ACL Anthology

Presentation on

Fluent Response Generation for Conversational Question Answering

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- BERT-based Response Classifier.
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- Final Evaluation: Seq2Seq vs Baseline models.

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- Summary of the Contributions

01 About the Research Paper

Paper Title: Fluent Response Generation for Conversational Question Answering

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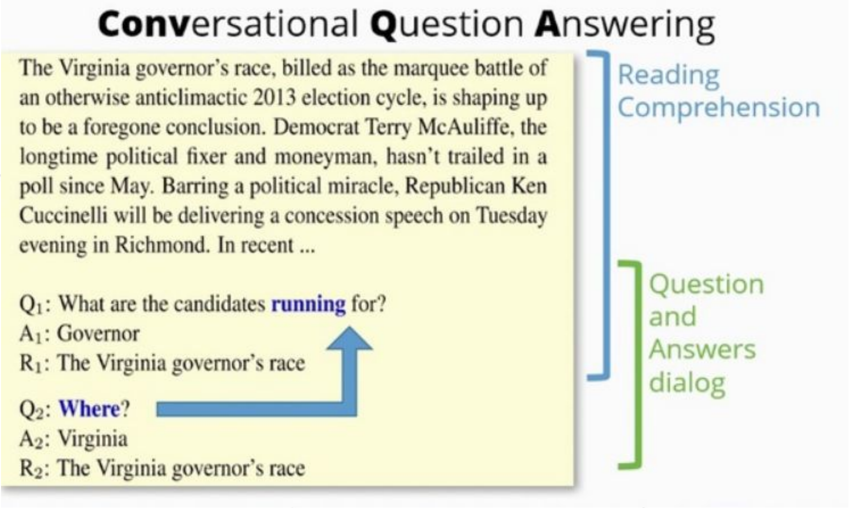
02 Fluent Conversational QA: Definition



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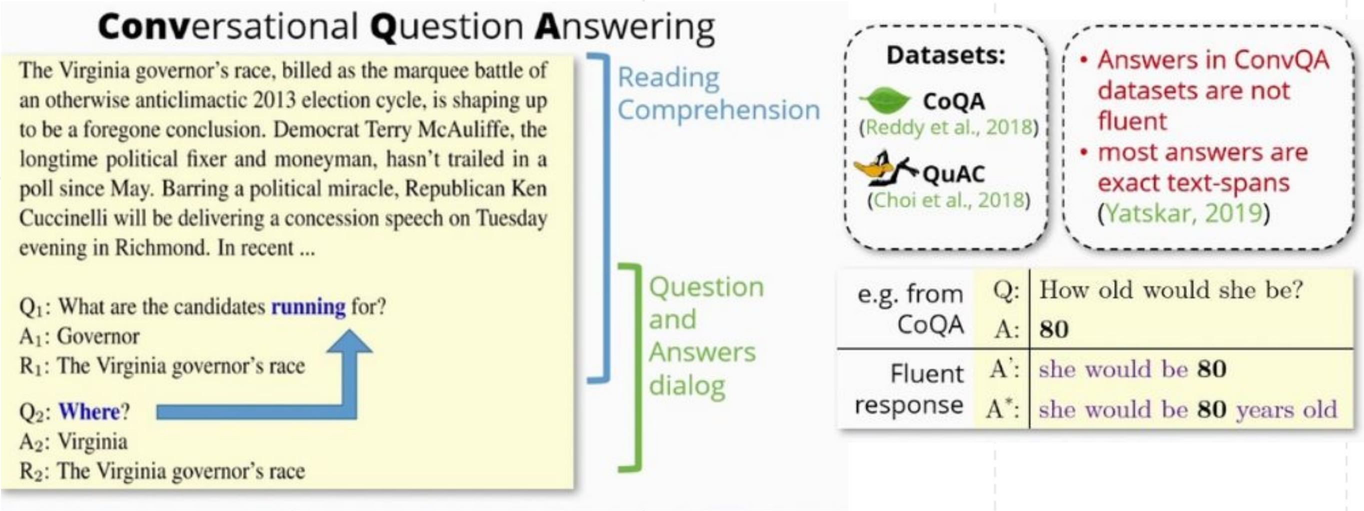

02 Fluent Conversational QA: Definition

Conversational Question Answering

The Virginia governor's race, billed as the marquee battle of an otherwise anticlimactic 2013 election cycle, is shaping up to be a foregone conclusion. Democrat Terry McAuliffe, the longtime political fixer and moneyman, hasn't trailed in a poll since May. Barring a political miracle, Republican Ken Cuccinelli will be delivering a concession speech on Tuesday evening in Richmond. In recent ...

Q_1: What are the candidates **running** for?
A_1: Governor
R_1: The Virginia governor's race

Q_2: **Where**?
A_2: Virginia
R_2: The Virginia governor's race

Reading Comprehension

Question and Answers dialog

Datasets:

- CoQA (Reddy et al., 2018)
- QuAC (Choi et al., 2018)

- Answers in ConvQA datasets are not fluent
- most answers are exact text-spans (Yatskar, 2019)

e.g. from CoQA	Q:	How old would she be?
	A:	**80**
Fluent response	A':	she would be **80**
	A*:	she would be **80** years old

Data augmentation + Neural Dialog models → Fluent Response Generation in ConvQA

Preview of our generation model

Q :	what revolt did he lead after that ?
CoQA:	**autumn harvest uprising**
Ours:	he led the **autumn harvest uprising**

02 Fluent Conversational QA: Case Study

Problem Statement: Given a question ***q*** and the answer span ***a***, have to generate an answer ***r*** which is right, fluent and grammatically correct.

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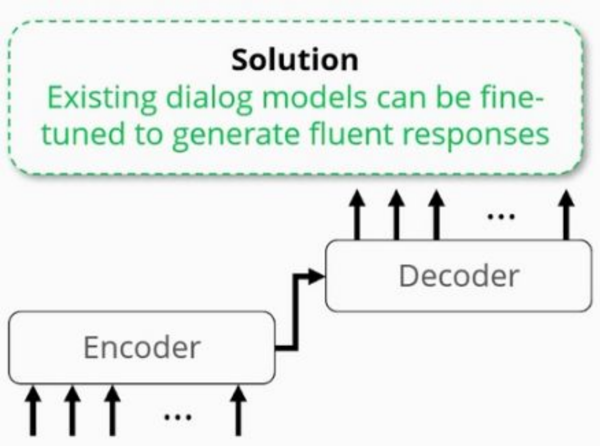

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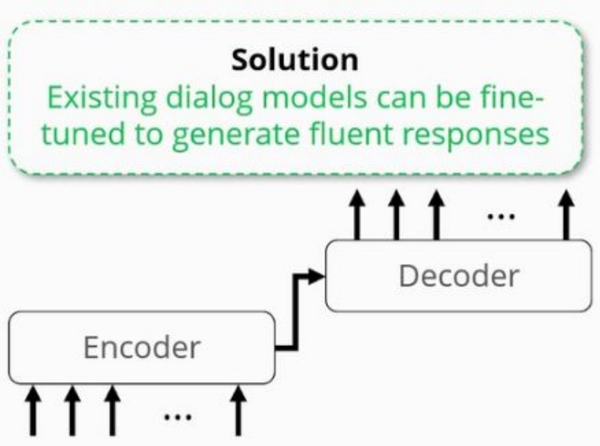

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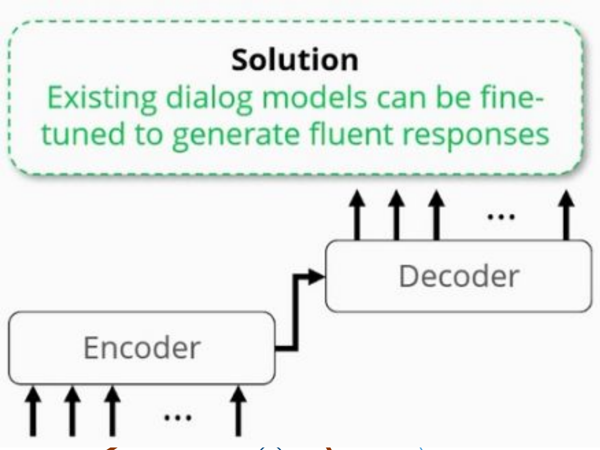
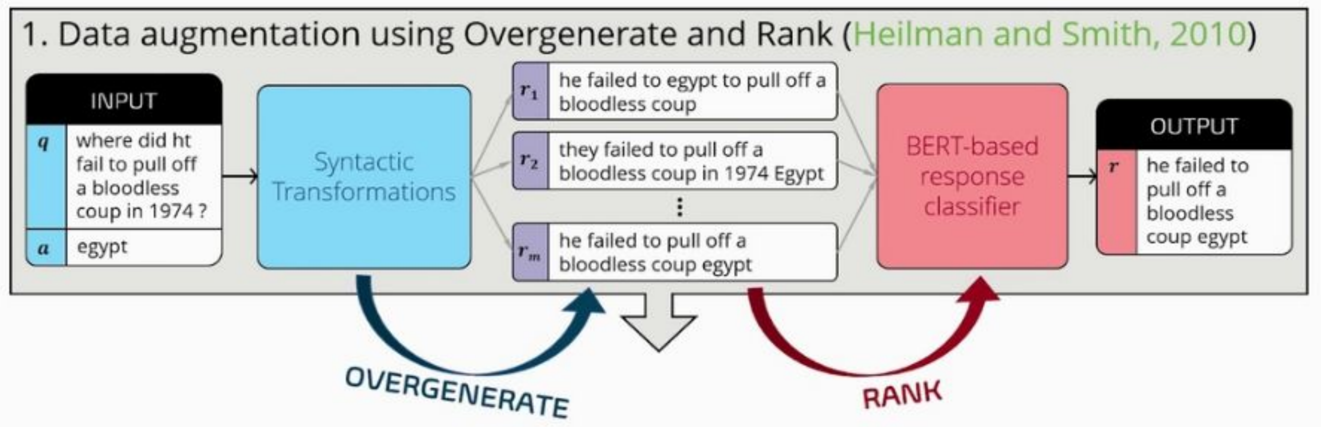


Crowdsourcing a fluent QA dataset is expensive

Transform existing QA dataset to support fluent answer-responses using **data augmentation**!

03 Proposed Model



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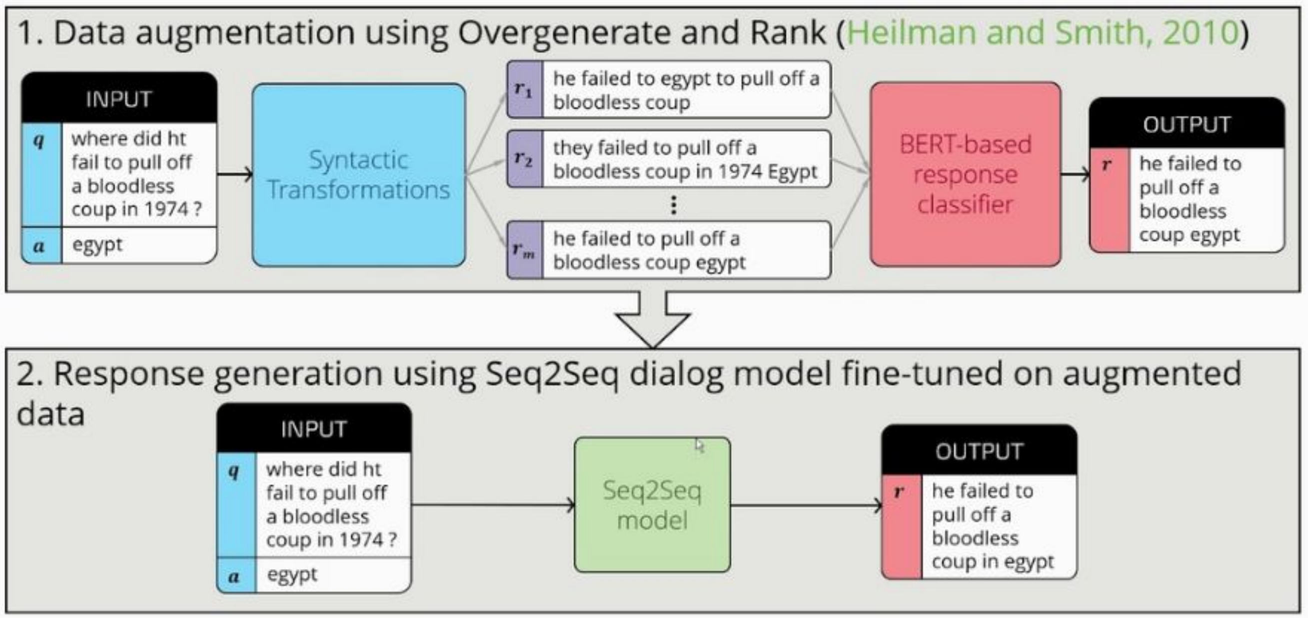

03 Syntactic Transformation

Multiple Syntactic Transformations (STs) on questions (***q***) builds parse tree to generate a huge list of candidate responses,

$$\boldsymbol{R}=\{r1, r2, \ldots, rm\}$$

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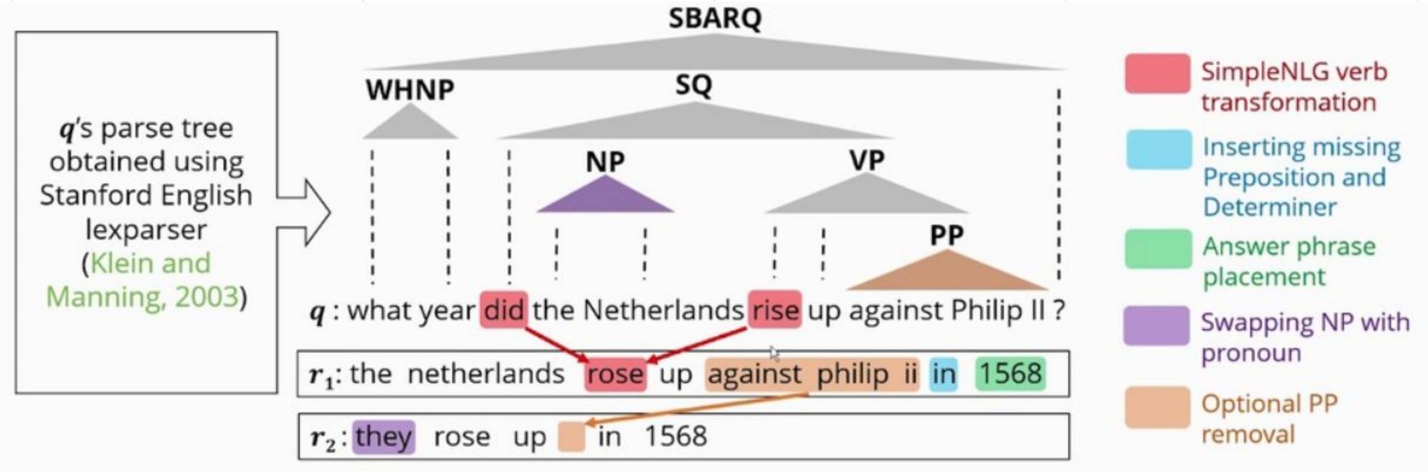

For the dataset used in this paper, this 5 properties of STs can generate **m>5000** responses

03 BERT based Classifier

BERT based sentence pair classifier (***F***) used to predict the most suitable response (***r***) for a question (***q***) from the candidate responses (***R***).

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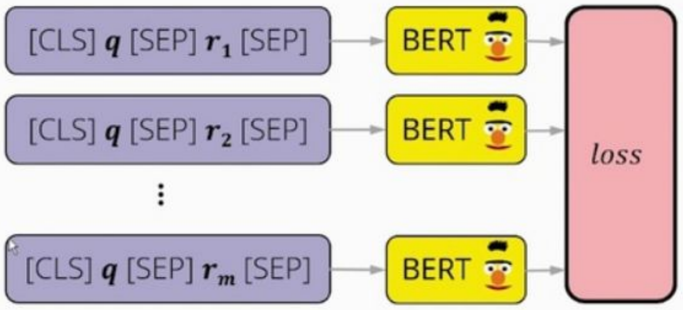
Model Trained using objective based error margins (***M***)

$$M_j(F) = F(q, a, r_1) - F(q, a, r_j)$$

$$Softmax\ loss = \log(1 + \sum_{j=2}^{m} e^{-M_j(F)})$$

Key idea:

Unsuitable responses should be ranked lower than the suitable ones



03 BERT based Classifier

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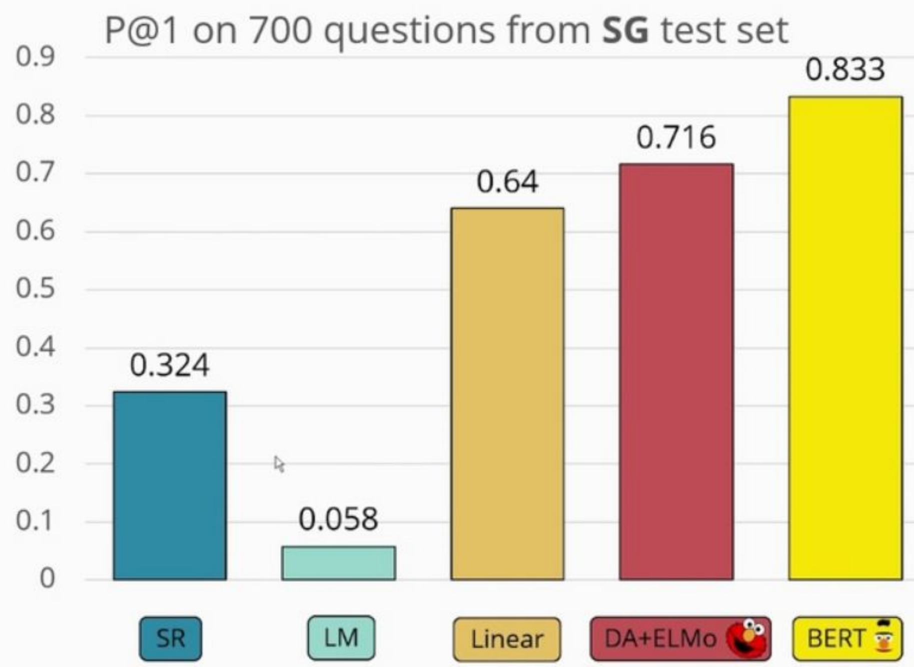
Training data Acquisition

1. Generate candidate responses for $(\boldsymbol{q}, \boldsymbol{a})$ from SQuAD 2.0 (Rajpurkar et al., 2018)
2. crowd-annotate best responses for ***3000*** $(\boldsymbol{q}, \boldsymbol{a})$ to get SQuAD Gold (**SG**) dataset
3. Split **SG** into ***2000/300/700*** to get ***train/dev/test*** segments

03 BERT vs Other Baseline Models

Abbr.	Sentence Pair Classification Model
SR	Shortest Response
LM	Language Model
Linear	Linear classifier using features inspired from (Heilman and Smith, 2010) and (Wan et al., 2006)
DA + ELMo	Decomposable Attention (Parikh et al., 2016) with ELMo (Peters et al., 2018) embedding
BERT	$\text{BERT}_{\text{BASE}}$ uncased (Devlin et al., 2019) response classifier



03 Sequence to Sequence (Seq2Seq) Dialogue Model

Why S2S is **NEED** even after ST+BERT can generate expected output?

1. Parser fails to recognize questions ~20% of the time
2. All the candidate responses generated by STs can be incorrect!
3. Extending STs requires lot of manual efforts

03 Seq2Seq vs Baseline Models

Using STs+BERT on (***q,a***) pairs from SQuAD Dataset, Natural Questions Dataset and HarvestingQA dataset, almost **1 million** instances for **SNH** data has been achieved.

Seq2Seq Dialogue Model	Dataset Details
Pointer Generator Network (**PGN**)	14 millions question-only subset of OpenSubtitles Dataset
Generative Pretrained Transformer (**GPT-2**)	
Dialogue GPT-2 (**DGPT**)	147 millions Reddit conversation

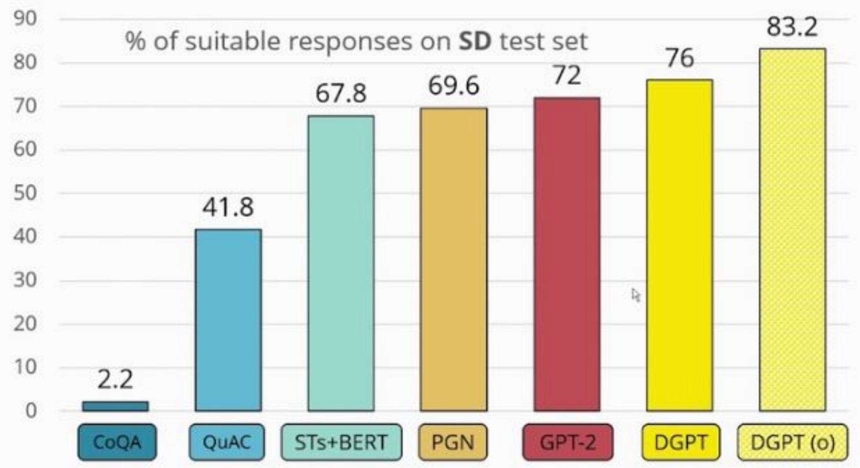
Baseline Models
BERT-based model trained on **CoQA** dataset
BiDAF model trained on **QuAC** dataset
Data augmentation used to create SNH data to train **STs+BERT** model

03 Seq2Seq vs Baseline Models

Evaluation on a sample of 500 test instances from SQuAD 2.0 Dataset, named SD test Data

Human annotators judge a response if it is suitable, grammatically correct, complete sentence with the fluent correct answers or not.

03 Seq2Seq vs Baseline Models



Most answers from **CoQA** and **QuAC** are either exact-answer spans or answer-spans with few surrounding words

~18% of **STs + BERT** responses are exact answer spans (parser failures)

All **Seq2Seq** models outperform **STs+BERT** baseline thanks to dialog pretraining

With oracle answer-spans **DGPT** can do even better!

04 In the End: Example Responses

	Question	**_Which sea was oil discovered in?_**
Answers	CoQA	North Sea
	QuAC	“It’s scotland’s oil” campaign of the scottish national party (snp)
	STs+BERT	Oil was discovered in north
	DGPT	It was discovered in the north sea

04 In the End: Summary of the Contributions

- Data Augmentation method: STs+BERT classifier can transform existing datasets to generate fluent responses.
- Dialogue GPT model outperforms the STs+BERT augmentation by exploiting dialogue pretraining.
- Proposed model in this research doesn’t require any QA passage to generate fluent responses.

“When you don’t understand, it’s sometimes easier to look like you do as you like.”

— Malcolm Forbes

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