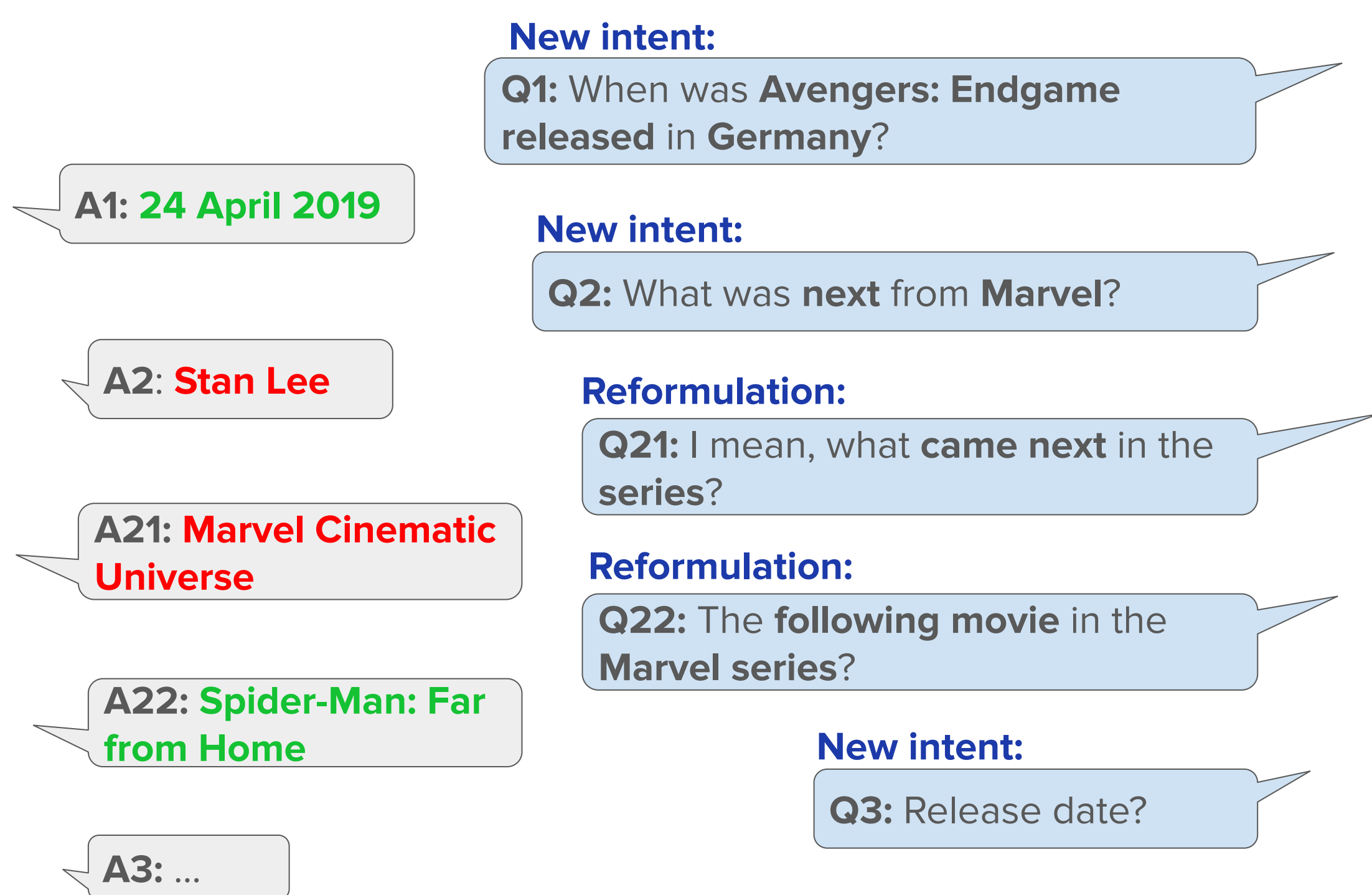


Reinforcement Learning from Reformulations in Conversational Question Answering over Knowledge Graphs

Magdalena Kaiser, Rishiraj Saha Roy and Gerhard Weikum

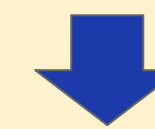
Max Planck Institute for Informatics, Germany

SAMPLE CONVERSATION



CONVERSATIONAL QA IS CHALLENGING

- **Short, incomplete** questions
- **Implicit** context



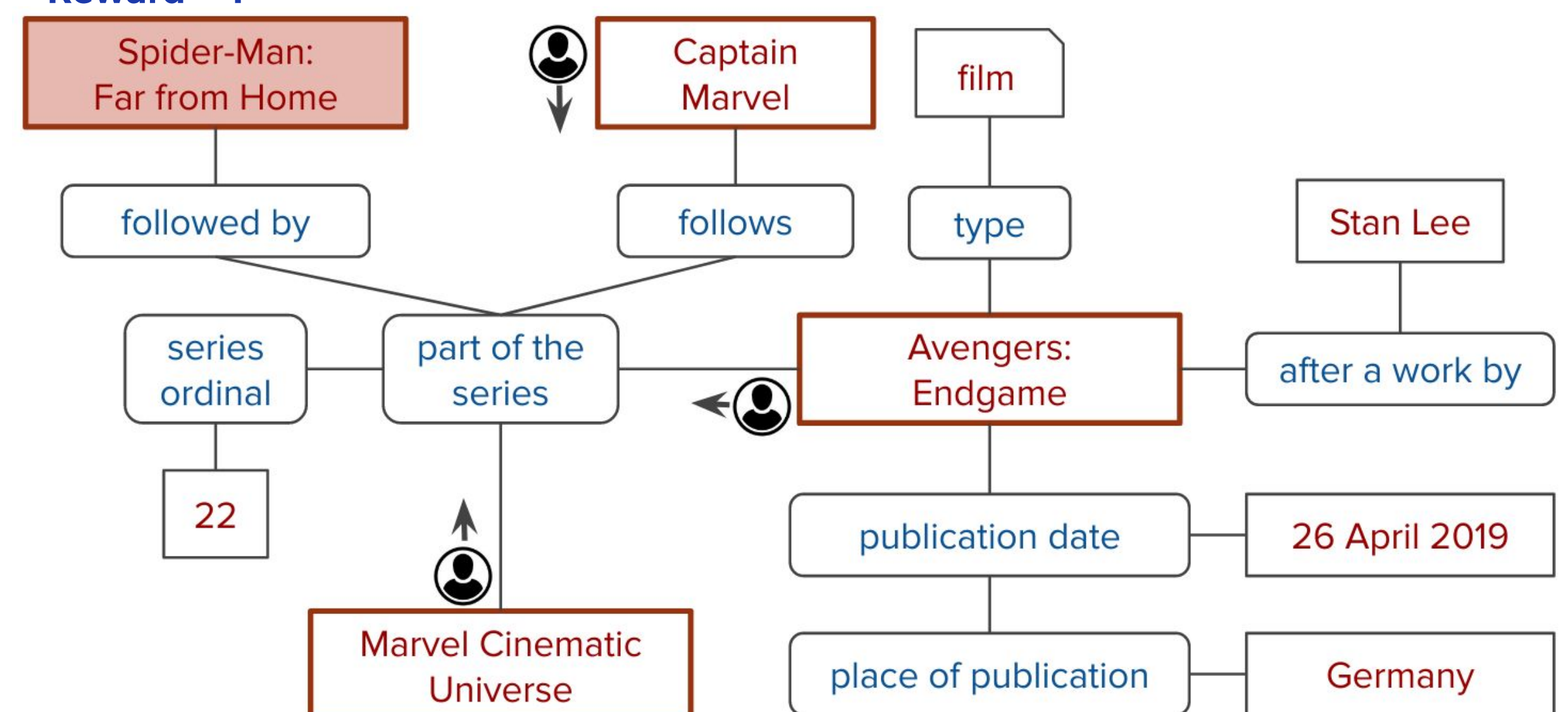
IMPROVING CONVQA BY LEARNING FROM FEEDBACK

- Current systems learn from gold QA pairs: unrealistic
- **CONQUER: Reinforcement learning model** for QA
 - Learns from **conversational stream** in the **absence of gold answers**
 - **Rewards** based on **reformulations: +1** (new intent = correct previous answer), **-1** (reformulation = wrong previous answer)
- **Reformulation detector** based on BERT
- **ConvRef: Conversational QA benchmark with reformulations**

CONQUER WORKFLOW

1. Detect **context entities** in conversation = **start points** for **agents' walk** by **scoring KG neighborhood**
2. **Predict path** by applying a **policy network trained with REINFORCE** algorithm
3. Generate answer: follow **sampled path** (during training), **take top scoring paths** and **aggregate answer** (at answering time)
4. **Predict** if **next question** is a **reformulation** by using a **fine-tuned BERT** model and give **reward** accordingly

Reward = 1

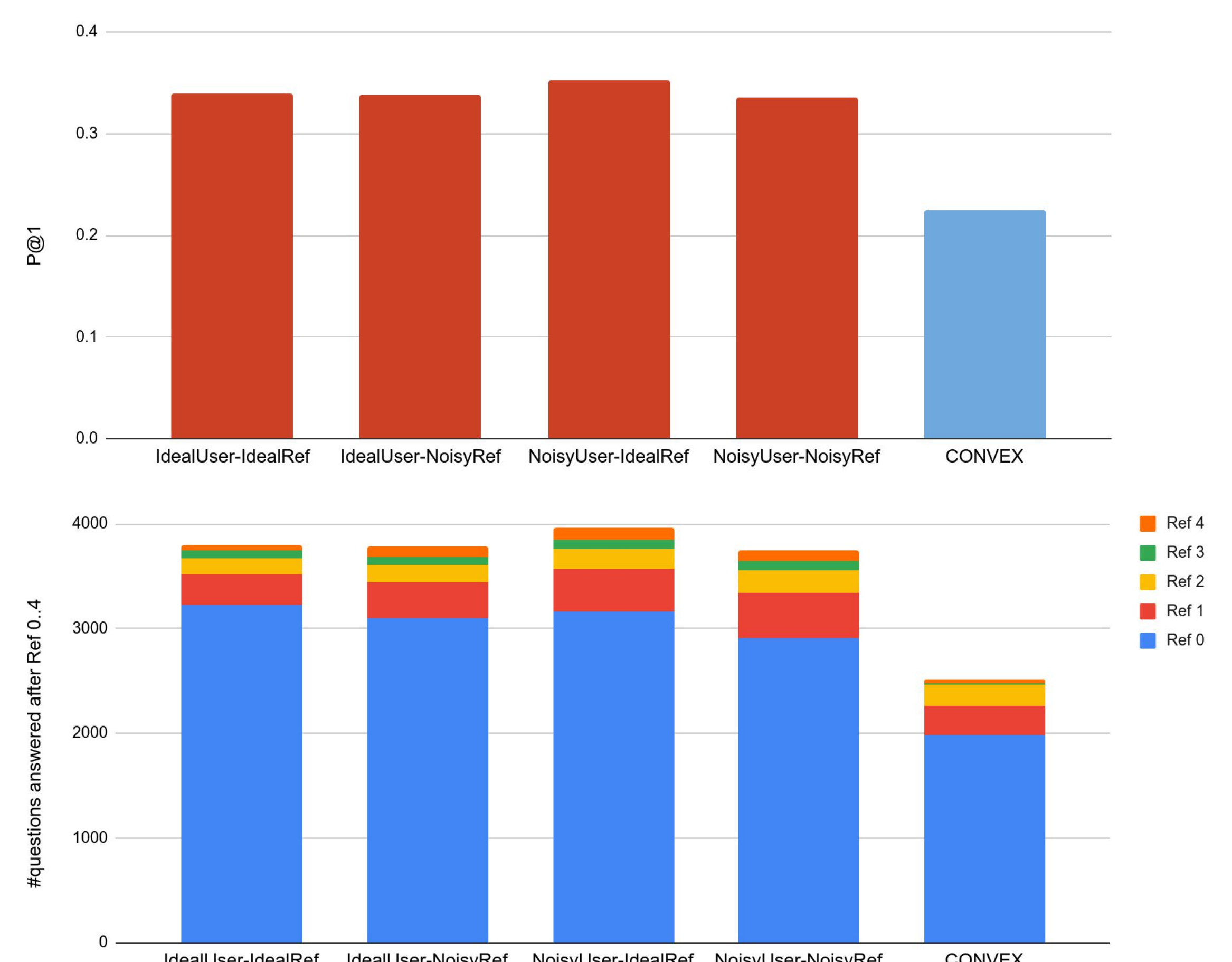


EXPERIMENTAL VARIANTS

- **Four variants** of CONQUER to model **two sources of noise** (**reformulation predictor** and **user behavior**):
- **Ideal Reformulation Predictor:**
 - No wrong predictions
- **Noisy Reformulation Predictor:**
 - Fine-tuned BERT model that can make wrong predictions
- **Ideal User Model:**
 - User behaves as in our assumption: reformulates if answer was wrong, otherwise issues new question
- **Noisy User Model:**
 - User can also ask new question even though previous answer was wrong

ConvRef BENCHMARK

- **Builds upon** conversational KG-QA dataset **ConvQuestions** (11k conversations from 5 different domains)
- **User study** to **collect reformulations** by **interacting** with **baseline QA system**
- **Different from paraphrases:** Reformulations **based on conversation history** and system-generated **wrong answer**



CONQUER SUCCESSFULLY LEARNS FROM REFORMULATIONS IN THE PRESENCE OF NOISE

- **CONQUER outperforms** SOTA **baseline CONVEX** on **ConvRef** and **ConvQuestions**
- **Similar performance** of CONQUER **variants**
- **CONQUER answers** more questions **earlier**: requires **less reformulations**

