Novel Methods in Natural Language Generation for Spoken Dialogue Systems

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June 12, 2017

Outline

1. Introduction to the problem
2. Surface Realization
3. A*/Perceptron Sentence Planning
4. Sequence-to-sequence Generation
5. Context-aware extensions (user adaptation/entrainment)
6. Generating Czech
7. Conclusions

NLG in Spoken Dialogue Systems

- converting a meaning representation (dialogue acts, DAs) to a sentence

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

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X is an Italian restaurant near the river.

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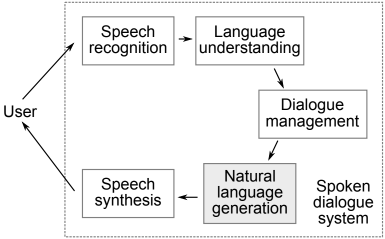
- input: from dialogue manager
- output: to TTS



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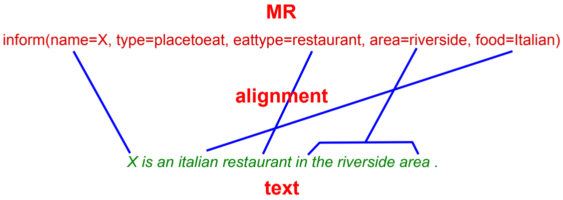
E) Create novel NLG datasets
- not many were available

Basic Ideas

Unaligned data

- earlier systems: manual alignments / preprocessing step


MR
inform(name=X, type=placetoeat, eattype=restaurant, area=riverside, food=Italian)
alignment
X is an italian restaurant in the riverside area .
text

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Addressing data sparsity: Delexicalization

- Some/all slot values replaced with placeholders

inform(direction="Fulton Street", from_stop="Rockefeller Center", line=M11,
vehicle=bus, departure_time=11:02am)
Take line M11 bus at 11:02am from Rockefeller Center direction Fulton Street.

inform(name="La Mediterranée", good_for_meal=lunch, kids_allowed=no)
La Mediterranée is good for lunch and no children are allowed.

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Take line **M11 bus** at **11:02am** from **Rockefeller Center** direction **Fulton Street**.

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La Mediterranée is good for **lunch** and no children are allowed.

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inform(direction="X-dir", from_stop="X-from", line=X-line,
    vehicle=X-vehicle, departure_time=X-departure)
Take line **X-line** **X-vehicle** at **X-departure** from **X-from** direction **X-dir**.

inform(name="X-name", good_for_meal=X-meal, kids_allowed=no)
X-name is good for **X-meal** and no children are allowed.

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- Different from full alignments – much easier to obtain

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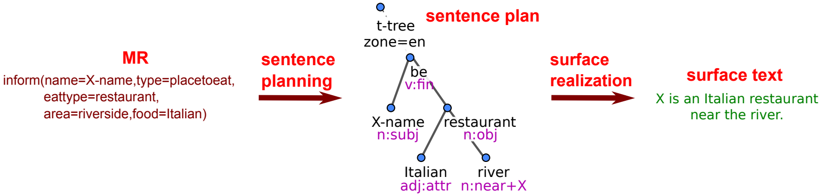

Pipeline / joint NLG

- traditional: sentence planning + surface realization

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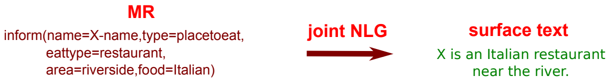

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joint NLG

surface text

X is an Italian restaurant
near the river.

Pipeline / joint NLG

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- newer: joint, end-to-end 1-step

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Pipeline / joint NLG

- traditional: sentence planning + surface realization
- newer: joint, end-to-end 1-step
- we compare both, use *t-trees* as sentence plan

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- Simple *t-tree* to text

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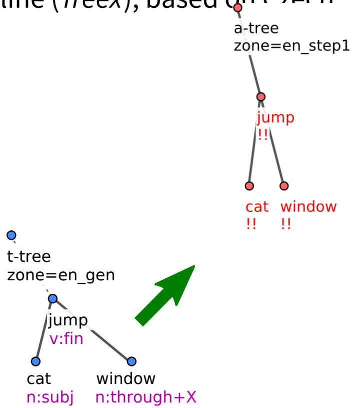

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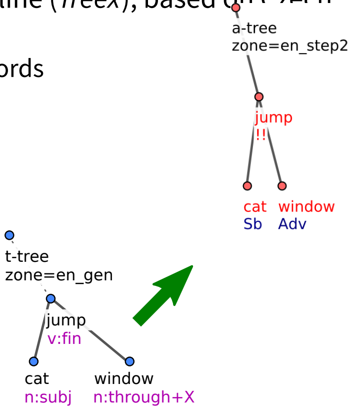

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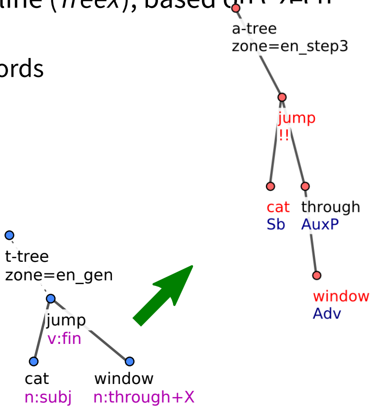

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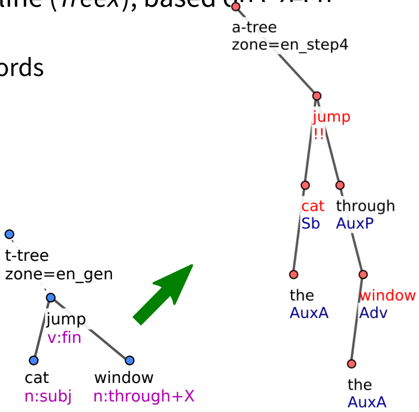

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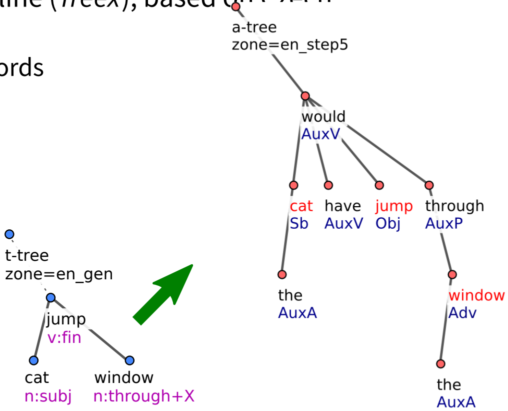

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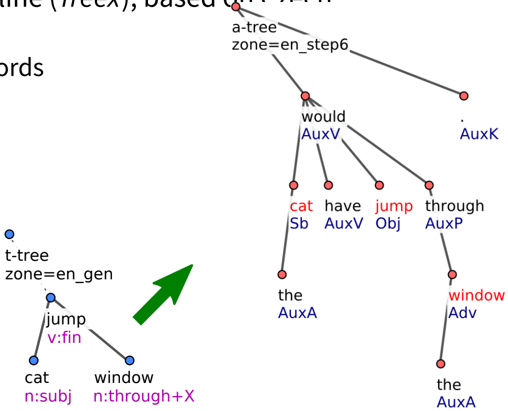

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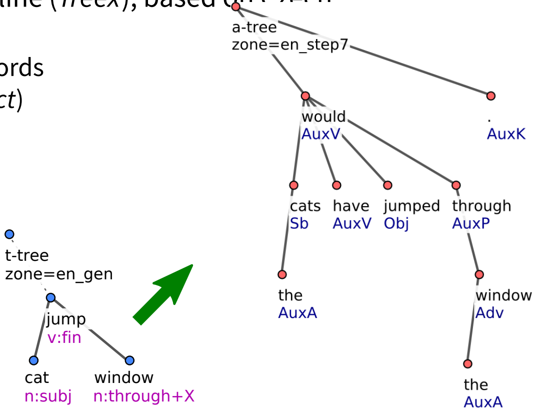

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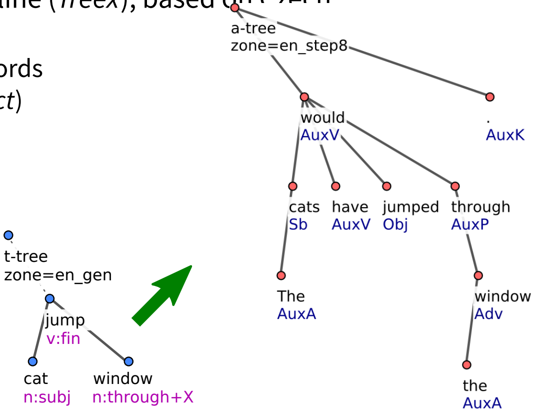

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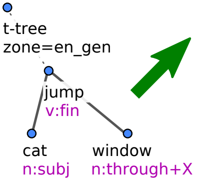

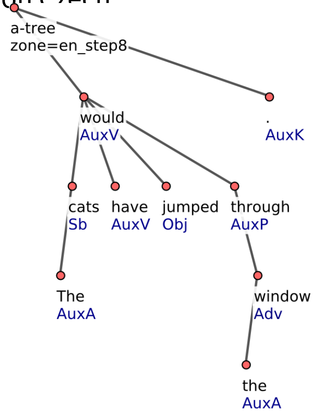

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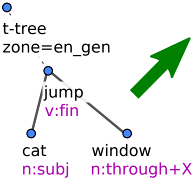

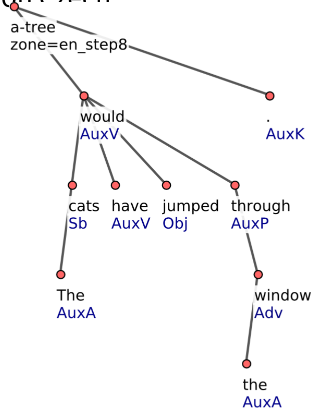

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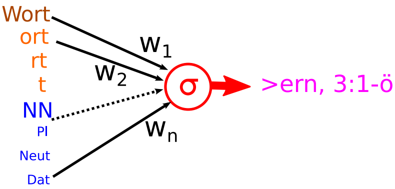

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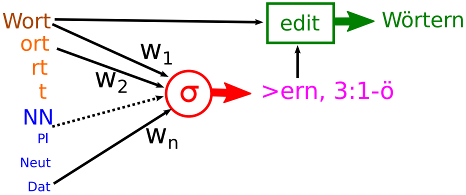

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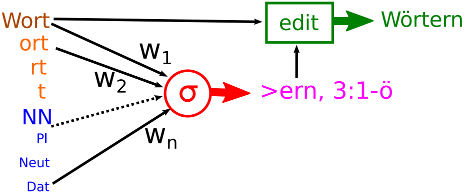

- Evaluated on 6 languages, 96-99% accuracy

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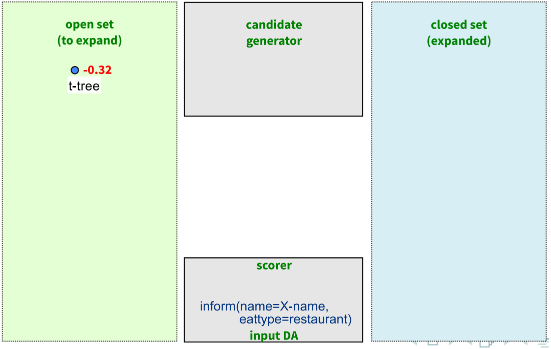

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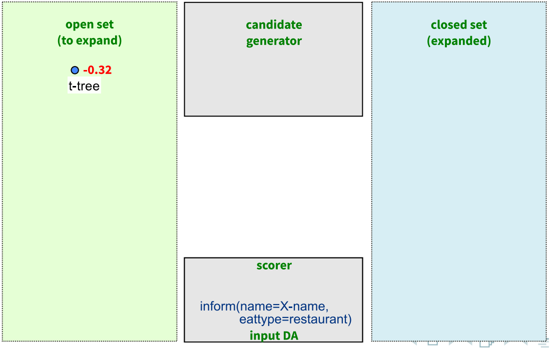

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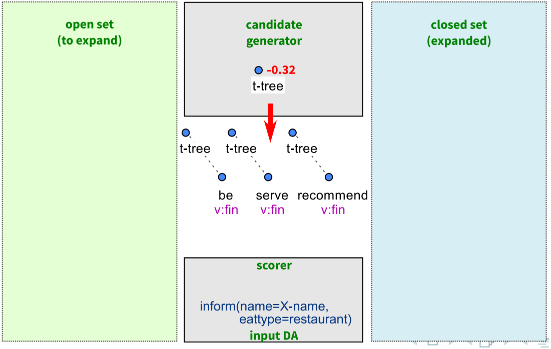

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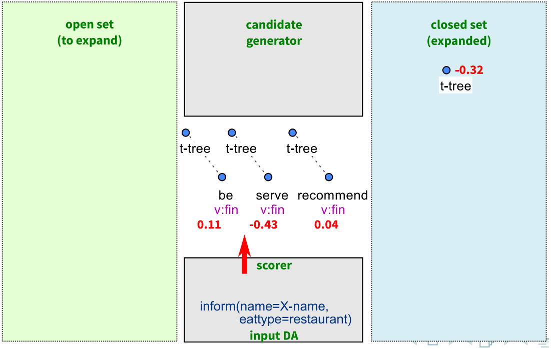

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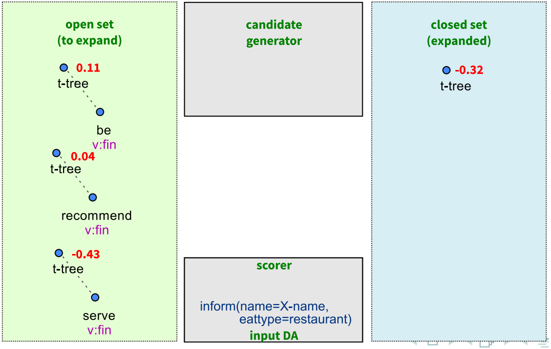

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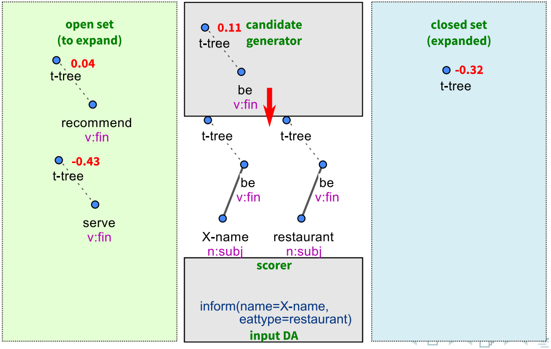

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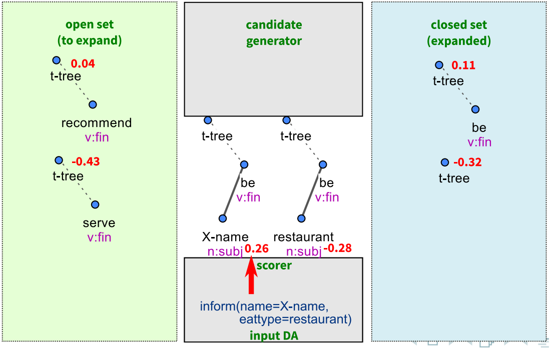

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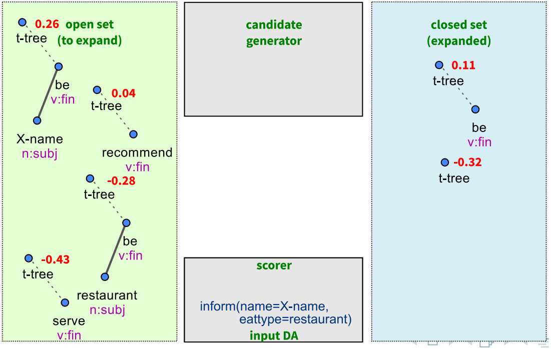

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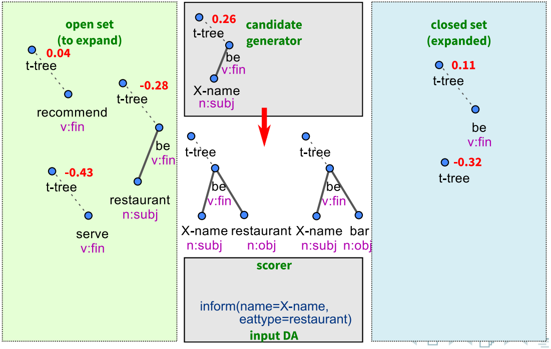

A*/Perceptron Sentence Planning

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  - worse than orig. with alignments (67% BLEU) (Mairesse et al., 2010)
- mostly fluent, but frequent errors (missed/added information)

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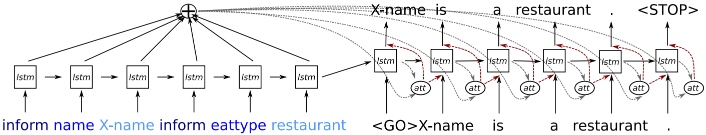
Sequence-to-sequence Generation: Our Model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- Main generator: seq2seq with attention (Bahdanau et al., 2015)

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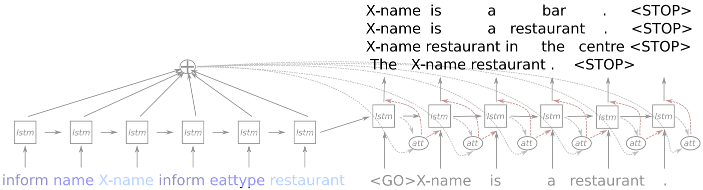
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+ beam search, *n*-best list outputs

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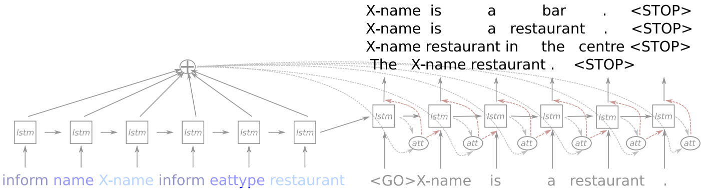
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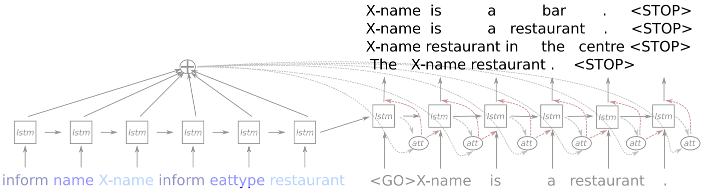
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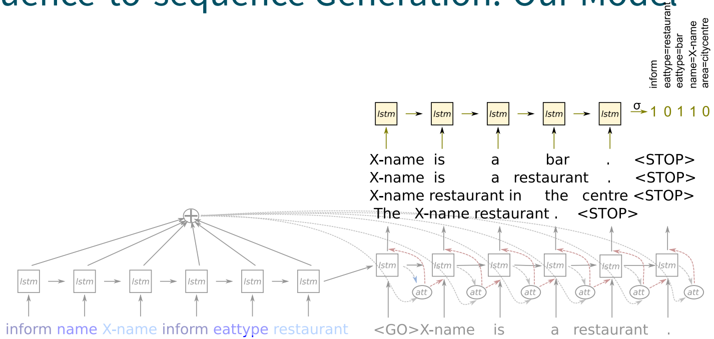
  - to penalize missing/superfluous information in outputs

Sequence-to-sequence Generation: Our Model


inform
eattype=restaurant
eattype=bar
name=X-name
area=citycentre
lstm
σ
1 0 1 1 0
X-name is a bar . <STOP>
X-name is a restaurant . <STOP>
X-name restaurant in the centre <STOP>
The X-name restaurant . <STOP>
att
inform name X-name inform eattype restaurant
<GO> X-name is a restaurant .

- Main generator: seq2seq with attention (Bahdanau et al., 2015)

+ beam search, *n*-best list outputs
+ *n*-best list **reranker**
  - to penalize missing/superfluous information in outputs
  - classify DA from output

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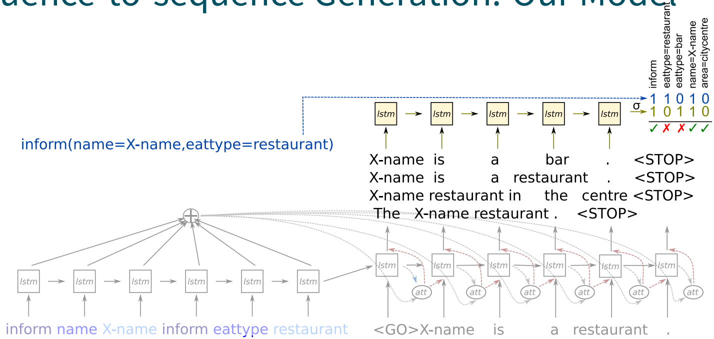

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✓ ✗ ✗ ✓ ✓

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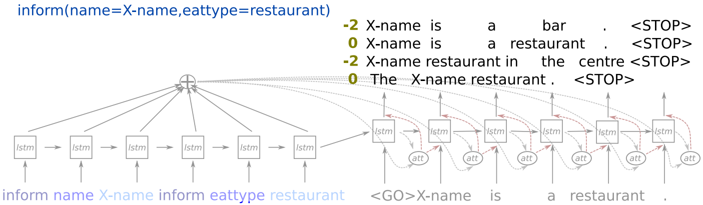
inform(name=X-name,eattype=restaurant)
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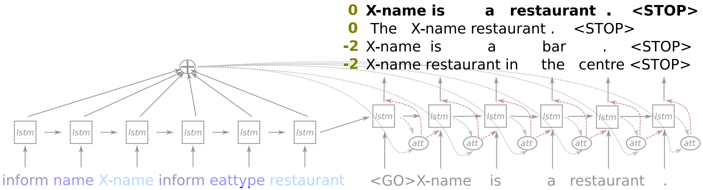
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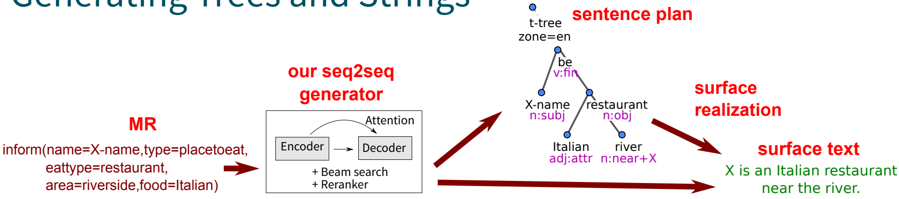
Generating Trees and Strings



MR

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

our seq2seq generator

+ Beam search
+ Reranker

sentence plan

surface realization

surface text

X is an Italian restaurant near the river.

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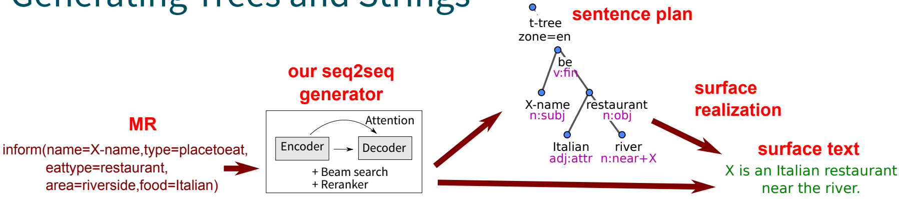

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Encoder
Decoder
Attention
+ Beam search
+ Reranker

sentence plan

t-tree
zone=en
be
v:fin
X-name
n:subj
restaurant
n:obj
Italian
adj:attr
river
n:near+X

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surface text

X is an Italian restaurant
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- input: tokenized DAs

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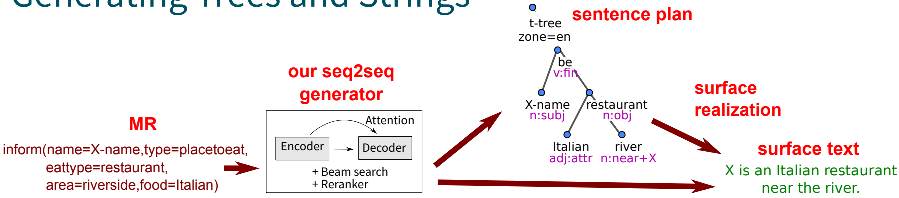

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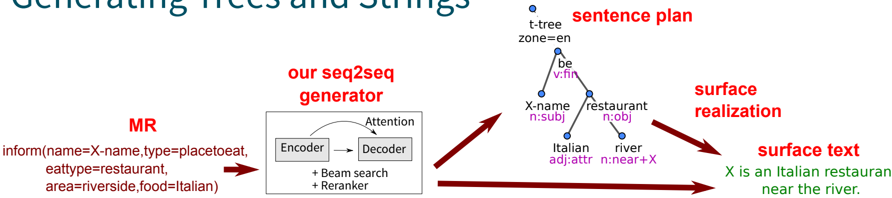
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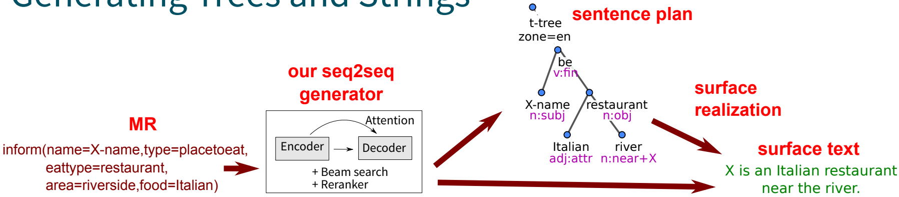
  2-step mode – t-trees, in bracketed format (→ surface realizer)

(<root> <root> ((X-name n:subj) be v:fin ((Italian adj:attr) restaurant n:obj (river n:near+X))))

Generating Trees and Strings



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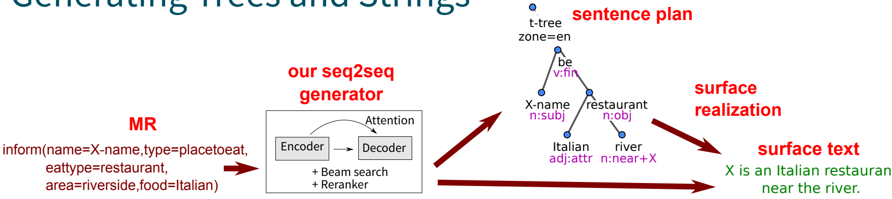
  - BLEU joint 63% vs. trees 60%, same # of semantic errors

Generating Trees and Strings



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  - BLEU joint 63% vs. trees 60%, same # of semantic errors
  - best without alignments (Mairesse et al. 2010: 67% BLEU)

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Entrainment in Trainable NLG: Data Needed

Entrainment in Dialogue

- speakers influenced by each other, reuse words & syntax

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- Aim: condition generation on preceding context

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- Instance = DA + sentence

inform(from_stop="Fulton Street", vehicle=bus, direction="Rector Street",
departure_time=9:13pm, line=M21)

Go by the 9:13pm bus on the M21 line from Fulton Street directly to Rector Street

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NEW→*I'm headed to Rector Street*

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- Instance = DA + context-aware sentence + preceding utterance

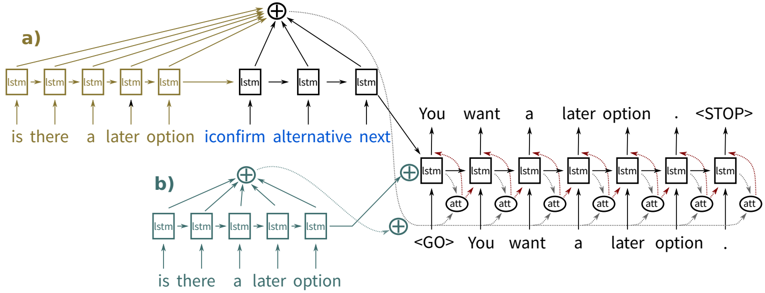
I'm headed to Rector Street

inform(from_stop="Fulton Street", vehicle=bus, direction="Rector Street",
departure_time=9:13pm, line=M21)

CONTEXT-AWARE → *Heading to Rector Street from Fulton Street, take a bus line M21 at 9:13pm.*

Context in our Seq2seq Generator

- Two direct context-aware extensions:


a)
lstm
is there a later option
iconfirm alternative next
b)
is there a later option
You want a later option . <STOP>
att
<GO> You want a later option .

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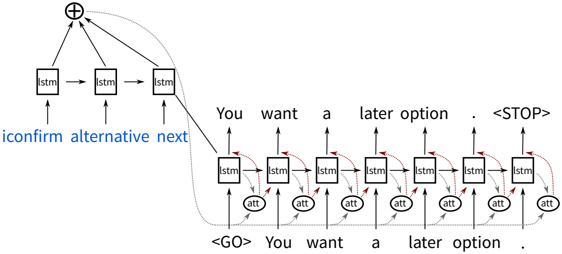

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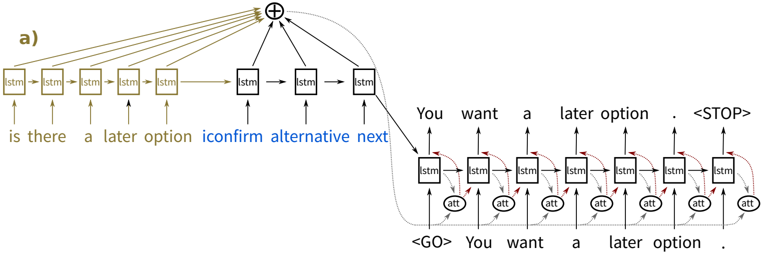
  a) preceding user utterance prepended to DA and fed into decoder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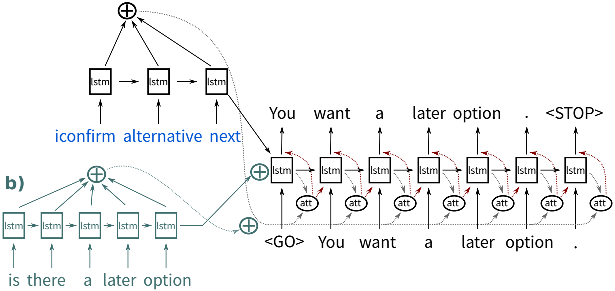

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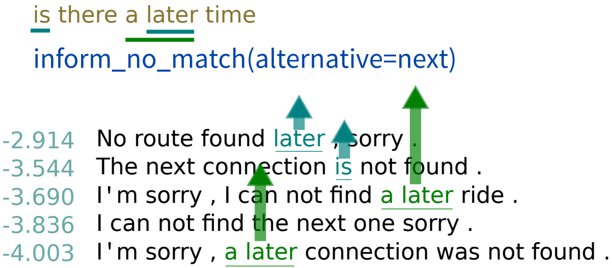
  - promote outputs having word/phrase overlap with context



is there a later time

inform_no_match(alternative=next)

-2.914	No route found later , sorry .
-3.544	The next connection is not found .
-3.690	I ' m sorry , I can not find a later ride .
-3.836	I can not find the next one sorry .
-4.003	I ' m sorry , a later connection was not found .

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  - a) or b) + reranker best (66→69% BLEU)
  - a) + reranker preferred by humans to baseline (52.5% cases, slight but significant)

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Czech NLG Data

- Virtually no non-English NLG datasets available
- Crowdsourcing not usable → translating an English set (restaurants, Wen et al. 2015)

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?confirm(good_for_meal=brunch)

chcete najít vhodnou restauraci na X-good_for_meal ?

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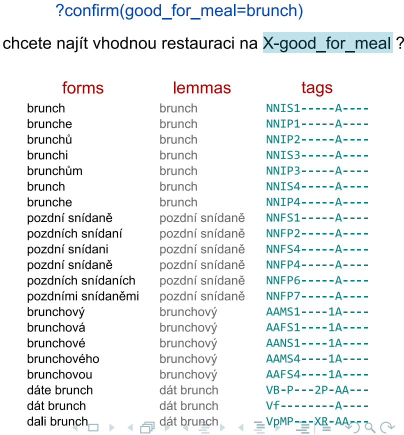

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forms	lemmas	tags
brunch	brunch	NNIS1-----A----
brunche	brunch	NNIP1-----A----
brunchů	brunch	NNIP2-----A----
brunchi	brunch	NNIS3-----A----
brunchům	brunch	NNIP3-----A----
brunch	brunch	NNIS4-----A----
brunche	brunch	NNIP4-----A----
pozdní snídaně	pozdní snídaně	NNFS1-----A----
pozdních snídaní	pozdní snídaně	NNFP2-----A----
pozdní snídani	pozdní snídaně	NNFS4-----A----
pozdní snídaně	pozdní snídaně	NNFP4-----A----
pozdních snídaních	pozdní snídaně	NNFP6-----A----
pozdními snídaněmi	pozdní snídaně	NNFP7-----A----
brunchový	brunchový	AAMS1----1A----
brunchová	brunchový	AAFS1----1A----
brunchové	brunchový	AANS1----1A----
brunchového	brunchový	AAMS4----1A----
brunchovou	brunchový	AAFS4----1A----
dáte brunch	dát brunch	VB-P---2P-AA---
dát brunch	dát brunch	Vf--------A----
dali brunch	dát brunch	VpMP---XR-AA---

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brunchů	brunch	NNIP2-----A----
brunchi	brunch	NNIS3-----A----
brunchům	brunch	NNIP3-----A----
brunch	brunch	NNIS4-----A----
brunche	brunch	NNIP4-----A----
pozdní snídaně	pozdní snídaně	NNFS1-----A----
pozdních snídaní	pozdní snídaně	NNFP2-----A----
pozdní snídani	pozdní snídaně	NNFS4-----A----
pozdní snídaně	pozdní snídaně	NNFP4-----A----
pozdních snídaních	pozdní snídaně	NNFP6-----A----
pozdními snídaněmi	pozdní snídaně	NNFP7-----A----
brunchový	brunchový	AAMS1----1A----
brunchová	brunchový	AAFS1----1A----
brunchové	brunchový	AANS1----1A----
brunchového	brunchový	AAMS4----1A----
brunchovou	brunchový	AAFS4----1A----
dáte brunch	dát brunch	VB-P---2P-AA---
dát brunch	dát brunch	Vf--------A----
dali brunch	dát brunch	VpMP---XR-AA---

Czech: Inflecting Proper Names

- Czech proper names & other DA slot values need to be inflected
- Generalized: selecting proper surface form
  - e.g., *obědvat* vs. *oběd*
    ('lunch' as noun/verb)
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  a) random form
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?confirm(good_for_meal=brunch)

chcete najít vhodnou restauraci na X-good_for_meal ?

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  - score options
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Further Architecture Extensions

- Aimed at morphology

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Evaluation

- BLEU & human (selected setups, WMT-style) on our dataset

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Thank you for your attention

Download my work

- Word Inflection Generator Code: bit.ly/flect
- A*+Seq2seq Generator Code: bit.ly/tgen_nlg
- Entrainment dataset: bit.ly/nlgdata
- Czech restaurant dataset: bit.ly/cs_rest

Contact me

Ondřej Dušek

odusek@ufal.mff.cuni.cz

References

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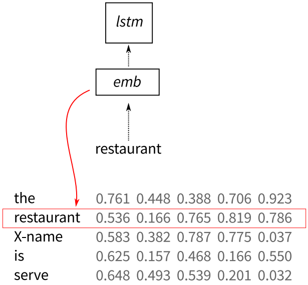
Wen, T. H. et al. 2015. Semantically conditioned LSTM-based natural language generation for spoken dialogue systems. *EMNLP*

Embeddings

- function: words $\rightarrow \mathbb{R}^n$
- equiv. to 1-hot encoding + fully connected layer
    - embedding values = weights in fully connected layer
- initialized randomly
- backpropagation during training
    - from output layer
    - through recurrent layers
    - to embedding layer



the	0.761	0.448	0.388	0.706	0.923
restaurant	0.536	0.166	0.765	0.819	0.786
X-name	0.583	0.382	0.787	0.775	0.037
is	0.625	0.157	0.468	0.166	0.550
serve	0.648	0.493	0.539	0.201	0.032

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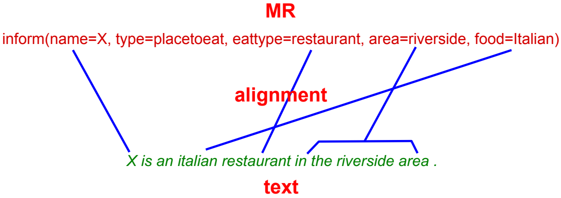
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inform(name=X, type=placetoeat, eattype=restaurant, area=riverside, food=Italian)
alignment
X is an italian restaurant in the riverside area .
text

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inform(name=X-name, type=placetoeat, **area=centre**, eattype=restaurant, near=X-near)
*The X restaurant is **conveniently** located near X, **right in the city center**.*

inform(name=X-name, type=placetoeat, **foodtype=Chinese_takeaway**)
*X serves **Chinese food** and has a **takeaway** possibility.*

inform(name=X-name, type=placetoeat, **pricerange=cheap**)
***Prices** at X are **quite cheap**.*

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enumerable:	food type, price range
non-enumerable:	restaurant name, phone number, postcode

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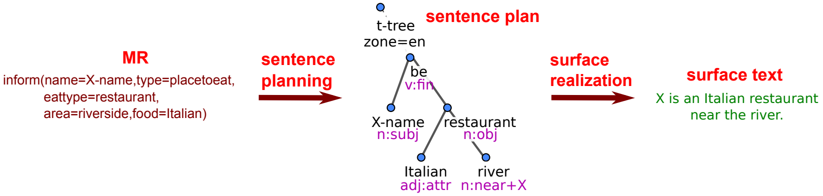

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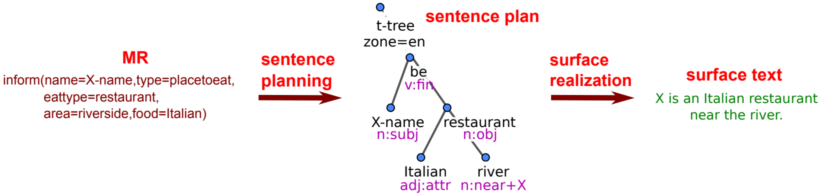

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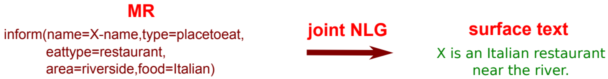

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- we try both in one system + compare

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how bout the next ride

Sorry, I did not find a later option.

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

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- entrainment is natural, subconscious
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			ě	é
Toto	se líbí	~~uživateli~~	Jana	Nováková.
This	*is liked by*	*user* [masc]	*(name)*	[fem]
		[dat]		[nom]

	e	u	
Děkujeme,	Jan	Novák,	vaše hlasování
Thank you,	*(name)*[nom]		bylo vytvořeno.
			your poll has been created

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This is liked by user [masc] [dat] *(name)* [fem] [nom]

Děkujeme, Jan e Novák u, vaše hlasování bylo vytvořeno.

Thank you, (name) [nom] *your poll has been created*

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Surface Realizer in TectoMT

- BLEU scores for TectoMT translation within the QTLeap project

Task	Dutch-English		Czech-English	
	IT	news	IT	news
Phrase-based	25.57	23.50	19.03	24.03
TectoMT	27.09	19.40	20.53	13.04

Surface Realizer in TectoMT

(1) *Output:* One Council, how into that moment to do: carefully this page snatch and make from it bookmark.

Source: Jedna rada, jak se v tu chvíli zachovat: Opatrně tuhle stránku vytrhněte a udělejte si z ní záložku.

Reference: *A piece of advice on how to proceed at that moment: gently excise this page and make it your bookmark.*

(2) *Output:* Mr. Englund a historian is swedish and a journalist.

Source: Pan Englund je švédský historik a novinář.

Reference: *Mr. Englund is a Swedish historian and journalist.*

(3) *Output:* Their lives flikkeren as votiefkaarsen in a church; new is added to the altar other is been.

Source: Hun levens flikkeren als votiefkaarsen in een kerk; nieuwe worden toegevoegd aan het altaar terwijl andere worden uitgemaakt.

Reference: *Their lives flicker like votive candles in a church; new ones are added to the altar while others are put out.*

(4) *Output:* From the almost beginning, this is an inspiring book.

Source: Vrijwel vanaf het begin is dit een bezielend boek.

Reference: *Almost from the start, this is a moving book.*

Errors: source parsing, t-lemma translation, untranslated , formeme translation, article assignment, word ordering (transfer), word ordering (realizer), inflection (realizer)

Flect: The need for morphology in generation

- English – not so much:
  hard-coded solutions often work well enough

Flect: The need for morphology in generation

- English – not so much:
  hard-coded solutions often work well enough
- Languages with more inflection (e.g. Czech):
  even for the simplest things

Toto se líbí ~~uživateli~~ Jan~~a~~ě Novákov~~á~~é.
This is liked by user [masc] [dat] *(name)* [fem] [nom]

Děkujeme, Jan e Novák u, vaše hlasování bylo vytvořeno.
Thank you, (name) [nom] *your poll has been created*

Flect: The task at hand

word + NNS → words

Wort + $\text{NN}_{\text{Neut,Pl,Dat}}$ → Wörtern

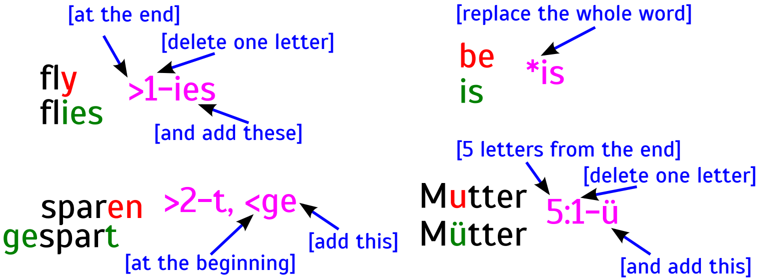
be + VBZ → is

ser + $\text{V}^{\text{gen=c,num=s,person=3,}}_{\text{mood=indicative,tense=present}}$ → es

- Input: Lemma (base form) or stem

  + morphological properties (POS, case, gender, etc.)
- Output: Inflected word form
- **Inverse to POS tagging**

Flect: Inflection patterns as multi-class classification



[at the end]
[delete one letter]
fly
flies
>1–ies
[and add these]

[replace the whole word]
be
is
*is

sparen
gespart
>2–t, <ge
[at the beginning]
[add this]

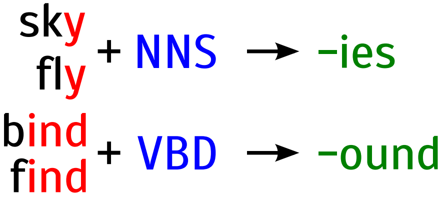
[5 letters from the end]
[delete one letter]
Mutter
Mütter
5:1–ü
[and add this]

Our inflection rules: *edit scripts*

- **A kind of diffs**: how to modify the lemma to get the form
- Based on Levenshtein distance

Flect: Features useful for morphology generation

- Same POS + same ending = (often) same inflection



sky

fly

+ NNS → –ies

bind

find

+ VBD → –ound

Flect: Features useful for morphology generation

- Same POS + same ending = (often) same inflection

sky
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- **Suffixes = good features to generalize to unseen inputs**
- Machine learning should be able to deal with counter-examples

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bind
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- **Suffixes = good features to generalize to unseen inputs**
- Machine learning should be able to deal with counter-examples
- **Capitalization: no influence on morphology**

Flect: Overall procedure

Wort

NN

Pl

Neut

Dat

Flect: Overall procedure

1. Get **features** from lemma, POS, suffixes
   (+morph. properties & their combinations, possibly context)

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Flect: Overall procedure

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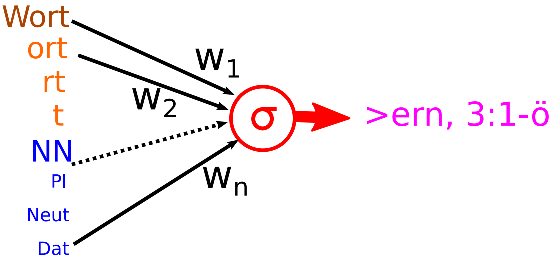
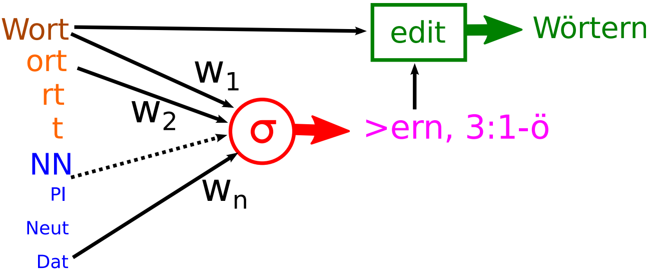


Flect: Overall procedure

1. Get **features** from lemma, POS, suffixes (+morph. properties & their combinations, possibly context)
2. Predict **edit scripts** using Logistic regression
3. Use them as rules to obtain **form** from lemma



Testing *Flect* on 6 languages

- **CoNLL 2009 data**: varying morphology richness & tagsets

Testing *Flect* on 6 languages

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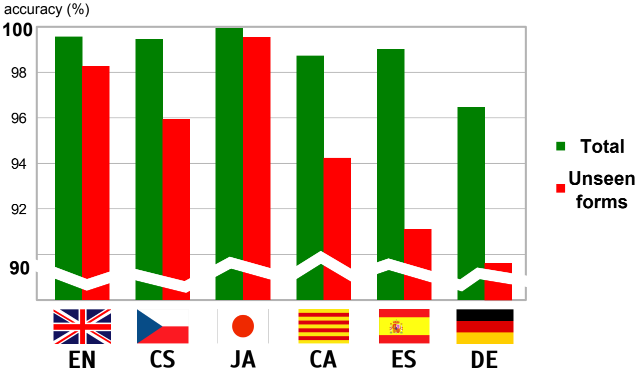

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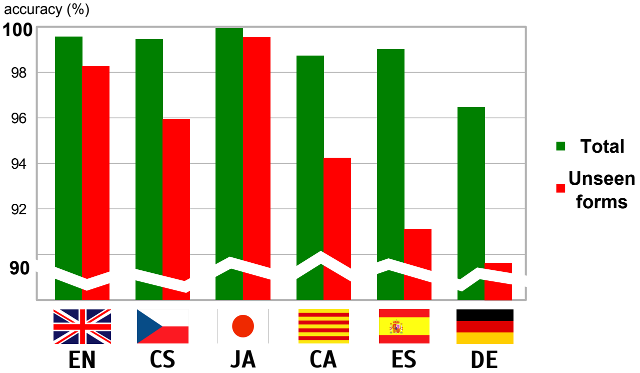

- Works well even on unseen forms: suffixes help

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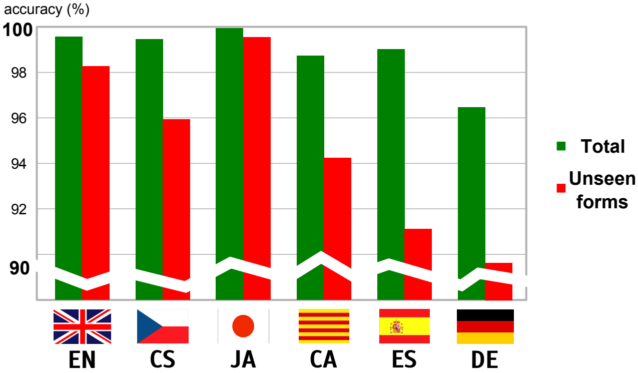
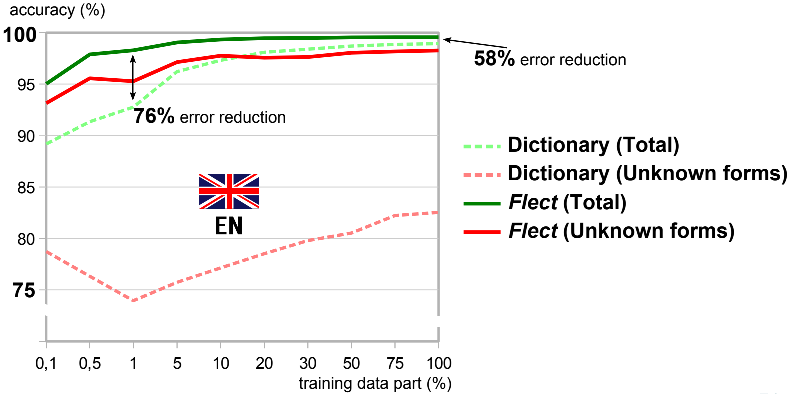


- Works well even on unseen forms: suffixes help
  - over-generalization errors, e.g. torpedo + VBN = torpedone
  - German: syntax-sensitive morphology

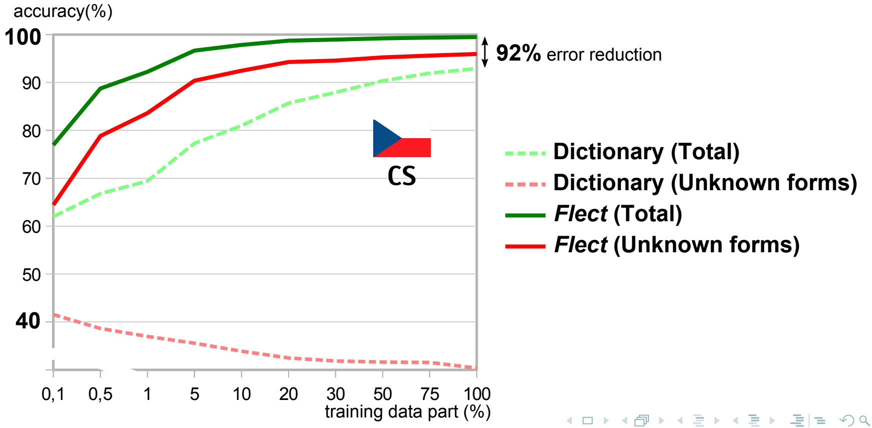
Flect vs. a dictionary from the same data

- English: Dictionary gets OK relatively soon



Flect vs. a dictionary from the same data

- English: Dictionary gets OK relatively soon
- Czech: Dictionary fails on unknown forms, our system works



Flect in English Surface Realization

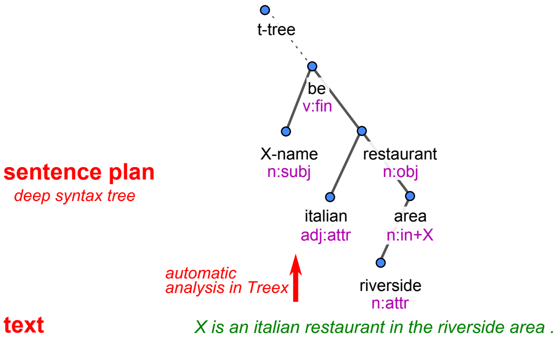
- TectoMT English Round-trip (PCEDT 2.0 Sect. 22+23)
  - analyzed and regenerated sentences compared to originals

Variant	**BLEU (%)**
Baseline (MorphoDiTa)	73.55
Flect alone	77.04
MorphoDiTa + Flect as a backoff	77.47

A*-search/Perceptron Sentence Planning

- Our generator learns alignments jointly
  - training from pairs: **MR + sentence**
  - with sentence planning (MR → deep syntax trees)

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



A*/Perceptron: Overall workflow

A two-step setup:

A*/Perceptron: Overall workflow

MR

A two-step setup:

- *Input*: a meaning representation

A*/Perceptron: Overall workflow

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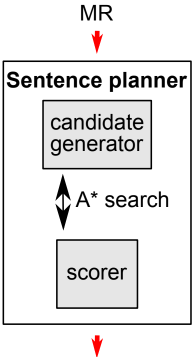
    - statistical, our main focus
    - expanding + ranking candidate sentence plans
    - A*-like search



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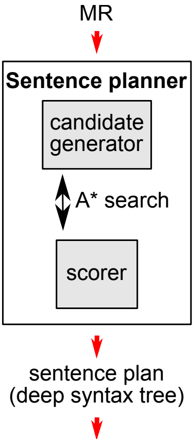

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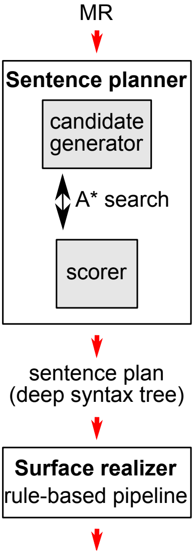
  - reusing *Treex/TectoMT* realizer
  - (mostly) rule-based pipeline



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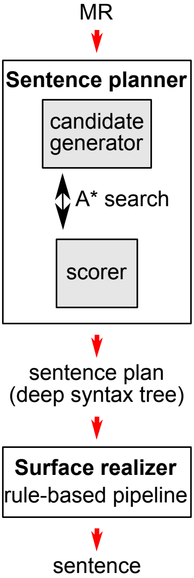
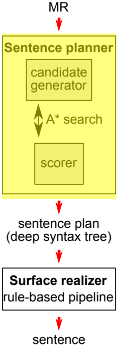
- *Output*: plain text sentence



A*/Perceptron Sentence planner

- A*-style search
  - "finding the path" from empty tree to full sentence plan tree
  - expand the most promising candidate sentence plan in each step
  - stop when candidates don't improve for a while



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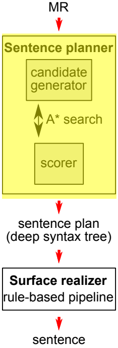

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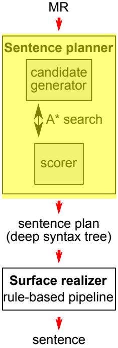

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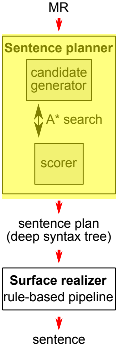
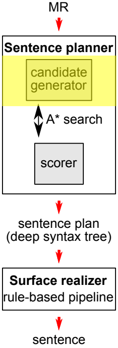
    - influences which candidate trees will be expanded
- Training data = MR + sentence plan tree pairs
  - trees obtained by automatic parsing in *Treex*



A*/Perceptron: Candidate generator

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


MR

Sentence planner

candidate generator

A* search

scorer

sentence plan (deep syntax tree)

Surface realizer

rule-based pipeline

sentence

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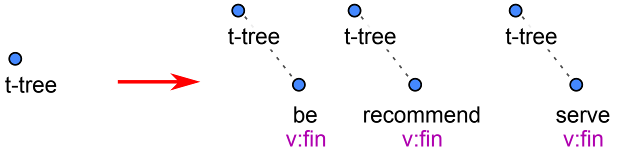

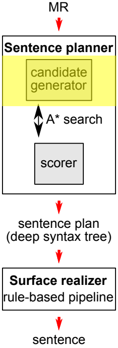

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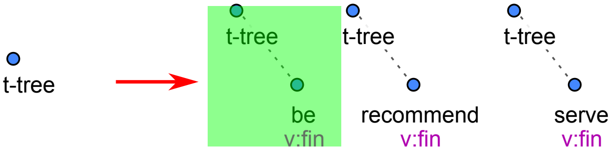

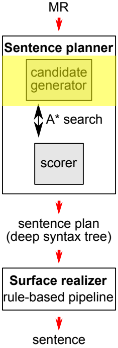

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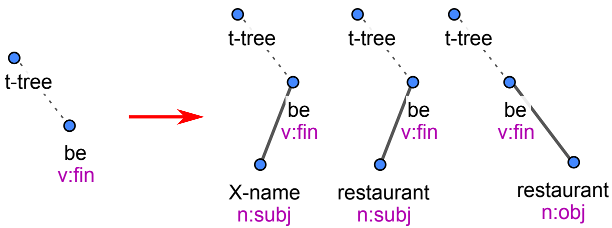

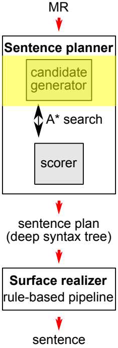

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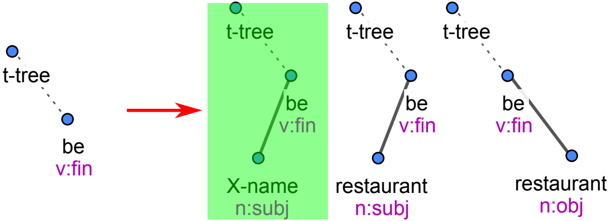

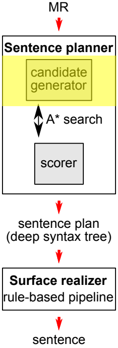

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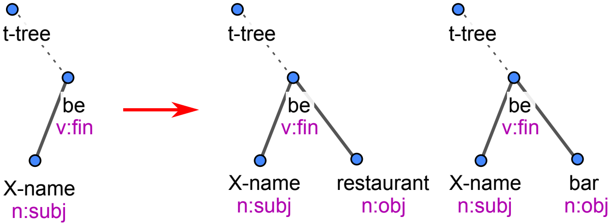

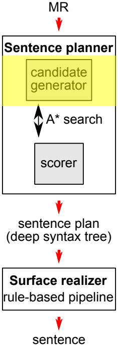

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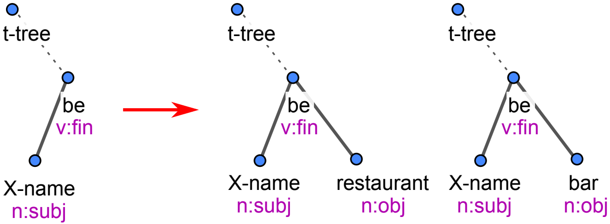
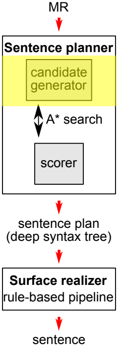


- Combinations explode even for small trees
- Limiting "possible places"
  - a few simple rules
  - based on context (elements of current MR, parent node)

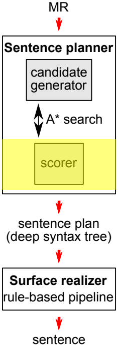


A*/Perceptron Sentence Planner: Scorer/Ranker

- a function:

  sentence plan tree + MR → real-valued score

  - describes the fitness of tree for MR



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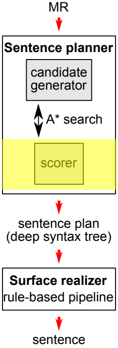
Linear perceptron scorer (Collins & Duffy, 2002)

- **score** = weights · features (from tree and MR)
  - features – elements of tree and MR
  - presence of nodes, slots, values + combination
  - tree size and shape, parent-child



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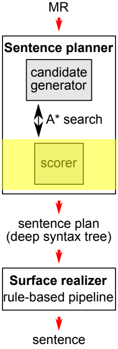

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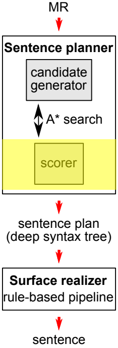

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- **training** loop:
  - given MR, generate the best tree with current weights
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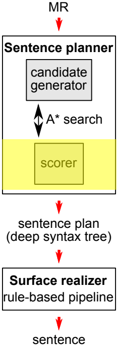
- **update** = $\alpha\cdot$ difference in features (gold$-$generated)
  - want gold to score better next time

A*/Perceptron Sentence Planner

Scoring problem

- Features are global over the whole sentence plan tree
  → bigger trees tend to score better



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  - bigger incomplete trees are not always right
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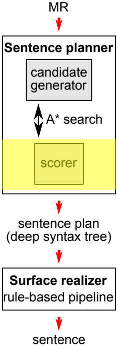

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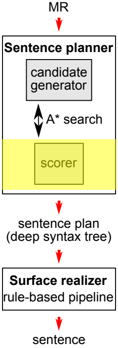

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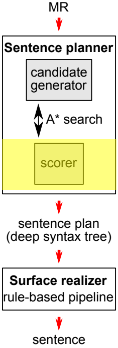

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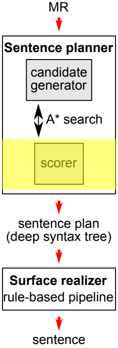
Our improvements to the scorer

- Differing tree updates
- Future promise

A*/Perceptron: Differing subtree updates

- Additional perceptron update
  - performed with the regular one
  - using pairs of differing subtrees of gold and generated tree (starting from common subtree)
  - promoting promising paths, demoting dead-ends



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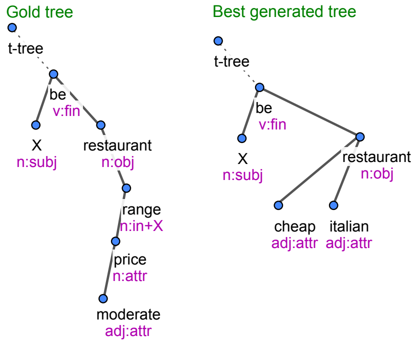

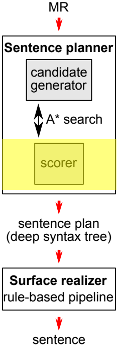

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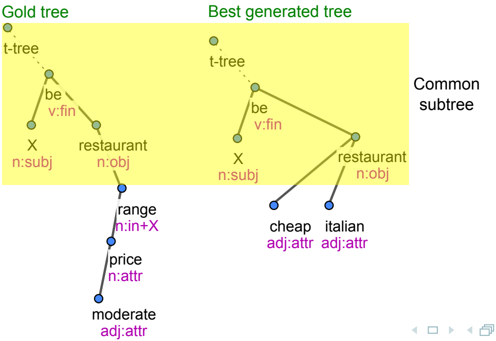

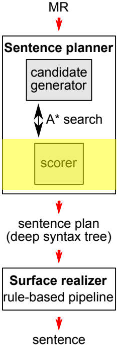

A*/Perceptron: Differing subtree updates

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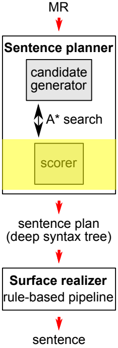

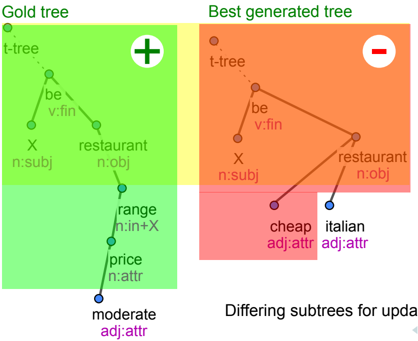

Differing subtrees for update

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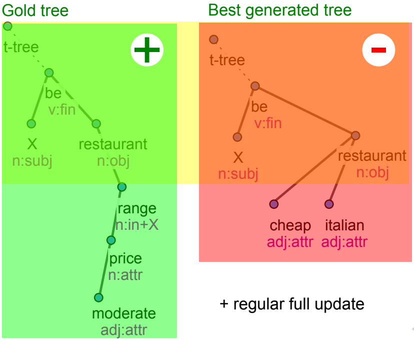
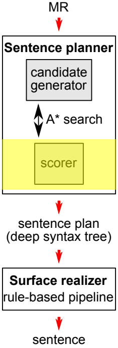
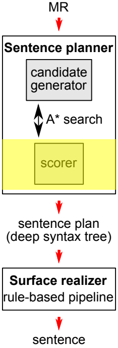


+ regular full update



A*/Perceptron: Future promise estimate

- Further score boost for incomplete trees



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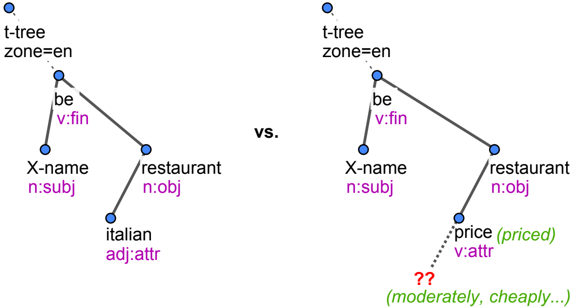

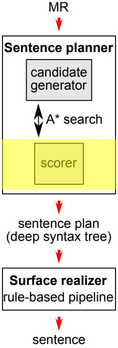

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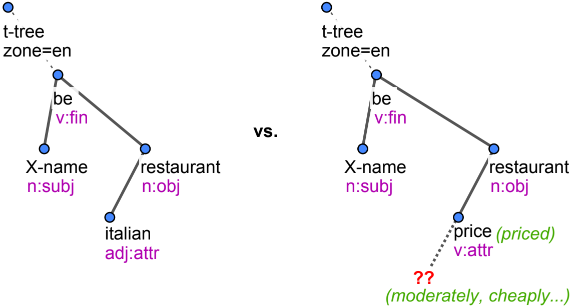

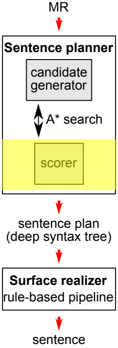

- **Future promise**:
  "how many children are missing to meet the expectation"
  - floored at zero, summed over the whole tree
- Added to scores, used to select next expansion path

A*/Perceptron Sentence Planner: Results

Setup	BLEU	NIST
perceptron scorer	54.24	4.643
+ differing subtree updates	58.70*	4.876
+ future promise	59.89*	5.231

- * both improvements statistically significant

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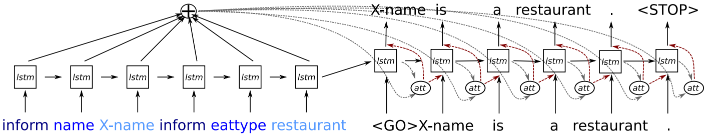
- * both improvements statistically significant
- Overall, lower scores than Mairesse et al.'s ~ 67% BLEU
- But our problem is harder:
  - we learn alignments jointly
  - our generator has to decide when to stop
    (whether all required information is included)

A*/Perceptron Example Outputs

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.
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.

- Mostly fluent and relevant
  - sometimes identical to reference, more often original
- Problems in some cases:
  - information missing / repeated / superfluous

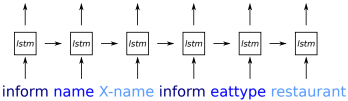
Sequence-to-sequence Generation: Our Model



X-name is a restaurant . <STOP>
lstm
att
inform name X-name inform eattype restaurant
<GO> X-name is a restaurant .

- Main generator: seq2seq with attention (Bahdanau et al., 2015)

Sequence-to-sequence Generation: Our Model



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    - Encoder LSTM RNN: encode DA into hidden states

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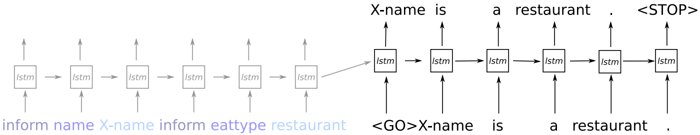
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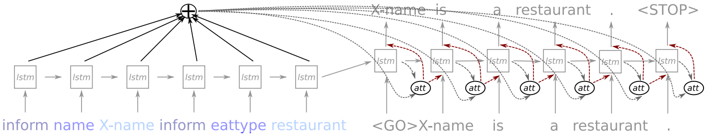

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    - Decoder LSTM RNN: generate output tokens
    - attention model: weighing encoder hidden states

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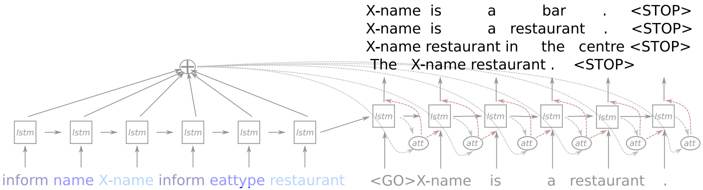

X-name is a bar . <STOP>
X-name is a restaurant . <STOP>
X-name restaurant in the centre <STOP>
The X-name restaurant . <STOP>

inform name X-name inform eattype restaurant

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+ beam search, *n*-best list outputs

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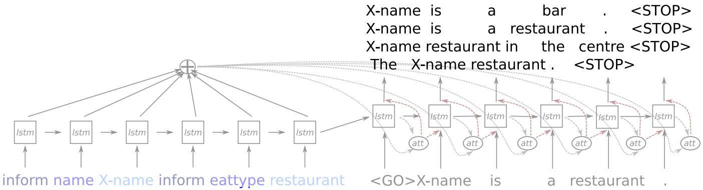
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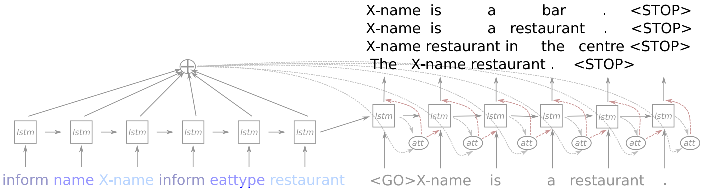

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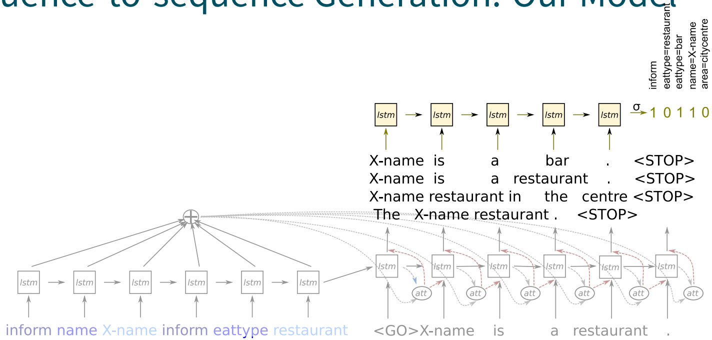

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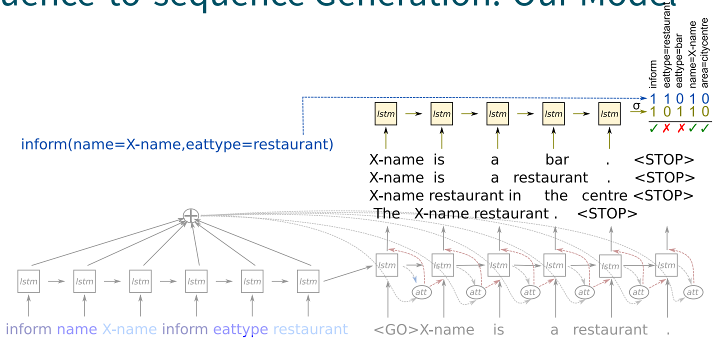
inform
eattype=restaurant
eattype=bar
name=X-name
area=citycentre
1 1 0 1 0
σ
1 0 1 1 0
✓ ✗ ✗ ✓ ✓
lstm
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X-name is a bar . <STOP>
X-name is a restaurant . <STOP>
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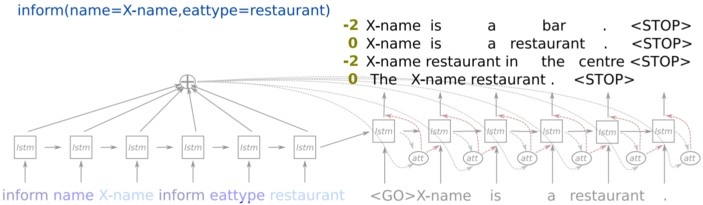

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-2 X-name is a bar . <STOP>
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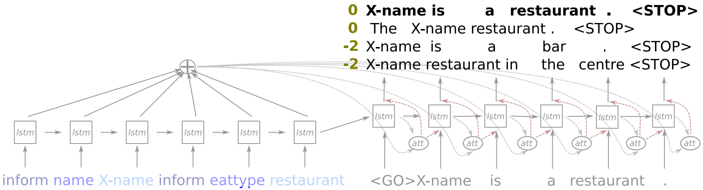

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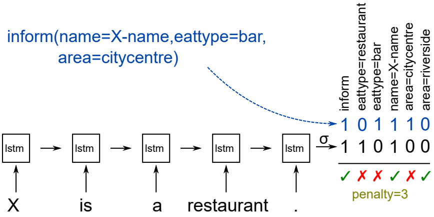

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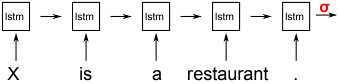

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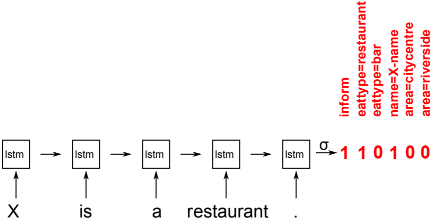

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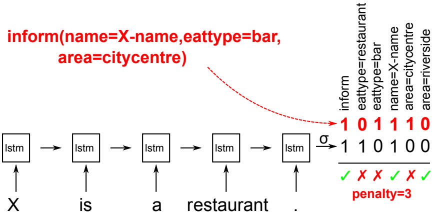

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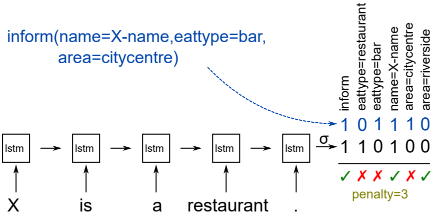

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  - manual evaluation: semantic errors on 20% data (missing/irrelevant/repeated)

BAGEL Seq2seq Results

prev

Setup	BLEU	NIST	ERR
Mairesse et al. (2010) *– alignments*	$\sim$67	-	0
Our A*/perceptron	59.89	5.231	30

BAGEL Seq2seq Results

		Setup	**BLEU**	**NIST**	**ERR**
prev		Mairesse et al. (2010) – *alignments*	∼67	-	0
		Our A*/perceptron	59.89	5.231	30
our	*two-step*	Greedy with trees	55.29	5.144	20
		+ Beam search (beam size 100)	58.59	5.293	28
		+ Reranker (beam size 5)	60.77	5.487	24
		(beam size 10)	60.93	5.510	25
		+ Reranker (beam size 100)	60.44	5.514	**19**
	joint	Greedy into strings	52.54	5.052	37
		+ Beam search (beam size 100)	55.84	5.228	32
		+ Reranker (beam size 5)	61.18	5.507	27
		(beam size 10)	62.40	5.614	21
		+ Reranker (beam size 100)	**62.76**	**5.669**	**19**

Sample Outputs on the BAGEL set

Input DA	inform(name=X-name, type=placetoeat, eattype=restaurant, area=riverside, food=French)
Reference	X is a French restaurant on the riverside.
Greedy with trees	X is a restaurant providing french and continental and by the river.
+ Beam search	X is a restaurant that serves french takeaway. [riverside]
+ Reranker	X is a french restaurant in the riverside area.
Greedy into strings	X is a restaurant in the riverside that serves italian food. [French]
+ Beam search	X is a restaurant in the riverside that serves italian food. [French]
+ Reranker	X is a restaurant in the riverside area that serves french food.

Sample Outputs on the BAGEL set

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.
Greedy with trees	X is a restaurant offering chinese takeaway in the centre of town near X. [Japanese]
+ Beam search	X is a restaurant and japanese food and chinese takeaway.
+ Reranker	X is a restaurant serving japanese food in the centre of the city that offers chinese takeaway.
Greedy into strings	X is a restaurant offering italian and indian takeaway in the city centre area near X. [Japanese, Chinese]
+ Beam search	X is a restaurant that serves fusion chinese takeaway in the riverside area near X. [Japanese, citycentre]
+ Reranker	X is a japanese restaurant in the city centre near X providing chinese food. [takeaway]

Sample Outputs on the BAGEL set

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.
Greedy with trees	X is a french restaurant that serves french food and near X. [Continental]
+ Beam search	X is a french restaurant that serves french food and near X. [Continental]
+ Reranker	X is a restaurant serving french and continental food near X.
Greedy into strings	X is a french and continental style restaurant near X.
+ Beam search	X is a french and continental style restaurant near X.
+ Reranker	X is a restaurant providing french and continental food, near X.

Collecting Context-aware Data via CrowdFlower

1. Get natural user utterances in calls to a live dialogue system

Collecting Context-aware Data via CrowdFlower

1. Get natural user utterances in calls to a live dialogue system
   - record calls to live Alex SDS,
     task descriptions use varying synonyms

You want a connection – your departure stop is *Marble Hill*, and you want to go to *Roosevelt Island*. Ask how long the journey will take. Ask about a schedule afterwards. Then modify your query: Ask for a ride at six o'clock in the evening. Ask for a connection by bus. Do as if you changed your mind: Say that your destination stop is *City Hall*.

You are searching for transit options leaving from *Houston Street* with the destination of *Marble Hill*. When you are offered a schedule, ask about the time of arrival at your destination. Then ask for a connection after that. Modify your query: Request information about an alternative at six p.m. and state that you prefer to go by bus.

Tell the system that you want to travel from *Park Place* to *Inwood*. When you are offered a trip, ask about the time needed. Then ask for another alternative. Change your search: Ask about a ride at 6 o'clock p.m. and tell the system that you would rather use the bus.

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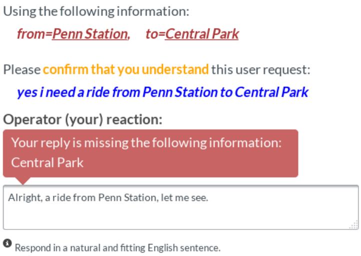

Using the following information:

from=Penn Station, to=Central Park

Please confirm that you understand this user request:

yes i need a ride from Penn Station to Central Park

Operator (your) reaction:

Your reply is missing the following information: Central Park

Alright, a ride from Penn Station, let me see.

Respond in a natural and fitting English sentence.

3. Collect natural language paraphrases for the response DAs
    - interface designed to support entrainment
        - context at hand
        - minimal slot description
        - short instructions

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   - interface designed to support entrainment
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     - minimal slot description
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   - checks: contents + spelling, automatic + manual
     - ca. 20% overhead (repeated job submission)

Collecting Context-aware Data: Generating response DA

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- Handcrafted simple rule-based bigram policy
- All possible replies for a single context utterance

what about a connection by bus

iconfirm(vehicle=bus)

inform(from_stop="Dyckman Street", direction="Park Place",
vehicle=bus, line=M103, departure_time=7:05pm)

inform_no_match(vehicle=bus)

request(to_stop)

Collecting Context-aware Data: Generating response DA

- Handcrafted simple rule-based bigram policy
- All possible replies for a single context utterance
    - confirmation
    - answer
    - apology
    - request for additional information

what about a connection by bus

iconfirm(vehicle=bus)

inform(from_stop=”Dyckman Street”, direction=”Park Place”,
vehicle=bus, line=M103, departure_time=7:05pm)

inform_no_match(vehicle=bus)

request(to_stop)

Collecting Context-aware Data: Generating response DA

- Handcrafted simple rule-based bigram policy
- All possible replies for a single context utterance
  - confirmation
  - answer
  - apology
  - request for additional information
- In a real dialogue, the correct reply would depend on longer history, but here we try them all

Entrainment Dataset Summary

Size

total response paraphrases	5,577
unique (delex.) context + response DA	1,859
unique (delex.) context	552
unique (delex.) context with min. 2 occurrences	119
unique response DA	83
unique response DA types	6
unique slots	13

Entrainment

Syntactic	∼59%
Lexical	∼31%
Both	∼19%

- subjective, based on word & phrase reuse, word order, pronouns

Entrainment Experiments

- Dataset: public transport information
  - 5.5k paraphrases for 1.8k DA-context combinations
  - delexicalized

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- Human pairwise preference ranking (crowdsourced)
  - baseline × prepending context + *n*-gram match reranker

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- Human pairwise preference ranking (crowdsourced)
  - baseline × prepending context + *n*-gram match reranker
  - context-aware **preferred in 52.5% cases** (significant)

Entrainment Output Examples

Context	is there a later option
Input DA	iconfirm(alternative=next)
Baseline	Next connection.
n-gram match reranker	You want a later connection.
Prepending context + *n*-gram match reranker	You want a later connection.
Context encoder + *n*-gram match reranker	You want a later option.

Entrainment Output Examples

Context	is there a later option
Input DA	iconfirm(alternative=next)
Baseline	Next connection.
n-gram match reranker	You want a later connection.
Prepending context + *n*-gram match reranker	You want a later connection.
Context encoder + *n*-gram match reranker	You want a later option.

Context	i need to find a bus connection
Input DA	inform_no_match(vehicle=bus)
Baseline	No bus found, sorry.
n-gram match reranker	I did not find a bus route.
Prepending context + *n*-gram match reranker	I’m sorry, I cannot find a bus connection.
Context encoder + *n*-gram match reranker	I’m sorry, I cannot find a bus connection.

Entrainment Output Examples (2)

Context	i rather take the bus
Input DA	inform(vehicle=bus, departure_time=8:01am, direction=Cathedral Parkway, from_stop=Bowling Green, line=M15)
Baseline	At 8:01am by bus line M15 from Bowling Green to Cathedral Parkway.
n-gram match reranker	At 8:01am by bus line M15 from Bowling Green to Cathedral Parkway.
Prepending context + *n*-gram match reranker	You can take the M15 bus from Bowling Green to Cathedral Parkway at 8:01am.
Context encoder + *n*-gram match reranker	At 8:01am by bus line M15 from Bowling Green to Cathedral Parkway.

Creating a Czech NLG Dataset

- Virtually no non-English NLG datasets available

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→ Translating an English set (restaurants, Wen et al. 2015)

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1. delexicalization

inform(name="Fog Harbor Fish House", price_range=cheap, area="Civic Center")
Fog Harbor Fish House is cheap and it is located in Civic Center.

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1. delexicalization

inform(name="X-name", price_range=X-pricerange, area="X-area")
X-name is X-pricerange and it is located in X-area.

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→ Translating an English set (restaurants, Wen et al. 2015)

1. delexicalization
2. localizing restaurant names, landmarks, etc., to Prague
   - (random combinations, names require inflection)

inform(name="Ferdinanda", price_range=expensive, area="Hradčany")
Ferdinanda is expensive and it is located in Hradčany.

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→ Translating an English set (restaurants, Wen et al. 2015)

1. delexicalization
2. localizing restaurant names, landmarks, etc., to Prague
   - (random combinations, names require inflection)
3. translation by hired translators

inform(name="Ferdinanda", price_range=expensive, area="Hradčany")
Ferdinanda je **levná** *(cheap)* a nachází se na Hradčanech.

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2. localizing restaurant names, landmarks, etc., to Prague
   - (random combinations, names require inflection)
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4. automatic & manual checks

inform(name="Ferdinanda", price_range=expensive, area="Hradčany")
Ferdinanda je drahá a nachází se na Hradčanech.

Czech NLG: Lemma-tag generation

- 3rd generator mode
    - compromise between full 2-step/joint setups

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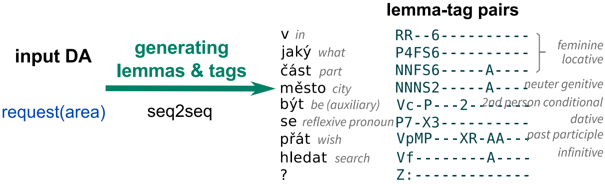


lemma-tag pairs

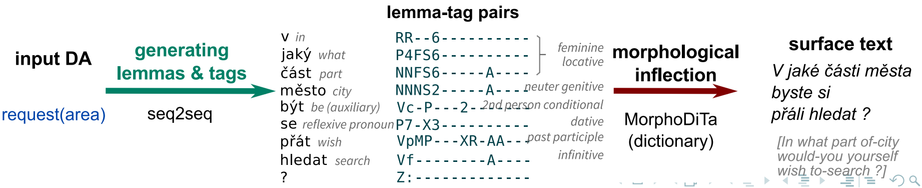
v	*in*	RR--6----------	*feminine locative*
jaký	*what*	P4FS6----------	
část	*part*	NNFS6-----A----	
město	*city*	NNNS2-----A----	*neuter genitive*
být	*be (auxiliary)*	Vc-P---2-------	*2nd person conditional*
se	*reflexive pronoun*	P7-X3----------	*dative*
přát	*wish*	VpMP---XR-AA---	*past participle*
hledat	*search*	Vf--------A----	*infinitive*
?		Z:-------------	

Czech NLG: Lemma-tag generation

- 3rd generator mode
  - compromise between full 2-step/joint setups

idea: let the seq2seq model decide everything...
but for complex morphological inflection

- generating into list of interleaved morph. tags and lemmas
- postprocessing:
  - MorphoDiTa dictionary
  - list of surface forms for names



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V jaké části města byste si přáli hledat ?

[In what part of-city would-you yourself wish to-search ?]

Czech NLG: Using Lexical Values in DAs

- Different slot values exhibit different morphological behavior
  - *Ananta je levn**á*** vs. *BarBar je levn**ý***   *(‘<name> is cheap’)*

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inform(name="X-name", price_range=X-pricerange, area="X-area")
X-name je X-pricerange a nachází se v X-area.
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→ Keep values in input DAs (don't delexicalize)

  - still generating delexicalized outputs

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inform(name=“**Café Savoy**”, price_range=**cheap**, area=“**Smíchov**”)
X-name je X-pricerange a nachází se **na** X-area.
X-name is X-pricerange and it is located in X-area.

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  - *Ananta je levn**á*** vs. *BarBar je levn**ý*** *('<name> is cheap')*
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! This is proof-of-concept

- exploiting small number of lexical values
- real world: morphological properties / character embeddings

inform(name="Café Savoy", price_range=cheap, area="Smíchov")
X-name je X-pricerange a nachází se na X-area.
X-name is X-pricerange and it is located in X-area.

Full Czech Restaurants BLEU/NIST Results

	Setup			
input DAs	**generator mode**	**lexicalization**	**BLEU**	**NIST**
delexicalized	joint (direct to strings)	random	13.47	3.442
		most frequent	19.31	**4.346**
		n-gram LM	19.40	4.274
		RNN LM	**19.54**	4.273
	lemma-tag	random	17.18	3.985
		most frequent	18.22	4.162
		n-gram LM	17.95	4.132
		RNN LM	18.51	4.162
	two-step with t-trees	random	14.93	3.784
		most frequent	16.16	3.969
		n-gram LM	16.13	3.970
		RNN LM	16.39	3.974
lexically informed	joint (direct to strings)	random	12.56	3.300
		most frequent	17.82	4.164
		n-gram LM	17.85	4.082
		RNN LM	17.93	4.094
	lemma-tag	random	19.96	4.306
		most frequent	20.86	4.427
		n-gram LM	20.54	4.399
		RNN LM	**21.18**	**4.448**
	two-step with t-trees	random	16.13	3.919
		most frequent	17.15	4.073
		n-gram LM	17.24	4.078
		RNN LM	17.62	4.112

- understandable Czech
- some fluency errors
- semantic errors very rare

- lexically informed better
- two-step with trees worse
- RNN lexicalization best

Czech: Human Evaluation

- Selected setups based on BLEU/NIST (7 out of 24)

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- WMT-style multi-way relative comparisons
- overall preference (no criteria)
- TrueSkill$^{\text{TM}}$, bootstrap clustering

	Setup		True	Rank	BLEU
input DAs	**generator mode**	**lexicalization**	**Skill**		
delexicalized	joint (direct to strings)	RNN LM	**0.511**	1	19.54
delexicalized	lemma-tag	RNN LM	0.479	2-4	18.51
lexically informed	lemma-tag	RNN LM	0.464	2-4	**21.18**
lexically informed	lemma-tag	most frequent	0.462	2-4	20.86
lexically informed	joint (direct to strings)	RNN LM	0.413	5	17.93
lexically informed	two-step with t-trees	RNN LM	0.343	6-7	17.62
lexically informed	lemma-tag	*n*-gram LM	0.329	6-7	20.54

Czech Output Examples (1)

Input DA	inform(name=“Švejk Restaurant”, near=Stromovka, price_range=cheap)
Reference	*Restaurace Švejk je poblíž Stromovky a nabízí nízké ceny.* Švejk Restaurant is near Stromovka and it offers low prices.
Best BLEU/NIST	*Restaurace Švejk je levná restaurace, poblíž Stromovky.* Švejk Restaurant is a cheap$_{\textbf{fem}}$ restaurant$_{\textbf{fem}}$, near Stromovka.
Most preferred	*Restaurace Švejk je levná podnik blízko Stromovky* Švejk Restaurant is a cheap$_{\textbf{fem}}$ place$_{\textbf{inan}}$ close to Stromovka
Input DA	inform(name=“U Konšelů”, phone=X-phone)
Reference	*Do U Konšelů můžete zavolat na telefonu 242817033.* to U Konšelů you can call on the phone 242817033.
Best BLEU/NIST	*Cenu do restaurace U Konšelů můžete volat na číslo 242817033.* price to the restaurant U Konšelů you can call the number 242817033.
Most preferred	*Telefonní číslo U Konšelů je 242817033.* the phone number of U Konšelů is 242817033.
Input DA	inform_no_match(area=Vinohrady)
Reference	*Lituji, ale v lokalitě Vinohrad se nenachází žádné* I am sorry but in the area of Vinohrady are not located any *restaurace.* restaurants
Best BLEU/NIST	*Na Vinohradech nejsou žádné restaurace vhodné pro děti.* in Vinohrady there are no restaurants appropriate for children.
Most preferred	*V Vinohrad nejsou žádné takové restaurace.* in Vinohrady$_{\textbf{gen}}$ there are no such restaurants.

Czech Output Examples (2)

Input DA	inform(type=restaurant, good_for_meal=dont_care, count=3)
Reference	*Jsou zde 3 restaurace, které jsou vhodné pro jakékoli jídlo* there are 3 restaurants$_{\textbf{nom}}$ that are suitable for any meal
Best BLEU/NIST	*Našla jsem 3 restaurací, které jsou vhodné pro jakékoli jídlo.* I found 3 restaurants$_{\textbf{gen}}$, which are suitable for any meal.
Most preferred	*V nabídce je 3 restaurací, které nabízí všechny druhy jídel.* on the list are 3 restaurants$_{\textbf{gen}}$, that offer all kinds of meals.
Input DA	inform(area=Hradčany, type=restaurant, kids_allowed=no, count=2)
Reference	*V lokalitě Hradčan jsem našla 2 restaurace, které nedovolují* in the area of Hradčany I found 2 restaurants, which do not allow *vstup dětem.* entry to children.
Best BLEU/NIST	*V oblasti Hradčan se nabízí 2 restaurace, které nejsou* in the area of Hradčany offer themselves 2 restaurants, which are not *vhodné pro děti.* appropriate for children.
Most preferred	*Na Hradčany se nehodí 2 restaurace, které nejsou vhodné* for Hradčany are not suitable 2 restaurants, which are not appropriate *pro děti.* for children.