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# CREAK: A Dataset for Commonsense Reasoning over Entity Knowledge

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## Abstract

Most benchmark datasets targeting commonsense reasoning focus on everyday scenarios: physical knowledge like knowing that you could fill a cup under a waterfall [Talmor et al., 2019], social knowledge like bumping into someone is awkward [Sap et al., 2019], and other generic situations. However, there is a rich space of commonsense inferences anchored to knowledge about specific entities: for example, deciding the truthfulness of a claim *Harry Potter can teach classes on how to fly on a broomstick*. Can models learn to combine entity knowledge with commonsense reasoning in this fashion? We introduce CREAK, a testbed for commonsense reasoning about entity knowledge, bridging fact-checking about entities (Harry Potter is a wizard and is skilled at riding a broomstick) with commonsense inferences (if you’re good at a skill you can teach others how to do it). Our dataset consists of 13k human-authored English claims about entities that are either true or false, in addition to a small contrast set. Crowdworkers can easily come up with these statements and human performance on the dataset is high (high 90s); we argue that models should be able to blend entity knowledge and commonsense reasoning to do well here. In our experiments, we focus on the closed-book setting and observe that a baseline model finetuned on existing fact verification benchmark struggles on CREAK. Training a model on CREAK improves accuracy by a substantial margin, but still falls short of human performance. Our benchmark provides a unique probe into natural language understanding models, testing both its ability to retrieve facts (e.g., who teaches at the University of Chicago?) and unstated commonsense knowledge (e.g., butlers do not yell at guests).

## 1 Introduction

To understand text, humans use rich background knowledge about the world. Despite the impressive ability of large-scale pretrained models, models often generate sentences that violate a reader’s expectations, particularly in terms of common sense. As these models are increasingly employed in settings like generative question answering [Fan et al., 2019, Lewis et al., 2020] and fact verification [Vlachos and Riedel, 2014, Wang, 2017, Thorne et al., 2018], they should exhibit not just commonsense about everyday scenarios (physical, social, etc.), but factual knowledge about entities as well. These concepts overlap in a set of inferences involving entities that we call *entity commonsense*. For example, to recognize that “*Many business owners rely on WordPress to create their websites.*” is true requires both knowledge about the entity (WordPress is a website hosting service) and a more nebulous piece of commonsense information (famous products like WordPress are widely used).

We present CREAK, a dataset aiming to evaluate two major desiderata of NLP models: entity understanding and commonsense inference. Figure 1 shows how these concepts interact in examples from CREAK. Building LMs with a stronger ability to perform this type of inference can help make NLP systems more effective and reliable.

**Claim:** Harry Potter can teach classes on how to fly on a broomstick. **TRUE**



Harry Potter is a wizard ...  
He plays Quidditch while riding on a broomstick.



Someone who's good at something can teach it.

**Claim:** One can drive La Jolla to New York City in less than two hours. **FALSE**



La Jolla is in California.  
NYC is in New York.



It takes 5h with airplane to fly from California to New York.

**Claim:** François Mitterrand became a Texas Senator in 2001. **FALSE**



François Mitterrand (26 Oct 1916 – 8 Jan 1996) was a French statesman.

Figure 1: CREAK claims with different reasoning types. Datasets like FEVER focus on retrieval (as in the last case); our dataset also features many claims that involve both retrieval and also commonsense reasoning (54% of the data according our manual study in Section 3.3).

Our dataset consists of 13k English claims covering 2.7k entities, each labeled as true or false. Each claim is generated by a crowdworker based on a Wikipedia entity, which can be named entities (e.g., John Dewey), common nouns (e.g., penguins), and abstract concepts (e.g., freedom of speech). Our lightweight task design provides annotators with a set of popular entity topics, and by not including explicit evidence documents to copy text from, annotators are encouraged to create examples fully from scratch. This results in sentences where annotators combine their knowledge about entities with common sense to generate claims. Even without resorting to adversarial filtering, which artificially biases a dataset against existing model checkpoints [Bowman and Dahl, 2021], we find our annotation protocol leads to challenging claims for existing models. We provide in-depth analysis on what makes our dataset uniquely challenging: for example, 18% of claims in CREAK contain quantifiers (e.g., enough, always, rarely etc.) that necessitate subtle commonsense reasoning, compared to existing fact verification datasets [Thorne et al., 2018] where only 5% of claims contain the quantifiers.

Asking crowdworkers to generate free-form sentences can introduce dataset artifacts [Gururangan et al., 2018, Geva et al., 2019]. We carefully examine such artifacts in our datasets using quantitative tools [Swayamdipta et al., 2020, Gardner et al., 2020] as well as qualitative inspection. We also provide a small set of expert-written contrast examples [Kaushik et al., 2019, Gardner et al., 2020] which pair true and false claims sharing almost identical context.

To establish an initial performance level on CREAK, we evaluate state-of-the-art pre-trained language models [Liu et al., 2019, Raffel et al., 2020]. Our experiments shows that CREAK is challenging even for a large model, with a gap between model and human accuracy of 10 points on the development set and about 27 points on the contrast set for the largest model. Moreover, the model trained on CREAK outperforms the model trained on other claim verification datasets [Thorne et al., 2018, Eisenschlos et al., 2021, Park et al., 2021], suggesting that CREAK tests different reasoning capabilities compared to existing datasets. We further characterize the performance based on model size, entity type, and the whether external knowledge is used. Our analysis supports that to achieve high performance on our dataset, models should possess not only entity knowledge but also complex reasoning skills. The code and data are publicly available at <https://www.cs.utexas.edu/~yasumasa/creak>.

## 2 Related Work

**Claim Verification** Our task is formulated as claim verification, which has seen increasing work in recent years. The largest claim verification dataset, FEVER [Thorne et al., 2018], has claims designed to be verifiable with a passage from English Wikipedia and typically covers simple facts such as attributes and records (e.g., “*Benjamin Franklin was a person,*” and “*Spider-Man 2 was released in 2004.*”). In fact, 58% of FEVER claims contain a simple copular verb (*is, are, was, were*) and many claims contain a definition. Prior work [Eisenschlos et al., 2021] observed high lexical overlap between claims and corresponding entity definitions in Wikipedia, and collected more complex claims using a human-in-the-loop adversarial approach. Similarly, recent work [Park et al., 2021] derives a challenging verification dataset from ambiguous questions [Min et al., 2020] and their different

interpretations. However, both datasets focus on a retrieval setting where there is a single paragraph in Wikipedia from which the claim can be easily verified. In contrast, our dataset contains claims where it is not easy to find a single paragraph that can verify them, testing models’ intrinsic abilities.

**Question Answering** Question answering and claim verification are closely related, particularly when it comes to binary questions [Clark et al., 2019]. Our dataset is purposely constructed to go beyond basic factoid information like that tested in open QA benchmarks like NaturalQuestions [Kwiatkowski et al., 2019] and focuses on information that is less likely to have textual support on the web. The recently proposed StrategyQA dataset [Geva et al., 2021] which contains binary questions requiring implicit reasoning that goes beyond evidence retrieval (e.g., “*would it be common to find a penguin in Miami?*”) captures a similar type of reasoning and knowledge as in our work. However, our annotation process does not require authoring strategies, allowing us to scale to a larger dataset (13K vs. 2.8K) while capturing a wide range of inference types. Finally, some QA datasets have been adapted for evaluating differentiable commonsense reasoning models [Lin et al., 2021], but these benchmarks still test very different knowledge from ours.

**Commonsense Reasoning** Commonsense reasoning tasks [Levesque et al., 2011, Zellers et al., 2018, Talmor et al., 2019, Lourie et al., 2021, inter alia] evaluate models’ reasoning skills in the physical world, with reporting bias being a principal challenge [Gordon and Van Durme, 2013]. Yet, most datasets assume hypothetical environments and do not address real-world entities. Our work relates to judging plausibility of events [Forbes and Choi, 2017, Wang et al., 2018], closely tied to inferences accessible from feature norms [McRae et al., 2005], but again these past efforts do not focus on judgments around specific entities.

**Knowledge Probing** The LAMA benchmark [Petroni et al., 2019] was proposed to query factual knowledge covered in language models. Our dataset also covers such factual knowledge but also requires commonsense reasoning capabilities. Our work also creates a moderately sized training dataset. Other datasets in the KILT benchmark [Petroni et al., 2020], an aggregate suite focusing on knowledge intensive tasks, are more focused on recognizing entities and relations, “low-level” factual knowledge which does not require the kinds of commonsense inferences in our dataset. Another recent commonsense-focused dataset [Lin et al., 2020], focuses on probing numeric claims.

### 3 CREAK

#### 3.1 Task Definition

**Problem Scope** Our benchmark covers claims that are typically quite easy for humans to verify but challenging for language models. We focus on factual claims about real-world entities, but our claims are more complex than existing fact verification examples which tend to state relatively simple facts (i.e., definitive sentences, *X is a Y*, or sentences expressing simple relations, like *X is CEO of Z*). To the extent possible, we avoid information that is obscure or requires computation, such as asking about the time between two arbitrary events or how many copies of an album were sold, which test either retrieval or memorization rather than commonsense reasoning. We found that our claims can often be verified with minimum knowledge of the entities combined with common sense (i.e., you can guess the answer accurately even if you do not know the entity very well).<sup>1</sup> We argue that this knowledge is what pre-trained LMs should possess about moderately well-known entities after seeing a few occurrences of them during pre-training. Therefore, our claims should be solvable in the closed-book setting where we can purely evaluate LMs’ commonsense reasoning skills, isolated from the performance of retrieval models.

We formally define the CREAK task as follows. Given a single sentence claim  $c$  containing at least one entity mention, the task is to assign a binary label  $y \in \{\text{TRUE}, \text{FALSE}\}$  indicating whether the claim is true or false. Dataset statistics can be found in Table 1.

**Dataset Properties** Our dataset has following key properties. The claims are **diverse** covering various types of entities: they are written by 684 distinct crowdworkers<sup>2</sup> only based on the entity

<sup>1</sup>During our validation, we could confidently judge about 30-50% of claims without searching the web.

<sup>2</sup>We limit the number of claims that a single crowdworker can generate (no more than 7% of any split).

Table 1: Data statistics of CREAK.

Split	# Claims			Average Length (# tokens)	# Unique Entities	Vocab Size
	Total	True	False			
Train	10,176	5,088	5,088	10.8	2,096	19,006
Dev	1,371	691	680	9.7	531	4,520
Test	1,371	707	664	9.9	538	4,620
Test (Contrast)	200	100	100	11.0	100	800

names and their minimal information. We rarely find lexical overlap between the claims and publicly available knowledge sources (e.g., the first paragraph of English Wikipedia). As a result, the claims contain a variety of reasoning types, but nevertheless are **typically not subjective** and **easily verifiable**. As discussed in Section 3.3, a majority of our examples do **involve a combination of commonsense reasoning and knowledge**. Finally, Sections 3.3 and 4 show that the dataset is **relatively robust to spurious correlations**.

### 3.2 Data Collection

We collect our data on the Amazon Mechanical Turk platform. Open-ended text generation is challenging to crowdsource, so we take several steps in our task design to ensure quality. First, we ask crowdworkers to write down the reason why the generated claim is true or false; although past work observes that this does not improve example quality in isolation [Nangia et al., 2021], we found it helpful for our task, and it additionally helped us spot workers who misunderstood the task. To keep the sentences natural, we use a minimal set of requirements and encourage crowdworkers to produce creative and diverse sentences. One key requirement is to use action verbs instead of copula, which prevent crowdworkers from writing simple definitive sentences. See Appendix A for more details about the annotation instructions.

We do not take a model-in-the-loop approach [Zellers et al., 2018, 2019, Nie et al., 2020, Bras et al., 2020] during data collection in order to keep our dataset organic, meaning that sentences preserve the original data distribution given by annotators. Therefore, this benchmark does not favor or disfavor particular LM checkpoints, providing a fair and comparable testbed [Bowman and Dahl, 2021].

**Seed Entities Curation** Entity selection plays a crucial role in this task, since authoring sentences is a much easier task if a crowdworker is familiar with the entity. We take two steps to enable crowdworkers to focus on known entities. First, we use the entity list created by Geva et al. [2021] as part of StrategyQA, which aligns with our needs; the authors select entities based on some popularity measures such as the number of contributors and the number of backward links from other pages. Second, we present five entities to each annotator and let them pick from that set of five when authoring their sentences. We manually inspect the seed entities to maintain the diversity of the types of entities so that the generated claims cover diverse topics (e.g., we want to avoid too many location entities that occur in English Wikipedia frequently). We finally obtain 6.4k entities after this process.

We split the seed entity list into two parts; one for the training instances and one for the development and test instances. In both sets, roughly 80% of entities are named entities. The 5 most popular entities in the train set are *Sloth*, *Giraffe*, *George Orwell*, *50 Cent*, *Mattel*. In the development and test sets, *Butterfly*, *Ray Charles*, *Whole Foods Market*, *Internet troll*, and *Bigfoot* are the top 5 popular entities. As can be seen, crowdworkers prefer to select relatively common entities.

**Quality Control** We split the data curation into two separate tasks such that no annotator contributed to both training and evaluation datasets. This mitigates the issue of learning to model the behavior of specific annotators [Geva et al., 2019] and annotation artifacts from annotator developing a template (e.g., ENTITY created ENTITY) across many instances. In total, CREAK is created by a large number of annotators: 153 crowdworkers annotated the development and test instances, and 531 crowdworkers worked on the training instances. We also use disjoint sets of entities between training and dev/test data so a model trained on the dataset is not simply learning properties of the entities under discussion here. We discuss more in Section 3.3.

During the annotation process, we monitored the sentence quality and barred crowdworkers who repeatedly produced low-quality sentences or examples following a single pattern. We then inspected the examples included in our evaluation dataset. During the inspection, we found some claims that are subjective, ambiguous, or non-factual (see Appendix B). These errors potentially lower the human performance on the development and test sets. Since automatically detecting these errors is non-trivial, the authors manually filtered all claims in the evaluation dataset. This process removed roughly 18% of crowdsourced claims. This process was crucial for very high human performance (99% majority human performance), as we will see in the experiments.

**Contrast Set** The authors of the paper created a small subset of contrastive examples [Kaushik et al., 2019, Gardner et al., 2020]. We select 100 seed claims from the evaluation set, then annotate true and false claims based on the seed claims by applying minimal modification (e.g., replacing a word with a similar one that changes the truth of the claim). Examples can be found in Appendix B.

### 3.3 Dataset Analysis

In this section, we examine the quality of our dataset. We first manually examine what types of reasoning are required to verify our claims. Then, we study potential lexical and syntactic artifacts in human-generated claims through statistical tests and training dynamics to identify word-level artifacts and learnability of the training instances.

**Manual Analysis of Reasoning Types** We manually validate whether the CREAK claims truly require both knowledge and commonsense. We classify reasoning types into three categories: 1) retrieval, 2) common sense, and 3) a mix of retrieval and common sense. These distinctions are somewhat subjective based on the background knowledge of the reader (i.e., is it common sense that NYC is a major city?); we use our own judgments as authors. The first category, retrieval, asks simple facts about entities which can be found in some knowledge sources such as English Wikipedia (e.g., *The Harry Potter series originally began with the books.*). The second category, common sense, requires more complex reasoning but are verifiable with the basic knowledge of the entities (e.g., *Only trumpet players can perform a solo.*). The third category is a mix of retrieval and common sense, meaning that it involves some degree of retrieval and commonsense reasoning. For example, the claim *One can drive from La Jolla to New York City in less than two hours.* requires knowing the locations of La Jolla and New York City (retrieval) and reasoning about driving times (common sense). We randomly sample 100 claims from the evaluation instances and classify them into the three categories. The proportion of the retrieval, common sense, and a mix of the two categories is 18%, 28%, and 54% respectively. You can find examples for each reasoning type in Appendix B.

**Dataset Artifacts** Past work on natural language inference has noted that “artifacts,” or spurious correlations with surface properties of text, may arise during the annotation process [Gururangan et al., 2018, Poliak et al., 2018]. The low performance of a bag-of-words model in our setting (see Table 2) gives some confidence that such correlations are not a dominant factor in performance on our data, but we undertake quantitative analysis to explore this further.

We identify the word-level artifacts in CREAK by computing the artifact statistics described in Gardner et al. [2021]. These statistics tell us, given a balanced dataset, if some words are highly correlated with either true or false claims in a way that a model can exploit. This boils down to a one-side binomial hypothesis test with the null hypothesis  $p(y|x_i) = 0.5$ , where  $y \in \{\text{TRUE}, \text{FALSE}\}$  is a label and  $x_i$  is a word in the vocabulary. We first count the occurrence of all words<sup>3</sup> in CREAK. For each word  $x_i$  that appears in the  $n_i$  claims, we count the number of the target label  $y$  in the  $n_i$  claims. We estimate  $p(y|x_i)$  with the observed probability  $\hat{p}(y|x_i)$ , which is given by a fraction of the count of  $y$  over  $n_i$ . Following Gardner et al. [2021], we then compute a  $z$ -statistic and reject/accept the null hypothesis using  $\alpha = 0.01$  with the Bonferroni correction.

Figure 2 plots the word counts  $n_i$  ( $x$ -axis) against the observed probability  $\hat{p}(y|x_i)$  ( $y$ -axis) for CREAK and FEVER dataset. We additionally draw the curve that represents the corresponding probability of  $\alpha = 0.01/13k$  (for CREAK) and  $\alpha = 0.01/10k$  (for FEVER) at each  $n_i$ . Any words above this line are considered to be artifacts in the dataset. We find 14 words (out of 13k words in the vocabulary) sit above the line. We label the most frequent words in the plot. Surprisingly, *and*

<sup>3</sup>We drop punctuation and lower all words.

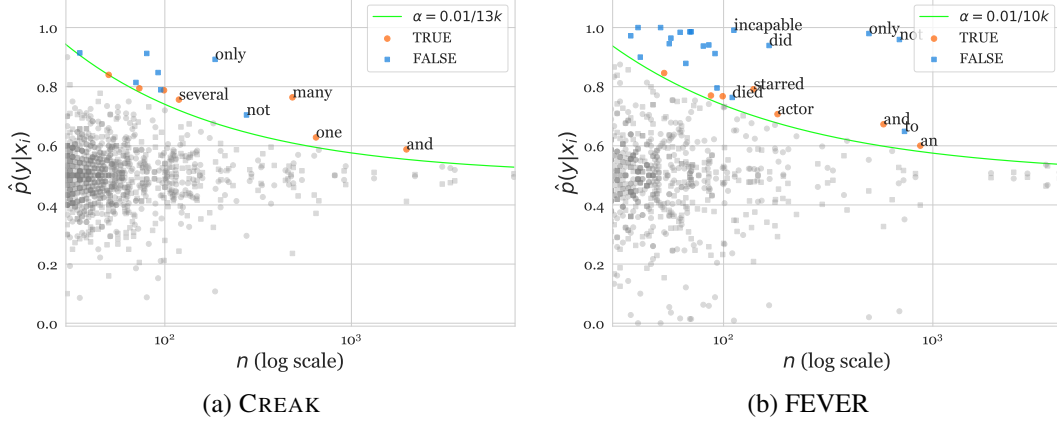


Figure 2: Artifact statistics of CREAK and FEVER train sets. Words (colored dots) above the green line have detectable correlation with class labels. CREAK contains relatively fewer artifacts, with low severity and frequency.

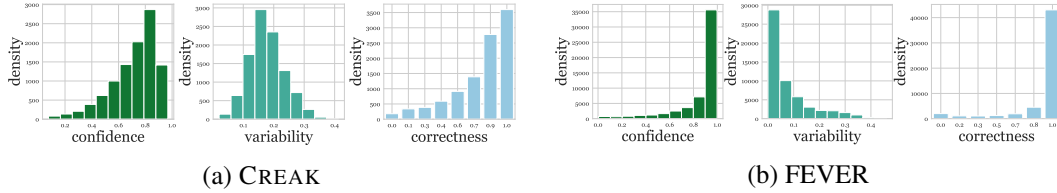


Figure 3: Training dynamics for CREAK and FEVER train sets. This figure shows histograms of CREAK or FEVER training instances bucketed by *confidence* (mean), *variability* (std.), or *correctness*. On all three measures, CREAK shows fatter distributions compared to FEVER, implying that CREAK consists of instances with different difficulties.

( $n = 1973$ ) is the most frequent artifact that signals the true label, followed by some quantifiers (*many*,  $n = 483$ , and *several*,  $n = 119$ ). *not* ( $n = 274$ ) and *only* ( $n = 186$ ) suggest the false label in both datasets. Overall, CREAK contains relatively few artifacts, and they do not impact the data quality significantly since their frequency is not very high. We observe fewer artifacts compared to FEVER dataset (14 words vs. 28 words above the threshold).

**Training Dynamics** We analyze training dynamics using the framework proposed by Swayamdipta et al. [2020]. The training dynamics of a training instance are defined by *confidence* and *variability*, the mean and the standard deviation of model predictions (probability) on the gold label over training epochs. Additionally, *correctness* is computed by the number of times a training instance is correctly predicted over the number of epochs. Figure 3 shows the histograms of those measurements<sup>4</sup> for CREAK (10k instances) and FEVER (105k instances). We use ROBERTA<sub>Large</sub><sup>5</sup> for all experiments. In the *confidence* plots, CREAK has a fatter distribution (i.e., certain instances get low probability on their gold labels) compared to FEVER’s skewed distribution where the majority of instances get very high probability (e.g.,  $> 0.9$ ) on the gold labels. CREAK’s *variability* histogram is nearly bell-shaped while FEVER’s histogram skews towards zero. As can be seen in the *correctness* plots, some training instances in CREAK are not always predicted correctly during training, as its distribution suggests. However, the most of training instances of FEVER are correctly predicted consistently through the training epochs. By aggregating these observations, we hypothesize that CREAK contains training instances with different difficulty levels compared to FEVER.

<sup>4</sup> All values are normalized between 0 and 1 then bucketed into subgroups.

<sup>5</sup> Following the suggestions by Swayamdipta et al. [2020], we train models with early stopping with the patience = 3, resulting in 7 epochs for CREAK and 6 epochs for FEVER.

## 4 Experiments

We focus on the closed-book setting where models are asked to make decisions based solely on claims without any additional retrieved evidence. To see if existing claim verification datasets provide entity commonsense supervision, we train claim-only baseline models on FEVER [Thorne et al., 2018], FAVIQ [Park et al., 2021], and FOOLMETWICE (FM2) [Eisenschlos et al., 2021] and then evaluate them on CREAK. Next, we train models on the CREAK training set and measure the improvements over the baselines. We also investigate the impacts of model sizes and external knowledge.

### 4.1 Experimental Setup

We investigate three training data settings. In the *Zero-Shot* setting, we train models on the train sets of FEVER<sub>KILT</sub>, FAVIQ-A, FAVIQ-R,<sup>6</sup> and FOOLMETWICE (FM2). In the *In-Domain* setting, we train models on the CREAK train set in a standard fashion. The *Finetuning* setting means that we train models on FEVER and then further finetune on CREAK.

We evaluate all models on the CREAK balanced development, test, and contrast sets and report accuracy. As we discussed in Section 3, these evaluation sets use distinct entities from the train set and are authored by a different set of crowdworkers.

### 4.2 Comparison Systems

**Closed-book (Claim-only) Models** In what we consider our standard setting, these models take a claim as input and predict if the claim is true or false. We use a RoBERTa encoder [Liu et al., 2019] with a MLP classifier for baseline models: ROBERTA<sub>Large</sub> and ROBERTA<sub>Base</sub>. We also train SVM with TF-IDF, which gives a linear baseline using far fewer parameters than the LM-based models. We further employ T5-3B to see if more parameters help to learn the complex reasoning in CREAK.

**Retrieval-based Models** These models are augmented with knowledge retrieved from Wikipedia. We feed a claim and  $k$  retrieved passages to a model, which can use the information in the passages to influence the decision. We use Dense Passage Retrieval (DPR) [Karpukhin et al., 2020]<sup>7</sup>, a dual-encoder based model, as a retriever and English Wikipedia as a knowledge base. Specifically, we use the DPR model trained on the KILT benchmark, which includes FEVER. We use this configuration for the open-book experiments, where we finetune models on our training set as well as on FEVER. For a claim classifier, we use the ROBERTA<sub>Large</sub> model and denote this retrieval-based model as ROBERTA<sub>Large-DPR</sub>. We retrieve  $k = 3$  passages for all experiments.

**Human Performance** To estimate human performance on the development set, we sample 100 examples and ask the authors of this paper to predict the corresponding labels. For the contrast set, three of the authors predict labels for claims that they did not annotate. We report the averaged human accuracy and the ensemble accuracy which we use the majority label as the final prediction to computer human performance.

## 5 Results and Discussion

Table 2 presents our main experimental results for closed book systems, and Table 3 presents results for retrieval augmented approaches. We observe that all baseline models fall behind our estimated human performance by a substantial margin.

**Transfer from existing datasets** The *zero-shot* block of Table 2 compares performance of RoBERTa models trained on four prior claim verification datasets. The models trained on FAVIQ-R and FAVIQ-A perform similarly with the majority label baseline. The model trained on FM2 shows better performance than the FAVIQ models, but the accuracy is still very low. We see much improved transfer from FEVER<sub>KILT</sub> dataset, reaching an accuracy of 70%. Although designed to be more challenging than FEVER, FAVIQ and FM2 may result in models that transfer less well because these

<sup>6</sup>The FAVIQ benchmark consists of two datasets based on the same source QA dataset.

<sup>7</sup>DPR is licensed under CC BY-NC 4.0

Table 2: Performance of closed-book approaches on CREAK. Transfer results from prior datasets show that our dataset is distinct from these. Larger models trained with in-domain data perform the best out of all models we consider, but still lag behind human performance.

	Model	#Params	Training Data		Accuracy		
			Type	Size	Dev	Test	Contrast
	Majority Label	–	–	–	51.6	51.6	50.0
<i>Zero-Shot</i>	ROBERTA <sub>Large</sub>	355M	FAVIQ-R	141k	49.6	48.4	50.0
	ROBERTA <sub>Large</sub>	355M	FAVIQ-A	17k	52.3	52.6	52.0
	ROBERTA <sub>Large</sub>	355M	FM2	10k	59.2	58.2	52.0
	ROBERTA <sub>Large</sub>	355M	FEVER <sub>KILT</sub>	105k	69.6	70.2	59.0
	T5-3B	3B	FEVER <sub>KILT</sub>	105k	72.9	76.7	61.5
<i>In-Domain</i>	SVM + TF-IDF	13k	CREAK	10k	60.2	60.3	52.0
	ROBERTA <sub>Base</sub>	125M	CREAK	10k	72.2	71.6	56.0
	ROBERTA <sub>Large</sub>	355M	CREAK	10k	80.6	80.3	61.5
	T5-3B	3B	CREAK	10k	<b>85.6</b>	<b>85.1</b>	<b>70.0</b>
<i>Finetuning</i>	ROBERTA <sub>Large</sub>	355M	FEV → CREAK	115k	80.5	81.1	64.0
	Human (averaged)	–	–	–	96.3	–	92.2
	Human (ensemble)	–	–	–	99.0	–	99.0

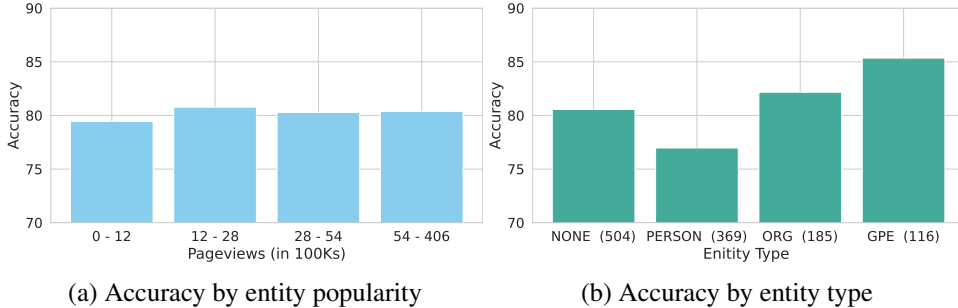


Figure 4: Performance breakdown on partitions of the development set, split by entity popularity and type, using the four most common entity types, which comprise 86% of examples (including “NONE” for non-named entities).

datasets are more dependent on retrieving specific passages to judge claims, containing fewer claims resolvable with commonsense reasoning. Additionally, T5-3B trained on FEVER<sub>KILT</sub> is only better than ROBERTA<sub>Large</sub> by 3 points on the development set and 6.5 points on the test set although it is 8 times larger, suggesting that FEVER<sub>KILT</sub> is bounded in terms of how useful it can be for CREAK.

In the *Finetuning* block of Table 2, we report the performance of ROBERTA<sub>Large</sub> first trained on FEVER<sub>KILT</sub> and then on CREAK. Compared to ROBERTA<sub>Large</sub> trained only CREAK, additional pre-training does not bring meaningful gains.

**Are larger models better?** The *In-Domain* block of Table 2 lists performance by models with different sizes ranging from 13k to 3B parameters. All models are trained on CREAK. ROBERTA<sub>Base</sub>, outperforms SVM with TF-IDF by 11 points on the test set, suggesting that a larger, knowledge-rich model can do better. But its advantage shrinks on the contrast set, only gaining 4 points over SVM with TF-IDF. A larger model ROBERTA<sub>Large</sub>, 355M parameters, further improves the performance, and this trend continues to an even larger model T5-3B, which outperforms ROBERTA<sub>Large</sub> by 5 points on the test set and 8.5 points on the contrast set. T5-3B achieves the highest accuracy in the closed-book setting. Given how the contrast set was constructed, the fact that higher-capacity models work better suggests that having more entity knowledge is a key to doing better on this task.

**Performance breakdown by entity types** We examine whether models are better equipped at verify claims about different entities depending on their popularity and type, as given by an NER tagger. We use ROBERTA<sub>Large</sub> as an in-domain baseline model for this analysis. To compare entity popularity, we partition our dataset into equally sized quartiles based on total number of views the



Table 3: Performance of retrieval-augmented approaches on CREAK. Large models retrieving from Wikipedia can do better, although the performance on the contrast set is still low.

	Model	#Params	Training Data		Accuracy		
			Type	Size	Dev	Test	Contrast
	Majority Label	–	–	–	51.6	51.6	50.0
<i>Zero-Shot</i>	ROBERTA <sub>Large+DPR</sub>	575M	FEVER <sub>KILT</sub>	105k	79.9	80.7	68.0
<i>In-Domain</i>	ROBERTA <sub>Large</sub>	355M	CREAK <sub>ENT_LESS</sub>	10k	69.2	67.3	52.0
	ROBERTA <sub>Large+DPR</sub>	575M	CREAK	10k	84.0	84.3	70.0
<i>Finetuning</i>	ROBERTA <sub>Large+DPR</sub>	575M	FEV $\rightarrow$ CREAK	115k	<b>88.7</b>	<b>86.8</b>	<b>72.0</b>
	Human (averaged)	–	–	–	96.3	–	92.2
	Human (ensemble)	–	–	–	99.0	–	99.0

entity’s Wikipedia page has received since Jan. 1, 2016. For entity types, we use an off-the-shelf NER tagger from spaCy [Honnibal et al., 2020] to group examples by the entity type. In Figure 4, we plot the performance on each partition of our dataset. We observe that the model performs comparably regardless of entity popularity, partially because we sampled from popular entities, and that entity type has a greater affect on accuracy.

**Retrieval-based models with external knowledge** To investigate the importance of entity knowledge in CREAK, we experiment in two additional settings. First, to confirm that entities are important, we experiment with the closed-book setting where all entities are dropped from the claims; this data is denoted as CREAK<sub>ENT\_LESS</sub>. Second, we explore the retrieval setting, where we append three English Wikipedia passages retrieved by DPR to the claims. Similar to the main experiments, we use three data settings: *Zero-Shot*, *In-Domain*, and *Finetuning*.

Table 3 shows the results of all models. ROBERTA<sub>Large</sub> trained on CREAK<sub>ENT\_LESS</sub> loses 10 points compared to the model trained on the standard CREAK training set (*In-Domain* ROBERTA<sub>Large</sub> in Table 2). This shows that seeing the entity mention in the claim is important. For open-book models, we again see that *In-Domain* models are better than *Zero-Shot* models. One distinction from the closed-book setting is that the additional finetuning on FEVER<sub>KILT</sub> improves performance. If we compare the *In-Domain* model from the closed and retrieval settings, the additional passages bring 4 points of improvement. Although adding more entity knowledge improves performance on CREAK, there is still a gap from the human performance, particularly on the contrast set. This shows that there are some facts immediately retrievable from Wikipedia; however, our analysis of the dataset also shows that significant additional reasoning is required as well. Moreover, we believe that this kind of knowledge should be accessible to models in a closed-book way, as annotators were able to create these examples without consulting Wikipedia or other knowledge sources.

## 6 Conclusion

We have presented a dataset CREAK of binary claims involving “entity commonsense,” a combination of entity knowledge and commonsense reasoning. This dataset is useful both as a training set for instilling this kind of reasoning into models as well as a test set for probing whether models can recognize factually incorrect statements about entities. We believe this can be a useful proving ground for models infused with entity knowledge (e.g., entities-as-experts [Férvy et al., 2020] or interpretable entity embeddings [Onoe and Durrett, 2020]) and contribute to development of these techniques.

**Limitations and Ethical Concerns** We emphasize that our dataset is not intended for training general fact-checking models; we do not support large-scale deployment of models trained on CREAK for this purpose. Furthermore, while we have tried to measure artifacts in this dataset and found them to be minimal, our claims are artificially generated and the nature of the dataset can differ significantly from claims naturally occurring in social media or web. Large language models fine-tuned on our dataset may preserve biases learned from the web text during pre-training or biases of our annotators and make biased judgments as a result. See the datasheet in the Supplementary Material for more information about specific harms that could arise from this dataset.

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## Appendix A Annotation Interface

We compensate crowdworkers \$0.60 USD per HIT. Each HIT is composed of generating one true and one false claim, along with a short explanation for each claim. Compensation was determined to approximate at least a \$12 USD hourly wage. The total amount spent on compensating crowdworkers was roughly \$4,000 USD. Our annotation instructions and interface are given in Figure 5.

### Testing Machines' Common Sense

The goal of this project is to create factual/non-factual sentences that can be verified by human commonsense. We want sentences that require deeper understanding of real-world entities but are something that you think you or your friends would probably be able to confirm without looking up on Google or in Wikipedia.

#### Instructions

Multiple Wikipedia entities (pages) are shown. For each entity, a *description* and *category keywords* (taken from Wikipedia) are listed in a scroll box to give more information about the entities. (Some entities have zero/many keywords; please scroll down to the bottom to see all the keywords.)

**Your Task:** Select one entity and write one factual and one non-factual sentence. Then, please explain why your sentence is TRUE or FALSE.

**Libel and Bias:** We plan to release these sentences as a public dataset. Please refrain from writing sentences (even false ones) which could be considered harmful to an individual or to a group. For example, avoid writing libelous (damaging and false) claims about real individuals and avoid stereotyping of groups of people.

#### Example Problem

You have a choice between multiple entities (three in this example) to write some statements about. Make sure to click on the radio button for the entity that you select. You may find it useful to select an entity you're already familiar with, but you can do the task with any of the three. For each entity, category keywords are provided as background knowledge that might be useful for you to disambiguate similar names.

☒ **The Police**

Reggae rock group  
British musical trio  
Grammy Award winner

☐ **Armadillo**

Armadillos  
Rolling animal  
Mammal common name

☐ **Bitcoin**

Application layer protocol  
Digital currency  
Alternative currency

Assume you are a fan of **The Police** and select this British rock band as your choice.

Now, you're asked to write one factual sentence and one non-factual sentence about **The Police** using your creativity. Also, please provide explanations why your sentences are factual/non-factual. Sample answers and explanations could be:

### (a) Instructions

#### Task 1 (Factual)

Good Sample Sentence: The Police released a series of albums.

Good Sample Explanation: The Police were a rock band that was active for a while and they had many hits.

This sentence is **definitely correct** and can be verified without doing a web search if you have a little knowledge about The Police. Please avoid definitional sentences (e.g., The Police is a best-selling band.) and **use action verbs** (e.g., released). In addition, you will be asked to select one of the radio buttons if your sentence is either **definitely TRUE** or **maybe TRUE**.

Good Sample Sentence: One can listen to The Police on music streaming services.

This sentence is acceptable since anyone using music streaming services (e.g., Spotify, Apple Music etc.) can easily verify if this statement is true.

Bad Sample Sentence: I went to The Police concert in Dallas.

Please avoid a sentence that starts with first person pronouns (e.g., I and we) since it is hard for anyone else to verify if this is factual. You could instead say, "Someone went to a concert by The Police in Dallas." (which would only be maybe true unless you knew for certain they had performed in Dallas).

#### Task 2 (Non-factual)

Good Sample Sentence: The members of The Police can perform lawful arrests.

Good Sample Explanation: "The Police" are actually a rock group and not a law enforcement organization.

This sentence is **definitely wrong** and can be spotted by human commonsense. It shouldn't require web searches, encyclopedia etc. Again, please avoid definitional sentences (e.g., The Police are a government organization.) and **use action verbs** (e.g., perform). In addition, you will be asked to select one of the radio buttons if your sentence is either **definitely FALSE** or **maybe FALSE**.

Bad Sample Sentence: The Police are older than the universe.

This sentence is very outlandish and clearly untrue. Better negatives are those that are at least plausible: false for that entity, but maybe would be true for some other entity.

Bad Sample Sentence: I was pulled over by the members of The Police.

Again, please avoid first person pronouns (e.g., I and we).

### (b) Examples

Figure 5: Annotation interface.

## Appendix B Examples

Table 4: CREAK claims with different reasoning types.

Claim	Reasoning Type	Label
Harry Potter can teach classes on how to fly on a broomstick.	Common Sense	TRUE
Grizzly bear live in danger of being hunted by other animals.	Common Sense	FALSE
The Atmosphere of Earth includes many types of gases.	Common Sense + Retrieval	TRUE
One can drive from La Jolla to New York City in less than two hours.	Common Sense + Retrieval	FALSE
J. P. Morgan restored the US Treasury surplus.	Retrieval	TRUE
François Mitterrand became a Texas Senator in 2001.	Retrieval	FALSE

Table 5: Unusable claims generated by crowdworkers.

Claim	Rejection Rationale	Label
It is alleged that a Nerd are computer geeks.	Subjective	TRUE
Green Day radiates a folksy vibe.	Subjective	FALSE
Dan Brown died in 2019 of heart failure.	Offensive	FALSE
It is very fun to be audited.	Ambiguous	FALSE
During the holidays people create performances.	Ambiguous	FALSE
You can tell that a Goose is an alligator.	Outlandish	FALSE

Table 6: Examples from contrast set.

True Claim	False Claim
U.S. Route 1 connects New York to Florida.	U.S. Route 1 connects New York to California.
The Beatles released their first album on vinyl.	The Beatles released their first album on Spotify.
Koi can cost someone hundreds of dollars.	Koi typically costs someone hundreds of dollars.
A nun takes a vow to remain unmarried and have no children.	A nun takes a vow to marry a priest and raise their children in the church.

## Appendix C Implementation Details

We train all models for a maximum of 10 epochs, with the exception of our T5-3B baseline finetuned on FEVER<sub>KILT</sub> which was trained for a maximum of 6. We select the best checkpoint, evaluated on development data after each epoch. All models are trained using the AdamW optimizer with no warmup steps. ROBERTA and T5-3B based models were trained with a learning rate of  $5 \times 10^{-6}$  and  $3 \times 10^{-5}$ , respectively. Our closed-book ROBERTA models and T5-3B model finetuned on FEVER<sub>KILT</sub> were trained with a batch size of 32 and our ROBERTA<sub>Large</sub> + DPR model with a batch size of 16. We use the transformers library Wolf et al. [2020]<sup>8</sup> for our baseline implementations, and use DeepSpeed Rasley et al. [2020]<sup>9</sup> for 16-bit floating point quantization on our T5-3B baselines. All experiments were run on four RTX 8000 GPUs, with our longest experiment taking three days. All our implementation details, including scripts for training/running each of our baselines are made available at <https://www.cs.utexas.edu/~yasumasa/creak>.

## Appendix D Datasheet for CREAK

### A Motivation for Datasheet Creation

**Why was the dataset created?** Despite their impressive abilities, large-scale pretrained models often fail at performing simple commonsense reasoning. While most benchmark datasets target

<sup>8</sup>transformers is licensed under the Apache-2.0 License

<sup>9</sup>DeepSpeed is licensed under the MIT License

commonsense reasoning within the context of everyday scenarios, there is a rich, unexplored space of commonsense inferences that are anchored in knowledge about specific entities. We therefore create this dataset to benchmark how well current systems are able to perform this type of reasoning and to promote the development of systems that can handle these challenges.

**Has the dataset been used already?** We require all papers reporting on our dataset to submit their results to our dataset website (<https://www.cs.utexas.edu/~yasumasa/creak>).

**Who funded the dataset?** This dataset was partially funded by the US National Science Foundation (NSF Grant IIS-1814522).

## B Dataset Composition

**What are the instances?** Each instance is a claim about an entity which may be either true or false. These claims are constructed such that validating them requires specific knowledge of each entity, with many also requiring commonsense reasoning incorporating these facts. All claims are written in English.

**How many instances are there?** Our dataset consists of 13K claims, some of which form a small-scale contrastive evaluation set. A detailed breakdown of the number of instances can be seen in Table 1 of the main paper.

**What data does each instance consist of?** Each instance is a human-written claim about a given Wikipedia entity with an associated TRUE / FALSE label of its factuality.

**Does the data rely on external resources?** No, all resources are included in our release.

**Are there recommended data splits or evaluation measures?** We include the recommended train, development, and test sets for our datasets. Each split is constructed such that there are no overlapping annotators nor entities between each set. We also include a small contrast set containing minimally edited pairs of examples with opposing labels of factuality. The distribution of examples across splits can be seen in Table 1.

## C Data Collection Process

**How was the data collected?** We use crowdsourcing to collect claims. Each worker is presented with 5 entities and are instructed to select one to generate two claims for, one true and one false. For each of these claims, workers are also instructed to provide a short explanation for why the claim is true or false.

**Who was involved in the collection process and what were their roles?** We recruit crowdworkers from Amazon Mechanical Turk to perform all the annotation steps outlined above.

**Over what time frame was the data collected?** The dataset was collected over a period of April to August 2021.

**Does the dataset contain all possible instances?** We source our list of popular Wikipedia entities, as measured by number of contributors and backlinks, from Geva et al. [2021]. Annotators are also instructed to select one of five entities to construct an example for. Our sampling process, therefore, selects for popular entities that exist in Wikipedia.

While we do not cover the entire space of possible entity-centric claims, we promote diversity in our dataset by limiting the total number of claims a single worker can generate to 7% of any single split and by sampling from a large pool of entities. In total, our dataset is comprised of claims that were generated from 684 total crowdworkers covering over 3,000 unique entities.

**If the dataset is a sample, then what is the population?** CREAK represents a subset of all possible entity-centric claims, including those which require commonsense in addition to retrievable facts to verify. Our dataset also only includes claims written in English.

## D Data Preprocessing

**What preprocessing / cleaning was done?** We do minimal preprocessing on the collected claims; however, we monitor crowdworker performance for sentence quality and remove repetitive examples produced by the same crowdworker. We also manually filter and clean our development and test sets for grammaticality. This process removed roughly 18% of crowdsourced claims and high human performance (99% majority human performance) on 100 randomly sampled examples from our development set.

**Was the raw data saved in addition to the cleaned data?** We maintain a record of all the original authored claims, as well as the explanations written by each claim’s author. This data will be made available upon request.

**Does this dataset collection/preprocessing procedure achieve the initial motivation?** Our collection process indeed achieves our initial goals of creating a diverse dataset of entity-centric claims requiring commonsense reasoning. Using this data, we are able to evaluate how models that are trained on past data generalize to answering questions in the future, asked at the time of our data collection.

## E Dataset Distribution

**How is the dataset distributed?** We make our dataset available at <https://www.cs.utexas.edu/~yasumasa/creak>.

**When was it released?** Our data and code is currently available.

**What license (if any) is it distributed under?** CREAK is distributed under the CC BY- SA 4.0 license.<sup>10</sup>

**Who is supporting and maintaining the dataset?** This dataset will be maintained by the authors of this paper. Updates will be posted on the dataset website.

## F Legal and Ethical Considerations

**Were workers told what the dataset would be used for and did they consent?** Crowd workers informed of the goals we sought to achieve through data collection. They also consented to have their responses used in this way through the Amazon Mechanical Turk Participation Agreement.

**If it relates to people, could this dataset expose people to harm or legal action?** Our dataset does not contain any personal information of crowd workers; however, our dataset can include incorrect information. We perform extensive quality control and error analysis to minimize the risk due to incorrect labels. We bear all responsibility in case of violation of rights.

Note that our dataset may, by design, contain false claims about real people or organizations. Most of the claims we saw are harmless in their incorrect nature rather than libelous; this includes all claims in the development and test data, which we manually inspected. However, there could be claims in the training set which are mislabeled and which could impart false “knowledge” to trained models.

We removed one entity from our dataset which was a deadname.

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<sup>10</sup><https://creativecommons.org/licenses/by-sa/4.0/legalcode>



**If it relates to people, does it unfairly advantage or disadvantage a particular social group?**

We acknowledge that, because our dataset only covers English and annotators are required to be located in the US, our dataset lacks representation of claims that are relevant in other languages and to people around the world.

The data itself could possibly contain generalizations about groups of people; for example, one of the entities is *Hopi people*. As above, we audited all claims in the development and test set (20% of the data) and uniformly found claims to be respectful even when incorrect. However, incorrectly labeled claims in the training data could potentially teach false associations to trained models.