Sequence-to-Sequence Natural Language Generation

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Interaction Lab
MACS, Heriot Watt University, Edinburgh

work done with Filip Jurčíček
at Charles University in Prague

November 10, 2016
DILiGENt project meeting, Edinburgh

Outline of this Talk

1. Introduction to the problem
    - our task + problems we are solving

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   a) making the basic seq2seq setup context-aware
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4. 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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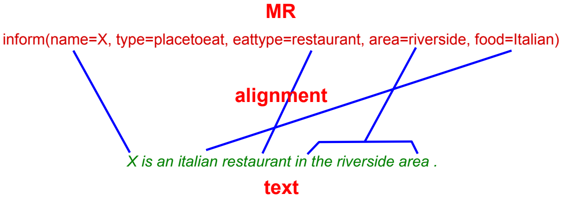

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MR

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

X is an italian restaurant in the riverside area .

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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**.*

Two-Step and Joint NLG Setups

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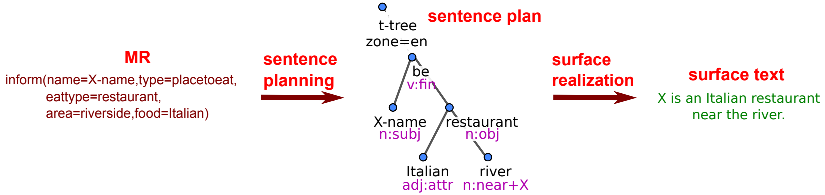

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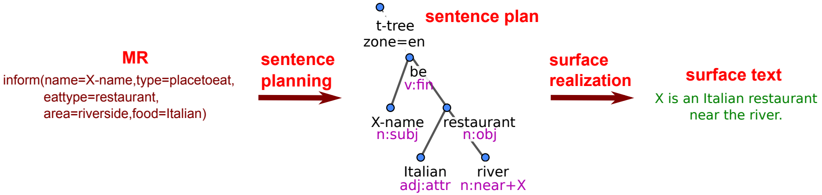

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- we can do both in one system

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- speakers are influenced by previous utterances
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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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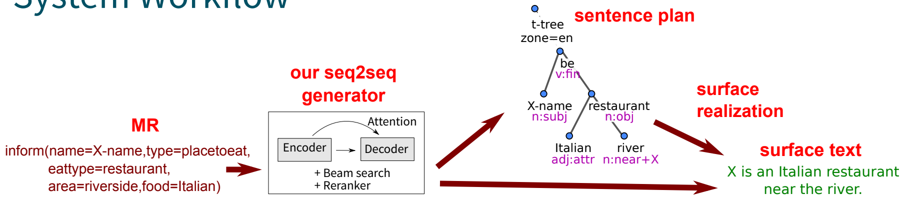
  - we can compare 2-step and joint setups in a single architecture
- ✓ learns to produce meaningful outputs from very little training data
- ✓ context-aware: adapts to previous user utterance

System Workflow



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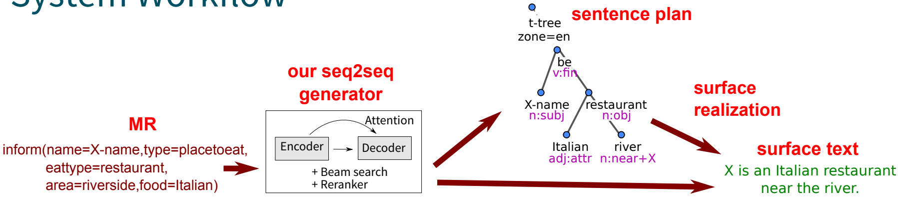

- main generator based on sequence-to-sequence NNs

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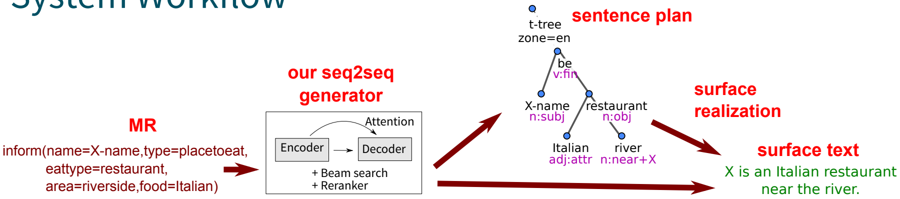

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- input: tokenized DAs

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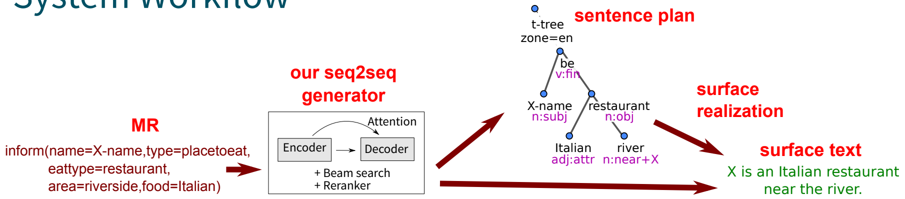

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  2-step mode – deep syntax trees, in bracketed format

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

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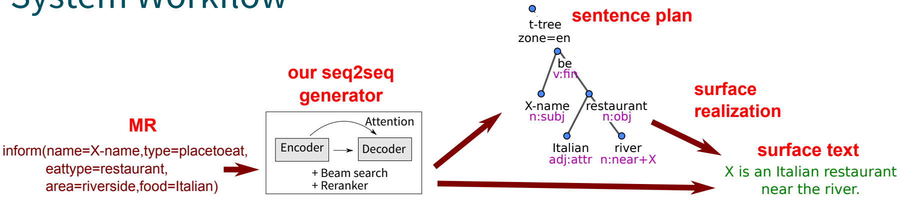

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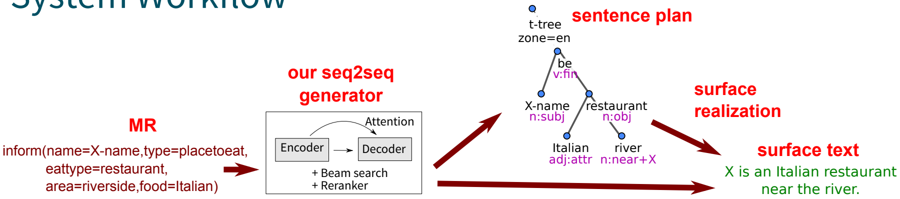

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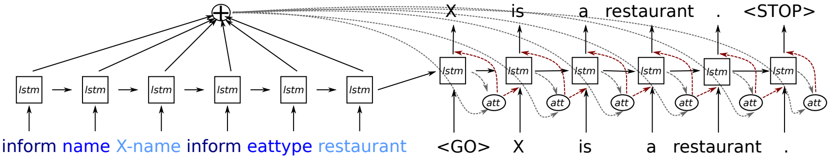
- 2-step mode: deep syntax trees post-processed by a surface realizer

Our Seq2seq Generator architecture



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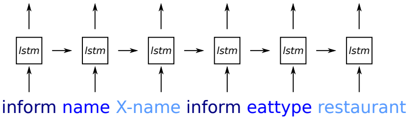

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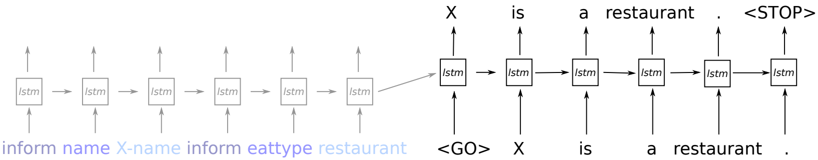

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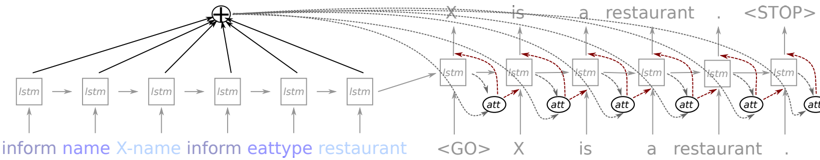

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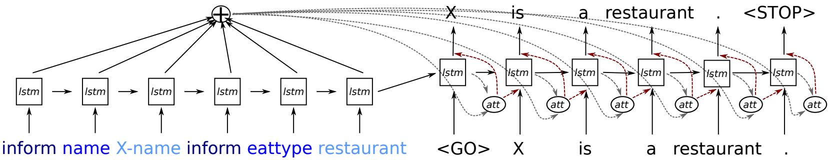

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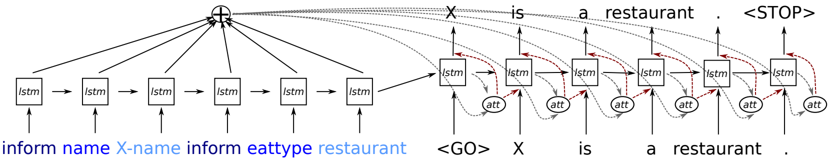

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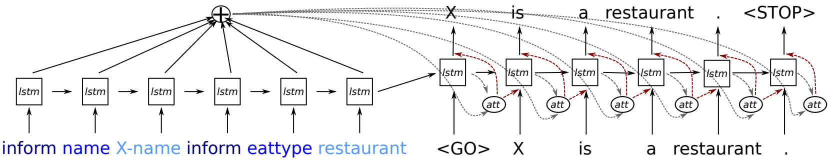

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  + reranker ($\rightarrow$)

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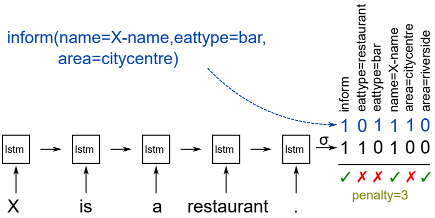

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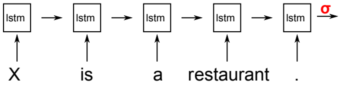

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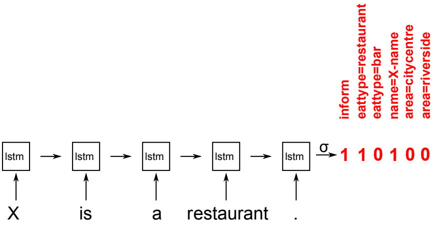

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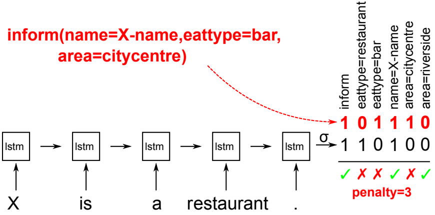

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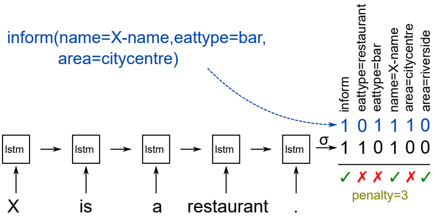

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- 10-fold cross-validation
    - automatic metrics: BLEU, NIST
    - manual evaluation: semantic errors on 20% data (missing/irrelevant/repeated)

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 5)	60.77	5.487	24
		(beam size 10)	60.93	5.510	25
		(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
		(beam size 100)	**62.76**	**5.669**	**19**

Sample Outputs

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

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

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.

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- different types of errors
  - joint: confusion of similar items (*Italian* vs. *French*)
  - 2-step: disfluency, missing/superfluous/repeated items
- joint generation works better on our domain (+2% BLEU)
- better results than our previous work with unaligned data

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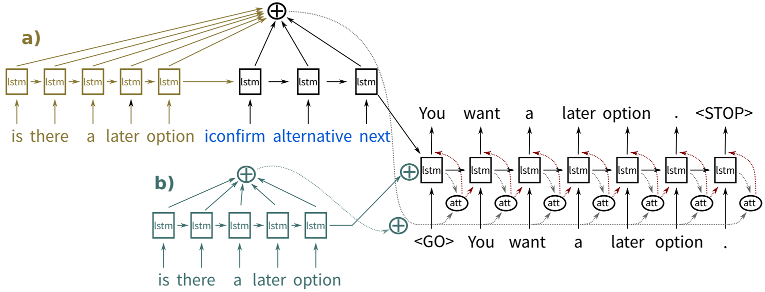
I'm headed to Rector Street
inform(from_stop="Fulton Street", vehicle=bus, direction="Rector Street",
departure_time=9:13pm, line=M21)
Heading to Rector Street from Fulton Street, take a bus line M21 at 9:13pm.

Context in our Seq2seq Generator (1)

- Two direct context-aware extensions:



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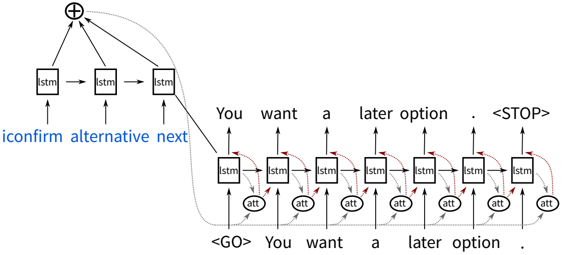
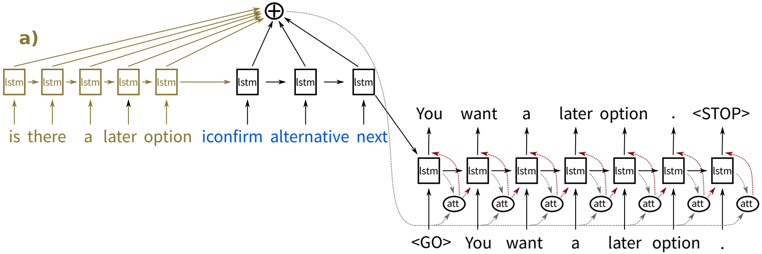


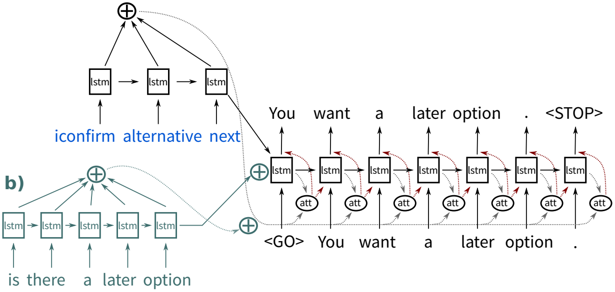
Context in our Seq2seq Generator (1)

- Two direct context-aware extensions:
  a) preceding user utterance prepended to the DA and fed into the decoder



Context in our Seq2seq Generator (1)

- Two direct context-aware extensions:
  a) preceding user utterance prepended to the DA and fed into the decoder
  b) separate context encoder, hidden states concatenated



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  - promoting outputs that have a word or phrase overlap with the context utterance

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 .

Context in our Seq2seq Generator (2)

- One (more) reranker: *n*-gram match
  - promoting outputs that have a word or phrase overlap with the context utterance
  - overlap measure: BLEU-2 without brevity penalty:

$$\text{logprob} \mathrel{+}= \text{weight} \cdot \sqrt{p_1 \cdot p_2}$$

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inform_no_match(alternative=next)

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  - delexicalized

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- Human pairwise preference ranking (crowdsourced)
  - baseline × 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.
Prepending context + *n*-gram match reranker	You want a later connection.
Context encoder + *n*-gram match reranker	You want a later option.

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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.

Output Examples

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.

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Future Plans

- Longer context
- Fuzzy *n*-gram matching
- Avoiding delexicalization
- Integrate into an end-to-end SDS

Thank you for your attention

Download it!

- Code: `bit.ly/tgen_nlg`
- Dataset: `bit.ly/nlgdata`

Contact me

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