KTRL+F: Knowledge-Augmented In-Document Search

Hanseok Oh^{1*} Haebin $Shin^{1,2*}$ Miyoung Ko^1 Hyunji Lee^1 Minjoon Seo^1 1KAIST AI 2Samsung Research {hanseok, haebin.shin, miyoungko, hyunji.amy.lee, minjoon}@kaist.ac.kr

Abstract

We introduce a new problem KTRL+F, a knowledge-augmented in-document search task that necessitates real-time identification of all semantic targets within a document with the awareness of external sources through a single natural query. This task addresses following unique challenges for in-document search: 1) utilizing knowledge outside the document for extended use of additional information about targets to bridge the semantic gap between the query and the targets, and 2) balancing between real-time applicability with the performance. We analyze various baselines in KTRL+F and find there are limitations of existing models, such as hallucinations, low latency, or difficulties in leveraging external knowledge. Therefore we propose a Knowledge-Augmented Phrase Retrieval model that shows a promising balance between speed and performance by simply augmenting external knowledge embedding in phrase embedding. Additionally, we conduct a user study to verify whether solving KTRL+F can enhance search experience of users. It demonstrates that even with our simple model, users can reduce the time for searching with less queries and reduced extra visits to other sources for collecting evidence. We encourage the research community to work on KTRL+F to enhance more efficient in-document information access.1

1 Introduction

Despite significant advancement in many Natural Language Processing applications, facilitated by transformer-based models (Devlin et al., 2019; Raffel et al., 2019), real-time in-document search still leans heavily on conventional lexical matching tools like the "Find" function (Ctrl+F) and regular expressions. These tools, while fast, have clear

limitations, especially with ambiguous keywords or multiple targets.

Machine Reading Comprehension (MRC) seems a promising solution to these issues. It reads documents, comprehends their context, and answers questions (Rajpurkar et al., 2016). However, MRC focuses on explicit contents, limiting its value when users need broader context not directly in the document (Trischler et al., 2017; Rajpurkar et al., 2018; Joshi et al., 2017). Consider, for instance, a scenario in which a user is reading a news article and searching for information related to "Social network platform of China." (Figure 1). Typically, users would need to consult external sources, such as Wikipedia, to gather additional details about candidate keywords that are not explicitly mentioned in the news, such as WeChat, Baidu, and Twitter. An alternative approach is harnessing the capabilities of powerful pre-trained language models (Brown et al., 2020; Touvron et al., 2023). However, their generative nature poses challenges in real-time search task.

To overcome the limitations of previous methods and enhance the efficiency and comprehensiveness of in-document search, we present a new problem KTRL+F (knowledge-augmented in-document search). This task aims to reduce redundancy and better meet the requirements of real users. Given a natural language query and a long input document, KTRL+F is designed to fulfill three key criteria: (REQ 1) Find all semantic targets. (REQ 2) Utilizes external knowledge. (REQ 3) Operates in real-time. In the absence of a suitable dataset to evaluate KTRL+F, we curate a new dataset comprising unique queries that demand matching external evidence. To measure model performance in KTRL+F, we introduce a set of reformulated metrics tailored to measure processing speed while maintaining robust and high performance.

We conduct an extensive analysis of various baselines for KTRL+F and find several limitations,

^{*} indicates equal contribution

¹Code,Chrome extension plugin, and dataset are available at https://github.com/kaistAI/KtrlF

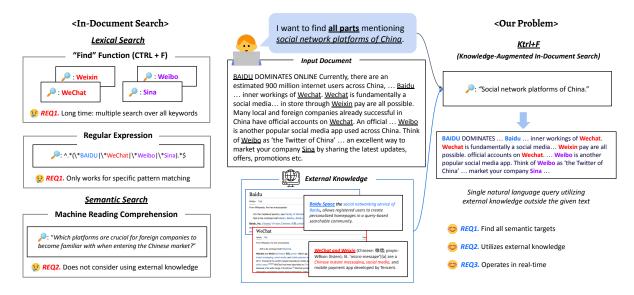


Figure 1: Comparison between in-document search and KTRL+F task. In-document search accesses the information in documents by either lexical search (Ctrl+F, Regular expression) or semantic search (MRC). Lexical search suffers from finding semantically matching keywords, and semantic search does not consider external knowledge. KTRL+F requires an efficient way to utilize external knowledge to find all semantic targets in real-time.

including issues such as hallucination, slow speed with generative models, and challenges in incorporating external knowledge into MRC models (see Section 6.2 for details). To strike a balance between real-time processing speed and achieving high performance through effective utilization of additional knowledge, we introduce a simple yet effective extension of phrase retrieval (Lee et al., 2021): Knowledge-Augmented Phrase Retrieval. This model seamlessly extends the phrase retrieval to cater to in-document search scenarios, all while integrating external knowledge without the need for additional training steps. Our experimental results support that by simply adding the knowledge embedding and the phrase embedding, Knowledge-Augmented Phrase Retrieval exhibits the potential to reflect external knowledge without sacrificing latency.

Furthermore, we conduct a user study to show the necessity of KTRL+F utilizing a Chrome extension plugin that operates in the real web environments, built upon our model. Results of the study demonstrate that search experience of users can be enhanced even with our simple model with seamless access to external knowledge during indocument searches. We encourage the research community to take on the unique challenge of solving KTRL+F requiring balance between performance and speed to enhance more efficient and effective information access.

2 Related Works

Machine Reading Comprehension (MRC) is a task to find the answer to a question in the provided context. Most MRC datasets assess the ability of context understanding of the model by extracting a single span for the query only grounding on the information within a provided context (Rajpurkar et al., 2016; Trischler et al., 2017; Joshi et al., 2017; Rajpurkar et al., 2018; Fisch et al., 2019; Kwiatkowski et al., 2019). Few works explore the identification of multiple targets for a query in the input document evaluating the model's comprehension of the given context (Dasigi et al., 2019; Zhu et al., 2020; Li et al., 2022). Some studies tackle information-seeking problem by utilizing external information missing from input document to gap knowledge (Ferguson et al., 2020; Dasigi et al., 2021). This external information aids in enhancing the understanding of the context. However, KTRL+F relies on external knowledge beyond the context to establish a connection between queries and target within the given context. Since much of the target information is not available in the given context, it is essential to explicitly ground external knowledge about the target. Consequently, the evaluation of KTRL+F focuses not on the understanding of the given context, but on information obtained from outside the given context.

Knowledge augmented information retrieval can be seen as an approach to enhance external

contextual information for the embedding. Lee et al. (2023) uses contextualized embeddings as vocab embeddings for text tokens in the generative retrieval model to enhance contextual information for naive text tokens. Raina et al. (2023) focuses on the retrieval augmented text embedding to find a way to efficiently reuse prebuilt dense representation with lightweight representation, and also discusses the necessity of systems for utilizing external contextual information to include contextual information outside the given context. Lin et al. (2022) tries to aggregate contextualized token embedding with [CLS] embedding. They focus on the augmenting contextual information using the embeddings from the given context, not focused on external knowledge.

3 Ktrl+F: Knowledge-Augmented In-Document Search

In this section, we define KTRL+F, which is knowledge-augmented in-document search task and its unique characteristics (section 3.1). Then we describe the evaluation metrics to measure each requirement (section 3.2).

3.1 Task Definition

KTRL+F is a task that requires finding all semantic targets from a given input document in real-time with the awareness of external knowledge, when given a natural language query. As illustrated in Figure 1, when presented with a natural language query and a input document, Ktrl+F is designed to meet three essential criteria.

REQ 1: Find all semantic targets. KTRL+F requires finding all relevant targets within a given document. The term "all" refers to multiple aspects: finding all multiple answers (baidu, wechat, weibo), all occurrences of each answer (baidu appears two times in the document), and all lexical variations of mentions for each answer (Weibo, Sina).

REQ 2: Utilize external knowledge. Expanding the matching space from lexical to semantic introduces a comprehensive connection between query and target units. However, in many cases, the targets contain additional information beyond the semantic information present in the input document. By effectively leveraging this additional information through utilization of external knowledge, we can further bridge the semantic gap between the query and the targets.

REQ 3: Search in real-time. KTRL+F inherits the practicality of in-document search, such as Ctrl+F, which emphasizes real-time search to minimize the time on finding targets within the input document. The complexity of KTRL+F lies in effectively balancing real-time applicability with the performance of finding all matching targets by leveraging external knowledge.

3.2 Evaluation Metrics

To assess various aspects of KTRL+F, we employ a range of metrics that collectively measure the overall balance of performance and speed. Evaluating the appropriateness of relevant external knowledge sources (REQ 2) is challenging as there is no definite gold standard answer. Therefore, following Izacard and Grave (2021), we indirectly assess the impact of utilizing external knowledge by comparing the overall performance of the system with and without its incorporation.

List EM, List Overlap F1, Robustness Score.

The three metrics measure if the model finds all semantic targets, and fulfills REQ 1. List EM and List Overlap F1 assess the model's ability to generate an accurate list of targets. List EM considers correct only when the prediction list is exactly the same as the ground truth list, whereas List Overlap F1 allows partial matches between individual elements of the predicted and the ground truth list. Note that List EM is different from Set EM, a commonly used metric in Machine Reading Comprehension (Rajpurkar et al., 2016), in that List EM aims to identify all occurrences of targets within a input document. Inspired by Zhong et al. (2022), we adjust robustness score to assess the robustness of system in predicting target answer entities as queries change within a given input document. By treating queries associated with the same input document as a cohesive cluster, we compute the robustness score by averaging the minimum score within each cluster; robustness score of List EM shows the average of minimum List EM score of each cluster and the same for List Overlap F1. This approach enhances the comprehensive evaluation of KTRL+F task, given that the knowledge-augmented design of KTRL+F allows for various queries with different target answers for in-document searches.

Latency. Latency is a metric for assessing realtime applicability, therefore satisfying REQ 3. We measure in ms/Q (millisecond per query) which is widely used in retrieval systems to represent

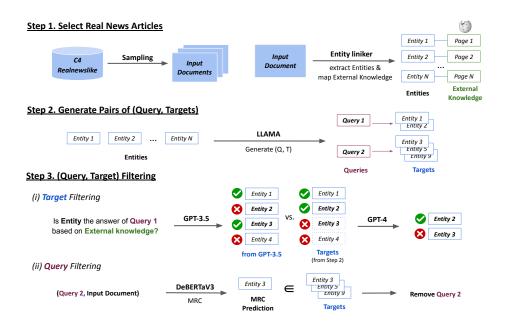


Figure 2: Overview of KTRL+F Dataset construction pipeline. We utilize real news articles as input documents (Step 1), and automatically generate queries and targets (Step 2). To improve the reliability of targets, we identify whether each entity is a target by referring to external knowledge, and finalize entities that differ from the Step 2 results (Step 3-1). We remove queries that do not satisfy REQ 2 using the MRC model (Step 3-2).

query inference speed (Khattab and Zaharia, 2020; Santhanam et al., 2022).

4 KTRL+F Dataset

In the absence of suitable benchmarks for evaluating the KTRL+F, we introduce a data construction pipeline that aims to collect sets of key components for KTRL+F: input document, query, corresponding targets, and external knowledge. We employ a pipeline to generate an evaluation set for KTRL+F and subsequently assess its quality through human verification. The overall process of pipeline is shown in Figure 2.

4.1 Dataset Construction Pipeline

Step 1. Select Real News Articles. To simulate real-world document scenarios, we randomly sample 100 English news articles from the publicly available Common Crawl (Raffel et al., 2019) after preprocessing them according to two criteria. Initially, to remove abnormal articles, we collect 6,936 articles from the 13,863 articles in the Common Crawl validation set, with lengths ranging from 991 to 3,298, covering the lower to upper quartiles. Subsequently, we utilize an entity linking API² to identify all entities within the article and extract ex-

ternal knowledge³ linked to the entities. To ensure diversity of questions and quality of documents, we collect 3,910 articles with 4 to 11 entities, covering the lower to upper quartiles.

Step 2. Generate Pairs of (Query, Targets). Using the entities extracted from each input document (Step 1), we utilize LLAMA-2 (Touvron et al., 2023) to generate diverse queries and targets (prompt in Figure 5). We generate 10 questions for each input document. To satisfy REQ 2 of KTRL+F, we provide only the extracted entities into the model, excluding the input document. This is done to remove the dependency on the document itself, as KTRL+F prioritizes queries that cannot be answered solely with the document and requires the integration of external knowledge.

Step 3-1. Target Filtering. To mitigate the potential problem of false positive and false negative in the generated targets by LLAMA-2 (Touvron et al., 2023), we implement an additional process inspired by Zhong et al. (2022). This process determines whether each entity is the answer to the query, leveraging external knowledge (prompt in Figure 6). Initially, we utilize GPT-3.5 (Ope-

²https://cloud.google.com/natural-language/docs/analyzing-entities

³We consider Wikipedia as an external knowledge source, wherein the acquisition of external knowledge for targets can be equated to utilizing the corresponding Wiki page linked to a particular entity (Wu et al., 2019).

nAI, 2022)⁴ to identify entities judged as potential answer targets. Subsequently, GPT-4 (OpenAI, 2023)⁵ makes the final decision for entities where there is a disagreement between GPT-3.5 and the results of Step 2. Detailed statistics of the results by each model are available in the Appendix A.

Step 3-2. Query Filtering. Though we prioritize queries that require integrating external knowledge in Step 2, there are still many queries that do not meet REQ 2. To further reduce the number of such queries, we utilize a DeBERTaV3-large (He et al., 2023)⁶, finetuned using the SQuAD 2.0 (Rajpurkar et al., 2018). We specifically exclude queries that the MRC model can answer solely based on the input document, leaving only suitable queries for REQ 2. Finally, 512 queries are collected out of the 1,000 queries generated in Step 2. See Appendix A for detailed scoring criteria of the MRC model.

4.2 Dataset Analysis

Human verification setup. To report the quality of the auto-generated dataset, we conduct human verification on a randomly sampled subset of the generated dataset. Four annotators evaluate a total of 32 queries, representing approximately 6% of the entire dataset ⁷. The human verification is designed to assign three annotators to each sample. Each sample is evaluated by responding to three specific questions.

The first question aims to evaluate how well the generated query meets REQ 2. Annotators are instructed to identify evidence for each target to answer the query. The ideal result is for annotators to respond that evidence cannot be found in the input document for all targets. The second question evaluates the naturalness of the generated query by choosing the type of unnatural query: "Ambivalent or subjective expressions", "Lack of factual basis", "Logical errors", "etc". The ideal result is for annotators to select "None of these options", indicating a naturalness in the generated queries. The third question focuses on evaluating the reliability of auto-generated targets. The annotator is instructed to select the correct target for the query by referring to Wikipedia. This is the same process as in target filtering (Step 3-1) in the dataset construction pipeline, to identify the reliability between the

Q1. Is it possible to answer using only the input doc?	
Need more external knowledge	71.9%
Don't need external knowledge	28.1%
% of answered targets	51.6%
Q2. Is it unnatural query?	
Natural Query	84.4%
Subjective Query	9.3%
etc.	6.3%
Q3. Reliability of Target determination	
kappa coefficient (κ)	0.6232

Table 1: Human Verification Results

	Avg.	Min.	Max.
Length of Input Document	1974	999	3254
Queries per Input Document	5.2	1	10
Answer Mentions per Query	4.2	1	30
Answer Entities per Query	1.8	1	8

Table 2: Statistics of KTRL+F Dataset

response by the annotator and the dataset. The user interface and detailed instructions for each question are shown in Figure 7.

Dataset quality and statistics. Since all samples are evaluated by three annotators, final human judgment is determined through majority voting. For the first question, 71.9% of samples are considered unable to answer the target solely based on the input document. While 28.1% of samples can be found using only an input document, only 51.6% of all targets could be inferred. This indicates that there are still limitations to finding all targets based on input documents alone. For the second question, asking about the naturalness of the query, 84.4% of samples are considered natural queries, while 9.4% of the samples are subjective queries. About 6.3% of the samples contain unnatural queries for other reasons, such as entities being directly mentioned in the query. For the third question, we find a kappa coefficient (Cohen, 1960) of $\kappa = 0.6232$ between humans and the dataset. Following the interpretation by Landis and Koch (1977), this indicates substantial agreement between human judgment and the criteria used by the data construction pipeline to determine targets. In total, the KTRL+F dataset has 512 queries for 98 input documents with an average of 4.2 mentions per query as shown in Table 2. More examples of the KTRL+F dataset are available in Table 5.

⁴gpt-3.5-turbo-0613

⁵gpt-4-0613

⁶https://huggingface.co/deepset/deberta-v3-large-squad2

⁷We plan to expand more examples in future versions.

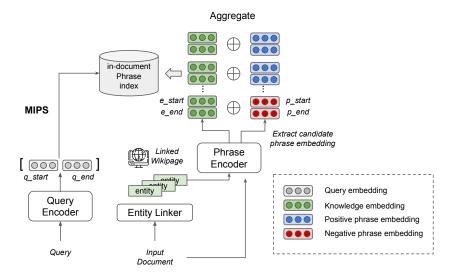


Figure 3: Overview of Knowledge-Augmented Phrase Retrieval. We redefine the phrase retrieval architecture originally proposed by DensePhrases (Lee et al., 2021) within the setting of in-document search and enrich external knowledge about potential targets. The original design of DensePhrases lacks the capability to integrate external knowledge. To address this limitation, we explicitly augment knowledge embedding, extracted with an entity linker, into the phrase embedding. This serves to bridge the semantic gap between the query and the targets (REQ 2).

5 Knowledge-Augmented Phrase Retrieval

The challenge of KTRL+F lies in effectively balancing real-time applicability and high performance while utilizing efficient use of external knowledge. To comprehensively address this challenge and fulfill three requirements of KTRL+F (REQ 1, REQ 2, REQ 3), we introduce Knowledge-Augmented Phrase Retrieval, which consists of multiple modules, as illustrated in Figure 3. Notably, our model doesn't need an additional training step; it represents a straightforward approach that combines and utilizes the modules as they are.

5.1 External Knowledge Linking Module

The external knowledge linking module skims the target text and identifies entities, which can be potential candidate targets, mapping each of them to the relevant Wikipedia knowledge base. The output of this module is a list of candidate targets along with Wikipeidia page linked to each target, which serves as external knowledge about the targets. To focus on building a model that can integrate external knowledge, we use existing entity linking models for this purpose. While there are various entity-linking models available for this purpose, we opt to utilize a Wikifier API (Brank et al., 2017) as an entity linker for ease of use.

5.2 Query and Phrase Encoder

The phrase and query encoder modules are responsible for encoding the candidate entity and the query, respectively. We employ the frozen DensePhrases model (Lee et al., 2021), which is trained on multiple question answering datasets, to extract phrase embeddings. For the query embedding, we extract the embedding of the special token [CLS] from the output embeddings of the query encoder. We use two distinct query encoders to extract the start and end position embeddings for the query, following Lee et al. (2021). Subsequently, we concatenate the corresponding token embeddings, denoted as $[q_{start}; q_{end}] \in \mathbb{R}^{2d}$, to create a query embedding. For the phrase encoder, we similarly utilize concatenated token-level embeddings of the entity's boundary tokens, namely the start and end token embedding denoted as $[e_{start}, e_{end}]$, as the entity embedding.

5.3 Knowledge Aggregation Module

To incorporate external knowledge related to the entity, we utilize the same phrase encoder that is used to extract embeddings for candidate entities. Following the approach in Lee et al. (2023), we generate knowledge embedding for the linked entity by concatenating the text of the name of entity and its corresponding Wikipedia page (see details in Figure 8 of Appendix). By adopting this approach, we can effectively encode pertinent

		Speed	Performance			
Type	Model	Latency (ms/Q) (↓)	List EM (†)	(R) List EM (↑)	List Overlap (†)	(R) List Overlap (↑)
	GPT-4	-	30.457	7.452	37.402	12.898
	GPT-3.5	-	30.346	8.284	41.929	19.446
C	LLAMA-2-Chat-7B	2359	28.529	8.947	40.546	20.008
Generative	LLAMA-2-Chat-13B	3176	28.846	8.024	37.098	14.367
	VICUNA-7B-v1.5	1951	17.831	3.694	31.216	12.532
	VICUNA-13B-v1.5	2420	24.490	6.977	39.278	<u>20.401</u>
Extractive	SequenceTagger	<u>26</u>	7.239	0.612	8.614	1.211
Dataianal	Ours (w/ Wikifier)	15	23.152	7.091	40.718	23.107
Retrieval	Ours (w/ Gold)	14	46.170	22.426	53.689	32.285

Table 3: Overall speed and performance evaluation results for KTRL+F dataset. Note that as we cannot measure the API-based models, we skip the speed evaluation for GPT-3.5 and GPT-4. Robustness score is noted with (R) with corresponding metric. Ours denotes Knowledge-Augmented Phrase Retrieval and the best results excluding Ours (w/ Gold) are in bold, while second-best ones are underlined.

knowledge about the entity into its embedding. To combine this external knowledge embedding with the entity embedding and create an in-document phrase index, we employ a simple element-wise addition operation. This demonstrates promising results in our experiments enabling the system to capture the contextual knowledge for more accurate and comprehensive search and retrieval within the document without requiring further tuning. With Maximum Inner Product Search (MIPS) operation, Knowledge-Augmented Phrase Retrieval can find all matching targets in real time.

6 Experiments

In section 6.1, we describe the baselines used in our experiment. In section 6.2, we present experimental results and conduct a comprehensive analysis of various aspects to solve KTRL+F.

6.1 Setup

We compare various baselines: generative, extractive, and retrieval-based models. Note that all models in the experiment are evaluated in a zero-shot manner, which haven't been trained with the dataset for KTRL+F. All speed measurements except LLM-API are done using a A6000 GPU on a server with two AMD EPYC 7513 CPUs, each with 32 physical cores.

Generative baselines solve KTRL+F as a text generation problem, where the model takes instructions, a input text, and a query as input and sequentially produces matching targets (see Appendix B). The parametric space of Large Language Models (LLM) serves as an implicit source of general knowledge (Yu et al., 2023). To explore the knowl-

edge within the parametric space, we utilize various LLM models, such as the LLM API versions GPT-3.5 (OpenAI, 2022) and GPT-4 (OpenAI, 2023), as well as open-source models like LLAMA-2 (Touvron et al., 2023) and VICUNA v1.5 (Chiang et al., 2023), ranging in size from 7B to 13B. In this experiment, we do not consider retrieval-augmented methods that use retrieval results by appending them to the input. We additionally post-process generated outputs of models to only extract targets for evaluation.

Extractive baseline is similar to extraction-based model for Machine Reading Comprehension task. This approach uses the internal knowledge within the target text to directly locate the answer spans. In order to find all relevant spans in the target text, we follow the previous works (Segal et al., 2020; Li et al., 2022) that helps identify multiple entities. We utilize a BERT based sequence tagging model which is fine-tuned using MultiSpanQA (Li et al., 2022) dataset, denoted as SequenceTagger.

6.2 Results

Generative and extractive baselines show difficulties in balancing real-time applicability and performance as shown in Table 3. Generative baselines demonstrate superior performances in addressing the KTRL+F, leveraging parametric knowledge of pre-trained language models to bridge the semantic gap between queries and targets. However, scaling up model capacity doesn't consistently improve performance and leads to increased latency. The generative nature of these models often causes problems in constraining the output to targets within the input document, such as hal-

Entity Linker	Model	List EM (†)	(R)List EM (↑)	List Overlap (↑)	(R)List Overlap (↑)
Gold (GCP API)	Ours - External - Internal	46.170 34.582 47.345	22.426 14.178 23.097	53.689 43.758 54.308	32.285 26.406 30.599
Wikifier	Ours - External - Internal	23.152 15.620 22.851	7.091 4.742 7.773	40.718 31.805 39.391	23.107 18.823 20.812

Table 4: Ablation study on the impact of existence and quality of external knowledge. We measure the performance when using different entity linkers (Gold w/ GCP API, Wikifier API). Also, we evaluate the impact of contextual phrase embedding and external embedding by removing the related part.

lucination and difficulty restricting the output to targets within the input document which need post-processing step. Conversely, the SequenceTagger, an extractive baseline using the same model capacity (BERT-base) as our model, falls short in KTRL+F. Its inability to utilize external knowledge highlights the importance of incorporating such knowledge beyond the input document for successful KTRL+F resolution. For a comprehensive baseline understanding, we additionally report extra experiments in Table 7 and Table 8 of Appendix E. Detailed prediction example for each model is available in Table 9 of Appendix D.

Knowledge-Augmented Phrase Retrieval demonstrates a balance between latency and achieving overall performance. By simply incorporating knowledge embedding into the phrase retrieval process, our model (Ours w/ Wikifier) shows competitive performance in List Overlap metrics, despite having a significantly smaller model capacity compared to other generative baselines. When provided gold entity linking information used in the dataset construction pipeline, our model can achieve the best performance among all (Ours w/ Gold). To compare with other baselines, we threshold the prediction results from top 4 according to the data distribution ⁸. Not only for performance we can see that retrieval-based design of our model is proper design for real-time applicability, which shows way faster latency than other baselines. While our model requires additional time to index the long input documents into searchable formats⁹, the subsequent querying of the indexed text incurs real-time latency.

6.3 Ablation Study

By integrating external knowledge into our models, we aim to enhance the knowledge of the model about candidate targets, thereby bridging the semantic gap between query and the targets beyond the information present in the input document. To measure the importance of using high-quality external knowledge in addressing KTRL+F, we compare the performance between our model with Wikifier and Gold entity linker utilized in the dataset construction pipeline. The one with the Gold entity linker (Ours w/ Gold) exhibits a significant performance improvement despite employing all other identical modules.

We also evaluate the importance of the knowledge aggregation design in our model. Our model utilizes in-document phrase index by adding external knowledge embedding from Wikipedia and phrase embedding from the input document. In Table 4, (-External) signifies the exclusion of external knowledge embedding, while (-Internal) indicates the removal of phrase embedding. Results indicate a notable performance drop with (-External) when both Gold and Wikifier entity linkers are used. When phrase embedding is removed (-Internal), the model with the Gold entity linker shows better performance overall, while the model with the Wikifier entity linker shows lower results overall compared to using both embeddings. However, robustness of List Overlap scores consistently remains higher than when partial components are removed. This highlights that internal knowledge about candidate targets might play a crucial role in constructing a robust embedding, especially when external information is of sub-optimal quality.

7 User Study

To verify whether solving KTRL+F can enhance search experience of users in the real web en-

⁸To provide a comprehensive understanding of the model, we additionally report MAP metrics in Table 6 of Appendix C.

⁹2.863 sec for ours (w/ Wikifier) and 0.955 sec for ours (w/ Gold). Note that the indexing process only needs to occur once for each input document.

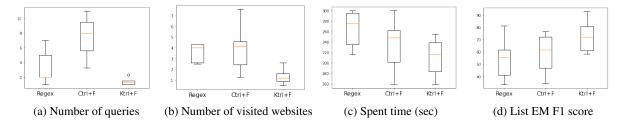


Figure 4: A Comprehensive comparison of in-document search systems: Ktrl+F plugin outperforms with fewest queries, minimal web surfing, least time spent, and best List EM F1 performance. We use abbreviation for regular expression as Regex in the figure.

vironments, we build Chrome extension plugin (KTRL+F plugin) built on our model to compare with other in-document search systems. We compare search experience of users using KTRL+F and other in-document search systems, specifically Ctrl+F and Regular expression¹⁰. The main objective is to analyze efficiency and convenience of each system for users.

7.1 Setup

We recruit 6 participants for an in-depth experiment, where they are tasked with using the given system to find information from 10 different examples on a given website within a limited time ¹¹. To ensure a fair comparison, each user is assigned, on an example-by-example basis, to use only a specific system among KTRL+F plugin, Ctrl+F, and Regular expression to help them find all parts of targets that match given search intent. The participants manually annotate the targets in the PDFs using the respective system. To capture the entire process, we record the screens of participants throughout the experiment. During the analysis phase, we focus on several key elements. These include the time each participant spent finding information using the specified system, the number of queries used to find the target parts, the count of additional websites visited to verify the identified targets for each example, and an overall score for the prediction results using List EM F1 to evaluate the effectiveness of searching for multiple targets.

7.2 Findings

For a comprehensive comparison of the usefulness and efficiency of the KTRL+F plugin with other indocument search systems, we present the results of

the conducted user study in Figure 4. More detailed results are available in Appendix F.

Less search time with KTRL+F plugin. As depicted in Figure 4(c), KTRL+F plugin exhibits the shortest median average time when searching for answers. Its ability to find multiple semantic targets in a single query, thus reducing the need for additional searches to verify results, contributes to its superior efficiency compared to other in-document search systems. It's worth noting that regular expressions can also search for multiple targets at once, which can be considered efficient. However, creating the appropriate regular expression for a given search intent can be complex and often challenging to debug, as demonstrated in the example queries for each system in Figure 12.

Fewer queries to find targets. Figure 4(a) illustrates the average number of queries used per example to find answers. Regular expressions and Ctrl+F are lexical matching systems that rely on user-generated candidate lexical prefixes to find answers. Transforming natural language search intent into the format supported by lexical matching systems increases query usage. While verifying each query using Ctrl+F is a quick process, users typically cannot predict which keywords will appear in unknown text prior to reading it all. Regular expressions can consolidate multiple simple searches into one, but crafting complex expressions dynamically can be challenging and debugging erroneous code compounds the difficulty.

Fewer visits for extra sources. The KTRL+F plugin's ability to enhance external knowledge beyond the current web page diminishes the necessity of consulting additional document sources for result verification, as Figure 4(b). The capability to augment external information beyond the document at hand, such as accessing Wikipedia page,

¹⁰We exclude MRC system, because it is not designed for seeking information without reading the text, which is hard to use for our user study.

¹¹We plan to expand more examples in future versions

enables knowledge-augmented in-document search and results in improved performance (Figure 4(d)). When a search intent encompasses multiple targets, as in the query "List all cities from California from the web page", the need for additional visits to external sources increases, as demonstrated by the generally higher values recorded in lexical matching systems.

8 Conclusion and Future Work

In this paper, we introduce a new problem KTRL+F, a knowledge-augmented in-document search which requires identifying all semantic targets with a single natural query in real-time. KTRL+F tackles unique challenge for in-document search that requires capturing targets containing additional information beyond the input document by utilizing external knowledge while balancing between speed and performance. We investigate various baselines for KTRL+F and find that existing models have limitations, such as hallucinations, high latency, or difficulties to incorporate external knowledge. Our experimental results show that our Knowledge-Augmented Phrase Retrieval, simple extension of phrase retrieval architecture for in-document search scenarios can be a robust model for KTRL+F. Furthermore, results of the study demonstrate that search experience of users can be enhanced even with our simple model with seamless access to external knowledge during in-document searches. Future work can explore how to build an end-toend trainable architecture that retrieves external knowledge and integrates it into a searchable index, all while maintaining real-time processing capabilities. Additionally, KTRL+F can be extended to reflect updated knowledge, like news, which cannot be easily addressed by Large Language Models alone (Ram et al., 2023; Peng et al., 2023; Kaddour et al., 2023). The scalability and practicality of KTRL+F will open up opportunities for various future advancements in the field of information retrieval and knowledge augmentation.

Limitations

The system design for KTRL+F can incorporate various forms of external knowledge, not limited to the Wikipedia page associated with the entity. It can also identify a wide range of target spans within the target text, including dates and numbers, without being restricted to entities. However, the primary focus of this paper revolves around

addressing KTRL+F, specifically emphasizing entities as the primary search targets. By narrowing our focus to entities, we make effective use of entity linking information as external knowledge. Furthermore, due to the inherent nature of retrieval systems, our Knowledge-Augmented Phrase Retrieval model requires an extra indexing stage whenever a change in the input document, which requires additional time to use. Also it relies on thresholding to truncate predicted results, which we employ top-k results based on the data distribution in our experiment. Exploring more efficient methods for enhancing external knowledge while reducing the time needed for the indexing stage is a potential avenue.

References

Janez Brank, Gregor Leban, and Marko Grobelnik. 2017. Annotating documents with relevant wikipedia concepts. In *SiKDD*.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. In *NeurIPS*.

Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E. Gonzalez, Ion Stoica, and Eric P. Xing. 2023. Vicuna: An open-source chatbot impressing gpt-4 with 90%* chatgpt quality.

Jacob Cohen. 1960. A coefficient of agreement for nominal scales. Educational and Psychological Measurement.

Pradeep Dasigi, Nelson F. Liu, Ana Marasović, Noah A. Smith, and Matt Gardner. 2019. Quoref: A reading comprehension dataset with questions requiring coreferential reasoning. In *EMNLP*.

Pradeep Dasigi, Kyle Lo, Iz Beltagy, Arman Cohan, Noah A. Smith, and Matt Gardner. 2021. A dataset of information-seeking questions and answers anchored in research papers. In *NAACL*.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In NAACL.

James Ferguson, Matt Gardner, Hannaneh Hajishirzi, Tushar Khot, and Pradeep Dasigi. 2020. Iirc: A dataset of incomplete information reading comprehension questions. In *EMNLP*.

Adam Fisch, Alon Talmor, Robin Jia, Minjoon Seo, Eunsol Choi, and Danqi Chen. 2019. MRQA 2019

- shared task: Evaluating generalization in reading comprehension. In *Proceedings of the 2nd Workshop on Machine Reading for Question Answering*.
- Pengcheng He, Jianfeng Gao, and Weizhu Chen. 2023. Debertav3: Improving deberta using electra-style pretraining with gradient-disentangled embedding sharing. In *ICLR*.
- Gautier Izacard and Edouard Grave. 2021. Leveraging passage retrieval with generative models for open domain question answering. In *EACL*.
- Mandar Joshi, Eunsol Choi, Daniel Weld, and Luke Zettlemoyer. 2017. TriviaQA: A large scale distantly supervised challenge dataset for reading comprehension. In *ACL*.
- Jean Kaddour, Joshua Harris, Maximilian Mozes, Herbie Bradley, Roberta Raileanu, and Robert McHardy. 2023. Challenges and applications of large language models. *arXiv*.
- Omar Khattab and Matei Zaharia. 2020. Colbert: Efficient and effective passage search via contextualized late interaction over bert. In *SIGIR*.
- Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. Natural questions: A benchmark for question answering research. *Transactions of the Association for Computational Linguistics*.
- J Richard Landis and Gary G. Koch. 1977. The measurement of observer agreement for categorical data. *Biometrics*.
- Hyunji Lee, Jaeyoung Kim, Hoyeon Chang, Hanseok Oh, Sohee Yang, Vladimir Karpukhin, Yi Lu, and Minjoon Seo. 2023. Nonparametric decoding for generative retrieval. In *Findings of ACL*.
- Jinhyuk Lee, Mujeen Sung, Jaewoo Kang, and Danqi Chen. 2021. Learning dense representations of phrases at scale. In *ACL*.
- Haonan Li, Martin Tomko, Maria Vasardani, and Timothy Baldwin. 2022. Multispanqa: A dataset for multi-span question answering. In *ACL*.
- Sheng-Chieh Lin, Minghan Li, and Jimmy Lin. 2022. Aggretriever: A simple approach to aggregate textual representations for robust dense passage retrieval. *Transactions of the Association for Computational Linguistics*.
- OpenAI. 2022. Chatgpt: Optimizing language models for dialogue.
- OpenAI. 2023. Gpt-4 technical report.

- Baolin Peng, Michel Galley, Pengcheng He, Hao Cheng, Yujia Xie, Yu Hu, Qiuyuan Huang, Lars Liden, Zhou Yu, Weizhu Chen, et al. 2023. Check your facts and try again: Improving large language models with external knowledge and automated feedback. *arXiv*.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2019. Exploring the limits of transfer learning with a unified text-to-text transformer. *JMLR*.
- Vatsal Raina, Nora Kassner, Kashyap Popat, Patrick Lewis, Nicola Cancedda, and Louis Martin. 2023. Erate: Efficient retrieval augmented text embeddings. In First Workshop on Insights from Negative Results in NLP.
- Pranav Rajpurkar, Robin Jia, and Percy Liang. 2018. Know what you don't know: Unanswerable questions for SQuAD. In *ACL*.
- Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. Squad: 100,000+ questions for machine comprehension of text. In *EMNLP*.
- Ori Ram, Yoav Levine, Itay Dalmedigos, Dor Muhlgay, Amnon Shashua, Kevin Leyton-Brown, and Yoav Shoham. 2023. In-context retrieval-augmented language models. *TACL*.
- Keshav Santhanam, Omar Khattab, Jon Saad-Falcon, Christopher Potts, and Matei Zaharia. 2022. Col-BERTv2: Effective and efficient retrieval via lightweight late interaction. In *NAACL*.
- Elad Segal, Avia Efrat, Mor Shoham, Amir Globerson, and Jonathan Berant. 2020. A simple and effective model for answering multi-span questions. In *EMNLP*.
- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. 2023. Llama 2: Open foundation and finetuned chat models. arXiv.

- Adam Trischler, Tong Wang, Xingdi Yuan, Justin Harris, Alessandro Sordoni, Philip Bachman, and Kaheer Suleman. 2017. NewsQA: A machine comprehension dataset. In *Proceedings of the 2nd Workshop on Representation Learning for NLP*.
- Ledell Yu Wu, Fabio Petroni, Martin Josifoski, Sebastian Riedel, and Luke Zettlemoyer. 2019. Scalable zero-shot entity linking with dense entity retrieval. In *EMNLP*.
- Wenhao Yu, Dan Iter, Shuohang Wang, Yichong Xu, Mingxuan Ju, Soumya Sanyal, Chenguang Zhu, Michael Zeng, and Meng Jiang. 2023. Generate rather than retrieve: Large language models are strong context generators. In *ICLR*.
- Victor Zhong, Weijia Shi, Wen-tau Yih, and Luke Zettlemoyer. 2022. Romqa: A benchmark for robust, multi-evidence, multi-answer question answering. *arXiv*.
- Ming Zhu, Aman Ahuja, Da-Cheng Juan, Wei Wei, and Chandan K. Reddy. 2020. Question answering with long multiple-span answers. In *EMNLP*.

A Details for Dataset Construction Pipeline

Step 3.1. Target Filtering. In this step, given a (query, entity, external knowledge) triple, we follow Zhong et al. (2022) to derive whether an entity is an answer to a query or not. We utilize the first 10 sentences from the Wikipedia article as an external knowledge, which covers more than 99% of the total sample within 4,096 tokens of GPT-3.5. GPT-3.5 processes a total of 7,060 triple samples, and the final judgment is made by GPT-4 on 1,226 samples that show different results from the target generated by LLAMA-2 in Step 2. On average, 1.6 entities disagreed per query, which is an average of 22% of the candidate entities per query. After the final judgment, queries with all targets determined to be false are discarded. As a result, 816 queries remained out of the total 1,000 queries generated by Step 2, and the average number of entities in a target increased slightly from 1.4 to 1.9.

Step 3.2. Query Filtering. In this step, we exclude a query if the MRC model answers any of the target entities. The MRC model is considered correct when it scores over 0.9 in F1 score, following the human performance described in Rajpurkar et al. (2018). As a result, 512 queries were collected from the 816 queries derived in Step 3-1.

B Implementation Details for Baselines

Generative baselines. To convert KTRL+F as generation problem, we use following instructions for generative models and then post-process the output text to only utilize the answer part. We use temparture 0.5, max new token 512.

Find all mentions from the article below that correspond to the query. Only generate mentions with comma separate.

Article: {Input Document}

Query: { Query } Mentions:

Extractive baseline. We solve KTRL+F using sequence tagging model following (Li et al., 2022). It can be regarded as a model without utilizing external knowledge. We reproduce the model trained on MultiSpanQA (Li et al., 2022) for 3 epochs.

C Analysis of Retrieval Approach for KTRL+F

Determining a proper threshold for retrieval is challenging, especially when the number of targets

varies. Therefore, we additionally measure the Mean Average Precision (MAP), which calculates the mean value per query Q of the Area under the Curve (AUC) of the precision-recall graph in Table 6. This metric provides a comprehensive measure of the system's ability to quantify the overall effectiveness.

D Prediction Examples

Table 9 shows the results of various approaches on same query and input document for qualitative analysis.

E Baseline Analysis from Different Perspectives

For a comprehensive baseline understanding, we additionally present set-base scores which doesn't require recognizing every target occurrences in Table 7. We can see the Set Overlap score gets a higher result than List Overlap overall, and especially generative models show major performance gain in Overlap score when using Set score, which shows finding all matching target is hard for generative models. Given that our model leverages entity linking information to identify targets from a restricted pool of candidates, we conduct an additional experiment by supplying additional information about potential targets for generative models (refer to Table 8). When adding extra information about potential targets for generative models, it proves to enhance the overall performance of generative models. Notably, in the case of LLM-API (GPT-4, GPT-3.5), it even outperforms our model with gold-standard information. However, it's important to note that enhancing information for generative models comes with increased costs and slower latency, making it impractical for realtime applicability.

F Details for User Study

We additionally compare existing in-document search systems in Table 10. The criteria are matching type, ability to search multiple targets, search intention of the system, and ability to augment external knowledge. Also, we add examples what queries users use with different in-document search systems for finding same targets in Table 12.

```
You are an expert of query generation for entity search.
You must follow this requirements.
Requirements:

    Your task is to generate queries that retrieve entities in a given list.
    The generated query must be able to list the multiple entities.
    The answers must be countable.

- The answers have to be entities.
- Make sure your questions are unambiguous and based on facts rather than temporal information.

Do not specify the number in a query.
Do not start with 'What' in a query.
Do not start with 'Which' in a query.
Do not include an expression in your query that tells it to find from a given list.

The example is as below.
Generate 4 queries from the following list and extract subset list.
Candidate List:
[Apple, Microsoft, Samsung Electronics, Alphabet, AT&T, Amazon, Verizon Communications, China Mobile, Walt
      Disney, Facebook, Alibaba, Intel, Softbank, IBM, Tencent Holdings, Nippon Telegraph & Tel, Cisco Systems, Oracle, Deutsche Telkom, Taiwan Semiconductor, KDDi, HP, Legend Holding, Lenovo Group, ebay]
1. IT companies in Computer Hardware industry
=> Apple, HP, Legend Holding, Lenovo Group
2. Find all IT companies that have software as main business.
=> Microsoft, Oracle
3. Companies that is known for retail service
=> Amazon, Alibaba, ebay
4. Name all IT companies that have license in USA
=> Apple, Microsoft, Alphabet, AT&T, Amazon, Verizon Communications, Walt Disney, Facebook, Intel, IBM, Cisco Systems, Oracle, HP, ebay
```

Figure 5: Prompt for generating queries and targets

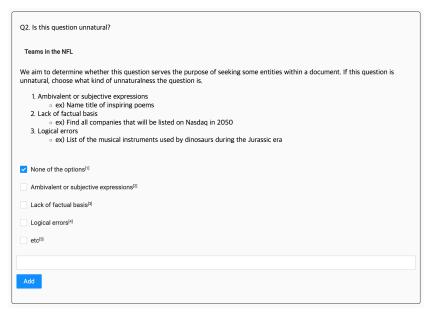
```
You are a QA system to identify the given entity is the answer.
The inputs are entity, query and evidence.
You must follow this requirements.
Requirements:
Output have to be either 'true' or 'false'

Do not say anything except 'true' or 'false'
The example is as below.
Entity: Google
Query: Find all IT companies in Computer industry
Evidence: Google LLC is an American multinational technology company focusing on artificial intelligence,
       online advertising, search engine technology, cloud computing, computer software, quantum computing, e-commerce, and consumer electronics. It has often been considered "the most powerful company in the
       world" and as one of the world's most valuable brands due to its market dominance, data collection, and technological advantages in the field of artificial intelligence. Its parent company Alphabet is often considered one of the Big Five American information technology companies, alongside Amazon,
       Apple, Meta, and Microsoft.
Output: true
Entity: Samsung
Query: Find all companies in United States
Evidence: Samsung Group, or simply Samsung, is a South Korean multinational manufacturing conglomerate headquartered in Samsung Town, Seoul, South Korea. It comprises numerous affiliated businesses, most of them united under the Samsung brand, and is the largest South Korean chaebol (business
       conglomerate). As of 2020, Samsung has the eighth highest global brand value.
Output: false
```

Figure 6: Prompt for target filtering

Question:
Teams in the NFL
Document:
RICHLAND — The Falcons couldn't rally past the Grizzlies in CBBN 3A action. Trailing 19-10 heading into the fourth quarter, Hanford's Cameron Wagar caught a 38-yard touchdown pass from Riley Shintaffer, but that was as close as the Falcons would get. Shintaffer threw for 130 yards and two touchdowns, while Wagar rushed 16 times for 105 yards. Hanford hosts Walla Walla at 7 p.m. Friday in a crossover game. Han—Matt Jones 61 pass from Riley Shintaffer (Pete Hanson kick). Sun—Rafael Salmeron 14 pass from Andrew Daley (kick failed). Sun—Steven Monterrey 14 run (pass failed). Sun—Monterrey 1 run (kick good). Han—Cameron Wagar 38 pass from Shintaffer (kick failed). RUSHING—S, Monterrey 33-194, Jacob Ross 4-1, Fernando Madrigal 2-7, Daley 7-(-23): H, Wagar 16-105, Shintaffer 3-(-11), Lamar Bowser 3-1, Matt McClendon 2-41, Chris Wilson 5-(-1). PASSINC—5, Daley 10-24-2—181. H, Shintaffer 4-15-2—130. RECEIVING—5, Madrigal 4-40, Salmeron 3-104, Monterrey 3-37. H, Wagar 1-38, Finn McMichael 1-16, Jones 2-76. FIRST DOWNS—5, 16; H, 8. FUMBLES-LOST—5, 1-0; H, 5-1. PENALTIES-YARDS—5, 3-25; H, 2-10.
Q1. Can you find evidence of the following entities in this document for the above question? Question:
Teams in the NFL
Entities:
☐ Atlanta Falcons ⁽⁶⁾
No. I can't find any evidences of the following entities. ^[7]

(a) The Q1 requests the identification of evidence for each target to evaluate whether the query satisfies $\mbox{REQ}\ 2$.



(b) The Q2 requests the selection of options to evaluate the naturalness of the query.

Please select all entities which are the actual answer to the question. You can refer the wikipedia link. (*Choose every entities) Question:					
Acti	resses who have portrayed strong female characters				
✓ Je	nnifer Lawrence ^{RI}				
_ Lo	rde ^[2]				
Th	e Hunger Games: Mockingjay – Part 1 ^[8]				
Ye	llow Flicker Beat ⁽⁴⁾				
✓ Ka	tniss Everdeen ^(S)				
✓ Ta	ylor Swift ^{lig}				
□ Ni	na Jacobson ^[7]				
Ev	ery Entities are false. ^[8]				

(c) The Q3 requests the selection of targets to evaluate the reliability of target determination.

Figure 7: User Interface for Human Verification.

[Query] Social network platform of China

[Input Document]

It is a highly competitive market with many local competitors who already understand the shopping habits of the Chinese, which are very different to those of consumers in the Western world. Chinese platforms such as Taobao and Tmall dominate the shopping world ... successfully. BAIDU DOMINATES ONLINE Currently, there are an estimated 900 million internet users across China, with most users spending 1.5 hours a day just browsing. Baidu is the most popular search engine across China. Think of it as 'the Google of China'.... time. Baidu also brings the ... social media app across China, it is imperative that your company becomes familiar with the inner workings of Wechat. Wechat is fundamentally a social media... in store through Wechat pay are all possible. Many local and foreign companies already successful in China have official accounts on Wechat. An official ... Wechat wallet. Many companies now also offer customer service through Wechat. Again, this is highly advisable as this is a service many Chinese consumers will now look for as it is quick and direct. Weibo is another popular social media app used across China. Think of Weibo as 'the Twitter of China'. Weibo is an open network site so users can see posts from anyone without being their friend or following them. Similar to Twitter, Weibo can be an excellent way to market your company by sharing the latest updates, offers, promotions etc. Your followers can also start to share your content helping your company's reputation spread by word of mouth.

[Ground Truth] ['Wechat', 'Wechat', 'Wechat', 'Wechat', 'Wechat', 'Wechat', 'Weibo', 'network site', 'Weibo', 'app', 'Weibo', 'Baidu', 'BAIDU']

[Query] Find all players who played in Premier League [Input Document]

McClaren banks on Mitrovic's influence. LONDON • If he performs half as well as the players he idolises, Aleksandar Mitrovic will not prove to be much of a gamble, even at £13 million (S\$27.7 million), the fourth-highest incoming transfer in Newcastle United's history. The Serbia striker on Tuesday became the club's second expensive new arrival this summer, leaving Anderlecht for a five-year contract at St James' Park. The arrival of Mitrovic, 20, was hailed for its significance by Newcastle manager Steve McClaren. Mitrovic scored 23 goals in 44 appearances for the Belgian club last season, including a goal against Arsenal in the 3-3 Champions League draw at the Emirates. ... But Mitrovic's signing on top of that of Georginio Wijnaldum, a £14.5 million addition from PSV Eindhoven, has restored a positive atmosphere at Tyneside. Only Michael Owen (£17.5 million) and Alan Shearer (£14.7 million) have cost more. ... Moreover, Chancel Mbemba, Mitrovic's former team-mate in Brussels, is also expected to join McClaren's team. Mitrovic is hoping to follow in some illustrious footsteps. "I am a real No. 9, the penalty box is my place," he said. "My position is through the middle. I'm like strikers who have played here before - from Alan Shearer to Papiss (Cisse). They are big names and I hope I can make a similar impact. "Alan Shearer is a real legend and one of my heroes. That and (Didier) Drogba is how I like to play and it's an honour to play at this club." THE TIMES, LONDON

[Ground Truth] ['Aleksandar Mitrovic', 'Mitrovic', 'Mitrovic', 'Mitrovic', 'Georginio Wijnaldum', 'Michael Owen', 'Alan Shearer', 'Chancel Mbemba', 'Mitrovic', 'Mitrovic', 'Alan Shearer', 'Papiss', 'Alan Shearer', '(Didier) Drogba']

[Query] Smaller geographical divisions within Monmouth County, New Jersey [Input Document]

New Jersey family of four was killed and their mansion set on fire, officials say. (CNN) — A family of four found dead at their mansion in Colts Neck, New Jersey, were the victims of homicide and their house was subsequently set on fire, Monmouth County Prosecutor Christopher Gramiccioni said Wednesday. ... Gramiccioni said authorities are investigating a separate house fire in nearby Ocean Township as arson and are looking into whether the two fires are related. The other house is the residence of Paul Caneiro, the brother of Keith Caneiro, Gramiccioni said. ... Gramiccioni cautioned against leaping to conclusions about the fires until authorities investigate further. "Both of those homes that we are talking about, they're owned by — under public records — by common family members," Grdamiccioni said. ... The call for the Colts Neck fire came in at 12:38 p.m. on Tuesday — more than seven hours after the Ocean Township fire — and more than 20 fire departments responded. Authorities said they were not aware of any law enforcement calls to the home before that time. ... A 2007 filing indicates that Keith was the president of the company. The brothers were best friends who talked almost daily, Honecker said Saturday, adding he had no reason to believe there was animosity between them.

[Ground Truth] ['Colts Neck', 'Colts Neck', 'Monmouth County', 'Ocean Township', 'Colts Neck', 'Ocean Township']

Model	Indexing time (Sec) (\downarrow)	ms/Q (\downarrow)	MAP(@IoU0.5) (†)	(R)MAP(@IoU0.5) (†)
Ours w/ Wikifier	3.555	14	0.464	0.209
w/o INT	3.027	14	0.494	0.220
w/o EXT	3.145	14	0.335	0.153
Ours w/ Gold	0.955	14	0.716	0.380
w/o INT	0.912	14	0.776	0.408
w/o EXT	0.799	14	0.508	0.213

Table 5: Example of KTRL+F evaluation dataset.

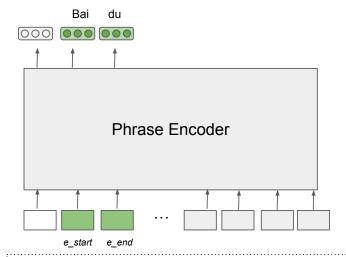
Table 6: MAP metric for retrieval approach. The result shows the effectiveness of phrase retrieval architecture. When using MAP as a metric, it reflect retrieved ranks of results and ours show slightly performance drop than ours w/o internal knowledge.

Model	List EM (↑)	Set EM (†)	List Overlap (†)	Set Overlap (†)
GPT-4	30.457	36.422	37.402	51.071
GPT-3.5	30.346	36.668	41.929	56.334
LLAMA-2-Chat-7B	28.529	34.235	40.546	52.843
LLAMA-2-Chat-13B	28.846	35.206	37.098	51.672
VICUNA-7B-v1.5	17.831	22.265	31.216	42.460
VICUNA-13B-v1.5	24.490	29.223	39.278	49.449
SequenceTagger	7.239	9.041	8.614	15.648
Knowledge-Augmented Phrase Retrieval (w/ Wikifier) Knowledge-Augmented Phrase Retrieval (w/ Gold)	23.152 46.170	24.793 50.254	40.718 53.689	46.841 <u>63.230</u>

Table 7: We additionally report Set-based scores with our List-based scores, which doesn't necessitate recognizing every target occurrences.

Model	List EM (↑)	(R) List EM (↑)	List Overlap (↑)	(R) List Overlap (↑)
GPT-4 (w/ Gold)	52.937	22.479	55.765	25.183
GPT-3.5 (w/ Gold)	44.697	22.048	56.615	35.874
LLAMA-2-Chat-7B (w/ Gold)	40.225	17.738	50.466	30.140
LLAMA-2-Chat-13B (w/ Gold)	45.674	19.329	50.172	23.291
VICUNA-7B-v1.5 (w/ Gold)	27.374	8.651	41.466	21.611
VICUNA-13B-v1.5 (w/ Gold)	39.898	17.065	54.695	33.814
Knowledge-Augmented Phrase Retrieval (w/ Gold)	<u>46.170</u>	22.426	53.689	<u>32.285</u>

Table 8: Results for when generative models use candidate entities from input document as additional input for instruction (denoted as w/ Gold). We evaluate the results by giving gold entity linking information version.



Title: { Baidu } Context: { It is also evident that Baidu is ... Internet social network market. As of 2011, it is discussing the possibility of working with Facebook, which would lead to a Chinese version of the international social network, managed by Baidu.... competition from the three popular Chinese social networks Qzone, Renren[96] and Kaixin001[97] as well as induce rivalry with instant-messaging giant, Tencent QQ.}

Figure 8: The figure demonstrates how to extract entity embedding, which is used for external knowledge for Knowledge-Augmented Phrase Retrieval. We utilize the frozen pre-trained phrase retrieval model (Lee et al., 2021), which shows good at encoding contextual information. The idea of using concatenated text with title and context and only extracting title embedding are following (Lee et al., 2023)

[Query] Social network platform of China

[Input Document]

It is a highly competitive market with many local competitors who already understand the shopping habits of the Chinese, which are very different to those of consumers in the Western world. Chinese platforms such as Taobao and Tmall dominate the shopping world ... successfully. BAIDU DOMINATES ONLINE Currently, there are an estimated 900 million internet users across China, with most users spending 1.5 hours a day just browsing. Baidu is the most popular search engine across China. Think of it as 'the Google of China'.... time. Baidu also brings the ... social media app across China, it is imperative that your company becomes familiar with the inner workings of Wechat. Wechat is fundamentally a social media... in store through Wechat pay are all possible. Many local and foreign companies already successful in China have official accounts on Wechat. An official ... Wechat wallet. Many companies now also offer customer service through Wechat. Again, this is highly advisable as this is a service many Chinese consumers will now look for as it is quick and direct. Weibo is another popular social media app used across China. Think of Weibo as 'the Twitter of China'. Weibo is an open network site so users can see posts from anyone without being their friend or following them. Similar to Twitter, Weibo can be an excellent way to market your company by sharing the latest updates, offers, promotions etc. Your followers can also start to share your content helping your company's reputation spread by word of mouth.

[Ground Truth] ['Wechat', 'Wechat', 'Wechat', 'Wechat', 'Wechat', 'Wechat', 'Weibo', 'network site', 'Weibo', 'app', 'Weibo', 'Baidu', 'BAIDU']

GPT-4: ['Wechat', 'Weibo']

GPT-3.5: ['Taobao', 'Tmall', 'Wechat', 'Weibo']

Vicuna-13B-v1.5: ['WeChat (official accounts, WeChat pay, customer service)', 'Taobao (dominates shopping world)', 'Tmall (dominates shopping world)', 'Baidu (most popular search engine, brings WeChat)', 'Weibo (open network, excellent way to market, Twitter of China)']

SequenceTagger: ['taobao, 'tmall']

Ours (w/o INT): ['service', 'Wechat', 'Wechat', 'Wechat', 'Wechat', 'Wechat', 'Wechat', 'Wechat', 'Way', 'Weibo', 'network site', 'Weibo', 'Weibo', 'Taobao', 'Tmall', 'Twitter', 'Twitter', 'China', 'China', 'China', 'China', 'China', 'China', 'Baidu', 'Baidu', 'Baidu', 'Baidu', 'Chinese', 'Chinese', 'Chinese', 'Chinese']

Ours (w/o EXT): ['Weibo', 'Weibo', 'Wechat', 'Wechat', 'Weibo', 'BAIDU', 'Weibo', 'Baidu', 'Wechat', 'Twitter', 'Taobao', 'Tmall', 'Wechat', 'Wechat', 'Baidu', 'China', 'Wechat', 'China', 'Service']

Ours: ['Wechat', 'Weibo', 'Weibo', 'Weibo', 'Wechat', 'Weibo', 'Wechat', 'Weibo', 'Wechat', 'Taobao', 'app', 'network site', 'Tmall', 'Twitter', 'BAIDU', 'Baidu', 'service', 'China', 'China', 'Twitter', 'Baidu', 'China', 'China'

Table 9: Prediction result per different approaches. Note that our model uses thresholding for find proper points per query. In this result we show all ranking results.

	Matching Type	Search Mulitple Targets	Search Intention	External Knowledge-Augmented
Ctrl+F	Lexical	NO	Skimming	Manual
Regular Expression	Lexical	YES	Skimming	Manual
MRC	Semantic	YES	After Understanding	NO
KTRL+F	Semantic	YES	Skimming	Automatic

Table 10: Comparing characteristics of KTRL+F with other systems.

	Time(s)	# of Queries	# of visited Websites	Performance(List EM F1)
Ctrl+F	235(248)	7.47(8)	3.95(4.12)	58.64(61.79)
Regular Expressio	n 265(275)	3.4(2)	3.54(4)	54.31(55.74)
KTRL+F plugin	211(217)	1.41(1.25)	1.08(1)	72.70(71.60)

Table 11: Evaluation table for comparing KTRL+F plugin with other systems. Averaged value is reported and median value are noted within bracket.

Search Intetion	Query per System	Result
List the cities from California	Ktrl+F: List the cities from California	SAN JOSE, Calif Paramount to the they played smarter than they did Sunday in Anaheim, The Rangers signed 23-year-old defenseman Vince Pedrie out of Penn State, for whom he had 30 points in 39 games this season.
	Ctrl+F: [San jose, California, Anaheim]	SAN JOSE, Calif Paramount to the they played smarter than they did Sunday in Anaheim, The Rangers signed 23-year-old defenseman Vince Pedrie out of Penn State, for whom he had 30 points in 39 games this season.
	Regex: (SAN JOSE Calif Anaheim)	SAN JOSE, Calif Paramount to the they played smarter than they did Sunday in Anaheim, The Rangers signed 23-year-old defenseman Vince Pedrie out of Penn State, for whom he had 30 points in 39 games this season.
List all football teams	Ktrl+F: List all football teams	LIVERPOOL star Fabinho has been caught on camera appearing to sneeze on Chelsea 's Eden Hazard. Liverpool took back top spot in the Premier League after beating Chelsea at Anfield earlier today. The Reds now have four games leading Manchester City by "He's a fantastic player. Chelsea is
	Ctrl+F: [Liverpool, Chelsea, Manchester City]	LIVERPOOL star Fabinho has been caught on camera appearing to sneeze on Chelsea 's Eden Hazard. Liverpool took back top spot in the Premier League after beating Chelsea at Anfield earlier today. The Reds now have four games leading Manchester City by "He's a fantastic player. Chelsea is
	Regex: (LIVERPOOL Chelsea Manchester City)	LIVERPOOL star Fabinho has been caught on camera appearing to sneeze on Chelsea 's Eden Hazard. Liverpool took back top spot in the Premier League after beating Chelsea at Anfield earlier today. The Reds now have four games leading Manchester City by "He's a fantastic player. Chelsea is

Table 12: The figure above illustrates how each system handles the same search intention. It is worth noting that Ctrl+F and Regex require additional search engines to convert natural language search intentions, such as "List the cities from California," into candidate keywords like "Los Angeles, San Diego, San Jose, San Francisco, etc." which consist of over a thousand cities. Moreover, there is no guarantee that these cities will appear on the web page. The highlighted text in yellow represents potential correct targets based on the query, while the red indicates possible false negative failures when using lexical search systems like Ctrl+F and Regex, which need to be highlighted.