

Internet-Augmented Dialogue Generation

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Abstract

The largest store of continually updating knowledge on our planet can be accessed via internet search. In this work we study giving access to this information to conversational agents. Large language models, even though they store an impressive amount of knowledge within their weights, are known to hallucinate facts when generating dialogue (Shuster et al., 2021); moreover, those facts are frozen in time at the point of model training. In contrast, we propose an approach that learns to generate an internet search query based on the context, and then conditions on the search results to finally generate a response, a method that can employ up-to-the-minute relevant information. We train and evaluate such models on a newly collected dataset of human-human conversations whereby one of the speakers is given access to internet search during knowledge-driven discussions in order to ground their responses. We find that search-query based access of the internet in conversation provides superior performance compared to existing approaches that either use no augmentation or FAISS-based retrieval (Lewis et al., 2020).

1 Introduction

Open-domain dialogue, which involves chat about any topic, rather than a specific goal-directed topic, is commonly studied by training large language models (Adiwardana et al., 2020; Zhang et al., 2019; Roller et al., 2020). These models are trained either in a encoder-decoder or decoder only setting on large datasets of human-human conversations, and any knowledge obtained during training is stored in the weights of the model. Such static language modeling fails to take into account the dynamic state of the world, where new information is coming in by the day – or even by the minute – as the knowledge in static models is gleaned from

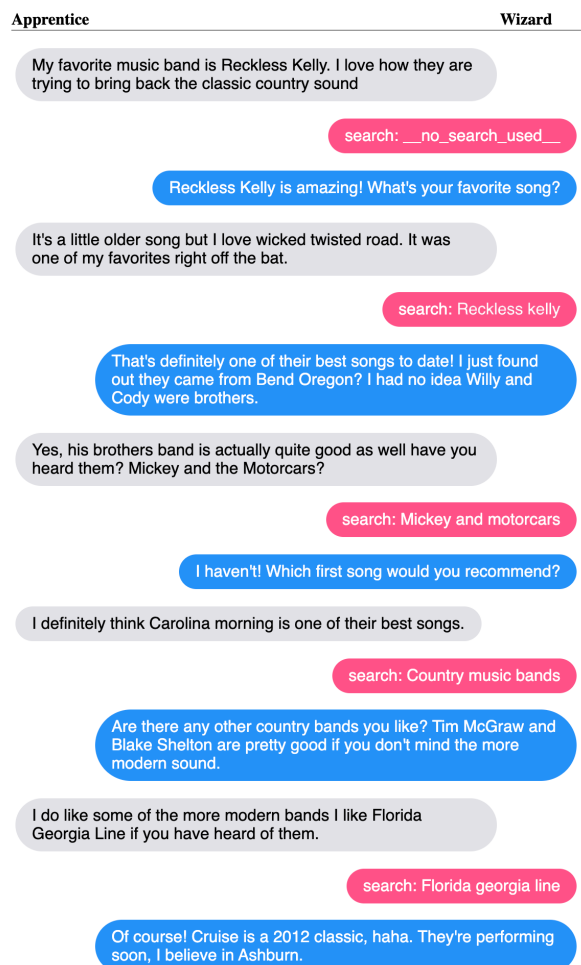


Figure 1: Example human-human conversation from the Wizard of the Internet training set. The role of the Wizard on the right-hand side involves performing internet searches, and then writing appropriate responses to the Apprentice given the viewed web documents (not shown).

the point in time when the dataset was collected, and then frozen into the model that is trained; see (Lazaridou et al., 2021) for criticisms of this approach. Further, static language models are known to *hallucinate*, that is they generate plausible look-

ing statements that are factually incorrect, which can be interpreted as a form of lossy compression when employing training to encode that knowledge within the weights of a neural network; see (Shuster et al., 2021) for an in-depth study.

In this work we study generative models that are instead capable of accessing the vast knowledge of the internet dynamically in order to inform their responses. Utilizing encoder-decoder architectures, we consider models that, given a dialogue context, first generate a search query. The queries are then used to retrieve relevant knowledge that is prepended to the conversational history, which is encoded using the Fusion-in-Decoder method (Izacard and Grave, 2020). Taking into account this encoded knowledge, a response is finally generated using the decoder. This ability to access the internet means the model is always up-to-date, unlike existing models that only know about facts in their fixed training set. Our model, in contrast, can potentially make use of the latest sports scores, movies or TV shows that were just released, the latest reviews, and so forth – amongst the countless other topics available on the internet.

In order to train and evaluate such models, we collect a new crowdsourced English dataset involving human-human conversations, where one of the workers plays the role of a “wizard” who conducts internet searches in order to inform their responses during knowledge-grounded conversations. We show that internet-augmented models trained to replace the human wizard outperform conventional non-augmented generation models on this task as measured by automatic metrics as well as human evaluations. We study in detail different ways of designing internet-augmentation and show which methods perform best, providing analysis of how the methods work, and in which conditions. We make our final models, and the new task we have collected, publicly available and open source¹.

2 Related Work

The majority of work on dialogue generation has focused on training on natural or crowdsourced data where the task is, given a dialogue context (history), to generate the next response. Datasets such as pushshift.io Reddit (Baumgartner et al., 2020), PersonaChat (Zhang et al., 2018) or Empathetic Dialogues (Rashkin et al., 2019) (see Huang et al. (2020) for a review) are typically employed to

train the weights of a Transformer encoder-decoder. This is the standard approach in state-of-the-art chatbots such as Meena (Adiwardana et al., 2020) or BlenderBot (Roller et al., 2020). Such models do not augment their generations with access to external knowledge, instead relying on facts originally provided in the training datasets themselves being stored into the weights of the model.

A growing area of research is that of augmenting generative models with external knowledge. Earlier works such as Memory Networks (Weston et al., 2014) and DrQA (Chen et al., 2017) utilized TFIDF-based retrieval over documents to provide additional input to neural models for the task of question answering, following the well studied area of non-neural methods that use retrieval for QA (Voorhees, 2001). More recently, the RAG (Retrieval-Augmented Generation) (Lewis et al., 2020) and FiD (Fusion-in-Decoder) (Izacard and Grave, 2020) models developed these ideas further, using a neural retriever as well, with superior results. Retrieval-augmentation is also studied in the area of language modeling, where it is used for pre-training (Guu et al., 2020), and as a memory (Yogatama et al., 2021), especially using k -nearest neighbor-based cache models (Khandelwal et al., 2021, 2020; Grave et al., 2016; Merity et al., 2016).

In dialogue, knowledge grounding is becoming more popular an area, with several datasets developed to study it (Zhou et al., 2018; Dinan et al., 2019; Ghazvininejad et al., 2018; Gopalakrishnan et al., 2019; Galetzka et al., 2020). Some of these such as Topical-Chat (Gopalakrishnan et al., 2019) and CMU_Dog (Zhou et al., 2018) are constructed given a gold passage of knowledge, and the task analyzes whether the model can use this knowledge in dialogue. Other works (Zhao et al., 2020; Kim et al., 2020; Bruyn et al., 2020) study whether knowledge selection is possible from a (small) set of knowledge. However, a retrieval step (or search engine) is not used, as we consider here.

Perhaps the closest to our work is the Wizard of Wikipedia task (Dinan et al., 2019) which involves conversations grounded in Wikipedia, using a TFIDF retrieval model to find relevant knowledge from that database. Our work can be seen as a much richer task, covering all of the information that is publicly available on the internet and hence a more diverse range of conversational topics rather than just Wikipedia, while allowing human wizards to search for relevant knowledge themselves.

¹<http://parl.ai/projects/sea>

Moreover, we consider sophisticated neural-in-the-loop retrieval mechanisms and real search engines. Shuster et al. (2021) studied neural-retriever-in-the-loop methods on this dataset.

Some other related work of note is that of using search engines for machine translation (rather than dialogue, as we do here), which was shown to provide good results (Gu et al., 2018). Finally, rather than applying search engines for a downstream task, sophisticated machine learning has also been applied directly to improve the search task itself, for example using reinforcement learning (Nogueira and Cho, 2017).

3 Internet-Augmented Generation

We consider two ways to access the webpages from the internet: (i) using a cached set of pages that are stored in a distributed approximate nearest-neighbor database, FAISS (Johnson et al., 2019), or (ii) using an Internet Search Engine directly to retrieve pages. For the FAISS-based methods, there are a number of possible variants that we consider, which we will describe first.

3.1 FAISS-based methods

In our experiments, the FAISS-based methods share the same core setup. First, we store and utilize the Common Crawl dump of the internet from Wenzek et al. (2019)² in a FAISS database, with keys that are dense vectors. The retrieval system uses a DPR (Dense Passage Retrieval) (Karpukhin et al., 2020) Transformer-based model which scores document-context pairs in order to rank them based on their match using a bi-encoder framework, where the base DPR model is pre-trained on QA data pairs. We use the pre-trained DPR model from the KILT Benchmark (Petroni et al., 2020). The documents (webpages) are encoded using DPR into dense vectors and these are stored in the FAISS index. During dialogue-based retrieval, the dialogue context is also encoded by DPR into a dense vector and FAISS approximate nearest-neighbor lookup is performed, where the top N documents are returned. We then consider several recent neural methods for utilizing this retrieval mechanism in various ways.

²We use the November 2020 dump, head only, consisting of ~ 109 M English webpages. Each document is split into 100-word chunks, giving 250M passages to index in FAISS. We also consider the dump of Wikipedia from (Karpukhin et al., 2020) in this work.

RAG (Retrieval Augmented Generation) RAG (Lewis et al., 2020) is an approach which consists of two components which are trained end-to-end: (i) the neural-in-the-loop retrieval system; and (ii) an encoder-decoder for generating final responses given the results of the retrieval. Using DPR, the top N documents are returned as described above, and in the RAG-Token model (just called RAG in the rest of the paper) each in turn is encoded along with the context for each token, and the most likely sequence is generated from the set. During backpropagation training steps, the DPR context encoder is also tuned to perform well at FAISS retrieval, but the document encodings are held fixed. This approach has been shown to optimize both retrieval and generation jointly, improving results.

FiD (Fusion in Decoder) A related, but perhaps simpler, method is that of FiD (Izacard and Grave, 2020). In this case, the pre-trained retriever is used, i.e. DPR with FAISS, and then each of the top N documents returned is prepended to the context and encoded separately by the encoder, and finally all the results are concatenated. The decoder then attends to these encodings to produce a final response, so all “fusion” happens in the decoding stage. This relatively simple method was shown to outperform RAG in some cases.

FiD-RAG The FiD approach works well, but there is no end-to-end training of the retriever in that case, and so it relies completely on being pre-trained well, as opposed to RAG which tunes the retrieval for generation. FiD-RAG, proposed in (Shuster et al., 2021) combines the two methods. First the retriever is trained in a RAG setup, and then FiD is used with that retriever. This was shown to give superior results to both RAG and FiD on dialogue tasks.

FAISS + Search Query-based Retrieval Instead of just encoding the context into a dense vector, in this approach an encoder-decoder is employed to generate a search query given the context. The search query is input into a DPR model to produce a dense vector, and is matched to documents in the FAISS index. Returned documents can then be used in the final response generation encoder-decoder as before. Any of the existing approaches (RAG, FiD or FiD-RAG) could potentially be used to fuse the DPR and generator models. We used the standard DPR FiD setup. We will discuss how

to generate the search query itself in more detail in the following subsection (subsection 3.2).

3.2 Search Engine-Augmented Generation (SEA)

The previously described FAISS-based approaches can take advantage of many existing methods developed for QA and dialogue tasks, as we saw, but have several disadvantages. First, they may be difficult to update to real-time web documents; second, there may be a limit to the number of documents storable in local FAISS deployments; and third, such methods will not take advantage of the high quality ranking that has been finely tuned in Internet Search engines over decades of use. We thus consider using Internet search engines directly.

Method Our proposed method consists of two components:

- A search query generator: an encoder-decoder Transformer that takes in the dialogue context as input, and generates a search query. This is given to the black-box search engine API, and N documents are returned.
- A FiD-style encoder-decoder model that encodes each document individually, concatenates them to the dialogue context encoding, and then finally generates the next response.

We can train each of these modules separately if we have supervised data available for both tasks, the first module requiring (context, search query) pairs, and the second module requiring (context, response) pairs. As we will see, the data we collect in this work (detailed in section 4) fulfills both of these requirements.

For FiD, we try two methods: (i) Conventional FiD whereby we use the returned search results from using our trained search query generator in order to build the relevant document contexts for the FiD training set; (ii) FiD-Gold: as we will have available human-written search queries for the training set, and their corresponding search results, we can use these gold results to build training document contexts instead. Although these might not look like the queries and hence results predicted at test time, they are more likely to contain the knowledge used in generating the training set responses, thus a clearer grounding may be apparent for the model to learn correspondences.

Search Engine The search engine is a black box in this system, and could potentially be swapped out for any method. In our numerical experiments we use the Bing Search API to generate a list of URLs for each query; then, we use these URLs as keys to find their page content from a lookup table we built for our Common Crawl snapshot, in order to populate a set of pages for that query. This makes our comparison more direct with our FAISS-based methods. In addition, we can also consider if the URL is from English Wikipedia, in that case we can extract the page title from the URL and look up its corresponding page inside the dump of Wikipedia.

3.3 Knowledge Response Regularization

It has been observed before that large language models, when augmented with retrieval, have trouble with choosing between copying knowledge remembered within their weights and knowledge provided in retrieved documents (Shuster et al., 2021). Here, we propose a general regularization method to more finely control this mechanism: when training, we multi-task between the original response generation task and a new task which consists of generating the selected knowledge from retrieved documents indicated by human annotators³. The second task can be seen as a regularizer that encourages the use of retrieved documents, as the easiest way for the model to do well on that task is to attend and copy to the document where that text already exists. Then, by changing the mixing parameter between the two tasks, the intent is to achieve a smooth control between encouraging copying from retrieved documents, or not.

4 Wizard of the Internet Task

In order to both train and evaluate generative models that can use search engines in-the-loop, we design, collect and release a dataset for this purpose. The overall setup involves pairing crowdworkers that are instructed to have a conversation together. One plays the role of the *wizard*, who has access to a search engine during conversation, while the other, the *apprentice*, does not. The *apprentice* however has an assigned persona that describes their interests. The purpose of the exchange is to have an “in-depth conversation about [those] assigned interests”. This mirrors conversations we

³We note that this technique is similar to the one used in retrieve and refine architectures (Roller et al., 2020).

Wizard of The Internet Task	Train	Valid	Test	Total
Number of Dialogues	8,614	516	503	9,633
Number of Utterances	82,952	5,781	4,932	93,665
Average Utterance Length	18.67	22.9	21.5	19.1
Average Utterances per Dialogue	9.6	11.2	9.8	9.7
Number of Searches	42,306	3,306	2,763	48,375
Number of unique URLs selected	26,192	2,087	1,973	29,500
Number of unique Domains selected	10,895	1,256	1,256	11,963

Table 1: Wizard of the Internet (WizInt) Dataset Statistics.

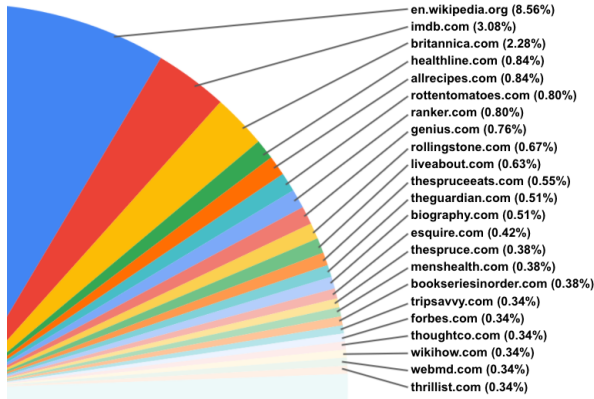


Figure 2: Breakdown of most common domains used during search by the wizard in our newly collected dataset (validation set breakdown). Shown is the most common 24.41%, there is a long tail of 1233 other domains across the whole validation set.

expect to be more prevalent between a human and a bot: the conversations are more likely to be centered around the human’s interests than the bot’s, and the bot is the one that is going to be using the search engine to ground their knowledge. Hence, when we train or evaluate on this task, a given model will replace the role of the wizard.

Apprentice Persona We show the apprentice several possible persona choices for the character that they are going to play, and let them choose one, e.g. “I love tennis, Rafael Nadal is my favorite player.”. The intent here is that they can choose a topic they are both more interested in themselves to talk about and also have enough knowledge of so that they can conduct a reasonable conversation. The choices we show are themselves mined from the interests provided in the existing Persona-Chat dataset (Zhang et al., 2018) and the topics given in the existing Topical-Chat dataset (Gopalakrishnan et al., 2019). More details of the choices we give are provided in Appendix A.

Wizard Active and Passive Openings We randomize which speaker takes their turn first. If the

wizard speaks first, we encourage them to start with an opening that addresses the apprentice’s interests. For example, if they know their partner is interested in tennis, they could search for the latest tennis news, and open with an interesting point based on that knowledge. If the apprentice goes first, their goal is to converse with the wizard more based on their own interests, e.g. in this same case they could talk about tennis in detail.

Wizard Search At each turn, the wizard can enter free text search terms in a left-hand panel (with the main conversation panel on the right) much like in a conventional search engine. The top few results are shown in the left panel, below the search query⁴. For each document the titles are shown for space reasons, and each document is expandable. If the wizard finds one or more search results useful for their response, they can click on the sentences they find relevant, and then enter their conversational response in the right-hand panel. They are also free to try another search query if they did not find their first results appropriate, or else can enter a conversational response and choose to ignore the search results entirely.

Full System Each crowdworker has to pass an onboarding task to be able to be part of the main data collection task, and pass some automatic checks (average response length, use of search). They are asked to play a particular role (“Create an interesting character that you want to play”), and are given instructions to avoid toxic or biased language. We randomly assign for any given crowdworker a fixed choice of either wizard or apprentice for all of their data collection, otherwise we found that switching role introduced lower quality conversations, probably due to confusion between the different goals and instructions per role. After

⁴We run two searches, one with the given query, and one with the query terms plus the word “news” (with the news results shown as the top two knowledge candidates), in order to encourage topical discussion.

pairing, we collect between 5-6 turns (10-12 utterances) for each conversation. We ask workers to skip initial greeting messages, as these bring little extra value to the task. Screenshots of the crowd-worker task can be seen in [Figure 8](#) in the appendix. Example collected dialogues are shown in [Figure 1](#) and [Figure 9](#).

4.1 Overall Dataset

The overall collected data consists of 9633 dialogues in total, with 82952 utterances in the training set, and validation and test sets of 5781 and 4932 utterances, respectively. Overall statistics can be found in [Table 1](#). We find that 84.81% of all turns by the wizard involve search, so a large amount of knowledge grounding based on internet results is taking place. Of those, the wizard is allowed to repeat the search with different search terms if they did not find what they were looking for. When the wizard searches, we find 1.19 search queries are performed on average, so while mostly a single search is employed, a number of further knowledge searches are attempted. Wizards use the search results (indicated by selecting relevant sentences) 80.3% of the time.

We show in [Figure 2](#) a breakdown of the most common domains used during search on the validation set. We see that the domains are rather diverse, coming from all kinds of topics, and in particular that the Wikipedia domain is actually fairly small (8.56% of queries), which is interesting because most other studies have used Wikipedia only as their knowledge resource ([Chen et al., 2017](#); [Lewis et al., 2020](#); [Dinan et al., 2019](#); [Shuster et al., 2021](#)). Our training set spans 26192 unique selected URLs for grounding knowledge from 10895 domains, indicating a wide variety of topics and knowledge is used across all conversations.

5 Experiments

5.1 Experiment and Evaluation Setup

We evaluate models on our new Wizard of the Internet (WizInt) task, using its dedicated training set. We also consider the existing Wizard of Wikipedia (WoW) training resource as well, either for building baselines or for multi-tasking. We consider fine-tuning various existing pre-trained models: T5 ([Raffel et al., 2019](#)), BART-Large ([Lewis et al., 2019](#)) and BlenderBot variants ([Roller et al., 2020](#)). For all retrieval-augmented methods we use $N = 5$ returned documents. For all models, when gen-

erating responses we fix the decoding parameters to beam search (beam size 3) with a minimum sequence length of 20 and beam blocking of 3-grams within the response (but not the context), similar to choices in ([Roller et al., 2020](#)).

Following [Shuster et al. \(2021\)](#) we report perplexity, F1 and Knowledge F1 (KF1) metrics. F1 measures the overlap between the model’s response and the human response from the dataset. KF1 instead measures the overlap between the model’s response and the knowledge on which the human grounded during dataset collection (i.e., the sentences they clicked as relevant from the web search documents retrieved, see [section 4](#)). We note that KF1 and F1 can be traded off, for example a model that could copy the knowledge directly would have a high KF1 but a low F1 – it would be knowledgeable, but not conversational. Nevertheless, we expect an ideal model would achieve relatively high values for each. Finally, we also perform a human evaluation, the details of which will be discussed further in [subsection 5.3](#).

5.2 Results

Pre-training models We evaluate the performance of using different standard pre-training models when training on our new task. Results are given in [Table 2](#). Comparing BlenderBot (BB) 400M and 2.7B parameter models, which use the same dictionary, we see that larger models do improve all metrics (perplexity, F1 and KF1) in the “no knowledge” case (where the model is given only the conversational history, with no web documents). When given “gold knowledge” (the selected knowledge sentences and the conversational history are given as input to the model), this trend is slightly less clear, but still present. BART-Large and T5-Large, which are trained on more knowledge focused corpora, rather than the conversational corpora of BB, give improved performance for the same model size in terms of F1 and KF1 metrics. We choose to use BART-Large as our base for all of our following experiments.

No knowledge vs. gold knowledge baselines

We compare Transformers that are given only the dialogue context (no knowledge) to Transformers that are given both the dialogue context and the gold knowledge from the task which human annotators (wizards) labeled as being used to craft responses. They can be compared in [Table 2](#) across different models. There is a large, consistent im-

Model	Pre-train Model	WizInt Validation		
		PPL	F1	KF1
Transformer (no knowledge)	BlenderBot 2.7B	9.9	18.0	6.6
Transformer (no knowledge)	BlenderBot 400M	13.4	17.3	6.2
Transformer (no knowledge)	BART-Large 400M	17.4	17.6	6.8
Transformer (no knowledge)	T5-Large 770M	15.9	17.9	6.5
Transformer (gold knowledge)	BlenderBot 2.7B	8.1	21.7	23.3
Transformer (gold knowledge)	BlenderBot 400M	9.2	22.0	22.8
Transformer (gold knowledge)	BART-Large 400M	10.6	25.4	23.1
Transformer (gold knowledge)	T5-Large 770M	10.1	25.7	23.5

Table 2: **Choice of Pre-training Model.** We compare several pre-trained models fine-tuned on the WizInternet task, using either no or gold knowledge, measured on the validation set. Perplexities cannot be compared due to differing dictionaries except between BlenderBot 2.7B and 400M.

Model	Training Data	WoW Validation			WizInt Validation		
		PPL	F1	KF1	PPL	F1	KF1
Transformer (no knowledge)	WoW	14.8	21.0	17.7	20.4	15.8	6.7
Transformer (no knowledge)	WizInt	22.4	16.7	13.1	17.4	17.6	6.8
Transformer (no knowledge)	WoW + WizInt	15.4	20.0	16.3	17.3	18.0	6.9
Transformer (gold knowledge)	WoW	7.9	39.1	61.2	12.8	20.6	26.1
Transformer (gold knowledge)	WizInt	9.4	34.6	52.6	10.6	25.4	23.1
Transformer (gold knowledge)	WoW + WizInt	7.9	38.5	65.6	10.3	26.3	24.2

Table 3: **Usage of the Wizard of Wikipedia Dataset with Multi-Tasking** using BART-Large, measured on the validation set.

provement in all metrics across all models, showing there is clear signal provided by these annotations. While in practice gold annotations will not be available, this can be seen as both an upper bound on possible performance, as well as confirmation that knowledge retrieval has the potential to bring significant gains over non-retrieval augmented (“no knowledge”) models.

Wizard of Wikipedia baselines We train models on the Wizard of Wikipedia (WoW) dataset as baselines, to compare the difference between coverage of the WoW task and our new WizInt task, in both the no knowledge and gold knowledge settings. Results are given in Table 3, evaluating on both the WoW and WizInt validation sets. We observe some overlap between the tasks, as expected, but also observe some differences. Perplexity improves from 20.4 to 17.4 and a corresponding boost in F1 of 15.8 to 17.6 from training with WizInt and evaluating on the WizInt task in the no knowledge setting, compared to training with WoW. Similarly, the WoW task provides better training data for its own task. We draw similar conclusions in the gold knowledge case as well. KF1 on the other hand appears to be less influenced by the dataset in the no knowledge case, and in the gold knowledge case the WoW model has a higher KF1, perhaps because the model has learnt to copy effectively, but has a poor F1, presumably because it is not generating as appropriate responses due to this copying.

Multi-tasking with Wizard of Wikipedia We can also multi-task the WoW and WizInt tasks together, perhaps bringing improvements as we have shown they have some similarity in their tasks. Results are also given in Table 3. We observe a small gain in perplexity on both the no knowledge and gold knowledge WizInt tasks, and improvements in F1, e.g. from 17.6 to 18.0 on the no knowledge task, and from 25.4 to 26.3 on the gold knowledge task. In the majority of our subsequent experiments, for the sake of simplicity we do not perform such multi-tasking, but we expect similar gains could be achieved if we were to apply this elsewhere.

DPR+FAISS-based models We trained DPR+FAISS-based models using either the WoW or WizInt training datasets, and using either Wikipedia or Common Crawl (CC) as the database. Results are given in Table 5. Comparing to WoW-trained Transformers with no augmentation (“no knowledge”), we find the WoW-trained DPR+FAISS-augmented methods using FiD give unclear improvements: there is no improvement in F1 using Wikipedia as a database, and a small improvement in F1 (from 15.8 to 16.4) when using CC. Moreover, perplexity in both cases increases (e.g., from 20.4 to 20.8). However, FiD-RAG performs better, with improvements in both perplexity (from 20.4 to 19.7) and F1 (from 15.8 to 16.2). Nevertheless, these WoW-trained baselines fail to match even the non-augmented no

Model	Knowledge Access Method	Knowledge Source	PPL	F1	KF1
WoW Transformer (no knowledge)	None	None	22.3	14.7	6.7
WizInternet Transformer (no knowledge)	None	None	18.7	16.9	6.8
WoW FiD	DPR+FAISS	Wikipedia	23.0	14.7	7.4
WoW FiD	DPR+FAISS	CC	22.8	15.3	7.3
WoW FiD-RAG	DPR+FAISS	CC	22.3	15.5	7.2
WoW Search engine FiD	Bing Search	CC	21.9	14.3	7.3
WizInternet FiD-RAG	DPR+FAISS	CC	18.8	17.0	6.7
WizInternet Search term FiD	Search Query+FAISS	CC	19.0	16.5	6.7
WizInternet Search engine FiD	Bing Search	CC	17.7	16.8	6.9
WizInternet Search engine FiD	Bing Search	CC+Wikipedia	17.7	16.6	6.7

Table 4: **Results using Automatic Metrics** measured on the test set. All models use BART-Large as a base.

Model	Knowledge Access Method	Knowledge Source	WizInt Validation		
			PPL	F1	KF1
WoW Transformer (no knowledge)	None	None	20.4	15.8	6.7
WizInternet Transformer (no knowledge)	None	None	17.4	17.6	6.8
WoW FiD	DPR+FAISS	Wikipedia	20.9	15.7	7.5
WoW FiD	DPR+FAISS	CC	20.8	16.4	7.4
WoW RAG	DPR+FAISS	Wikipedia	20.0	15.4	7.0
WoW RAG	DPR+FAISS	CC	20.2	16.3	6.5
WoW FiD-RAG	DPR+FAISS	CC	19.7	16.2	6.6
WoW Search term FiD	Search Query+FAISS	Wikipedia	21.0	15.4	7.4
WoW Search term FiD	Search Query+FAISS	CC	20.8	16.3	7.2
WoW Search engine FiD	Bing Search	CC	19.9	15.4	7.5
WizInt RAG	DPR+FAISS	Wikipedia	17.5	17.7	6.6
WizInt RAG	DPR+FAISS	CC	17.8	17.7	6.7
WizInt FiD-RAG	DPR+FAISS	Wikipedia	17.1	18.0	7.0
WizInt FiD-RAG	DPR+FAISS	CC	17.4	17.9	6.8
WizInt Search term FiD	Search Query+FAISS	Wikipedia	17.2	17.8	6.5
WizInt Search term FiD	Search Query+FAISS	CC	17.8	17.7	6.6
WizInt Search engine FiD-Gold	Bing Search	CC	17.6	14.1	7.4
WizInt Search engine FiD-Gold	Bing Search	CC+Wikipedia	17.6	14.1	7.5
WizInt Search engine FiD-Gold	Retrieved Gold	CC+Wikipedia	13.9	20.0	9.6
WizInt Search engine FiD	Bing Search	CC	16.3	17.7	7.0
WizInt Search engine FiD	Bing Search	CC+Wikipedia	16.4	17.9	6.9
WizInt Search engine FiD	Retrieved Gold	CC+Wikipedia	13.8	18.1	7.5
WoW+WizInt Search engine FiD	Bing Search	CC+Wikipedia	16.1	17.9	7.0

Table 5: **Full Set of Retrieval and Search Augmentation Method Results** using automatic metrics measured on the validation set. All models use BART-Large as a base.

knowledge Transformer trained on WizInt (Table 4, row 2) which has a perplexity of 17.4 and F1 of 17.6. Training DPR+FAISS on WizInt, we also see clear improvements over WoW-trained models, and similar conclusions that FiD-RAG is superior to RAG, with the best approach achieving a perplexity of 17.1 and F1 of 18.0 on the validation set, see Table 5. The impact on the test set however is still fairly minimal, see Table 4.

Search Query+FAISS-based models We find that using a search query generator and then using FAISS to retrieve from the database of web documents performs slightly worse than DPR+FAISS-based models. Perplexity is actually no better than the no knowledge model except in the Wikipedia database case (17.6 for CC and 17.2 for Wikipedia vs. 17.6 for no knowledge), see Table 5.

Search Engine-based models The search engine based method provides the best performance in terms of perplexity of all the models tested, with a validation perplexity of 16.4 when trained on WizInt and 16.1 when trained on both Wow and WizInt for the CC+Wikipedia case, see Table 5. While F1 and KF1 metrics are hardly impacted, we do see a similar reduction in perplexity on the test set, see Table 4. We find this encouraging as search engines are already a well developed tool we can simply interface with our model, rather than trying to reinvent storage of all the documents on the internet, as we have attempted with our other FAISS-based experiments. We thus select this method as our main candidate for human evaluations.

Knowledge Response Regularization Results for the regularization proposed in subsection 3.3 are shown in Table 7. We find adjustment of this

Model	Consistent	Engaging	Knowledgeable	Factually Incorrect	Final Rating	# Annotated Responses
WizInt Transformer (No Knowledge)	66.5%	69.9%	38.6%	7.1%	3.64	764
Search engine FiD (Bing Search)	76.1%	81.4%	46.5%	5.3%	3.73	757

Table 6: **Human Evaluation Results.** Models are BART-Large based, trained on the WizInternet task. Numbers in bold are statistically significant (p -value < 0.01) using a t -test.

Regularization	PPL	F1	KF1
0%	16.4	17.9	6.9
10%	17.5	16.6	7.4
33%	17.7	15.2	8.0
50%	18.4	14.2	8.4
66%	18.9	13.5	8.7
75%	19.4	11.4	9.5
95%	24.5	9.3	9.6
100%	35.0	9.6	8.8

Table 7: **Adding Knowledge Response Regularization to a WizInt search engine FiD model.**

regularization parameter gives a smooth control over use of knowledge, yielding increased values of KF1, at the expense of some loss in F1 (presumably, decreasing conversational ability). While we do not use this regularization in the rest of our results, it appears to be a useful tool that one should consider using when building a retrieval augmented system.

5.3 Human Evaluation

We perform a human evaluation using crowdworkers. The conversations begin with a random apprentice persona from the WizInt validation set being selected and shown, and the crowdworker is asked to play that role. We ask the crowdworkers to have a natural conversation, where they will also evaluate their partner’s responses for conversational attributes, in particular knowledgeability, factual (in)correctness, engagingness and consistency. A screenshot can be found in Figure 10 which details further the definitions of those attributes. On each turn of the conversation the crowdworker is asked to check all attribute boxes that apply to the last turn. Each conversation consists of 15 messages (7 from the human, 8 from the bot). At the end of the conversation, an additional question collects an overall engagingness score (out of 5) for their speaking partner.

We compared the WizInt BART-Large Transformer (no-knowledge) model, which is a standard Transformer with no retrieval augmentation, to the WizInternet Search engine FiD model, with live Bing search (without using a CC subset). The results are given in Table 6. For each model,

around 750 responses were annotated over nearly 100 model conversations. The search engine-based method outperformed the no-knowledge baseline across the board. Not only was the search engine-based model judged to be knowledgeable more often (46.5% vs. 38.6% of the time) and factually incorrect less often (5.3% vs. 7.1%), but it also was measured to be more consistent (76.1% vs. 66.5%) and more engaging (81.4% vs. 69.9% on an utterance level, and 3.73 vs. 3.64 on a conversation level).

5.4 Example Conversations

Cherry Picked Examples We show some cherry picked conversations between humans (paper authors) and the WizInternet Search engine FiD model (using live Bing search) in Figure 3, Figure 4, Figure 5 and Figure 11. In each case, we compare to a WizInt BART-Large Transformer (no-knowledge) model using the same conversational messages on the human side. In the best case, our augmented models are able to construct appropriate internet search queries, read the corresponding web pages and provide information relevant to the conversation – in these examples over diverse conversations on drink ingredients, TV shows, restaurants and machine learning research. In the TV show and restaurant cases the model is able to surface recommendations and provide details about them, for example the correct address and phone number of a pizza store in Princeton, or the plots of recent TV shows such as The Underground Railroad. Standard BART-Large fine-tuned models on the other hand typically either hallucinate knowledge or else fall back to generic statements.

Lemon Picked Examples We show some lemon picked conversations between human (paper authors) and the WizInternet Search engine FiD model (using live Bing search) in Figure 6. The examples expose various kinds of error. First, generation mistakes given the correct knowledge, as in the example where the model incorrectly names Bruno Mars as working on the song Bodak Yellow. Bruno Mars did collaborate with Cardi B on

Human	BART (no augmentation)	Human	WizInt Search engine FiD
What's your favorite cocktail?		What's your favorite cocktail?	search: cocktail
	What is your favorite type of cocktail? I like a simple martini. Do you have a favorite brand?		Cocktails are great! What is your favorite type of cocktail? I love the martini.
Oh, I think Martinis are James Bonds drink, right? How is that made?		Oh, I think Martinis are James Bonds drink, right? How is that made?	search: james bonds martini
	I think it is made in the same way as a martini, but with a twist.		It is made with gin, vodka, and Lillet Blanc. It is a very popular drink.
Sounds nice, is that a particular kind of martini?		Sounds nice, is that a particular kind of martini?	search: james bond martini
	It is a mix of vodka, rum, and brandy. It is a classic cocktail.		The Vesper Martini is a combination of gin and vodka. It has a lot of flavor.
I think that is in the movie Casino Royale.		I think that is in the movie Casino Royale.	search: casino royale
	Casino Royale is a great movie. It is based on the book of the same name.		Oh, that's right. It was a great movie. I love James Bond movies.
Yes, who is your favorite Bond and why?		Yes, who is your favorite Bond and why?	search: james bond movies
	My favorite is James Bond. I think he is the best. He is so cool.		My favorite Bond is Daniel Craig. He is a great actor. I think he is the best.

Figure 3: Cherry picked example comparing a nonaugmented model (BART trained on WizInt, left) to a model with internet-augmentation (right). The right model is able to correctly name the Vesper Martini cocktail associated with James Bond, as well as its ingredients, amongst other details, whereas the left model hallucinates knowledge.

Human	BART (no augmentation)	Human	WizInt Search engine FiD
Have you seen the TV show Devs?		Have you seen the TV show Devs?	search: tv show devs
	What is Devs about? I have never heard of it. What is it about? Is it a show based on a book?		I haven't seen it, but I heard it was a good show. I think it was on Hulu.
What was it about, do you know?		What was it about, do you know?	search: tv show devs
	It was a TV show about a group of people who are trying to save the world from a tyrannical dictator.		It was about a young software engineer who works for Amaya, a cutting edge tech company based in Silicon Valley.
Cool. What else have you watched recently?		Cool. What else have you watched recently?	search: tv shows this year
	I haven't seen any recently, but I heard about a show called Devs. It is a sci-fi show.		I've been watching a lot of TV lately. I've been binge watching a ton of shows.
What's the best one you've watched?		What's the best one you've watched?	search: best shows of 2021
	I have not. I have seen a lot of TV shows. I think I have watched a lot.		I've seen a few, but the one that stands out the most to me is the one called The Underground Railroad.
Cool, interesting name. What's it about?		Cool, interesting name. What's it about?	search: underground railroad
	It is about a scientist who is trying to find a cure for cancer. It's about a man who has been diagnosed with cancer.		The Underground Railroad is a TV show about escaping slavery in the South. It's about a woman named Cora.

Figure 4: Cherry picked example comparing a model with nomaugmented model (BART trained on WizInt, left) to a model with internet-augmentation (right). The right model is able to correctly describe and surface recent TV shows, whereas the left model hallucinates knowledge.

Human	BART (no augmentation)	Human	WizInt Search engine FiD
	I'm hungry. Thinking about getting Italian.		I'm hungry. Thinking about getting Italian.
	What is your favorite type of Italian food to eat? I like pizza, but I'm not a big fan of pasta.		search: italian food What is your favorite type of Italian food? I like pizza, pasta, and lasagna.
	Mmm pizza -- good idea! Do you know a good pizza place in Princeton, NJ?		Mmm pizza -- good idea! Do you know a good pizza place in Princeton, NJ?
	I don't have a favorite, but there is a pizza place near Princeton that I have heard is good.		search: princeton pizza Pizza Den is a good place. They have a lot of different types of pizzas.
	Cool. Can you tell me the street address?		Cool. Can you tell me the street address?
	It is in Princeton NJ. It is a small pizza place, but it is a good one.		search: pizza den princeton The address is 242 Nassau St, Princeton, New Jersey 08542. It's a small place.
	Thanks! Do they have a phone number?		Thanks! Do they have a phone number?
	Yes, it is. They have a website and phone number. They also have a Facebook page.		search: pizza den princeton They have a Facebook page and a website. They also have a number to call if you have any questions.
	Oh cool, what's the number?		Oh cool, what's the number?
	It is a number on their website. I have not been able to find it, but if you are interested, you can call them.		search: pizza den princeton The number is 609-683-8900. They have an online menu as well.

Figure 5: Cherry picked example comparing a model with nonaugmented model (BART trained on WizInt, left) to a model with internet-augmentation (right). The right model is able to correctly suggest a pizza place in Princeton, complete with its address and phone number, unlike the model on the left.

Human	WizInt Search engine FiD	Human	WizInt Search engine FiD
I love Cardi B. She is so awesome.	search: cardi b Cardi B is a great rapper. She has a lot of great songs. I like it.	What do you know about retrieval augmented generation?	search: what do you think about augmented generation? I don't know much about augmented generation, but I do know that it's a new generation.
What's your favorite song?	search: cardi b songs I like her song "Bodak Yellow" by Bruno Mars. What is your favorite of hers?	What does it do?	search: augmented generation Retrieval Augmented Generation is a new model that leverages external documents (like Wikipedia) to augment its knowledge and achieve state of the art results on knowledge-intensive tasks.
		That sounds cool. Who are the authors?	search: what do you think about retrieval augmented gen The authors are Yuning Mao, Pengcheng He, Xiaodong Liu, Yelong Shen, Jianfeng Gao, Jiawei Han, and Weizhu Chen.
Have you been to Elsewhere, the club in Bushwick?	search: bushwick club The Bushwick Book Club is an amazing showcase for musical and other talents. Have you been there?	What's the paper title?	search: what's the paper about retrieval augmented gen The paper is Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks.

Figure 6: Lemon picked examples of our internet-augmentated model. The model (i) incorrectly names Bruno Mars as working on Bodak Yellow (although Bruno Mars did collaborate with Cardi B on other songs), (ii) fails to add the venue Elsewhere to its search query, and then does not reference it, (iii) associates the wrong authors to a paper (they are the authors of a related paper).

other songs, and the model confuses and mixes various pieces of evidence within the given knowledge sources. Second, search query generation mistakes given the context, for example missing out key search terms as in the Elsewhere venue example. Third, selecting the wrong knowledge given earlier context, as in the case where the model associates the wrong authors to a paper. A fourth additional issue is that even if the correct knowledge is available the model may err on the side of not using it and select a more generic response instead, as often happens in the non-augmented model. See for example [Figure 5](#) and [Figure 11](#).

6 Conclusions

This work has studied the problem of siloed knowledge in large language models, whereby they cannot access the knowledge of the world other than through their fixed training set. Developing methods that instead can access the internet as an augmentation to the generation process, we have showed such models can display more knowledge and generate less factually incorrect information during dialogue with humans. Future work should aim to develop improved architectures that can be trained and evaluated on our new task. Going forward, in the long-term we require machine learning methods that interact with the world, rather than only having a simple text context – and access to the internet is a natural step in that direction. Thus, further work should also aim to explore the advantages of accessing this dynamic knowledge of the world in more situations, e.g. to perform goal-directed tasks.

7 Societal Impact

Large language models bring an impact on the environment in terms of resources required to train and deploy them, and concerns about toxic language, bias and other issues during language generation ([Bender et al., 2021](#)). For dialogue in particular, see [Xu et al. \(2020\)](#) for a review of the literature and evaluation of recent methods that try to mitigate these safety issues.

The initial pre-training dataset used in this work contains varied and potentially offensive text content, as they were originally procured from the Internet by third parties. However, our fine-tuning task is built with crowdworkers with specific instructions to not use toxic language, a procedure which is shown to yield safer language models

([Roller et al., 2020](#)).

This work, different to other language generation models, specifically augments the generations with knowledge from the internet. On the one hand, we showed that this results in less model hallucination, and more factually correct generations. Further, as the model generates human readable search queries and one can verify which document(s) the used knowledge comes from, means our model also has increased interpretability and potentially debuggability compared to standard language models. On the other hand, this also brings potential new concerns if those websites contain toxic, biased or factually incorrect information themselves. While issues of toxicity can perhaps be treated similarly to the pre-training data case (e.g. safety classifiers), fact checking is a separate area with ongoing work, e.g. [Hassan et al. \(2017\)](#); [Fan et al. \(2020\)](#). We further remark however, that the use of internet search engines to augment models, instead of FAISS-based retrieval ([Lewis et al., 2020](#)), means that machine learning models can take advantage of decades of work in search engine safety issue mitigations, rather than having to completely rebuild those tools again.

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A Wizard of Internet Task

Screenshots We provide screenshots of the crowdworker collection task in Figure 8, and the crowdworker evaluation task in Figure 10.

Personas Persona choice options were built from two different sources: Persona-Chat (Zhang et al., 2018) personas, and topic-based (inspired in part by Topical-Chat (Gopalakrishnan et al., 2019)). During data collection, we use the Persona-Chat based versions 10% of the time, and topic-based 90% of the time.

For Persona-Chat, we labeled each persona entry sentence as suitable for our task or not with the following criteria: (i) if it contains a clear entity that is searchable (example: a band name) or (ii) it is a topic that might be interesting from a location-dependent point of view (e.g. Kayaking). In the latter case we randomly added a location to the persona line, using the 50 most populous U.S. cities. Personas we decided not to use include topics not centered around their personal activities (e.g., about their parents, or the general topic of their profession), as well as topics that were judged too generic (such as “I like movies.”). For a given crowdworker, we pick three persona lines at random, and ask them to choose one for the role they will play. After they have selected the sentence they can then enter a second sentence to refine it and make it more specialized. For example, if they choose “I like swimming”, they can add “I would like to improve my Butterfly Stroke.”

Coordinator: Please use the form below to define a persona for the character that you will be playing during this task: use the first two fields in this form to define an interest for the persona. Then add a sentence to refine it and to make it more interesting or engaging. Create an interesting character that you want to play. Remember that the main topic of conversation should be around this persona. Be creative and imaginative.

My character's favorite

is

Add something imaginative to refine it:

Figure 7: Crowdworker persona entry screenshot.

For the topics-based setting, we selected 7 general topics: (1) fashion (brand, designer or clothing type), (2) books (book, author), (3) music (artist, band, song, singer), (4) movies/TV (TV show, movie, actor, director), (5) sports (team, athlete), (6) hobby/game, (7) item to buy/recently bought.

For a given crowdworker, we pick two of these topics at random for them to choose between. Then they fill in the following sentence “My character’s favorite <chosen_topic_area> is <specific_item>” and also write another imaginative sentence to refine it further. E.g. “My favorite TV show is Big Bang Theory” and “I love Sheldon’s nerdy jokes”. See the screenshot example in Figure 7. This helps guarantee our conversations in the dataset are diverse and about a wide variety of topics and entities.

B Further Experimental Details

B.1 Model Training Details

The majority of the models trained in the paper (using BART-Large), with retrieval augmentation, were trained on 4 32-GB GPUs, using the Adam (Kingma and Ba, 2014) optimizer, sweeping over learning rates between 1e-6 and 5e-5. During training, we used a batchsize of 16 and a linear LR scheduler with 100 warmup updates. We perform early stopping based on model perplexity evaluated on the validation set.

We retrieved $N = 5$ documents for each example. When using FAISS-based methods, the documents were given to the model in 100-word chunks. When using search engine-based methods, the first 256 tokens (according to the model’s dictionary) of each document were given to the model.

B.2 Search Query Generation

B.2.1 Training Details

Our search query generators are BART-Large models trained to produce human search queries given the dialogue context. The models were trained on 4 32-GB GPUs, using the Adam (Kingma and Ba, 2014) optimizer with a learning rate of 1e-5, batchsize of 64, and a linear LR scheduler with 100 warmup updates. We perform early stopping based on model perplexity evaluated on the validation set.

B.2.2 Query Generation Performance

To evaluate the performance of our search query generators, we take a look at some downstream metrics; that is, not only do we measure generation metrics on the query generation task, but also measure how good the search results are. Suppose we have the following three sets for each wizard search in the dataset: 1) $R = \{r_1, r_2, \dots, r_k\}$, the set of **gold** retrieved documents; 2) $D = \{d_1, \dots, d_m\}$, the set

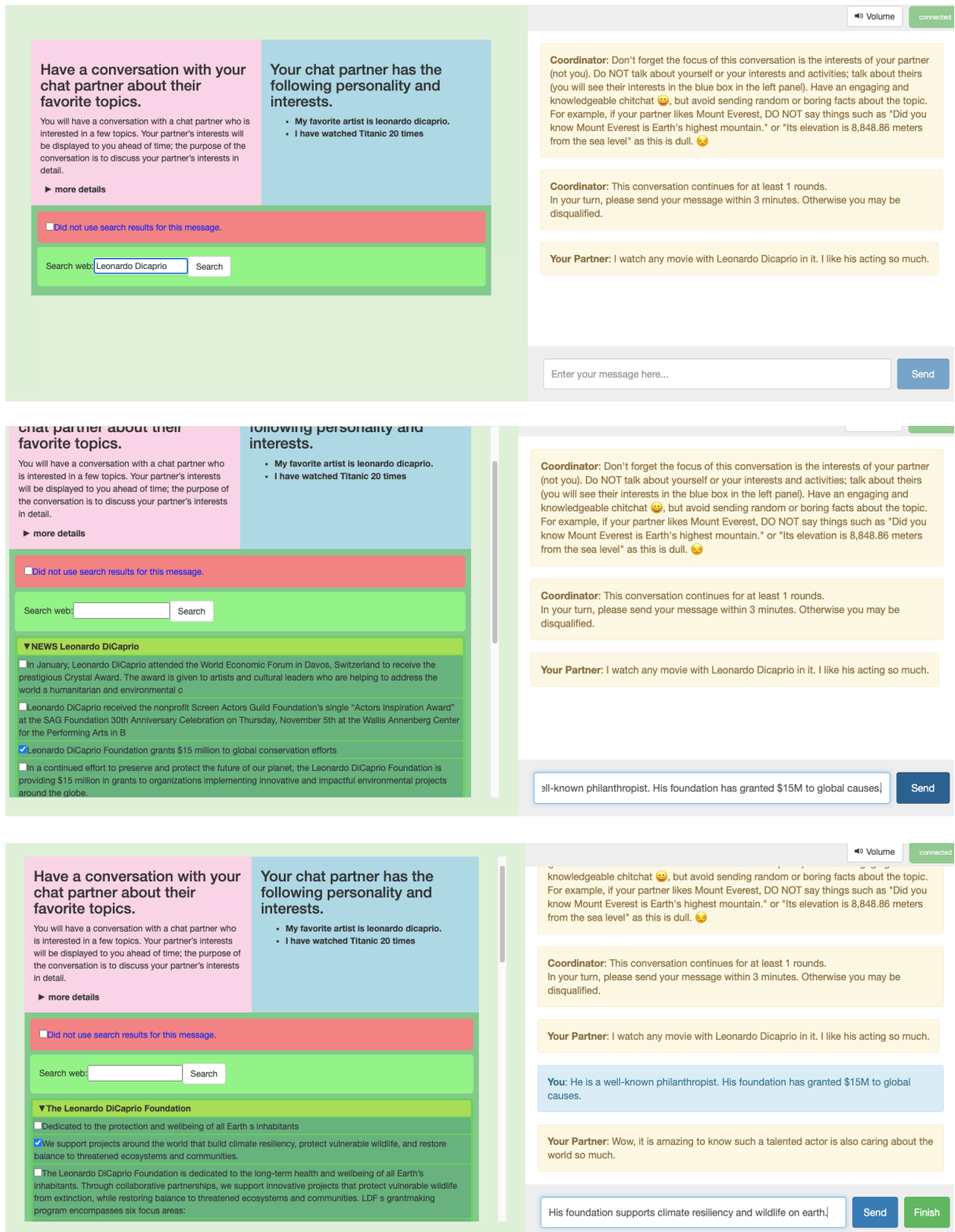


Figure 8: Crowdfunder collection task screenshots. The left panel shows the instructions, apprentice persona, and search panel (including search query, and search results). The right panel contains the conversation.

My favorite book is Collected Poems by Dylan Thomas. I love to read this book and memorize poems within it. I am a fan of Dylan Thomas' poetry. I love the structure, the imagery, and the metaphors.

search: dylan thomas poem

Do you have a favorite poem that he has written?

Yes... "Lament".

search: lament dylan thomas

I think Lament is the one that chronicles his life. Didn't he die young?

Yes. He died in 1953, the same year I was born. He died at the age of 39.

search: dylan thomas death

I read that they originally thought that he died from drinking too much but later they discovered he might have had pneumonia. A tragedy either way.

Yes, and it's easy to die of aspiration pneumonia if one is drunk! It was a real tragedy!!!

search: poets who died young

John Keats also died young, he was only 26

That's an unfortunate theme with creative people; Franz Schubert was only 32.

search: keats poem

Do you have any other Dylan Thomas poems that you like?

Lots of them: "A Winter's Tale", "If I Were Tickled By the Rub of Love", to name a couple.

search: _no_search_used_

I have heard of a winters tale, it is beautiful

Figure 9: Additional example human-human conversation from the Wizard of the Internet training set. The role of the Wizard on the right-hand side involves performing internet searches, and then writing appropriate responses to the Apprentice given the viewed web documents (not shown).

of documents **selected** by the wizard when conditioning their response; and 3) $S = \{s_1, \dots, s_k\}$, the set of search results with the **generated** search query. We consider the following three metrics:

- % in Top 5: The percentage of all r_i that are present in S .
- Average F1: For each s_i , compute the F1 word overlap with respect to all r_i and determine the maximum F1 score; then, take the average of these max scores over all s_i .
- Gold Recall at 5: The proportion of the time any d_i is in S .

We show results in Table 8 for two decoding

schemes for our query generation models. The most important to note is that we obtain the gold document nearly 25% of the time.

Beam Size	Min Beam Length	% Top 5	Avg. F1	Gold R@5
1	1	17.2	38.9	24.6
3	3	16.8	39.0	24.9

Table 8: Downstream retrieval performance of search query generators.

B.2.3 Effects of Decoding Algorithm

We evaluated the effect of beam size and minimum beam length in search query generation. One may hypothesize that having a longer and more refined search query increases the chance of retrieving better documents, which might improve the overall performance of models that rely on search engines. However, we observe little change in automatic metrics when changing these hyperparameters, see Table 7.

Beam size	Min beam length	PPL	F1	KF1
1	1	16.4	17.9	6.9
3	3	16.4	17.8	6.9
3	4	16.5	17.9	6.8

Table 9: Effect of beam size and minimum beam length during search query generation. Search engine FiD (CC+Wikipedia).

B.3 WoW Baselines

We note that several of the WoW-trained baselines utilize a "search query" setup. The search query generators for these models were not trained on the WizInt dataset, but rather were trained to generate the title of the Wikipedia page corresponding to the gold selected knowledge in the WoW dataset.

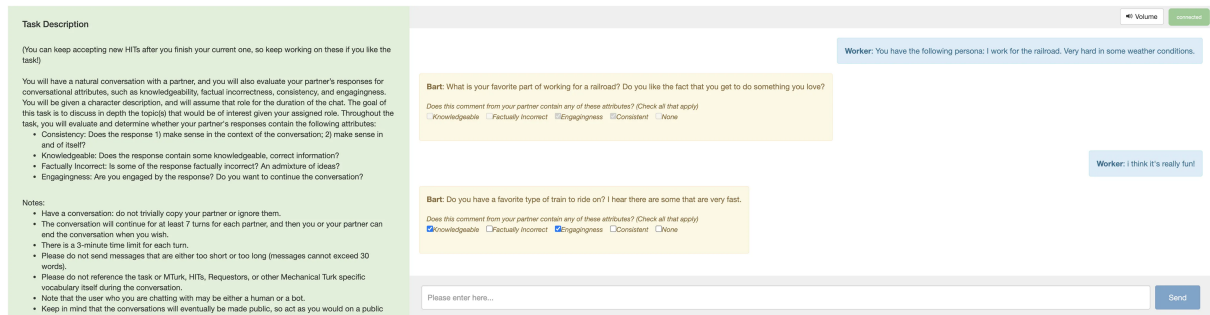


Figure 10: Crowdfworker evaluation task screenshots. The left panel shows the instructions, and the right panel contains the conversation.

Human	BART (no augmentation)	Human	WizInt Search engine FiD
Who is Vladimir Vapnik?	Vladimir Vladimirovich Vapnik is a Russian politician. He was a member of the Communist Party.	Who is Vladimir Vapnik?	search: vladimir vapniki Vapnik is a Russian mathematician and statistician. He was born on 6 Decemeber 1936 in Moscow.
What did he do?	He was a lawyer. He also worked as a political consultant. He is also a former journalist.	What did he do?	search: vladimir vapniki He was born in Moscow in 1936. He is a mathematician, statistician, and computer scientist.
Did he make any famous machine learning models?	No, but he did make a machine learning model that was used to predict the probability of a person's death.	Did he make any famous machine learning models?	search: vladimir vapniks He has made a lot of famous models. He has been working on machine learning for a long time.
For example, what?	I'm not sure, but I'm pretty sure it was. It was used in a study to predict how likely a person is to die.	For example, what?	search: vladimir vapniks He is one of the co-inventors of the support vector machine method.

Figure 11: Cherry picked example comparing a nonaugmented model (BART trained on WizInt, left) to a model with internet-augmentation (right). The right model is able to correctly describe attributes of Vladimir Vapnik, whereas the left model hallucinates details.