

# Event2Mind: Commonsense Inference on Events, Intents, and Reactions

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[uwnlp.github.io/event2mind](https://uwnlp.github.io/event2mind)

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## Takeaways

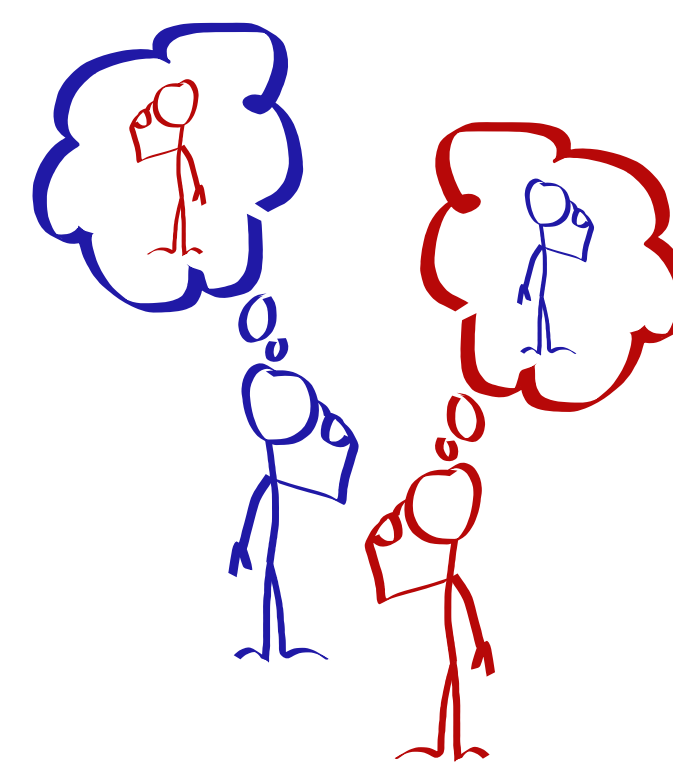
In this work, we:

- introduce the **new task** of reasoning about and generating people's **intents and reactions** in relation to events
- create a **new large knowledge graph** of **77K nodes** that supports this type of commonsense inference
- provide a **novel way to analyze gender bias** in movies using commonsense inference

## Commonsense Inference

Pragmatic reasoning about the mental states of people in relation to events

- Numerous AI systems need to anticipate people's *intents* and emotional *reactions* (e.g., conversational AI, ad ranking, narrative understanding)
- This type of social commonsense reasoning goes far beyond the widely studied entailment tasks (e.g., SNLI).



## Collecting Inference Data

### Annotated dimensions

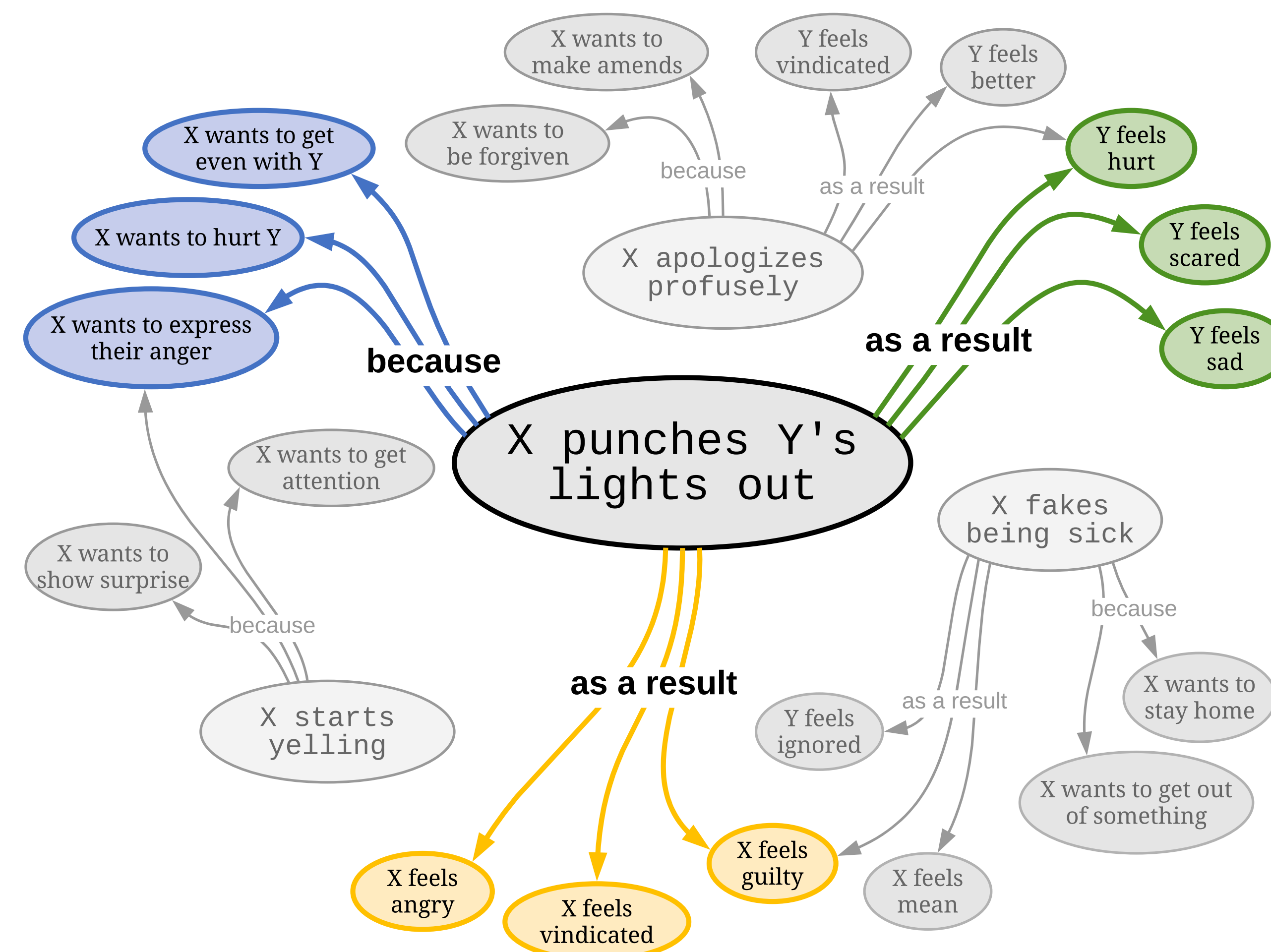
- PersonX's Intent** Why does X cause the event?
- PersonX's Reaction** How does X feel after the event?
- Others' Reaction** How do others feel after the event?

- Automatically extracted events from: ROC Stories, Google NGrams, Spinn3r, Wiktionary Idioms<sup>1</sup>
- Annotated by 3 Amazon MTurkers
- Moderate agreement  $\kappa = .45$



<sup>1</sup>Mostafazadeh et al., 2016; Goldberg & Orwant, 2013; Gordon & Swanson, 2008

## Commonsense Knowledge Graph



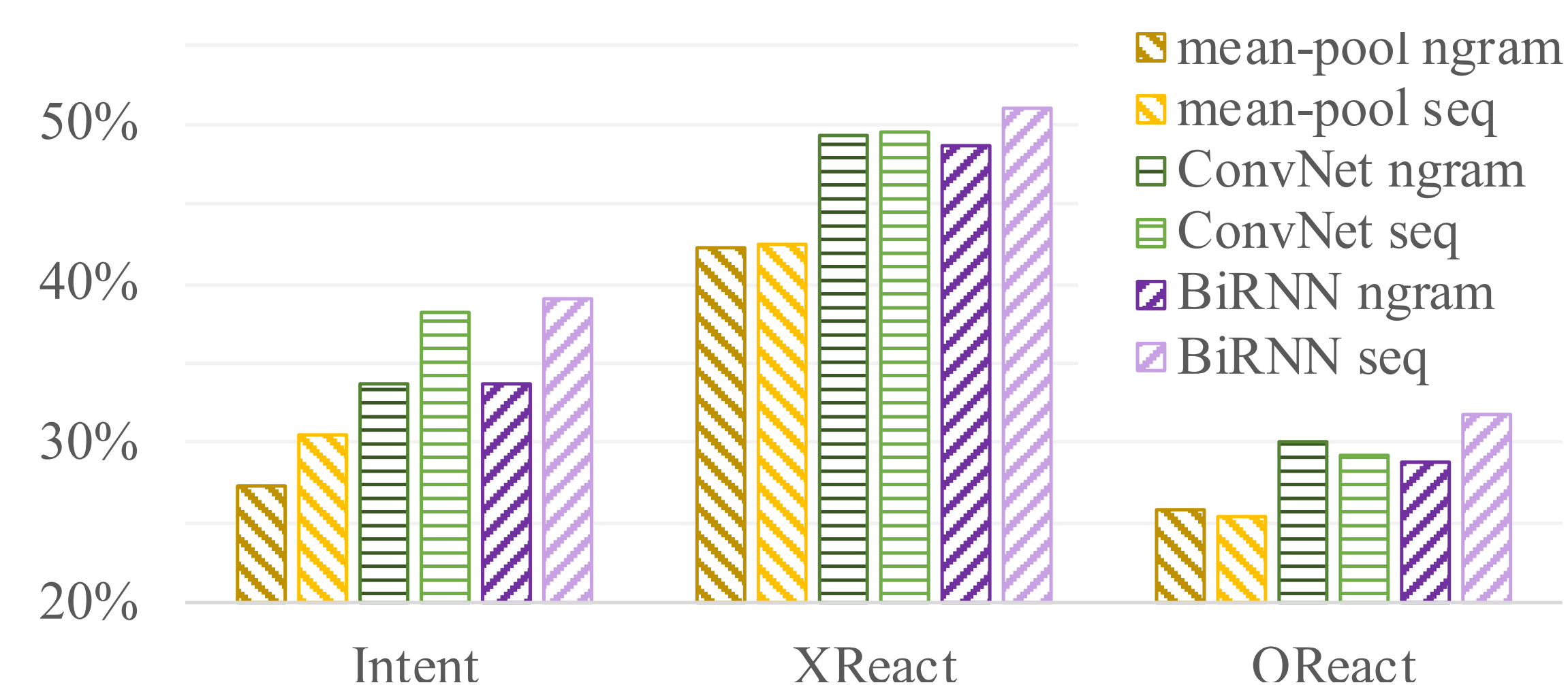
### Knowledge graph statistics

# unique events	24,716
# unique intents	33,373
# unique reactions	19,083
<b>total # nodes</b>	<b>77,172</b>

### Annotation statistics

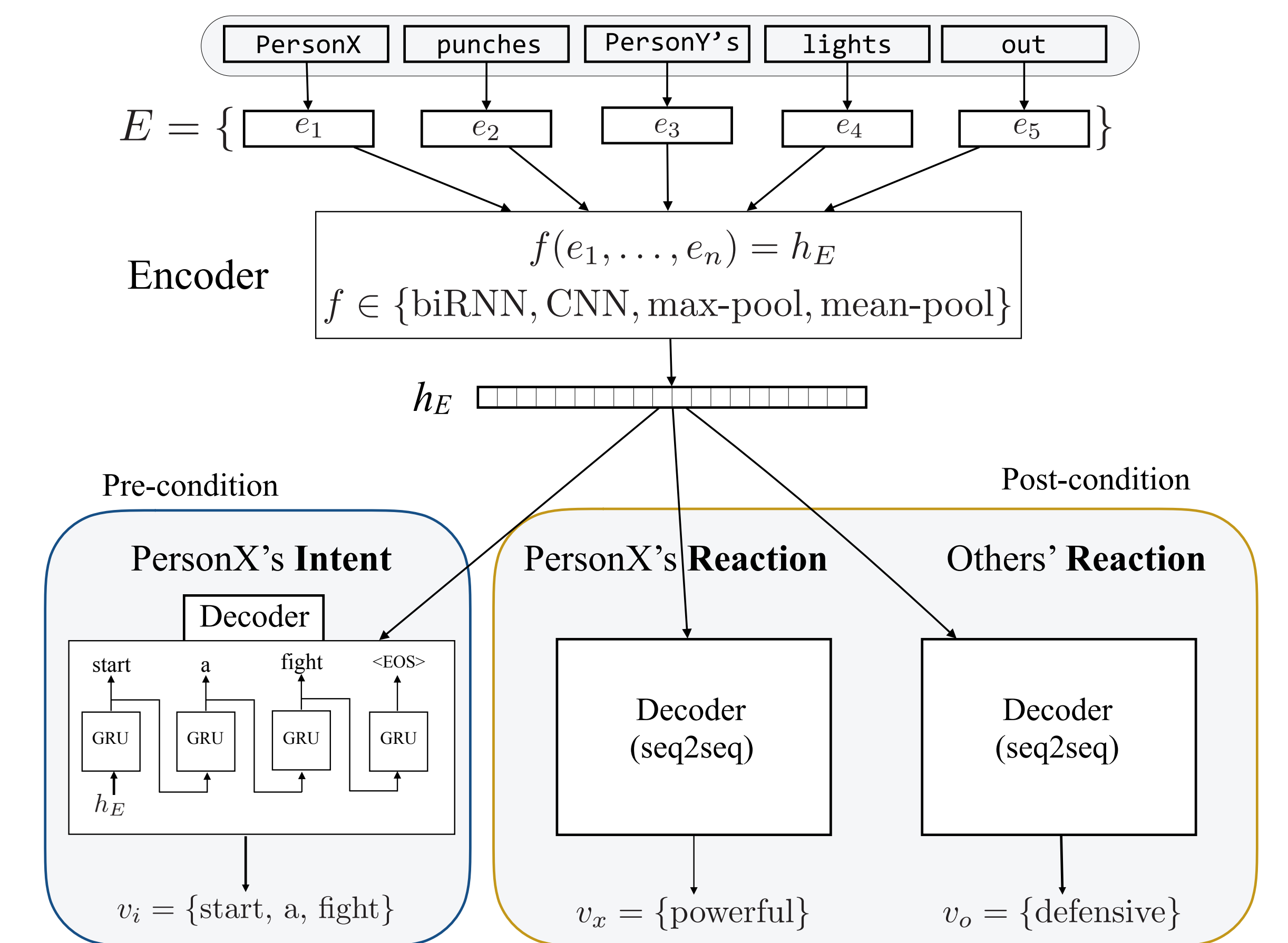
- Intents longer than reactions (3.4 vs. 1.5 words)
- 26% of events involve other participants
- 22% contain blanks

## Evaluation of Generated Inference



- 5 MTurk raters evaluated precision@10 of generations
- Compositional encoders (ConvNet, BiRNN) > pooling
- Sequence generation is preferred over n-gram re-ranking

## Neural Inference Model



- Encoder-decoder setup; given an event, generate intents and reactions in a multi-task way
- Two decoders: n-gram re-ranking and sequence generation

## Gender Bias in Movies

- 21K characters from 772 modern english movies
- Parse narratives describing characters into events, generate intents & reactions (with BiRNN-seq model)
- Extract LIWC features from generated inference
- Logistic regression to find gender correlates

Women	Men
<p>show affection</p> <p>show love</p> <p>loving</p> <p>none</p> <p>because</p> <p>Juno laughs and <b>hugs her father, planting a smooch on his cheek.</b> - Juno (2007)</p>	<p>hurt</p> <p>angry</p> <p>sad</p> <p>upset</p> <p>as a result</p> <p>Dignan <b>punches Anthony in the face.</b> - Bottle Rocket (1996)</p>
<b>Intents:</b> to be helpful, to be felt/seen	<b>Intents:</b> to accomplish, violence
<b>Reactions:</b> pro-social, sexual	<b>Reactions:</b> negative, achievement