A Conversational Neural Language Model for Speech Recognition in Digital Assistants

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1. Introduction

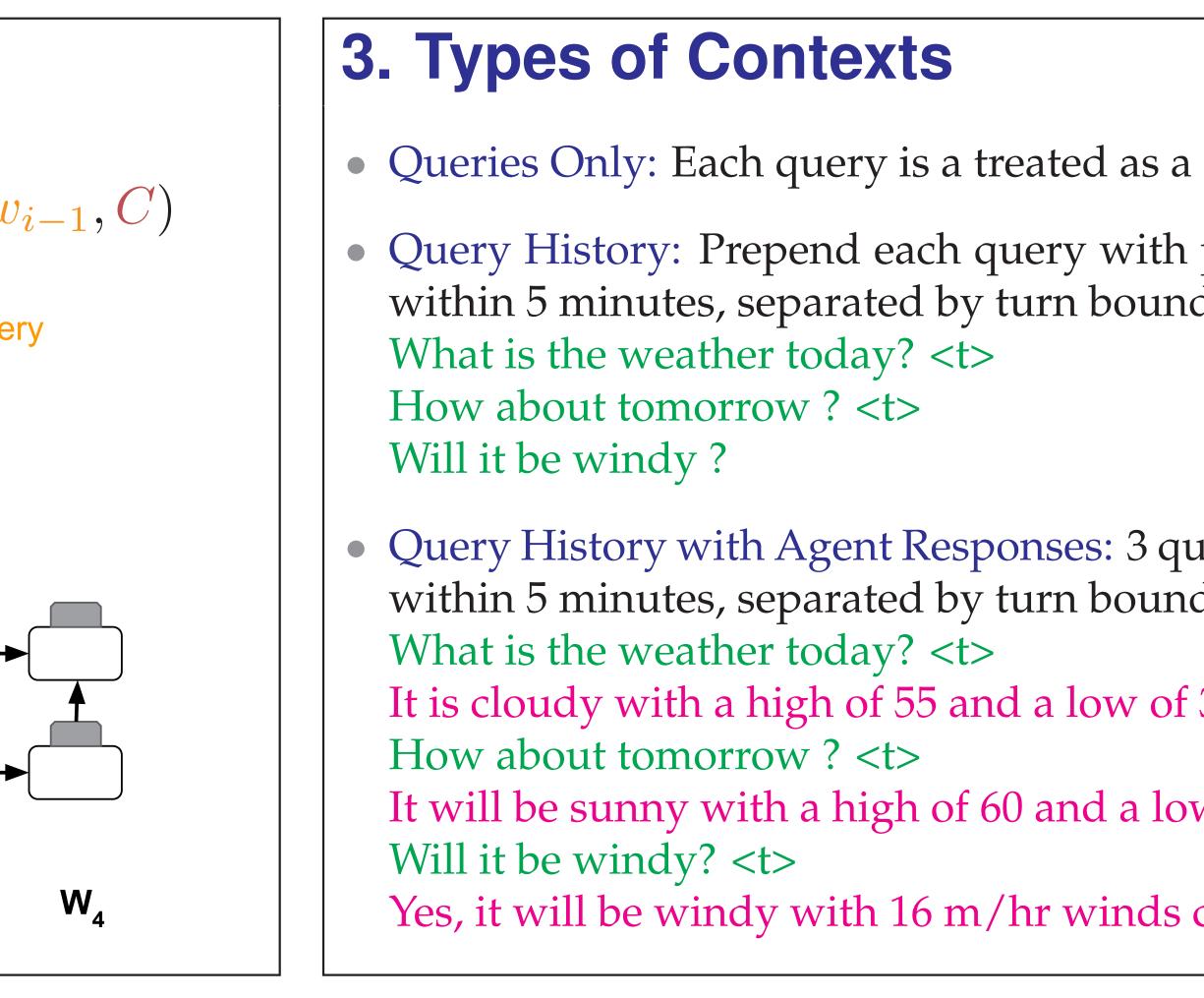
- Conversations with digital assistants are centered around topics
- Can a recurrent neural network language model make use of context in a conversation to improve ASR?
- Prior work in modifying network architectures to incorporate the speaker turn/context
- This work:
- Uses a standard LSTM language model architecture
- Achieves a 4% relative WER reduction on Google Assistant

2. Conversational Context LSTM LM $P(w_1, w_2, \dots, w_T | C) = \prod_{i=1}^T p(w_i | w_1 w_2, \dots, w_{i-1}, C)$ **Current Query** Context Target Vocabulary 100k W, W'_ **W'** Softmax Recurrent Projection 512 LSTM layer 2048 **Recurrent Projection** 512 2048 LSTM layer Word Embedding 1024 Input Vocabulary 100k W_2 W₁ W₂

4. Speech Recognition setup

- Training data: Anonymized queries/responses from Ga in US English
- 16.9B tokens from sequences with responses and 6.3E sequences without responses
- LSTM LM has a vocabulary of 100k tokens
- LSTM LM rescoring on lattices generated using a 5-gram
- 2nd pass interpolation weight of 0.5

• Given the previous queries with/without agent responses, can we improve the language model for the current quer



oogle Assistant	 LSTM LM initialized using tokens with/without the agent responses
B tokens from	 Previous queries are from the ASR outpute tem
	• Test sets
n LM	• Testset A has 16k tokens sampled from (
	 Testset B is a subset of Testset A with 1 previous query/response pairs per utter

	Model	Testset A	Testset B
	No context	11.9	12.5
	w/ query context	11.6	12.2
	 Using previous queries improves recognition 		
	Gains are mostly from question	answering	type conversa
'Y?	Common corrections are acoust	tically confu	sable words:
	 If previous query includes a nunner 	mber, the co	ontextual mod
	6. Do previous respor	ises hel	p?
sentence	Model	Testset A	
previous 2 queries spoken laries	Only queries Queries + Response	s 11.6 11.5	12.2 12.1
	• Wins on short queries such as <i>n</i>	o, where age	ent response i
	• Question words (e.g. <i>what</i>) had more errors wrt baseline		
eries with agent responses aries	 Hypothesis: Model is trained on both queries/responses a proportion of question words than baseline trained on question 		
32 <t></t>	• Two approaches to address the mismatch:		
v of 40 <t></t>	 Restrict LSTM LM vocabulary to words from queries c Add a recency bias for queries by presenting respon lowed by queries. 		
oming from the west	query ₁ , response ₁ , query ₂ , response ₂ , query ₃ , response \Rightarrow response ₁ , response ₂ , response ₃ , query ₁ query ₂ , query ₂		
	Model	Testset A	Testset B
from previous queries	Vocab from queries Priority on queries	11.6	12.3 12.1
to simulate an actual sys-	 Restricting the vocabulary to queries does not help 		
	 Recency bias on queries helps! 		
oogle Assistant traffic	6. Conclusions		
2.6k tokens with exactly 2 nce	 Strategies for training a standard LSTM LM on conver from a digital assistant 		
	• Experimented with a variety of	inputs for th	raining the m
	• Obtained a 4% relative improve	mont in orr	or rata on Caa

ations

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is useful

and sees less ueries only

only

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ogle Assistant

