Sequence-to-Sequence Natural Language Generation

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University of Sheffield

1. Introduction to the problem
   a) our task + problems we are solving
2. Sequence-to-sequence Generation
   a) basic model architecture
   b) generating directly / via deep syntax trees
   c) experiments on the BAGEL Set
3. Context-aware extensions (user adaptation/entrainment)
   a) collecting a context-aware dataset
   b) making the basic seq2seq setup context-aware
   c) experiments on our dataset
4. Generating Czech
   a) creating a Czech NLG dataset
   b) generator extensions for Czech
   c) experiments on our dataset
5. Conclusions and future work ideas

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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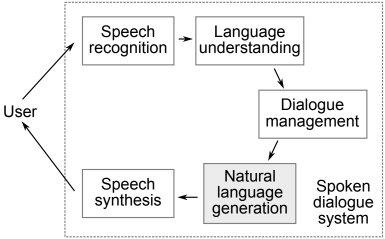
- input: from dialogue manager
- output: to TTS



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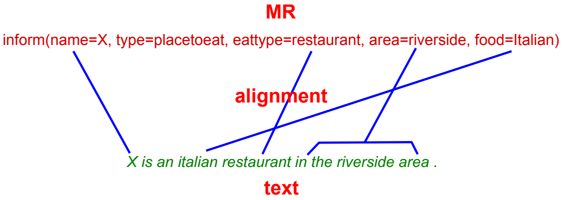

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inform(name=X, type=placetoeat, eattype=restaurant, area=riverside, food=Italian)

X is an italian restaurant in the riverside area .

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  a) manual alignments
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- we learn alignments jointly
  - no error acummulation / manual annotation
  - alignment is latent (needs not be hard/1:1)

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Problem 1: Generating from Unaligned Data

Delexicalization

- Way to address data sparsity

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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  - → replaced with placeholders for generation

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- Still different from full semantic alignments
  - can be obtained by simple string replacement
- Can be applied to some or all slots

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

Problem 2: Comparing Different NLG Architectures

- NLG pipeline traditionally divided into:
  1. sentence planning – decide on the overall sentence structure
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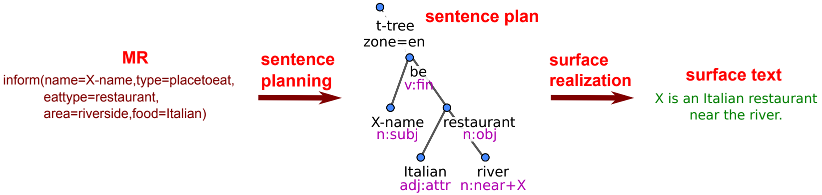

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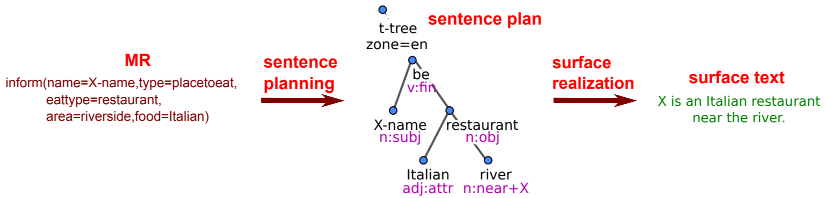

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  joint: avoids error accumulation over a pipeline
- we try both in one system + compare

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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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- our system is trainable and entrains/adapts

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Děkujeme, Jan Novák, vaše hlasování bylo vytvořeno.
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  c) 3rd generator mode: lemma-tag pairs

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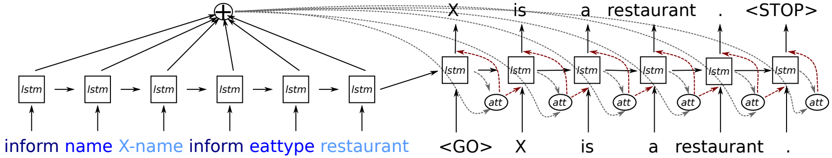

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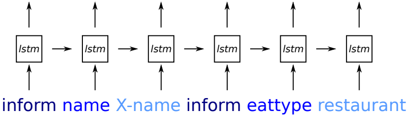

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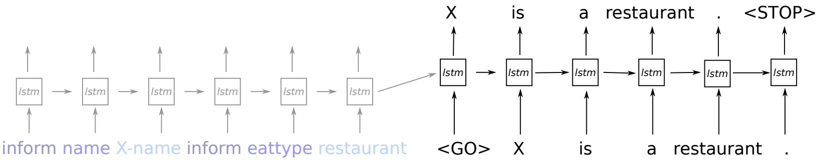

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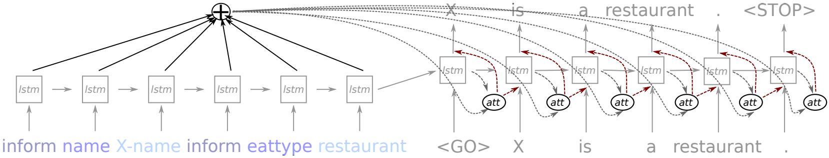

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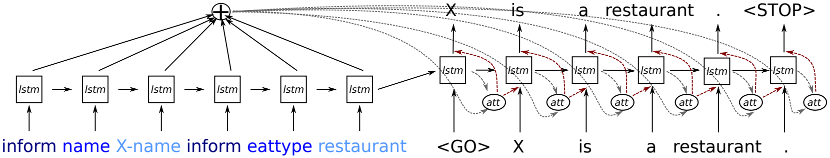

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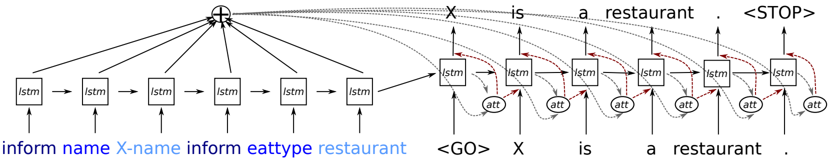

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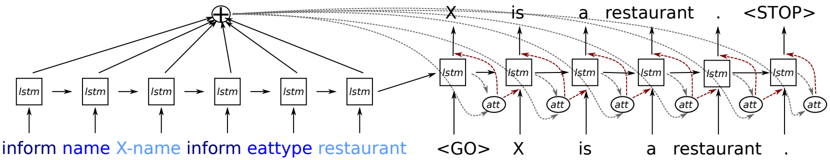

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\+ reranker (→)

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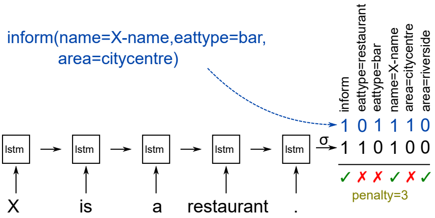

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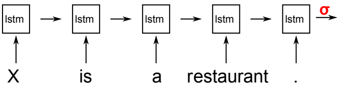

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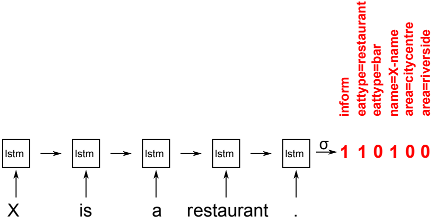

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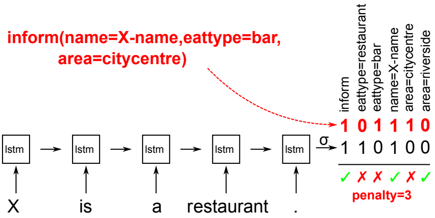

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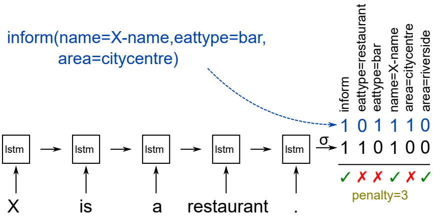

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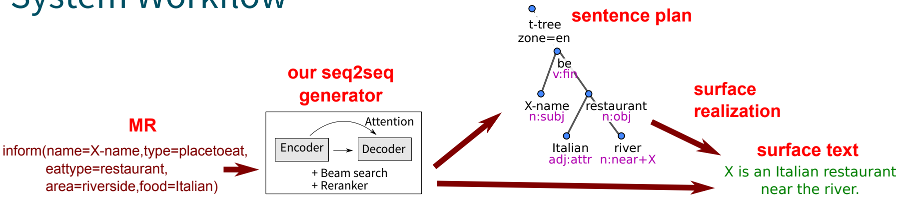

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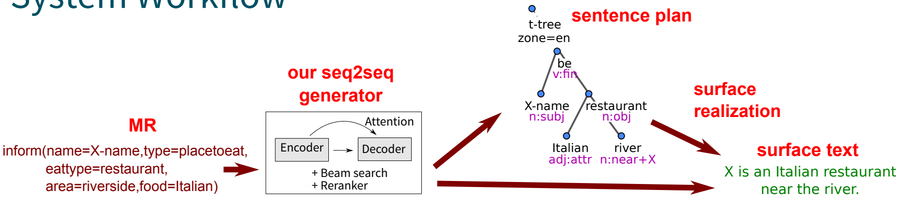

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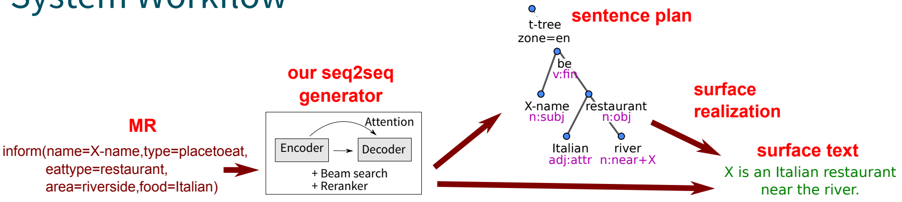

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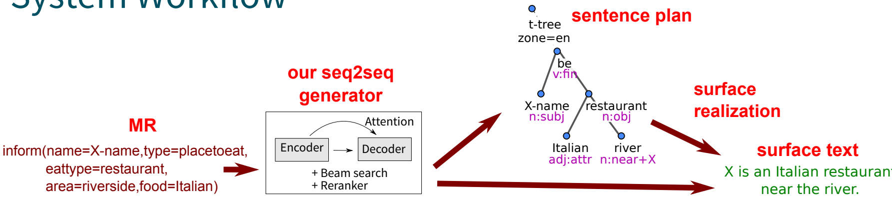

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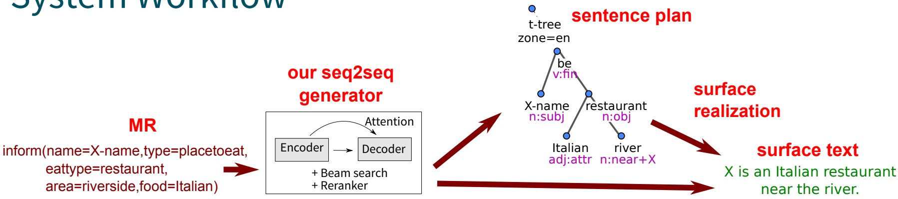

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  joint mode – sentences

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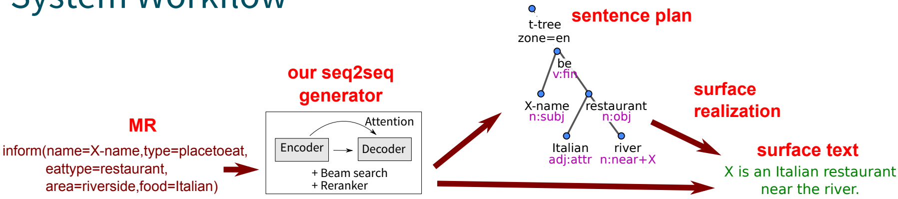

- main generator based on sequence-to-sequence NNs
- input: tokenized DAs
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  2-step mode – deep syntax trees, in bracketed format

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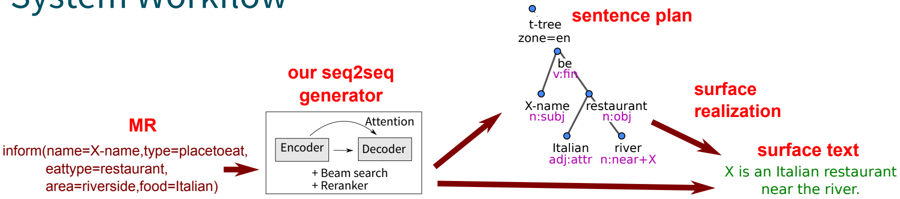

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Results

prev

Setup	BLEU	NIST	ERR
Mairesse et al. (2010) – *alignments*	∼67	-	0
Dušek & Jurčíček (2015)	59.89	5.231	30

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	Dušek & Jurčíček (2015)	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 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 100)	**62.76**	**5.669**	**19**

Sample Outputs

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.

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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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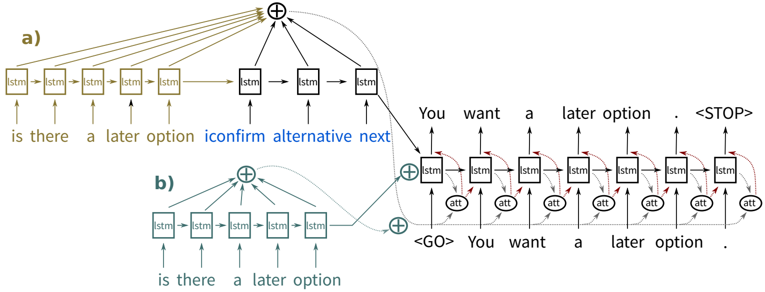
I'm headed to Rector Street
inform(from_stop="Fulton Street", vehicle=bus, direction="Rector Street", departure_time=9:13pm, line=M21)
CONTEXT-AWARE → *Heading to Rector Street from Fulton Street, take a bus line M21 at 9:13pm.*

Context in our Seq2seq Generator (1)

- Two direct context-aware extensions:



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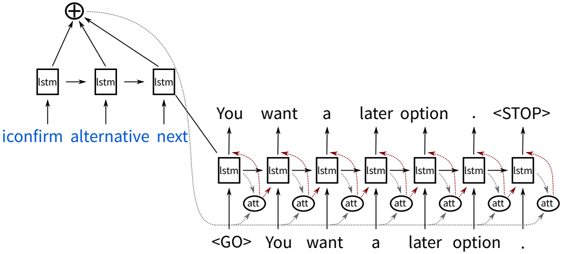

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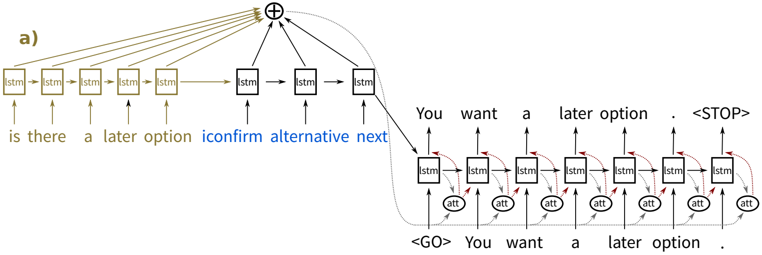

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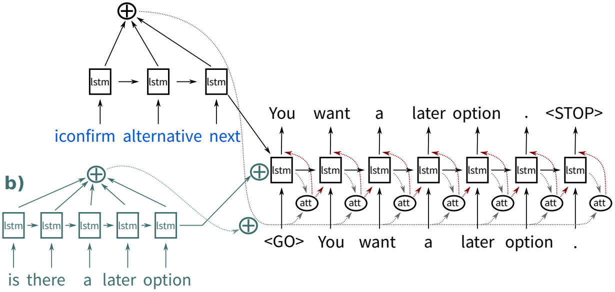
  b) separate context encoder, hidden states concatenated



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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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  - baseline $\times$ prepending context + *n*-gram match reranker
  - context-aware **preferred in 52.5% cases** (significant)

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.
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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.

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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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inform(name="X-name", price_range=X-pricerange, area="X-area")
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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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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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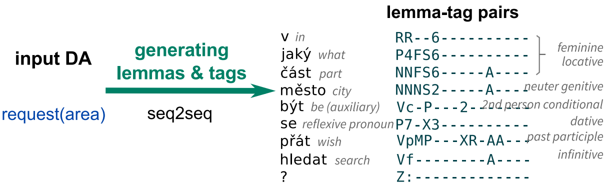

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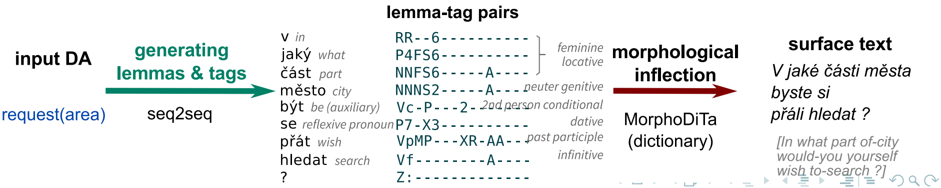
- generating into list of interleaved morph. tags and lemmas
- postprocessing:
  - MorphoDiTa dictionary
  - list of surface forms for names



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chcete najít vhodnou restauraci na X-good_for_meal ?

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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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  - e.g., *obědvat* vs. *oběd* *('lunch' as noun/verb)*
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  - e.g., *obědvat* vs. *oběd*
    ('lunch' as noun/verb)
- Two baselines:
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  b) most frequent form

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chcete najít vhodnou restauraci na X-good_for_meal ?

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pozdní snídani	pozdní snídaně	NNFS4-----A----
pozdní snídaně	pozdní snídaně	NNFP4-----A----
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X-name je X-pricerange a nachází se v X-area.
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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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! 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”)
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input DAs	Setup generator mode	lexicalization	True Skill	Rank	BLEU
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

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- RNN lexicalization is better than other methods

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 restaurace.* I am sorry but in the area of Vinohrady are not located any 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.

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- better than our previous work on the BAGEL set

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Future Work Ideas

- Remove delexicalization

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Future Work Ideas

- Remove delexicalization
- Integrate into an end-to-end SDS

Thank you for your attention

Download it!

- Code: `bit.ly/tgen_nlg`
- Entrainment dataset: `bit.ly/nlgdata`
- Czech restaurant dataset: `bit.ly/cs_rest`

Contact me

Ondřej Dušek

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References

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Mairesse, F. et al. 2010. Phrase-based statistical language generation using graphical models and active learning. *ACL*

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

Latent Alignment – Example

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****.*

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

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    - 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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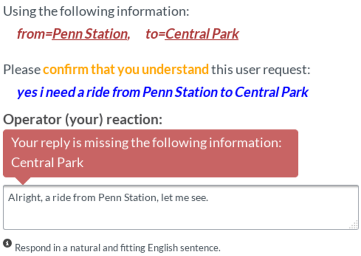

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   - checks: contents + spelling, automatic + manual
     - ca. 20% overhead (repeated job submission)

Collecting Context-aware Data: Generating response DA

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- 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
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- 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	$\sim$59%
Lexical	$\sim$31%
Both	$\sim$19%

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

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.

Full Czech Restaurants BLEU/NIST Results

Setup			BLEU	NIST
input DAs	generator mode	lexicalization		
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 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.