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POQue: Asking Participant-specific Outcome Questions for a Deeper Understanding of Complex Events

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Abstract

Knowledge about outcomes is critical for complex event understanding but is hard to acquire. We show that by pre-identifying a participant in a complex event, crowdworkers are able to (1) infer the collective impact of salient events that make up the situation, (2) annotate the volitional engagement of participants in causing the situation, and (3) ground the outcome of the situation in state changes of the participants. By creating a multi-step interface and a careful quality control strategy, we collect a high quality annotated dataset of 8K short newswire narratives and ROCStories with high inter-annotator agreement (0.74-0.96 weighted Fleiss Kappa). Our dataset, POQue (Participant Outcome Questions), enables the exploration and development of models that address multiple aspects of semantic understanding. Experimentally, we show that current language models lag behind human performance in subtle ways through our task formulations that target abstract and specific comprehension of a complex event, its outcome, and a participant’s influence over the event culmination.

1 Introduction

Situations that people experience or describe can be complex, and developing a computational understanding of these situations is not straightforward. Consider the short narrative from Fig. 1:

After a decade as renters, [the Brofmans] were finally able to buy a small house here four years ago. But if the Argentine government yields to [IMF] pressure to rescind emergency legislation meant to protect ordinary families like the Brofmans, the couple stand to lose their home and the \$32,000 they have paid for it so far.

Across multiple, interwoven events with multiple participants, this narrative describes part of the process of losing one’s house. A *possible* ending (the loss of a home) is suggested, which is the result of a confluence of these events. This ending can

be semantically grounded in various changes of state that the participants experience, though note how the use of counterfactual considerations, conditional statements (“if the Argentine government...”), and varying levels of certainty over whether events have actually happened (e.g., *realis* vs. *irrealis*) contribute to the difficulty in understanding this complex event (Herman, 2002; Ryan, 1991).

Knowledge about how event outcomes affect individual participants can help identify salient events in a narrative, fill in implicit missing information (LoBue and Yates, 2011) and chain events that lead to improved understanding of complex events (Graesser et al., 1994). To infuse AI models with similar knowledge, narrative comprehension research has focused on learning event relationships (Mostafazadeh et al., 2016; Chambers and Jurafsky, 2008; O’Gorman et al., 2016; Caselli and Vossen, 2016), using temporal (Pustejovsky et al., 2003), causal (Mirza et al., 2014) and discourse (Prasad et al., 2008) relationships in text. However, as Dunietz et al. (2020) and Piper et al. (2021) argue, for a more useful, generalizable, and robust comprehension, we need to take a holistic view of complex events. In this paper, we tackle an understudied notion of this holistic view and examine knowledge of post-conditions based in states to support inferences of the form “who did what to whom and with what end result.”

A core insight we make is that viewing complex events through the lens of a single participant at a time, either from an agent (how the participant affects others) or a patient (how the participant is affected) view, can help mitigate the complexities we have discussed. In this we build on cross-disciplinary research that shows that humans mentally structure events along single participants (Black and Bower, 1980; Morrow et al., 1989), and that participant-based event and outcome analysis improves complex event understanding (Dijk and Kintsch, 1983; Liveley, 2019). We

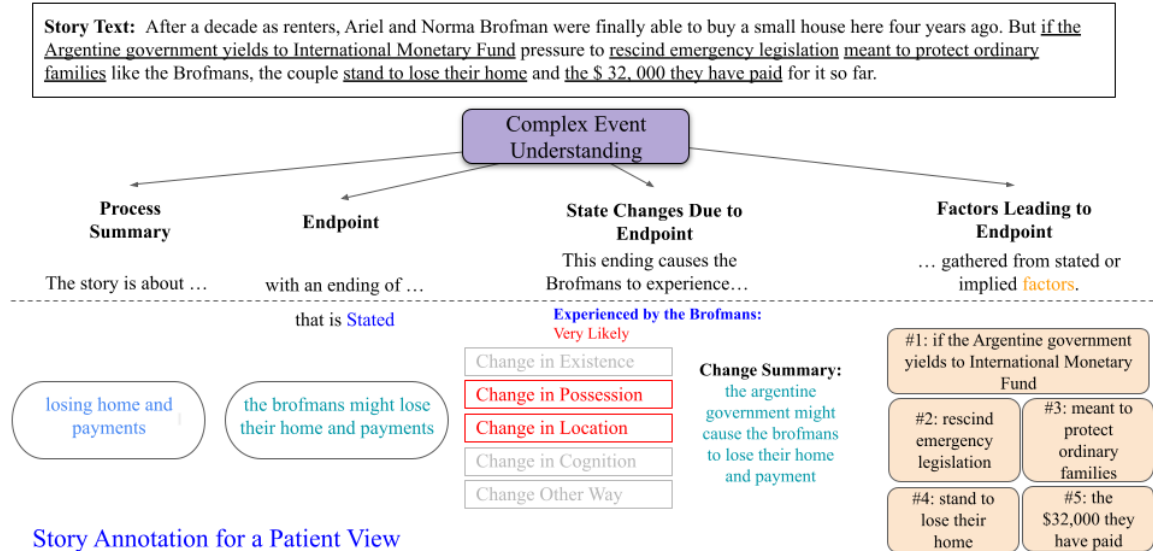


Figure 1: Our approach to understanding state change outcome of complex events. Our four step annotation process involves describing abstractly what a story is about; writing an endpoint for the story; identifying and describing the changes that are a result of the endpoint, and identifying the salient sub-events that lead or support to those changes. To mitigate this complexity, we focus annotator’s attention on one particular participant, and how that participant either causes or experiences the identified changes. This process has resulted in 4k annotated documents.

also note that a complex event is not exhaustively described by what is stated in the text: it is well known that speakers often omit narrative steps that can be inferred (Grice, 1975), including outcomes and effects of a narrative that are often left implicit.

We present POQue, a dataset with post-conditional knowledge about complex events. We identify cumulative outcome-oriented endpoints of the stories caused by related events and the consequences or post-conditions of those events as state-based changes in participants. Seen in Fig. 1, in a storyline involving a participant ("the Brofmans"), we identify an ending outcome for the complex event (the *Endpoint*, "the brofmans might lose their home and payments"), with salient events that lead to this (*Factors Leading to the Endpoint*). We relate a participant’s involvement in the complex event (as a "patient" who "Very Likely" experienced the ending outcome) and the changes of state occurring as a result of the complex event (the changes in possession and location experienced by the Brofmans and other families, and the change in possession by the Argentine government and IMF).

To facilitate high quality annotations we designed a multi-stage crowd sourcing solution to acquire, monitor, assess and curate annotations at scale. We collected 7772 annotations across 4001 stories and assessed a random 1545 annotations (20%) in a multistage pipeline to obtain a highly curated test set. Using POQue, we test current lan-

guage models on reasoning about complex events in narratives: we formulate challenge tasks to identify and generate post-conditions from a story, and evaluate how well trained models predict a participant’s involvement in enabling a complex event.

We summarize our contributions as follows: (1) we introduce a new annotation scheme focusing on complex events from the point of view of a single participant. (2) We create a new dataset of complex events from three collections of everyday stories, using free form text to obtain insight into implied outcomes. (3) We obtain high quality annotations from crowd workers without the use of requester generated qualification tests. (4) We formulate challenge tasks aimed at evaluating the ability of language models to perform richer complex event comprehension, specifically: a) generating a process summary of the complex event b) generating an endpoint of the complex event, c) generating the outcome of a complex event based on a participant’s semantic role d) identifying a participant’s involvement in a complex event, and e) generating post-conditions or changes caused by a complex event. Our dataset and code are publicly available at <https://github.com/saiumbc/POQue>.

2 Related Work

Narrative texts communicate experiences and situations by connecting related events (Brooks, 1984; Mateas and Sengers, 1999) through events involv-

ing participants (Bal, 1997; Eisenberg and Finlayson, 2017; Liveley, 2019). Previous works, viewing narratives as sequences of events, annotated event pairs for event coreference, temporal, and causal relationships (O’Gorman et al., 2016; Caselli and Vossen, 2016; Mirza and Tonelli, 2016; Mostafazadeh et al., 2016). Newer works have studied event groups using predicate hierarchies (Qi et al., 2022) and temporal graphs (Li et al., 2021). However, these approaches focus on event-event relationships, without diving deeply into participant or entity analysis. Unsupervised methods assume narratives are coherent and learn partially ordered event chains (Chambers and Jurafsky, 2008; Balasubramanian et al., 2013) or sub event relationships (Yao et al., 2020) but these are limited to what occurs in the text itself, which can lead to well-known issues of bias or evaluation limitations (Gordon and Van Durme, 2013; Rudinger et al., 2015).

Caselli and Inel (2018) obtain crowd annotations of causal relationships between events and assess their quality by relating them to expert annotations. PeKo (Kwon et al., 2020) uses crowd annotations of precondition relationships and fine tunes a language model for finding such relationships. However, both works limit their study to event pairs in short text snippets. The ESTER dataset (Han et al., 2021) consists of more comprehensive relationships in a story, though limited to within-text (i.e., stated) mentions of events only. GLUCOSE (Mostafazadeh et al., 2020) provides elaborate causal relationships for several event dimensions for each event in a story. However, in contrast to our effort, these works address direct causal relationships between within-text events and do not focus on participants.

Understanding complex events has long attracted cross-disciplinary attention. For example, theoretical linguistics and cognitive science work has shown that humans understand a narrative text using simulative inference (Kaplan and Schubert, 2000; Boella et al., 1999; Schubert and Hwang, 2000). Prior work has also shown how observing participants’ events and the resulting consequences can lead to improved understanding of events (Dijk and Kintsch, 1983; Zwaan and Radvansky, 1998).

3 Knowledge Representation

As an underlying motivation for our efforts, we posit that for language models to be able to reason about complex events from narratives, they should

be able to identify a likely ending of that complex event, component events that lead to that ending, and the state changes that result from that ending. However, this type of knowledge is complex and has been computationally understudied, leading to a scarcity of sizable datasets. In our efforts to correct this, we appeal to classic, cognitively- and linguistically-backed results.

First, inspired by the idea from Kintsch and van Dijk (1978) that text comprehension involves reducing relevant details into an abstract coherent semantic text, our targeted annotations include an abstract high level summary and the minimal set of salient events that make up the complex event. Second, we extend the idea of thematic roles for verbal arguments (Dowty, 1991) to a generalized semantic role for the complex event. Specifically, Dowty showed that easily verifiable characteristics and properties, such as volitional participation in an event or whether a participant underwent a change of state because of a *particular* event, can be used to define predicate-level prototypical semantic roles. Inspired by this, we characterize the roles of complex events through the intentional engagement in changes of state of participants. As such, our targeted annotations account for both the intentional involvement of the participants in the complex event and the cumulative impact of all the events that make up the complex event.

Story and Participant Stories in our dataset are either a ROCStory or heuristically salient portions of newswire (first 100-150 tokens).¹ For more information on story processing see §4.1. We define a participant as an entity that was mentioned several times in the story. See §4.1 for more on participant selection. Multiple entities are considered a single Participant if these entities are mentioned together and participate together in all the events. In Fig. 1, "the Brofmans" are a Participant.

3.1 Targeted Knowledge Annotations

Given a story S , a participant P , and P taking on a agent-like or patient-like cumulative semantic role, PR , we obtain the following annotations.

Process Summary (PS): A high-level, free-form description of the situation, which provides the topical context for the complex event. For example, "Losing home and payments" for the story in Fig. 1.

¹While we acknowledge they have important differences, we use "narrative" and "story" interchangeably.

Endpoint Description (ED): A free-form description of the inference of what happened or is likely to happen in the story, conditioned on the process summary. It is the result of an aggregate of story events that leads to state changes for participants. For the story in Fig. 1, the endpoint is “The Brofmans might lose their home and payments.”

Endpoint Anchoring (EA): An endpoint may be (inferentially) *stated* in the text, or it may be *implied/suggested*. We judge this via a three-way choice (stated, implied, unsure). For the story in Fig. 1, the endpoint is *stated* by the text.

Participant Involvement (PI): Whether the participant caused the endpoint, or experienced it, indicated with a 5 point Likert scale, from very unlikely to have caused [experienced] the endpoint, to very likely to have caused [experienced] it. For the story in Fig. 1, the complex event maximally affects *P*. Hence this rating is a “very likely.”

Change Summary (CS): A templated text description of state changes caused or experienced by participants as a result of the endpoint. In Fig. 1, this is “The Argentine government might cause the Brofmans to lose their home and payment.”

Change Modes ((c_1, c_2, \dots, c_k)): The various ways in which participants experience changes. These change modes are: change in existence, feeling, location, possession, some other way, or no changes. This list was inspired by classic linguistics, c.f., Dowty (1991), though refined during early examination of our stories.

Factors ((f_1, f_2, \dots, f_n)): Salient events that lead to the endpoint and state changes where each factor captures an event in a phrase comprising of at least a subject and verb. For the story in Fig. 1, ““if the Argentine government yields to International Monetary Fund,” is one of the factors leading to the Endpoint.

3.2 Crowd Annotations

We created a human intelligence task (HIT), deployed on Amazon Mechanical Turk (AMT). The HIT consists of a story with highlighted participant mentions displayed in the left column and four annotation steps in the right column which vary slightly for the agent and patient views. The protocol was IRB approved.

Crowd workers were instructed to read the story, focus on the highlighted participant, and provide

annotations. We provide several annotated examples, general instructions for completing the HIT, and specific instructions for each step suggesting a template to follow for some steps. More details and the layout of the HIT are in Appendix B.

The annotation task consists of 4 steps and each story is assigned to two workers, one where the highlighted participant is assigned the role of “agent” and another with the assigned role as “patient.” Step 1 asks for a high level description of the story, a process summary of the situation described. Step 2 of the HIT asks for a description of an endpoint in the story. We assume a story’s endpoint typically signifies a state change caused by a complex event. Step 3 asks for a summary of changes caused by the complex event in the story participants and also asks to identify the type of changes. Step 4 of the HIT asks an annotator to identify the salient events, or factors, that lead up to the complex event and changes from it.

4 Dataset

We selected stories from three narrative English language datasets – the ESTER dataset (Han et al., 2021), the ROC stories dataset (Mostafazadeh et al., 2016) and passages from the Annotated New York Times newswire dataset (Sandhaus, 2008). We selected these given the prominence the underlying documents have in the broader NLP community (the ESTER documents are a subset of the TempEval3 (TE3) workshop dataset (UzZaman et al., 2013)). We included ROC stories because they often contain a single situation with mostly salient information. We noticed these stories help crowd workers easily focus on salient events, providing cues for factors and state changes. Meanwhile, ESTER and the selected Newswire stories provide a variety of complex situations and discourse text. Additionally, by selecting subsets of these well-known datasets, we hope that future efforts may be able to aggregate our annotations with existing ones, enabling richer phenomena to be examined.

4.1 Story Preparation

We sampled stories from the Annotated New York Times (ANYT) corpus, ROCStories, and ESTER. We then identified participants via an automatic entity coreference system. We heuristically selected relevant and annotable excerpts of the document by identifying “continuant story lines” (see Appendix A). After identifying a participant and a

| | # Stories | # Agent | # Patient |
|-------|-----------|---------|-----------|
| Total | 4001 | 3896 | 3876 |
| ROC | 1383 | 1364 | 1356 |
| ESTER | 1275 | 1237 | 1218 |
| NYT | 1343 | 1295 | 1302 |

Table 1: Document-level data statistics. Note that the number of stories refers to the number of unique stories annotated, while the agent and patient numbers refer to the number of instances annotated on those documents. Additionally, 260 of the ROCStories are from the CATERS (Mostafazadeh et al., 2016) collection. CATERS stories and ESTER stories containing subevents are useful for relating causal and compositional events in a complex event.

| | |
|--|------------------|
| Avg. process summary length | 5.7 words |
| Avg. endpoint length | 9.4 words |
| Endpoint stated/implied/unsure % | 68.5%/28.9%/2.6% |
| Avg. change descr. length | 8.9 words |
| Avg. likelihood of causing change (agent) | 4.0 (likely) |
| Avg. likelihood of experiencing change (patient) | 4.1 (likely) |
| Avg. # of factors | 3.7 |
| Avg. factor length | 8.0 words |

Table 2: Additional statistics about POQue.

continuant story line, we randomly selected 4001 stories for annotation; see Table 1 for details.

4.2 Dataset Annotation & Pricing

Our dataset has 4001 stories, annotated by 163 different crowd workers. The average number of stories annotated per worker is 43. When possible, we annotated from both an agent and a patient view for a participant, so in total we obtained 7773 annotations. Workers were paid an average of \$0.50 for annotating a single HIT, either an agent or a patient view of the story. For more detailed information on payment and training see Appendix B.3. We tackle the positivity bias in AMT work (Matherly, 2018) using a thorough initial verification and training (see Appendix B) and ensured workers understood the task and provided quality annotations.

4.3 Dataset Statistics

For most stories we obtained two annotations, with the two participant semantic roles. We show high-level document statistics in Table 1. Annotations for the two different roles of the highlighted participant are shown in separate columns. We show more detailed annotation statistics in Table 2, and examine the frequency of change modes in Fig. 2.

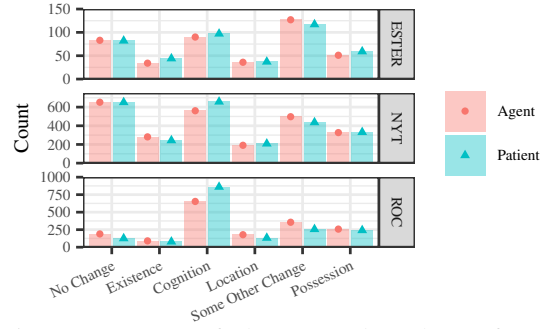


Figure 2: Count of change modes, shown for each of the agent and patient roles, and broken out across the originating datasets our annotated narratives come from.

4.4 Dataset Quality and Analysis

We noticed that the nature of the stories and the task steps elicit a variation in the text style and format, even from the same worker. Our experiments (§6) and ablation studies (§7) did not uncover any easy biases attributable to a small number of workers producing most of the annotations. Due to space limitations we explain our process for evaluating 1545 random annotations in Appendix C.2.

5 Tasks for State Change Knowledge

Based upon our collected dataset, we propose several tasks. These tasks are designed to test various aspects of comprehension involving complex events, their participants, and outcomes.

5.1 Task 1: Generating Process Summaries

Categorizing stories based on the type of situation they describe is necessary for generalization. For this, we fine-tune models to generate an abstract and high level process summary of the complex action described in a story. Because we annotated salient events for the story, i.e., the factors, we have two task formulations. We fine-tune models to generate PS either given S or (f_1, f_2, \dots, f_n) . Both are standard summarization tasks which we compare with a baseline where the process summary is assumed to be “About P .”

5.2 Task 2: Generating Complex Event Endpoints and Salient Events

Understanding a story involves the identification and decomposition of salient events that lead to an endpoint, for the described complex event. We test this understanding with two complementary formulations where we generate either the endpoint description or the salient events, i.e., factors. For generating ED we have two sub formulations where

we fine-tune models either on S or (f_1, f_2, \dots, f_n) . For generating (f_1, f_2, \dots, f_n) we fine-tune models on (S, ED) . These are all standard summarization tasks which we compare with a baseline where ED is assumed to be the last sentence of the story.

5.3 Task 3: Generating Changes Resulting from a Complex Event

Knowing the changes caused by a complex event gives us an insight into its importance and the intentions (addressed in Task 5) behind it. In this task, we generate changes caused by a complex event through the lens of the semantic role tracking we have employed throughout our effort. Using standard summarization, we fine-tune models to generate CS given (S, ED, PR) .

5.4 Task 4: Identifying Types of Changes

Grounding the impact of a complex event in the various change modes a participant undergoes helps in understanding the importance of new situations by relating them to known situations with similar post-conditions. We formulate this as a multi-label binary classification and fine-tune models to identify $k = 5$ change modes (c_1, c_2, \dots, c_k) given S .

5.5 Task 5: Assessing Participant’s Involvement in the Complex Event

Besides the story context, the participant’s semantic role heavily influences our decision of whether the participant intended or enabled the complex event or the changes caused by it. In this binary classification task, we predict the participant involvement rating PI given (S, ED, PR) . This prediction demonstrates a model’s ability to identify a participant’s intentional engagement and enablement of the complex event and its impact.

6 State Change Benchmark Experiments

We benchmark the performance of current encoder-decoder transformer language models, T5 (Raffel et al., 2020) and BART (Lewis et al., 2020), which are effective for both text generation and classification. We compare fine-tuned base and large² models with multiple automated metrics and crowd sourced human evaluation. We use bootstrap for calculating statistical significance via the mlxtend library (Raschka, 2018).

²We found that training a bart-large model was finicky, with some training runs not converging. For these cases, we do not include results for the bart-large model. See <https://github.com/huggingface/transformers/issues/15559>.

6.1 Automated Evaluation

We use the classic metrics of **ROUGE** (Lin, 2004), **BLEU** (Papineni et al., 2002), and **METEOR** (Lavie and Agarwal, 2007), and the more recent **BertScore** (Zhang et al., 2020). Due to space limitations, we present ROUGE-L and BertScore in the main paper, and additional ROUGE-1, ROUGE-2, METEOR, and BLEU scores in the appendix (Appendix F). We use standard metrics used for single and multi-label classification: **Accuracy** and **macro F1**. In multi-label classification, we calculate **Subset Accuracy** and **macro F1** using sklearn and a **Hamming Score** which is computed as $\frac{1}{n} \sum_{i=1}^n \frac{|Y_i \cap Z_i|}{|Y_i \cup Z_i|}$, where Y and Z are true and predicted labels for n examples.

6.2 Human Study of Model Generations

We perform a human evaluation of the generation tasks (1, 2, and 3) using 50 randomly selected generations for each model and the corresponding human annotations. We obtained qualitative ratings from 3 crowd workers experienced in annotating our HITs and measured IAA using a weighted Fleiss’s Kappa as in Appendix C. For each summary, workers are presented with the story and the summary and asked to rate the summary on aspects that relate to the task such as abstractness, factuality and salience using a 5-point Likert scale. See Appendix D for more information on these aspects and the HITs used for evaluation.

6.3 Task 1: Generating Process Summaries

To test whether a model generates a more focused process summary when trained on salient information, we compare pre-trained models fine-tuned on S and (f_1, f_2, \dots, f_n) with an easy baseline process summary of “About P ,” where P is the participant. Less than 1% of the process summaries in dataset and model generations contain this baseline format. Results from this task training are listed partially in Table 3 and fully in Table 11. For all models, Rouge, BLEU and METEOR scores show less lexical overlap, but BertScore indicates a high similarity between the model generated and reference summaries. Inspired by previous work in measuring abstractiveness (See et al., 2017; Dreyer et al., 2021; Gao et al., 2019; Narayan et al., 2018), we compare average number of tokens (Len) across all summaries, the percentage of exactly matched trigram spans in the story (Ext), and the average of Abstractness Likert scores ($Abstr$) from the evalua-

| | Model | Len | Ext. (↓) | RougeL | BertScr | Abstr. |
|-------|----------------|------------|-------------|--------------|--------------|--------------|
| | Reference | 3.6 | .13* | - | - | 3.57* |
| | About <i>P</i> | 1.7 | .27 | 10.43 | 83.86 | 2.37 |
| | | | | | | |
| Story | Bart-base | 4.0 | .46 | 21.43 | 86.70 | 2.77 |
| | T5-base | 10.0 | .60 | 19.50 | 85.99 | 2.32 |
| | T5-large | 6.9 | .63 | 20.30 | 86.15 | 2.13 |
| Fact. | Bart-base | 4.2 | .33 | 23.81 | 87.66 | 3.22 |
| | T5-base | 9.9 | .56 | 18.29 | 86.10 | 2.73 |

Table 3: Generating Process Summaries (Task 1). See appendix Table 11 for the full results. Bart-large is not included because we were unable to get it to properly converge. The best scores are bolded. We use * to indicate a significantly higher value than other values in the column with a p value between 0.001 and 0.0001 (except for Bart-base trained on Factors where the p value is 0.13). *Len* value for Reference is considered the best as the baseline value is not meaningful.

tion HIT (see Fig. 17) for process summaries. We provide *Len*, *Ext* and *Abstr.* values to help contextualize scores. While a lower value of *Ext* does not necessarily mean a better generation, it does mean there is less direct copying of length-3 phrases.

Discussion: BART generations are brief, less extractive and more abstractive, whereas T5 generations are longer, less abstractive and more directly drawing upon spans of story text. The Reference summaries are brief, significantly less extractive and at a significantly higher abstractness score compared to all the models. Models fine-tuned only on the factors produce more abstractive summaries. However, this increase in the abstractness for the BART model increased the factual errors, in line with previous observations (Cao et al., 2017; Kryscinski et al., 2019; Dreyer et al., 2021). The significantly higher brevity and abstractness of the Reference summaries point to a substantial gap between human and LMs’ ability at capturing complex actions in a brief, high-level, abstract phrase.

6.4 Task 2: Generating Endpoints & Factors

To test how well models generate endpoints, models are fine-tuned to generate *ED*, given *S* or (f_1, f_2, \dots, f_n) and compared with the baseline version where the *ED* is assumed to be the story’s last sentence. Partial results for this task formulation are listed in Table 4 and the full results in Table 12 for the trained models. We also compare models trained on the complementary task of generating (f_1, f_2, \dots, f_n) given (S, ED) . A special token separates factors in all the task formulations involving factors. Partial results for this complementary task are listed in Table 5 with the full results in Table 13.

For all models, Rouge, BLEU and METEOR scores show higher lexical overlap, and BertScore

| | Model | Len | Ext↓ | RougeL | BertScr | Fact. | Sal. |
|-------|------------|------|------|--------------|--------------|--------------|--------------|
| | Reference | 7.9 | .27 | - | - | 4.15 | 3.46 |
| | Last sent. | 23.3 | .79 | 21.82 | 85.60 | 4.49 | 3.35 |
| | | | | | | | |
| Story | Bart-base | 11 | .72 | 25.43 | 87.61 | 4.66 | 3.97 |
| | Bart-large | 10.3 | .63 | 24.74 | 87.62 | 4.59 | 3.81 |
| | T5-base | 13.6 | .70 | 24.07 | 87.19 | 4.71* | 4.03 |
| | T5-large | 12.9 | .67 | 25.71 | 87.54 | 4.71* | 4.23* |
| Fact. | Bart-base | 7.3 | .49 | 24.09 | 87.93 | 4.11 | 3.28 |
| | T5-base | 10.4 | .47 | 22.01 | 87.07 | 3.99 | 3.02 |

Table 4: Generating Endpoints for stories and factors (Task 2a). See appendix Table 12 for the full results. The best scores are bolded. * indicates the value is significantly higher than the Reference value with a p value of .002 for Factualty and .0008 for Salience.

| Model | # fact. | Len | RougeL | BertS | Brev. | Fact. | Sal. |
|------------|---------|------|--------------|--------------|--------------|--------------|--------------|
| Reference | 3.6 | 8.3 | - | - | 3.35* | 3.25 | 3.04 |
| Bart-base | 3.5 | 14.0 | 45.28 | 88.06 | 2.54 | 3.49 | 3.57 |
| Bart-large | 3.6 | 13.7 | 45.98 | 88.10 | 2.12 | 3.2 | 3.31 |
| T5-base | 2.6 | 19.6 | 43.31 | 87.74 | 3.23 | 3.69 | 4.01* |
| T5-large | 3.7 | 13.9 | 47.96 | 88.44 | 2.85 | 3.80* | 3.96* |

Table 5: Generating Factors from stories and their endpoints (Task 2b). See appendix Table 13 for the full results. The best scores are bolded. * indicates the value is significantly higher than the Reference value for Factualty and Salience with a p value of .0001. The Reference value for Brevity is significantly higher than all values in the column with a p value of .0001.

indicates a high similarity between the generated and reference summaries. We compare the average of the Factualty and Salience scores (*Fact.* and *Sal.*, resp.) from the endpoint summary evaluation HIT (see Fig. 18) along with the average number of tokens (*Len*) across all summaries and the percentage of exactly matched trigram spans in the story (*Ext*). We also compare the average of the Brevity, Factualty and Salience scores (*Brev.*, *Fact.*, and *Sal.*) from the evaluation HIT (see Fig. 20) for factors along with the average number of factors (*# fact.*) across all stories and the average number of tokens (*Len*) across all factors and stories.

Discussion: Scores are significantly higher for LM generations than Reference endpoint descriptions on both Factualty and Salience. We looked at a random 100 Reference endpoint descriptions and the corresponding model generations. The first author of this paper identified which of the endpoints were not directly stated in the story, but rather implied by the story, and which ones were not-factual. As shown in Fig. 3, very few of the model generations are implied endpoints and a third of the Reference endpoints contain implied descriptions. Our HIT instructions asked workers to annotate not only explicit endpoints but also the ones implied by the story and they identified 29% of them as implied. Evaluators lowered their scores both

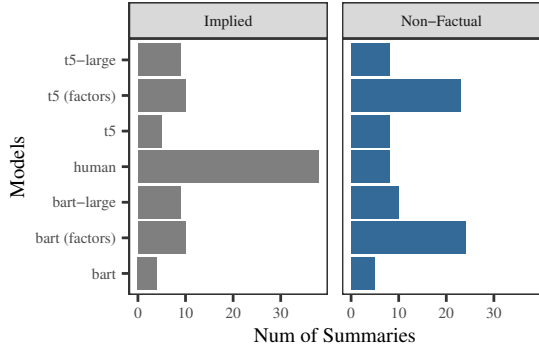


Figure 3: Non-factual and implied endpoint types.

for factuality and salience for these implied endpoints as the description may be a possible but not strictly entailed outcome. Models trained on factors generated more implied endpoint descriptions but these implied endpoints contained more factual errors possibly because of less available context. We conclude that LMs try to generate stated endpoint descriptions unless challenged by limited context.

Fine-tuning on stories and endpoints generates salient factors, indicated by the high assessment scores. However, the generated factors on average contain multiple facts making them less concise and focused than human written factors.

6.5 Task 3: Generating Change Summaries

We compare model generations of state changes, by fine-tuning models to generate *CS* conditioned on (ED, PR) . Given the pair (S, t) , where t is either “ P caused this: ED ” if PR =“agent” or “ P experienced this: ED ” if PR =“patient”, fine-tuned models generate *CS*. Partial results for this task are listed in Table 6, and the full results in Table 14. For all models, Rouge, BLEU and METEOR scores show high lexical overlap and BertScore indicates a high similarity between model generations and Reference summaries. We compare the average of the Factuality and Salience Likert scores (*Fact.* and *Sal.* resp.) from the evaluation HIT (see Fig. 19) which measures whether the generated text contains change(s) resulting from the complex action.

Discussion: T5 models generate change summaries that are significantly more factual and salient than the BART models. While T5 generations score higher than Reference summaries, the difference is not significant. To explain these results, we inspected the 50 evaluated stories and found that less than 10% of the stories have no changes even though annotators indicated “no changes” for 25% of the stories in these 50 (and in the entire dataset). To see if crowd workers

| Model | RougeL | BertScr | Fact. | Sal. |
|------------|--------------|--------------|-------------|-------------|
| Reference | - | - | 3.36 | 3.32 |
| Bart-base | 34.79 | 88.39 | 3.03 | 2.93 |
| Bart-large | 32.80 | 88.23 | 2.99 | 3.05 |
| T5-base | 26.81 | 87.20 | 3.74 | 3.23 |
| T5-large | 27.14 | 87.38 | 3.81 | 3.53 |

Table 6: Generating changes resulting from a complex event (Task 3). See appendix Table 14 for the full results. The best scores are bolded.

| Model | Subset Acc | Hamming Score | macro F1 |
|--------------------|-------------|---------------|-------------|
| Bart-base | 64.6 | 71.7 | 61.2 |
| T5-base (Enc Only) | 59.4 | 66.1 | 50.3 |
| T5-base (Enc-Dec) | 65.8 | 67.3 | 62.0 |

Table 7: Results for identifying various Change Modes in Participants (Post Conditions) resulting from the endpoint of a complex action (Task 4).

can identify these no-change stories, we ran a HIT where the change summary for these 50 stories was set to no-changes. From the results of this HIT we found that human evaluators also think there are 3 times as many stories with no-changes. Workers missed subtle changes in a story especially when they relate to changes in cognition. T5 was able to identify story text that contained subtle changes while the BART models seem to be learning the data distribution from the training data. BART generations also contain a higher number of factual errors leading to its subpar performance.

6.6 Task 4: Identifying Types of Changes

We fine-tune base models on a multi-label ($n=5$) binary classification task and assign change mode labels, (c_1, c_2, \dots, c_k) , for an input context consisting of two sentences: story S , and (PI, c, ED) where c is a connector phrase. The value of c is “caused this:” when PR =“agent,” and “experienced this:” when PR =“patient.” The results from this classification are reported in Table 7 and consist of Subset accuracy, Hamming Score and Macro F1. The *Enc Only* models consists of a T5 encoder model with a classification head on top. The classification head consists of the following sequence of transformations: Dropout ($p = 0.3$) \rightarrow Linear(768x 512) \rightarrow tanh() \rightarrow Dropout ($p = 0.3$) \rightarrow Linear(512 x 5) \rightarrow sigmoid(). We also fine-tuned a pretrained T5 encoder-decoder model in a text-to-text multi-label RTE setting.

Discussion: These results indicate that while the fine-tuned models are good at generating change summaries, assigning the various change model labels is a challenging task for these LMs.

| Model | Combined Acc./F1 | Agent Acc./F1 | Patient Acc./F1 |
|------------|---------------------|-------------------|--------------------|
| Bart-base | 82.7/76.8 | 80.7/ 75.2 | 84.2 /76.4 |
| Bart-large | 76.0/43.2 | 75.5/49.1 | 79.2/50.8 |
| T5-base | 82.6/76.5 | 80.1/73.2 | 84.2/77.4 |
| T5-large | 83.0/77.4 | 80.3/74.3 | 84.5/78.1 |

Table 8: Identifying Participant’s involvement (Task 5). The best results are bolded. The different folds of the Bart-large models converge at different checkpoints resulting in lower average scores but the best scores for any fold are comparable to the Bart-base model.

6.7 Task 5: Assessing Participant Involvement

We turn the 5-point Likert scale for *PI* into a binary class: the first two options (unlikely to be involved) make up the negative class and the latter three (neutral to likely to be involved) are the positive class. We formulate participant involvement and enablement of changes as entailment: the story *S* is the premise and the hypothesis is framed as the *P*’s involvement in the changes of state indicated by *CS*.³ We fine-tuned models on all story annotations; only annotations where *P*’s semantic role is “agent”; and only the annotations where *P*’s semantic role is “patient.” Results are in Table 8.

Discussion: While all the models are able to classify a participant’s involvement and enablement of changes with high accuracy there is still room for improvement. Error analysis indicated models are not able to identify enablement when there are no state changes. This usually happens when the complex action is a hypothetical situation or the changes involve subtle cognition (discussed in Task 3). In T5 models, we noticed some errors contradicted the hypothesis statement; these may be due to the model’s external knowledge from pre-training, but this requires further study.

7 Effect of Discourse Text on Models

We study the effect of discourse text on model generations of endpoint descriptions using the two story types we annotated: ROCStories and newswire stories. ROCStories are simpler with short, concise and focused salient events, while newswire are more complex, containing more text not always salient to the complex action we annotated. We wish to answer the following questions: (1) How does training domain affect endpoint gen-

³We formulate agent-based hypotheses as “What the actions of *P* caused was this: *CS*,” and patient-based hypotheses as “What happened to *P* was this: *CS*.”

| Train-on | Model | Test-on | Len | Ext↓ | Fact. | Sal. |
|----------|-----------|---------|------|------|-------|------|
| ROC | Bart-base | ROC | 5.6 | .55 | 4.43 | 4.25 |
| | T5-base | ROC | 8.4 | .55 | 4.43 | 4.24 |
| | Bart-base | News | 9.8 | .39 | 3.98 | 3.59 |
| | T5-base | News | 23.8 | .64 | 4.46 | 4.01 |
| News | Bart-base | ROC | 6.2 | .89 | 4.55 | 4.09 |
| | T5-base | ROC | 9.0 | .74 | 4.45 | 3.43 |
| | Bart-base | News | 11.5 | .77 | 4.62 | 4.01 |
| | T5-base | News | 15.5 | .75 | 4.59 | 3.95 |

Table 9: Comparing Endpoint generations of models trained on ROCStories and on Newswire stories. See appendix Table 15 for the full results.

eration? (2) Are the endpoint generations more/less concise, varied, focused and factual for the story context? (3) Do models trained on one type of stories transfer their learnt knowledge to generate equally good endpoints for the other type?

We fine-tuned BART and T5 base models separately on ROCStories vs. Newswire, and evaluated them on test sets for both story types. We calculated human scores from the endpoint evaluation HIT. From Table 9, we observe the following: (1) ROCStories models generate shorter, more varied and abstract descriptions. (2) Newswire generations are longer and more extractive. (3) ROC-trained BART has significantly lower salience when tested on Newswire stories. News-trained BART does not suffer from poorer salience. News-trained T5 has lower salience when tested on ROCStories, while ROC-trained T5 does not result in significantly lower salience. (4) BART generations are less factual than T5, possibly because of higher abstractness (Dreyer et al., 2021). (5) ROC-trained T5 and News-trained BART obtain similar high scores for factuality and salience.

8 Conclusions

We have argued that a deeper understanding of complex events can be achieved by examining their cumulative outcomes, grounded as changes of state. By focusing on a specific participant in a complex event, and a broad notion of its semantic role, we developed a crowdsourcing protocol to obtain 7.7k annotations about complex events and participant state change across 4k stories. We validated 20% of the annotations, with high inter-annotator agreement. We have formulated five challenge tasks that stress model’s understanding of story outcomes, state changes and complex event understanding. Our evaluations suggest that additional modeling advances are needed to achieve this understanding; we hope that our dataset spurs this future work.

9 Limitations

We acknowledge the following limitations of our approach:

- Though the documents we base our annotations on come from well known data sources, our efforts focus on more formal levels of written English. Generation and classification abilities can vary as the formality, style, or language change.
- Though our work is heavily grounded in interdisciplinary literature, we adopt a limited two-argument view of complex event participants: either they are an “agent” or a “patient.” Expanding to other types, or finer-grained notions, of arguments requires more investigation.
- We use large, pre-trained language models in our experiments. While powerful, they can echo biases, either implicitly or explicitly. We do not attempt to control for these in this work.

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A Additional Details on Data Preparation

In this section, we expand on data processing described in §4.1.

Document Selection From the Annotated New York Times (ANYT) newswire articles, we found that stories from the Financial, National and Foreign desks contained the type of complex events that were most reliable to annotate: those with focused discourse text that required less external, societal, or cultural knowledge to understand the story. We did not specifically target obituaries as they could lead to less varied endpoint and cumulative state changes. The ROCStories were randomly sampled, and we subsampled stories from ESTER that had subevent annotations in that dataset.

Participant Identification We used spanBERT (Joshi et al., 2019) to resolve coreferent mentions in the text, and selected the largest cluster of mentions. To find clusters containing a valid participant, we selected the shortest text span from all the mentions in the cluster making sure that it is at least 3 characters long and matched it with the names database published by the SSA. This ensured that the "participant or prop" we selected is a person, place, group or organization. In ROCStories and ESTER, the largest cluster is always a person, place or group and did not require this name filtering.

Continuant Story Lines We selected the first few lines containing approximately 100 tokens, which resulted in stories similar in length to previous work (Han et al., 2021; Glavaš et al., 2014; O’Gorman et al., 2016). We highlighted mentions of the participant to outline a “continuant” story-line, i.e., a set of related events that lead to a coherent story involving the participant. Focusing on the events in a continuant story line helps an annotator observe a complex action and its effects. By identifying and highlighting a single participant we limit the scope of possible valid endpoints an annotator might consider. Assigning a semantic role to the participant, of an agent, or a patient, helps cue the annotator to identify a participant’s role in the complex action, and the changes resulting from it.

B Additional Details on Crowd Annotation

B.1 Worker Qualifications

We did not use requester generated qualification tests to filter out workers because we target the understanding of everyday reported events, not domain or expert-level matter. However, we used community standard quality criteria, such as requiring a 98% or greater HIT acceptance rate and the completion of 1000 approved HITs. In addition, we required the worker's stated location to be in the USA, UK, Canada, Australia, or New Zealand. Given the language-dependent semantic phenomena we pursue in this work, this location requirement was used for avoiding language-based artifacts. While qualification tests can filter for spam, initial misunderstandings could exclude capable workers who benefit from additional feedback. By providing positive and constructive feedback to ensure workers understood the task, we were able to retain workers who improved over time and provided quality annotations, a requirement for any crowdsourced task.

B.2 Annotation HIT Streamlining

Our initial development tested selection of textspans vs. free form text and noticed workers preferred one over the other for some of the steps. To reduce annotation time, we refined the HIT to prime workers to hone in on the salient information in the story, provided functionality that allowed for a quick highlight and paste of relevant text when needed. We encouraged free form text in steps 1 and 2., an easy to fill in template for step 3, and highlight and paste for step 4.

Despite instructions to be concise, early annotations suggested that some workers would try to include as much information as possible into the free form text fields, resulting in lengthy descriptions that provided too much detail (e.g., going beyond immediate outcomes, or providing explanation/justification for why those changes happened). To address this issue, we implemented two-tiered length limitations on the free form text. The first tier was a "soft constraint": if, e.g., a worker typed in a endpoint greater than 8 words, they were prompted to consider revising, but they did not have to. The second tier was a "hard constraint": if, e.g., the endpoint was greater than 15 words, they were prevented from submitting until they rephrased and satisfied the hard constraint limit.

These limits were set based on the examination of early annotations.

In addition, in each HIT batch, we included a mix of the lengthier Newswire and short ROCStory texts to reduce the monotony of annotation. From the alpha run annotation times, and internal annotation timing, we estimated the average annotation time for a HIT completion to be under 2 minutes. The bulk of annotations for our HITs were completed within 5 minutes, with a median and mean of approximately 2.5 minutes.

B.3 Worker Training and Pay

Our HITs were priced to target an hourly pay of \$10-\$12. We carefully tracked and analyzed the user response times across pilot runs to arrive at the HIT pricing. For each worker, we carefully examined the first 10-30 annotations to check task understanding, providing feedback and a bonus as appropriate to compensate for the time spent on communication. We initially had an additional 26 crowd workers who attempted the HIT, but we removed their annotations from the dataset for obvious bad-faith efforts (10 workers) and for benefit-of-the-doubt good faith efforts but where the workers (16 workers) did not follow instructions even with repeated feedback. Anyone construed to have completed the annotation in good faith was paid, even when their responses were not included in our dataset.

B.4 Annotation Quality Checking

Our cursory visual check of the annotation and an automatic lexical check of a list of novel unigrams that are not part of the story ensured the annotation content was focused on the story. We gave iterative feedback to workers not following task instructions and excluded them with a qualification type when there was no improvement.

Additional Data Analysis In Fig. 4 we show the distribution of crowd workers for our annotation effort.

B.5 Annotation HITs

The HIT for acquiring story annotations from crowd workers displays two different views based on participant's semantic role in the story. General and specific instructions for Step 1-3 are different in two views.

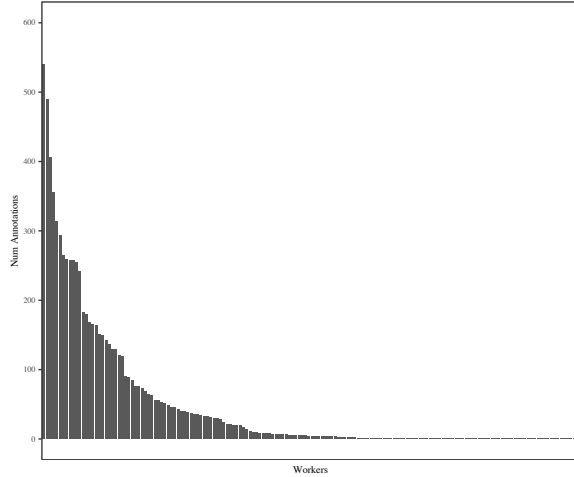


Figure 4: Distribution of story annotations completed by workers

C Quality Assessment of Crowd Annotations

In the initial phases of data collection the first two authors of this paper evaluated both the agent and patient views of 50 random stories (= 100 annotations) to ensure annotator responsiveness and quality. After collecting all the data, 3 crowd workers evaluated a random 1545 annotations and an expert evaluated a random 100 of these annotations (equal agent and patient views) for comparison. Table 10 lists the inter-rater reliability (IRR) measured using weighted Fleiss’s Kappa (Marasini et al., 2016) with the weighting scheme used by (Bastan et al., 2020), which penalises each dissimilar class by an amount based on the distance between classes (e.g., an item with responses of “very likely” and “very unlikely” will be penalized more heavily than with responses of “very likely” and “somewhat likely”).

Our evaluation consisted of 4 validation HITs, where 3 crowd workers rated the various annotation steps (see Appendix C.2). The results from this evaluation are listed in Table 10. The IRR scores suggest substantial-to-high agreement. Notably, these demonstrate that we can obtain high quality process and change of state summaries, endpoint descriptions and enabling sub-event factors.

C.1 Evaluation Set Curation

From the 1545 validated annotations we selected annotations where the average score of the crowd workers for each of the 4 validation HITs is at least 3.0. This curation resulted in 1196 carefully produced annotations for a given story. The test data set is made up of these curated annotations and

| Evaluations | Crowd | C+E | Experts |
|----------------------|-------|------|---------|
| 1. Process Sum. | 0.81 | 0.81 | 0.90 |
| 2. Endpoint Desc. | 0.81 | 0.80 | 0.89 |
| 3. Change Sum. | 0.81 | 0.80 | 0.76 |
| 4. Change Modes | 0.74 | 0.78 | 0.82 |
| 5. Factors’ Saliency | 0.77 | 0.85 | 0.84 |

Table 10: Inter-rater Agreement scores using weighted Fleiss’s Kappa (Marasini et al., 2016). C+E shows the IRR for the crowd and expert on 100 annotations. See Appendix C.2 for the various evaluations and what we looked for in the evaluation.

the training data set is made up of the remaining validated and unvalidated annotations.

C.2 Validation HITs

The various annotation steps are validated using 4 HITs. 3 workers evaluate the following using a 1-5 Likert scale with the options: Strongly Disagree, Somewhat Disagree, Neutral, Somewhat Agree and Strongly Agree.

1. Whether the Process Summary is a valid high level summary of the story.
2. Whether the endpoint description describes a valid endpoint for the complex action in the story.
3. Whether the change summary describes changes that happened as result of the complex event described in the story.
4. Whether the categorization of changes into the five change modes is consistent with the changes inferred from the story.
5. Whether the factors are salient to the complex event’s endpoint.

D HITs for Human Evaluation of Generated Summaries and Factors

Here, we show sample UIs for the human evaluation we performed in §6.2 for reference, baseline and model-generated process (Fig. 17), endpoint (Fig. 18), change summaries (Fig. 19) and factors (Fig. 20). These HITs are used to evaluate the following aspects of a summary using a 1-5 likert scale with the options Strongly Disagree, Somewhat Disagree, Neutral, Somewhat Agree and Strongly Agree.

1) *Abstractness (Task 1)*: Whether the summary is a brief, high level, abstract description that faithfully captures the complex action in the story.

2) *Validity (Tasks 2 and 3)*: Whether the summary is a valid ending for the situation described in

| MOTIVATION | |
|---|--|
| TASK INSTRUCTIONS | |
| <p>About the task:</p> <ul style="list-style-type: none"> In each HIT, you will be presented with a short newspaper story in the left column, and the task questions to complete in the right column. In the story, we identified one entity which we refer to as the Participant or Prop. For example, for the story in the illustration below, Pat is the Participant or Prop. The Participant or Prop can be a person, a thing, a place (city, country, etc.), a company, an organization, a group of persons/things/places, etc. We used automatic tools for highlighting several mentions of the participant or prop. It is possible the highlighting contains errors. In those cases, please use your best judgment. The story contains events involving the Participant or Prop. Some of these events determine the story's ending, impacting either the Participant or Prop, or some other entity or entities, in some way. We wish to capture these specific events as either stated or implied phrases from the story text, which we refer to as factors. For example, factors in the illustrated example below are based on the underlined story text. <p>What we need from you:</p> <p>Step 0: Read the story and understand the various events that lead up to an ending. Please consider any implied events and endings, i.e., ones not mentioned in the story, but highly relevant to the story, its ending, or impacts.</p> <p>Step 1: In your own words, briefly summarize what the story is about. This is a high level story plot or story logic we understand from a story.</p> <p>Step 2a: In your own words, describe the story's ending using specific names and details from the story.</p> <p>Step 2b: Identify how explicitly this ending is mentioned in the story.</p> <p>Step 3: Identify the impact of the story's ending.</p> <p>Step 3a: Identify how likely the participant or prop caused, or was responsible for, the story's ending and the resulting change(s).</p> <p>Step 3b: Identify particular ways in which entities in the story changed as a result of the ending.</p> <p>Step 3c: In your own words, describe the identified change(s).</p> <p>Please see the TYPES AND MEANINGS OF CHANGE section for various change ways and when to use them.</p> <p>Step 4: Identify "factors," i.e., phrases in the story which include events that lead to the ending and the change(s). Please select factors that are simple short clauses covering a single event. These identified factors do not need to be in any order, but they should along with the story's ending in Step 2a, outline a coherent story.</p> | |
| <p>Story Text:</p> <p><u>Pat</u> wasn't worried about illness. <u>Chris</u> got sick. <u>Pat</u> took care of her. <u>Chris</u> got better. <u>Pat</u> made a vaccine appointment.</p> | <p>Step 1: The story is about ...</p> <p>Step 2: ... with an ending of ...</p> <p>Step 3: ... impacts with changes ...</p> <p>Step 4: ... gathered from stated or implied factors.</p> <p>Factors:</p> <ul style="list-style-type: none"> Factor 1: Pat wasn't worried about illness Factor 2: Chris got sick Factor 3: Pat took care of her Factor 4: Pat made a vaccine appointment |
| <p>Please look through additional Examples in the tabs above.</p> | |
| TYPES AND MEANINGS OF CHANGE | |
| TASK | |

Figure 5: Instructions provided for the Agent view of the annotation HIT. The distinguishing aspect that makes it the Agent view is in step 3, where changes are attributable to what the participant or prop caused. In 7, 8, 10 and 12 we show the interface for each of the steps.

| MOTIVATION | |
|---|--|
| TASK INSTRUCTIONS | |
| <p>About the task:</p> <ul style="list-style-type: none"> In each HIT, you will be presented with a short newspaper story in the left column, and the task questions to complete in the right column. In the story, we identified one entity which we refer to as the Participant or Prop. For example, for the story in the illustration below, Pat is the Participant or Prop. The Participant or Prop can be a person, a thing, a place (city, country, etc.), a company, an organization, a group of persons/things/places, etc. We used automatic tools for highlighting several mentions of the participant or prop. It is possible the highlighting contains errors. In those cases, please use your best judgment. The story contains events involving the Participant or Prop. Some of these events determine the story's ending, impacting either the Participant or Prop, or some other entity or entities, in some way. We wish to capture these specific events as either stated or implied phrases from the story text, which we refer to as factors. For example, factors in the illustrated example below are based on the underlined story text. <p>What we need from you:</p> <p>Step 0: Read the story and understand the various events that lead up to an ending. Please consider any implied events and endings, i.e., ones not mentioned in the story, but highly relevant to the story, its ending, or impacts.</p> <p>Step 1: In your own words, briefly summarize what the story is about. Please give a short high level summary without any specific names.</p> <p>Step 2a: In your own words, describe the story's ending using specific names and details from the story.</p> <p>Step 2b: Identify how explicitly this ending is mentioned in the story.</p> <p>Step 3: Identify the impact of the story's ending.</p> <p>Step 3a: Identify how likely the participant or prop experienced changes as a result of the ending.</p> <p>Step 3b: Identify particular ways in which the participant or prop changed as a result of the story's ending.</p> <p>Step 3c: In your own words, summarize the identified change(s).</p> <p>Please see the TYPES AND MEANINGS OF CHANGE section for various change ways and when to use them.</p> <p>Step 4: Identify "factors," i.e., phrases in the story which include events that lead to the ending and the change(s). Please select factors that are simple short clauses covering a single event. These identified factors do not need to be in any order, but they should along with the story's ending in Step 2a, outline a coherent story.</p> | |
| <p>Story Text:</p> <p><u>Pat</u> wasn't worried about illness. <u>Chris</u> got sick. <u>Pat</u> took care of her. <u>Chris</u> got better. <u>Pat</u> made a vaccine appointment.</p> | <p>Step 1: The story is about ...</p> <p>Step 2: ... with an ending of ...</p> <p>Step 3: ... impacts with changes ...</p> <p>Step 4: ... gathered from stated or implied factors.</p> <p>Factors:</p> <ul style="list-style-type: none"> Factor 1: Pat wasn't worried about illness Factor 2: Chris got sick Factor 3: Pat took care of her Factor 4: Pat made a vaccine appointment |
| <p>Please look through additional Examples in the tabs above.</p> | |
| TYPES AND MEANINGS OF CHANGE | |
| TASK | |

Story Text

As each step is completed, the answers are displayed in the left column.

Figure 6: Instructions provided for the Patient view of the annotation HIT. The distinguishing aspect that makes it the Patient view is in step 3, where we ask about changes the participant or prop likely experienced. In 7, 9, 11 and 12 we show the interface for each of the steps.

Task

Example 1

Example 2

Example 3

Example 4

Example 5

Understanding How an Entity Facilitates Changes and Outcomes in a Story

By performing this HIT, you agree that you have read the description of the study being undertaken, and give consent for the data you enter to be used for research. Please read the consent form, if you would prefer not to take part in this experiment, please return this HIT.

- Please click on the buttons below and read through the material.
- In addition to the TASK INSTRUCTIONS with the illustrated example, we have several explained examples in the various tabs above. We hope these will help you complete the task.
- If you still have question(s), please email us at anonymized for review or send us a message through AMT.

MOTIVATION

TASK INSTRUCTIONS

TYPES AND MEANINGS OF CHANGE

TASK

As each step is completed, the answers are displayed in the left column.

Step 1: Summarize the story.

In your own words, briefly summarize what the story is about. Please type a generic phrase, giving a short high level summary, without any specific names from the story.

Reset

Step 2: Identify the story's ending.

a. In your own words, briefly describe the story's ending, even if it is an implied ending. If you think the story contains multiple endings, please pick the ending most salient to the summary you provided in Step 1.

Reset

b. The story ending you provided in Step 2a was --- by the story text.

Submit

Figure 7: Steps 1 and 2 of the Agent view of the annotation HIT. The Patient view for these steps is similar except for the title of the HIT.

Task

Example 1

Example 2

Example 3

Example 4

Example 5

Understanding How an Entity Facilitates Changes and Outcomes in a Story

By performing this HIT, you agree that you have read the description of the study being undertaken, and give consent for the data you enter to be used for research. Please read the consent form, if you would prefer not to take part in this experiment, please return this HIT.

- Please click on the buttons below and read through the material.
- In addition to the TASK INSTRUCTIONS with the illustrated example, we have several explained examples in the various tabs above. We hope these will help you complete the task.
- If you still have question(s), please email us at anonymized for review or send us a message through AMT.

MOTIVATION

TASK INSTRUCTIONS

TYPES AND MEANINGS OF CHANGE

TASK

Step 3: Identify the impact of the story ending.

a. The story's ending could have impacted one or more entities causing change(s). How likely was He the instigator, or the causer of this impact and change(s)?

b. What change(s) from the impact did He cause, or is responsible for? Select all the applicable changes. Please hover over the options to know more about when to use them. Please remember these are changes that happened as a result of the story's ending

change in location

change in feeling/emotion/perception/belief/thought

change in existence

change in possession

change some other way

no change

c. In your own words, describe the change(s) caused by He. Please make sure this description is consistent with the changes listed in Step 3b. You may separate multiple descriptions with a semicolon (;).

Submit

Figure 8: Steps 3a & 3b of the Agent view of the annotation HIT.

Task

Example 1

Example 2

Example 3

Example 4

Example 5

Understanding How an Entity Experiences Changes and Outcomes in a Story

By performing this HIT, you agree that you have read the description of the study being undertaken, and give consent for the data you enter to be used for research. Please read the consent form, if you would prefer not to take part in this experiment, please return this HIT.

- Please click on the buttons below and read through the material.
- In addition to the TASK INSTRUCTIONS with the illustrated example, we have several explained examples in the various tabs above. We hope these will help you complete the task.
- If you still have question(s), please email us at anonymized for review or send us a message through AMT.

MOTIVATION

TASK INSTRUCTIONS

TYPES AND MEANINGS OF CHANGE

TASK

Step 3: Identify the impact of the story ending.

a. The story's ending could have impacted one or more entities causing change(s). How likely was Israel changed in some way due to this impact?

b. In what way did Israel change from the impact? Select all the applicable changes. Please hover over the options to know more about when to use them. Please remember these are changes that happened as a result of the story's ending.

change in location

change in feeling/emotion/perception/belief/thought

change in existence

change in possession

change some other way

no change

c. In your own words, describe the change(s) experienced by Israel. Please make sure this description is consistent with the changes listed in Step 3b. You may separate multiple descriptions with a semicolon (;).

Submit

Figure 9: Steps 3a & 3b of the Patient view of the annotation HIT.

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Task

Example 1

Example 2

Example 3

Example 4

Example 5

Understanding How an Entity Facilitates Changes and Outcomes in a Story

By performing this HIT, you agree that you have read the description of the study being undertaken, and give consent for the data you enter to be used for research. Please read the consent form, if you would prefer not to take part in this experiment, please return this HIT.

- Please click on the buttons below and read through the material.
- In addition to the TASK INSTRUCTIONS with the illustrated example, we have several explained examples in the various tabs above. We hope these will help you complete the task.
- If you still have question(s), please email us at [anonymized for review](#) or send us a message through AMT.

MOTIVATION

TASK INSTRUCTIONS

TYPES AND MEANINGS OF CHANGE

TASK

Story Text

Paul's car broke down shortly after leaving the driveway. He decided to push it back home and repair it himself. Paul found himself in over his head and called a tow truck for repair. The tow truck took the car to a garage where it was repaired. Paul then realized attempting repairs yourself can be expensive.

Step 1:

At a high level, this story is about _____

Step 2:

The story ending is _____ and it is _____

Step 3:

It is _____ that He _____ the impact which resulted in the changes:

Submit

c. In your own words, describe the change(s) caused by He. Please make sure this description is consistent with the changes listed in Step 3b. You may separate multiple descriptions with a semicolon (;). This is not required, but you may follow the following format for describing the change:

He changed [other participant]'s [property, characteristic, belief, etc.]

The textbox below is prefilled with the above format. Please replace the blank (underscore) character with the appropriate text from the story, or click the reset button to clear the textbox, and type a description in your own words.

He changed _____'s _____

Reset

Step 4: What contributed to the story ending and change(s)?

Select phrases in the story which helped you understand the events from the beginning upto the story ending in step 2a, and the change(s) selected in step 3b & 3c. Please select factors that are simple short clauses, with each factor covering a single event.

You can either type the phrases one per textbox, or select each phrase in the story, and click the below

Figure 10: Step 3c of the Agent view of the annotation HIT.

Task

Example 1

Example 2

Example 3

Example 4

Example 5

Understanding How an Entity Experiences Changes and Outcomes in a Story

By performing this HIT, you agree that you have read the description of the study being undertaken, and give consent for the data you enter to be used for research. Please read the consent form, if you would prefer not to take part in this experiment, please return this HIT.

- Please click on the buttons below and read through the material.
- In addition to the TASK INSTRUCTIONS with the illustrated example, we have several explained examples in the various tabs above. We hope these will help you complete the task.
- If you still have question(s), please email us at [anonymized for review](#) or send us a message through AMT.

MOTIVATION

TASK INSTRUCTIONS

TYPES AND MEANINGS OF CHANGE

TASK

Story Text

Defense Secretary Robert M. Gates said Thursday that he had reassured Israel that a planned major American arms sale to Saudi Arabia and other Persian Gulf countries would not threaten Israel's military superiority and was necessary to counter a threat from Iran.

Speaking to reporters here after talks with Prime Minister Ehud Olmert and other top officials on his visit to the Middle East, Mr. Gates said that he had emphasized that Iran posed a greater threat to Israel than did the Arab countries that were to receive the sophisticated weaponry.

Step 1:

At a high level, this story is about _____

Step 2:

The story ending is _____ and it is _____

Step 3:

It is _____ that Israel _____ the impact which resulted in the changes:

Submit

c. In your own words, describe the change(s) experienced by Israel. Please make sure this description is consistent with the changes listed in Step 3b. You may separate multiple descriptions with a semicolon (;). This is not required, but you may follow the following format for describing the change:

[other participant] changed Israel's [property, characteristic, belief, etc.]

The textbox below is prefilled with the above format. Please replace the blank (underscore) character with the appropriate text from the story, or click the reset button to clear the textbox, and type a description in your own words.

_____ changed Israel's _____

Reset

Step 4: What contributed to the story ending and change(s)?

Select phrases in the story which helped you understand the events from the beginning upto the story ending in step 2a, and the change(s) selected in step 3b & 3c. Please select factors that are simple short clauses, with each factor covering a single event.

You can either type the phrases one per textbox, or select each phrase in the story, and click the below

Figure 11: Step 3c of the Patient view of the annotation HIT.

Task

Example 1

Example 2

Example 3

Example 4

Example 5

Understanding How an Entity Facilitates Changes and Outcomes in a Story

By performing this HIT, you agree that you have read the description of the study being undertaken, and give consent for the data you enter to be used for research. Please read the consent form, if you would prefer not to take part in this experiment, please return this HIT.

- Please click on the buttons below and read through the material.
- In addition to the TASK INSTRUCTIONS with the illustrated example, we have several explained examples in the various tabs above. We hope these will help you complete the task.
- If you still have question(s), please email us at [anonymized for review](#) or send us a message through AMT.

MOTIVATION

TASK INSTRUCTIONS

TYPES AND MEANINGS OF CHANGE

TASK

Story Text

Paul's car broke down shortly after leaving the driveway. He decided to push it back home and repair it himself. Paul found himself in over his head and called a tow truck for repair. The tow truck took the car to a garage where it was repaired. Paul then realized attempting repairs yourself can be expensive.

Step 1:

At a high level, this story is about _____

Step 2:

The story ending is _____ and it is _____

Step 3:

It is _____ that He _____ the impact which resulted in the changes:

Submit

Step 4: What contributed to the story ending and change(s)?

Select phrases in the story which helped you understand the events from the beginning upto the story ending in step 2a, and the change(s) selected in step 3b & 3c. Please select factors that are simple short clauses, with each factor covering a single event.

You can either type the phrases one per textbox, or select each phrase in the story, and click the below "Copy Factor" button. The factors do not need to be in any order. It is ok to leave some text boxes empty.

Copy Factor

Please make sure the selected factors and the story ending in Step 2a outline a coherent story.

Selected Factors:

Reset

Reset

Reset

Figure 12: Step 4 of the Agent view of the annotation HIT. The Patient view for this step is similar except for the title of the HIT.

Verification of a Story's Summary

By performing this HIT, you agree that you have read the description of the study being undertaken, and give consent for the data you enter to be used for research. Please read the consent form, if you would prefer not to take part in this experiment, please return this HIT.

- We want to build and train AI systems to understand stories.
- We are asking you to assess annotations we collected in a previous HIT.
- If you have question(s), please email us at [anonymized for review](#) or send us a message through AMT.

Instructions: Please indicate whether the **story summary** provided is an appropriate high-level summary of the situation described by the **story text**.

Story Text:

Senators Barack Obama and Hillary Rodham Clinton said for the first time on Tuesday that they would support legislation to curtail major combat operations in Iraq by March 31, 2008, cutting off financing for all but a limited mission of American forces.

Mr. Obama and Mrs. Clinton, two leading candidates for the Democratic presidential nomination, made separate announcements on the eve of a largely symbolic Senate debate on using the power of the purse to end the war. For weeks, the two senators had declined to state their positions, but they issued statements after rivals - and liberal groups - criticized their silence.

Story Summary: senators support ending military operations

I this is a valid summary for a high level understanding of the story.

Submit

Figure 13: HIT for Validating Process Summaries

Verification of a Story's Endpoint Annotation

By performing this HIT, you agree that you have read the description of the study being undertaken, and give consent for the data you enter to be used for research. Please read the consent form, if you would prefer not to take part in this experiment, please return this HIT.

- We want to build and train AI systems to understand stories.
- We are asking you to assess annotations we collected in a previous HIT.
- If you have question(s), please email us at [anonymized for review](#) or send us a message through AMT.

Instructions: Please indicate whether the provided ending is a valid ending for the story, and whether or not that ending was stated or implied in the story.

Story Text:

The city' s mayor and its police chief said Monday that one of the highest - ranking officials in the Police Department would be demoted and transferred in the wake of a violent confrontation between officers and demonstrators at an immigration rally last week.

The police official, Deputy Chief Cayler Carter Jr., a 30 - year veteran of the department, will be reduced one rank, to commander, and moved out of the Central Bureau, which he currently heads.

Mr. Carter has been ordered to work from home while investigations into the episode proceed.

Story Ending: Deputy Chief Cayler Carter Jr is demoted and transferred.

Please note that the story could have multiple endpoints with the above story ending being one of them.

I this is a valid endpoint in the story, and this is by the story text.

Submit

Figure 14: HIT for Validating Endpoint Descriptions

Verification of a Story's Change Annotation

By performing this HIT, you agree that you have read the description of the study being undertaken, and give consent for the data you enter to be used for research. Please read the consent form, if you would prefer not to take part in this experiment, please return this HIT.

- We want to build and train AI systems to understand stories.
- We are asking you to assess annotations we collected in a previous HIT.
- If you have question(s), please email us at [anonymized for review](#) or send us a message through AMT.

Instructions: In this HIT, you are presented with a story, a statement describing changes that a character (or multiple characters) in that story experiences. Please indicate

- whether the statement describes valid changes experienced as a result of the situation described in the story.
- whether the categorization of that change description is valid. For example, for a story that results in someone being fired from a job, a valid change could be that the person lost their job, which can be viewed as a change in possession.
- whether the story ending is consistent with the ending of the situation described in the story.

Story Text:

A year ago, this relatively small, forgettable city in the heart of **India** did not have an air - conditioned cinema. In the sweltering heat of summer, the rich would fly one hour to Mumbai, **India**' s financial hub, to see a movie and stock up on Levi' s jeans, Domino' s Pizza and other big - city treats that they could not find at home.

But if the government has its way, Nagpur will become a destination city itself.

Description of Changes: The government changed India's metropolitan geography by growing the economy of Nagpur.

Story Ending: Nagpur growing in size.

I this is a valid description of the changes experienced by **India** as a result of the situation described in the story, and the description is with a change in location.

I the above the story ending is consistent with the ending of the situation described in the story.

Submit

Figure 15: HIT for Validating Change Summaries

Verification of What Events Lead to a Story's Endpoint.

By performing this HIT, you agree that **you have read the description of the study being undertaken, and give consent for the data you enter to be used for research.** Please [read the consent form](#), if you would prefer not to take part in this experiment, please return this HIT.

- We want to **build and train AI systems** to understand stories.
- We are asking you to assess annotations we collected in a previous HIT.
- If you have question(s), please email us at [anonymized for review](#) or send us a message through AMT.

Instructions: In this HIT, you are presented with a **story**, an **ending** for the story, and **"factors"**. "Factors" are events or situations relevant to understand the story from the beginning to the given ending, and any changes resulting from this ending.

After reading the story, ending, and factors, please indicate whether --

- each factor is important for understanding the story leading up to the ending.
- any important events are missing from the Factors.
- the ending can be concluded from the Factors.

Story Text:

President Vladimir V. Putin seemed to obliquely compare the foreign policy of the United States to the Third Reich in a speech on Wednesday commemorating the 62nd anniversary of the defeat of Nazi Germany.

The comments were the latest in a series of sharply worded Russian criticisms of the foreign policy of the United States - on Iraq, missile defense, NATO expansion and, more broadly, United States unilateralism in foreign affairs.

Many Russians say the sharper edge reflects a frustration that Russia's views, in particular opposition to NATO expansion, have been ignored in the West.

Story Ending: Russian frustration with Western views is continuing.

Factors:

Is each factor important for understanding the story and ending.

| Yes | No | |
|-----------------------|-----------------------|---|
| <input type="radio"/> | <input type="radio"/> | 1. There have been Russian criticism on the following issues: |
| <input type="radio"/> | <input type="radio"/> | 2. Iraq, |
| <input type="radio"/> | <input type="radio"/> | 3. missile defense, |
| <input type="radio"/> | <input type="radio"/> | 4. NATO expansion |
| <input type="radio"/> | <input type="radio"/> | 5. United States unilateralism in foreign affairs. |
| <input type="radio"/> | <input type="radio"/> | 6. Putin compared the US to the Third Reich |
| <input type="radio"/> | <input type="radio"/> | 7. Russia thinks its views have been ignored. |
| <input type="radio"/> | <input type="radio"/> | Some important factors are missing in the above list. |

I that we can conclude the above story ending from the important factors.

Figure 16: HIT for Validating Factors

the story for task 2. In task 2, when evaluating factors, we check whether each factor contains story related information. For task 3, we check whether the summary mentions a change that is consistent with the details in the story. A blank summary is valid, if the story does not contain any changes.

3) *Salience (Tasks 2 and 3)*: Whether the summary is a valid ending for the situation described in the story for task 2. In task 2, when evaluating factors, we check whether each factor is necessary for understanding the situation. For task 3, we check whether the summary mentions a change that is consistent with the details in the story. When a story does not contain any changes, the annotation of no-changes is considered salient.

E Model Training

To perform early development experiments, we used 5-fold cross validation for 2 epochs. We found that while the evaluation loss plateaued after training for an epoch, recall improved with further training for another epoch. Classification results are the average of the 5-fold cross validation after 2 epochs for T5 and 1 epoch for BART for the single label classification in Task 5. The Multi-label binary classification for Task 4 was trained for 5 epochs for the BART models, 10 epochs for the T5 Encoder Only and the Encoder-Decoder model. For the summarization tasks, we trained models on the entire training set without subsequent hyperparameter tuning for 2 epochs for all tasks.

F Expanded Results

In this section we present expanded results from §6. In addition to average number of tokens in a summary or factor (*Len*) and percentage of extractive trigrams from the story text (*Ext*), ROUGE-L (longest word sequences) and BertScore that were reported in the paper, we use the ROUGE scores based on unigrams (ROUGE-1) and bigrams (ROUGE-2), corpus and sentence level BLEU, and METEOR. Unlike the lexical- and ontological-based metrics of ROUGE, BLEU and METEOR, BertScore aims to provide a modern, embedding-based approach for handling semantic equivalence/similarity even when the texts being compared have different surface forms (e.g., different words are used). These automated scores are calculated using all the test data where as the human evaluation scores are for the 50 randomly selected data items for evaluation. The automated scores of ROUGE, BLEU, METEOR and BertScore are not reported for the reference summaries, as these summaries were used as gold references when calculating automated scores for the baseline and model generations. For the human evaluation we report the IAA by crowd workers. The difference in IAA for the crowd + expert scores and the crowd scores was < 0.1. The metrics reported on the left of the double line are calculated for all the test data. The best value for each score category are bolded and those that are significantly higher than all other values are marked with a *.

Verification of Story Process Summaries

By performing this HIT, you agree that **you have read the description of the study being undertaken, and give consent for the data you enter to be used for research.** Please [read the consent form](#), if you would prefer not to take part in this experiment, please return this HIT.

- We want to **build and train AI systems** to understand stories.
- We are asking you to assess summaries for the story.
- If you have question(s), please email us at language-understanding@googlegroups.com or send us a message through AMT.

Instructions: Determine if the given summary gives an abstract description of the situation in the story text.

An abstract description —

- is brief and captures the situation in the story at a high level,
- is topically related, and consistent with the facts in the story, without any made up untrue information,
- is not copied, or minimally revised text, from the story, and
- does not contain any specific participant names from the story.

Please note that summary text may be entirely in lower case. Please do not lower your ratings because of this.

Story Text:

Israeli and Palestinian leaders reached agreement tonight for Israeli forces to begin withdrawing from areas of the Gaza Strip and returning security control to Palestinian officers, officials familiar with the negotiations said. The withdrawal, which could begin Sunday, would be the first joint step forward, beyond oratory, under a new international peace plan known as the road map. Palestinian security officials committed themselves to capturing what Israeli calls "ticking bombs" - attackers on their way to strike - while **Israel** promised to permit Palestinians to travel more freely, to ease **its** military choke points on Gaza's main north - south road, and to draw back forces in northern Gaza, officials said.

Story Summary: israeli and palestinian leaders reached agreement

Is the above summary an abstract description of the situation in the story text?

☐ Strongly Disagree ☐ Somewhat Disagree ☐ Neutral ☐ Somewhat Agree ☐ Strongly Agree

Submit

Figure 17: HIT for Evaluating Reference, Baseline and Generated Process Summaries

Verification of Story Endings

By performing this HIT, you agree that **you have read the description of the study being undertaken, and give consent for the data you enter to be used for research.** Please [read the consent form](#), if you would prefer not to take part in this experiment, please return this HIT.

- We want to **build and train AI systems** to understand stories.
- We are asking you to assess endings for the story.
- If you have question(s), please email us at language-understanding@googlegroups.com or send us a message through AMT.

Instructions: Determine if the given story ending describes a likely outcome of the situation and is factually consistent with the story.

A **factual ending** contains only facts stated or implied by the story. It does not contain incorrect participant names, or implied facts that are incorrect or impossible based on the story.

A **salient ending** contains enough information relating to the story to describe an outcome that is most likely for the situation in the story.

Please note that the story ending may be entirely in lower case. Please do not lower your ratings because of this.

Story Text:

The American military said Thursday that a **senior commander at Camp Cropper, its main detention center here**, was being investigated for possibly "aiding the enemy." A military spokeswoman, Lt. Col. Josslyn L. Aberle, identified **the commander** as **Lt. Col. William H. Steele** and said **he** was being held in Kuwait for the equivalent of a grand jury investigation. Lt. Kyung Choi of the Navy, a spokesman at Central Command in Tampa, Fla., said there were nine charges, including aiding the enemy.

Story Ending: lt. col. william h. steele was being investigated for aiding the enemy.

Factual: Is the above story ending factually consistent with the story text?

☐ Strongly Disagree ☐ Somewhat Disagree ☐ Neutral ☐ Somewhat Agree ☐ Strongly Agree

Salient: Is the above story ending the most likely outcome for the situation described in the story text?

☐ Strongly Disagree ☐ Somewhat Disagree ☐ Neutral ☐ Somewhat Agree ☐ Strongly Agree

Submit

Figure 18: HIT for Evaluating Reference, Baseline and Generated Endpoint Summaries

Verification of Change Summaries

By performing this HIT, you agree that **you have read the description of the study being undertaken, and give consent for the data you enter to be used for research.** Please [read the consent form](#), if you would prefer not to take part in this experiment, please return this HIT.

- We want to **build and train AI systems** to understand stories.
- We are asking you to assess change summaries for the story.
- If you have question(s), please email us at language-understanding@googlegroups.com or send us a message through AMT.

Instructions: Determine if the given change summary describes factually consistent change(s) resulting from the situation described in the story. *Sometimes, a story may not contain any changes. For such a story, "no changes" is an appropriate summary.*

A **factual** change summary only contains facts stated or implied by the story. It does not contain incorrect participant names, incorrectly implied, or impossible facts.

A **salient** change summary contains enough information that describes specific change(s) in story participants resulting from the situation described in the story.

Please note that summary text may be entirely in lower case. Please do not lower your ratings because of this.

Story Text:

Shocked by the murder of **the man many assumed would be their next President**, Mexicans today mourned the violent death of **Luis Donaldo Colosio** as the governing party began to choose a new candidate who can keep the party's long hold on power and bind the country's wounds. Though Mexicans were left stunned and grieving by the assassination on Wednesday evening, there were signs that the contest for the future leadership of the Institutional Revolutionary Party, and very likely the country, would begin immediately, and would prove to be divisive and contentious. No one emerged today as a consensus candidate, but it was clear that President Carlos Salinas de Gortari would make the choice personally, as he did in **Mr. Colosio's** case, after consulting with a coterie of advisers and the leaders of his party, which has 16 million members.

Change Summary: luis donaldo colosio changed the governing party's ability to choose a new president.

Factual: Is the above change summary factually consistent with the story text?

☐ Strongly Disagree ☐ Somewhat Disagree ☐ Neutral ☐ Somewhat Agree ☐ Strongly Agree

Salient: Does the above change summary describe changes in story participants?

☐ Strongly Disagree ☐ Somewhat Disagree ☐ Neutral ☐ Somewhat Agree ☐ Strongly Agree

Submit

Figure 19: HIT for Evaluating Reference and Generated Change Summaries

Verification of Story Factors

By performing this HIT, you agree that you have read the description of the study being undertaken, and give consent for the data you enter to be used for research. Please [read the consent form](#), if you would prefer not to take part in this experiment, please return this HIT.

- We want to build and train AI systems to understand stories.
- We are asking you to assess factors identified for the story.
- If you have question(s), please email us at language-understanding@googlegroups.com or send us a message through AMT.

Instructions: Determine if the given factor is concise and contains important story information needed to understand the situation described in the story.

A **multi-factor** contains multiple story related facts.

A **concise** factor contains story related information that is clear and direct, without unnecessary details.

A **salient** factor contains story related information that is necessary to understand the situation described in the story.

Please note that the story ending may be entirely in lower case. Please do not lower your ratings because of this.

Story Text:

My friend Carlos was in jail for a DUI. He called me from jail, asking me to help manage his life. He signed a Power of Attorney form, and I began paying his bills. This included his mortgage, as he owned a condo. He got out eventually, and thanked me for my efforts.

Story Factor: asking me to help manage his life

Multi-Fact: Does the above story factor contain multiple story related facts?
☐ Strongly Disagree ☐ Somewhat Disagree ☐ Neutral ☐ Somewhat Agree ☐ Strongly Agree

Concise: Does the above story factor contain clear and direct story related information without unnecessary details?
☐ Strongly Disagree ☐ Somewhat Disagree ☐ Neutral ☐ Somewhat Agree ☐ Strongly Agree

Salient: Does the above story factor contain information that is necessary for understanding the situation described in the story text?
☐ Strongly Disagree ☐ Somewhat Disagree ☐ Neutral ☐ Somewhat Agree ☐ Strongly Agree

Submit

Figure 20: HIT for Evaluating Reference and Generated Factors

| | Model | Len | Ext↓ | Rouge | | | MET-EOR | BLEU | | Bert | Abstractness | | |
|-------|-----------|-----|------|--------------|-------------|--------------|--------------|-------------|-------------|--------------|--------------|-----|------|
| | | | | 1 | 2 | L | | sent. | corpus | Score | AvgLS | IAA | %Abs |
| | Reference | 3.6 | .13* | - | | | | | | | 3.57* | .82 | 72 |
| | About P | 1.7 | .27 | 10.55 | 4.22 | 10.43 | 0.07 | 0.35 | 2.70 | 83.86 | 2.37 | .48 | 16 |
| Story | Bart-base | 4.0 | .46 | 22.43 | 8.34 | 21.43 | 15.26 | 7.89 | 4.27 | 86.70 | 2.77 | .86 | 42 |
| | T5-base | 10 | .60 | 21.14 | 7.48 | 19.50 | 18.43 | 5.55 | 2.81 | 85.99 | 2.32 | .72 | 28 |
| | T5-large | 6.9 | .63 | 21.73 | 8.47 | 20.30 | 17.59 | 7.78 | 4.16 | 86.15 | 2.13 | .77 | 20 |
| Fact. | Bart-base | 4.2 | .33 | 25.17 | 9.05 | 23.81 | 17.61 | 6.73 | 4.89 | 87.66 | 3.22 | .76 | 54 |
| | T5-base | 9.9 | .56 | 19.94 | 6.39 | 18.29 | 17.47 | 4.19 | 2.63 | 86.10 | 2.73 | .69 | 36 |

Table 11: Generating Process Summaries for stories and factors+endpoint (Task 1). The best scores are bolded. * indicates the Reference value for Abstractness is significantly higher than other values in the column with a p value between 0.001 - 0.0001 (except for Bart-base trained on Factors where the p value is 0.13). Len value for Reference is considered the best as the baseline value is not meaningful. The column AvgLS is the average of 3 crowd worker 1-5 Likert scores, and the column % Abs is percentage of instances with a score ≥ 3 .

| | Model | Tok | Ext↓ | Rouge | | | MET- | BLEU | | Bert | Factuality | | | Salience | | |
|-------|------------|------|------|--------------|--------------|--------------|--------------|--------------|-------------|--------------|--------------|------|------|--------------|------|------|
| | | | | 1 | 2 | L | EOR | sent. | corpus | Score | AvgLS | IAA | %Abs | AvgLS | IAA | %Abs |
| | Reference | 7.9 | .27 | | | | - | | | | | 4.15 | .87 | 80 | 3.46 | .76 |
| | Last sent. | 23.3 | .79 | 24.08 | 12.33 | 21.82 | 24.62 | 0.58 | 6.59 | 85.60 | 4.49 | .82 | 90 | 3.35 | .82 | 62 |
| Story | Bart-base | 11 | .72 | 27.83 | 13.05 | 25.43 | 22.88 | 11.12 | 8.31 | 87.61 | 4.66 | .73 | 96 | 3.97 | .69 | 80 |
| | Bart-large | 10.3 | .63 | 27.00 | 12.51 | 24.74 | 21.44 | 10.82 | 8.30 | 87.62 | 4.59 | .78 | 96 | 3.81 | .72 | 74 |
| | T5-base | 13.6 | .70 | 26.66 | 11.79 | 24.07 | 22.69 | 9.79 | 6.62 | 87.19 | 4.71* | .75 | 96 | 4.03 | .76 | 82 |
| | T5-large | 12.9 | .67 | 28.36 | 13.15 | 25.71 | 24.31 | 10.93 | 7.83 | 87.54 | 4.71* | .77 | 100 | 4.23* | .72 | 90 |
| Fact. | Bart-base | 7.3 | .49 | 26.26 | 10.86 | 24.09 | 18.28 | 9.15 | 7.32 | 87.93 | 4.11 | .77 | 80 | 3.28 | .76 | 52 |
| | T5-base | 10.4 | .47 | 24.74 | 9.52 | 22.01 | 18.53 | 7.31 | 5.69 | 87.07 | 3.99 | .72 | 82 | 3.02 | .69 | 44 |

Table 12: Generating Endpoints for stories and factors (Task 2a). The best scores are bolded. * indicates the value is significantly higher than the Reference with a p value of .002 for Factuality and .0008 for Salience. The column AvgLS is the average of 3 crowd worker 1-5 Likert scores, and the column % Abs is percentage of instances with a score ≥ 3 .

| Model | Factors | | Rouge | | | MET-EOR | BLEU | | Bert Score | Brevity | | | Factuality | | | Saliency | | |
|------------|---------|------|--------------|--------------|--------------|--------------|-------------|-------------|--------------|-------------|-----|------|--------------|-----|------|--------------|-----|------|
| | Num | Len | 1 | 2 | L | | sent. | corpus | | AvgLS | IAA | %Abs | AvgLS | IAA | %Abs | AvgLS | IAA | %Abs |
| Reference | 3.6 | 8.3 | | | | | | | | 3.35 | .73 | 90 | 3.25 | .67 | 52 | 3.04 | .73 | 42 |
| Bart-base | 3.5 | 14.0 | 49.90 | 37.35 | 45.28 | 43.04 | 0.42 | 25.18 | 88.06 | 2.46 | .62 | .60 | 3.49 | .69 | 59 | 3.57 | .76 | 63 |
| Bart-large | 3.6 | 13.7 | 50.51 | 38.11 | 45.98 | 43.63 | 0.44 | 25.32 | 88.10 | 2.88 | .65 | 67 | 3.2 | .68 | 50 | 3.31 | .73 | 52 |
| T5-base | 2.6 | 19.6 | 47.89 | 35.86 | 43.31 | 44.12 | 0.38 | 24.61 | 87.74 | 1.77 | .66 | 38 | 3.69 | .76 | 68 | 4.01* | .79 | 79 |
| T5-large | 3.7 | 13.9 | 52.26 | 40.57 | 47.96 | 46.83 | 0.40 | 26.8 | 88.44 | 2.15 | .65 | 48 | 3.80* | .70 | 71 | 3.96 | .77 | 78 |

Table 13: Generating Factors from stories and their endpoints (Task 2b). The best scores are bolded. The * for factuality and saliency indicates the value is significantly higher than the Reference with a p value of .0001. The Reference value for Brevity is significantly higher than all values in the column with a p value of .0001. The column AvgLS is the average of 3 crowd workers’ 1-5 Likert scores, and the column % Abs is percentage of instances with a score ≥ 3 .

| Model | Rouge | | | MET-EOR | BLEU | | Bert-Score | Factuality | | | Saliency | | |
|------------|--------------|--------------|--------------|--------------|-------------|-------------|--------------|-------------|-----|------|-------------|-----|------|
| | 1 | 2 | L | | sent. | corpus | | AvgLS | IAA | %Abs | AvgLS | IAA | %Abs |
| Reference | - | | | | | | | 3.36 | .78 | 60 | 3.32 | .76 | 64 |
| Bart-base | 39.56 | 23.66 | 34.79 | 28.68 | 7.97 | 5.29 | 88.39 | 3.03 | .69 | 48 | 2.93 | .71 | 50 |
| Bart-large | 39.28 | 20.68 | 32.80 | 27.87 | 7.10 | 6.91 | 88.23 | 2.99 | .72 | 44 | 3.05 | .74 | 48 |
| T5-base | 32.82 | 14.74 | 26.81 | 24.62 | 5.91 | 6.73 | 87.20 | 3.74 | .75 | 52 | 3.23 | .66 | 66 |
| T5-large | 34.40 | 15.53 | 27.14 | 24.65 | 6.11 | 7.07 | 87.38 | 3.81 | .70 | 70 | 3.53 | .70 | 72 |

Table 14: Generating changes resulting from a complex event (Task 3). The best scores are bolded. The column AvgLS is the average of 3 crowd workers’ 1-5 Likert scores, and the column % Abs is percentage of instances with a score ≥ 3 .

| Trained-on | Model | Test-on | Len | Ext | Rouge | | | MET-EOR | BLEU | | Bert Score | Factuality | Saliency |
|------------|-----------|---------|------|-----|-------|-------|-------|---------|-------|--------|------------|------------|----------|
| | | | | | 1 | 2 | L | | Sent. | corpus | | | |
| ROC | Bart-base | ROC | 5.6 | .55 | 42.54 | 21.13 | 39.16 | 31.20 | 18.54 | 12.37 | 91.46 | 4.43 | 4.25 |
| | T5-base | ROC | 8.4 | .55 | 43.13 | 20.66 | 38.53 | 33.35 | 16.56 | 9.77 | 90.83 | 4.43 | 4.24 |
| | Bart-base | News | 9.8 | .39 | 22.53 | 8.25 | 20.49 | 16.27 | 6.46 | 4.97 | 87.17 | 3.98 | 3.59 |
| | T5-base | News | 23.8 | .64 | 23.60 | 10.03 | 20.60 | 24.54 | 6.99 | 4.64 | 86.44 | 4.46 | 4.01 |
| News | Bart-base | ROC | 6.2 | .89 | 39.39 | 18.80 | 36.41 | 29.64 | 15.55 | 10.95 | 90.46 | 4.55 | 4.09 |
| | T5-base | ROC | 9.0 | .74 | 35.42 | 14.41 | 31.39 | 26.94 | 11.75 | 7.01 | 90.26 | 4.45 | 3.43 |
| | Bart-base | News | 11.5 | .77 | 25.28 | 11.58 | 23.12 | 20.77 | 10.16 | 7.78 | 86.95 | 4.62 | 4.01 |
| | T5-base | News | 15.5 | .75 | 22.94 | 9.69 | 20.51 | 20.22 | 8.05 | 5.48 | 86.51 | 4.59 | 3.95 |

Table 15: Comparing Endpoint generations of models trained on ROCStories and models trained on Newswire stories

G Computing Infrastructure & Processing information

Infrastructure We trained our models on a single RTX 8000 with 48GB of GPU memory. Approximate run time was 1 hour.

Model Parameters In addition to the number of parameters in each of the models we consider (e.g., Bart-Base, T5-base, T5-large), each of our fine-tuned classification models has a separate classifier layer. This layer takes in a D dimension embedding from the encoder and uses a single linear layer to compute K dimensional logits (therefore, an additional $D \times K$ parameters). The value of D will depend on the model, and the value of K will depend on the number of label types that could be predicted. For the generation tasks, we do not add any additional parameters to the models.

Hyperparameters For all experiments we used AdamW (Loshchilov and Hutter, 2017) optimizer, a learning rate of 10^{-4} , a weight decay of 10^{-4} and a random seed of 11. We applied manual tuning and tried various learning rates from .001 to .00001 as suggested for the BART and T5 models. For the generation we used Top-K sampling with a beam size of 2. These parameters worked well for all the models and this was selected based on accuracy for the classification tasks and Rouge scores for the summarization tasks.

Results statistics With our 5-fold cross-validation, the automated metrics for summarization and the accuracy/F1 values for classification varied by less than 3 percent.