Natural Language Generation

(mostly) for Spoken Dialogue Systems

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Outline of this talk

1. Introduction: what is NLG?

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3. What next?

Introduction

Objective of NLG

Given (whatever) input and a **communication goal**, create a natural language string that is **well-formed** and **human-like**.

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Usage

- Spoken dialogue systems
- Machine translation
- Short texts: Personalized letters, weather reports …
- Summarization
- Question answering in knowledge bases

Standard NLG Pipeline (*Textbook*)

[Inputs]

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- Content selection, basic ordering

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↓ Sentence planning/microplanning ("middle ground")

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[Sentence plan(s)]

↓ Surface realization ("how to say it")

- linearization, conforming to rules of the target language

[Text]

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Inputs

- Communication goal (e.g. “inform user about search results”)
- Knowledge base (e.g. list of matching entries in database, weather report numbers etc.)
- User model (constraints, e.g. user wants short answers)
- Dialogue history (referring expressions, repetition)

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Content planning

- Content selection according to communication goal
- Basic structuring (ordering)

Standard NLG Pipeline (*Textbook*)

Sentence planning (micro-planning)

- Word and syntax selection (e.g. choose templates)
- Dividing content into sentences
- Aggregation (merging simple sentences)
- Lexicalization
- Referring expressions

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Surface realization

- Creating linear text from (typically) structured input
- Ensuring grammatical correctness

Real NLG Systems

Few systems implement the whole pipeline

- Systems focused on content planning with trivial surface realization
- Surface-realization-only, word-order-only systems
- One-step (holistic) approaches
- SDS: content planning done by dialogue manager
  → **only sentence planning and realization here**

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Data representations

- Varied, custom-tailored, non-compatible

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Why go one-step

- Problem of all pipelines: error propagation
  - the more steps, the more chance to screw it up
- Need to provide training sentence plans (statistical planners)
  - sometimes you may use existing analysis tools

NLG systems examples

- Divided by NLG stage:

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  1. Sentence planning

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NLG systems examples

- Divided by NLG stage:
  1. Sentence planning
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  3. One-step approaches to NLG
- Each stage:
  1. History
  2. Current state-of-the art / our works

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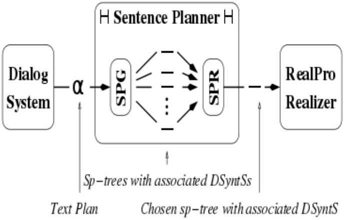
- Various input/output formats, not very comparable
- Actually typically handcrafted or non-existent
  - One-step approaches or simplistic systems
- Here we focus on trainable approaches
  - …and especially on our own ☺

Trainable Sentence Planning: *SPoT*

- Spoken Dialogue System in the flight information domain
- Handcrafted generator + overgeneration
- Statistical reranker (RankBoost) trained on hand-annotated sentence plans



implicit-confirm(orig-city:NEWARK)
implicit-confirm(dest-city:DALLAS)
implicit-confirm(month:9)
implicit-confirm(day-number:1)
request(depart-time)

Alt	Realization	H	RB
0	What time would you like to travel on September the 1st to Dallas from Newark?	5	.85
5	Leaving on September the 1st. What time would you like to travel from Newark to Dallas?	4.5	.82
8	Leaving in September. Leaving on the 1st. What time would you, traveling from Newark to Dallas, like to leave?	2	.39

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- No overgeneration
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I see, oh Chimichurri Grill is a latin american place with sort of poor atmosphere. Although it doesn’t have rather nasty food, its price is 41 dollars. I suspect it’s kind of alright.	extra=2.50 ems=4.50 agree=3.50 consc=4.75 open=4.25
Did you say Ce-Cent’anni? I see, I mean, I would consider it because it has friendly staff and tasty food, you know buddy.	extra=4.75 ems=5.00 agree=6.25 consc=6.25 open=5.25

Examples

- *Paiva&Evans*: linguistic features annotated in corpus generated with many parameter settings, correlation analysis
- *PERSONAGE-PE*: personality traits connected to linguistic features via machine learning

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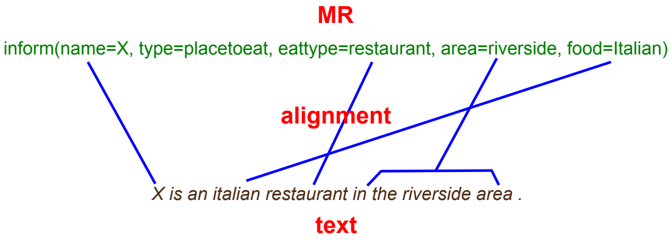

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   - Typical NLG training:
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   - Our sentence planner learns alignments jointly
     - training from pairs: **MR + sentence**

MR

inform(name=X, type=placetoeat, eattype=restaurant, area=riverside, food=Italian)

X is an italian restaurant in the riverside area .

text

I/O formats

inform(name=X, type=placetoeat,
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- **Input**: a MR
  - dialogue acts: “inform” + slot-value pairs
  - other formats possible

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- **Output**: deep-syntax dependency trees
  - based on *TectoMT*'s t-layer, but very simplified
  - two attributes per tree node: *t-lemma* + *formeme*
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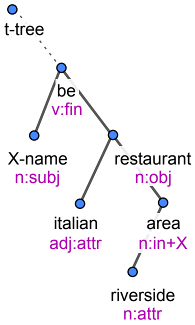

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- Conversion to plain text sentences – surface realization
  - *Treex*/*TectoMT* English synthesis (rule-based, later)

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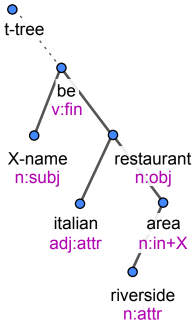

X is an Italian restaurant in the riverside area.

Overall Structure of Our Sentence Planner

- A*-style search – “finding the path”
  empty tree $\rightarrow$ full sentence plan tree
  - always expand the most promising candidate sentence plan
  - stop when candidates don't improve for a while

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    - churning out candidate sentence plan trees
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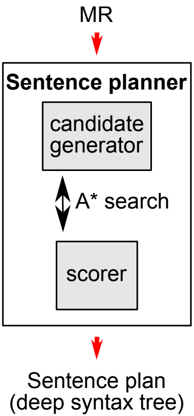

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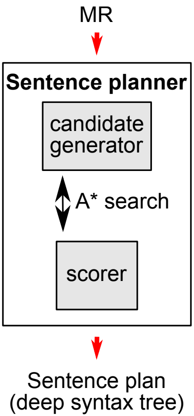
  - **scorer**/ranker for the candidates
    - influences which candidate trees will be expanded (selects the most promising)



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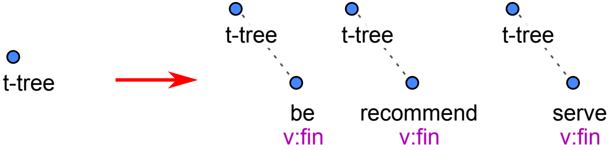

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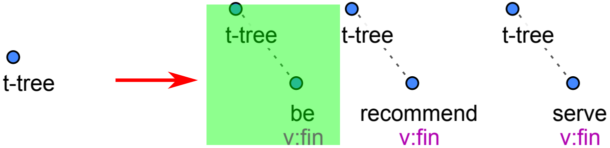

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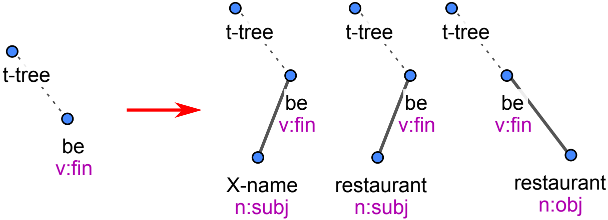

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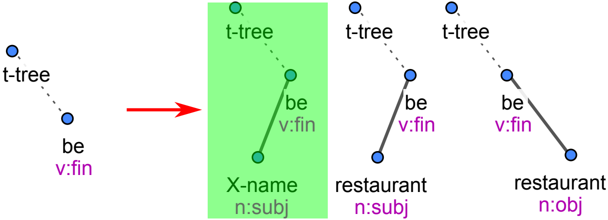

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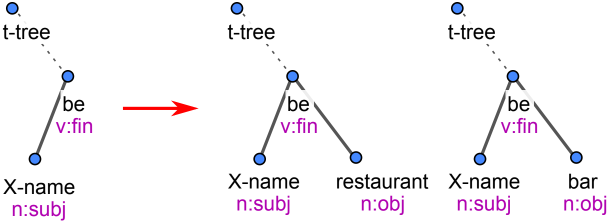

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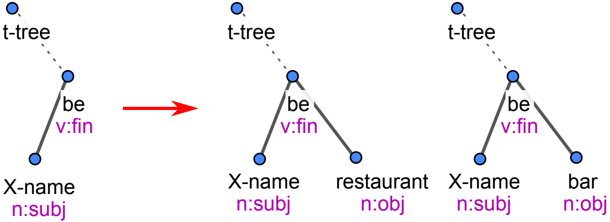

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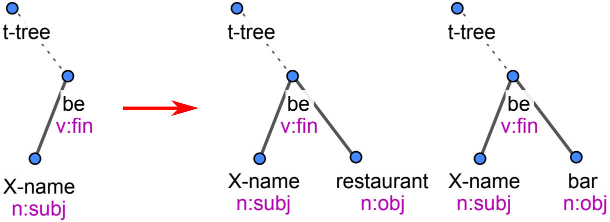

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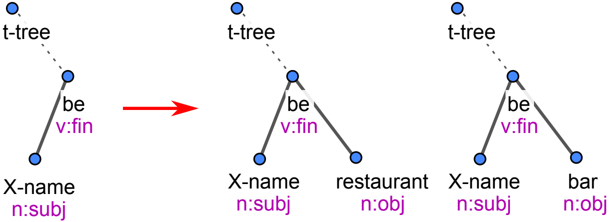

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- using combination of things seen in training data
  - parent–child
  - t-lemma + formeme
  - number of children, tree size …

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  - slooooow, doesn't scale very well

Example Outputs

Input DA	inform(name=X-name, type=placetoeat, area=riverside, near=X-near, eattype=restaurant)
Reference	X restaurant is near X on the riverside.
Generated	X is a restaurant in the riverside area near X.

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Reference	X is a French restaurant on the riverside.
Generated	X is a French restaurant in the riverside area which serves French food.
Input DA	inform(name=X-name, type=placetoeat, eattype=restaurant, area=citycentre, near=X-near, food="Chinese takeaway", food=Japanese)
Reference	X is a Chinese takeaway and Japanese restaurant in the city centre near X.
Generated	X is a Japanese restaurant in the centre of town near X and X.

Surface Realization Examples

- Also various input formats, at least output is always text
- From handcrafted to different trainable realizers
- Also including our own (developed here at ÚFAL): *Treex/TectoMT* realizer
    - actually handcrafted for the most part

Grammar-based Realizers (90's): *KPML*, *FUF/SURGE*

KPML

- General purpose, multilingual
- Systemic Functional Grammar

```
(EXAMPLE
  :NAME   EX-SET-1
  :TARGETFORM   "It is raining cats and dogs."
  :LOGICALFORM
    (A / AMBIENT-PROCESS :LEX RAIN
        :TENSE PRESENT-CONTINUOUS :ACTEE
      (C / OBJECT :LEX CATS-AND-DOGS :NUMBER MASS))
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FUF/SURGE

- General purpose
- Functional Unification Grammar

Input Specification (I_1):

$$\begin{bmatrix} cat & clause \\ process & \begin{bmatrix} type & composite \\ relation & possessive \\ lex & \text{“hand”} \end{bmatrix} \\ partic & \begin{bmatrix} agent & \begin{bmatrix} cat & pers\_pro \\ gender & feminine \end{bmatrix} \\ affected & \boxed{1} \begin{bmatrix} cat & np \\ lex & \text{“editor”} \end{bmatrix} \\ possessor & \boxed{1} \\ possessed & \begin{bmatrix} cat & np \\ lex & \text{“draft”} \end{bmatrix} \end{bmatrix} \end{bmatrix}$$

Output Sentence (S_1): "She hands the draft to the editor"

Grammar-based Realizer: *OpenCCG*

- General purpose, multi-lingual
- Combinatory Categorial Grammar
- Used in several projects
- With statistical enhancements

$$
\begin{array}{llll}
(>) & X/Y \;\; Y & \Rightarrow & X \\
(<) & Y \;\; X\backslash Y & \Rightarrow & X \\
(>\mathbf{B}) & X/Y \;\; Y/Z & \Rightarrow & X/Z \\
(<\mathbf{B}) & Y\backslash Z \;\; X\backslash Y & \Rightarrow & X\backslash Z \\
(>\mathbf{T}) & X & \Rightarrow & Y/(Y\backslash X) \\
(<\mathbf{T}) & X & \Rightarrow & Y\backslash(Y/X)
\end{array}
$$

man $\vdash$ n
that $\vdash$ $(n\backslash n)/(s_{vform=fin}/np)$
Bob $\vdash$ np
saw $\vdash$ $(s_{tense=past,vform=fin}\backslash np)/np$

$$
\dfrac{\dfrac{man}{n} \quad \dfrac{\dfrac{that}{(n\backslash n)/(s/np)} \quad \dfrac{\dfrac{\dfrac{Bob}{np}}{s/(s\backslash np)}{>T} \quad \dfrac{saw}{(s\backslash np)/np}}{s/np}{>B}}{n\backslash n}{>}}{n}{<}
$$

```
be [tense=pres info=rh id=n1]
<Arg> flight [num=sg det=the info=th id=f2]
      <HasProp> cheapest [kon=+ id=n2]
<Prop> has-rel [id=n3]
       <Of> f2
       <Airline> Ryanair [kon=+ id=n4]
```

$$
@_x(\mathbf{man} \wedge \langle \textsc{GenRel}\rangle(e \wedge \mathbf{see} \wedge \langle \textsc{tense}\rangle\mathbf{past} \\ \wedge \langle \textsc{Act}\rangle(b \wedge \mathbf{Bob}) \wedge \langle \textsc{Pat}\rangle x))
$$

Procedural Realizer: *SimpleNLG*

- General purpose
- English, adapted to several other languages
- Java implementation (procedural)

```
Lexicon lexicon = new XMLLexicon("my-lexicon.xml");
NLGFactory nlgFactory = new NLGFactory(lexicon);
Realiser realiser = new Realiser(lexicon);

SPhraseSpec p = nlgFactory.createClause();

p.setSubject("Mary");
p.setVerb("chase");
p.setObject("the monkey");

p.setFeature(Feature.TENSE, Tense.PAST);

String output = realiser.realiseSentence(p);
System.out.println(output);

>>> Mary chased the monkey.
```

Trainable Realizers: Overgenerate and Rank

- Require a handcrafted realizer, e.g. CCG realizer
- Input underspecified $\rightarrow$ more outputs possible
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- Then use a statistical reranker

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- Provides variance, but at a greater computational cost

Trainable Realizers: Syntax-Based

- *StuMaBa*: general realizer based on SVMs
- Pipeline:
  - ↓ Deep syntax/semantics
  - ↓ surface syntax
  - ↓ linearization
  - ↓ morphologization

Treex/TectoMT Surface Realizer

- Domain-independent

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- Mostly simple, single-purpose, rule-based modules (blocks)
  - Word inflection: statistical (*Flect*)
- Gradual transformation of deep trees into surface dependency trees
  - Surface trees are then simply linearized

Treex/TectoMT Surface Realization Example

- Realizer steps (simplified):

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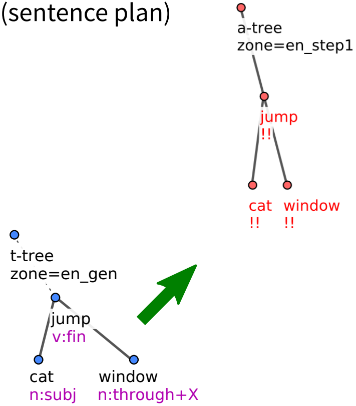
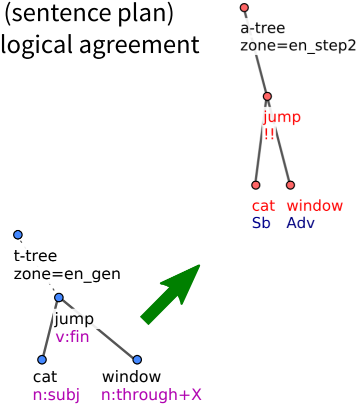
  - Copy the deep tree (sentence plan)



Treex/TectoMT Surface Realization Example

- Realizer steps (simplified):
  - Copy the deep tree (sentence plan)
  - Determine morphological agreement



Treex/TectoMT Surface Realization Example

- Realizer steps (simplified):
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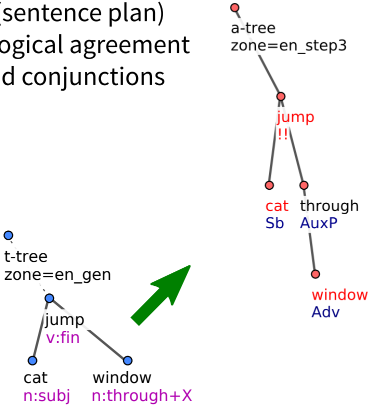
  - Add prepositions and conjunctions



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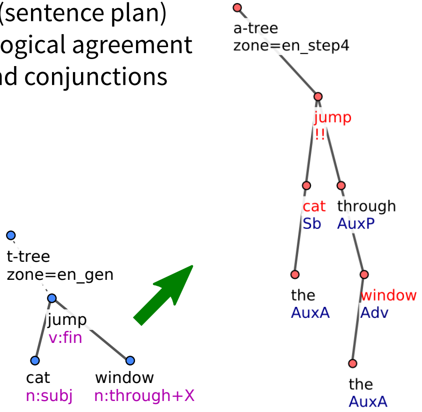

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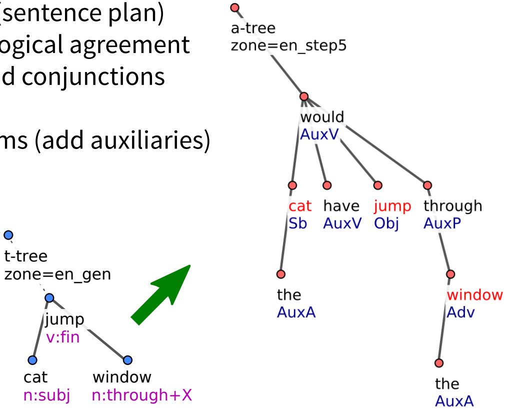

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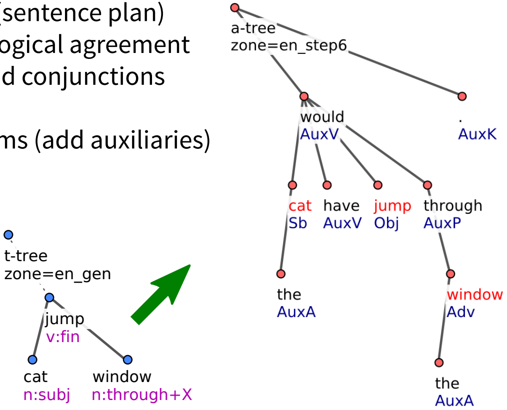

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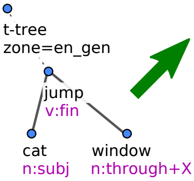

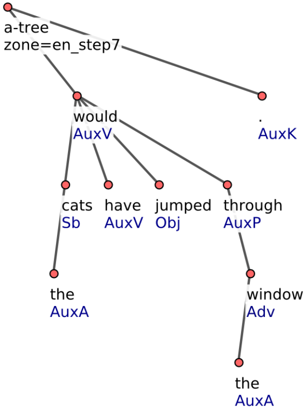

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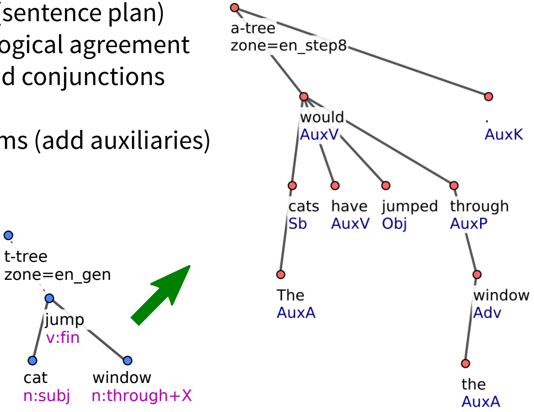
  - Capitalization



One-step NLG

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- Only one stage – no distinction
- Typical for limited domains, also in SDS
- Handcrafted/templates + statistical
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Template-based systems

- Most common, also in commercial NLG systems
- Simple, straightforward, reliable (custom-tailored for domain)
- Lack generality and variation, difficult to maintain
- Enhancements for more complex utterances: rules

Example: Templates

- Just filling variables into slots
- Possibly a few enhancements, e. g. articles

```
inform(pricerange="{pricerange}"):
'It is in the {pricerange} price range.'

affirm()&inform(task="find")
    &inform(pricerange="{pricerange}"):
'Ok, you are looking for something in the'
    + ' {pricerange} price range.'

affirm()&inform(area="{area}"):
'Ok, you want something in the {area} area.'

affirm()&inform(food="{food}")
    &inform(pricerange="{pricerange}"):
'Ok, you want something with the {food} food'
    + ' in the {pricerange} price range.'

inform(food="None"):
'I do not have any information'
    + ' about the type of food.'
```

Alex (English restaurant domain)

Facebook templates

One-step Statistical Non-neural NLG Approaches

- Limited domain
- Based on supervised learning
  (typically: MR + sentence + alignment)
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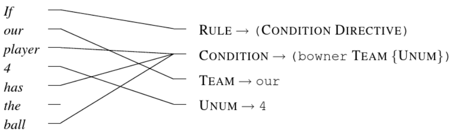

Examples

- *BAGEL*: Bayesian networks
  - semantic stacks, ordering
- *Angeli et al.*: log-linear model
  - records ↘ fields ↘ templates
- *WASP*$^{-1}$: Synchronous CFGs
  - noisy channel, similar to MT

Neural NLG

- Using recurrent neural networks
- Input: 1-hot DA representation

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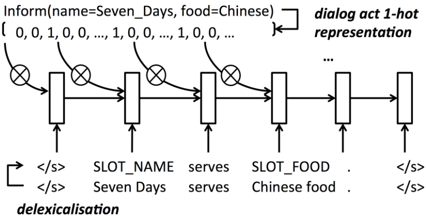

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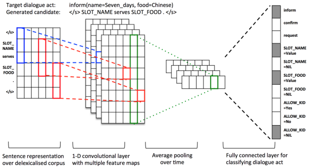

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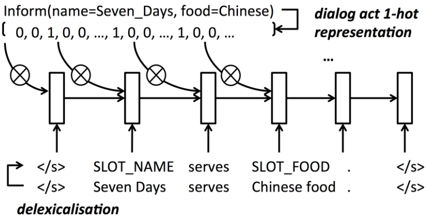

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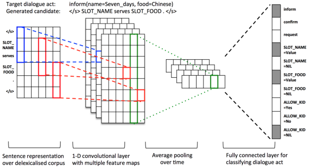

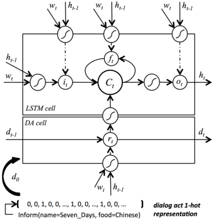

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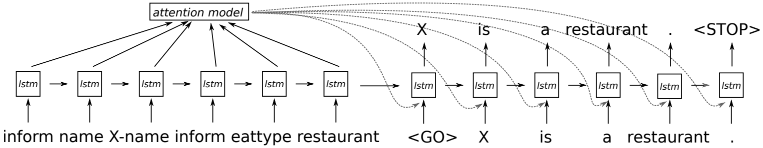

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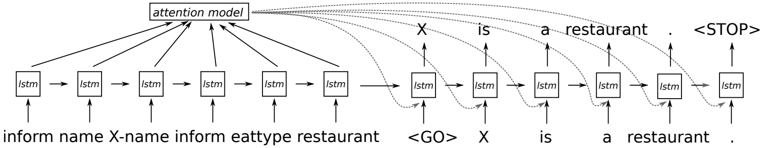

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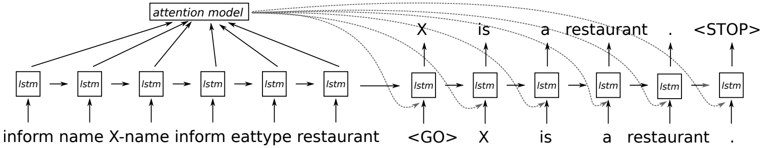

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  - encode: DAs converted step-by-step by a RNN into a *hidden state*
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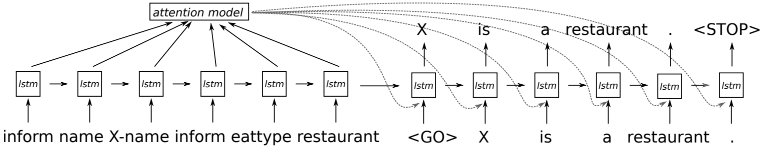
- attention model – access to all encoder states
  - weighted by a simple feed-forward NN



Seq2Seq NLG variants

Trees/Strings

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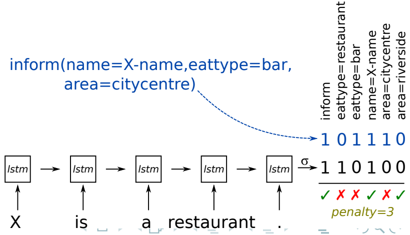
- Reranker: RNN + classifying
  0/1 presence of all DA slots/values



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Setup		**BLEU**	**NIST**	**ERR**
BAGEL (with alignments)		∼67	-	0
TGEN1		59.89	5.231	30
TGEN2	Greedy with trees	53.95	5.110	22
	+ Beam search	58.86	5.336	25
	+ Reranking classifier	59.72	5.491	19
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- one-step (into strings) works better

New NLG developments

Multi-domain NLG *(DT-RNN)*

- Large out-of-domain data
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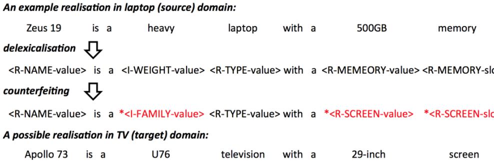

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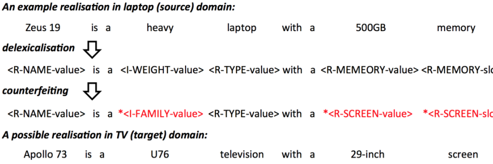

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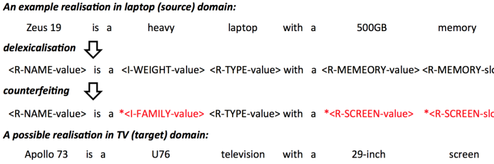
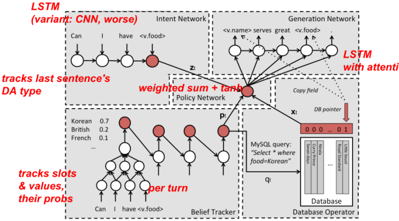


End-to-end *(E2E)* Spoken Dialogue Systems

- Based on a complex neural network
- Generation (word-by-word) is a part of the whole setup, trained jointly



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Sorry, I did not find a later option.

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  - uses the same words, phrases

how bout the next ride
inform_no_match(alternative=next)
Sorry, I did not find a later option.

Our Latest Experiments

- Using context in NLG
- NLG system “entrains” (aligns) to the user
  - uses the same words, phrases

how bout the next ride

inform_no_match(alternative=next)

I'm sorry, the next ride was not found.

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  - Adding context to the encoder with the DA

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  - Two encoders & combining their hidden state

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  - Adding context to the encoder with the DA
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  - Reranker with BLEU against the context
- Mild success (BLEU 66.7% $\rightarrow$ 69.5% at best)
  - wish me luck with manual rankings 😨😉

Thank you for your attention

Any comments, questions?
Corrections, protests?

Download these slides:

`http://bit.ly/nlg2016`

Contact me:

`odusek@ufal.mff.cuni.cz`
office 424

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Further Links

C. DiMarco's slides: https://cs.uwaterloo.ca/~jchampai/CohenClass.en.pdf
F. Mairesse's slides: http://people.csail.mit.edu/francois/research/papers/ART-NLG.pdf
J. Moore's NLG course: http://www.inf.ed.ac.uk/teaching/courses/nlg/
NLG Systems Wiki: http://www.nlg-wiki.org
Wikipedia: http://en.wikipedia.org/wiki/Natural_language_generation