ReasonBERT: Pre-trained to Reason with Distant Supervision

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Abstract

We present ReasonBERT, a pre-training method that augments language models with the ability to reason over long-range relations and multiple, possibly hybrid, contexts. Unlike existing pre-training methods that only harvest learning signals from local contexts of naturally occurring texts, we propose a generalized notion of distant supervision to automatically connect multiple pieces of text and tables to create pre-training examples that require long-range reasoning. Different types of reasoning are simulated, including intersecting multiple pieces of evidence, bridging from one piece of evidence to another, and detecting unanswerable cases. We conduct a comprehensive evaluation on a variety of extractive question answering datasets ranging from single-hop to multi-hop and from text-only to table-only to hybrid that require various reasoning capabilities and show that ReasonBERT achieves remarkable improvement over an array of strong baselines. Few-shot experiments further demonstrate that our pre-training method substantially improves sample efficiency.[1]

1 Introduction

Recent advances in pre-trained language models (LMs) have remarkably transformed the landscape of natural language processing. Pre-trained with self-supervised objectives such as autoregressive language modeling (Radford and Narasimhan, 2018; Radford et al., 2019; Brown et al., 2020) and masked language modeling (MLM) (Devlin et al., 2019; Liu et al., 2019b; Joshi et al., 2020), LMs encode a great deal of knowledge about language and significantly boost model performance on a wide range of downstream tasks (Liu et al., 2019a; Wang et al., 2019a,b) ranging from spell checking (Awasthi et al., 2019) to sentiment analysis (Xu et al., 2019) and semantic parsing (Rongali et al., 2020), just to name a few.

Existing self-supervised objectives for LM pre-training primarily focus on consecutive, naturally occurring text. For example, MLM enables LMs to correctly predict the missing word "*daughters*" in the sentence "*Obama has two __ , Malia and Sasha.*" based on the local context and the knowledge stored in the parameters. However, many tasks require reasoning beyond local contexts: multi-hop question answering (QA) (Yang et al., 2018; Welbl et al., 2018) and fact verification (Jiang et al., 2020) require reasoning over multiple pieces of evidence, hybrid QA (Chen et al., 2020) requires simultaneously reasoning over unstructured text and structured tables, and dialogue systems require reasoning over the whole dialogue history to accurately understand the current user utterance (Andreas et al., 2020).

To address this limitation in existing LM pre-training, we propose ReasonBERT, a pre-training method to augment LMs for explicitly reasoning over long-range relations and multiple contexts. ReasonBERT pairs a query sentence with multiple relevant pieces of evidence drawn from possibly different places and defines a new LM pre-training objective, *span reasoning*, to recover entity spans that are masked out from the query sentence by jointly reasoning over the query sentence and the relevant evidence (Figure 1). In addition to text, we also include tables as evidence to further empower LMs to reason over hybrid contexts.

One major challenge in developing ReasonBERT lies in how to create a large set of query-evidence pairs for pre-training. Unlike existing self-supervised pre-training methods, examples with complex reasoning cannot be easily harvested from naturally occurring texts. Instead, we draw inspiration from *distant supervision* (Mintz et al., 2009a), which assumes

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[1] Our code and pre-trained models are available at https://github.com/sunlab-osu/ReasonBERT.

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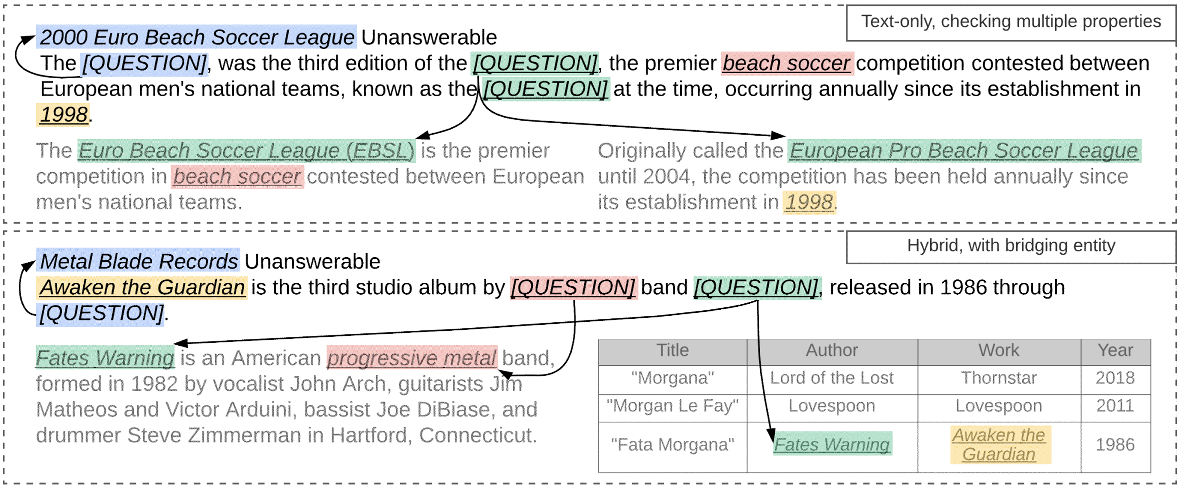
Text-only, checking multiple properties
Hybrid, with bridging entity

2000 Euro Beach Soccer League Unanswerable

The [QUESTION], was the third edition of the [QUESTION], the premier beach soccer competition contested between European men's national teams, known as the [QUESTION] at the time, occurring annually since its establishment in 1998.

The Euro Beach Soccer League (EBSL) is the premier competition in beach soccer contested between European men's national teams.

Originally called the European Pro Beach Soccer League until 2004, the competition has been held annually since its establishment in 1998.

Metal Blade Records Unanswerable

Awaken the Guardian is the third studio album by [QUESTION] band [QUESTION], released in 1986 through [QUESTION].

Fates Warning is an American progressive metal band, formed in 1982 by vocalist John Arch, guitarists Jim Matheos and Victor Arduini, bassist Joe DiBiase, and drummer Steve Zimmerman in Hartford, Connecticut.

Title	Author	Work	Year
"Morgana"	Lord of the Lost	Thornstar	2018
"Morgan Le Fay"	Lovespoon	Lovespoon	2011
"Fata Morgana"	Fates Warning	Awaken the Guardian	1986

Figure 1: Examples of our pre-training data acquired via distant supervision, which covers a wide range of topics with both textual and tabular evidence. For each query sentence (in black), we first select two pairs of entities (underlined) to find two pieces of evidence (in grey) via distant supervision. We then randomly mask one entity from each selected pair and aim to recover it by reasoning over the evidence. Note that the two selected pairs may share a common entity; in case this entity is masked, we can mimic different types of multi-hop reasoning, e.g., intersection (Ex. 1) and bridging (Ex. 2). To simulate unanswerable cases, we additionally mask one entity (in blue) that does not exist in the evidence. Figure best viewed in color.

that "*any sentence containing a pair of entities that are known to participate in a relation is likely to express that relation*," and generalize it to our setting of multiple pieces of evidence from text and tables. Specifically, given a query sentence containing an entity pair, if we mask one of the entities, another sentence or table that contains the same pair of entities can likely be used as evidence to recover the masked entity. Moreover, to encourage deeper reasoning, we collect multiple pieces of evidence that are jointly used to recover the masked entities in the query sentence, allowing us to scatter the masked entities among different pieces of evidence to mimic different types of reasoning. Figure 1 illustrates several examples using such distant supervision. In Ex. 1, a model needs to check multiple constraints (i.e., intersection reasoning type) and find "*the beach soccer competition that is established in 1998*." In Ex. 2, a model needs to find "*the type of the band that released Awaken the Guardian*," by first inferring the name of the band "*Fates Warning*" (i.e., bridging reasoning type).

We first replace the masked entities in a query sentence with the `[QUESTION]` tokens. The new pre-training objective, span reasoning, then extracts the masked entities from the provided evidence. We augment existing LMs like BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019b) by continuing to train them with the new objective, which leads to ReasonBERT, a new LM with better reasoning capabilities. Then query sentence and textual evidence are encoded via the LM. When tabular evidence is present, we use the structure-aware transformer TAPAS (Herzig et al., 2020) as the encoder to capture the table structure.

We evaluate ReasonBERT on the extractive QA task, which is arguably the most representative task requiring reasoning about world knowledge. We conduct a comprehensive evaluation using a variety of popular datasets: MRQA (Fisch et al., 2019), a single-hop QA benchmark including six datasets from different domains; HotpotQA (Yang et al., 2018), a multi-hop QA dataset; NQTables, a subset of the Natural Questions dataset (Kwiatkowski et al., 2019) where answers can be found in tables; and HybridQA (Chen et al., 2020), a hybrid multi-hop QA dataset that requires reasoning over both tables and text. Under the few-shot setting, ReasonBERT substantially outperforms the baselines in almost all datasets, demonstrating that the reasoning ability learned from pre-training can easily transfer to downstream QA tasks and generalize well across domains. Under the full-data setting, ReasonBERT obtains substantial gains in multi-hop and hybrid QA datasets. Despite its simple model architecture, ReasonBERT achieves similar or better performance compared with more sophisticated state-of-the-art models for each dataset.

2 Background

Language model pre-training. Existing pre-training objectives such as MLMs (Devlin et al., 2019; Joshi et al., 2020) tend to implicitly memorize the learned knowledge in the parameters of the underlying neural network. In this work, we aim to augment pre-training by encouraging a model to *reason* about (instead of memorizing) world knowledge over the given contexts.

Extractive question answering. To measure a model's reasoning ability about world knowledge, we select extractive QA as a downstream task, which is perhaps one of the most representative tasks for this purpose. Given a question q and provided evidence E, an extractive QA model $p_\theta(a|q, E)$ aims to select a contiguous span a from E that answers the question, or output a special token if E is not sufficient to answer the question.

Our approach, ReasonBERT, is inspired by this formulation and extends it to language model pre-training. The challenge in defining such a self-supervised task is in the creation of question-evidence pairs from unlabeled data. Moreover, we aim for a generic approach that works for a wide range of extractive QA settings including single-hop and multi-hop reasoning, hybrid contexts with both unstructured texts and structured tables, as well as few-shot settings. We discuss how to address the challenge and achieve this goal in the next two sections.

3 Distant Supervision (DS) for Pre-training

We use English Wikipedia as our data source for pre-training. We first extract sentences and tables from Wikipedia pages and then identify salient spans (such as named entities) from them. We apply the idea of distant supervision and match the sentences and tables to form query-evidence pairs, which are used to create pre-training examples.

3.1 Data Collection

Text. We first extract paragraphs from Wikipedia pages and split them into sentences. We consider named entities including both real-world entities (e.g., person, location) and temporal and numeric expressions (e.g., date and quantity) as potential answer entities for pre-training. We first identify real-world entities using existing hyperlinks. Since Wikipedia pages generally do not contain links to themselves, we additionally detect such self-mentions by searching the names and aliases of the topic entity for each page. Temporal and numeric expressions are identified using an existing NER tool[2].

Tables. We extract tables that are labeled as <wikitable> from Wikipedia, and only consider tables with no more than 500 cells. First, real-world entities are detected using existing hyperlinks. Unlike our method employed for textual sentences, we do not use traditional NER tools here as they are not tailored to work well on tables. Instead, for a cell that does not contain hyperlinks, we match the complete cell value with sentences that are closely related to the table, sourced either from the same page or a page containing a hyperlink pointing to the current page. If the matched span in the sentence contains a named entity, we consider the same entity as being linked to the cell as well. Otherwise we consider this cell as a unique entity in the table.

Please see Appendix A.1 for details about the tools and resources we use.

3.2 Query-Evidence Pairing via DS

As described in Section 2, a standard QA sample is composed of a question, an answer and evidence. The model infers the relationship between the answer and other entities in the question, and extracts it from the evidence. In this work, we try to simulate such samples in pre-training. Given a sentence with entities, it can be viewed as a question by masking some entities as answers for prediction. The key issue is then how to find evidence that contains not only the answer entity, but also the relational information for inference. Here we borrow the idea of distant supervision (Mintz et al., 2009b).

Given a sentence as a query, we first extract pairs of entities in it. For each entity pair, we then find other sentences and tables that also contain the same pair as evidence. Since we do not have the known relation constraint in the original assumption of distant supervision, we use the following heuristics to collect evidence that has high quality relational knowledge about the entities and is relevant to the query. First, we only consider entity pairs that contain at least one real-world entity. For textual evidence, the entity pair needs to contain the topic entity of the Wikipedia page, which is more likely to have relations to other entities. For

[2] https://nlp.johnsnowlabs.com/

Setting	# queries	# sent.	# tab.	# ent. pairs
Text-only	7.6M	8.4M	-	5.5M
Hybrid	3.2M	4.3M	0.9M	6.0M

Table 1: Statistics about the pre-training data.

Setting	All the same	One different	All different
Text-only	50%	30%	20%
Hybrid	60%	8%	32%

Table 2: Analysis of pre-training data quality with 50 examples for each setting. *One different* is when the relation between the selected entities is different from the relation expressed in the query sentence for of the two pieces of evidence.

tabular evidence, we consider only entity pairs that are in the same row of the table, but they do not need to contain the topic entity, as in many cases the topic entity is not present in the tables. In both cases, the query and evidence should come from the same page, or the query contains a hyperlink pointing to the evidence page. For tabular evidence, we also allow for the case where the table contains a hyperlink pointing to the query page.

3.3 Pre-training Data Generation

Given the query-evidence pairs, a naive way to construct pre-training examples is to sample a single piece of evidence for the query, and mask a shared entity as "answer", as in Glass et al. (2020). However, this only simulates simple single-hop questions. In this work, we construct complex pre-training examples that require the model to conduct multi-hop reasoning. Here we draw inspiration from how people constructed multi-hop QA datasets. Take HotpotQA (Yang et al., 2018) as an example. It first collected candidate evidence pairs that contain two paragraphs (A, B), with a hyperlink from A to B so that the topic entity of B is a bridging entity that connects A and B. Crowd workers then wrote questions based on each evidence pair. Inspired by this process, we combine multiple pieces of evidence in each pre-training example and predict multiple masked entities simultaneously. The detailed process is described below. Figure 1 shows two examples. For more examples, please check Appendix A.1.

We start by sampling up to two entity pairs from the query sentence and one piece of evidence (sentence or table) for each entity pair. We then mask one entity in each pair as the "answer" to predict. The resulting pre-training examples fall into three categories: (1) Two disjoint entity pairs $\{(a, b), (c, d)\}$ are sampled from the query, and one entity from each pair, e.g., $\{a, c\}$, is masked. This is similar to a combination of two single-hop questions. (2) The two sampled entity pairs $\{(a, b), (b, c)\}$ share a common entity b, and b is masked. The model needs to find two sets of entities that respectively satisfy the relationship with a and c, and take an intersection (Type II in HotpotQA; see Ex. 1 in Figure 1). (3) The two sampled entity pairs $\{(a, b), (b, c)\}$ share a common entity b, and $\{b, c\}$ are masked. Here b is the bridging entity that connects a and c. The model needs to first identify b and then recover c based on its relationship with b (Type I and Type III in HotpotQA; see Ex. 2 in Figure 1). We also mask an entity from the query that is not shown in the evidence to simulate unanswerable cases. All sampling is done randomly during pre-training.

3.4 Data Statistics and Analysis

We prepare pre-training data for two settings: (1) one with only textual evidence (text-only) and (2) the other including at least one piece of tabular evidence in each sample (hybrid). Some statistics of the collected data are summarized in Table 1. For the text-only setting, we extract approximately 7.6M query sentences, each containing 2 entity pairs that are matched with 3 different pieces of textual evidence on average. For the hybrid setting, we select approximately 3.2M query sentences, each containing 3.5 entity pairs, matched with 5.8 different pieces of evidence on average.

We also conduct an analysis of the pre-training data quality using 50 randomly sampled examples from each setting. We compare the query sentence and the evidence to see if they are expressing the same relation between the selected entities. Results are summarized in Table 2. We can see that in both settings, almost 70% of the examples have the desired characteristic that the evidence contains useful relational knowledge for recovering missing entities in the query sentence.

4 Pre-training

4.1 Encoder

For the text-only setting, we use the standard transformer encoder in BERT (Devlin et al., 2019). For settings where the input contains tables, we adopt the transformer variant recently introduced in TAPAS (Herzig et al., 2020), which uses extra token-type embeddings (indicating the row/column position of a token) to model the table structure.

4.2 Span Reasoning Objective

Now we describe our *span reasoning objective*, which can advance the reasoning capabilities of a pre-trained model.

Given a sample collected for pre-training as described in Section 3.3, we replace the masked entities $\mathcal{A} = \{a_1, \ldots, a_n\}$ $(n{\leq}3)$ in the query sentence q with special [QUESTION] tokens. The task then becomes recovering these masked entities from the given evidence E (concatenation of the sampled evidence). Specifically, we first concatenate q, E and add special tokens to form the input sequence as [[CLS], q, [SEP], E], and get the contextualized representation $\mathbf{x}$ with the encoder. Since we have multiple entities in q masked with [QUESTION], for each a_i, we use its associated [QUESTION] representation as a dynamic query vector $\mathbf{x}_{a_i}$ to extract its start and end position s, e of a_i in E (i.e., *question-aware* answer extraction).

$$\begin{aligned} P(s|q,E) &= \frac{\exp\left(\mathbf{x}_s^\top \mathbf{S}\mathbf{x}_{a_i}\right)}{\sum_k \exp\left(\mathbf{x}_k^\top \mathbf{S}\mathbf{x}_{a_i}\right)} \\ P(e|q,E) &= \frac{\exp\left(\mathbf{x}_e^\top \mathbf{E}\mathbf{x}_{a_i}\right)}{\sum_k \exp\left(\mathbf{x}_k^\top \mathbf{E}\mathbf{x}_{a_i}\right)} \end{aligned} \quad (1)$$

Here $\mathbf{S}, \mathbf{E}$ are trainable parameters. $\mathbf{x}_{a_i}$ is the representation of special token [QUESTION] corresponding to a_i; $\mathbf{x}_k$ is the representation of the k-th token in E. If no answer can be found in the provided evidence, we set s, e to point to the [CLS] token.

The *span reasoning* loss is then calculated as follows:

$$L_{SR} = -\sum_{a_i \in \mathcal{A}} \left(\log P\left(s_{a_i}|q,E\right) + \log P\left(e_{a_i}|q,E\right)\right) \quad (2)$$

We name this objective as *span reasoning*, as it differs from the *span prediction/selection* objectives in existing pre-training work such as SpanBert (Joshi et al., 2020), Splinter (Ram et al., 2021), and SSPT (Glass et al., 2020) in the following ways: (1) Unlike SpanBert and Splinter that use single contiguous paragraph as context, where the models may focus on local cues, we encourage the model to do long-range contextualization by including both query and evidence as input, which can come from different passages, and recovering the masked entities by grounding them on the evidence E. (2) Unlike SSPT, we improve the model's ability to reason across multiple pieces of evidence by including two disjoint pieces of evidence in a single sample and scattering the answer entities among them to mimic different types of reasoning chains. (3) We mimic the scenario where a span cannot be inferred based on the given contexts, by masking entities in q that do not appear in E, in which case the model is trained to select the special [CLS] token.

	MRQA	HotpotQA	NQTables	HybridQA
# train	86136.5	88881	17112	62686
# dev	-	1566	1901	3466
# test	9704	7405	1118	3463
# evidence	1	10	8.7	34.7
# tokens*	374.9	89.1	289.6	156.3
has text/table	✓/✗	✓/✗	✗/✓	✓/✓

Table 3: Dataset statistics. The statistics for MRQA are averaged over all 6 datasets. # tokens* is the average number of tokens per evidence.

4.3 Final Objective

We also include the *masked language modeling* (MLM) objective in pre-training to leverage other tokens in the input that are not entities. In particular, we randomly mask tokens that are not an entity or token in the header row for tables, and use an MLM objective to recover them. Following the default parameters from BERT, we use a masking probability of 15%.

The final loss is the sum of *span reasoning* loss and *masked language modeling* loss. Following previous work (Glass et al., 2020; Herzig et al., 2020), we initialize with a pre-trained encoder, and extend the pre-training with our objectives. For the text part, we pre-train two models with BERT-Base (denoted as ReasonBERT$_\text{B}$) and RoBERTa-Base (denoted as ReasonBERT$_\text{R}$); for the table part, we use TAPAS-Base (denoted as ReasonBERT$_\text{T}$). More implementation details of pre-training are included in Appendix A.2.

5 Experiments

5.1 Datasets

We conduct experiments with a wide range of extractive QA datasets. Statistics are summarized in Table 3.

MRQA (Fisch et al., 2019). A single-hop extractive QA benchmark that unifies various existing QA datasets into the same format. Here we use the in-domain subset that contains 6 datasets: SQuAD (Rajpurkar et al., 2016), NewsQA (Trischler et al., 2017), TriviaQA (Joshi et al., 2017), SearchQA (Dunn et al., 2017), HotpotQA (Yang et al., 2018) and Natural Questions (Kwiatkowski et al., 2019). Similar to Ram et al. (2021), we adapt these

Train. Size	Model	SQuAD	TriviaQA	NQ	NewsQA	SearchQA	HotpotQA	Average
16	BERT	9.9±0.6	15.4±1.3	20.5±1.5	6.5±1.2	16.8±1.2	9.6±1.6	13.1
	RoBERTa	10.3±1.1	21.0±3.1	22.5±2.1	6.7±2.0	23.4±3.5	11.2±1.0	15.9
	SpanBERT	15.7±3.6	27.4±4.1	24.3±2.1	8.1±1.4	24.1±3.2	16.3±2.0	19.3
	SSPT	10.8±1.2	21.2±3.8	23.7±4.1	6.5±1.9	25.8±2.6	9.1±1.5	16.2
	Splinter	16.7±5.9	23.9±3.8	25.1±2.8	11.6±1.0	23.6±4.5	15.1±3.5	19.3
	Splinter*	**54.6**	18.9	27.4	**20.8**	26.3	24.0	28.7
	ReasonBERTB	33.2±4.0	37.2±2.6	33.1±2.7	11.8±2.3	**46.1**±5.2	22.4±2.8	30.6
	ReasonBERTR	41.3±5.5	**45.5**±5.8	**33.6**±3.9	16.2±3.2	45.8±4.5	**34.1**±2.9	**36.1**
128	BERT	21.5±1.4	23.9±0.8	31.7±0.8	11.3±1.3	32.6±2.3	14.0±0.8	22.5
	RoBERTa	48.8±4.2	36.0±2.9	36.4±2.0	22.8±2.4	41.3±2.0	35.2±1.4	36.7
	SpanBERT	61.2±4.7	48.8±6.6	38.8±2.6	31.0±5.3	50.0±3.7	44.0±2.3	45.7
	SSPT	41.5±5.0	30.3±3.7	35.0±2.4	14.0±3.6	42.8±3.5	23.7±3.4	31.2
	Splinter	55.0±10.3	45.7±4.1	41.1±2.7	33.9±2.8	48.8±3.7	46.9±7.1	45.2
	Splinter*	**72.7**	44.7	46.3	**43.5**	47.2	54.7	51.5
	ReasonBERTB	58.5±2.2	56.2±0.6	46.7±2.6	27.8±0.6	60.8±1.7	45.2±2.3	49.2
	ReasonBERTR	66.7±2.9	**62.1**±0.9	**49.8**±1.6	35.7±1.5	**62.3**±1.7	**57.2**±0.6	**55.6**
1024	BERT	64.1±0.9	41.6±2.6	50.1±0.6	43.0±0.3	53.1±1.0	46.5±1.9	49.7
	RoBERTa	77.9±0.5	62.2±1.3	60.3±0.6	55.0±0.5	67.5±0.8	63.4±0.8	64.4
	SpanBERT	81.1±0.7	67.0±1.0	63.2±0.9	56.4±0.4	70.0±0.8	67.6±1.1	67.5
	SSPT	77.6±1.4	60.1±2.0	58.7±0.7	52.8±1.1	65.9±0.8	63.3±1.6	63.1
	Splinter	79.8±3.5	67.3±1.5	63.8±0.5	54.6±1.4	68.9±0.3	68.4±1.2	67.1
	Splinter*	**82.8**	64.8	**65.5**	**57.3**	67.3	**70.3**	68.0
	ReasonBERTB	76.9±0.5	67.4±0.5	63.6±0.6	52.2±0.5	70.6±0.6	67.8±0.5	66.4
	ReasonBERTR	79.7±0.3	**70.1**±0.2	65.0±0.9	54.7±0.6	**72.8**±0.4	69.7±0.6	**68.7**
All	BERT	88.8	73.6	78.7	67.5	82.0	76.2	77.8
	RoBERTa	92.0	78.1	80.6	**71.9**	85.2	79.1	81.2
	SpanBERT	**92.5**	**79.9**	80.7	71.1	84.8	**80.7**	**81.6**
	SSPT	91.1	77.0	80.0	69.7	83.3	79.7	80.1
	Splinter	92.4	79.7	80.3	70.8	84.0	80.6	81.3
	Splinter*	92.2	76.5	**81.0**	71.3	83.0	**80.7**	80.8
	ReasonBERTB	90.3	77.5	79.9	68.7	83.7	80.5	80.1
	ReasonBERTR	91.4	78.9	80.8	71.4	**85.3**	80.6	81.4

Table 4: Results on MRQA datasets. **Best** and Second Best results are highlighted. We report the average F1 score over five runs for each dataset, and the macro-average of the six datasets. Splinter* is the result reported in the original paper, where the authors use a deeper model with additional transformation layers on top of the encoder.

datasets to the few-shot setting by randomly sampling smaller subsets from the original training set for training, and use the original development set for testing.

HotpotQA (Yang et al., 2018). A multi-hop QA dataset that requires reasoning over multiple pieces of evidence. Here we follow the distractor setting, where 10 paragraphs are provided to answer a question while only two of them contain relevant information. We split 10% of the original train-hard split for development, and use the original development set for testing.

NQTables (Kwiatkowski et al., 2019). A subset of the Natural Questions dataset, where at least one answer to the question is present in a table. We extract 19,013 examples from the original training set (307,373 examples) and split them with a 9:1 ratio for training and development. The test set is then created from the original development split (7,830 examples) and contains 1,118 examples. Here we only keep tables from the original Wikipedia article as evidence. Similar subsets are also used in Herzig et al. (2021) and Zayats et al. (2021).

HybridQA (Chen et al., 2020). A multi-hop QA dataset with hybrid contexts. Each example contains a table and several linked paragraphs.

We adopt the evaluation script from MRQA[3], which evaluates the predicted answer using exact match (EM) and token-level F1 metrics.

5.2 Baselines

BERT (Devlin et al., 2019). A deep transformer model pre-trained with masked languge model (MLM) and next sentence prediction objectives.

RoBERTa (Liu et al., 2019b). An optimized version of BERT that is pre-trained with a larger text

[3] `https://github.com/mrqa/MRQA-Shared-Task-2019`

corpus.

SpanBERT (Joshi et al., 2020). A pre-training method designed to better represent and predict spans of text. It extends BERT by masking contiguous random spans, and training the span boundary representation to predict the entire masked span.

SSPT (Glass et al., 2020). A pre-training method designed to improve question answering by training on cloze-like training instances. Unlike ReasonBERT, SSPT only masks a single span in the query sentence and predicts it based on an evidence paragraph provided by a separate retriever.

Splinter (Ram et al., 2021). A pre-training method optimized for few-shot question answering, where the model is pre-trained by masking and predicting recurring spans in a passage.

TAPAS (Herzig et al., 2020). A pre-training method designed to learn representations for tables. The model is pre-trained with MLM on tables and surrounding texts extracted from Wikipedia.

For fair comparison, in each task, we use the same model architecture with different pre-trained encoders, which is similar to the one used for span reasoning in pre-training. We append the `[QUESTION]` token to a question and construct the input sequence the same way as in pre-training. We then score all the start, end locations and rank all spans (s, e) (See Eqn. 3 and 4 in Appendix). We use a pre-trained encoder and learn the answer extraction layers ($\mathbf{S}, \mathbf{E}$ in Eqn. 1) from scratch during fine-tuning.

Unless otherwise stated, we use the pre-trained base version so that all models have similar capacity (110M parameters for ReasonBERTB, 125M parameters for ReasonBERTR, and 111M parameters for ReasonBERTT).

5.3 Few-shot Single-hop Text QA

We first experiment with the easier, single-hop MRQA benchmark under the few-shot setting to show that our pre-training approach learns general knowledge that can be transferred to downstream QA tasks effectively. Results are shown in Table 4. We can see that ReasonBERT outperforms pre-trained language models such as BERT, RoBERTa and SpanBERT by a large margin on all datasets, particularly with an average absolute gain of 20.3% and 14.5% over BERT and RoBERTa respectively. Compared with pre-training methods such as SSPT and Splinter, ReasonBERT also shows superior performance and obtains the best results on average.

Model	Recall		1%		Full	
	Top 2	Top 3	F1	EM	F1	EM
HGNRoBERTa-Large	-	-	-	-	82.2	-
HGNBERT	-	-	-	-	74.8	-
BERT	92.4	96.9	39.8	28.6	71.9	57.9
RoBERTa	93.1	97.5	56.0	43.1	76.3	62.9
SpanBERT	93.6	97.7	56.5	44.1	76.3	62.9
SSPT	93.9	97.9	54.7	41.8	75.4	61.5
Splinter	94.1	97.9	57.0	44.2	76.5	62.5
ReasonBERTB	93.8	97.8	57.6	45.3	77.2	63.4
ReasonBERTR	**94.0**	**98.0**	**63.1**	**50.2**	**78.1**	**64.8**

Table 5: Results on HotpotQA.

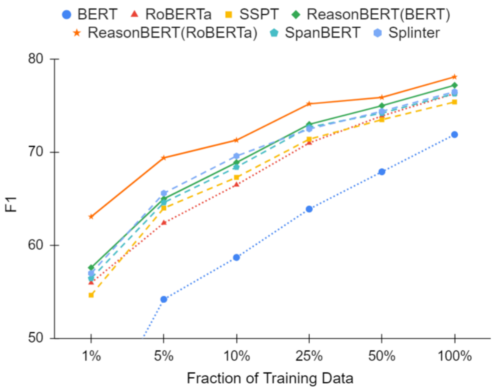

Figure 2: Few-shot learning results on HotpotQA.

Under the full-data setting, ReasonBERT performs competitively and all methods achieve similarly high accuracy. We still demonstrate improvements upon BERT and RoBERTa, and ReasonBERTR second best average score.

5.4 Multi-hop Text QA

To demonstrate that our approach is useful in conducting deep reasoning over multiple contexts, we experiment with the HotpotQA dataset. Here we design a simplified multi-hop QA model that first selects relevant paragraphs as evidence, and then extracts the answer from the top selected evidence. Please see Appendix A.3 for implementation details. In addition to comparing ReasonBERT with other pre-training methods using the same base model, we also show results for HGN (Fang et al., 2020), which is one of the top ranked models on the HotpotQA leaderboard that uses a more sophisticated model design.

Results are shown in Table 5. All models perform very well for evidence selection, with over 96% top 3 recall, but ReasonBERT still maintains a slim lead over baselines. ReasonBERT provides a 5.3% improvement for BERT and a 1.8% improvement for RoBERTa on overall F1 score, and outperforms all other pre-training methods. ReasonBERT also outperforms the HGN model with BERT, but

Model	Dev		Test	
	F1	EM	F1	EM
RoBERTa	58.9	52.8	63.6	58.1
ReasonBERT$_R$	61.9	56.4	66.3	60.9
TAPAS	64.9	57.8	65.9	59.6
ReasonBERT$_T$	**69.2**	**63.5**	**72.5**	**67.3**

Table 6: Results on NQTables.

is lower than the one using RoBERTa-Large, which is probably due to simpler design and smaller size of the model. We further experiment under the few-shot setting. Here we focus on the QA performance, so we reuse the evidence selector trained with full data for each model, and train the QA module with different fractions of training data. We can see that the advantage of using ReasonBERT is more obvious with limited training data. With 1% of training data, ReasonBERT$_R$ obtains F1 score of 63.1%, a 7.1% absolute gain over RoBERTa. Results for training the QA model with different fraction of training data is shown in Figure 2. We can see that ReasonBERT obtains larger gain under the few-shot setting.

5.5 Table QA

We demonstrate our approach also works with structured data such as tables using the NQTables dataset. We first use a text based RoBERTa encoder as baseline, which linearizes a table as a text sequence, by concatenating tokens row by row and separating cells with the `[SEP]` token. We then experiment with the structure-aware encoder from TAPAS and compare the pre-trained TAPAS encoder with the one pre-trained using ReasonBERT. Results are shown in Table 6. First, we can see that TAPAS outperforms RoBERTa by 2.3%, demonstrating the importance of modeling the table structure. ReasonBERT$_R$ slightly outperforms TAPAS on test set, but ReasonBERT$_T$ further boosts F1 to 72.5%, resulting in at least 6.6% absolute gains over existing methods. Results for training the Table QA model with different fractions of training data are shown in Figure 3. ReasonBERT$_T$ consistently outperforms TAPAS while ReasonBERT$_R$ gradually matches the performance of TAPAS with the increasing of training data.

5.6 Hybrid QA

We further evaluate our approach on HybridQA, a multi-hop question answering dataset using both text and tables as evidence. Chen et al. (2020) proposes a baseline model HYBRIDER that divides the problem into four tasks: linking, ranking, hopping and reading comprehension. We follow their design but simplify the model by merging ranking and hopping into a single cell selection task. We use the linking results from Chen et al. (2020), and then train a table based cell selector to select the cell which is the answer or is linked to the passage that contains the answer. Finally, we train a text based QA model to extract the final answer by taking the table snippet that contains the selected cell, and concatenating it with the hyperlinked passage as evidence. Please see Appendix A.3 for implementation details. Results are shown in Table 7. First, we can see that our simplified architecture works surprisingly well, with TAPAS for cell selection and RoBERTa for QA, we already outperform HYBRIDER. The performance is further improved by replacing the encoders with ReasonBERT$_T$ and ReasonBERT$_R$, and substantially outperforms the best model on the leaderboard (52.04 EM) at the time of submission.

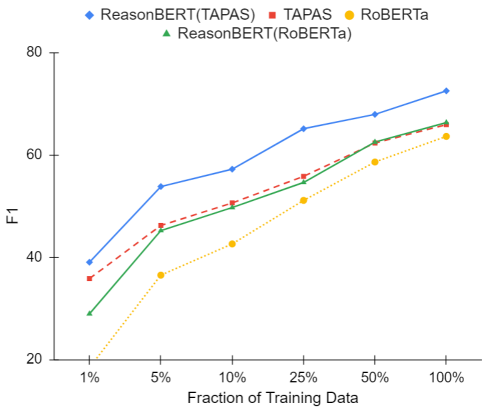

Figure 3: Few-shot learning results on NQTables.

Model	Cell Selection		Dev		Test	
	Top 1	Top 2	F1	EM	F1	EM
HYBRIDER$_{\text{BERT-Base}}$	-	-	50.9	43.7	50.2	42.5
HYBRIDER$_{\text{BERT-Large}}$	68.5	-	50.7	44.0	50.6	43.8
TAPAS+RoBERTa	73.3	79.7	64.0	57.3	63.3	56.1
ReasonBERT	**76.1**	**81.3**	**67.2**	**60.3**	**65.3**	**58.0**

Table 7: Results on HybridQA.

6 Ablation Study

We further conduct ablation studies on HotpotQA to verify our design choices, summarized in Table 8. Here we remove different components of ReasonBERT$_R$ and test them under both the full-data and few-shot setting (with 1024 examples). To save computing resources, here all models are pre-trained with 5 epochs. We can see that combining multiple pieces of evidence and predicting

Model	1024		Full	
	F1	EM	F1	EM
ReasonBERTR	65.2	52.8	79.2	65.8
– MLM	63.7	51.3	77.7	64.0
– Unanswerable Ent.	64.4	51.8	78.4	65.0
– Multiple Evidences	60.8	48.6	77.8	64.5

Table 8: Ablation study on HotpotQA.

multiple masked spans simultaneously brings the most gain, especially under the few-shot setting. This is probably because the setting allows us to simulate complex reasoning chains and encourage the model to do deep reasoning. Masking unanswerable entities and utilizing MLM also help to improve performance.

7 Related Work

Language Model Pre-training. Contextualized word representations pre-trained on large-scale unlabeled text corpus have been widely used in NLP lately. Most prevalent approaches are variants of pre-trained language models such as BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019b). More recently, self-supervised pre-training has also shown promising results on modalities other than plain text, such as tables (Herzig et al., 2020; Deng et al., 2020; Iida et al., 2021), knowledge bases (Zhang et al., 2019; Peters et al., 2019) and image-text (Su et al., 2020). Meanwhile, there has also been work that uses pre-training to accommodate specific needs of downstream NLP tasks, such as open-domain retrieval (Guu et al., 2020), representing and predicting spans of text (Joshi et al., 2020) and semantic parsing (Yu et al., 2020; Deng et al., 2021).

Machine Reading Comprehension. Machine reading comprehension (MRC) or extractive QA has become an important testbed for natural language understanding evaluation (Fisch et al., 2019). The conventional method to train an MRC model usually relies on large-scale supervised training data (Chen et al., 2017; Zhang et al., 2020). Recently, more and more work has focused on developing self-supervised methods that can reduce the need for labeled data for more efficient domain adaptation, while achieving the same or even better performance. One direction is question generation (Pan et al., 2021), which automatically generates questions and answers from unstructured and structured data sources using rules or neural generators. Recent work also tries to directly simulate questions with cloze-like query sentences. Splinter (Ram et al., 2021) proposes to pre-train the model by masking and predicting recurring spans. However, this limits the query and context to come from the same passage. In contrast, SSPT (Glass et al., 2020) also pre-trains with a span selection objective, but uses a separate document retriever to get relevant paragraphs as context.

Our work is most related to SSPT, but uses distant supervision to collect query-evidence pairs and thus obviate the need for a retriever. Meanwhile, to encourage the model to learn complex reasoning, we mimic different types of reasoning chains by masking multiple entities, including unanswerable ones, and simultaneously inferring them from disjoint pieces of evidence. Our method also works with heterogeneous sources including both text and tables, while most existing work considers only text-based question answering.

8 Conclusion and Future Work

We propose ReasonBERT, a novel pre-training method to enhance the reasoning ability of language models. The resulting model obtains substantial improvements on multi-hop and hybrid QA tasks that require complex reasoning, and demonstrates superior few-shot performance. In the future, we plan to use our query-evidence pairs collected by distant supervision to improve the retrieval performance for open-domain QA, as well as empower ReasonBERT to handle more types of reasoning, like comparison and numeric reasoning, in natural language understanding.

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A Implementation Details

A.1 Pre-training Data Details

We extract paragraphs from Wikipedia XML dump[4] use JWPL[5] and tables use wikitextparser[6]. The paragraphs are then processed with SparkNLP[7] for sentence boundary detection and named entity recognition.

Table 9 and Table 10 show some examples of the query-evidence pairs we collected for pre-training. The selected entities are underlined. During pre-training, we will mask some of the entities in the query and recover them based on the evidence. As the pre-training data is collected via distant supervision, it contains some noise. Here we also include some bad examples where the evidence does not express the same relation between the selected entities as the query sentence (highlighted in red).

A.2 Pre-training Details

We set the max length of query sentences to 100 tokens and the max length of single piece of evidence to 200 if there are two evidence selections or 400 if there is only one. For textual evidence, we include the neighbouring sentences from the same paragraph as extra context for the selected evidence sentence and clip to the max evidence length. For tabular evidence, we take a snippet of the original table, and truncate the cells to 20 tokens. We always keep the first row and column in the table, as they often contain important information such as headers and subject entities. Based on the selected entity pair, we sample up to 5 columns and include as many rows as possible until reaching the budget.

We initialize our encoder with BERT-Base[8] and RoBERTa-Base[9] for the text part, and TAPAS-base[10] for the table part. We train ReasonBERT using AdamW (Loshchilov and Hutter, 2019) for 10 epochs with batches of 256 sequences of length 512; this is approximately 290k steps with text-only data, and 120k steps with hybrid data. We base our implementation on Huggingface Transformers (Wolf et al., 2020), and train on a single eight-core TPU on the Google Cloud Platform.

A.3 Fine-tuning Details

To extract the answer span from given evidence, we score all the start, end locations and rank all spans (s, e) by $g(s, e|q, E)$ as follows:

$$f_{\textbf{start}} = \mathbf{x}_s^\top \mathbf{S}\mathbf{x}_q, \quad f_{\textbf{end}} = \mathbf{x}_e^\top \mathbf{E}\mathbf{x}_q \tag{3}$$

$$\begin{aligned} g(s, e|q, E) = &\, f_{\textbf{start}}(s|q, E) \\ &+ f_{\textbf{end}}(e|q, E) \\ &- f_{\textbf{start}}(\texttt{[CLS]}|q, E) \\ &- f_{\textbf{end}}(\texttt{[CLS]}|q, E) \end{aligned} \tag{4}$$

For all fine-tuning experiments, we set the batch size to 20 and use a maximal learning rate of $5 \cdot 10^{-5}$, which warms up in the first 10% of the steps, and then decays linearly. We use the development set for model selection if it is present, otherwise we use the last model checkpoint.

Single-hop text QA. We split the text sequence to fit the max input length by sliding a window with a stride of 128 tokens.

For the few-shot setting, we fine-tune the model for either 10 epochs or 200 steps (whichever is larger). For the fully supervised setting, we fine-tune the model for 2 epochs.

Multi-hop text QA. We design a simplified multi-hop QA model that first selects relevant paragraphs as evidence, and then extracts the answer from the selected evidence samples. Specifically, we first generate all possible paragraphs by sliding a 200-token window over all articles with a stride of 128 tokens. We then train an evidence selector to pick the top 3 evidence samples. As the information for answering a question in HotpotQA is scattered in two articles, we list all possible combinations of paragraphs that come from two different articles and concatenate them together to form the final evidence. We then use the base QA model to extract the answer based on the question and the combined evidence.

We fine-tune the evidence selector model for 2 epochs, and the QA model for 5 epochs with full data. For the few-shot setting, we fine-tune the QA model for 10 epochs with 1&, 5% and 10% of the training data, and for 5 epochs with 25% and 50% of the training data.

Table QA. For the text based model, We split the text sequence to fit the max input length by sliding a window with a stride of 128 tokens. For the table based model, we truncate each cell to 50 tokens,

[4] https://dumps.wikimedia.org/

[5] https://dkpro.github.io/dkpro-jwpl/

[6] https://github.com/5j9/wikitextparser

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[8] https://huggingface.co/bert-base-uncased/tree/main

[9] https://huggingface.co/roberta-base/tree/main

[10] https://huggingface.co/google/tapas-base/tree/no_reset

and split the table into snippets horizontally. Same as pre-training, we include the first row and column in each table snippet.

We fine-tune the model for 5 epochs with full data. For the few-shot setting, we fine-tune the QA model for 10 epochs with 1&, 5% and 10% of the training data, and for 5 epochs with 25% and 50% of the training data.

Hybrid QA. Chen et al. (2020) proposes a baseline model that divides the problem into four tasks: 1) linking: link questions to their corresponding cells using heuristics. 2) ranking: rank the linked cells use a neural model. 3) hopping: based on the cell selected in the last step, decide which neighboring cell or itself contains the final answer. 4) reading comprehension: extract the answer from the predicted cell or its linked paragraph. We follow their design and simplify the model by merging ranking and hopping into a single cell selection task. We use the linking results from Chen et al. (2020). For each linked cell, we take a snippet out of the original table including the headers, the entire row of the linked cell, and concatenate the evidence sentence to the cell if it is linked through the hyperlinked passage. To select the cell, we train the model to select separately on the token, row and column level, and aggregate the final scores . More specifically, we calculate the probability of selecting on the token and row level as follows:

$$\begin{aligned} P(t|q,E) &= \frac{\exp\left(\mathbf{x}_t^\top \mathbf{S}\mathbf{x}_{a_i}\right)}{\sum_k \exp\left(\mathbf{x}_k^\top \mathbf{S}\mathbf{x}_{a_i}\right)} \\ S_{cell} &= \mathrm{mean}_{x_i \in cell}\left(\mathbf{x}_i^\top \mathbf{R}\mathbf{x}_a\right) \qquad (5) \\ P(r_a = j \mid q, E) &= \frac{\exp\left(\max_{cell \in r_j} S_{cell}\right)}{\sum_k \exp\left(\max_{cell \in r_k} S_{cell}\right)} \end{aligned}$$

Here $\mathbf{S}$ is the weight matrix of the token selection header, we only consider the first token in each cell, and t is the first token of the selected cell. $\mathbf{R}$ is the weight matrix of row selection header, and the column selection probability is calculated similarly with another column selection header. We first score each cell by averaging over all tokens in that cell. We then do a max pooling over all cells in the row or column so the model can focus on the strongest signal, for example the column header. The final probability of selecting a cell is the sum of token, row and column scores.

The input for the QA model then contains the header of the table, the row of the selected cell, and the hyperlinked passage.

We fine-tune the cell selection model for 2 epochs and the QA model for 3 epochs.

Query	Evidence
"*I Thought I Lost You*" was nominated for Broadcast Film Critics Association Award for Best Song and Golden Globe Award for Best Original Song, but lost both to *Bruce Springsteen*'s "*The Wrestler*" from *The Wrestler* (2008).	On January 11, 2009, *Springsteen* won the Golden Globe Award for Best Song for "*The Wrestler*", from the Darren Aronofsky *film by the same name*. "*I Thought I Lost You*" was nominated for the Broadcast Film Critics Association Award for Best Song at the 14th Broadcast Film Critics Association Award, but lost to *Bruce Springsteen*'s "*The Wrestler*" from *The Wrestler* (2008).
Film critic *Roger Ebert* compared it to *John Carpenter*'s *Halloween*, noting: "Blue Steel" is a sophisticated update of Halloween, the movie that first made *Jamie Lee Curtis* a star.	Historian Nicholas Rogers notes that film critics contend that Carpenter's direction and camera work made *Halloween* a "resounding success." *Roger Ebert* remarks, ... Since *Jamie Lee Curtis*, the main actress from the original and the sequel Halloween II (1981), wanted to reunite the cast and crew of the original film, she asked *Carpenter* to direct Halloween H20: 20 Years Later.
A hybrid disc is an optical disc that has multiple *file system* installed on it, typically *ISO 9660* and HFS+ (or *HFS* on older discs).	Hierarchical File System (*HFS*) is a proprietary *file system* developed by Apple Inc. for use in computer systems running Mac OS. *ISO 9660* is a *file system* for optical disc media. Being sold by the International Organization for Standardization (ISO) the file system is considered an international technical standard.
After *1709* , the heads of the *House of Orleans* branch of *the House of Bourbon* ranked as the prince of the Blood – this meant that the dukes could be addressed as Monsieur le Prince (a style they did not, however, use).	From *1709* until the French Revolution, the *Orleans* dukes were next in the order of succession to the French throne after members of the senior branch of the House of Bourbon, descended from Louis XIV. Restored briefly in 1814 and definitively in 1815 after the fall of the First French Empire, the senior line of the Bourbons was finally overthrown in the July Revolution of 1830. A cadet *Bourbon* branch, the *House of Orleans*, then ruled for 18 years (1830–1848), until it too was overthrown.
The *Citroen C6* is an *executive car* produced by the French car maker *Citroen* from 2005 to *2012*.	The *C6* was aimed as a stylish alternative to *executive cars*, like the BMW 5 Series and the Audi A6, and it has been described as "spaceship that rides on air", "charmingly idiosyncratic" and "refreshingly different". In *2012*, *Citroen* announced plans to enter the World Touring Car Championship. The team transformed a DS3 WRC into a laboratory vehicle to help with early development, while ...
Leaving the *Market Street subway* at Ferry Portal heading south, the T Third Street follows *The Embarcadero* south of Market Street, then veers onto King Street in front of *Oracle Park* until it reaches the *Caltrain* station terminal.	the 4th & King *Caltrain* station is 1.5 blocks from the stadium, and the *Oracle Park* Ferry Terminal is outside the east edge of the ballpark beyond the center field bleachers. the southwestern end of the *Market Street subway* connects to the much-older Twin Peaks Tunnel, and the northeastern end connects to surface tracks along the *The Embarcadero*.

Table 9: Pre-training data examples, text-only setting.

<table>
<tr><th>Query</th><th>Evidence</th></tr>
<tr><td>*Rowland Barran* (7 August 1858 – 6 August 1949) was an English *Liberal Party* politician and *Member of Parliament*.</td><td>*Rowland Barran* was the youngest son of Sir John Barran, a pioneer in clothing manufacture and *Member of Parliament* for Leeds and Otley.
<table>
<tr><th>Year</th><th>Member</th><th>Party</th></tr>
<tr><td>1885</td><td>William Jackson</td><td>Conservative</td></tr>
<tr><td>1902</td><td>*Rowland Barran*</td><td>*Liberal*</td></tr>
<tr><td>1918</td><td>Alexander Farquharson</td><td>Coalition Liberal</td></tr>
</table></td></tr>
<tr><td>"*It Ain't Over 'til It's Over*" is a song recorded, written, and produced by American musician *Lenny Kravitz* for his second studio album, Mama Said (1991).</td><td>Retrieved on August 19, 2007. *Kravitz*'s biggest single yet, "*It Ain't Over 'til It's Over*", went to number 2 on the Billboard Hot 100.
<table>
<tr><th>Act</th><th>Order</th><th>Song</th><th>Rock Artist</th></tr>
<tr><td>In Stereo</td><td>4</td><td>Demons</td><td>Imagine Dragons</td></tr>
<tr><td>Cyrus Villanueva</td><td>5</td><td>*It Ain't Over 'til It's Over*</td><td>*Lenny Kravitz*</td></tr>
<tr><td>Michaela Baranov</td><td>6</td><td>Wild Horses</td><td>The Rolling Stones</td></tr>
</table></td></tr>
<tr><td>*Ronnie Bremer* raced the first five races of the season with *Brooks Associates Racing*, before moving to Polestar Motor Racing.</td><td>
<table>
<tr><th>Place</th><th>Name</th><th>Team</th></tr>
<tr><td>5</td><td>*Ronnie Bremer*</td><td>*Brooks Associates Racing*</td></tr>
<tr><td>6</td><td>Bryan Sellers</td><td>Lynx Racing</td></tr>
<tr><td>9</td><td>Jonathan Bomarito</td><td>Transnet Racing</td></tr>
</table></td></tr>
<tr><td>Donovan also appeared in the *1980* film *Breaker Morant*, but in a subsidiary role, rather than as the title character.</td><td>
<table>
<tr><th>Title</th><th>Year</th><th>Role</th></tr>
<tr><td>Cop Shop (TV series)</td><td>1978-1980</td><td>Detective Sgt. Vic</td></tr>
<tr><td>*Breaker Morant*</td><td>*1980*</td><td>Captain Simon Hunt</td></tr>
<tr><td>Smash Palace</td><td>1981</td><td>Traffic Officer</td></tr>
</table></td></tr>
<tr><td>*Try a Little Kindness* is the sixteenth album by American singer/guitarist *Glen Campbell*, released in *1970*.</td><td>At the height of his popularity, a *1970* biography by Freda Kramer, The *Glen Campbell* Story, was published.
<table>
<tr><th>Day</th><th>Album</th><th>Artist</th><th>Notes</th></tr>
<tr><td>1</td><td>On the Boards</td><td>Taste</td><td>-</td></tr>
<tr><td>26</td><td>Chicago</td><td>Chicago</td><td>aka Chicago II</td></tr>
<tr><td>-</td><td>*Try a Little Kindness*</td><td>*Glen Campbell*</td><td>-</td></tr>
</table></td></tr>
</table>

Table 10: Pre-training data examples, hybrid setting.