

# Ditch the Gold Standard: Re-evaluating Conversational Question Answering

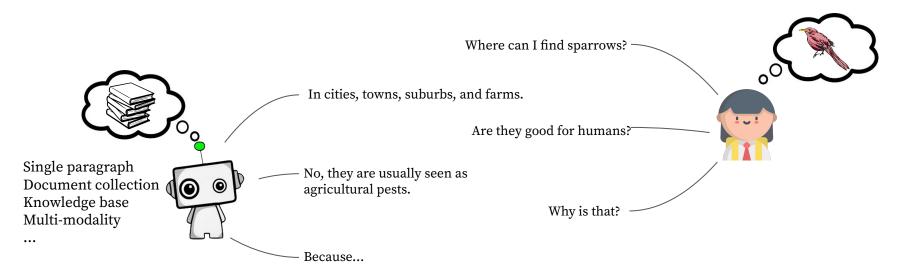
Huihan Li\*, Tianyu Gao\*, Manan Goenka, Danqi Chen

ACL 2022



## Background: Conversational Question Answering

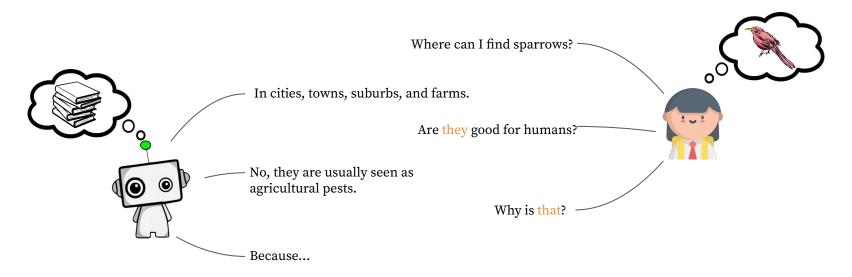
Conversational QA aims to build machines that answer human questions in *information-seeking conversations* 





## Background: Conversational Question Answering

Conversational QA aims to build machines that answer human questions in *information-seeking conversations* 



Challenge: Questions need to be understood from *conversation history* 



### Conversational Question Answering Datasets

QuAC (Choi et al., 2018) CoQA (Reddy et al., 2019) DoQA (Campos et al., 2020)

#### Single paragraph

OR-QuAC (Qu et al., 2020) TopiOCQA (Adlakha et al., 2021) QReCC (Anantha et al., 2021)

**Document collection** 

Visual Dialog (Das et al., 2017) ShARC (Saeidi et al., 2018) CSQA (Saha et al., 2018)

**Knowledge bases or other modalities** 



## Flaws in Conversational QA Evaluation

Benchmarks consist of *pre-collected* human-human conversations

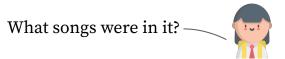
QuAC (Choi et al. 2018)



What was the band's first success album at the international level?











## Flaws in Conversational QA Evaluation

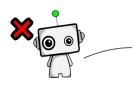
Benchmarks consist of *pre-collected* human-human conversations



What was the band's first success album at the international level?

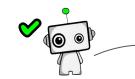


Gold answers are always provided during evaluation even when predictions are wrong



They achieved platinum status. "Parade" from 1984.

**Problem:** Models *do not* have access to gold answers in real-world human-machine conversations!



What songs were in it?



"Only When You Leave".



## Questions of Interest

- How do current conversational QA models perform in **human-machine conversations**?
- Can current automatic evaluation **reflect human judgment**?
- How can we improve current automatic evaluation?
- What are important for a **good** conversational question answering **model**?

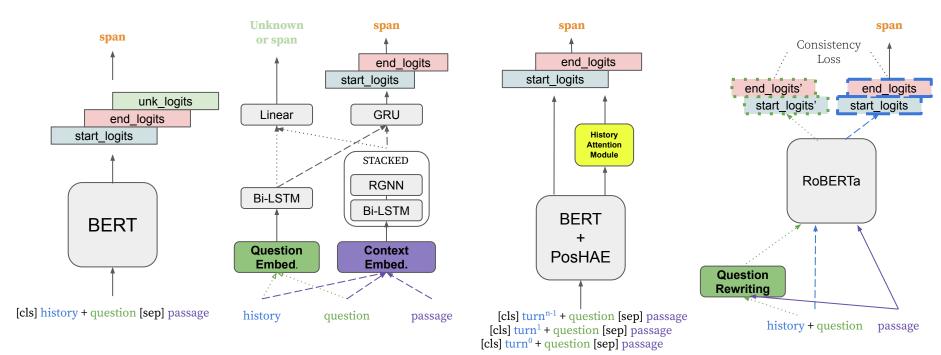
#### Models



We experiment with four state-of-the-art ConvQA models

BERT (Devlin et al. 2019) GraphFlow (Chen et al. 2019) HAM (Qu et al. 2019)

ExCorD (Kim et al. 2021)





#### What do human-machine conversations look like?

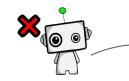


Humans can *adjust* the next question based on the model prediction.

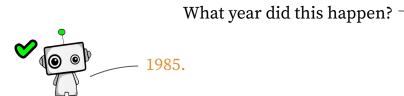
Different models might result in different conversations.

What was the band's first success album at the international level?





They achieved platinum status.





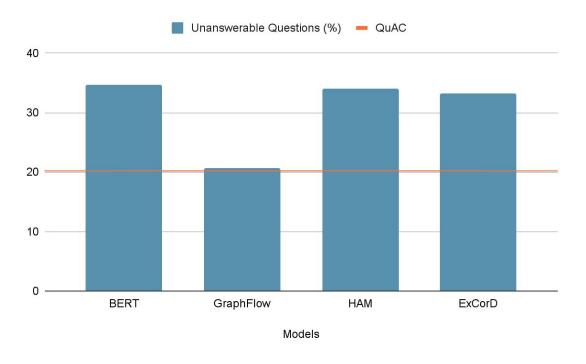


### **Human Evaluation**

- uation amazon mechanical turk
- 100 QuAC (Choi et al. 2018) dev set evidence passages
- 1,446 human-machine conversation
- 15,059 question-answer pairs
- Released on https://github.com/princeton-nlp/EvalConvQA/



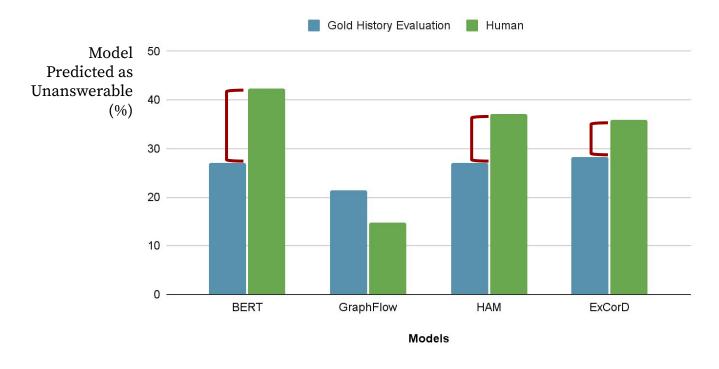
#### 1. Are human-machine conversations similar to human-human conversations?



Humans ask more unanswerable questions in human-machine conversations than in human-human conversations



#### 1. Are human-machine conversations similar to human-human conversations?



Models predict more questions as unanswerable in human-machine conversations than in gold history evaluation



#### 1. Are human-machine conversations similar to human-human conversations?

**Title:** Superstar Billy Graham

**Section title:** Disputes with the McMahons

**Q1:** What disputes did he have? — We provide the first question from QuAC

**A1:** *CANNOTANSWER* 

**Q2:** Where is Billy from? Asks an unanswerable question

**A2:** *CANNOTANSWER* 

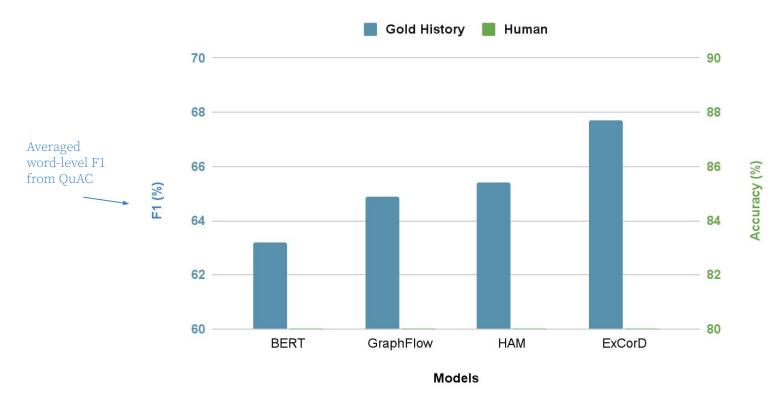
**Q3**: What else is interesting about this article? Asks an open question

**A3:** Graham personally sued Zahorian and the WWF

Because of *low-quality model answers*, humans ask more **unanswerable questions** and **open questions** 

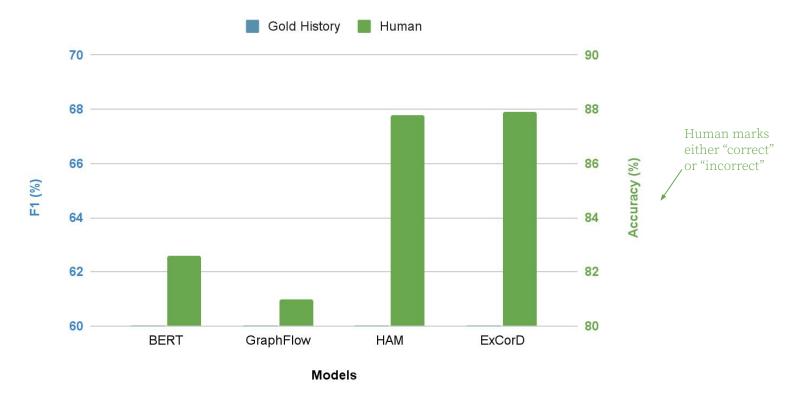


### 2. Does gold history evaluation agree with human judgement?



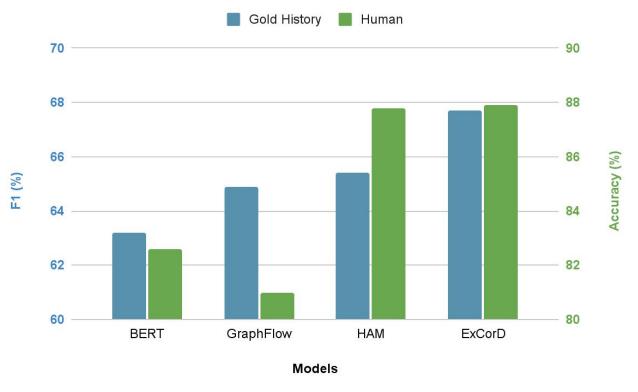


### 2. Does gold history evaluation agree with human judgement?





### 2. Does gold history evaluation agree with human judgement?

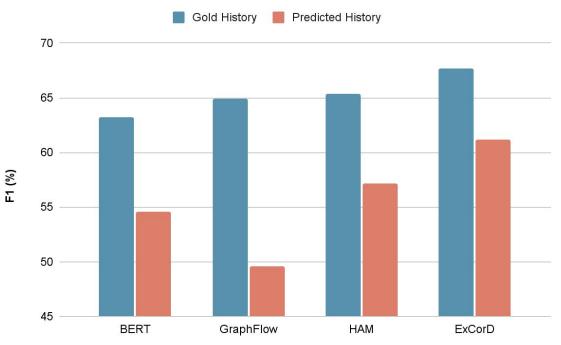


Gold history evaluation ranks models differently from human judgement!

Can we do better in automatic evaluation?



#### 1. Can we simply use the models' prediction in history? (Mandya et al., 2020; Siblini et al., 2021)

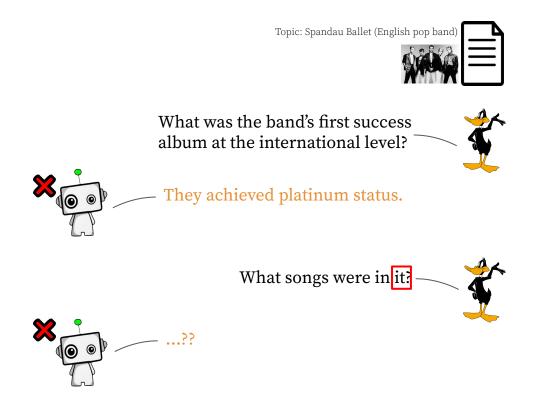


Predicted history evaluation has a large performance drop from gold history evaluation

... which is expected from low-quality model predictions

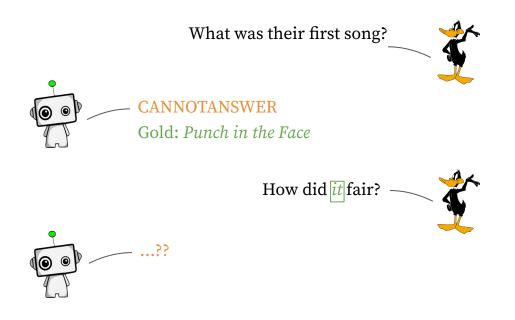


#### Simply using model predictions may invalidate the next question





#### Unresolvable Coreference



A pronoun or a definite article reference (eg. *the film*) that is **not resolvable** from the conversation history



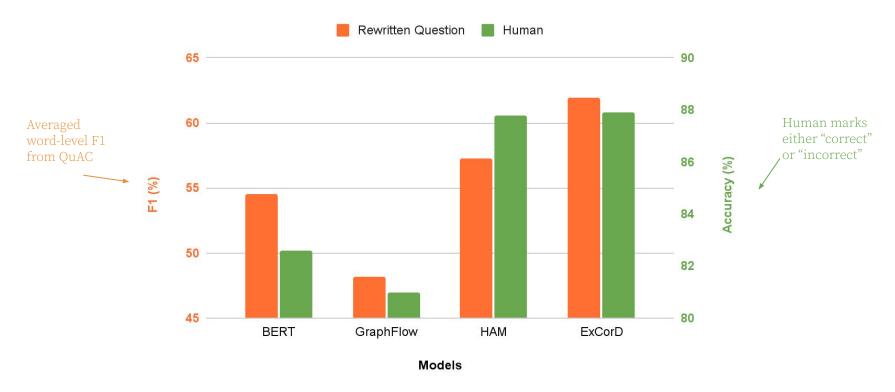
### Rewrite question with unresolvable coreference





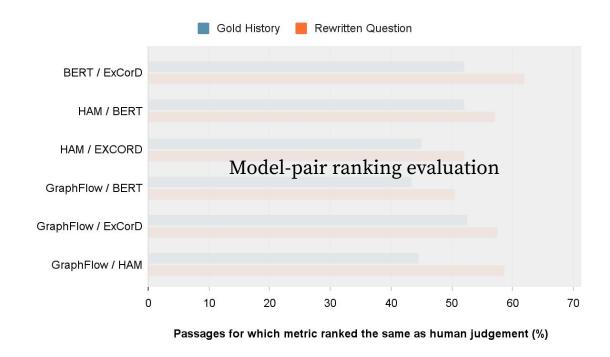
- Use coreference resolution model (Lee et al. 2018) to resolve the entity-of-interest in current question using the *gold history* and *predicted history*, separately
- If the resolutions do not match, substitute the entity-of-interest with its mention in *gold history*
- If the resolutions match, no need to rewrite





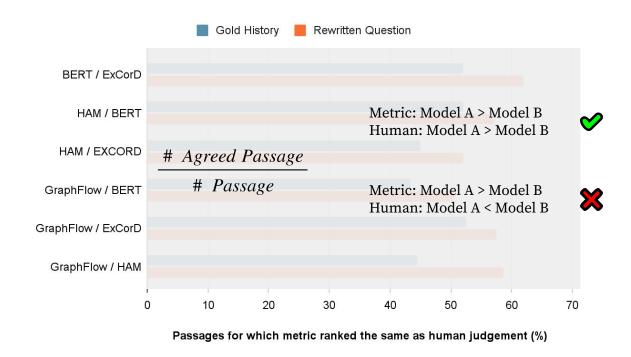
Rewritten question evaluation ranks the models the same way as human judgement



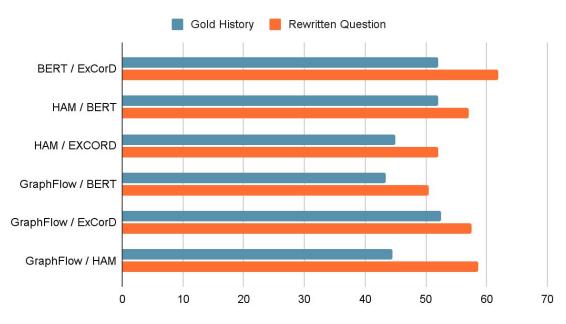


23



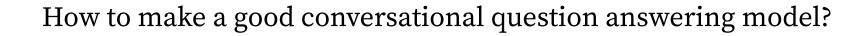






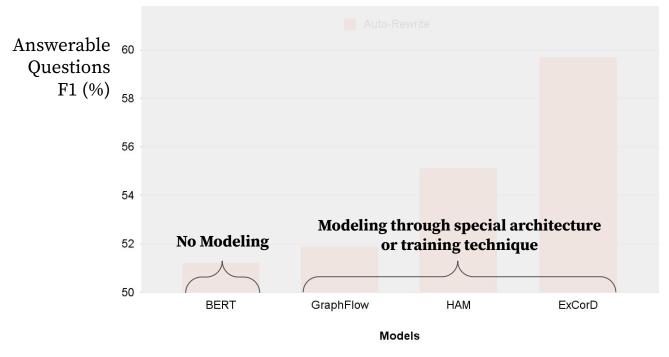
Passages for which metric ranked the same as human judgement (%)

Rewritten question evaluation ranks the *passage-wise model performance* **more similarly to humans** than gold history evaluation





#### 1. Modeling question dependencies on conversational context



Modeling question-history and question-context dependency helps with span prediction

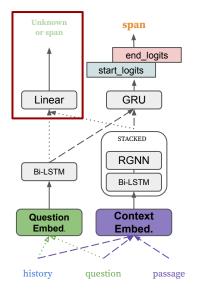


#### 2. Calculate "unanswerable" probability together with span probability



GraphFlow uses a *separate network* for predicting answerability, which is *harder to calibrate*.

GraphFlow (Chen et al. 2019)





### Summary

- We conduct the **first large-scale human evaluation** on conversational QA systems.
  - \* Human-machine conversations have *different question distribution* and *answer distribution* from human-human conversations.
  - ❖ Gold history evaluation of current benchmarks *does not agree* with human judgement in human-machine conversations.



### Summary

• We propose **a new evaluation protocol** with question rewriting.

- Simply using the model's prediction in history will result in *invalid* questions because of incoherent history.
- Rewriting question evaluation *resolves* the invalid questions, and is *closer to human judgment*.



### Summary

- We provide some insight on better ConvQA Modeling.
  - \* Modeling question dependencies on conversational context helps with *span prediction*.
  - Calculating "unanswerable" probability together with span probability helps with answerability prediction.



#### **Future Direction**

- Training model for the Rewritten Question Evaluation protocol
  - o Train model using model's own prediction history (Mandya et al., 2020; Siblini et al., 2021)





### **Code & Human Evaluation Data**

https://github.com/princeton-nlp/EvalConvQA

#### **Email**

huihanl@princeton.edu