Natural Language Generation

for Spoken Dialogue Systems

Ondřej Dušek

Institute of Formal and Applied Linguistics
Faculty of Mathematics and Physics
Charles University in Prague

May 14th, 2015

Outline of this talk

1. Introduction to NLG
   a) Textbook NLG pipeline
   b) How real systems differ
2. Examples of real NLG systems
3. Our NLG system
   a) Structure
   b) Experiments
   c) How to improve?

Introduction

Objective of NLG

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

- Desired properties: variation, simplicity, trainability (?)

Usage

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

Standard NLG Pipeline (*Textbook*)

[Input]

Standard NLG Pipeline (*Textbook*)

[Input]

↓ Content/text planning (“what to say”)

- Content selection, basic ordering

[Content plan]

Standard NLG Pipeline (*Textbook*)

[Input]

↓ Content/text planning (“what to say”)

- Content selection, basic ordering

[Content plan]

↓ Sentence planning/microplanning (“middle ground”)

- aggregation, lexical choice, referring…

[Sentence plan(s)]

Standard NLG Pipeline (*Textbook*)

[Input]

↓ Content/text planning (“what to say”)

- Content selection, basic ordering

[Content plan]

↓ Sentence planning/microplanning (“middle ground”)

- aggregation, lexical choice, referring…

[Sentence plan(s)]

↓ Surface realization (“how to say it”)

- linearization according to grammar

[Text]

Standard NLG Pipeline (*Textbook*)

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)

Standard NLG Pipeline (*Textbook*)

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)

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

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

Surface realization

- Creating linear text from (typically) structured input
- Ensuring syntactic 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

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

Approaches

- Templates, Grammars, Rules, Statistics, or a mix thereof

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

Approaches

- Templates, Grammars, Rules, Statistics, or a mix thereof

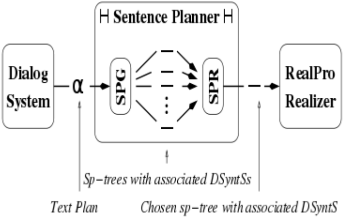
Data representations

- Varied, custom-tailored, non-compatible

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

Trainable Sentence Planning: Parameter Optimization

- Requires a flexible handcrafed planner
- No overgeneration
- Adjusting its parameters “somehow”

Trainable Sentence Planning: Parameter Optimization

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

- Requires a flexible handcrafed planner
- No overgeneration
- Adjusting its parameters "somehow"

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

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))
)
```

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

KPML

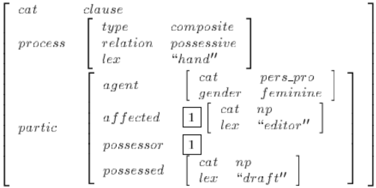
- General purpose, multilingual
- Systemic Functional Grammar

FUF/SURGE

- General purpose
- Functional Unification 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))
)
```

Input Specification (I_1):



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

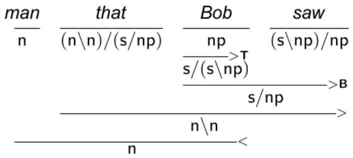
Grammar-based Realizer: *OpenCCG*

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

$(>)$	$X/Y \quad Y$	$\Rightarrow$	X
$(<)$	$Y \quad X\backslash Y$	$\Rightarrow$	X
$(>\mathbf{B})$	$X/Y \quad Y/Z$	$\Rightarrow$	X/Z
$(<\mathbf{B})$	$Y\backslash Z \quad X\backslash Y$	$\Rightarrow$	$X\backslash Z$
$(>\mathbf{T})$	X	$\Rightarrow$	$Y/(Y\backslash X)$
$(<\mathbf{T})$	X	$\Rightarrow$	$Y\backslash(Y/X)$

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

```
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]
```



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 → more outputs possible
- Overgenerate
- Then use a statistical reranker

Trainable Realizers: Overgenerate and Rank

- Require a handcrafted realizer, e.g. CCG realizer
- Input underspecified $\rightarrow$ more outputs possible
- Overgenerate
- Then use a statistical reranker
- Ranking according to:
  - *n*-gram models (*NITROGEN, HALOGEN*)
  - Tree models (XTAG grammar – *FERGUS*)
  - Predicted Text-to-Speech quality (*Nakatsu and White*)
  - Personality traits (extraversion, agreeableness… – *CRAG*)
    + alignment (repeating words uttered by dialogue counterpart)

Trainable Realizers: Overgenerate and Rank

- Require a handcrafted realizer, e.g. CCG realizer
- Input underspecified $\rightarrow$ more outputs possible
- Overgenerate
- Then use a statistical reranker
- Ranking according to:
  - *n*-gram models (*NITROGEN, HALOGEN*)
  - Tree models (XTAG grammar – *FERGUS*)
  - Predicted Text-to-Speech quality (*Nakatsu and White*)
  - Personality traits (extraversion, agreeableness… – *CRAG*)
    + alignment (repeating words uttered by dialogue counterpart)
- 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

Holistic NLG

Holistic NLG

- Only one stage – no distinction
- “Good enough” for limited domains, also in SDS

Holistic NLG

Holistic NLG

- Only one stage – no distinction
- "Good enough" for limited domains, also in SDS

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)

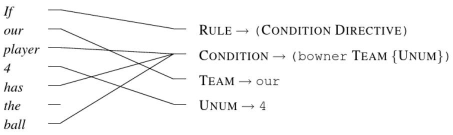
Facebook templates

Statistical Holistic NLG

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

Statistical Holistic NLG

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



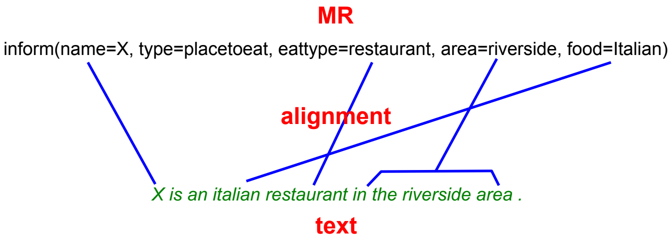
Examples

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

Our experiments: Two-Step NLG for SDS

Learning from unaligned data

- Typical NLG training:
  - a) requires detailed alignments of MR elements and words/phrases
  - b) uses a separate alignment step



Our experiments: Two-Step NLG for SDS

Learning from unaligned data

- Typical NLG training:
  a) requires detailed alignments
     of MR elements and words/phrases
  b) uses a separate alignment step

- Our generator learns alignments jointly
  - (with sentence planning)
  - 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

Overall workflow of our generator

- **Input**: a MR
  - here – dialogue acts: “inform” + slot-value pairs
  - other formats possible

Overall workflow of our generator

- **Input**: a MR
  - here – dialogue acts: “inform” + slot-value pairs
  - other formats possible
- **Step 1.** – sentence planning
  - statistical, our main focus

Overall workflow of our generator

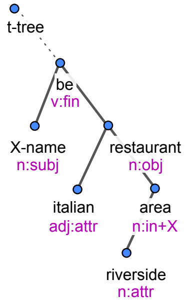
- **Input**: a MR
  - here – dialogue acts: “inform” + slot-value pairs
  - other formats possible
- **Step 1.** – sentence planning
  - statistical, our main focus
- **Sentence plan**: deep-syntax dependency trees
  - based on *TectoMT*'s t-layer, but very simplified
  - two attributes per tree node: *t-lemma* + *formeme*
  - using surface word order
- **Step 2.** – surface realization
  - reusing *Treex*/*TectoMT* English synthesis (rule-based)

Overall workflow of our generator

- **Input**: a MR
  - here – dialogue acts: “inform” + slot-value pairs
  - other formats possible
- **Step 1.** – sentence planning
  - statistical, our main focus
- **Sentence plan**: deep-syntax dependency trees
  - based on *TectoMT*'s t-layer, but very simplified
  - two attributes per tree node: *t-lemma* + *formeme*
  - using surface word order
- **Step 2.** – surface realization
  - reusing *Treex*/*TectoMT* English synthesis (rule-based)
- **Output**: plain text sentence

Data structures used

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



X is an italian restaurant in the riverside area .

Why we keep the two-step approach

- It makes the 1st – statistical – task simpler
  - no need to worry about morphology
  - this will be more important for Czech (and similar)

Why we keep the two-step approach

- It makes the 1st – statistical – task simpler
  - no need to worry about morphology
  - this will be more important for Czech (and similar)
- The 2nd step – rule based – can ensure grammatical correctness
  - or at least it's more straightforward to fix when it doesn't

Why we keep the two-step approach

- It makes the 1st – statistical – task simpler
  - no need to worry about morphology
  - this will be more important for Czech (and similar)
- The 2nd step – rule based – can ensure grammatical correctness
  - or at least it's more straightforward to fix when it doesn't
- The realizer is (relatively) easy to implement and domain-independent
  - + why not use it if we have it already in *Treex/TectoMT*

Downside of the two-step approach

- We need to analyze training sentences into deep trees

Downside of the two-step approach

- We need to analyze training sentences into deep trees
  - but we can do it easily using *Treex*
    – t-layer analysis implemented for several languages
  - automatic annotation is good enough

Sentence planner – overall

- Two main components:
  - **candidate generator**:
    – churning out more and more sentence plan trees
  - **scorer**/ranker for the candidates

Sentence planner – overall

- Two main components:
  - **candidate generator**:
    – churning out more and more sentence plan trees
  - **scorer**/ranker for the candidates
- A*-style search
  - incrementally finding the path
    - from an empty tree
    - to a full sentence plan tree which contains all information

Sentence planner – overall

- Two main components:
  - **candidate generator**:
    – churning out more and more sentence plan trees
  - **scorer**/ranker for the candidates
- A*-style search
  - incrementally finding the path
    - from an empty tree
    - to a full sentence plan tree which contains all information
  - using `open_set`, `close_set` – heaps sorted by score

Sentence planner – workflow

- Init: `open_set` = {empty tree}, `close_set` = ∅

Sentence planner – workflow

- Init: `open_set` = {empty tree}, `close_set` = ∅
- Loop:
  1. get top-scoring C ← `open_set`
     put C → `close_set`

Sentence planner – workflow

- Init: `open_set` = {empty tree}, `close_set` = ∅
- Loop:
  1. get top-scoring $C \leftarrow$ `open_set`
     put $C \rightarrow$ `close_set`
  2. **C** $=$ candidate generator successors(C)
     - viable trees, C + some node(s)
     - **C** may be empty

Sentence planner – workflow

- Init: `open_set` = {empty tree}, `close_set` = $\varnothing$
- Loop:
  1. get top-scoring $C \leftarrow$ `open_set`
     put $C \rightarrow$ `close_set`
  2. $\mathbf{C} =$ candidate generator successors(C)
     - viable trees, C + some node(s)
     - $\mathbf{C}$ may be empty
  3. score $C' \ \forall C' \in \mathbf{C}$
     put $C' \rightarrow$ `open_set`

Sentence planner – workflow

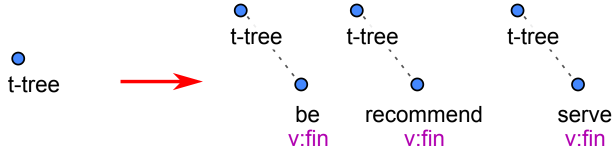
- Init: `open_set` = {empty tree}, `close_set` = ∅
- Loop:
  1. get top-scoring $C \leftarrow$ `open_set`
     put $C \rightarrow$ `close_set`
  2. $\mathbf{C} =$ candidate generator successors(C)
     - viable trees, C + some node(s)
     - $\mathbf{C}$ may be empty
  3. score $C' \ \forall C' \in \mathbf{C}$
     put $C' \rightarrow$ `open_set`
  4. check if top score(`open_set`) $>$ top score(`close_set`)
- Stop if:
  a) `close_set` has better top score than `open_set` for d consecutive iterations
  b) there's nothing left on the open list (unlikely)

Candidate generator

- Given a candidate plan tree, generate its successors by adding 1 node (at every possible place)

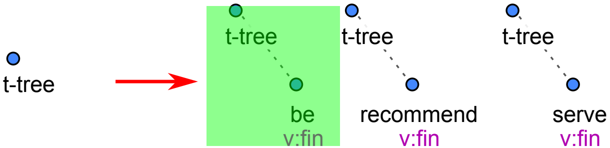
Candidate generator

- Given a candidate plan tree, generate its successors by adding 1 node (at every possible place)



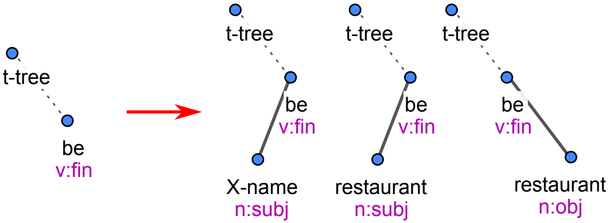
Candidate generator

- Given a candidate plan tree, generate its successors by adding 1 node (at every possible place)



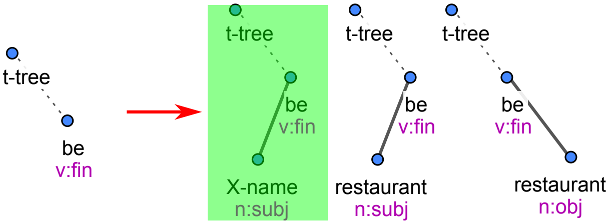
Candidate generator

- Given a candidate plan tree, generate its successors by adding 1 node (at every possible place)



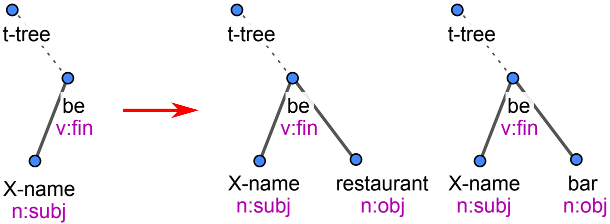
Candidate generator

- Given a candidate plan tree, generate its successors by adding 1 node (at every possible place)



Candidate generator

- Given a candidate plan tree, generate its successors by adding 1 node (at every possible place)



Candidate generator – limiting the space

- Number of candidates very high even for small domains
- We need to lower the number of “possible” successors

Candidate generator – limiting the space

- Number of candidates very high even for small domains
- We need to lower the number of "possible" successors
- Limiting by things seen in training data:
  1. t-lemma + formeme combination
  2. parent–child combination
  3. number of children
  4. tree size
     - + at depth levels
     - + given input MR
  5. "weak" compatibility with input MR:
     - nodes seen with current slot-values
  6. "strong" compatibility with input MR:
     - required slot-values for each node (minimum seen in training data)

Scorer

- a function:

  sentence plan tree t, MR m $\longrightarrow$ real-valued score

  - describes the fitness of t for m

Scorer

- a function:

  sentence plan tree t, MR $m \rightarrow$ real-valued score

  - describes the fitness of t for m

Basic perceptron scorer

- score $= \mathbf{w}^\top \cdot \text{feat}(t, m)$

Scorer

- a function:

  sentence plan tree t, MR $m \rightarrow$ real-valued score

  - describes the fitness of t for m

Basic perceptron scorer

- score $= \mathbf{w}^\top \cdot \text{feat}(t, m)$
- Training:
  - given m, generate the best tree t_{top} with current weights
  - update weights if $t_{top} \neq t_{gold}$ (gold-standard)

Scorer

- a function:

  sentence plan tree t, MR m $\rightarrow$ real-valued score

  - describes the fitness of t for m

Basic perceptron scorer

- score $= \mathbf{w}^\top \cdot \text{feat}(t, m)$
- Training:
  - given m, generate the best tree t_{top} with current weights
  - update weights if $t_{top} \neq t_{gold}$ (gold-standard)
- Update: $\mathbf{w} = \mathbf{w} + \alpha \cdot (\text{feat}(t_{gold}, m) - \text{feat}(t_{top}, m))$

Differing subtree updates

- Features are global $\rightarrow$ bigger trees score better
  - need to promote "promising" incomplete trees

Differing subtree updates

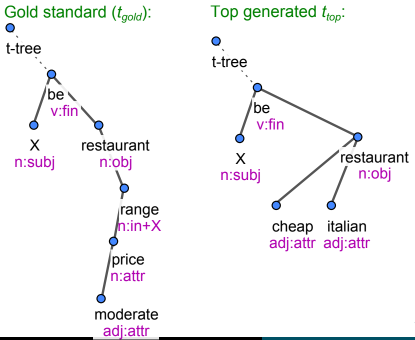
- Features are global → bigger trees score better
  - need to promote “promising” incomplete trees
  - → promoting subtrees of gold-standard trees
  - + demoting subtrees of wrong generation outputs

Differing subtree updates

- Features are global $\rightarrow$ bigger trees score better
  - need to promote "promising" incomplete trees
  - $\rightarrow$ promoting subtrees of gold-standard trees
  - + demoting subtrees of wrong generation outputs
- Update: find common subtree, start from it and update using pairs of subtrees t^i_{gold}, t^i_{top}

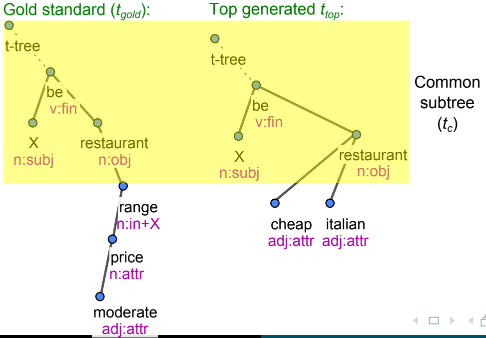
Differing subtree updates

- Features are global → bigger trees score better
  - need to promote "promising" incomplete trees
  - → promoting subtrees of gold-standard trees
  - + demoting subtrees of wrong generation outputs
- Update: find common subtree, start from it and update using pairs of subtrees t^i_{gold}, t^i_{top}



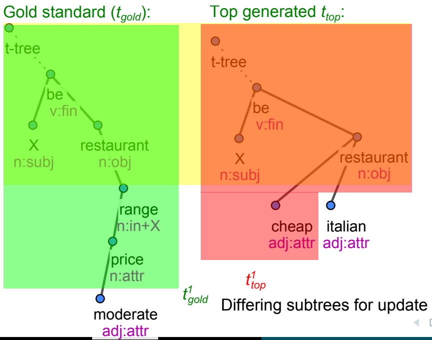
Differing subtree updates

- Features are global → bigger trees score better
  - need to promote "promising" incomplete trees
  - → promoting subtrees of gold-standard trees
  - \+ demoting subtrees of wrong generation outputs
- Update: find common subtree, start from it and update using pairs of subtrees t^i_{gold}, t^i_{top}



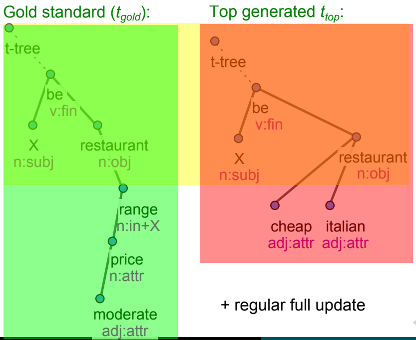
Differing subtree updates

- Features are global → bigger trees score better
  - need to promote "promising" incomplete trees
  - → promoting subtrees of gold-standard trees
  - + demoting subtrees of wrong generation outputs
- Update: find common subtree, start from it and update using pairs of subtrees t^i_{gold}, t^i_{top}



Differing subtree updates

- Features are global → bigger trees score better
  - need to promote "promising" incomplete trees
  - → promoting subtrees of gold-standard trees
  - + demoting subtrees of wrong generation outputs
- Update: find common subtree, start from it and update using pairs of subtrees t^i_{gold}, t^i_{top}



+ regular full update

Future promise estimate

- Further boost for incomplete trees

Future promise estimate

- Further boost for incomplete trees
- Using expected number of children $E_c(n)$ of a node

Future promise estimate

- Further boost for incomplete trees
- Using expected number of children $E_c(n)$ of a node
- Future promise:
  "how many children are missing to meet the expectation"

$$\text{fc} = \sum_{n \in t} \max\{0, E_c(n) - c(n)\}$$

Future promise estimate

- Further boost for incomplete trees
- Using expected number of children $E_c(n)$ of a node
- Future promise:
  "how many children are missing to meet the expectation"

$$\text{fc} = \sum_{n \in t} \max\{0, E_c(n) - c(n)\}$$

- over the whole tree
- + multiplied by feature sum
- + weighted

Future promise estimate

- Further boost for incomplete trees
- Using expected number of children $E_c(n)$ of a node
- Future promise:
  "how many children are missing to meet the expectation"

$$\text{fc} = \sum_{n \in t} \max\{0, E_c(n) - c(n)\}$$

  - over the whole tree
  - + multiplied by feature sum
  - + weighted
- used on the `open_set`, not `close_set`
  - not for perceptron updates, not for stopping generation

Surface realizer overview

- English synthesis pipeline from *Treex*/*TectoMT*
  - domain-independent

Surface realizer overview

- English synthesis pipeline from *Treex*/*TectoMT*
  - domain-independent
- Mostly simple, single-purpose, rule-based modules (blocks)
  - Word inflection: statistical (*Flect*)

Surface realizer overview

- English synthesis pipeline from *Treex/TectoMT*
    - domain-independent
- 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

Surface realizer overview

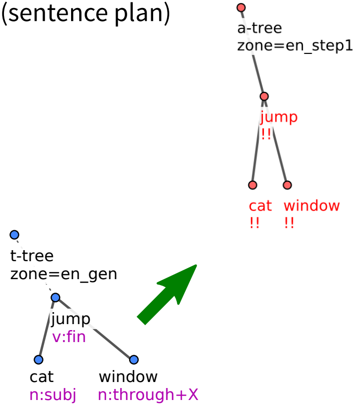
- English synthesis pipeline from *Treex*/*TectoMT*
  - domain-independent
- Mostly simple, single-purpose, rule-based modules (blocks)
  - Word inflection: statistical (*Flect*)
- Gradual transformation of deep trees into surface dependency trees
  - Surface trees are then simply linearized
- Works OK: analysis $\rightarrow$ synthesis on our data = 89.79% BLEU

Surface realization example

- Realizer steps (simplified):

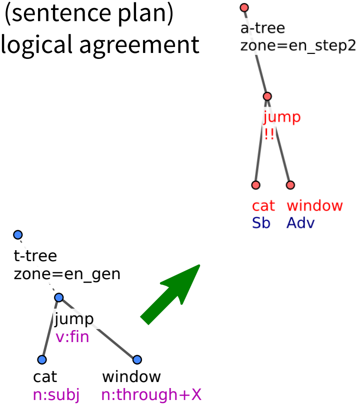
Surface realization example

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



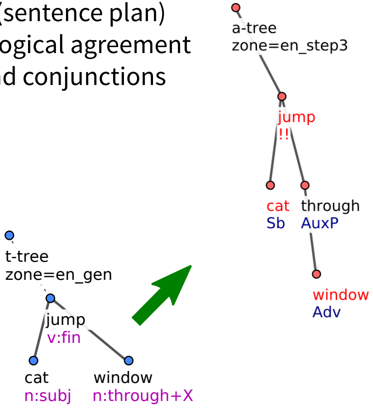
Surface realization example

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



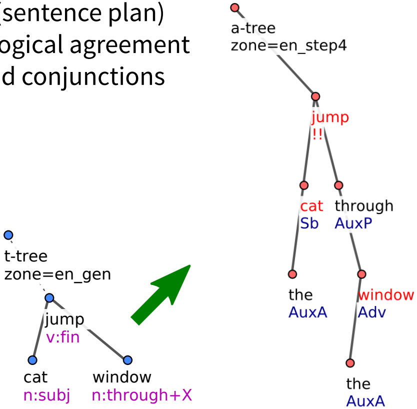
Surface realization example

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



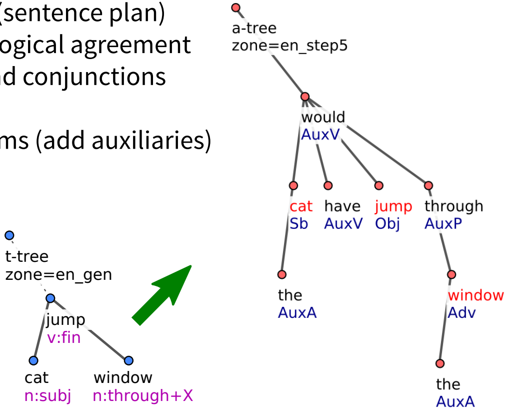
Surface realization example

- Realizer steps (simplified):
  - Copy the deep tree (sentence plan)
  - Determine morphological agreement
  - Add prepositions and conjunctions
  - Add articles



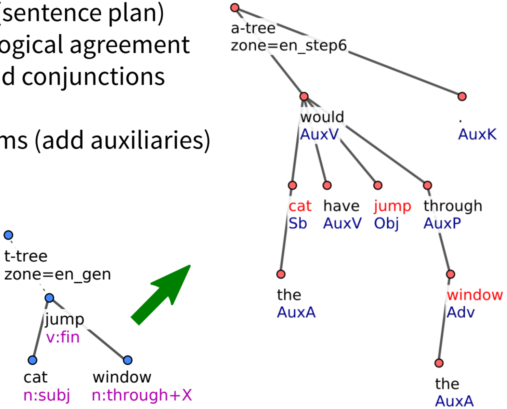
Surface realization example

- Realizer steps (simplified):
    - Copy the deep tree (sentence plan)
    - Determine morphological agreement
    - Add prepositions and conjunctions
    - Add articles
    - Compound verb forms (add auxiliaries)



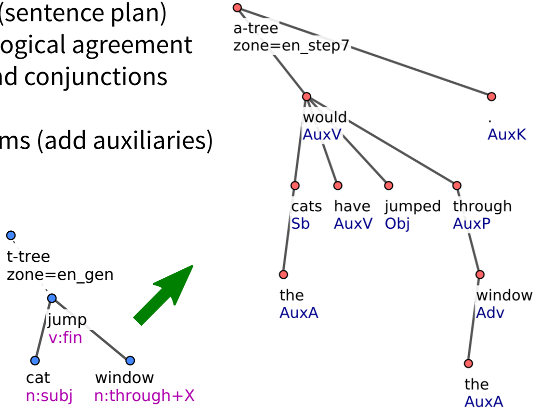
Surface realization example

- Realizer steps (simplified):
  - Copy the deep tree (sentence plan)
  - Determine morphological agreement
  - Add prepositions and conjunctions
  - Add articles
  - Compound verb forms (add auxiliaries)
  - Punctuation



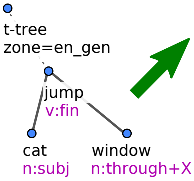
Surface realization example

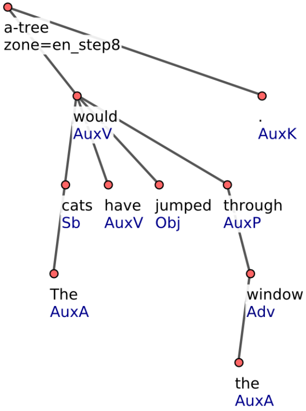
- Realizer steps (simplified):
  - Copy the deep tree (sentence plan)
  - Determine morphological agreement
  - Add prepositions and conjunctions
  - Add articles
  - Compound verb forms (add auxiliaries)
  - Punctuation
  - Word inflection



Surface realization example

- Realizer steps (simplified):
  - Copy the deep tree (sentence plan)
  - Determine morphological agreement
  - Add prepositions and conjunctions
  - Add articles
  - Compound verb forms (add auxiliaries)
  - Punctuation
  - Word inflection
  - Capitalization





Experiments – data set

- Restaurant recommendations from the *BAGEL* generator
    - restaurant location, food type, etc.
- 404 utterances for 202 input dialogue acts (DAs)
    - two paraphrases for each DA

Experiments – data set

- Restaurant recommendations from the *BAGEL* generator
  - restaurant location, food type, etc.
- 404 utterances for 202 input dialogue acts (DAs)
  - two paraphrases for each DA
- Alignment provided, but we don't use it

Experiments – data set

- Restaurant recommendations from the *BAGEL* generator
  - restaurant location, food type, etc.
- 404 utterances for 202 input dialogue acts (DAs)
  - two paraphrases for each DA
- Alignment provided, but we don't use it
- "Non-enumerable" information replaced by "X" symbol
  - restaurant names, postcodes, phone numbers etc.

Experiments – features

- Tailored for the input MR format

Experiments – features

- Tailored for the input MR format
- Basic feature types:
  - tree properties (size, depth…)
  - tree + input DA (nodes per slot-value pair…)
  - node features
  - input DA feautres (slots, values, pairs of slots)
  - node + input DA features
  - repeat features (repeated nodes/slots/values)
  - dependency features (parent-child)
  - siblings features (+DA)
  - bigram features (+DA)

Experiments – features

- Tailored for the input MR format
- Basic feature types:
  - tree properties (size, depth…)
  - tree + input DA (nodes per slot-value pair…)
  - node features
  - input DA feautres (slots, values, pairs of slots)
  - node + input DA features
  - repeat features (repeated nodes/slots/values)
  - dependency features (parent-child)
  - siblings features (+DA)
  - bigram features (+DA)
- Typical case: counts over whole tree
  - normalized

Results

- Using 10-fold cross-validation, measuring BLEU/NIST
  - training DAs never used for testing
  - using 2 paraphrases for BLEU/NIST measurements

Results

- Using 10-fold cross-validation, measuring BLEU/NIST
  - training DAs never used for testing
  - using 2 paraphrases for BLEU/NIST measurements

Setup	BLEU	NIST
basic perceptron	54.24	4.643
+ diff-tree updates	58.70	4.876
+ future promise	59.89	5.231

Results

- Using 10-fold cross-validation, measuring BLEU/NIST
  - training DAs never used for testing
  - using 2 paraphrases for BLEU/NIST measurements

Setup	BLEU	NIST
basic perceptron	54.24	4.643
+ diff-tree updates	58.70	4.876
+ future promise	59.89	5.231

- less than *BAGEL*'s ~ 67% BLEU

Results

- Using 10-fold cross-validation, measuring BLEU/NIST
  - training DAs never used for testing
  - using 2 paraphrases for BLEU/NIST measurements

Setup	BLEU	NIST
basic perceptron	54.24	4.643
+ diff-tree updates	58.70	4.876
+ future promise	59.89	5.231

- less than *BAGEL*'s ~ 67% BLEU
- But:
  - we do not use alignments
  - our generator has to know when to stop (whether all information is already included)

Example Outputs

Input DA	inform(name=X-name, type=placetoeat, eattype=restaurant, near=X-near, food=Continental, food=French)
Reference	X is a French and continental restaurant near X.
Generated	X is a French and continental restaurant near X.

Example Outputs

Input DA	inform(name=X-name, type=placetoeat, eattype=restaurant, near=X-near, food=Continental, food=French)
Reference	X is a French and continental restaurant near X.
Generated	X is a French and continental restaurant near X.
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.

Example Outputs

Input DA	inform(name=X-name, type=placetoeat, eattype=restaurant, near=X-near, food=Continental, food=French)
Reference	X is a French and continental restaurant near X.
Generated	X is a French and continental restaurant near X.
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.
Input DA	inform(name=X-name, type=placetoeat, area=X-area, pricerange=moderate, eattype=restaurant)
Reference	X is a moderately priced restaurant in X.
Generated	X is a restaurant in the X area.

Example Outputs

Input DA	inform(name=X-name, type=placetoeat, eattype=restaurant, near=X-near, food=Continental, food=French)
Reference	X is a French and continental restaurant near X.
Generated	X is a French and continental restaurant near X.
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.
Input DA	inform(name=X-name, type=placetoeat, area=X-area, pricerange=moderate, eattype=restaurant)
Reference	X is a moderately priced restaurant in X.
Generated	X is a restaurant in the X area.
Input DA	inform(name=X-name, type=placetoeat, eattype=restaurant, area=riverside, food=French)
Reference	X is a French restaurant on the riverside.
Generated	X is a French restaurant in the riverside area which serves French food.

Example Outputs

Input DA	inform(name=X-name, type=placetoeat, eattype=restaurant, pricerange=moderate, area=X-area, food=Contemporary, food=English)
Reference	X is a moderately priced English contemporary restaurant in X.
Generated	X is an English restaurant in the X area which serves expensive food in the moderate price range located in X.

Example Outputs

Input DA	inform(name=X-name, type=placetoeat, eattype=restaurant, pricerange=moderate, area=X-area, food=Contemporary, food=English)
Reference	X is a moderately priced English contemporary restaurant in X.
Generated	X is an English restaurant in the X area which serves expensive food in the moderate price range located in X.
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.

Example Outputs

Input DA	inform(name=X-name, type=placetoeat, eattype=restaurant, pricerange=moderate, area=X-area, food=Contemporary, food=English)
Reference	X is a moderately priced English contemporary restaurant in X.
Generated	X is an English restaurant in the X area which serves expensive food in the moderate price range located in X.
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.
Input DA	inform(name=X-name, type=placetoeat, pricerange=moderate, eattype=restaurant)
Reference	X is a restaurant that offers moderate price range.
Generated	X is a restaurant in the moderate price range.

Results

- The outputs are mostly fluent and meaningful/relevant
  - Sometimes identical to reference
  - More often original (unseen) paraphrases

Results

- The outputs are mostly fluent and meaningful/relevant
  - Sometimes identical to reference
  - More often original (unseen) paraphrases
- Alignment can be learnt together with sentence planning

Results

- The outputs are mostly fluent and meaningful/relevant
  - Sometimes identical to reference
  - More often original (unseen) paraphrases
- Alignment can be learnt together with sentence planning
- Differing tree updates + future promise bring significant improvements

Results

- The outputs are mostly fluent and meaningful/relevant
  - Sometimes identical to reference
  - More often original (unseen) paraphrases
- Alignment can be learnt together with sentence planning
- Differing tree updates + future promise bring significant improvements
- Errors:
  - information missing
  - information is repeated
  - irrelevant information
- $\rightarrow$ Scoring should be improved (?)

What to do to make it better?

- Larger training set – better weight estimates
- Refine features?
- Using neural networks
  - no need for sophisticated features
  - probably will be faster

What to do to make it better?

- Larger training set – better weight estimates
- Refine features?
- Using neural networks
  - no need for sophisticated features
  - probably will be faster
- Any suggestions?

What to do to make it better?

- Larger training set – better weight estimates
- Refine features?
- Using neural networks
  - no need for sophisticated features
  - probably will be faster
- Any suggestions?

Thank you for your attention

Contact me:

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

References

Angeli	Angeli, G. et al. 2010. A Simple Domain-Independent Probabilistic Approach to Generation. *EMNLP*
BAGEL	Mairesse, F. et al. 2010. Phrase-based statistical language generation using graphical models and active learning. *ACL*
CRAG	Isard, A. et al. 2006. Individuality and alignment in generated dialogues. *INLG*
FERGUS	Bangalore, S. and Rambow, O. 2000. Exploiting a probabilistic hierarchical model for generation. *COLING*
Flect	Dušek, O. and Jurčíček, F. 2013. Robust Multilingual Statistical Morphological Generation Models. *ACL-SRW*
FUF/SURGE	Elhadad, M. and Robin, J. 1996. An overview of SURGE: A reusable comprehensive syntactic realization component. `http://www.cs.bgu.ac.il/surge/`
HALOGEN	Langkilde-Geary, I. 2002. An empirical verification of coverage and correctness for a general-purpose sentence generator. *INLG*
KPML	Bateman, J. A. 1997. Enabling technology for multilingual natural language generation: the KPML development environment. *Natural Language Engineering* `http://purl.org/net/kpml`
OpenCCG	White, M. and Baldrige, J. 2003. Adapting Chart Realization to CCG. *ENLG* Moore, J. et al. 2004. Generating Tailored, Comparative Descriptions in Spoken Dialogue. *FLAIRS* `http://openccg.sourceforge.net/`
Nakatsu&White	Nakatsu, C. and White, M. 2006. Learning to say it well: reranking realizations by predicted synthesis quality. *COLING-ACL*
NITROGEN	Langkilde, I. and Knight, K. 1998. Generation that exploits corpus-based statistical knowledge. *ACL-COLING*

References

Paiva&Evans Paiva, D. S. and Evans, R. 2005. Empirically-based control of natural language generation. *ACL*

PERSONAGE-PE Mairesse, F. and Walker, M. 2008. Trainable generation of big-five personality styles through data-driven parameter estimation. *ACL*

RL-NLG Rieser, V. and Lemon, O. 2010. Natural language generation as planning under uncertainty for spoken dialogue systems. *EMNLP*

SimpleNLG Gatt, A. and Reiter, E. 2009. SimpleNLG: A realisation engine for practical applications. *ENLG*

SPoT Walker, M. et al. 2001. SPoT: A trainable sentence planner. *NAACL*

StuMaBa Bohnet, B. et al. 2010. Broad coverage multilingual deep sentence generation with a stochastic multi-level realizer. *COLING*

TectoMT Žabokrtský, Z. et al. 2008. TectoMT: highly modular MT system with tectogrammatics used as transfer layer. *WMT*

Textbook Reiter, E. and Dale, R. 2000. *Building natural language generation systems*. Cambridge Univ. Press

Treex Popel, M. and Žabokrtský, Z. 2010. TectoMT: modular NLP framework. *IceTAL*
`http://ufal.cz/treex`

WASP^{-1} Wong, Y. W. and Mooney, R. 2007. Generation by inverting a semantic parser that uses statistical machine translation. *NAACL-HLT*

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`