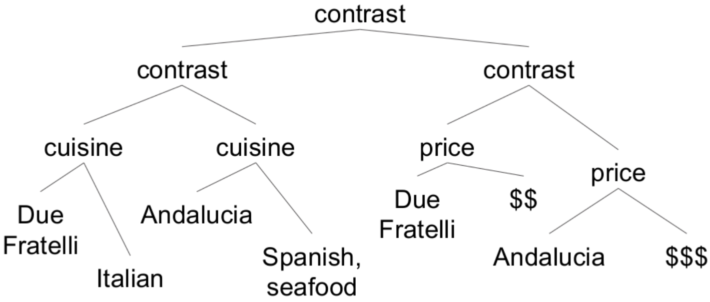

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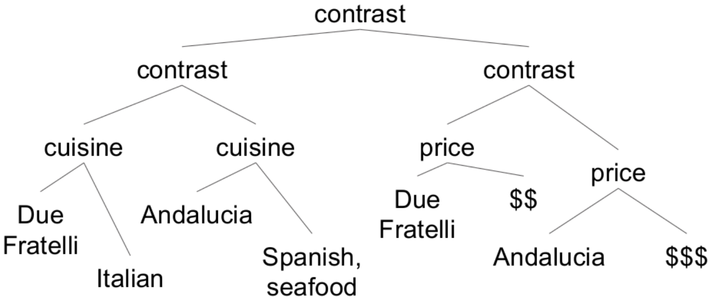

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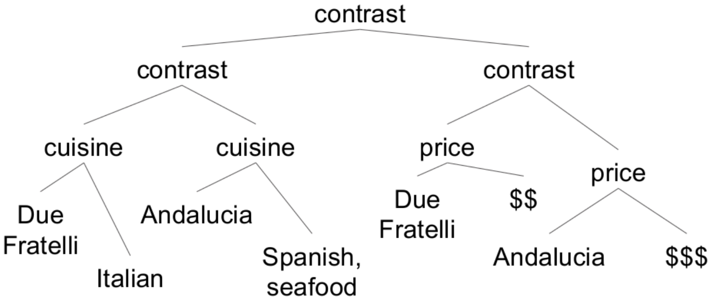

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  - 1800 texts from an NLG system
  - discourse semantics, but limited variation

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E2E Challenge Dataset (Novikova et al. 2016, 2017)

- 50k utterances+DAs
- increased variation (image-based elicitation)

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2 conditions: default vs. elderly audience

We are adding variety to an existing dialogue system and we need your help!

In this task, you will be given a text about one or more restaurants written by our existing system.

Your job is to express the same facts, describing the restaurant(s) as you would describe them to your...
default: **...friends or family.**
elderly: **...85-year-old grandmother.**

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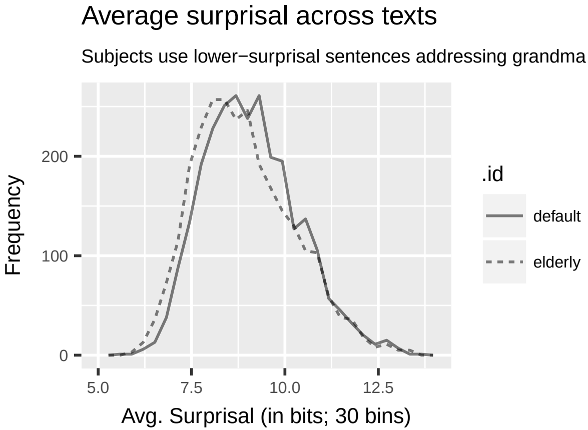
- significantly lower information density in the elderly condition



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Choose Caffe Buon Gusto if you desire a traditional Italian restaurant. Otherwise, try out John's Pizzeria.

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cf. Caffe Buon Gusto is an Italian restaurant. John's Pizzeria, on the other hand, is an Italian, Pizza restaurant.

Examples (2)

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cf. Chez Josephine has the best overall quality among the selected restaurants. It has very good service, with very good decor. It has very good food quality.

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Thank you!

Did we achieve greater lexical variety?

corpus	# texts	Vocabulary
BAGEL	404	74
SFX-restaurant	5192	353
Novikova et al.	1243	238
Original SRC	1760	99
Extended SRC	**5356**	**577**

Table: Vocabulary diversity and corpus size