# Semantic Operators: A Declarative Model for Rich, Al-based Analytics Over Text Data

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#### **ABSTRACT**

The semantic capabilities of language models (LMs) have the potential to enable rich analytics and reasoning over vast knowledge corpora. Unfortunately, existing systems lack high-level abstractions to perform bulk semantic queries across large corpora. We introduce semantic operators, a declarative programming interface that extends the relational model with composable AI-based operations for bulk semantic queries (e.g., filtering, sorting, joining or aggregating records using natural language criteria). Each operator can be implemented and optimized in multiple ways, opening a rich space for execution plans similar to relational operators. We implement our operators in LOTUS, an open source query engine with a DataFrame API. Furthermore, we develop several novel optimizations that take advantage of the declarative nature of semantic operators to accelerate semantic filtering, clustering and join operators by up to 400× while offering statistical accuracy guarantees. We demonstrate LO-TUS' effectiveness on real AI applications including fact-checking, extreme multi-label classification, and search. We show that the semantic operator model is expressive, capturing state-of-the-art AI pipelines in a few operator calls, and making it easy to express new pipelines that achieve up to 180% higher quality. Overall, LO-TUS queries match or exceed the accuracy of state-of-the-art AI pipelines for each task while running up to 28× faster. LOTUS is publicly available at https://github.com/stanford-futuredata/lotus.

### 1 INTRODUCTION

The powerful semantic capabilities of modern language models (LMs) create exciting opportunities for building AI-based analytics systems that reason over vast knowledge corpora. Many applications require complex reasoning over large amounts of data, including both unstructured and structured data. For example a researcher reviewing recent ArXiv [2] preprints may want to quickly obtain a summary of relevant papers from the past week, or find the papers that report the best performance for a particular task and dataset. Similarly, a medical professional may automatically extract biomedical characteristics and candidate diagnoses from many patient reports [25]. Likewise, organizations wish to automatically digest lengthy transcripts from internal meeting transcripts and chat histories to validate hypotheses about their business [4].

Each of these tasks require a form of *bulk semantic processing*, where the analytics system must process large amounts of data and apply semantic-based analysis across a whole dataset. Supporting

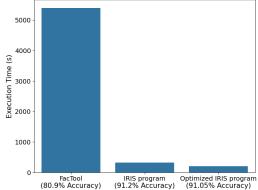


Figure 1: Execution time (y-axis) and accuracy, shown in parentheses, for 3 fact-checking implementations: (i) FacTool [21], a recent state-of-the-art research work, (ii) a short LOTUS program, and (iii) the same LOTUS program implemented with our declarative optimizations and accuracy guarantees. Section 5 provides our full methodology.

the full generality of these applications with efficient and easy-touse analytics systems would have a transformative impact, similar to what RDBMSes had for tabular data. This prospect, however, raises two challenging questions: first, how should developers express semantic queries, and secondly, how should we design the underlying analytics system to achieve high efficiency and accuracy.

Unfortunately, existing systems are insufficient for applications that require bulk semantic processing. Several systems provide logically row-wise LM operators, either in the form of a generalprupose LLM user-defined function (UDF) [1, 8, 13, 45] or specialized row-wise operators [44, 47, 48] for specific applications, such as conversational chat or data cleaning and extract-transform-load (ETL) tasks. These programming models fail to support a range of LM-based transformations across rows, such as ranking, grouping or joining records. Alternatively, many LM programming frameworks [7, 12, 39] and research works [16, 27, 30, 38, 42, 68, 71] support combining LLM calls with retrieval-augmented generation (RAG) and Text2SQL, however these models are limited to point lookups to the data. RAG and Text2SQL methods first retrieve data using semantic search or LM-generated SQL calls, and then process the results with an LLM. Both are limited to analyses where an LLM can be fed a small number of documents or rows that are placed into a single model call's context window (e.g., questions

answered in one document in the corpus). However, bulk semantic processing applications may involve analysis across multiple rows, for clustering, ranking or joining an entire dataset.

Towards a declarative programming interface for bulk semantic processing, we propose semantic operators, which extend the relational model with AI-based operations that users can compose into powerful, reasoning-based query pipelines over structured and unstructured data. These operators include semantic filters, joins, rankings, aggregations, and projections, which take natural language expressions given by the programmer. To provide an implementation of these operators, we present the LOTUS system, which exposes these operators through a simple DataFrame-based programming interface. LOTUS' query engine efficiently and accurately executes queries with semantic operators, while abstracting away low-level details like model context length limits and algorithmic choices. Finally, we propose novel optimizations for the semantic filter, join, ranking and groupby operators that can improve performance by up to 400× over a naive, expensive implementation while guaranteeing accuracy similar to the naive implementation.

Figure 1 begins to demonstrate the power of LOTUS' declarative programming model and optimized query engine. For a fact-checking task on the FEVER dataset [59], we write an intuitive LOTUS program in less than 50 lines of code by composing 3 semantic operators (i.e., filters, maps, and joins). The modularity and composability of these semantic operators make it easy to quickly write programs and explore the design space on this task. In doing so, we find the un-optimized LOTUS programs can reproduce and improve accuracy on this task by 10 percentage points compared to a recent state-of-the-art fact-checking pipeline, FacTool [21], which was written in over 750 lines of code. LOTUS also provides query efficiency by default, yielding 8× lower execution time than the FacTool implementation.

LOTUS' optimizer exploits the rich implementation design space of semantic operators to provide novel optimizations for bulk semantic operations. To demonstrate the power of programming with semantic operators, we implement optimizations for several costly operators, i.e., semantic filter, join, ranking and group-by. Specifically, we develop a novel, lossless optimization for ranking. Additionally, for filters, joins and group-bys, we define and implement both a tractable, but expensive, reference algorithm as well as an approximation algorithms with probabilistic guarantees on accuracy with respect to the reference algorithm. Our approximation algorithms leverage build on statistical techniques used in prior works [34, 36] with novel and efficient proxy scorers that leverage small LMs or semantic embeddings. Figure 1 demonstrates the effectiveness of these methods. The program implemented using LOTUS' optimizations with 0.9 recall and precision targets and a 0.2 error probability attains high accuracy, 99.8% of the unoptimized program's accuracy, and runs 1.7× faster than the unoptimized program.

We systematically evaluate the expressiveness of the semantic operator model and the efficiency of our algorithms and optimizations with statistical accuracy guarantees through several real applications, including fact-checking, extreme multi-label classification, and search, which had previously been implemented by hand in AI research papers. We show that LOTUS' programming model is highly expressive, capturing high quality and state-of-the-art query

pipelines with low development overhead for these wide-ranging applications. Furthermore, our algorithms and optimizations can speed up query execution by up to  $400\times$  while offering statistical guarantees on accuracy.

Specifically, on the FEVER dataset [59] for fact-checking, LOTUS programs can reproduce a recent state-of-the-art pipeline [21], as shown in Figure 1, in few lines of code, and implement a new pipeline with a simple change of operators that improves accuracy by 10.1%, while offering 28× or 7× lower execution time with or without batching, respectively, while providing statistical accuracy guarantees. In the extreme multi-label classification task on the BioDEX dataset [25], LOTUS reproduces state-of-the art result quality [24] with it's join operator, while providing an efficient algorithm that provides 400× lower execution time than the naive algorithm, while again offering statistical guarantees on accuracy. In the search and ranking application, LOTUS allows a simple composition of operators to achieve 8 - 180% higher nDCG@10 than the vanilla retriever and re-ranker, while also providing query efficiency, with 1.67 - 10× lower execution time than LM-based ranking methods [54] used by prior works.

Our main contributions are the following:

- We propose semantic operators as a programming model for AI-based analytics. Semantic operators (e.g., filters, joins, top-k ranking, aggregations, and group-bys) are declarative and can be implemented in multiple ways, creating a rich design space for execution plans.
- We present efficient algorithms and query optimizations for several costly operators, i.e., semantic filter, join, top-k ranking and group-by. We develop a novel, lossless optimization for ranking and approximations for filters, joins and group-bys that provide statistical accuracy guarantees with respect to tractable, but expensive, reference algorithms.
- We provide a reference implementation of semantic operators and optimizations in the open-source LOTUS system.

## 2 SEMANTIC OPERATORS

We define semantic operators as declarative transformations on one or more relations, parameterized by a natural language expression, that can be implemented by a variety of AI-based algorithms. Semantic operators provide a seamless extension to the relational model, operating over tables that may contain traditional structured data as well as unstructured fields such as free-form text. These new operators can be composed with traditional relational operators to build rich queries that can be transparently optimized, which we discuss in Section 4. Table 1 lists a core set of semantic operators we propose in this paper, which cover the common semantic transformations we observe in real-world applications and mirror the key transformation patterns in standard relational operators. Specific analytics systems may of course provide additional semantic operators or APIs that combine the ones we discuss here.

Each semantic operator takes a *parameterized natural language expressions* (*langex* for short), which are natural language expressions that specify a function over one or more attributes for the given semantic transformation. The langex signature depends on its

Table 1: Summary of Key Semantic Operators. T denotes a relation, X and Y denote arbitrary tuple types, L[X] denotes a list of elements with type X, and A denotes the type of a particular column or attribute. l denotes a parameterized natural language expression ("langex" for short), which takes tuples as input and performs a function such as a predicate, an aggregation, a comparator, or a projection, depending on the operator's signature.

Operator	Description
$sem\_filter(l{:}X \to Bool)$	Returns the tuples in a table that pass the provided langex predicate.
$sem\_join(t:T, l:(X,Y) \rightarrow Bool)$	Joins a table against a second table $t$ by keeping all pairs of tuples that pass the provided langex predicate.
$sem\_agg(l:L[X] \to X)$	Performs an aggregation over the input tuples according to the langex, which specifies a commutative, associative aggregation function over a list of tuples.
$sem\_topk(l:L[X] \rightarrow L[X], k:int)$	Ranks each tuple and returns the $k$ best according to the langex, which specifies a ranking function that sorts a list of tuples.
$sem\_group\_by(l:X \rightarrow Y, C:int)$	Groups the tuples into $\mathcal C$ categories based on the langex, which specifies a grouping criteria.
$sem\_map(l{:}X \to Y)$	Performs a projection, returning a new column, according to the provided langex.

semantic operator and may represent a predicate, aggregation, comparator function, or projection in natural language. Figure 2 shows an example of using semantic operators in LOTUS' dataframe API to load data about ArXiv papers and perform a summarization task, which finds relevant papers using a top-k search, filters according to whether the paper claims to outperform a specific baseline, and then summarizes the remaining papers into a single digest with an aggregation. The code in Figure 2 highlights various langex signatures: the sem\_filter langex provides a predicate that indicates a filter criteria to apply over the title and abstract attributes, while sem\_agg takes a langex that provides an associative aggregation expression, which here indicates a many-to-one summarization task over abstracts. Together, each langex and semantic operator specifies a modular semantic transformation, whose behavior is defined with respect to a world model M, which may be a powerful LLM that captures a probability distribution over the vocabulary V.

We briefly overview several semantic operators, both ones whose definitions directly extend their analogs in traditional relational algebra, and those with more complex definitions.

**Semantic Filter** is a unary operator over the relation T and returns the relation  $\{t_i \in T | l_M(t_i) = 1\}$ , where the natural language predicate is specified by the langex l with respect to model M. The langex is paramterized by one or more attributes from the relation T that are relevant for evaluating the predicate.

**Semantic Join** provides a binary operator over relations  $T_1$  and  $T_2$  to return the relation  $\{(t_i, t_j) | l_M(t_i, t_j) = 1, t_i \in T_1, t_j \in T_2\}$ , once again taking the langex l with respect to model M. Here the langex is parameterized by the left and right join keys and describes a natural language predicate over both.

**Semantic Top-k** imposes a ranking<sup>1</sup> over the relation T and returns  $t_1, ..., t_k$   $st \, \forall (t_i, t_j), i < j \implies l_M(t_i, t_j) = t_i, t_j$ . Here the signature of the langex provides a general ranking criteria according to one or more attributes of the input relation. The underlying system can use this langex to impose a ranking over any subset of rows, according to the chosen implementation.

```
def get_paper_digest(research_interests: str, baseline:
    str):
    return papers_df\
    .sem_search("abstract", research_interests, 100)\
    .sem_filter(f"the paper {{abstract}} claims to outperform {baseline} "\
    .sem_agg(f"Write a digest summarizing the {{ abstracts}} and their relevance to { research_interests}")
```

Figure 2: Example LOTUS program using semantic operators to return a summary of relevant papers. The function takes a description of the user's research interests. The program searches over papers, then filters based on whether the paper outperforms the baseline, and finally constructs a summary.

**Semantic Aggregation** performs an aggregation over the input relation, returning  $l_M(t_1,...,t_n)$  st  $t_1,...,t_n \in T$ . Here, the the langex signature provides a commutative and associative aggregation function, which can be applied over any subset of rows to produce an intermediate results. We note that the langex with respect to model M assumes infinite context and can take an arbitrary number of input tuples. Managing finite context limits of the underlying model M is an implementation detail left to the system. Semantic aggregations can be useful for many tasks involving many-to-one reduction patterns, such as summarization or question-answering over multiple documents.

Semantic Group-by takes a langex that specifies a grouping criteria and a target number of groups. As a example extending that of Figure 2, we might group-by the topics presented in each paper abstract with a target of 10 group. Here, the group-by operator must discover representative group labels and assign each tuple a label. In general, performing the unsupervised group discovery is a clustering task, which is NP-hard [22]. Clustering algorithms over points in a metric space typically optimize the potential function tractably using coordinate descent algorithms, such as k-means. In the semantic group-by, the clustering task is over unstructured documents with a natural language similarity function specified by the user langex  $l(t_i, \mu_j)$ , which imposes a real-valued score between a tuple  $t_i$  and a candidate label  $\mu_j$ , and the operator poses the following optimization problem:

 $<sup>^1{\</sup>rm This}$  definition implies that  $l_M$  imposes a total and consistent ordering. However, this definition can also be softened to assume partial orderings and noisy comparisons with respect to model M.

$$\mathop{\arg\max}_{\{\mu_1,\dots,\mu_C\},\;\mu_i\in V^{\mathbb{N}}} \sum_{t_i\in T} \mathop{\max}_{j\in 1\dots C} l_M(t_i,\mu_j)$$

where  $\mu_1, ..., \mu_C$  are C group labels, each consisting of tokens in the vocabulary, V.

#### 3 THE LOTUS PROGRAMMING INTERFACE

In this section we describe the LOTUS API, which implements the semantic operator model as an extension of Pandas [10]. We chose a Pandas-like API in our initial system implementation to make it easy for users to integrate LOTUS with popular AI libraries in Python. However, semantic operators could also be added to a variety of other data processing APIs and query languages, such as SQL.

# 3.1 Datatypes

3.1.1 Data Model. LOTUS' data model consists of tables with structured and unstructured text fields. LOTUS' semantic operators can take both of these data-types as inputs. For instance, Figure 2 shows an example LOTUS program, where the table schema over ArXiv papers consists of attributes for the paper's title, ArXiv URL, abstract, ArXiv domain categories, and the publication date. These columns are then passed as parameters to semantic operators, such as sem\_search, sem\_filter, sem\_agg.

Additionally, LOTUS supports semantic indices over natural-language text columns to provide optimized query processing. These indices leverage semantic embeddings over each document in the column to capture semantic similarity using embedding distance metrics. Semantic indices can be created off-line with sem\_index and a specified retriever model, and then loaded using load\_sem\_index.

3.1.2 Parameterized Natural Language Expressions (langex). Programmers write each langex in natural language, parameterized by one or more data columns, which are indicated in the brackets within a string, or double brackets within a formatted string, as Figure 2 shows. Notably, these language expressions are sufficiently versatile and easy to program with, providing an intuitive and higher-level interface to the user. Operator-specific LLM prompts based on these expressions are automatically constructed by LOTUS' underlying query engine, and the underlying system can leverage existing prompt optimization techniques [39, 67] on- or off-line.

### 3.2 Semantic Operators in LOTUS

API, which includes the core set of operators described in Section 2, as well as several additional variants provided for convenience. <code>Sem\_filter, Sem\_join, & Sem\_sim\_join.</code> The LOTUS API supports <code>sem\_filter</code> and <code>sem\_join</code>, both of which take a langex predicate, as described in Section 2. In addition, LOTUS provides a join variant, <code>sem\_sim\_join</code>, where tuples are matched according to their <code>semantic similarity</code>, rather than an arbitrary natural-language predicate. Akin to an equi-join in standard relational algebra, the semantic similarity join is a specialized semantic join, which indicates additional optimization opportunities to the query engine. Figure 3 provides an example of the <code>sem\_join</code> compared to the <code>sem\_sim\_join</code>, where

We now overview the semantic operators supported in the LOTUS

the user specifies the left and right table join keys, and a parameter K. The operator performs a left join such that for each row in the left table, the output table will contain K matching rows from the right table with the highest semantically similarity scores.

Figure 3: Example usage of sem\_join and sem\_sim\_join.

Sem\_topk & Sem\_search . LOTUS supports a semantic top-k, which takes the langex ranking criteria, as described in Section 2. Programmers can optionally specify a group-by parameter to indicate a subset of columns to group over during ranking, as shown in Figure 4. The groupings are defined using standard equality matches over the group-by columns. Additionally, as the Figure shows, LOTUS also provides a top-k variant, sem\_search, which assumes a semantic similarity-based ranking criteria relative to a natural language query. LOTUS also exposes advanced relevance-based re-ranking functionality for search, allowing users to specify the n\_rerank parameter during the semantic search. The semantic search in this case will first find the top-K most relevant documents and then re-rank the top-K found documents to return the top n\_rerank.

```
papers_df.sem_topk("the {abstract} makes the most
    outrageous claim", K=10, group_by=[arxiv_domain])
papers_df.sem_search("abstract", "vector databases", 10)
```

Figure 4: Example usage of sem\_topk and sem\_search.

**Sem\_agg** performs an aggregation over the input relation, with as langex signature that provides a commutative and associative aggregation function, as shown by Figure 2. Similar to sem\_topk, LOTUS allows users to specify a group-by parameter.

Sem\_group\_by creates groups over the input dataframe according to the langex grouping criteria by clustering the data into a target number of groups (e.g., papers\_df.sem\_group\_by("the topic of the abstract", 20)). By default, the operator automatically selects group labels, but the user can also optionally specify target labels. This operator is useful both for unsupervised discovery of semantic groups, and for semantic classification tasks.

**Sem\_map & Sem\_extract** both perform a natural language projection over an existing column. While sem\_map projects to an arbitrary text attribute, sem\_extract projects each tuple to a list of sub-strings from the source text. This is useful for applications, such as entity extraction or fact-checking, where finding snippets or verified quotes may be preferable to synthesized answers.

# 4 EXECUTION PLANS AND OPTIMIZATIONS FOR SEMANTIC OPERATORS

Semantic operators create a rich design space of diverse execution plans which have significant consequences on system efficiency and accuracy. For example, there are many possible algorithms to join two collections of records using a LLM and a natural language expression (all the standard join algorithms, as well as ML heuristics to approximate the join, e.g., by semantically clustering similar records using an embedding model).

#### **Algorithm 1:** SEM-FILTER(T, l, M(x), A(x), $\gamma_R$ , $\gamma_P$ , $\delta$ ) **Input:** Relation T, langex predicate l, oracle model M(x), proxy model A(x), recall target $\gamma_R$ , precision target $\gamma_P$ , error probability $\delta$ Output: Filtered relation T $s \leftarrow 100 \, / /$ Sample size $S \leftarrow \text{ImportanceSample}(T, A(x), s)$ $M_S \leftarrow \{M(x): x \in S\}$ $A_D \leftarrow \{A(x) : x \in D\}$ $A_S \leftarrow \{A(x) : x \in S\}$ $\tau_{+} \leftarrow \text{PT\_threshold\_estimation}(S, l, M_S, A_S, \gamma_P, \delta/2)$ $\tau_{-} \leftarrow \mathsf{RT\_threshold\_estimation}(S, l, M_S, A_S, \gamma_R, \delta/2)$ $\tau_+ \leftarrow \max(\tau_+, \tau_-)$ // Evaluate predicate for each tuple for $t \in T$ do if $A(x) \ge \tau_+$ then $T' \leftarrow T' \cup \{t\}$ else if $A(x) \ge \tau_-$ then if M(x) then $T' \leftarrow T' \cup \{t\}$ end return T

Specifically our goal is to offer an efficient plan while while guaranteeing high accuracy. Defining accuracy for semantic transformations, however, presents a fundamental challenge in the absence of ground truth labels. Therefore, we define accuracy of each operator plan with respect to a "gold" algorithm, which uses a powerful oracle model M. These "gold" algorithms are tractable solutions that can achieve high quality results, but may be expensive in terms of execution time and LM call complexity. We discuss the design space of these "gold" algorithms for several core semantic operators we introduced. In addition, we present several novel optimizations for semantic filters, joins, top-k and group-by. These optimizations are either lossless or provide statistical guarantees on accuracy with respect to a "gold" algorithm with the expensive model M. Specifically, our approximations emulate the results of the expensive but high-quality algorithm by using model cascades [20, 33, 35, 60, 66] or semantic indexes, building on past work on accelerating MLbased query processing with guarantees [32, 35] but achieving this property for new types of operators. Notably, these optimizations can all be performed declaratively given a user's accuracy targets. We show in Section 5 that they significantly accelerate real applications.

While this paper proposes new optimizations for only a few, expensive semantic operators, we envision that a wide range of other new and traditional optimizations are possible under the semantic operator model. For example, several prior works demonstrate performance gains in both logical query plan optimizations (e.g. operator re-ordering [44, 45, 48, 49]) and other general LM-approximation techniques (e.g. code synthesis [17, 45] and prompt adaptation [20]).

#### 4.1 sem filter

4.1.1 Gold Algorithm. Our gold algorithm for the semantic filter runs batched LLM calls over the tuples in relation T. Each tuple, x, is processed independently using the model M(x), which is prompted to output a boolean value indicating whether the tuple passes the langex predicate.

4.1.2 Algorithmic Approximation. We can declaratively optimize semantic filters by providing an approximation which will obtain recall and precision targets  $\gamma_R$  and  $\gamma_P$  with respect to the gold implementation with probability  $1 - \delta$ . To achieve reduced cost we leverage the cheaper, but less accurate proxy model A(x), which provides a score indicating whether the tuple *x* passes the predicate, in conjunctions with the oracle LLM M(x). This idea is inspired by prior works [20, 33, 35, 60, 66, 66], which leverage model cascades for different problem settings. Specifically, several works study cascades in the video analytics setting with vision models, which have significantly different properties than LLMs, requiring different proxy scoring mechanisms. Additionally, other works, which study cascades for LLMs, use heavy-weight scoring mechanisms to decide whether to use the proxy model, which incurs a heavy execution time penalty, and does not provide accuracy guarantees. In contrast, we focus on providing accuracy guarantees for the constrained problem of applying cascades for filters, which allows us to use lighter-weight scoring functions than the more general case studied in prior works.

Providing accuracy guarantees is important because, in general, we cannot assume the proxy model is accurate. In fact, the proxy model, may perform very poorly for some tasks and datasets. The goal of our algorithm is to automatically discover the quality of the proxy by sampling and comparing to the gold algorithm with the oracle model. If the proxy provides high quality results, our algorithm will exploit it, leading to lower execution time. However, if the proxy model performs poorly, we will selectively route to it according to the proxy scores A(x), and a learned threshold  $\tau$  on the proxy scores. As prior work [34] discusses, such sampling-based algorithms to learn a threshold,  $\tau$ , introduce multiple-hypothesis testing problems, requiring statistical corrections using confidence intervals, which we carefully apply in our algorithm.

Our algorithm leverages a small LLM as the proxy model. We generate scores A(x) using the the log-probabilities corresponding to the True or False output tokens of the proxy model's answer and re-scaling by the quantiles over the proxy scores of tuples in the relation. Algorithm 1 shows the full procedure for performing the approximate semantic filter. We begin by using an collecting a sample *S*, which we label with the oracle and proxy models. The sampling procedure uses importance sampling and defensively mixes a uniform sample following prior work [35]. Using a the central limit theorem and the normal approximation on the distribution of sample statistics, we then find thresholds  $\tau_+$  and  $\tau_-$ , which will respectively ensure the desired precision target and recall target are met, each with an error probability of  $\delta/2$ . These sub-procedures follow the statistical techniques used in prior work [35], but applies them to this new setting where we must ensure both targets are met, requiring a correction for hypothesis testing and multiple failure modes. Finally the algorithm proceeds to process each tuple in the relation. If the tuple's proxy score is at least  $\tau_+$ , we mark it as passing the predicate. If the tuple's proxy score is less than or equal to  $\tau_-$ , we mark it as failing the predicate, and for tuples with proxy scores between  $\tau_+$  and  $\tau_-$ , we resort to the oracle model to provide a label.

# 4.2 sem\_join

4.2.1 Gold Algorithm. Performing the semantic join involves evaluating the user's natural language predicate on each pair of rows in the left table,  $T_1$  and right table,  $T_2$ . The gold algorithm implements a **nested-loop join pattern** with efficient batched inference to maximize GPU utilization. This yields an  $O(N_1 \cdot N_2)$  LM call complexity, where  $N_1$  and  $N_2$  are the table sizes of the left and right join tables respectively. Each LM call instructs the model to output a boolean value after evaluating the user's natural language predicate. This quadratic join algorithm is suitable for small join tables but scales poorly for large tables.

4.2.2 Algorithmic Approximation. Similar to semantic filters, we declaratively optimize semantic joins by providing an approximation that obtains recall and precision targets  $\gamma_R$  and  $\gamma_P$  with respect to the gold algorithm with probability  $1-\delta$ . Due to the expensive quadratic scaling of the nested-loop join, rather than using a small LLM as the proxy model, we leverage an even cheaper proxy based on semantic similarity scores, which can be obtained efficiently with a semantic index over the join keys. We leverage two possible join approximation algorithms and dynamically chooses the lowest cost one, which will minimize the number of LLM calls.

The first approximation, **sim-filter** produces a proxy score  $A(x_i, x_j)$ ,  $x_i \in T_1, x_j \in T_2$  based on embedding similarity. We leverage the semantic index to perform batched similarity search and re-calibrate similarity scores according to the quantiles of the distribution over all pairs to obtain proxy scores. This approximation is likely to perform efficiently when tuple pairs with high semantic similarity between the the right and left join key are more likely to pass the predicate. This correlation phenomenon between predicate matches and embedding similarity has been studied by prior works [51] and is not always present. Thus, we introduce an alternative approximation suitable when correlation is not present.

The second approximation, map-sim-filter first performs a projection over the left join key and then uses the projected column to compute proxy scores  $A(x_i', x_j)$  uses the embedding similarity between the projected value  $x_i'$  and  $x_j$ . As before we also re-calibrate the proxy scores taking their quantiles. Intuitively, performing the projection is useful when tuple pairs that pass the user's natural language predicate exhibit low semantic similarity. The projection step invokes the LM over each tuple in left join table, prompting it to predict values in the attribute domain of the right join key that match. Notably, this LM projection is ungrounded, i.e., it is done without knowledge of the right join key's attribute domain and can thus be performed in a fully parallelized semantic map operation, which can optionally take user-provided demonstrations. Figure 5 provides an example of a semantic join between a table of papers and datasets, where the predicate evaluates whether a given paper abstract uses a specific dataset. Here, the map step would invoke the LM over each abstract, instructing the model to output the dataset used, conditioned only on the abstract.

To dynamically choose between these two approximations, we follow a procedure similar to Algorithm 1 used for semantic filters. We begin by importance sampling to collect the sample S and construct the set of oracle labels,  $O_S$ , over the sample. We then obtain  $A_D$ ,  $A_S$   $\tau_+$  and  $\tau_-$  independently for each approximation algorithm using their respective proxy scores. Using the tuned thresholds and

```
papers_df.sem_join(dataset_df, "The paper {abstract:left
} uses the {dataset:right}.", recall_target=0.9,
precision_target=0.9, delta=0.1)
```

Figure 5: Example sem\_join for matching papers and datasets.

known proxy scores over for both algorithms over the dataset, we then determine the exact oracle cost needed to execute either algorithm, and we take the least cost plan with its associated learned thresholds to proceed to evaluate the predicate for each tuple pair.

# 4.3 sem\_group\_by

Performing this semantic operator entails discovering group labels and classifying each input tuple using the discovered labels. In general, performing the unsupervised group discovery is a clustering task, which is NP-hard [22]. Our gold algorithm instead offers a tractable implementation to obtain group labels using a linear pass over the data with the reference model M. Furthermore, once the labels are discovered, we perform the LM-based classification task and show how to optimize this step using an approximation with probabilistic guarantees.

4.3.1 Gold Algorithm. Our semantic group-by algorithm proceeds in two stages. The first stage performs the unsupervised label discovery, given the user's grouping criteria and target number of groups. This stage first performs a semantic projection, prompting the LM to predict a label for each input tuple. Then, we create a semantic index over the projected column and perform a vector clustering over these predicted labels, using FAISS' efficient k-means implementation to construct *C* groups. Lastly, for each group, we top-k sample documents based on their similarity to the centroid, and few-shot prompt the LM to generate a label describing the given documents according to the user-provided grouping criteria (e.g. the topics of the documents) using a semantic aggregation.

In the second stage of the algorithm, we use the  $\mathcal{C}$  generated labels to perform classification over each document. We do this using a semantic map, which prompts the LM to output a label conditioned on the candidate labels and document.

4.3.2 Algorithmic Approximation. We provide an efficient approximation, specifically for the classification task in the second stage of the algorithm. Similar to semantic filters and join, we perform this optimization declaratively, while guaranteeing a classification accuracy target is met with probability  $1 - \delta$ . Similar, to semantic joins, we leverage semantic similarity scores as a cheap proxy. Specifically, we leverage the index constructed in stage one of the algorithm and compute similarity scores between the embeddings of each document's un-grounded prediction and the embeddings of each class label. The proxy score of the tuple  $t_i$  with a predicted label,  $x_i$ , for group label  $\mu_i$  is given by  $A(x_i, \mu_i) = sim(x_i, \mu_i)$ . Our goal is then to learn a threshold,  $\tau$ , such that if the similarity between an embedding and the class label's embedding is greater than  $\tau$ , we return the class label, and otherwise we resort to the more expensive LM-based classification procedure. We accomplish this by uniform sampling and running the sub procedure equivalent to the PT\_threshold\_estimation used in Algorithm 1 for semantic filters, where the metric we evaluate is classification accuracy over the C groups.

# 4.4 sem\_topk

Performing a semantic top-k ranking requires logically reasoning *across* rows, entailing joint reasoning over often large amounts of data. While prior works have studied LM-based passage reranking [23, 26, 43, 50, 52–55, 57] and ranking with noisy comparisons [18, 56] with the goal of achieving high quality results in a modest number of total LM calls or comparisons, our implementations provides a generalized ranking algorithms for arbitrary natural language expressions and aims to produce both high quality results and low execution time. Here we outline leverage several algorithmic design decisions for the gold algorithm as well as a lossless optimization.

4.4.1 Gold Algorithm. Two important algorithmic design decisions for the semantic top-k include how to implement the LM-based comparison and how to aggregate ranking information across LM-based comparisons. Our implementation uses pairwise LM-based comparisons for the former, and a quick-select based top-k algorithm [29] for the latter.

We briefly describe the reason for these choices and alternatives considered. Pairwise-prompting methods offer a simple and effective approach that feeds a single pair of documents to the LM in each invocation, prompting the model to perform a comparison and output a binary label. The two main classes of alternatives are point-wise ranking methods [23, 26, 43, 55, 63], and list-wise ranking methods [50, 52, 53, 57], both of which have been shown to face quality issues [23, 54, 57]. In contrast, pairwise comparisons have been shown to be an effective base unit for ranking with relatively high robustness to input order sensitivity [54].

In addition, we studied several alternative rank-aggregation algorithm, including quadratic sorting algorithms, a heap-based top-k algorithm and a quick-select-based top-k ranking algorithm, which we discuss in Section 5. The quick-select based algorithm proceeds in successive rounds, each time choosing a pivot, and comparing all other remaining elements in the document set to the pivot item to determine the rank of the pivot. Because each round is fully parallelizable, we can efficiently batch these LM-based comparisons before recursing in the next round. In section 5, we find that the quick-select-based algorithm offers high accuracy while also offering an efficient implementation with at least an order magnitude fewer total calls then the quadratic sorting algorithm and more opportunities for efficient batched inference, leading to lower execution time, compared to a heap-based implementation.

4.4.2 Optimizations. We leverage the semantic index to optimize pivot selection for some queries, while incurring no accuracy loss. This optimization is useful when there exists correlation between the rankings imposed by the user's arbitrary sorting criteria and the rankings imposed by semantic similarity scores. In this case, LOTUS can sort the document set based on embedding distances to the user's query, and select the  $(k+\epsilon)$ -th item, rather than a random item, as the first pivot. This can reduce the number of LM comparisons required by subsequent rounds in the quick-select algorithm, leading to higher query efficiency at no accuracy loss. In the case of no correlation between the langex-based ranking and similarity-based ranking, this method amounts to random pivot selection, and in the worst case of an adversarial pivot, the algorithm

will incur one extra pivot round, which can impact execution time, but not degrade quality.

## 4.5 sem\_agg

Performing semantic aggregations is inherently challenging because, similar to the semantic top-k, it requires logically reasoning *across* rows. Thus, the operator's implementation must efficiently orchestrate the LM over large amounts of data, while managing long context inputs, which may degrade result quality [46] or overflow the underlying model's context length. LOTUS aims to abstract away such low-level details from the user and provides an efficient implementation, designed to support high quality results.

4.5.1 Gold Algorithm. Our implementation builds on the LM-based summarization pattern studied by prior research works [15, 19, 62] and deployed systems [7, 12]. These implementations primarily leverage one of two aggregation patterns: either a **fold pattern**, which produces a sequential, linear pass over the data while iteratively updating an accumulated partial answer, or a **hierarchical reduce pattern**, which recursively aggregates the input data to produce partial answers until a single answer remains. Our aggregation implements the hierarchical pattern, which allows for greater parallelism during query processing and has been shown to produce higher quality results for tasks like summarization in prior work [19].

#### **5 EVALUATION**

We now evaluate the expressiveness of the semantic operator model as well as the efficiency of our algorithms and optimizations through four diverse applications: fact-checking (Section 5.1), extreme multilabel classification (Section 5.2), search and ranking (Section 5.3), and paper analysis (Section 5.4). We find that the semantic operator model is expressive and easy to program with, capturing state-of-the-art AI pipelines in a few operator calls, and making it easy to express new pipelines that achieve up to 180% higher quality. We also find that our optimizations that take advantage of the declarative nature of semantic operators can accelerate semantic filtering, top-k, group-by and join operators by up to  $400\times$  while offering statistical accuracy guarantees. Overall, LOTUS queries match or exceed the accuracy of state-of-the-art AI pipelines for each task while executing up to  $28\times$  faster end-to-end.

LOTUS' current implementation extends the Pandas API [10]. We leverage vLLM [41] to perform efficient batched inference, and we use FAISS [31] to support efficient vector search for LOTUS' semantic search, similarity join and cluster operations.

Unless otherwise stated, we run our local model experiments with 4 A100 GPUs using Llama-3 models [6], with a batch size of 64 running on vLLM [41]. For our experiments that use OpenAI's GPT-40-2024-05-13 model [9], we control for cost by limiting execution to 64-way thread parallelism. We set temperature to t=0, unless otherwise stated.

# 5.1 Application: Fact-Checking

**Application.** We evaluate on FEVER [59], a claim verification dataset. We use the development dataset, which contains about 38,000 total claims, of which we sample 1,000 for our evaluation. Each claim is labeled with one of three labels, "Supported", "Refuted",

Table 2: Fact-checking Results on the Fever Dataset.

Method	Accuracy	Execution Time (s), batched	Execution Time (s), no batching	LoC
FacTool	80.9	N/A	5396.11	>
				750
LOTUS-Factool	89.9	688.90	4,454.24	< 50
LOTUS-fact-filter	91.2	329.1	988.95	< 50
LOTUS-fact-filter (opt.)*	91.0	189.88	776.37	< 50
LOTUS-fact-join	84.5	11,951.35	60,364.39	< 50

\*  $\gamma_R = \gamma_P = .9, \delta = 0.2, s = 100$ 

or "NotEnoughInfo", and the task is to correctly determine the label of each claim, leveraging evidence from a corpus of 5.5 million Wikipedia articles. We merge the latter two labels in to a single class, "Not Supported", following prior work [21] for our evaluation. *Baselines.* FacTool [21] is a recent research work that proposes a multi-step pipeline for fact-checking involving, claim extraction, query generation, tool querying, evidence collection, and verification. We use FactTool's open source codebase [5] to measure its performance. FactTool's pipeline, by default, performs retrieval with a Google Search API [3]. We evaluate the pipeline with both the default retrieval API, and with the open-source ColBERT [40] index. We find that the results are similar, and we report the results using ColBERT for retrieval to hold the retriever model constant with the implemented LOTUS programs.

**LOTUS Programs.** We compose several intuitive LOTUS programs, each in less than 50 lines of code. For each one, we use ColBERT as the retriever model for creating the semantic index, and we use Llama-70B as the primary LM, and Llama-8B as the cascade proxy.

First, we compose a pipeline designed to directly re-implement FacTool's information flow in LOTUS. Figure 6 shows the pseudocode for the LOTUS-FacTool pipeline. The two tables are shown by wiki\_df, which stores the Wikipedia articles, and claim\_df, which stores the claims from the FEVER dataset. After loading the semantic index to wiki\_df, the pipeline first performs a semantic map over each claim to generate two search queries, which are then used to perform a semantic similarity join over the corpus of Wikipedia articles. The program then concatenates the context retrieved for each claim, and performs a sem\_map to output whether the claim is true or false, along with a revised claim if the claim is false. We use the same prompts found in FacTool [5], which include 3 demonstrations for generating search queries in the first sem\_map, and chain-of-thought prompting in the second sem\_map.

The next program, LOTUS-fact-filter, makes a simple, single-operator modification to the LOTUS-FacTool program, replacing the semantic map at the end of the program, with a semantic filter. We use 3 demonstrations for the filter. Figure 7 shows the pseudocode for this program. We evaluate this program with and without model cascades applied to the semantic filter.

Lastly, we compose an alternative pipeline, LOTUS-fact-join. As the pseudocode shows in Figure 8, the pipeline first performs a semantic map over each claim to obtain a set of sub-claims. From this, we create the claimed\_facts\_df, which separates each sub-claim into a different row. Next, the pipeline uses these sub-claims to perform a semantic similarity join over the Wikipedia corpus, then

```
wiki_df.load_sem_index("article", "index_dir")
claim_df.sem_map("write 2 search queries given the {
    claim}", name="query")\
    .sem_sim_join(wiki_df, left_on="query", right_on="
    articles", K=10)\
    # concatenate articles for each claim
    .groupby(["claim"]).apply(lambda x: "\n".join(x["
    articles"]))\
    .sem_map("Identify whether there are any factual
    errors in the {claim} based on the {articles}.
    Include your resasoning, any errors found in the
    claim, and the factuality of the claim.")
```

Figure 6: LOTUS-FacTool pipeline, using semantic map, sim-join, and map for fact-checking

```
wiki_df.load_sem_index("article", "index_dir")
claim_df.sem_map("write 2 search queries given the {
    claim}", name="query")\
sem_sim_join(wiki_df, left_on="query", right_on="
    articles", K=10)\
# concatenate articles for each claim
sgroupby(["claim"]).apply(lambda x: "\n".join(x["
    articles"]))\
sem_filter("given the {context}, the {claim} is
    factual.", confidence_threshold=0.9)
```

Figure 7: LOTUS-fact-filter pipeline, using semantic map, sim-join, and filter for fact-checking

```
for claim in claims_df["claim]:
    df = pd.DataFrame({"claim": [claim]})\
        .sem_map("what sub-claims are made in the {claim} 
}", name=claimed_facts")
        .apply(lambda x: x[claimed_facts].split(","))
    claimed_facts_df = pd.DataFrame({"claims": df[claims]})
        .sem_sim_join(wiki_df, left_on="claim", right_on ="articles", K=20, n_rerank=10)\
        .sem_map("summarize the important facts in the { article}", name=facts)\
        .sem_join(claimed_fact_df, "is the { claimed_facts:right} verified by the {facts:left}")
```

Figure 8: LOTUS-fact-join pipeline, using semantic map, sim-join, map, and join for fact-checking

performs a semantic map over each retrieved article to generate the important facts in each one. Lastly, the program performs a semantic join between the sub-claims and the facts described in the retrieved passages. If the returned table contains a supporting fact for each sub-claim, the claim is labeled as "Supported". For the sem\_map and join operations, we use 3 demonstrations each.

Results. Table 2 demonstrates the powerful abstraction that semantic operators provide, allowing programmers to quickly write and test programs that compose a few operators to obtain state-of-the-art results. We report the accuracy of each benchmarked method, an estimate of lines of code (LoC), and execution time in seconds both with and without batching averaged over 10 runs. We see that FacTool's implementation offers strong accuracy performance on the FEVER dataset, however the full repository was written from scratch in several hundred lines of code, representing a significant development burden. By contrast, each LOTUS program offers comparable or higher accuracy, in relatively few lines of code. We also note that FacTool implements its method without batching, whereas LOTUS, by default, leverages batched LM execution for efficiency. To provide an apples-to-apples comparison, we compare

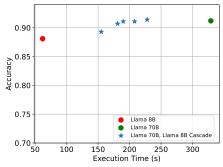


Figure 9: Accuracy versus execution time (s) for the LOTUS-fact-filter pipeline on the FEVER dataset for fact-checking. We compare the pipeline implemented using a single model (circles) to the pipeline implemented using cascades with two models (stars) with varied the precision and recall target, at  $\delta = 0.2$ .

FacTool's un-batched implementation to the LOTUS programs both with and without batching.

First, we see from the Table 2 that LOTUS-FacTool is able to reproduce the result quality and efficiency of the original method's implementation, with 9.0 points higher accuracy and 1.2× lower execution time without batching. The LOTUS-FacTool implementation with batching further decreases execution time compared to FacTool by 7.8×. We see that the next LOTUS pipeline simply changes a single operation, switching the sem\_map to a sem\_filter, and maintains similar result quality to LOTUS-FacTool while further reducing execution time by 2.1× in the batched implementation.

Leveraging LOTUS' filter operation allows the programmer to further declaratively optimize the program using an approximation, which maintains high accuracy and reduces the batched execution time by 3.62× compared to LOTUS-FacTool. Figure 9 highlights the diverse performance trade-offs presented by the model cascade optimizations used in LOTUS' filter sem\_filter. The plot shows the accuracy and execution time of the LOTUS-fact-filter pipeline using a single model, either Llama 8b, or Llama 70B, shown by the circles. We compare this to the performance attainable using a pair of models, Llama 8B and Llama 70B, to implement the filter with our casacade-based approximation. We generate multiple cascade points, shown by the stars, by varying the recall and precision targets of the filter operator, and setting the error probability  $\delta = 0.2$ . The plot shows that this filter optimization can substantially reduce execution time, and offer diverse accuracy trade-offs, compared to implementing the pipeline with the oracle model, Llama 70B, alone. We also verify that the algorithm's probabilistic guarantees hold by testing 100 trials for 0.9 recall and precision targets at  $\delta = 0.2$ . We find the targets are met in 99 of the 100 trials, satisfying and exceeding the guaranteed 0.8 success rate.

Returning to Table 2, we find that the last LOTUS pipeline (LOTUS-fact-join), reduces accuracy and increases execution time. Notably the performance trade-offs of different AI programs are non-obvious, highlighting the need for programmable, declarative abstractions so programmers can quickly explore and iterate on their query pipelines. Each LOTUS program we described can be implemented easily in relatively few lines of code, and the best performing one offers 10.1% higher accuracy and 28× lower execution time than FacTool's original, un-batched implementation.

Table 3: Extreme Multi-label Classification Results on Biodex Dataset with Llama-70b

Time (s)         Cal           Sem-sim-join         0.106         0.120         2.91         0.0	LM lls
•	
LOTUS Sem-join** 0.244 0.261 5,891.6 15,	0
	107
nested-loop pattern $N/A$ $N/A$ $2,144,560^*$ $6,0$	92,500
map-sim-filter pattern** 0.244 0.261 5,891.6 15,	107
sim-filter pattern** 0.154 0.191 24,206.8 63,	

<sup>\*</sup> Estimated under linear-scaling assumption in number of batch calls. \*\*  $\gamma_R = \gamma_P = 0.9, \delta = 0.2, s = 0.01|T_1||T_2|$ 

# 5.2 Application: Extreme Multi-label Classification

**Dataset.** We evaluate on the Biodex Dataset [25], which consists of a corpus of 65,000 biomedical articles, and expert-created drug safety reports constructed from each article. The task is to correctly label the drug reactions experience by the patient in each medical article. We sample 250 patient articles for our evaluation. Notably, there are 24,000 possible drug-reaction labels, making this task an extreme multi-label classification task. Due to the large number of possible labels, leveraging an LM to perform inference is difficult, and this setting has been studied in prior works [24]. We show below that this task can be efficiently modeled and programmed using the semantic join.

*Baselines* We consider a retrieval baseline which uses an E5Model [61] as the retriever and performs a semantic-similarity join between the patient articles and the reaction labels.

**LOTUS Programs.** Our LOTUS program performs a semantic join over the drug reaction labels and the medical articles, as shown in Figure 10. We perform the semantic join using at most 7 map demonstrations. We use Llama-70b as the LM and the E5Model [61] as the retriever for the semantic index.

```
1 articles_df.sem_join(reaction_labels_df, "The {article}
    indicates that the patient is experiencing the {
        drug_reaction}", map_dems=dems, call_budget=10000)
```

Figure 10: Extreme multi-label classification LOTUS program

Results. Table 3 shows that the proposed LOTUS program makes meaningful traction, obtaining high quality results on this task, while providing query efficiency compared to naive join implementations. The table reports the rank-precision@5 (RP@5) and rank-precision@10 (RP@10), following prior work [24], as well as execution time in seconds and the number of LM calls used. Since the nested-loop join pattern is prohibitively expensive to run, we show an estimate of the execution time assuming linear scaling in the number of batched calls.

First we compare performance of the LOTUS join program, declaratively optimized, to the baseline, a semantic similarity join. As expected, the optimized LOTUS join offers substantially higher quality results, with 2.3× and 2.18× higher RP@5 and RP@10 respectively compared to the similarity join. This highlights the effectiveness of leveraging LMs over the data for complex reasoning-based tasks. We informally compare these accuracy results to recent work [24] which composes a multi-step DSPy [39] program compiled using Llama-2-7b-chat as the student LM and GPT-3.5-turbo as the teacher LM to perform a semantic mapping, followed by a

re-ranking step using GPT-4-turbo. D'Oosterlinck et al. report 24.73 RP@5 and 27.67 RP@10 for the compiled program, representing comparable result quality to LOTUS' program, although notably the LOTUS program was not compiled with a prompt optimization system.

We now consider several interesting performance trade-offs presented by semantic join algorithms. We compare the map-sim-filter join pattern, which was automatically selected in the LOTUS semjoin, to the naive nested-loop join algorithm and the sim-filter join pattern shown in Table 3. We see that nested-loop join pattern, which involves a quadratic LM budget of over 6 million LM calls, is prohibitively costly. By contrast, the sim-filter and map-sim-filter pattern substantially reduce the LM call budget of the naive algorithm by 95× and 400× respectively. LOTUS' optimizer automatically selects the lower cost algorithm, in this case map-sim-filter. The selected pattern also results in significantly better accuracy due to its higher quality proxy score for this task. Specifically, the map-sim-filter pattern offers 58% higher RP@5 and 37% higher RP@10 compared to the sim-filter.

# 5.3 Application: Search & Ranking

**Dataset.** We evaluate LOTUS' performance on the search and ranking task using three datasets: BEIR's SciFact test set [58], a widely used benchmark for retrieval and re-ranking, and two new benchmarks, CIFAR-bench, and HellaSwag-bench, which we generated to evaluate more complex ranking criteria over the data. For each, we report nDCG@10 and execution time (ET) in seconds.

The SciFact dataset consists of a set of scientific claims and a corpus of articles, where the task is to rank articles by relevance to a given claim. We sample 300 claims for our evaluation, and report the average ranking execution time across these samples.

While the SciFact dataset provides a sorting task based on a simple relevance criterion, our generated benchmarks provide a more complex sorting criteria each over a corpus of paper abstracts. The task is to rank papers according to highest reported accuracy on CIFAR-10 and HellaSwag in CIFAR-bench and HellaSwag-bench, respectively. To generate CIFAR-bench, we took 100 abstracts from the Papers with Code Dataset [11] that state performance on CIFAR-10 in the abstract, and we and manually labeled their accuracy to obtain ground truth. We then synthetically generated HellaSwagbench by prompting Llama-70B to create 200 paper abstracts, each with a specified accuracy value, randomly sampled from 0 - 100%. These datasets allows us to evaluate LOTUS' LM-based sorting algorithms on a task with objective ground truth an ranking criteria other than relevance-based ones. We note that an alternative approach to these tasks could efficiently leverage sem\_map to extract accuracy values on abstracts from either dataset, then perform a structured sort. However, our evaluation focuses on assessing the semantic ranking capabilities of various top-k algorithms, and we find this benchmark useful for understanding performance trade-offs, which may generalize to a wider set of reasoning-based ranking queries. We report results for n = 20 trials at temperature t = 0.7, similar to prior works [39]

**Baselines.** We consider two simple baselines: a semantic search, using the E5Model [61] for retrieval, and a search with re-ranking, using the E5Model for retrieval and the MixedBread cross-encoder [14]

Table 4: Ranking Results on SciFact

Method	nDCG@10	ET (s)
Search	0.712	0.009
Search + Reranker	0.741	2.64
LOTUS Top-k - Llama-70B	0.775	33.6
LOTUS Top-k - GPT-40	0.800	11.2

Table 5: Ranking Results on CIFAR- & HellaSwag-bench

Method	CIFA	R	HellaSwag		
	nDCG@10	ET (s)	nDCG@10	ET (s)	
Search	0.252	0.008	0.119	0.008	
Search + Reranker	0.001	2.57	0.461	2.36	
LOTUS Top-k - Llama 70B	0.710	39.6	0.975	63.6	

for re-ranking. We use choose these models because they are recent high quality embedding and re-rankers.

**LOTUS Program.** Our LOTUS program performs a semantic top-*k* over the documents. The langex for the semantic top-*k* on SciFact sorts based on relevance to the given claim, while the langex for the CIFAR-bench and HellaSwag-bench datasets sort abstracts by accuracy performance on the respective datasets. For SciFact, we perform a semantic search using the E5Model as the retriever to obtain 100 articles, before ranking them with the sem\_topk. We report results using both Llama-70B and GPT-40 as the LM.

Results. Tables 4 and 5 demonstrate the effectiveness of LOTUS' semantic top-k for complex search tasks. In addition, Table 6 highlights the rich implementation design space that this task presents. We walk through several note-worthy findings. We first turn our attention to Table 4, which presents the results for each bench-marked method on the SciFact dataset, which uses a relevance-based sorting criterion. As expected, both semantic search programs with and without re-ranking present strong baselines. Specifically, the reranker model, which is a supervised model trained specifically for the task of relevance-based ranking, increases nDCG@10 by 3 percentage points, while trading off query efficiency compared to the semantic search baseline. Notably, the unsupervised LM-based LO-TUS programs outperform the supervised re-ranker's result quality. The table shows LOTUS semantic top-k program with Llama-70B and GPT-40, which outperform the semantic search baseline by 6 and 9 percentage points respectively. The LOTUS programs with Llama-70B and GPT-40 also outperform the re-ranker by 3 and 5 points respectively, improving upon the quality of the supervised baseline. As expected, the improved result quality comes at a trade-off to query efficiency due to the cost of LM calls. Notably, LOTUS' versatility allows programmers to easily compose each of these query pipelines and trade-off result quality and efficiency depending on application-specific requirements.

Turning our attention to Table 5, we study LOTUS' generality in supporting arbitrary language-based ranking criteria over the dataset. On the CIFAR-bench and HellaSwag-bench datasets, which use a complex sorting criteria, we see that both semantic search baselines with and without re-ranking provide poor result quality with consistently low nDCG@10. The LOTUS program, using a semantic top-k with Llama 70B, acheives significant accuracy gains,

Method	Scifact		CIFAR			HellaSwag			
	nDCG@10	ET (s)	# LM Calls	nDCG@10	ET (s)	# LM Calls	nDCG@10	ET (s)	# LM Calls
Quadratic Sort	0.836	712	4950	0.868	634	4950	0.966	1,803	19,900
Heap Top-k	0.776	65.0	216	0.832	99.6	350	0.907	98.9	415.2
QuickSelect Top-k	0.776	42.4	285	0.746	41.3	303.95	0.909	59.1	620.95
QuickSelect Top-k + Semantic Index	0.775	33.6	229	0.710	39.6	307.7	0.975	63.6	672.7

Table 6: Comparison of Ranking Results for Different Semantic Top-k Algorithms using Llama-70B

with 180% and 110% higher nDCG@10 than the best performing baseline on CIFAR-bench and HellaSwag respectively. These accuracy gains reflect the powerful reasoning capabilities of LMs efficiently orchestrated over the data. As expected, these significant accuracy gains come at an increase to execution time.

We now analyze the efficiency of our semantic top-k implementation along with it's proposed optimizations compared to alternatives. Table 6 compares several semantic top-k algorithms, namely a quick-select top-k algorithm, a quick-select top-k that leverages the similarity index for pivot selection, a heap-based top-k algorithm, and a quadratic sorting algorithm. First, we see that the quadratic algorithm, which performs an LM comparison between each pair of input documents, offers consistently high result quality across each dataset. However, this method is prohibitively expensive, requiring  $16 - 30 \times$  more LM calls and over  $10 \times$  higher execution time than the alternative implementations. The heap top-k and quick-select top-k methods offer comparable result quality, but with interesting trade-offs in query efficiency. Notably the quick-select top-k method offers 1.67 - 2.24× lower execution time than the heapbased sorting method across all datasets, despite requiring more LM calls in some cases. This is because the quick-select top-k implementation allows for efficient batch-processing in each round of the algorithm, whereas the heap-based top-k incurs sequential LM calls during heap updates. For this reason, our current implementation leverages the quick-select top-k algorithm, although we envision future iterations may leverage multiple algorithms and allow the user to declaratively trade-off accuracy, query throughput, and cost.

In addition to providing an efficient top-k algorithm, the table also demonstrates our use of the similarity index for optimizing top-k query performance. The quick-select top-k algorithm optimized with the semantic similarity index for pivot selection demonstrates  $1.2\times$  lower execution time at no accuracy loss on SciFact, where the ranking criteria correlates likely with semantic similarity. On the other hand, for the CIFAR-bench and HellaSwag-bench datasets, where the ranking criteria does not correlate with semantic similarity, we see that the similarity index has no significant impact on the accuracy or efficiency top-k performance.

## 5.4 Application: ArXiv Paper Analysis

**Dataset.** Lastly, we evaluate LOTUS' use in analyzing a large corpus of documents, specifically focusing on the performance of sem\_group\_by and its approximation algorithm with accuracy guarantees. The dataset consists of 647 recent ArXiv articles we scraped, from the database (cs.DB), information retrieval (cs.IR), cryptography and security (cs.CR), and robotics (cs.RO) domains. The task is to group the papers according to the topics they discuss. **Baselines.** The sem\_group\_by consists of two sub-tasks: (a) discovering the groups and labels, and (b) classifying each document

Table 7: Discovered Group Labels Over ArXiv Papers

(μ<sub>1</sub>) Advancements in Recommender Systems and Multimodal Data Integration (μ<sub>2</sub>) Advancements in Generative Information Retrieval Systems (μ<sub>3</sub>) Advancements in Large Language Models for Various Applications (μ<sub>4</sub>) Advancements in AI Security and Malware Detection Techniques (μ<sub>5</sub>) Advancements in Robotic Navigation and Manipulation Techniques

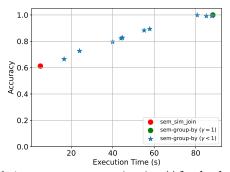


Figure 11: Accuracy versus execution time (s) for the classification sub-procedure of sem-group-by on the ArXiv dataset. By varying the classification accuracy target and using  $\delta=0.2$ , we generate several points and compare this to the performance of a retriever-based similarity join.

using the discovered labels. As a baseline for the latter, we consider a semantic similarity join between the labels and each abstract. We use the E5 embedding model for retrieval.

*IRIS Programs.* We use the LOTUS sem\_group\_by operator to find 5 groups based on the topic abstracts. We use Llama-70B as the LM, the E5Model as the retrieval model, and 100 samples for the approximation algorithm described in Section 4.

**Results.** We first qualitatively analyze the labels discovered, in the first phase of LOTUS' implementation. As Figure 7 shows, the discovered labels intuitively align with the ArXiv domains included in the paper scrap, including important and timely topics related to recommendation systems, retrieval, LLM applications, AI security, and robotics. Performing this unsupervised group discovery took 44.03 seconds, representing a tractable and efficient implementation.

Finally, turning our analysis to the classification subprocedure in our sem\_group\_by implementation, we evaluate the declarative algorithmic approximation. Figure 11 compares the execution time and classification accuracy with respect to the oracle implementation for the operator implemented with varying accuracy targets using  $\delta=0.2$ . We see that the oracle implementation, at  $\gamma=1$ , offers the slowest execution time. On the other hand, the similarity-join baseline has 17.4× faster execution time, but only 61% accuracy with respect to the LM. We find our proxy-based optimization offers diverse performance trade-offs and allows the user to declaratively

interpolate between these two extremes. We also note that the sampling procedure used to perform this optimization took less than 5 seconds, representing a small relatives cost.

#### 6 RELATED WORK

Specialized LLM-based Relational Extensions. Several prior works extend relational languages with a set of logically row-wise LM-based operations to serve specialized tasks. Palimpzest [45] presents a declarative approach to data cleaning and extract-transform-load (ETL) tasks. The authors propose to automatically optimize relational operators with LM calls, and implement two row-wise relational operators, a newly proposed convert operator, which can be transparently optimized to perform entity extraction using LLMs, and an AI-based filter operation, logically similar to LOTUS' sem\_filter. The system also implements several query optimizations, such as operator re-ordering, model selection, and code synthesis and proposes several others as future work.

SUQL [48] presents a SQL extension to support *conversational* agents with knowledge grounding over structured and unstructured data. Specifically, the system extends SQL with two new logically row-wise operators, answer, which prompts an LM to answer the user question over each row, and summary, which prompts an LM to provide a summary to the user over each row. The system can provide automatic optimizations, such as predicate re-ordering using a lazy evaluation approach and proposes to use retrieval to optimize some answer queries.

ZenDB [44] and EVAPORATE [17] tackle the task of automatically *ingesting and extracting semi-structured documents* into structured tables that can be queried using standard relational operators and languages. ZenDB extracts structure using a semantic hierarchical tree index, which is integrated with a SQL query engine to support efficient query processing over the extracted attribute values. The systems implements several optimizations, including predicate reordering, push-down, and projection pull-up. Additionally, EVAPORATE performs efficient entity extraction from semi-structured data using LM-based code generation and weak supervision to ensemble candidate functions.

In contrast to these works, semantic operators are a *general-purpose query model* designed to capture broad-ranging applications, including both logically row-wise ones and more complex ones, such as joins, aggregation, ranking and search functions, as an extension of the relational model. For example, users can use sem\_map for row-wise entity extraction over unstructured text fields, but can also perform other operations over entire tables, such as sem\_join. We also propose multiple execution algorithms and novel optimizations for these bulk operators (Section 4). Some of the optimizations in prior specialized systems, such as lazy evaluation, operator reordering, model selection, and code synthesis, are worthwhile future work for LOTUS' optimizer.

LLM UDFs. Recent research [47] and some existing DBMS vendors, such as BigQuery [8], Databricks [1] and Redshift [13], offer LLM user-defined functions (UDFs) in SQL. LLM UDFs are a lower-level programming interface that is limited to row-wise LLM execution over the data, equivalent to our sem\_map semantic operator. In contrast, our semantic operator programming model is high-level and declarative, allowing the system to automatically select which

an algorithm to use and manage calls to the LM to support complex operations, including aggregations, ranking, and joins.

Liu et al. [47] study how to optimize LLM UDF calls, demonstrating performance gains with a de-duplication and prefix-sharing method that reorders rows and input fields to maximize key-value (KV) cache reuse during LLM calls. This is orthogonal to our optimizations but could likely accelerate batch LLM calls from LOTUS. LM Programming Frameworks. LM programming frameworks such as LangChain [7], LlamaIndex [12], and DSPy [39], have gained significant popularity. They provide abstractions for programming with LMs, including utilities for creating prompts and post-processing LM outputs, and modules for common calling patterns such as RAG, chat-bots, and agents. DSPy also optimizes a pipeline of LLM calls to maximize a target metric by tuning prompts and model weights. However, all these frameworks focus on expressing a pipeline of LLM calls that takes a single small input (or a stream of inputs for chat), as opposed to programs for processing large datasets. While some of them support batched calls with multi-threading, support for bulk-processing is sparsely supported and largely un-optimized. In contrast, semantic operators and LO-TUS are designed for bulk semantic processing and introduce novel operators and optimizations for this task.

**ML-based Query Processing.** Many prior works study the use of machine learning (ML) in databases, but do not focus on LLMs, which present unique usage patterns and optimization opportunities. MADLib [28] extends SQL with abstractions for machine learning and descriptive statistics. Prior works such as NoScope [33], TASTI [37], SUPG [34], BlazeIt [32] and probabilistic predicates [49] propose methods to optimize queries involving expensive ML models over large datasets, typically in video analytics. Some optimizations proposed in these works, such as model cascades and predicate re-ordering, are also useful for optimizing LOTUS pipelines with language models. However, our bulk semantic processing setting requires new operators with significantly different semantics, such as sem\_join and sem\_groupby, which were not optimized in this prior work. These motivate our novel optimizations that can approximate these operators with statistical guarantees (Section 4). Text2SQL A large body of prior work looks at Text2SQL [64, 65, 69, 70], using LMs to translate natural language queries to executable SQL code. These methods serve semantic queries that are expressible in traditioanl relational operators. By contrast, semantic operators provide new AI-based transformations, such as aggregations for summarizing large document sets, or rankings, joins and filters according to natural language expressions, which are not expressible in SQL. We note an interesting line of future work may build a natural language interface on top of semantic operators.

#### 7 CONCLUSION

In this work, we proposed semantic operators to provide the first declarative and general-purpose interface to serve bulk-semantic processing. We implement these operators in the LOTUS system to seamlessly extend the relational model and allow programmers to easily compose powerful reasoning-based query pipelines over vast corpora of structured and unstructured data. Our results across a diverse set of applications, including fact-checking, extreme multilabel classification, and search, demonstrate the generality and

effectiveness of the semantic operator model as well as new opportunities for efficient algorithms and optimizations. For each task, we find that LOTUS programs capture high quality and state-of-the-art query pipelines with low development overhead, and that they can be automatically optimized with accuracy guarantees to achieve higher performance than existing implementations.

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