

# A Qualitative Comparison of CoQA, SQuAD 2.0 and 🦉QuAC

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## Abstract

In this work, we compare three datasets which build on the paradigm defined in SQuAD for question answering: SQuAD 2.0, QuAC, and CoQA. We compare these three datasets along several of their new features: (1) unanswerable questions, (2) multi-turn interactions, and (3) abstractive answers. We show that the datasets provide complementary coverage of the first two aspects, but weak coverage of the third. Because of the datasets' structural similarity, a single extractive model can be easily adapted to any of the datasets. We show that this model can improve baseline results on both SQuAD 2.0 and CoQA. Despite the core similarity between the datasets, models trained on one dataset are ineffective on another dataset, but we do find moderate performance improvement through pretraining. To encourage evaluation of methods on all of these datasets, we release code for conversion between them.

## 1 Introduction

Question answering on textual data has served as a challenge problem for the NLP community (Voorhees, 2001; Richardson et al., 2013). With the development of large scale benchmarks and sufficiently simple evaluations (Trischler et al., 2016; Nguyen et al., 2016; Hermann et al., 2015) progress has been rapid. In recent evaluation on a popular question-answering dataset, SQuAD (Rajpurkar et al., 2016), performance exceeded that of annotators (Wang et al., 2018; Hu et al., 2017; Wang et al., 2017).

In response to this development, there have been a flurry of new datasets trying to remove simplifications in SQuAD. In this work, we analyze three such new proposed datasets, SQuAD 2.0 (Rajpurkar et al., 2018), 🦉QuAC (Choi et al., 2018), and CoQA (Reddy

et al., 2018).<sup>1</sup> In each of these datasets, crowd workers are asked to (1) produce questions about a paragraph of text (context) and (2) produce a reply by either indicating there is no answer, or providing an extractive answer from the context by highlighting one contiguous span. QuAC and CoQA contain two other features: questions are asked in the form of a dialog, where co-reference to previous interactions is possible and directly answering yes/no is possible. CoQA also uniquely allows workers to edit the spans to anything they like to provide abstractive answers<sup>2</sup>

We compare these three datasets along several of their new features: (1) unanswerable questions, (2) multi-turn interactions, and (3) abstractive answers. The coverage of unanswerable questions is complementary among datasets; SQuAD 2.0 covers all types of unanswerable questions present in other datasets, but focuses more on questions of extreme confusion, such as false premise questions, while QuAC primarily focuses on missing information. QuAC and CoQA dialogs simulate different types of user behavior: QuAC dialogs often switch topics while CoQA dialogs include more queries for details and cover twice as many sentences in the context as QuAC dialogs. Unfortunately, no dataset provides significant coverage of abstractive answers beyond yes/no answers, and we show that a method can achieve an extractive answer upper bound of 100 and 97.8 F1 on QuAC and CoQA, respectively.

Motivated by the above analysis, the same model can be applied to any of these three datasets. We apply the baseline presented in QuAC (Choi et al., 2018), BiDAF++, a model

<sup>1</sup>A review of other new datasets is in the related work.

<sup>2</sup>Also, SQuAD 2.0 and QuAC cover only Wikipedia text, CoQA covers six other domains and QuAC is the only one of these datasets that doesn't allow the questioner to see the context before formulating a question.

Dataset	Entity Salad	False Premise	Topic Error	Missing Information	Content Negation	Answerable Questions	Total Questions
CoQA	0.0	0.0	0.0	60.0	0.0	40.0	5 (0.5%)
SQuAD 2.0	21.3	21.3	13.5	16.1	16.1	10.9	230 (50.1%)
QuAC	5.5	0.0	16.4	71.2	0.0	6.8	73 (20.2%)

Table 1: Comparison of unanswerable questions on 50 random contexts from the development set of each dataset. SQuAD 2.0 contains a diverse set of circumstances that make questions unanswerable, QuAC focuses on information that could plausibly be in context material and CoQA does not significantly cover unanswerable questions.

based on BiDAF (Seo et al., 2016), augmented with self attention (Clark and Gardner, 2018). The model also uses ELMo contextualized embeddings (Peters et al., 2018), and is available through AllenNLP (Gardner et al., 2017). Our experiments show that this extractive baseline outperforms existing extractive and abstractive baselines on CoQA by 14.2 and 2.7 F1 respectively, and can improve on a different implementation of the same baseline model on SQuAD 2.0 by 2.9 F1. Finally, we consider whether models can transfer from one to setting to another. By pretraining we are able to improve 2.7, 1.2 and 1.6 F1 on QuAC, CoQA, SQuAD 2.0, respectively, suggesting models can tap into the similarity between the datasets.<sup>3</sup>

## 2 Dataset Analysis

In this section we analyze unanswerable questions, dialog features, abstractive answers in SQuAD 2.0, QuAC, and CoQA. All analysis was performed by the author, on a random sample of 50 contexts from the development set of each dataset. Because the datasets contain radically different numbers of questions per context, we annotated between 300 and 700 questions per dataset.

### 2.1 Unanswerable Questions

In Table 1 we compare types of unanswerable questions across dataset. We identify five types of questions found between the datasets:

- Entity Salad: a nonsensical reference to entities found in the context or made-up entities (e.g. *“What infinite hierarchy implies that the graph isomorphism problem is NQ-complete?”*). Such questions are unanswerable for any context.
- False Premise: a fact that contradicts something stated in the context is asserted in the question (e.g. *“When is the correlation oc-*

*casionally positive?”* but the context says *“there is a strictly negative correlation”*).

- Topic Error: a questions that references an entity in the context but the context does not focus on that entity (e.g. *“How many earthquakes occur in California?”* when the article focus is actually about *“Southern California”*). Such questions potentially have an answer, but it would be unlikely for the answer to be found in the particular context.
- Missing Information: a question who’s answer could be plausibly in be in the context but for some reason is not (e.g. *“What is the record high in January?”* and the article is about temperature extremes). Such questions have an answer but it is not mentioned.
- Content Negation: a question which asks for the opposite information of something mentioned in the context (e.g. *“Who **didn’t** cause the dissolution of the Holy Roman Empire?”*). Such questions either have answers that are the set of all entities other than the one mentioned in the context or answers that could be found in some other context.

SQuAD 2.0 contains the highest diversity of unanswerable questions of all datasets analyzed. Some SQuAD 2.0 questions are unlikely to be asked without significant foreknowledge of the context material, such as content negation and false premise, and do not occur in QuAC. Such questions resemble text from entailment datasets such as SNLI (Bowman et al., 2015) and seem more likely to arise if questioners are receiving very complex information and become confused.

Topic error and missing information questions are in both SQuAD 2.0 and QuAC. Such questions likely arise in QuAC because the focus of the article may not be immediately obvious in early interactions. Both SQuAD 2.0 and QuAC cover a significant number of unanswerable questions that could be plausibly in the article. The differ-

<sup>3</sup>To facilitate easy future cross-evaluation, we release tools for conversion between these dataset.

Dataset	Topic Shift	Drill Down	Return to Topic	Clarification Question	Definition Question	Sentence Coverage	Total Questions
CoQA	21.6	72.0	2.9	0.0	0.7	63.3	722
QuAC	35.4	55.3	5.6	0.7	3.0	28.4	302

Table 2: Comparison of dialog features in 50 random contexts from the development set of each dataset. CoQA contains questions that drill into details about topics and cover 60% of sentences in the context while in QuAC dialog switch topic more often and cover less than 30% of sentences. Neither dataset has a significant number of returns to previous topics, clarifications, or definitional interactions.

Dataset	Yes/No	Coref	Counting	Picking	Fluency	Max F1
CoQA	21.4	3.2	1.3	0.6	4.2	97.8
QuAC	21.1	0.0	0.0	0.0	0.0	100.0

Table 3: Comparison of abstractive features in 50 random contexts in the development set of each dataset. Both QuAC and CoQA contain yes/no questions while CoQA also contains answers that improve fluency through abstractive behavior. The extractive upper bound from CoQA is high because most abstractive answers involve adding a pronoun (Coref) or inserting prepositions and changing word forms (Fluency) to existing extractive answers, resulting in extremely high overlap with possible extractive answers.

ence in settings and distributions of unanswerable questions in SQuAD 2.0 and QuAC appear to be complementary: SQuAD 2.0 focuses more on questions simulating questioner confusion, while QuAC primarily focuses on missing information. Finally, CoQA does not contain a significant number of unanswerable questions, and many of the ones that do exist are erroneously marked.

## 2.2 Dialog Features

In Table 2 we analyze five types of dialog behavior in QuAC and CoQA:

- **Topic Shift:** a question about something previously discussed (e.g. “Q: How does he try to take over? ... Q: Where do they live?”).
- **Drill Down:** a request for more information about a topic being discussed (e.g. “A: The Sherpas call Mount Everest Chomolungma. Q: Is Mt. Everest a holy site for them?”)
- **Topic Return:** Asking about a topic again after it had previously been shifted away from.
- **Clarification:** Reformulating a question that had previously been asked.
- **Definition:** Asking what is meant by a term (e.g. “What are polygenes?”)

QuAC and CoQA contain many similar features but at very different rates, offering complementary coverage of types of user behavior. CoQA dialogs drill down for details significantly more frequently and cover more than 60% of sentences in the context material (Sentence Coverage). On the

other hand, QuAC dialogs shift to new topics frequently and cover less than 30% of sentences in the context. Both datasets contain only a small numbers of definition questions and returns to previous topics and essentially no requests for clarification. These are areas of potential future work.

## 2.3 Abstractive Answers

Table 3 compares abstractive behavior in CoQA and QuAC. We observed five phenomena:

- **Yes/No:** Questions annotated with yes/no. In QuAC such questions and their corresponding yes or no are marked in addition to an extractive answer. In CoQA, the single token “yes” or “no” is simply asserted as the abstractive answer, with an extractive answer provided in the rationale (e.g. “Q: Is atmosphere one of them? A: yes”).
- **Coref:** Coreference is added to previously mentioned entities in either context or question (e.g. “Q: How was France’s economy in the late 2000s? A: **it** entered the recession”).
- **Count:** Counting how many entities of some type were mentioned (e.g. “Q: how many specific genetic traits are named? A: five”)
- **Picking:** A question that requires the answer to pick from a set defined in the question (e.g. “Q: Is this a boy or a girl? A: boy)
- **Fluency:** Either adding a preposition, changing the form of a word, or merging two non-contiguous spans (e.g. “Q: how did he get away? A: **by** foot)

	Child.	Liter.	Mid-High.	News	Wiki	Overall
DrQA (Extractive)	52.4	52.6	51.4	56.8	60.3	54.7
DrQA + PGNet (Abstractive)	64.5	62.0	63.8	68.0	72.6	66.2
BiDAF++ w/ 0-ctx	62.5	61.2	61.9	65.4	65.9	63.4
BiDAF++ w/ 1-ctx	67.4	66.1	66.4	70.7	72.3	68.6
BiDAF++ w/ 2-ctx	<b>67.8</b>	66.7	65.5	71.4	72.1	68.7
BiDAF++ w/ 3-ctx	67.3	66.7	67.6	70.7	<b>73.3</b>	<b>69.2</b>
BiDAF++ w/ 4-ctx	67.2	<b>66.9</b>	65.8	71.8	72.8	68.9

Table 4: Development set performance by training BiDAF++ (Choi et al., 2018) models (extractive) on CoQA data with handling yes/no and no-answer questions as in QuAC. Despite being extractive, these models significantly outperform reported baselines, DrQA and DrQA + PGNet (Reddy et al., 2018).

	in-F1	out-F1	F1
DrQA	54.5	47.9	52.6
DrQA + PGNet	67.0	60.4	65.1
BiDAF++ w/ 3-ctx	<b>69.4</b>	<b>63.8</b>	<b>67.8</b>

Table 5: Test set results on CoQA. We report in domain F1 (in-F1), out of domain F1 on two held out domains, Reddit and Science (out-F1) and the overall F1 (F1).

Both QuAC and CoQA have a similar rate of yes/no questions. QuAC contains no other abstractive phenomena while CoQA contains a small number of predominately insertions, often at the beginning of an extractive span, for coreference and or other fluency improvements. Because abstractive behavior in CoQA includes mostly small modifications to spans occurring in the context, the maximum achievable performance by a model that predicts spans from the context is 97.8 F1.<sup>4</sup>

### 3 New Extractive Baseline for CoQA

Our analysis strongly implies that beyond yes/no questions, abstractive behavior is not a significant component in either QuAC or CoQA. As such, QuAC models can be trivially adapted to CoQA.

We train a set of BiDAF++ baselines from the original QuAC dataset release (Choi et al., 2018) by optimizing the model to predict the span with maximum F1 overlap with respect to annotated abstractive answers.<sup>5</sup> If the abstractive answer is ex-

<sup>4</sup>To compute the upper bound, if abstractive answer is exactly “yes”, “no”, or “unknown”, we consider the upper bound to be 100. Otherwise, we use the CoQA evaluation script to find a span in the context that has maximum F1 with respect to the abstractive answer.

<sup>5</sup>We use the implementation on <http://allennlp.org>, and do not modify any hyper-parameters except the the maximum dialog length and that models were allowed to train up to 65 epochs.

actly “yes” or “no”, we train the model to output the whole rationale span, and classify the question as yes/no with the appropriate answer. At evaluation time, if the model predicts a question is a yes/no question, instead of returning the extracted span, we simply return “yes” or “no”.

Table 4 and Table 5 summarize our results for training BiDAF++ with varying contexts on CoQA. Beyond the difference of underlying base question-answer models (DrQA (Chen et al., 2017) vs. BiDAF (Seo et al., 2016) with self attention (Clark and Gardner, 2018)), BiDAF++ has two core differences with respect to DRQA+PGNet: (1) instead of appending previous questions and answers to input question tokens, BiDAF++ marks answers of previous questions directly on the context, and (2) BiDAF++ uses contextualized word embeddings through ELMo (Peters et al., 2018). These differences, in combination with appropriate handling of yes/no and unanswerable questions significantly improves on the existing extractive baseline (+14.2 F1) and even on the existing abstractive baseline (+2.7 F1).

### 4 Cross-Dataset Experiments

In this section we consider whether models can benefit from transfer between SQuAD 2.0, QuAC, and CoQA, and show that the datasets, while ineffective for direct transfer, can be used as pre-training. In all experiments, we use BiDAF++, either with two context or no context, depending on if we are training for dialog settings or not, with default configurations. Models are trained by initializing from other models trained on different datasets and we do not decrease initial learning rates from just training directly on the target dataset. When SQuAD 2.0 is used to initialize



	F1	HEQQ	HEQD
BiDAF++ w/ 2-ctx	60.6	55.7	4.0
Train SQuAD 2.0	34.3	18.0	0.3
Train CoQA	31.2	19.2	0.0
Ft from SQuAD 2.0	62.8	58.4	<b>6.0</b>
Ft from CoQA	<b>63.3</b>	<b>59.2</b>	5.3

Table 6: Cross dataset transfer to QuAC development set. Models do not transfer directly (rows 3 and 4), but after fine tuning improve performance (rows 5 and 6).

	In Domain F1
DrQA + PGNet	66.2
BiDAF++ w/ 2-ctx	68.7
SQuAD 2.0	41.4
QuAC	29.1
Ft from SQuAD 2.0	<b>69.9</b>
Ft from QuAC	68.9

Table 7: Cross dataset transfer to CoQA development set. Models do not transfer directly (rows 3 and 4), but after fine tuning improve performance (rows 5 and 6). For an explanation of why BiDAF++ outperforms DrQA + PGNet, see Section 3.

models that use context, we randomly order questions in SQuAD 2.0 and train as if questions were asked in the form of a dialog.<sup>6</sup> We only report development numbers as this manuscript is a work in progress.

**Transfer to QuAC** Table 6 summarizes the results. Models trained on either SQuAD 2.0 or CoQA, evaluated directly on QuAC do not perform well, while initializing from those models significantly improves the quality of a QuAC model (**+2.7 F1**).

**Transfer to CoQA** Table 7 summarizes the results. Models initially trained on either SQuAD 2.0 or QuAC are ineffective initially, although the SQuAD 2.0 model performs surprisingly well. When tuning from QuAC we observe no gains, while SQuAD 2.0 improves CoQA performance moderately (**+1.2 F1**).

**Transfer to SQuAD 2.0** Table 8 summarizes the results. BiDAF++ works significantly better than the baseline, although they are different implementations of the same model. Models

<sup>6</sup>Likely a better strategy exists, but we would like to demonstrate transfer in the simplest possible way.

	F1	EM
Baseline	67.6	65.1
BiDAF++	70.5	67.4
CoQA	38.1	32.4
QuAC	25.4	16.8
Ft from CoQA	<b>72.1</b>	<b>69.2</b>
Ft from QuAC	69.6	66.9

Table 8: Cross dataset transfer to SQuAD 2.0 development set. BiDAF++ (Choi et al., 2018) outperforms the baseline, a different implementation of the same model (Rajpurkar et al., 2018) likely because of better hyper parameter tuning.

are again ineffective initially, although the initial CoQA model transfers significantly better than the initial QuAC model. While the QuAC initialized model fails to improve, the CoQA model is able to get significant improvement (**+1.6 F1**).

**Summary** Across all of the datasets, there exists at least one other dataset that significantly improves performance on a target dataset. These experiments do not support that direct transfer is possible, but that pretraining is at least somewhat effective. QuAC appears to transfer the least to any of other datasets, likely because questioners were not allowed to see underlying context documents while formulating questions. Since transfer is effective between these related tasks, we recommend that future work indicate any pretraining.

## 5 Related Work

Other proposals exist other than the three we analyzed that expand on features in SQuAD (Rajpurkar et al., 2016). For example, maintaining question independence of context to reduce the role of string matching and having long context length (Joshi et al., 2017; Kociský et al., 2017), higher level reasoning (Khashabi et al., 2018; Clark et al., 2018; Yang et al., 2018), multi-turn information seeking interactions, in either table settings (Iyyer et al., 2017; Talmor and Berant, 2018; Saha et al., 2018), regulation settings (Saeidi et al., 2018), or Quiz Bowl settings (Elgohary et al., 2018). Other work considers multi-modal contexts where interactions are a single turn (Tapaswi et al., 2016; Antol et al., 2015; Lei et al., 2018) or multi-turn (Das et al., 2017; Pasunuru and Bansal, 2018). These efforts contain alternative challenges than ones we analyze in this paper.

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