LLM-Powered Proactive Data Systems

Sepanta Zeighami, Yiming Lin, Shreya Shankar, Aditya Parameswaran
UC Berkeley
{zeighami, yiminglin, shreyashankar, adityagp}@berkeley.edu

Abstract

With the power of LLMs, we now have the ability to query data that was previously impossible to query, including text, images, and video. However, despite this enormous potential, most present-day data systems that leverage LLMs are reactive, reflecting our community's desire to map LLMs to known abstractions. Most data systems treat LLMs as an opaque black box that operates on user inputs and data as is, optimizing them much like any other approximate, expensive UDFs, in conjunction with other relational operators. Such data systems do as they are told, but fail to understand and leverage what the LLM is being asked to do (i.e. the underlying operations, which may be error-prone), the data the LLM is operating on (e.g., long, complex documents), or what the user really needs. They don't take advantage of the characteristics of the operations and/or the data at hand, or ensure correctness of results when there are imprecisions and ambiguities. We argue that data systems instead need to be *proactive*: they need to be given more agency—armed with the power of LLMs—to understand and rework the user inputs and the data and to make decisions on how the operations and the data should be represented and processed. By allowing the data system to parse, rewrite, and decompose user inputs and data, or to interact with the user in ways that go beyond the standard single-shot query-result paradigm, the data system is able to address user needs more efficiently and effectively. These new capabilities lead to a rich design space where the data system takes more initiative: they are empowered to perform optimization based on the transformation operations, data characteristics, and user intent. We discuss various successful examples of how this framework has been and can be applied in real-world tasks, and present future directions for this ambitious research agenda.

1 Introduction

The database community has long acknowledged the need to store, process, and query data in various degrees of structure, from relational, to semi-structured, and more recently, to unstructured data, including text, images, and video. Recent developments in AI models, and LLMs in particular, have unlocked the ability to better process and make sense of unstructured data, in addition to structured data, for tasks including information extraction [1, 2], summarization [3], data cleaning [4], dataset search [5], and data integration [6]. LLMs also enable us to better understand users, manifesting in rapid progress in benchmarks on translating natural language queries into SQL [7, 8]. LLMs truly have the potential to disrupt our entire field [9].

All of this progress in harnessing LLMs for data management—for processing both unstructured and structured data—is valuable. However, our belief is that we are still not leveraging the full potential of LLMs for data management. In most data systems that leverage LLMs for data processing, including those proposed in recent work [2, 10, 11], LLM operations are treated as a given, i.e., as black-box invocations on monolithic user inputs and data, where, akin to other types of UDFs, the data system doesn't attempt to fully understand the underlying data, user intent, or constituent operations, and just does as they are told. We call such data systems **reactive**, in that *they passively execute user-specified* *operations, without understanding the underlying intent, the semantics of the operations, or the data on which it should be applied*. Reactive data systems are fundamentally limited in their ability to accurately and efficiently address user needs. If the LLM operations as expressed in the user query have low accuracy or throw an error, reactive data systems will faithfully pass the burden of low accuracy or errors back to the user, without attempting to proactively correct for this. To understand the limitations of reactive database systems, consider the following example.

Example 7: *(Police Misconduct)* At UC Berkeley, we are co-leading an effort, along with journalists and public defenders, to build a state-wide police misconduct and use-of-force database*. As part of this effort, our collaborators have gathered, through public records requests, millions of documents detailing incidents across 700 agencies. Each incident can be split across multiple files, and can name several officers. Each file itself can have many sub-documents, including officer testimonies, medical examiner reports, eyewitness reports, and internal affairs determinations. The officers themselves may be part of several incidents. Journalists and public defenders are interested in both investigating the behavior of individual officers, as well as broader systemic patterns, all in an effort to ensure greater accountability. In such a setting, a reactive data system would encounter various difficulties, as follows:

- *(Difficulties with the Data)*. Suppose a journalist is interested in understanding the medical impacts of use of force. This is typically detailed in the medical examiner report within the broader use-of-force document. Simply providing the LLM the entire document as is (often hundreds of pages) can lead to the LLM making errors [12]; instead, by decomposing the document into specific semantically meaningful portions and focusing LLM attention on those portions can both improve accuracy and reduce cost. Another alternative is RAG (Retrieval-Augmented Generation) on pages or chunks, but RAG once again doesn't try to proactively identify the meaning of the documents, or chunks, leading to low accuracies. Here, *treating unstructured data as a black box monolith*, as in present-day reactive systems, is problematic.

- *(Difficulties with the Operations)*. The journalists have identified dozens of fields of interest in the incidents, including, but not limited to: dates, people mentioned, locations, use of firearms, drug use, use of batons and K9 units, among others. Some fields are dependent on other fields, e.g., whether there was disciplinary action is contingent on whether there was an internal affairs investigation. Simply specifying all of the fields to be extracted as is in a single prompt (as a map operation or equivalently, a projection) can lead to the LLM making errors on some of them; instead, by decomposing this operation into smaller "well-scoped" operations, we can ensure greater accuracy of LLM outputs. Here, *treating the operations as a black box*, without understanding their semantics, as in present-day reactive systems, is problematic.

- *(Difficulties with the User Intent)*. Suppose a journalist is interested in exploring the documents for mentions of a specific officer, "John Smith". While a reactive data system would faithfully return mentions of John Smith, if any, it would omit mentions of officers where the first name is an initial, i.e., "J. Smith", as well as mentions where the middle initial is present, e.g, "John M. Smith". One could certainly change the query by requiring a semantic match instead of an exact match—but the journalist would have no way of knowing that such mentions exist in the first place. A better approach would be to provide, as feedback to the journalist, what the query does not currently cover (but could), so that they can make a more informed choice about what it is they are actually after. Here, *treating the user intent as given*, as is done in present-day reactive data systems, is problematic.

*https://bids.berkeley.edu/california-police-records-access-project

In all three instances, we find that present-day data systems, especially those that harness LLMs to help make sense of unstructured data, are reactive: they treat the data, user query, and operations as black-box indivisible monoliths. Instead, we argue that data systems should be *proactive*: rather than treating LLM invocations on data as a given, such data systems should *posess the agency to understand user intent, transformation operations, and the underlying data*—and to make decisions on how to best reconfigure the data, operations, and user input to suit the analysis need. In the example above, this may include, for example, uncovering underlying layout or patterns in unstructured documents, decomposing (or fusing) operations into semantically equivalent but more accurate ones, or going above and beyond immediate user input to determine the actual underlying user intent, in concert with the user. We argue for *truly harnessing the power of LLMs, to understand and make sense of both structured and unstructured data, rather than simply treating them as black box unstructured data processors*. We believe the three axes of understanding (1) user intent, (2) data operations and (3) the data itself are key to the data systems' ability to accurately and efficiently processes structured and unstructured data.

In the following, we will put forth our vision for *proactive data systems—systems that more effectively harness LLMs for structured and unstructured data processing by improving our understanding of data, intent, and operations.* While our vision is ambitious and expansive, our early work has already shown promise:

- Our work has shown how understanding unstructured document collections better, especially those that obey similar templates, can pay rich dividends in both cost and accuracy for document processing [1, 13].
- Our work has shown how a better understanding of error-prone LLM-based unstructured data processing operators, as well as the ability to decompose or rewrite these operators can lead to data processing pipelines that are a lot more accurate [14, 15].
- Our work has also shown that tailoring our responses to the underlying user intent, especially as part of a dialog with the user, rather than just strictly adhering to the user request as stated, can be very helpful, as evidenced in tasks that range from data visualization to dataset search [16–18].

Our experience is grounded in our police misconduct analysis application, as well as our other work in understanding where and how LLMs go wrong, and how we may be able to avoid these mistakes [19, 20].

By moving beyond simply executing user instructions "as is" and treating LLM invocations as a black box, the effective offline and online execution space of proactive data systems is effectively unbounded and open-ended. For example, a user task for extracting information from documents can be decomposed in a potentially unbounded number of different ways, with different accuracies. Simply leveraging an LLM to, in turn, do this query planning and optimization for us can lead to suboptimal results. Instead, in this vision paper, we discuss various recipes for proactive systems to help make sense of each of our three axes of data, intent, and operations, such as performing decompositions and rewrites to improve accuracy when performing a given operation, finding structure in unstructured data to better understand the data and answer queries on it, and by adjusting data and query representations based on user feedback to better align with user intent. We discuss future directions along each axis to build better proactive database systems.

2 Typical User Workflows with Proactive Data Systems

A proactive data system understands, at a deeper semantic level, user intent, the specific operations it performs, and the data it performs operations on. Typical user workflows with such a system are similar to traditional database systems, where the user first provides (or ingests) the data, potentially alongside

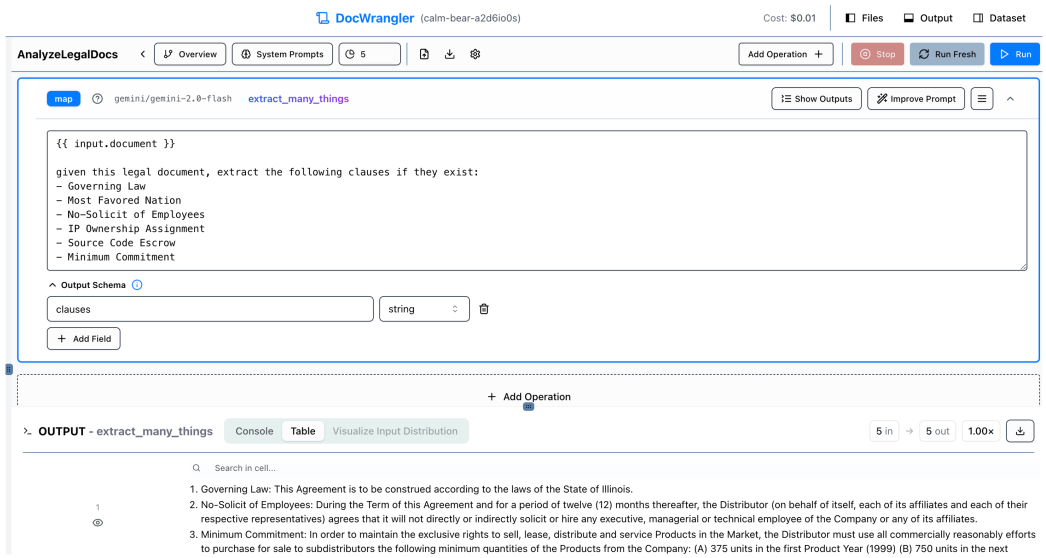


Figure 1: A potential interface for the data system. The user provides a task to be performed on a set of documents, here a collection of legal documents.

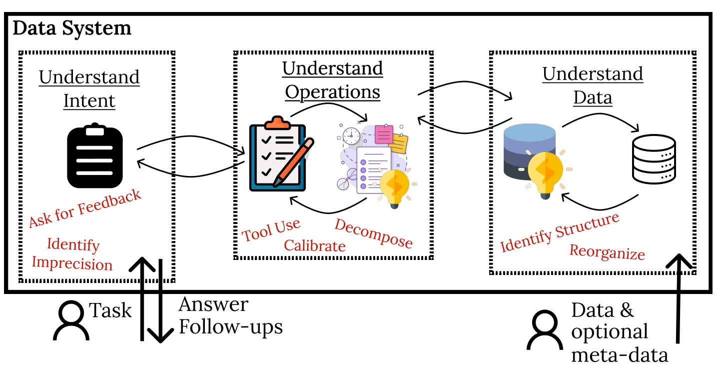


Figure 2: A Proactive Data System (red = LLM-powered)

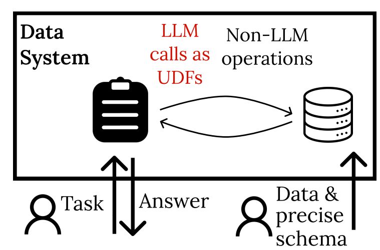


Figure 3: A Reactive Data System

additional descriptive information about its content or schema, and then proceeds to execute queries on this data. We describe this workflow in more detail next, while acknowledging that a range of design choices may all be appropriate, depending on the use cases.

Data Definition. The user first ingests or registers their data (e.g., a PDF document collection of incident reports, police officer employment CSVs, as well as audio/video of incidents in the police misconduct case), along with metadata if any. Unlike traditional database systems, this metadata is optional, and the system is free to proactively understand the structure and semantics of the data. That said, any user-provided specification or description can help improve accuracy and better specialize the system for specific use-cases of interest. In Example 7, such a specification can be similar to the first paragraph of Example 7 as plain text, or could include definitions about technical terms or additional background providing domain knowledge, e.g., defining police misconduct. We note that such information is often needed to allow users to query the data meaningfully even in relational databases when using text-to-SQL [21]. We also envision that in certain use-cases, the users may proactively identify the entities of interest for downstream querying, even if they don't register the attributes they may care about in the future. For example, in the police misconduct setting, the users may want to indicate that they intend to analyze information about incidents, police officers, and agencies. Armed with all of this information, the system can proactively add indexes, reorganize the data, and extract certain fields, among other such offline actions, as we will describe in Section 4.

Task Specification. Users are then free to issue queries or tasks on the data, which can be specified in natural language, or a combination of natural language prompts associated with data processing operators, as shown in Figure 1 for a map operation on a collection of contracts, with a prompt extracting a number of legal clauses, within DocWrangler, our IDE for DocETL [14]. If the user instead chose to preregister a schema during the data definition stage, they are free to extend it with additional LLM-populated attributes and issue SQL queries based on these lazily populated attributes, as we do in ZenDB [1].

Task Execution. The system then performs the task on the underlying data. Rather than performing the task as is on predefined data monoliths, a proactive data system will try to understand the task and the data, performing reformulations of this task by decomposing the corresponding operators, as well as the data, all in an effort to maximize accuracy and minimize cost. For example, the system can decompose the user-provided task into smaller easier-to-do operations, and can leverage the semantics of the document(s) to intelligently focus the LLM's attention on relevant portions.

In Section 3 we discuss various ways for a proactive data system to understand user-defined operations and reformulate them, and we extend the discussion in Section 4 on how the system can similarly understand the data and perform data transformations to improve accuracy. In Section 5, we discuss how the data system can ensure the task was performed as the user intended. When it comes to unstructured data, we focus our attention mostly on documents for concreteness, though our general approach may be applicable to a variety of formats.

To further differentiate a proactive data system from a reactive one, Figs. 2 and 3 provide a high-level overview of different components in these systems. While a reactive data system considers tasks and data as is, and performs operations on the components as instructed, a proactive data system leverages LLMs to understand user intent, the operations it performs, as well as the data to ensure maximal accuracy at minimum cost.

3 Proactive Operation Understanding

In reactive data systems, the onus is on the user to author queries involving the "right" LLM-powered operators, with the system then determining how to execute these in conjunction with other relational operators. However, even in cases where users are able to specify clear, unambiguous operations, the granularity at which they specify them may not be optimal for execution. Fundamentally, this stems from a lack of understanding of what LLMs can do well versus what they can't—something most users are not aware of. In this section, we discuss various approaches to operation reformulation that can improve accuracy while maintaining or reducing computational costs. We first describe new operators that we may introduce, and then methods for assessing and improving cost and accuracy when leveraging new or existing operators.

3.1 How and Where to Introduce New Operators

We now describe ways to reformulate existing LLM-powered operations into different ones.

Decomposition into simpler LLM operations. In Example 7, we described how sometimes journalists want to extract dozens of fields from a given document (e.g., police officer names, descriptions of misconduct, locations, use of firearms, among others). The journalist may specify the entire list of fields along with instructions within a prompt. However, executing this as is in a single LLM call may lead to poor accuracies as LLMs often struggle to identify multiple concepts simultaneously [14]. A proactive system can decompose such an operation into separate focused ones that each extract one type of information, improving accuracy. An LLM can be asked rewrite a prompt that says "extract fields f_1, ..., f_n from the following ..." into "extract field f_i from the following ...". In prior work, we have identified several new decomposition-based rewrite rules [14] that can lead to higher accuracies, when coupled with LLMs being used to instantiate the rewrites themselves. Recent work on Text-2-SQL also leverages similar ideas [22]: rather than attempting translation in "one-shot" (i.e., single LLM call), which often fails due to schema mismatches or poorly-named schemas [23], it is beneficial to parse the operation into smaller units, e.g., given "find all employees who joined before 2020", first identify the core concepts: employee records and hire dates, and treat each separately.

Leveraging non-LLM components. In certain cases, operations that are assigned to an LLM may be better done through other means, e.g., through SQL. For example, finding the average settlement amount for misconduct cases can be decomposed into an LLM operation to identify relevant cases and their settlement amounts, followed by a SQL aggregation to compute the average. We have employed similar techniques where we separate operations that require real-world reasoning (suited for LLMs) from mathematical computations (better handled by traditional database engines or calculators) in our work on ZenDB [1]. Determining how to do this automatically is challenging.

Leveraging reasoning or data feedback for reformulation. As described avove, a proactive data system must reformulate (e.g., decompose or rework) operations to execute them better. However, finding good reformulations is difficult. Current approaches to discovering good reformulations or decompositions are quite naive. Systems like DocETL [14] simply prompt LLMs to suggest rewrites, either taking the first suggestion or selecting from multiple candidates. One option is to use a powerful "reasoning" model like OpenAI's o1 model to rewrite the task, but this still fundamentally relies on one-shot prompting, and is unaware of how the rewrite will actually perform on the data. We need approaches that can learn what characteristics of the data make tasks challenging, what types of LLM errors occur in different contexts, and use this knowledge to guide reformulation—perhaps even in an agentic fashion.

Calibrating LLM outputs. Independent of which decomposition or reformulation is used, when LLMs are independently being applied to a set of items (documents, tuples), the outputs can often be inconsistent and non-calibrated. For example, if we ask LLMs to rate the severity of every incident in our document collection, it often gives all of them the same score, or worse, gives them scores that are only losely correlated with the severity. To remedy this lack of consistency, we can take various actions. We can leverage the LLMs themselves to pick representative examples that indicate the full range of the categories of interest, provided as few-shot examples. Or they can rework the prompt to describe in more detail the criteria used for evaluation—to ensure consistency. Finally, they can also restrict the space of possible outputs (e.g., when LLMs are asked to extract state information from a collection of US addresses, they may extract CA in some cases and California in others). While this doesn't change the semantic meaning of the operation, it can significantly improve LLM accuracy by providing better context and guidance, as has also been explored in work on prompt optimization [24].

3.2 Assessing and Improving Performance with Reformulation

Next, we describe ways to assess the benefits of reformulations, and reduce cost while preserving accuracy.

Leveraging LLMs to assess benefits. One question that naturally emerges when considering decomposing operations into smaller units is how to assess the benefits of such decompositions. While it is a-priori hard to tell whether a decomposition will help, we can run both the non-decomposed and decomposed variants on a sample. LLMs are much better at evaluating outputs than generating them, so LLMs can be used to tell which version performs better. For example, one can employ a "generate-fix

& rewrite-verify" pattern: generate an initial operation formulation, verify its correctness (e.g., through automated checks or LLM verification), and if verification fails, attempt alternative formulations [25]. This pattern, which we also use in DocETL [14], allows a system to systematically explore the space of possible formulations until finding one that passes verification, effectively optimizing for accuracy through trial and refinement. However, doing evaluation in a cost-effective manner remains a challenge.

Deferring to cheaper LLMs for the "easy bits". One concern with decomposition is that it may increase the cost of the overall pipeline, since one LLM call per document may now become multiple. One way to defray the cost is to couple decomposition with cost optimization: for the simpler newly decomposed operations, we can alternatively use cheaper and smaller models to handle them, and only use the more expensive model for the most complicated operations. For example, when we're trying to extract many fields from a police record document, we can use a cheaper model for extraction of locations and dates, while using a more expensive model for harder tasks such as determining the type of misconduct incident. While the idea of cheaper proxy models isn't new [10, 26], here, since the space of decompositions is infinite, and for each decomposition (or sequences thereof), we could use different models and different confidence thresholds, each with different cost-accuracy tradeoffs, the problem becomes a lot more compliacated. Additionally, unlike previous settings which focused primarily on tasks with well-defined accuracy metrics, we now must provide guarantees for open-ended generative operations—where quality is harder to quantify.

Expensive predicate ordering, but with synthesized predicates. For operations that involve subselecting documents based on certain criteria (all expressed together in one prompt), we can leverage existing related work on expensive predicate ordering [27, 28]; however, in our context, we can introduce an arbitrary number of new dependent predicates (that are potentially easier to check and therefore cheaper). For example, instead of using an expensive model to examine each police record document to extract medical impacts to the victims, if any, we can consider cheaper filters that are easier to check, for example, if the document contains any medical information at all. This check could potentially be done by a cheaper model and rule out a substantial fraction of the documents. Similarly, when decomposing a complex filter like "find incidents involving both use of force and drug use" into two filters, one for "use of force" and one for "drug use," the system can evaluate the more selective filter first to minimize expensive LLM calls.

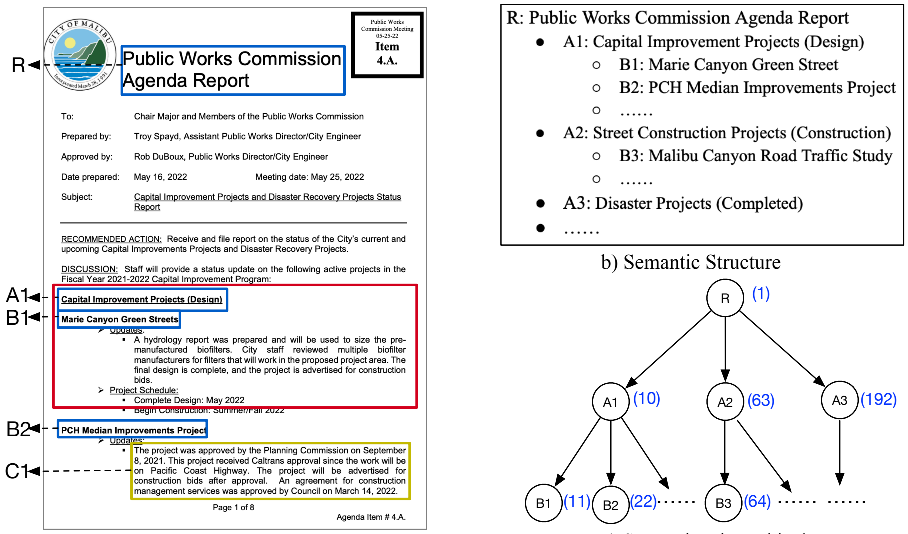
4 Proactive Data Understanding

Proactive data systems take initiative to truly understand the data, rather than simply treating it as inputs to opaque UDF (here LLM) calls. It can leverage the provided data descriptions, as well as actual content, to create representations that are useful for downstream data processing tasks. The system can understand each document on its own (Section 4.1), understand relationships between documents or portions thereof (Section 4.2), or preprocess documents based on anticipated future tasks (Section 4.3).

4.1 Identifying Semantic Structure within a Document

Although documents may appear unstructured, they often are semantically structured. This structure may be implicit in the text, e.g., content in adjoining portions of the text is often related. They can also be explicit, e.g., tables or figures embedded within a PDF document. We discuss how to identify, extract, and leverage hidden structure from unstructured documents.

Leveraging implicit hierarchical structure. Portions of documents are often semantically related. A section or subsection within a document often contains information that is semantically related, while other parts are less related or unrelated. For example, the medical examiner report within a



a) Civic Project Agenda Report

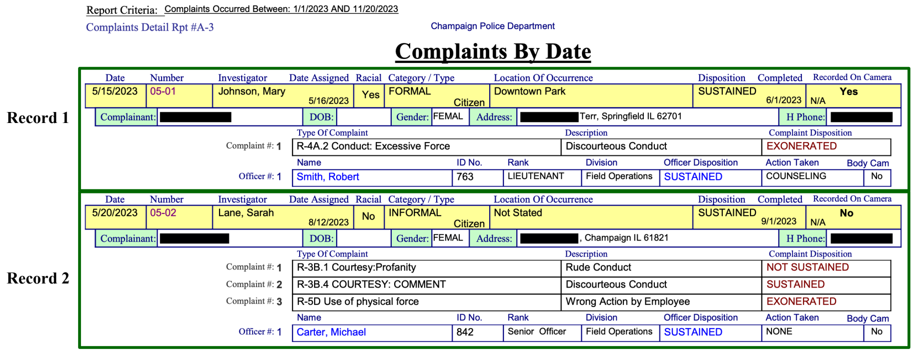
b) Semantic Structure

c) Semantic Hierarchical Tree

Figure 4: Semantic Hierarchy in a Civic Agenda Document (a) the Document itself (b) the Corresponding "Table of Contents" (c) the Corresponding Semantic Hierarchy.

broader police record PDF contains most of the medically relevant information about an incident, while the eyewitness report contains most of the relevant information from eyewitnesses. Identifying these subdivisions within a document and routing a query to the subdivision at the "right" granularity can lead to higher accuracy than both RAG or providing the entire document to an LLM [1]. This structure is best represented as a semantic hierarchy. There are various ways to construct such a hierarchy, including leveraging formatting information that distinguishes headers from other portions, or using an LLM to identify which phrases may be headers as we do in ZenDB [1]—see Figure 4 for an example. Another approach is to construct this semantic hierarchy on content alone, where summaries of related chunks are merged and recursively summarized [29]. Nonetheless, building semantic structures that are useful for downstream tasks remains a challenge, as different views of the document may be useful for different tasks, where even simple information such as location can have different connotations. For instance, when organizing police activities in a specific case based on location they occurred in, a user might be interested in geographical location of activities (i.e., at a specific address) while another user might be interested in types of locations (e.g., if the police activity was outdoor or inside). The system needs to consider various possible semantics of the data when identifying the semantic structure.

Leveraging explicit structure. Unstructured documents often contain structured portions, such as embedded tables and key-value pairs. Treating them as plain text for data processing is ineffective and error-prone. For example, if we're not careful in preserving visual information, a missing value in a key-value pair could lead to the next key being misinterpreted as the corresponding value. Moreover, depending on the approach used to query such tables, we may lose visual information (used to show table structure and group columns and rows), and be unable to effectively process numerical information. A proactive data system therefore will identify and extract such structured portions and represent them in a structured format, for example, as tabular data or key-value pairs in Figure 5, while preserving their context within the document (e.g., their location and semantic relationships to the rest of the document). Our recent tool, TWIX [13], proposes an efficient approach for automatically extracting structured portions from documents, using a combination of visual and LLM-based inference, while preserving this context for the extracted information. However, many challenges remain, such as accurately representing the semantic relationship between structured and unstructured document portions, e.g., to understand which queries should be answered based on the structured and unstructured portions, and how much background context is necessary to make sense of the structured portions.



Report Criteria: Complaints Occurred Between: 1/1/2023 AND 11/20/2023

Complaints Detail Rpt #A-3

Champaign Police Department

Complaints By Date

Record 1

Date	Number	Investigator	Date Assigned	Racial	Category / Type	Location Of Occurrence	Disposition	Completed	Recorded On Camera
5/15/2023	05-01	Johnson, Mary	5/16/2023	Yes	FORMAL Citizen	Downtown Park	SUSTAINED	6/1/2023	N/A Yes

Complainant: [redacted] DOB: Gender: FEMAL Address: [redacted]Terr, Springfield IL 62701 H Phone: [redacted]

	Type Of Complaint	Description	Complaint Disposition
Complaint #: 1	R-4A.2 Conduct: Excessive Force	Discourteous Conduct	EXONERATED

	Name	ID No.	Rank	Division	Officer Disposition	Action Taken	Body Cam
Officer #: 1	Smith, Robert	763	LIEUTENANT	Field Operations	SUSTAINED	COUNSELING	No

Record 2

Date	Number	Investigator	Date Assigned	Racial	Category / Type	Location Of Occurrence	Disposition	Completed	Recorded On Camera
5/20/2023	05-02	Lane, Sarah	8/12/2023	No	INFORMAL Citizen	Not Stated	SUSTAINED	9/1/2023	N/A No

Complainant: [redacted] DOB: Gender: FEMAL Address: [redacted], Champaign IL 61821 H Phone: [redacted]

	Type Of Complaint	Description	Complaint Disposition
Complaint #: 1	R-3B.1 Courtesy:Profanity	Rude Conduct	NOT SUSTAINED
Complaint #: 2	R-3B.4 COURTESY: COMMENT	Discourteous Conduct	SUSTAINED
Complaint #: 3	R-5D Use of physical force	Wrong Action by Employee	EXONERATED

	Name	ID No.	Rank	Division	Officer Disposition	Action Taken	Body Cam
Officer #: 1	Carter, Michael	842	Senior Officer	Field Operations	SUSTAINED	NONE	No

Figure 5: Tables and Key-Value Pairs in Use of Force Records.

4.2 Identifying Cross-Document Relationships

There are multiple reasons to perform cross-document organization.

Identifying documents that may be queried together. Beyond understanding structure within a single document, it is important to understand relationships across documents, since these related documents may often be queried together. In Example 7, the dataset, a single incident can span several PDF documents, often without such information being linked to each other. The data system needs to proactively identify relationships between such documents to organize the data prior to querying. This, for instance, can be done by clustering the documents. However, clustering is challenging, since the system needs to understand the documents to be able to cluster them properly. Simply embedding the documents, and clustering the embeddings does not work since the documents can vary considerably in length. Another approach is to leverage LLMs to check if two documents correspond to the same incident, but this is expensive, especially when there are $O(n^2)$ comparisons. We may be able to leverage LLMs to identify cheaper proxies or blocking rules (e.g., two documents may not be related unless the date ranges overlap) for this organization. In some settings, folder organization provides cues for identifying cross-document relationships (e.g., documents that are very "far apart" from a folder structure standpoint may be unlikely to be related).

Identifying shared templates across documents. A separate concern is to combine semantic hierarchy construction with cross-document relationships, so that we are able to identify shared "templates" across documents. These templates can both help scale up extraction across documents, but also help identify documents whose structure differs considerably. For example, journalists may want to identify incidents where there is an internal affairs report within a broader police record document, since these are ones where there is a corresponding disciplinary action.

4.3 Task-Aware Data Pre-Processing

The system can attempt to proactively find and organize portions of the data that will be useful to improve performance on a reasonable subset of data processing tasks downstream. Given that document collections can span in the millions, it can be expensive to do extensive processing of the data upfront, for instance, by populating a materialized view with all the attributes a user can ever hope to query; it can also be time-consuming to leave all the data processing to when the user issues a task. As such the system needs to decide how much preprocessing is beneficial upfront, and what to perform at query time. To strike a balance between the two extremes, one option is for the system to identify and/or extract data units that it deems to be useful in the future for a wide variety of queries. This can be done by understanding the semantics of the data. For instance, in Example 7, the system can decide that sections that describe police incidents at a high level (e.g., the internal affairs report) are typically useful for future task processing as they provide a comprehensive summary of most relevant aspects. The system can keep pointers to such sections as lightweight indexes, but leave more specific data processing to when the user issues queries. Similarly, the system can do schema identification in advance to find what type of data is represented in the documents, and use the identified schema to answer queries. The system can decide whether to extract information upfront to populate the schema, or keep pointers to where the information can be found at query time. For instance, the system may choose to retain pointers to all portions that mention police officers in the document so as to accelerate analysis of those aspects downstream, without going all the way to populating a materialized view with officer attributes (since these can vary depending on user need).

5 Proactive User Understanding

Even with best-effort operation reformulation and data understanding capabilities, a fundamental challenge remains: the gap between what users specify and what they actually need. This challenge manifests in multiple ways—users may provide ambiguous specifications, fail to articulate implicit assumptions, or simply not know how to express their requirements fully [20, 30]. To bridge this gap between the user's intent and the operations performed, a proactive data system needs to be internally aware of this gap when executing the task (Section 5.1), leverage user feedback to bridge the gap (Section 5.2) and provide mechanisms for users to externally validate query results (Section 5.3).

5.1 Imprecision-Aware Processing

Unlike reactive data systems that only execute the query as stated, proactive data systems can leverage LLMs to help truly identify user intent, despite the user-provided tasks representing an imprecise or incomplete specification thereof. The system should therefore internally consider multiple possible user intents when processing tasks, potentially providing different answers that correspond to these different interpretations. This can be done to varying degrees. In the simplest form, the system can consider multiple interpretations of the statements provided by the user. In Example 7, the system can consider various spellings of the same name, either in the input provided by the user or derived from the data. Such attempts are similar to possible world notions in the database community [31], where the database can consider various possibilities for "fuzzy" data and queries.

A proactive system can take more aggressive steps to understand user intent. For example, the system can consider adding new predicates that the user may be interested in—e.g., if a user has previously asked several questions about police misconduct in a specific city but submits a new query without specifying location, the system might prioritize results from that city. This intent discovery can be data-driven—the system might determine that records from certain cities are more relevant or interesting and prioritize them in the output. Moreover, if the output for an operation is too large, the system can selectively display what it determines to be the most relevant answers or provide appropriate summaries or sample outputs.

The system can also anticipate user questions, for example, "why was a certain record not provided in the answer", and proactively relevant records that, while not strictly matching the query, might be of interest to the user. Additionally, the system can modify queries by dropping or relaxing certain predicates—e.g., if the user has specified a predicate that leads to empty results. Or, the system might expand query scope, for example, geographically, to include potentially interesting results (such as when a specific type of police misconduct, while not present in the queried city, occurred in neighboring jurisdictions).

5.2 Leveraging User Feedback

A proactive system can leverage feedback from users to clarify intent in a lightweight manner. This feedback serves two purposes: improving accuracy for the current task, and enhancing the system's understanding of user intent for future queries.

To improve the accuracy on the current task, the system can decide to ask follow-up questions [32]. This might include asking for clarification about task goals, gathering additional specifications, or presenting example results for users to indicate which best match their needs. The important challenge is balancing the need for clarity with minimizing user burden: for example, when processing police misconduct documents, rather than asking multiple detailed questions, the system might show representative document types and let users select which are most relevant—then apply this learning broadly across the document collection. Similarly, when encountering potential name variations in Example 7, the system might ask a single question about handling typos that can inform its overall matching strategy, rather than asking the user to confirm every typo correction. While LLMs offer promising capabilities for generating targeted feedback requests, automatically determining what feedback to request and when remains an open research challenge. Prior work on predictive interaction is highly relevant here [33].

User feedback can also be leveraged to improve system performance on `future` tasks. For example, if the user provides feedback that a certain document is relevant or not relevant to a task, the system can then update its data and task processing mechanism to take that feedback into account. This can, for instance, change operation rewrite rules used internally for processing (Section 3), modify data representation [16] or change how semantic structure is extracted from the data (Section 4). While this approach shares similarities with query-by-example systems that learn from user-provided examples, e.g., [34], it extends the concept more broadly—–allowing the system to refine its understanding of user intent across a diverse range of tasks and feedback types.

5.3 Verifying Execution

A proactive system must provide users with the means to verify that their tasks were executed correctly. Verification is particularly important when the system makes autonomous decisions—for instance, when correcting potential typos in names, the system should clearly show which corrections were made to allow users to catch any incorrect modifications. If, during processing, the system encountered anomalous documents, it's best to indicate them as such to the users so that they don't pollute the rest of the analysis.

While the system can provide comprehensive execution traces, including details of LLM operations performed and data sources accessed [35], presenting this information in a user-friendly way remains challenging. Simply showing raw execution traces or complete datasets is overwhelming and impractical, as users cannot reasonably review large amounts of data to verify correctness. An interesting open challenge is to determine a small subset or explanation that conveys the same information as the entire provenance; we can always verify such explanations using an LLM.

6 Conclusion

The database community stands at a pivotal moment where LLMs offer unprecedented capabilities for processing both structured and unstructured data. In this vision paper, we proposed *proactive* data systems: systems that possess agency in understanding and optimizing data processing tasks. Unlike traditional *reactive* systems that treat LLMs as black-box UDFs operating on monolithic inputs, proactive systems go further in leveraging LLMs to aid data processing along three axes. We presented these axes—operations, data, and user intent—and demonstrated the potential of LLMs to help in each one through our recent work on operator reformulation, document organization and analytics, and intent-aware optimization. Overall, proactive data systems can achieve both higher accuracy and lower costs than reactive systems that treat LLMs as black boxes.

References

[1] Y. Lin, M. Hulsebos, R. Ma, S. Shankar, S. Zeigham, A. G. Parameswaran, and E. Wu, "Towards accurate and efficient document analytics with large language models," *arXiv preprint arXiv:2405.04674*, 2024.

[2] C. Liu, M. Russo, M. Cafarella, L. Cao, P. B. Chen, Z. Chen, M. Franklin, T. Kraska, S. Madden, and G. Vitagliano, "A declarative system for optimizing ai workloads," *arXiv preprint arXiv:2405.14696*, 2024.

[3] J. Fang, C.-T. Liu, J. Kim, Y. Bhedaru, E. Liu, N. Singh, N. Lipka, P. Mathur, N. K. Ahmed, F. Dernoncourt, *et al.*, "Multi-llm text summarization," *arXiv preprint arXiv:2412.15487*, 2024.

[4] A. Narayan, I. Chami, L. J. Orr, and C. R'e, "Can foundation models wrangle your data?," *Proc. VLDB Endow.*, vol. 16, pp. 738–746, 2022.

[5] Z. Huang, J. Liu, H. Wang, and E. Wu, "The fast and the private: Task-based dataset search," *arXiv preprint arXiv:2308.05637*, 2023.

[6] M. Kayali, F. Wenz, N. Tatbul, and Ç. Demiralp, "Mind the data gap: Bridging llms to enterprise data integration," *arXiv preprint arXiv:2412.20331*, 2024.

[7] B. Li, Y. Luo, C. Chai, G. Li, and N. Tang, "The dawn of natural language to sql: Are we fully ready?," *arXiv preprint arXiv:2406.01265*, 2024.

[8] A. Floratou, F. Psallidas, F. Zhao, S. Deep, G. Hagleither, W. Tan, J. Cahoon, R. Alotaibi, J. Henkel, A. Singla, *et al.*, "Nl2sql is a solved problem... not!," in *CIDR*, 2024.

[9] R. C. Fernandez, A. J. Elmore, M. J. Franklin, S. Krishnan, and C. Tan, "How large language models will disrupt data management," *Proc. VLDB Endow.*, vol. 16, p. 3302–3309, jul 2023.

[10] L. Patel, S. Jha, P. Asawa, M. Pan, C. Guestrin, and M. Zaharia, "Semantic operators: A declarative model for rich, ai-based analytics over text data," *arXiv preprint arXiv:2407.11418*, 2024.

[11] E. Anderson, J. Fritz, A. Lee, B. Li, M. Lindblad, H. Lindeman, A. Meyer, P. Parmar, T. Ranade, M. A. Shah, B. Sowell, D. Tecuci, V. Thapliyal, and M. Welsh, "The design of an llm-powered unstructured analytics system," 2024.

[12] N. F. Liu, K. Lin, J. Hewitt, A. Paranjape, M. Bevilacqua, F. Petroni, and P. Liang, "Lost in the middle: How language models use long contexts," *Transactions of the Association for Computational Linguistics*, vol. 12, pp. 157–173, 2024.

[13] Y. Lin, M. Hasan, R. Kosalge, A. Cheung, and A. G. Parameswaran, "Twix: Automatically reconstructing structured data from templatized documents," *arXiv preprint arXiv:2501.06659*, 2025.

[14] S. Shankar, T. Chambers, T. Shah, A. G. Parameswaran, and E. Wu, "Docetl: Agentic query rewriting and evaluation for complex document processing," *arXiv preprint arXiv:2410.12189*, 2024.

[15] A. G. Parameswaran, S. Shankar, P. Asawa, N. Jain, and Y. Wang, "Revisiting prompt engineering via declarative crowdsourcing," *Cidr*, 2024.

[16] S. Zeighami, Z. Wellmer, and A. Parameswaran, "Nudge: Lightweight non-parametric fine-tuning of embeddings for retrieval," *arXiv preprint arXiv:2409.02343*, 2024.

[17] H. Li, N. Chalapathi, H. Qu, A. Cheung, and A. G. Parameswaran, "Inferring visualization intent from conversation," in *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management*, pp. 1184–1194, 2024.

[18] M. Hulsebos, W. Lin, S. Shankar, and A. Parameswaran, "It took longer than i was expecting: Why is dataset search still so hard?," in *Proceedings of the 2024 Workshop on Human-In-the-Loop Data Analytics*, pp. 1–4, 2024.

[19] S. Shankar, H. Li, P. Asawa, M. Hulsebos, Y. Lin, J. Zamfirescu-Pereira, H. Chase, W. Fu-Hinthorn, A. G. Parameswaran, and E. Wu, "Spade: Synthesizing assertions for large language model pipelines," *arXiv preprint arXiv:2401.03038*, 2024.

[20] S. Shankar, J. Zamfirescu-Pereira, B. Hartmann, A. Parameswaran, and I. Arawjo, "Who validates the validators? aligning llm-assisted evaluation of llm outputs with human preferences," in *Proceedings of the 37th Annual ACM Symposium on User Interface Software and Technology*, pp. 1–14, 2024.

[21] J. Li, B. Hui, G. Qu, J. Yang, B. Li, B. Li, B. Wang, B. Qin, R. Geng, N. Huo, *et al.*, "Can llm already serve as a database interface? a big bench for large-scale database grounded text-to-sqls," *Advances in Neural Information Processing Systems*, vol. 36, 2024.

[22] M. Pourreza, H. Li, R. Sun, Y. Chung, S. Talaei, G. T. Kakkar, Y. Gan, A. Saberi, F. Ozcan, and S. O. Arik, "Chase-sql: Multi-path reasoning and preference optimized candidate selection in text-to-sql," *arXiv preprint arXiv:2410.01943*, 2024.

[23] K. Luoma and A. Kumar, "Snails: Schema naming assessments for improved llm-based sql inference," *Proc. ACM Manag. Data*, vol. 3, Feb. 2025.

[24] O. Khattab, A. Singhvi, P. Maheshwari, Z. Zhang, K. Santhanam, S. Vardhamanan, S. Haq, A. Sharma, T. T. Joshi, H. Moazam, *et al.*, "Dspy: Compiling declarative language model calls into self-improving pipelines," *arXiv preprint arXiv:2310.03714*, 2023.

[25] Y. Chung, G. T. Kakkar, Y. Gan, B. Milne, and F. Ozcan, "Is long context all you need? leveraging llm's extended context for nl2sql," *arXiv preprint arXiv:2501.12372*, 2025.

[26] D. Kang, J. Emmons, F. Abuzaid, P. Bailis, and M. Zaharia, "Noscope: optimizing neural network queries over video at scale," *Proc. VLDB Endow.*, vol. 10, p. 1586–1597, Aug. 2017.

[27] J. M. Hellerstein and M. Stonebraker, "Predicate migration: Optimizing queries with expensive predicates," in *Proceedings of the 1993 ACM SIGMOD international conference on Management of data*, pp. 267–276, 1993.

[28] V. Raman, B. Raman, and J. M. Hellerstein, "Online dynamic reordering for interactive data processing," in *VLDB*, vol. 99, pp. 709–720, Citeseer, 1999.

[29] P. Sarthi, S. Abdullah, A. Tuli, S. Khanna, A. Goldie, and C. D. Manning, "Raptor: Recursive abstractive processing for tree-organized retrieval," *arXiv preprint arXiv:2401.18059*, 2024.

[30] S. Papicchio, P. Papotti, and L. Cagliero, "Evaluating ambiguous questions in semantic parsing," in *2024 IEEE 40th International Conference on Data Engineering Workshops (ICDEW)*, pp. 338–342, IEEE, 2024.

[31] D. Suciu, D. Olteanu, C. Ré, and C. Koch, *Probabilistic databases.* Springer Nature, 2022.

[32] Y. Li and D. Jobson, "Llms as an interactive database interface for designing large queries," in *Proceedings of the 2024 Workshop on Human-In-the-Loop Data Analytics*, pp. 1–7, 2024.

[33] J. Heer, J. Hellerstein, and S. Kandel, "Predictive interaction for data transformation," in *Conference on Innovative Data Systems Research (CIDR)*, 2015.

[34] A. Fariha, S. M. Sarwar, and A. Meliou, "Squid: Semantic similarity-aware query intent discovery," in *Proceedings of the 2018 International Conference on Management of Data*, pp. 1745–1748, 2018.

[35] W. C. Tan *et al.*, "Provenance in databases: Past, current, and future.," *IEEE Data Eng. Bull.*, vol. 30, no. 4, pp. 3–12, 2007.