



LLM/Agent-as-Data-Analyst: A Survey

Zirui Tang^{*¶}, Weizheng Wang^{*¶}, Zihang Zhou*, Yang Jiao*, Bangrui Xu*, Boyu Niu*, Xuanhe Zhou^{*††}, Guoliang Li[†], Yeye He[‡], Wei Zhou*, Yitong Song*, Cheng Tan[§], Xue Yang*, Bin Wang[§], Conghui He[§], Xiaoyang Wang^{||}, Fan Wu*

^{*}Shanghai Jiao Tong University [†]Tsinghua University [‡]Microsoft Research

[§]Shanghai AI Laboratory ^{||}Fudan University

<https://github.com/weAIDB/awesome-data-llm>

Abstract—Large language model (LLM) and agent techniques for data analysis (a.k.a LLM/Agent-as-Data-Analyst) have demonstrated substantial impact in both academia and industry. In comparison with traditional rule or small-model based approaches, (agentic) LLMs enable complex data understanding, natural language interfaces, semantic analysis functions, and autonomous pipeline orchestration. From a modality perspective, we review LLM-based techniques for (i) structured data (e.g., table question answering for relational data and NL2GQL for graph data), (ii) semi-structured data (e.g., markup languages understanding and semi-structured table modeling), (iii) unstructured data (e.g., chart understanding, document understanding, code completion), and (iv) heterogeneous data (e.g., data retrieval and modality alignment for data lakes). The technical evolution further distills five key design goals for *intelligent data analysis agents*, namely semantic-aware design, modality-hybrid integration, autonomous pipelines, tool-augmented workflows, and support for open-world tasks. Finally, we outline the remaining challenges and propose several insights and practical directions for advancing LLM/Agent-powered data analysis.

Index Terms—LLM, Agent, Data Analysis, Structured Data, Semi-Structured Data, Unstructured Data, Heterogeneous Data

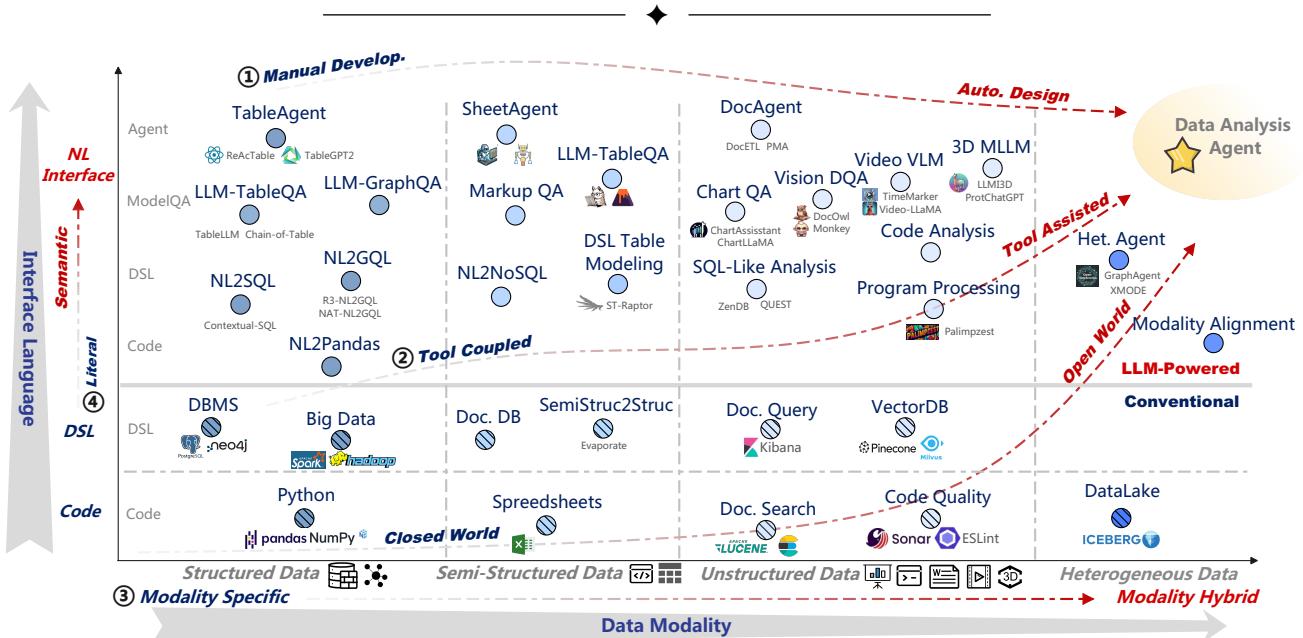


Fig. 1: The Evolution of **LLM/Agent-as-Data-Analyst** Techniques follows a five-dimension trajectory: (1) Data Modality (homogeneous → heterogeneous); (2) Analysis Functionality (literal → semantic); (3) Knowledge Scope (closed-world → open-world); (4) Tool Integration (tool-coupled → tool-assisted); (5) Development Autonomy (manual → fully autonomous).

1 INTRODUCTION

DATA analysis, broadly defined as the process of inspecting, transforming, and modeling data to discover useful information and support decision-making, constitutes a cornerstone of modern scientific research and business intelligence [70, 13, 113, 281]. It spans a wide spectrum of data

modalities, from structured databases and semi-structured tables to unstructured documents and videos, underpinning critical applications across domains such as finance, healthcare, engineering, and social sciences [161, 23, 27].

1.1 Limitations of Conventional Data Analysis

Traditional data analysis pipelines, although effective in extracting information and statistical patterns, often demand

• ¶ Co-first authors with equal contributions.
• †† Corresponding author.

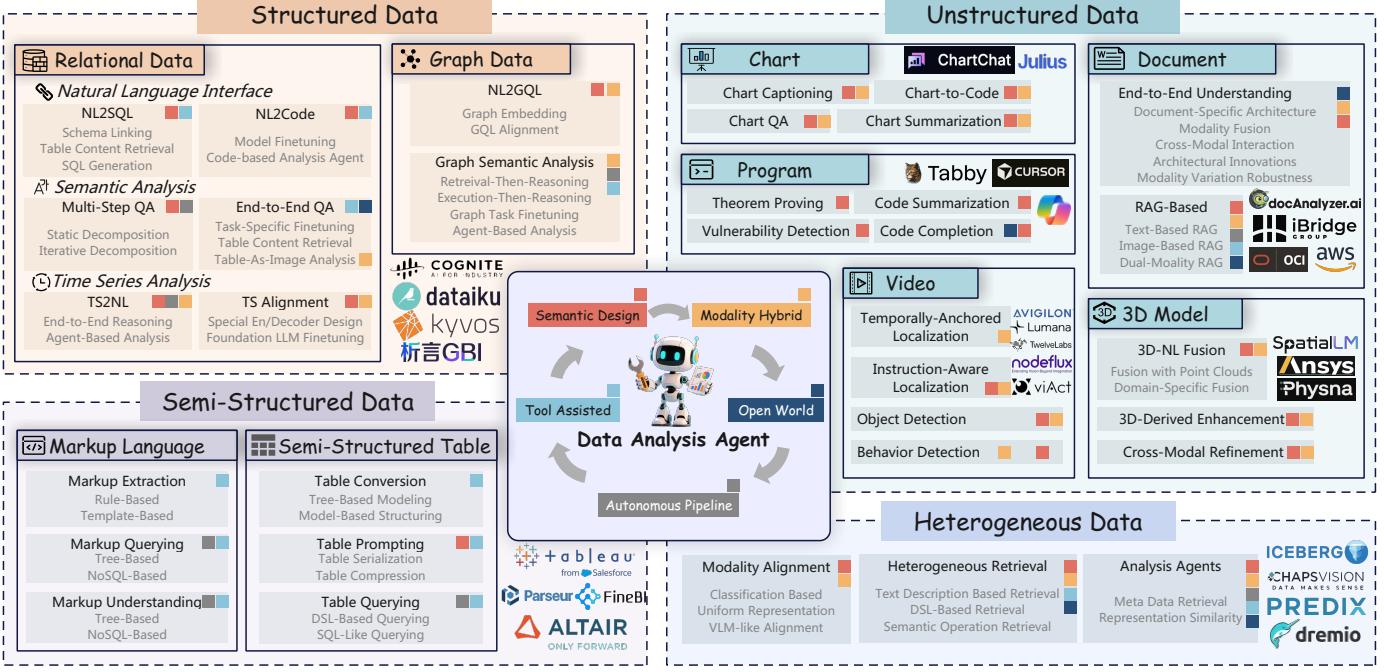


Fig. 2: Technical Overview of LLM/Agent-as-Data-Analyst. The five key design goals are illustrated in the center of the figure using distinct colors. The colored icons next to each technique indicate the specific design goal it supports.

substantial domain expertise, manual feature engineering, and the integration of multiple specialized tools [243]. These limitations become more pronounced as data grows in scale, complexity, and heterogeneity [130], ultimately constituting the inherent weakness of conventional data analysis.

L1: Manual Development. The most labor-intensive challenge is that traditional data analysis workflows rely on rigid, manually designed pipelines that require domain experts to specify modeling steps in advance [285, 286, 279]. In large-scale enterprise databases, where separate tables for customers, orders, payments, shipments, and products each contain dozens of attributes, answering even simple business queries such as *“What is the average delivery time for premium customers in the last quarter?”* may necessitate the analysts to choose related tables, find corresponding attributes, process complex multi-table joins, apply domain-specific constraints, and reconcile the timestamp fields. For document query answering, retrieving query-relevant information from long documents containing diverse elements (e.g., text blocks, tables, charts, images) typically requires analysts to examine pages sequentially and summarize the content, which is a highly labor-intensive process. Such handcrafted pipelines are time-consuming to build and difficult to adapt when data characteristics or analysis goals change.

L2: Hard-Coded Tool Dependency. One observation is that existing data analysis systems often come with a suite of tightly coupled built-in tools (e.g., visualization dashboards, statistical packages, or machine learning modules [5]) tailored to specific workflows, which stems from the inherent complexity of the underlying data types. For instance, to extract statistical information from a knowledge graph and subsequently model it with linear regression, a human analyst must first formulate GQL queries and invoke the built-in APIs of graph databases to obtain the data, and then

employ machine learning libraries (e.g., scikit-learn, PyTorch) for further analysis. In contrast, analyzing 3D models relies more heavily on domain-specific expertise and specialized systems (e.g., AutoCAD, PyMOL [4]). Such analyses are often constrained to the functionalities embedded in these systems, requiring analysts, particularly those without coding expertise, to integrate multiple systems in order to complete a single task. The integration of heterogeneous systems not only increases the complexity and overhead of the analysis process, but also hampers extensibility and complicates integration into broader analytical workflows.

L3: Homogeneous Modality Support. Current data analysis systems are generally optimized for specific data types, with architectures and query engines tailored to particular formats. For example, relational databases are well-suited for structured data [95], while systems such as MongoDB are designed for semi-structured formats like JSON [6]. When analyzing videos with accompanying timestamped descriptions, human analysts must manually align frames with their corresponding documents to enable cross-modal analysis [157]. This specialization hampers the analysis of heterogeneous data across modalities, thereby increasing analytical complexity, introducing errors, and limiting both the scope and efficiency of data-driven insights.

L4: Basic Format-Based Analysis. While conventional analysis methods efficiently support operations such as filtering, aggregation, they lack the ability to reason over semantic information embedded in data. For example, in table analysis, if a cell contains lengthy textual paragraphs, SQL queries can only retrieve or match keywords without understanding the semantics (e.g., sentiment, intent, causal relationships) [279]. Likewise, for unstructured data such as charts or documents, analysts must manually interpret and summarize content to fulfill analytical needs [69]. The

absence of semantic understanding constrains the analytical depth of current systems and limits their ability to address complex, knowledge-intensive tasks that demand reasoning beyond surface-level patterns.

1.2 Opportunities by LLM/Agent-As-Data-Analyst

Recent advances in large language models (LLMs) and LLM-based agents have introduced new opportunities to alleviate these challenges. As shown in Figure 1, by enabling auto-designed analysis pipelines, adaptive tool-assisted workflows, and natural language interaction, LLMs hold the potential to lower technical barriers, enhance interpretability, and accelerate the discovery of actionable insights from diverse forms of data.

O1: Complex Data Understanding. LLMs are capable of processing and reasoning across complex data, including relational data, semi-structured tables, and unstructured texts, owing to their ability to capture latent patterns and contextual dependencies [195, 199]. For example, they can not only comprehend the semantic content associated with nodes and edges but can also reason about the underlying structural properties (e.g., connectivity, community patterns, or hierarchical organizations). Such a deep and holistic understanding empowers analysts to derive richer insights that integrate quantitative measures with qualitative nuances [18].

O2: NL-Based Interface. An LLM-powered analysis agent leverages natural language as the primary interface for interaction, enabling users to articulate analytical requirements without the need for specialized query languages such as SQL or advanced programming skills [130, 115]. This natural language interface enhances convenience for analysts, accelerates the overall analysis process, and broadens participation in data-driven decision-making across diverse user groups [201, 69].

O3: Semantic Operators. LLMs enable semantic-level operations such as structural interpretation and content summarization, which are particularly beneficial for data rich in structural relationships or textual content [218]. For example, when querying a medical record database, a conventional query may retrieve only documents containing the term “fever”, whereas an LLM-based operator can also recognize semantically related expressions such as “high temperature” or “febrile condition”. This semantic enrichment enhances the expressive power of queries, enabling analysts to obtain more accurate, context-aware results [94, 231].

O4: Autonomous Evolution. LLM agents function not as static tools but as adaptive systems capable of refining their performance through continuous interaction and learning. Such adaptability is essential, as analytical requirements and data environments inevitably evolve over time [76]. For instance, a financial analysis agent may initially concentrate on trend forecasting but, through iterative feedback, expand its capabilities to detect anomalies in real time or incorporate emerging risk factors. This capacity for autonomous evolution ensures that the system remains advanced, alleviates the need for manual reconfiguration, and delivers increasingly personalized and efficient analytical support [19].

1.3 Techniques of LLM-Powered Data Analysis

As shown in Figure 1 and Figure 2, given the diversity of data formats and application scenarios, we establish a

taxonomy of LLM-powered data analysis which progresses along two dimensions: (i) the range of **data modalities** supported, i.e., structured, semi-structured, unstructured, and heterogeneous (the x-axis), and (ii) the evolution of **interaction paradigms**, i.e., code-based, domain-specific language (DSL)-based, and natural language (NL)-based (the y-axis).

LLM/Agent for Structured Data Analysis. Structured data, including relational databases [42] and graphs [16], remains central in industry for its standardized schema and well-defined semantics. Traditional methods rely on SQL or related query languages, later extended with DSLs for domain-specific tasks [2]. With LLMs, users can interact with structured data via natural language through code generation, DSL mapping, or LLM-based question answering [139, 187], while agent frameworks further orchestrate multi-step analytical workflows [290]. The core of LLM-driven structured data analysis lies in employing LLMs for pipeline automation or end-to-end processing.

- *Relational Data.* Relational data is typically stored and managed in specialized databases. An LLM-based approach to relational data analysis leverages the model as a natural language interface that translates analytical intents into SQL or executable code, which is then used to query the database. To enhance alignment between natural and formal languages, techniques such as schema linking [271], information retrieval [173], and task decomposition [76] are integrated into the pipeline, while task-specific fine-tuning [265] improves end-to-end generation. An alternative direction bypasses direct database manipulation, employing LLMs for semantic-level analysis. This requires deeper understanding of analytical intent and intra-table relationships. Accordingly, RAG [169], prompt engineering [288], and task decomposition [282] are incorporated to enhance reasoning, while MLLMs [284] or LLMs [195] are trained or fine-tuned on textual or visual table representations. Time-series data, a specialized subclass of relational data characterized by temporal dependencies, can similarly benefit from LLM-powered techniques, including natural language-to-code translation [96], sequence retrieval and transformation, and direct temporal reasoning [14].

- *Graph Data.* Graph data represents entities and their interdependencies to model complex network semantics, posing challenges due to its vast search space and intricate path reasoning. Specialized graph databases and query languages [3, 1] enable direct access, while LLMs can serve as natural language interfaces for generating graph queries. Techniques such as agent-based frameworks [130], fine-tuning, and prompt engineering [129] enhance the model’s understanding of graph structures and query syntax. For semantic-level graph analysis, mainstream approaches leverage concepts from RAG [275], agent-based reasoning [145], and fine-tuning [264] to improve graph-aware comprehension and reasoning.

LLM/Agent for Semi-structured Data Analysis. Semi-structured data lies between unstructured text and fully structured relational databases. It typically contains some organizational structure but does not conform to rigid schemas.

- *Markup Language.* XML, JSON, and HTML are common forms of markup language data. As markup languages consist of both tags and content, and inherently exhibit structural properties, their evolution bears strong similarity to that of

semi-structured tables, which has also motivated the development of structure-aware PLMs [18, 220].

- *Semi-Structured Tables* represent a flexible form of tabular data whose evolution is closely tied to advances in structured table understanding and the semantic capabilities of LLMs. Traditional approaches, often based on PLMs [73, 140], struggle to capture the complex layouts, irregular headers, and hierarchical structures due to their limited ability to encode semantics. With the advent of LLMs, new paradigms have emerged for handling such tables, including semi-structured to structured transformations that convert semi-structured tables into relational-like forms [54, 117], and DSL-based modeling that leverages domain-specific languages to explicitly encode structure and operations [201].

LLM/Agent for Unstructured Data Analysis. Unstructured data encompass a wide range of modalities such as charts, videos, documents, and 3D models, which lack a fixed schema and therefore pose significant challenges for conventional analysis pipelines.

- *Chart.* Traditional chart analysis systems typically rely on handcrafted feature extraction, template matching, or rule-based parsing techniques [99, 156, 179], which often struggle with variations in design, layout, and data representation. With the advent of LLMs, we can leverage multimodal understanding capabilities to interpret visual and structural elements of charts [153], generate contextual descriptions, perform semantic data extraction, and support natural language-based reasoning [153], captioning [135, 163, 192] and QA [242, 46, 256] tasks over different graphical data.

- *Video.* Video encodes spatial content that evolves over time, requiring joint modeling of semantics and dynamics. Conventional methods rely on vision backbones with temporal pooling or attention, which struggle with annotation costs and long-sequence efficiency [33] [209]. Recent advances reformulate videos as structured token sequences for LLM reasoning. Agents further decompose queries into temporal grounding, multimodal fusion, and summarization, enabling richer temporal understanding and efficient computation [33] [49]. Building upon this, LLMs have also been extended to Video Emotional Analysis , where multimodal fusion of visual, acoustic, and textual cues enables affective state inference.In addition, posture-based emotion analysis and 3D mesh reconstruction support nuanced social interaction modeling and relational emotional predictions [90, 158]. For Object Detection, integrating high-precision detectors with multimodal reasoning allows object-centric summarization and reference grounding in videos to make correct object detections in videos [48, 269]. Furthermore, Gesture and Behavior Detection leverages LLM-driven pipelines to extract fine-grained motion features and gestures, supporting interaction analysis and embodied behavior reasoning, often via 3D reconstructions for higher fidelity [235, 234].

- *Document.* Documents, such as PDFs, web pages, and scanned reports, serve as primary carriers of information in business and academia. Traditional document analysis relies on Optical Character Recognition (OCR) and rule-based template matching [276, 67], which are often ineffective for complex or varied layouts and fail to grasp the deep semantics of the content. LLMs, particularly Multimodal LLMs, have revolutionized document understanding by unifying the processing of text, layout, and visual information in three

aspects: (i) Architectural innovations from the LayoutLM series to DocLLM, enable a synergistic understanding of document structure and content [253, 254, 86, 208]. Concurrently, (ii) Retrieval-Augmented Generation (RAG) is employed for question answering and summarization across long or multiple documents [110, 108], and (iii) synthetic data generation effectively alleviates the scarcity of labeled data [183, 186]. These techniques collectively drive the shift from simple information extraction to deep document reasoning and synthesis.

- *Program.* Program analysis, which aims to understand, verify, and optimize source code, is a cornerstone of software engineering. Traditional methods depend on static analysis (e.g., compiler theory) and dynamic analysis (e.g., unit testing), which, while rigorous, require extensive expertise and are difficult to scale to large, semantically complex codebases. By learning from vast amounts of code, LLMs have acquired powerful capabilities for code generation and comprehension, giving rise to new analytical paradigms. The core of this advancement lies in the construction and utilization of code-task pairs—paired data of code snippets with their specific attributes (e.g., vulnerability labels, functional descriptions). Through advanced data synthesis techniques like iterative refinement and self-correction [147, 34], models can generate high-quality training data, thereby empowering frontier applications such as Automated Theorem Proving (ATP), vulnerability detection, and repository-level code completion [246, 142, 272]. Notably, the deep evolution of Retrieval-Augmented Generation (RAG) in the code domain has significantly enhanced the model’s ability to leverage context from entire repositories [128, 238, 63].

- *3D Model.* 3D models represent objects or scenes in Euclidean space, expressed as point clouds, meshes, or voxels, and are widely applied in scene understanding and scientific analysis. Conventional pipelines rely on geometric processing (e.g., mesh simplification, point cloud registration) [78, 59, 37] and modeling software such as Blender or Maya [25, 203], which require manual annotation and lack semantic understanding. Recent LLM-based approaches enable 3D–language alignment [77], where geometry is transformed into structured embeddings or textual descriptions for reasoning. Agents orchestrate specialized 3D encoders and toolchains to support downstream tasks such as captioning, navigation, and scientific QA [77, 250]. Building on this foundation, 3D-Language Fusion provides unified frameworks that map point clouds and meshes into embeddings aligned with natural language, enabling tasks such as captioning and QA 3D-LLM [77], 3UR-LLM [250] Domain-specific extensions integrate molecular and protein structures into multimodal reasoning, as in 3D-MoLM [119], ProteinChat [61], and ProtChatGPT [207]. Moreover, 3D-Derived Task Enhancement leverages multi-agent systems leverage textual mediation of geometry for scene description, navigation, and retrieval, improving interpretability and efficiency [77, 250, 119]. Finally, Cross-Modal Refinement employs feature enhancement and domain adaptation techniques(e.g., visual grounding, 2D–3D alignment, or joint pretraining) to bridge 2D and 3D modalities, strengthening generalization in multimodal LLMs [77, 119, 119, 250].

LLM/Agent for Heterogeneous Data Analysis. Heterogeneous data refers to the integration of diverse data types (e.g., relational data, semi-structured tables, document images) [216]. Early research focused on heterogeneous data

management [7], which supports data retrieval through SQL-like languages. More recent advances with LLMs address three main directions: (i) modality alignment across data types [204, 38] (e.g., leveraging natural language descriptions to compute cross-modal similarity), (ii) natural language interfaces for heterogeneous data retrieval [168, 217] (e.g., translating user queries into sequences of predefined APIs), and (iii) heterogeneous data analysis agents [161, 218] (e.g., equipping LLMs with semantic operation tools tailored to different modalities).

LLM/Agent for Data Analysis Evolution. As shown in Figure 1, the technological evolution of LLM-powered Data Analysis Agents can be summarized along five key dimensions, each corresponding to the design goals of a unified data analysis agent.

- From Literal to Semantic. Early LLM-powered data analysis agents primarily assist data analysis by generating executable code or domain-specific languages (DSLs). Their evolution has shifted toward leveraging semantic understanding to derive analytical results directly, reducing the need for intermediary procedural steps.
- From Modality-Specific to Modality-Hybrid. Initial data analysis agents are limited to analyzing a single type of data. The current trend emphasizes the integration of multiple data modalities, enabling agents to perform coordinated analyses across heterogeneous data.
- From Manual Development to Autonomous Design. Early agents require manual decomposition of analytical workflows (e.g., task decomposition, code generation, operation execution). Modern agents increasingly support autonomous workflow design, with broader operational capabilities and reduced human intervention.
- From Tightly-Coupled to Flexible Tools. Traditional agents rely on tightly integrated, framework-specific tools. The evolution favors decoupled architectures, where LLMs can leverage arbitrary toolsets, enhancing flexibility and adaptability in diverse analytical contexts.
- From Closed World to Open World. Initially, agents are predominantly tailored to domain-specific tasks (e.g., financial or industry analysis). The trend is toward general-purpose agents capable of analyzing diverse and real-world data (e.g., documents, videos), lowering user entry barriers.

1.4 Comparison & Contributions

Compared with existing surveys on LLMs for data analysis [139, 187, 290, 184, 180, 97, 241, 53, 22, 58, 12, 200], our work provides a more comprehensive and detailed overview of the key techniques applied across different data types, while also emphasizing the interrelationships among these data types. We uniquely examine the development trends from the perspectives of data modalities and interface languages, and further outline key dimensions for the design of a general LLM-based data analysis agent.

- Full-Vision Introduction to Typical Data Analysis Tasks. Different from existing surveys that typically focus on a single modality or task (e.g., NL2SQL [139, 187, 290], graph understanding [184, 180], table question answering [97, 241], document understanding [53, 22], chart understanding [58, 12], video understanding [200]), we systematically organize the landscape of data analysis by categorizing techniques across

structured, semi-structured, unstructured, and heterogeneous data. This roadmap also traces the technical evolution of LLM-powered data analysis and identifies five key dimensions that serve as design goals for a general-purpose data analysis agent.

• Detailed Review of Data Analysis Techniques. Beyond high-level summaries, we provide an in-depth examination of representative methods, discussing their underlying principles, technical designs, and application scenarios. In contrast to existing surveys, we further emphasize the critical role of data curation methods tailored to specific downstream tasks and offer corresponding data analysis insights.

• Recent Advances in LLM/Agent-as-Data-Analyst. In addition to established techniques, we emphasize the latest developments that leverage LLM for data analysis (e.g., agentic design, multimodal alignment, interaction techniques). By incorporating these cutting-edge advances, our survey provides an up-to-date reference for researchers and practitioners seeking to understand the state-of-the-art.

• Open Challenges and Future Directions. We identify the key technical and practical challenges that remain unresolved, such as scalability, evaluation, and integration into real-world systems. Building on these insights, we also outline promising future research directions to guide the development of general-purpose LLM-based data analysis agents.

1.5 Organization of Our Survey

Section 2 discusses LLMs for structured data analysis, covering relational data (Section 2.1) and graph data (Section 2.2). Section 3 reviews LLMs for semi-structured data analysis, including markup languages (Section 3.1) and semi-structured tables (Section 3.2). Section 4 examines LLMs for unstructured data analysis, encompassing charts (Section 4.1), videos (Section 4.2), documents (Section 4.3), programming languages (Section 4.4), and 3D models (Section 4.5). Section 5 addresses LLMs for heterogeneous data analysis. For each data type, we first present the data analysis techniques, followed by a subsection on data curation. Finally, we discuss the challenges and future directions associated with each data type in Section 6, and conclude the survey in Section 7.

2 LLM for Structured Data Analysis

Structured data refers to data with well-defined schemas like relational data [42] and graph data [16]. The commonality of them is pre-defined patterns that ensure clear organization and efficient querying. Relational data is characterized by row and column tables, or associated keys. Graph data models entities and their relationships through nodes and edges.

2.1 Relational Data Analysis

LLM for Natural Language Interfaces. Relational data analysis typically involves well-defined operations such as aggregation (e.g., summation, averaging, ranking) [42], statistical modeling (e.g., regression, clustering) [75, 202], and data quality assurance (e.g., constraint validation, outlier detection) [151], often supported by SQL or Python libraries like Pandas. While traditional methods depend on rigid SQL syntax and predefined analytical rules, LLMs extend these

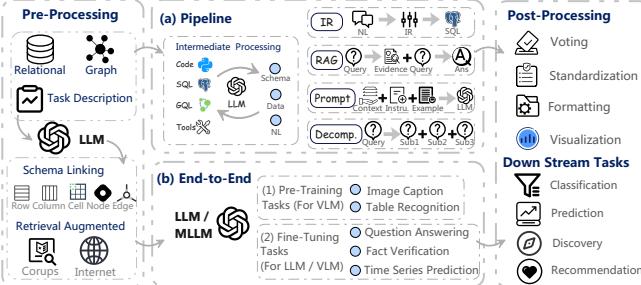


Fig. 3: LLM for Structured Data Workflows - (a) Pipeline Method. (b) End-to-End Method.

capabilities by enabling natural language to SQL/code translation and advanced semantic reasoning through their strong language understanding and inference abilities.

- **NL2SQL.** With the help of LLM, users can directly perform operations using natural language. NL2SQL focuses on translating natural language queries into SQL commands by leveraging techniques such as (i) schema linking, which aligns user intents with database schema to resolve ambiguities and filters out irrelevant schema to enhance the conciseness of input [271, 127], (ii) content retrieval, which dynamically extracts relevant information from the database to refine query generation [197, 114], and (iii) SQL generation strategies such as multi-step generation that concentrates on different SQL parts at each step [56, 285, 286], intermediate SQL representation or hybrid table representation for better LLM comprehension [173, 244, 143], and different decoding strategies (e.g., beam search, greedy search, or PICARD [111]). Other surveys provide more comprehensive overviews for NL2SQL techniques [138, 146, 188].

- **NL2Code.** Different from NL2SQL, NL2Code approaches emphasize enhancing relational data analysis through generating Python code (e.g., Pandas, NumPy), which includes a vast number of library APIs characterized by high variability and complexity, and often requiring the handling of complex chain operations. Recent studies have made progress in alleviating these challenges, though many remain open.

(1) Model Fine-Tuning: PACHINCO [265] fine-tunes a 62B parameter PALM [41] model in two stages (i.e., separately using a Python source code corpus with 64B tokens and a Jupyter notebook corpus with 9.6B tokens) so as to improve model performance on analysis-related tasks (e.g., calculate the amount of games added in each year for each month). DataCoder [82] utilizes different types of contexts (e.g., code, text, and data) by employing dual encoders (e.g., data encoder and code + text encoder) and one general decoder to generate code in notebooks.

(2) **LLM-Based Analysis Agent:** Data Interpreter [76] employs LLMs via APIs to generate task and action graphs, leveraging their semantic reasoning to decompose complex user queries (e.g., correlation analysis, data exploration, anomaly detection) into subproblems and iteratively refine and verify each to improve code generation for data science tasks. Another approach [20] fine-tunes a BART model [109] as an intelligent agent using datasets derived from task-instruction and role-definition prompts. The agent produces detailed prompts to guide LLMs through stepwise NL2Code execution, including role definition, requirement optimization,

code writing, and code review.

LLM for Semantic Analysis. Moreover, tasks requiring semantic understanding or natural language outputs (e.g., table summarization) benefit from LLM-based methods, including (i) multi-step question answering with decomposition strategies and (ii) end-to-end QA using optimized LLMs.

- **Multi-Step QA.** Multi-step question answering decomposes complex queries into sequential sub-questions for stepwise reasoning. Existing methods include (i) static decomposition, following fixed processing steps (e.g., retrieve-select-reason), and (ii) LLM-driven iterative decomposition, where the LLM dynamically determines each step based on contextual reasoning history.

(1) **Static Decomposition:** Static decomposition frameworks, such as Retriever–Selector–Reasoner and its variants, divide tasks into modular components to support multi-step inference and improve interpretability. The Extractor–Reasoner–Executor paradigm [288] extracts relevant context, generates logic rules or equations, and executes them via LLM prompting to get the final answer. Similarly, S3HQA [107] uses a retriever to filter heterogeneous resources, a selector to identify relevant knowledge, and a generation-based reasoner to produce the final answer. For multi-table scenarios, SGAM [223] encodes schema links and join paths as a graph, converts queries into reasoning chains on the graph, and executes them to produce the final answer.

(2) **Iterative Decomposition:** Static decomposition often struggles with multi-hop queries, whereas LLM-driven iterative decomposition dynamically overcomes it by refining sub-tasks via recursive reasoning. TAPER [282] applies this approach by introducing query decomposition, where the Planner breaks the query into sub-queries, the Reasoner generates executable programs for each, and the Answer Generator derives results to fulfill the plan. Finally, the Planner updates or finalizes the plan as needed. Similarly, ReActTable [279] and CHAIN-OF-TABLE [231] iteratively generate operations and update tables, using LLMs and in-context learning to produce reasoning chains as proxies for intermediate thoughts.

- **End-to-End QA.** End-to-End Question Answering refers to methods where the LLM directly generates the final answer without intermediate steps or iterative refinement. Approaches are classified by data handling into table-specific LLM fine-tuning, table content retrieval, and table-as-image analysis.

(1) **Table-Specific LLM Fine-Tuning:** Fine-tuning LLMs on task-specific table datasets embeds analytical knowledge directly into model parameters. TableGPT [118] fine-tunes GPT-3.5 on diverse real-world table tasks, while TableGPT2 [195], built on Qwen2.5 [176] and pre-trained on 593.8K tables and fine-tuned on 2.36M QA pairs, introduces a table encoder for hybrid table representation, an adapter for query encoding, and an LLM decoder to generate agent workflows like tool execution pipelines for deriving the final answer.

(2) **Table Content Retrieval:** Rather than embedding entire tables, content retrieval selects relevant rows and columns to reduce noise. CABINET [169] employs a weakly supervised component to produce a parsing statement that defines the criteria for selecting relevant cells, while TableMaster [28] refines subtables via row and column lookup, ranks candidate columns using LLM prompts, selects query-relevant subsets,

and generates SQL queries to extract the most pertinent rows. On the Multi-table and Multi-hop QA dataset (MMQA) [239], LLMs must retrieve relevant tables from a corpus and perform multiple inferences. Iterative multi-table retrieval (MTR), fetching question- and table-related tables stepwise, achieves the best performance.

(3) Table-As-Image Analysis: To overcome text-only LLM limitations in understanding table structures, tables are converted to images for multimodal LLM analysis. Table-LLaVA [284] pretrains LLaVA-7B [134] on 150K table recognition samples (e.g., output HTML of the input table) to align table structures and elements with textual modality and fine-tunes on 232K downstream tasks (e.g., fact verification, question answering) to enhance its instruction-following ability. TabPedia [280] enables a single model to handle diverse table analysis tasks via a concept-synergy mechanism that abstracts tasks into concepts. Built on Vicuna-7B [283], it adds meditative tokens to the LLM decoder input, adaptively activating visual token regions to interpret task-specific intents. However, limitations remain for such methods when processing twisted, distorted tables and direct document-image inputs.

LLM for Time Series Analysis. Time series data, a specialized form of relational data stored in relational or time-series databases (e.g., InfluxDB [160]), captures sequential observations over time, with each step recording one or more variables. Analysis focuses on temporal trends, periodic patterns, and inter-variable dependencies (e.g., causality, correlation, coupling) to support prediction, classification, and detection [133]. Unlike static relational analysis, time series emphasizes the dynamic evolution of variables along the timeline.

Traditional time series analysis relies on statistical and machine-learning methods, such as ARIMA and LSTM [190]. However, statistical approaches are limited by linear assumptions, manual feature engineering, and difficulty capturing complex nonlinear patterns [178]. Advances in machine and deep learning offer more flexible solutions [189], alongside efforts to improve result interpretability [213]. Recently, LLMs have emerged for time series analysis, leveraging their sequence modeling, generalization capacity, and ability to capture long-term dependencies.

- TS2NL. Due to the sequential similarity between time series and natural language, TS2NL converts time series data into natural language for LLMs, enhancing intuitiveness and interpretability.

(1) End-to-End Reasoning: End-to-end reasoning requires the LLM to generate results directly from a prompt containing time series data, instructions, and contextual information (e.g., news, events, logs). For instance, SIGLLM [14] explores anomaly detection by either directly querying the LLM or using it for prediction and comparing results with actual data. TimeRAG [261] leverages historical time series for domain adaptation, retrieving reference sequences via dynamic time warping (DTW) [182] to strengthen predictions. Other studies examine LLMs' zero- or few-shot forecasting abilities in domains like finance [268] and climate [227].

(2) Agent-Based Methods: Agent-based methods employ multiple LLM agents, each completing tasks under specific prompts, to collaboratively perform analysis. TimeCAP [105] uses two agents and a multi-modal encoder. The summary

agent generates contextual summaries of time series data, while the prediction agent uses these summaries for forecasting. The encoder integrates both data and summaries, reinforced by sampled relevant text, and the final prediction derived from the linear combination of encoder and agent outputs. TimeXL [94] extends this with a prototype-based encoder and three agents based on GPT-4o. The encoder produces preliminary predictions and explanations based on time series and textual inputs, while one agent generates predictions from text and explanations, another compares predictions with actual series to provide feedback, and the third refines text quality and triggers encoder updates. The final prediction is a weighted combination of encoder and agent outputs. For context-augmented forecasting [224], a reasoning agent selects relevant news to provide context for predictions, while an evaluation agent critiques both the news selection and prediction against ground truth, updating the reasoning agent's logic.

- Time Series Alignment. To address modality differences between time series data and natural language, some methods align the modalities to enable LLMs to capture temporal patterns and dependencies more effectively. Based on the model architecture, these approaches are classified into designed encoder/decoder frameworks and fine-tuned LLM bodies, with a comparison summarized in Table 1.

(1) Designed Encoder/Decoder: Specialized encoder or decoder modules adapt time series data to LLM input or output formats without modifying the LLM backbone. TIME-LLM [96] integrates time series and textual context by encoding time series with a patch reprogram module using text prototypes from pre-trained embeddings, prepending prompts encoded by a frozen LLaMA-7B embedder, and generating forecasts through a trainable projection module. SEED [112] bridges structural, numerical, and semantic gaps using a token-aware structural encoder, patch projection and alignment, and semantic reprogramming, concatenating multivariate time series tokens with the task prompt as LLM input. In contrast, TimeCMA [132] avoids feeding all embeddings into the LLM due to its limitations in learning disentangled representations. It encodes time series through two branches, a time series branch and an LLM-empowered branch, and combines them via cross-modality alignment for multivariate forecasting.

(2) Fine-Tuned LLM Body: Some methods fine-tune LLMs with encoder or decoder modules on time-series tasks, enhancing their understanding and analysis of complex time series. CALF [136] targets embeddings, hidden features, and predictions, applying cross-modal token alignment to derive aligned text tokens queried by time tokens, feature regularization loss between the textual and temporal hidden feature and output consistency loss between textual and temporal prediction to reduce distribution discrepancies during training. S2IP-LLM [166], on the other hand, decomposes time series by seasonal-trend to explicitly encode each component. Tokens of components and relevant prompts are concatenated as input, while the component predictions are combined as the overall prediction. LLM4TS [29] uses a two-stage fine-tuning which aligns LLMs with time series data, then fine-tuning on forecasting tasks. A two-layer aggregation pools the sum of embeddings across time scales to improving temporal understanding ability. Apart from prediction tasks, LLMFew [36]

TABLE 1: Comparison of Time-Series Analysis Methods.

Method	Encoder	Backbone	Decoder
TIME-LLM	Concatenation	–	Linear Projection
SEED	Concatenation	–	Linear Projection
TimeCMA	Dual-Modality	–	Multivariate Transformer
CALF	Dual-Modality	LoRA	Dual-Modality
S2IP-LLM	Decomposition	PEFT	Combination
LLM4TS	Multi-Scale	Two-Stage PEFT	RevIN
LLMFew	PTCEnc	LoRA	Classification Head

addresses multivariate time series classification, using a patch-wise temporal convolution encoder (PTCEnc) to align time series with LLM input, and fine-tunes LLMs via LoRA to enhance feature representation.

Relational Data Generation.

On one hand, training or fine-tuning with the training set is essential to adapt LLMs to domain-specific knowledge (e.g., finance, medical, climate) and structured data patterns (e.g., relational, time series, and graph). On the other hand, the test sets are widely used as benchmarks to evaluate the performance of LLMs.

The traditional method of dataset construction is usually the combination of real data collection and manual annotation. For example, the widely used table QA dataset WikiTQ [167] uses tables from Wikipedia and question-label pairs annotated by humans. Similarly, the NL2SQL dataset Spider [267] uses databases collected from existing resources and question-SQL pairs annotated by college students. The correctness, diversity and readability of annotation results are ensured through multiple rounds of manual inspection. In addition, the correctness of SQL is further verified by script. MMTU [247] provides a comprehensive collection of 52 such manually curated benchmarks on structured tables, organized across different tasks and benchmark datasets.

However, for some fields, the data may be scattered in small batches, or kept confidential for business or personal privacy needs, making manual collection difficult. To make matters worse, some manual annotation work not only requires a lot of manpower and time costs, but also requires participants to have a high level of professional knowledge. In this situation, semi-automatic or fully automated dataset generation is increasingly needed.

REaLTaBFormer [193] can generate relational datasets with the transformer. It first generates the parent table with a GPT-2 model and then generates the relational dataset conditioned on that with a Seq2Seq model. The GPT-2 and Seq2Seq model are trained on their corresponding task respectively. Another method [87] utilizes the structural representation capability of GNNs and the generative capability of diffusion models. It represents a relational database by a heterogeneous graph with the method in [252], where a parent-child table pair connected by a foreign key is modeled as an attributed bipartite graph. Based on the GNN embeddings of the graph, the diffusion-based TabSyn [273] is used for conditional tabular data generation.

Regarding data augmentation, SyntaxSQLNet [266] proposes a method to expand complex SQL datasets. It extracts some universal templates of question-SQL pairs from Spider, and then fill the templates with the schema and values from the target database. Furthermore, CodeS [114] achieves domain adaptation with low annotation costs by Bi-directional augmentation. The Question-to-SQL augmentation gives LLMs a few annotated question-SQL pairs, and LLMs can generate new pairs by simulating them. The SQL-to-question augmentation fills in question-SQL templates with the target domain database, and the LLMs then rewrite the question to more natural language.

[103] generates time series dataset by two interpretable methods. The first is the ITF-FM that operates the feature manipulation process based on the given dataset, The second is the ITF-GAN that is trained to generate indistinguishable data samples compared to the original data. ChatTS [245] comes up with the Attribute-Based Time Series Generator to get synthetic text-time series pairs for model training. LLMs are used to select proper features according to real-world settings for each attributes like trend, periodicity, local fluctuation and noise. The subsequent modules will generate the final time series based on the selection of the LLMs.

2.2 Graph Data Analysis

Unlike relational data, graph data captures entities (vertices) and their relationships (edges), enabling explicit modeling of complex network semantics (e.g., social networks, knowledge graphs). While highly expressive, this structure introduces unique challenges, including vast search spaces and intricate multi-hop reasoning [15].

Graph data analysis, compared with relational data, entails more complex tasks, such as summarizing multi-hop relationships and reasoning over text-attributed graphs, where nodes and edges carry textual information [130, 287]. Graphs can be stored not only in relational databases but also in knowledge graphs, accessed via SPARQL in RDF databases (e.g., Blazegraph [1], GraphDB [3]) or Cypher in Neo4j [2].

Traditional graph analysis (e.g., statistical methods, graph neural network (GNN) based methods) encompasses a spectrum of tasks, including node classification (e.g., categorizing academic papers into research domains), graph classification (e.g., predicting node properties over molecular graphs), link prediction (i.e., inferring latent relationships between graph nodes), community detection (i.e., identifying densely connected subgraphs), anomaly detection (i.e., identifying deviations from expected patterns), graph clustering, and etc. However, these methods have their own limitations. Statistics-based methods fail to handle complex semantic information (e.g., query can be extremely complex and requires human expertise), while graph neural networks (GNNs) exhibit limited generalization capabilities, necessitating task-specific retraining on different tasks.

In contrast, the advent of LLMs offers transformative potential by leveraging their advanced reasoning capacities and cross-domain generalization abilities, which can (i) simplify the query writing costs (e.g., NL interfaces) and (ii) achieve semantic-aware analysis unsupported in traditional ones.

Natural Language to Graph Analysis Query. Different from NL2SQL, the syntax of graph query language generation

is more complex (i.e., MATCH, LOOKUP, GET and other operations unique to graph data manipulation) and there exist two operation objects (i.e., vertex and edge) [287]. By integrating natural language interfaces with graph data, LLMs facilitate flexible and efficient query generation without the need for specialized model architectures.

To enhance LLMs' comprehension of the complex syntax of Graph Query Language (GQL), $R^3\text{-NL2GQL}$ [287] proposes a hybrid approach leveraging relatively small LLM (e.g., LLaMA3-7B) as a selector and GQL rewriter, while employing a larger LLM (e.g., GPT-4) as a reasoner. The selector identifies the necessary CRUD functions, clauses, and schema, while the rewriter refines the query by aligning it with the relevant graph data retrieved by minimum edit distance and semantic similarity calculation. The LLM then synthesizes the aligned question, selected operations, and schema to generate the final GQL query.

To address the limitations of LLMs in planning and collaborating with other LLMs, NAT-NL2GQL [130] introduces a three-agent framework. The Preprocessor agent constructs context information, including query rewriting, path linking, and the extraction of query-relevant schemas. The Generator agent, an LLM fine-tuned with NL-GQL data, generates GQL statements based on the rewritten queries and extracted schemas. The Refiner agent iteratively enhances the GQL or contextual information by leveraging error feedback from GQL execution results.

To align LLMs with graph databases in specific fields such as finance and medicine, [129] proposes a pipeline combining the fine-tuning and the prompt method. NL-GQL pairs are generated by LLMs for fine-tuning, and the consistency is ensured by the background graph databases and two mutual verification self-instruct methods. In addition, due to the importance of relevant schema in the queries generating of LLMs, it will be extracted and integrated into prompts.

Note that, within the context of AI for Science (AI4Science), the integration of LLMs with graph data analysis has also shown significant potential and wide-ranging applications (e.g., treat polymers as graphs and predict their properties [122, 171]), which is not the primary focus of this survey.

LLM-Based Semantic Analysis. Furthermore, certain jobs necessitate semantic-aware analysis, such as summarizing textual paragraphs embedded within graph nodes. Based on the adopted LLM strategies, we classify the relevant methods into retrieval-then-reasoning methods, execution-then-reasoning methods, graph-task-based fine-tuning methods, and agent-based methods.

- Retrieval-Then-Reasoning. Retrieval-then-reasoning first extracts a question-specific subgraph from the graph to identify the most relevant entities and then generates answers using LLMs. To address the challenge of a vast search space, [275] introduces a two-stage approach. First, a trainable and decoupled subgraph retriever selects a relevant subgraph based on the query. Then, reasoning is performed over the retrieved subgraph to derive the final answer. UniKGQA [93] integrates retrieval and reasoning within a unified model architecture. It consists of a semantic matching module and an information propagation module where the former employs a pre-trained RoBERTa [140] to align questions with graph relations and the latter propagates matching signals along

directed edges. Regarding the real-world textual graphs QA, G-Retriever [72] retrieves relevant nodes and edges based on text encoding, and then uses PCST optimization algorithm to construct subgraphs. The subgraph structure is encoded through Graph Attention Network (GAT) while its content is extracted in text format. These representations are then fed into LLMs to generate the final answer.

- Execution-Then-Reasoning. Execution-then-reasoning refers to the process of parsing natural language queries into executable logical forms (e.g., SPARQL) that align with the graph data, followed by reasoning based on the output of the executed program. Interactive-KBQA [248] introduces an interactive LLM QA framework with a unified SPARQL-based toolset (e.g., entity search, graph pattern search, SPARQL execution, etc.) designed to address complex queries. MCTS-KBQA [249] introduces the MCTS method into KBQA, which iteratively executes selection, expansion, evaluation, backpropagation and termination in the graph. A step-wise reward mechanism was designed, using LLMs to evaluate and score each step. FlexKBQA [126] addresses the challenge of lacking high-quality annotated data in real-world scenarios. By prompting LLMs as program translators, it samples program-answer pairs from the knowledge base and generates corresponding natural language questions. The synthetic question-program-answer dataset is used to train lightweight models through execution-guided self-training, which are subsequently employed to annotate real user queries. This approach addresses the distribution shifts between synthetic and actual data, leading to significant improvements in few-shot learning scenarios.

- Graph-Task-Based Fine-Tuning Methods. InstructGLM [264] enables generative graph learning by fine-tuning an LLM and leveraging natural language descriptions of graph structures (e.g., offer the first node and the 1-/2-/3-hop neighbors' information). InstructGraph [215] introduces a stricter code-like graph representation format which constructs entities and triples in the form of list, whose backbone LLM (LLaMA2-7B) is fine-tuned on a graph-centric corpus comprising 1.6 million instances. To mitigate the issue of hallucination, it incorporates Direct Preference Optimization (DPO) algorithm [177] for preference alignment. GraphGPT [199] enhances model performance in zero-shot scenarios by incorporating a structural information encoding module based on Graph-SAGE [68] and GCN [102]. It fine-tunes the projector bridging the graph encoder and the LLM decoder to align the language capabilities of the foundation LLM (Vicuna-7B) with the graph learning tasks. GLaM [51] fine-tunes LLMs to integrate domain-specific knowledge graphs directly into them, which enhances their reasoning capacity. It iteratively partitions and encodes the neighborhood subgraph around each node in a knowledge graph to obtain the context and QA data for fine-tuning.

- Agent-Based Methods. Agent-based methods involve leveraging LLM-based agents with predefined tools (e.g., human-written interfaces or graph processing library APIs) that iteratively interact with the graph data to retrieve, refine, and operate information. StructGPT [92] introduces an iterative reading-then-reasoning framework, leveraging specialized interfaces to operate on graph data. It repeatedly applies an invoke-linearize-generate procedure to derive query results. KBQA-o1 [145] utilizes a ReAct agent and MCTS to explore

the knowledge base. During the exploration process, the agent gradually generates the logical form of knowledge base operations. The MCTS with policy and reward models helps balance the exploration’s performance and search space. Another approach is to generate an entire reasoning path based on the query and refine it only when necessary. Readi [39] initially constructs a reasoning path and instantiates it on the graph. When execution errors occur, it collects error messages and invokes an LLM to revise the path. The final answer is inferred from the instantiated graphs.

Graph Data Generation. To cope with the lack of large-scale structured graph datasets, a framework [45] to generate Large-Scale Graph Dataset is proposed. It generates structures and features separately by fitting the original graphs, and aligns them to obtain the generated graph. [289] presents the pipeline that generates temporal knowledge graph (TKG) datasets based on documents. It utilizes LLMs to generate timestamps for existing triplets, thereby obtaining the quadruples needed for constructing TKG.

Takeaway: For structured data analysis, LLM-based agents demonstrate significant abilities: **Complex Data Understanding (O1):** LLMs capture structural and semantic relations across tables, graphs, and time series data, enabling unified understanding. **NL-Based Interface (O2):** LLMs translate user intents into executable queries (e.g., SQL, graph queries), facilitating intuitive data interaction. **Semantic Operators (O3):** LLMs integrate symbolic and neural reasoning to execute compositional operations with semantic awareness. **Autonomous Evolution (O4):** Through continual learning and schema adaptation, LLM agents refine their analytical abilities and evolve with dynamic data and tasks.

3 LLM for Semi-Structured Data Analysis

Semi-structured data are neither strictly schema-defined like relational data nor completely raw like text or images [8]. They retain partial organizational properties (e.g., tags, headers) and often have hierarchical or nested structures (e.g., *County–Province–City* in JSON). This allows representation in diverse formats such as web tables, spreadsheets, HTML, JSON, and XML. They can be broadly categorized into markup languages and semi-structured tables, both challenging downstream tasks due to their structural complexity.

3.1 Markup Language

Markup languages (e.g., XML, JSON, HTML) are widely used for structuring and exchanging data, yet research on integrating LLMs with them remains limited. Traditional approaches for markup understanding fall into two categories. Token Linearization converts markup documents into plain text sequences for PLMs [73], but this often oversimplifies and fails to capture structural complexity. Tree/Graph-Based PLMs explicitly encode structures (e.g., DOM trees), yet they suffer from limited generalization, short context windows, high pre-training costs, and poor scalability.

LLM-based methods have recently emerged as a promising alternative, offering stronger semantic reasoning and greater

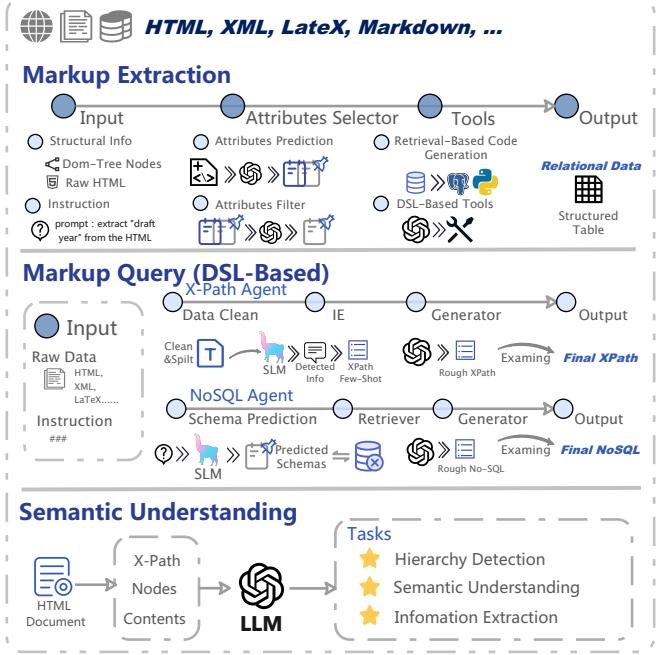


Fig. 4: LLM for Markup Language Overview

adaptability for complex markup data, which is summarized in Figure 4.

Markup Extraction. Markup Extraction aims to transform semi-structured data (e.g., HTML, XML) into structured formats such as relational tables. Traditional methods rely on heuristic rules (e.g., extracting content within `<h1>` or `<title>` tags [226]) or data templates (e.g., extracting product names from `<h1 class="product-name">` [43]), but they often suffer from template drift and high annotation costs. Leveraging LLMs enables direct extraction and interpretation of hierarchical relationships, attributes, and nested structures, reducing dependence on tags or templates.

Evaporate [18] is a prototype system that uses LLMs to generate structured views from semi-structured documents. It employs Evaporate-Code+, which first synthesizes multiple candidate extraction functions via LLMs. Functions are generated in two modes, where one provides few-shot examples encouraging general-purpose Python solutions, and the other specifies only task requirements to produce regex-based solutions. A weak supervision-inspired aggregation mechanism then evaluates and filters candidates based on output quality.

Similarly, WebFormer [220] targets HTML specifically by leveraging its layout structure. It encodes DOM nodes as graph-attended tokens and models text with relative-position self-attention. Field tokens guide heterogeneous cross-attention with HTML and text tokens, enabling accurate and scalable structured field extraction.

Markup Information Querying. Markup information querying extracts user-intended data from markup languages. While conceptually similar to SQL querying over relational databases, markup files are often irregular and loosely structured, posing unique challenges. Existing research mainly explores tree-based and NoSQL-based approaches.

- **Tree-Based Approaches.** XPath Agent [124] uses a two-stage pipeline for XPath queries. In the information extraction

stage, a lightweight LLM analyzes a simplified webpage, with irrelevant nodes and attributes removed via HTML cleaning algorithm to produce a compressed HTML. In the XPath Programming stage, a stronger LLM constructs XPath queries bottom-up, traversing from target nodes to parent elements and flexibly using attributes like class names and IDs.

- *NoSQL-Based Approaches.* SMART [144] is a Text-to-NoSQL agent that integrates small language models (SLMs), retrieval-augmented generation (RAG), and LLMs. An SLM first predicts schemas and an initial NoSQL query from the natural language input. RAG then retrieves relevant data using the preliminary query and schema, which, combined with few-shot exemplars, guides the LLM to generate a refined NoSQL query applicable to large-scale semi-structured data.

Markup Information Understanding. Unlike markup querying, markup information understanding focuses on using LLMs for more complex operations on markup data (e.g., revision and error correction). To support this, both end-to-end and pipeline-based models have been developed for comprehensive markup file understanding.

DOM-LM [50] introduces a structure-aware Transformer that jointly encodes HTML text and DOM tree structure. To handle large DOM trees, it partitions them into subtrees and uses structure-aware positional embeddings (e.g., node depth, parent, and sibling indices) to capture hierarchy. The model is trained with a self-supervised masking strategy over both tokens and DOM nodes. MarkupLM [116] extends token representations from four perspectives, including text embeddings, 1D positional embeddings for horizontal order, segment embeddings for paragraph distinctions, and XPath embeddings. XPath embeddings are created by decomposing an XPath into hierarchical layers of tags and subscripts, combining each layer’s tag and subscript embeddings, concatenating across layers, and passing through a feed-forward network to produce the final representation. For pre-training, MarkupLM uses three markup-specific objectives. Masked Markup Language Modeling (MMLM) for joint textual-structural understanding, Node Relationship Prediction (NRP) to learn DOM hierarchies, and Title–Page Matching (TPM) for global document coherence.

WebLM [251] presents a hierarchical multimodal pre-training framework for HTML webpage understanding, integrating structural, textual, and visual information within a unified Transformer. Visual features are aligned with HTML nodes, and two training objectives are used. Tree Structure Prediction (TSP) captures parent-child and sibling relations, and Visual Misalignment Detection (VMD) improves robustness to layout variations.

Insights of Markup Language Analysis. Most studies on markup language understanding still rely on PLMs for two reasons. (i) Controllability: PLMs allow explicit control over model size, training data, and task settings, whereas LLM APIs are often closed-source and costly. (ii) Structural Adaptation: PLMs can use specialized tokenization and positional encodings to capture HTML/XML hierarchies [50, 251], while general-purpose LLMs depend on prompt engineering, leading to redundant tokenization, long prompts, and difficulty jointly modeling semantics and structure (e.g., converting an HTML table to text requires auxiliary schemas).

However, given the strong semantic capabilities of LLMs,

Employee										
ID	Name	F	Sa	Su	M	Tu	W	Th	#REF!	Totals
1	Emp1	15	16	17	18	19	29	21	#REF!	1.5
2	Emp2									-
3	Emp3									-
4	Emp4									-
5										-
Summary										
										-
										-
										-

Fig. 5: Example Characters of Semi-Structured Tables.

leveraging them for markup language understanding remains promising, provided that effective methods are developed to compensate for their limitations while maximizing their semantic reasoning power. To this end, we identify two key research insights, which can be categorized into information compression and tool integration.

- *Information Compression.* Information compression addresses the challenge of encoding markup languages by providing LLMs with more concise representations. Traditional methods, such as structural or schema-aware prompting, often produce redundant rules and long prompts. Segment-wise prompting partitions documents into manageable segments and selectively filters relevant content. For renderable languages like HTML or LaTeX, vision-language models can assist by extracting visual anchors and generating tree-structured encodings, allowing LLMs to receive task-relevant information while reducing prompt length and preserving structural context.

- *Tool Integration.* Tool Integration for LLMs aims to enable LLMs to interact with and modify external environments. Existing methods such as DSL-based soft tools, retrieval-based code generation, and API-calling frameworks, are often rigid, with APIs providing fixed mappings from natural language to predefined functions. More dynamic approaches are needed, including planning modules, learning-based tool selection, and self-reflective reasoning loops.

3.2 Semi-Structured Tables

This section focuses on semi-structured table processing, encompassing techniques for understanding, representing, and extracting information from such tables. Unlike structured relational data, semi-structured tables feature complex structures, including merged cells, hierarchical headers, and nested tables.

Semi-structured tables share a set of properties, which can be summarized into five core characteristics, illustrated in Figure 5: (i) Wrong Index: row or column indices may be missing, ambiguous, or inconsistent [196]. (ii) Hierarchical Content: rows or columns may not follow a uniform schema (e.g., a “summary” cell under an “ID” column) [260]. (iii) Merged Cell: a single cell may span multiple rows or columns [64]. (iv) Flexible Header Orientation: keys and values can appear in varying positions (e.g., left-of or above their associated values). (v) Inconsistent Content: cell values vary widely, including words, numbers, or full sentences.

With the aid of LLMs, it becomes possible to directly reason over semi-structured tables, interpret their intricate layouts, and bridge the gap between natural language queries

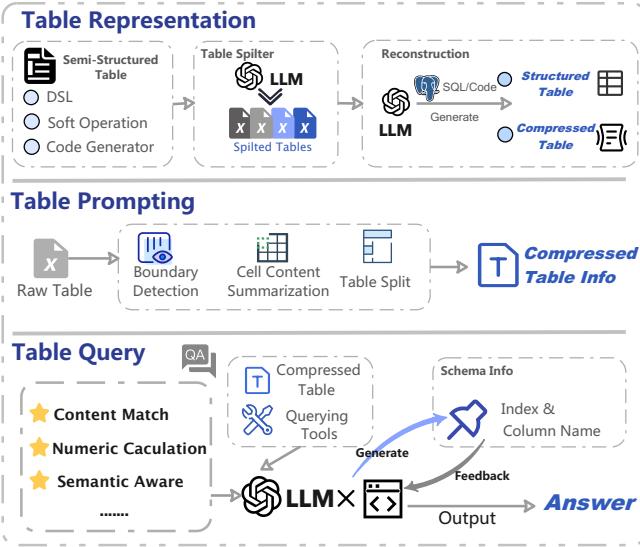


Fig. 6: Overview of LLM for Semi-Structured Table.

and heterogeneous table structures, thereby enabling more accurate and context-aware query answering.

Traditional table processing approaches like TAPAS [73] mainly rely on lightweight models (e.g., BERT[52], RoBERTa[141]) to analyze the table. These methods rely on specialized embedding mechanisms to capture the two-dimensional structure of tables, including rows, columns, and numerical order. To support tasks such as cell selection or aggregation, they usually require large-scale weakly supervised pre-training [260]. However, due to the small number of parameters and weak NLP capabilities of lightweight models, this method cannot handle some tasks based on semi-structured tables with confusing layouts. Leveraging the strong semantic understanding capabilities of LLMs, LLM-based approaches generally preprocess the semi-structured table and then perform table understanding or reasoning. We conducted some research on this, and the work is shown in Figure 6.

Table Representation. By converting semi-structured tables into structured representations, LLMs can better capture the underlying logical relationships within tables, thereby improving their effectiveness in downstream tasks. However, the diverse and complex layouts of semi-structured tables (e.g., hierarchical headers, merged cells, and nested subtables) pose significant challenges to this process. To address these issues, tree-based modeling approaches and model-driven methods have been proposed.

- **Tree-based Table Modeling.** TUTA [229] introduces a tree-based encoding for semi-structured tables, where the root splits into row and column nodes, each expanding hierarchically into trees. Table entries are nodes with parents corresponding to their row and column (e.g., column nodes like “ID” or “Phone Number” and row nodes representing individual names). ST-Raptor [201] proposes a HO-Tree to encode tables, combining a Meta-Tree for header structure and semantics with a Body-Tree for content. It uses a VLM to detect meta-information, heuristic rules to segment tables, and a depth-first strategy to construct the HO-Tree.

- **Model-based Structuring.** TabFormer [54] converts semi-structured tables into relational data using a chain-of-thought (CoT) approach. LLMs first apply step-by-step transformations with “soft operators” (e.g., splitting tables with multiple header groups). After preprocessing, SQL is used to reconstruct the table, including predicting indices, generating CREATE statements for the schema, and inserting the extracted contents into the relational table.

Auto-Tables [117] integrates OCR for structure recognition and applies domain-specific language (DSL) operators. These operators abstract common spreadsheet operations (e.g., melt, transpose), thereby enhancing generalization and adaptability in table conversion tasks. TradeSweep [104], while closely related to Auto-Tables, differs in its approach. Instead of predefined DSL operators, it accepts user-specified transformation requirements and directly generates table conversion code by leveraging a code repository, offering greater flexibility in addressing diverse user needs.

Table Prompting. Table prompting converts table data into text input for LLMs. Traditional approaches, like table linearization, flatten all cell contents into a single string, often producing overly long prompts and losing structural information. To address this, table content and structure should be compressed, enabling LLMs to handle large tables while keeping structural loss controllable.

SHEETCOMPRESSOR [55] efficiently serializes large spreadsheets for LLM prompting. Structural Anchors identify key heterogeneous rows and columns, pruning redundant ones to create a skeletonized sheet. Inverted-Index Translation encodes non-empty cells in a JSON dictionary, merging duplicates to reduce storage. Data Format Aggregation clusters adjacent numerical cells of the same type or format, capturing distribution patterns without redundancy. HySem [174] introduces a lightweight LLM pipeline for local deployment. Its Context Optimizer compresses HTML table tokens so each cell uses only one or two words (e.g., compress “Theme 3: Factors affecting stuff response” into “Theme 3”), establishing a direct mapping between markup and content while minimizing token usage.

Table Querying. LLMs require effective methods to extract table contents, known as table querying. While conceptually similar to SQL, this section focuses on approaches that directly extract information from semi-structured tables rather than traditional SQL querying. CoS [55] is a downstream table query system built on SHEETCOMPRESSOR. Given a spreadsheet and a natural language query, it first performs Table Identification and Boundary Detection to locate the relevant subtable. The subtable and query are then passed to the LLM for focused, context-aware response generation. In ST-Raptor [201], table querying relies on the HO-Tree. Complex questions are decomposed into sub-questions mapped to sequences of basic operations (e.g., retrieval, condition). The alignment operation grounds abstract query terms to actual headers or values, while Top-down and Bottom-up retrieval navigate the HO-Tree. For large tables, Column-Type Annotation (e.g., discrete or continuous) limits the search space. A dual validation mechanism—forward constraints for intermediate consistency and backward reasoning to reconstruct the query—reduces errors and hallucinations.

Semi-Structured Data for LLM To facilitate research on

TABLE 2: Statistics of Semi-Structured Table Datasets.

	Table Features		Q&A Features		
	#-Cell	#-Merged-Cell	Content Match	Numeric Computation	Semantic Aware
TEMPTABQA	11–100	1–10	✓	✗	✗
SPREADSHEETBENCH	101–1K	11–100	✓	✓	✓
MiMoTable	11–100	1–10	✓	✗	✗
INFOTABS	11–100	1–10	✗	✗	✓
WikiTableQuestions	101–1K	11–100	✓	✓	✓
FeTaQA	101–1K	1–10	✓	✗	✗

table understanding and reasoning under challenging conditions, a number of datasets have been developed. Below, we introduce several representative datasets that are widely used for semi-structured table understanding.

TEMPTABQA [65] contains 11,454 question-answer pairs centered on temporal queries while SPREADSHEETBENCH [150] provides a challenging benchmark for spreadsheet manipulation, consisting of 912 questions derived from real-world scenarios. MiMoTable [125] targets reasoning across multiple sheets and files, with 1,719 queries distributed over 428 spreadsheets. Evaluation results on these benchmarks reveal a significant performance gap, ranging from 20% to 50% between state-of-the-art models and human performance, underscoring the need for further advances in this area. INFOTABS [66] is designed for the natural language inference task on semi-structured tables. It contains 23,738 premise–hypothesis pairs, where premises are Wikipedia infoboxes and hypotheses are short sentences. WikiTable-Questions [167] focuses on question answering over semi-structured HTML tables, comprising 22,033 question–answer pairs together with their associated tables. FeTaQA [159] is a free-form table question answering dataset containing 10k Wikipedia-based pairs of tables, questions, answers, and supporting table cells. Unlike extractive QA datasets, Fe-TaQA provides human-written free-form answers including entities and their high-level relations. For comparison, Table 2 summarizes the characteristics of different datasets. The table highlights structural complexity including total cell counts and the number of merged cells, as well as question–answering types, including: (i) Content Match, where the task is to locate the correct cells, (ii) Numeric Computation, which requires performing arithmetic or aggregation operations, and (iii) Semantic Awareness, which involves semantically related or reasoning-intensive tasks. For instance, INFOTABS contains a large number of natural language inference questions, whereas SPREADSHEETBENCH features long, complex natural language queries (often exceeding 50 words) that describe multi-step tasks.

Takeaway: Semi-structured data remains challenging due to its irregular and nested nature. LLMs show strong potential to address these difficulties through three main directions. **Complex Data Understanding (O1):** Enable reasoning over irregular and nested structures. **NL-based Interfaces (O2):** Facilitate intuitive interaction and query generation through natural language. **Semantic Operators (O3):** Empower models to perform semantic-level operations such as structural interpretation, summarization, and context-aware reasoning.

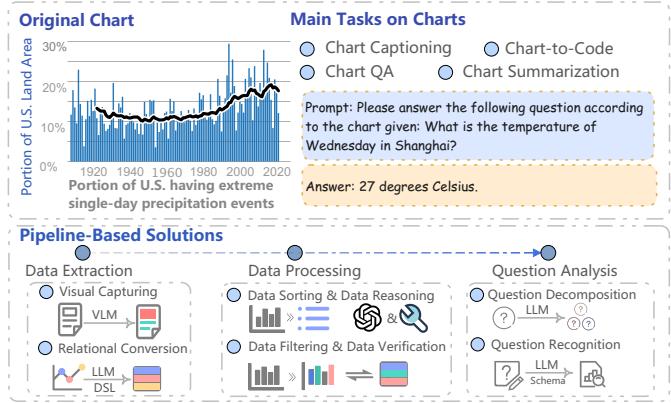


Fig. 7: Overview of Chart Data Analysis.

4 LLM for Unstructured Data Analysis

Unstructured data refers to data that lacks explicit structure, as it does not adhere to a predefined schema [47]. Additionally, it exhibits high variability in format, length, and modality, which further complicates its processing and analysis [24, 212].

4.1 Chart

A chart is a graphical method for representing data. Since humans generally process visual information more effectively than raw tabular data, charts visualize data in symbolic forms such as bars, pies, and lines. However, as charts are inherently designed for human perception, developing rule-based methods for comprehensive understanding remains difficult. Early approaches introduced an additional layer with a fixed vocabulary to simulate rules. For example, DVQA [99] employed LSTM networks to encode questions and CNNs to encode chart images, but the reliance on a fixed vocabulary limited generalization. Subsequent works such as SANDY [99] alleviate this issue by leveraging OCR ground truth to link chart elements with dictionary entries, though the accuracy of OCR recognition remained a critical bottleneck.

From a technical perspective, chart understanding poses unique challenges as it requires integrating visual perception with structured data extraction, numerical reasoning, and logical inference. As shown in Figure 7, tasks on charts show diverse features, requiring a multi-perspective understanding on the structure and content of charts. As a result, multiple tools are useful for chart understanding, each focusing on a specific side of the task. Research in this domain has primarily followed two paradigms: (i) pipeline-based methods, which decompose the task into modality conversion and semantic reasoning, and (ii) end-to-end models, which directly map chart images and instructions to responses within a unified framework. In the following, we provide an overview of chart-related tasks and examine these two LLM-based technical paradigms.

Chart Captioning. Chart Captioning (or Summarization, Chart-to-Text) refers to a task on generating a descriptive caption for a given chart. The caption should contain key information or serve as a summary of the graph. Early studies primarily target common graphical features such as axes and legends. These features enable different charts can be summarized by successively mentioning all of the features,

giving rise to planning-based pipelines for caption generation. For instance, Mittal et al [156] propose feature-specific strategies for different types of graphs, while Reiter [179] outline a four-stage data-to-text framework comprising (*i*) Signal Analysis to look for possible patterns and trends, (*ii*) Data Interpretation to identify more complex messages, (*iii*) Document Planning to decide which of the messages should be mentioned in the generated text, and (*iv*) Microplanning and Realisation to create an actual text. Such pipeline-based approaches are stable and extensible in fixed scenarios but tend to be heavy and lack general applicability. Building on this line of work, ChartThinker [135] employs a large-scale dataset and a chain-of-thought strategy to enhance the logical coherence and accuracy of chart summarization. Leveraging LLMs, it first identifies the chart type and then iteratively generates reasoning steps to capture a holistic understanding of the chart.

At the same time, end-to-end solutions have also emerged. [163] introduces a transformer-based model that generates summaries containing data by taking both the underlying table and chart metadata as input. FigCaps-HF [192] fine-tunes a figure-captioning model using RLHF. Other approaches extend beyond captioning to jointly address captioning and question answering by encoding chart elements with a grounded text decoder. For instance, UniChart [153] is a pretrained model that incorporates both low-level tasks (e.g., extracting visual elements) and high-level tasks (e.g., chart interpretation) into its training objectives, enabling more comprehensive chart understanding.

Chart Question Answering. Chart question answering (Chart QA) requires a model to answer questions related to the content of a chart. Compared to the task of captioning a chart, QA also has to grab the key information of a chart. However, the task requires a more flexible understanding of the charts, since a question may focus on subtle and imperceptible features of the charts. As mentioned in ChartQA[154], the questions might involve both visual and logical reasoning on charts.

Researches relevant to chart QA explores specific aspects of Chart QA task. [242] addresses the underexplored area of low-level ChartQA tasks (e.g., identifying correlations) by introducing the ChartInsights dataset and a tailored “Chain-of-Charts” prompt strategy. For the explainability of answering, Charts-of-Thought [46] designed prompts for altogether four steps in data processing: extraction, sorting, verification and question analysis. For multimodal alignment, ChartMoE [256] used Mixture of Expert architecture to bridge the modality gap, as well as building ChartMoE-Align, a dataset with nearly 1 million chart-table-JSON-code quadruples to conduct alignment tasks.

Besides, some researches noticed the few-shot ability of LLM and designed relevant end-to-end solutions. Chart-Gemma [155], for example, is trained on instruction-tuning data generated directly from chart images, thus exploiting both high-level and low-level information of charts. mPLUG-Owl[263] is a general-purposed model that also fits the problem. Researchers design a two-stage method to align visual information with text: In the first stage, visual knowledge and abstractor modules are trained; In the second stage, LLM and abstractor modules are fine-tuned using LoRA while freezing

visual knowlegde model.

Chart-to-Code. Chart-to-Code refers to generating executable code (e.g., in matplotlib) that can be rendered into chart images, thereby transforming charts into editable forms. Current solutions are primarily end-to-end and rely on VLMs. ChartMimic [258] and ChartMoE [256] provide large-scale benchmarks with extensive chart–code pairs to support this task.

Text2Chart31 [270] introduces a reinforcement learning-based instruction tuning approach for chart generation without requiring human feedback. The models are trained under two phases: supervised fine-tuning followed by reinforcement learning with tailored rewards to enhance performance. Chen et al. [31] employ multimodal structured reinforcement learning to surpass the performance plateau of supervised fine-tuning in chart-to-code tasks. The study leverages a multi-granularity structured reward system that uses multimodal textual and visual feedback to guide the RL training. The rewards are rule-based at textual level and model-based at the visual level.

LLM-Based Data Synthesis. A primary challenge in Chart QA is the scarcity of high-quality, multimodal instruction tuning datasets. To address this, several works have focused on data synthesis. Using GPT-4, ChartLlama [69] introduces a sophisticated pipeline with three phases successively: Chart data generation, chart figure generation, and instruction data(code, QA pairs, narrative paragraphs, etc.) generation. The pipeline enables the dataset to cover a wide array of chart types and tasks including QA, summarization and even chart editing. Similarly, ChartBench [255] adopts both desensitized and GPT-generated data. For QA diversity, the work provides GPT with 200 different question templates, with human checks to ensure their correctness. [83] presents EvoChart. It is a self-training method with three phases: Compositional chart generation, chart evaluation and refinement, and QA pair generation and training. The three phases will run cyclically until the completion of data synthesis.

Takeaway: Charts present structured data in a visually interpretable form. Future work should focus on mechanisms that emulate human attention for chart understanding, whether through end-to-end or pipeline-based reasoning. **Complex Data Understanding (O1):** Process charts with different patterns and organize data results [156, 179, 135, 155]. **NL-Based Interface (O2):** Pay attention to details that users care about while allowing NL interactions [46, 263]. **Semantic Operators (O3):** Capture semantic information hidden in positional relationships among the elements [153, 242, 256]. **Autonomous Evolution (O4):** Notice the distribution of information in charts, and extend its ability to solve a lot of downstream tasks[69, 83].

4.2 Video

Video inherently represents evolving spatial content over time, requiring models to jointly capture spatial semantics and temporal dynamics [209]. Traditional methods use vision backbones for frame-level features followed by pooling, token merging, or attention to model temporal relations.

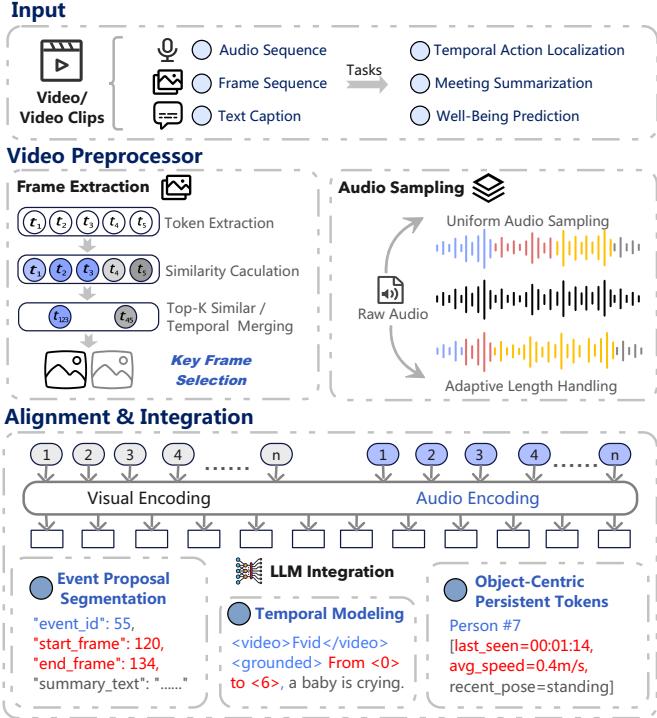


Fig. 8: Overview of Video Data Analysis.

Although effective, these architectures are manually designed, annotation-heavy, and computationally inefficient for long sequences, often losing fine-grained temporal details during compression.

Recent advances integrate LLMs into multi-modal video understanding by representing videos as structured token sequences instead of independent frames. This design improves visual–text alignment and addresses key limitations of prior methods: (i) computational inefficiency via adaptive frame selection and token reduction, (ii) visual fidelity loss through selective filtering of redundant frames, and (iii) weak temporal grounding using modules that encode event order and duration [185, 209]. Rather than replacing vision encoders, lightweight adapters and temporal reasoning components extend their capabilities while maintaining efficiency.

Figure 8 illustrates the general pipeline for LLM-aided video analysis, where existing work primarily focuses on optimizing video preprocessing (e.g., frame extraction, temporal sampling, and feature extraction) and semantic understanding (e.g., temporal modeling, multimodal fusion, and LLM integration).

Temporally-Anchored. Existing video–language models struggle with precise temporal localization, as it requires detecting sparse, transient signals within long and redundant sequences. This entails (i) distinguish relevant information (e.g., object appearance, key gestures, or sound onsets) [185], (ii) identifying event boundaries (e.g., action start/end or scene transitions), and (iii) maintaining temporal coherence by preventing misalignment of object states or actions across time [33]. Moreover, handling videos of varying lengths remains challenging, where fixed input sizes waste computation on short clips, and uniform sampling in long videos often overlooks critical events.

To tackle these challenges, Temporally-Anchored methods explicitly align model reasoning with specific time points or intervals. They integrate three key techniques: (i) dynamic sampling, which adaptively selects frames by visual or semantic importance (e.g., [33] adjusts sampling density based on motion intensity, allocating more frames near action boundaries); (ii) temporal positional encoding, which injects explicit time-aware representations into token sequences (e.g., [209] augments frame embeddings with temporal position codes to model event order and duration); and (iii) flexible tokenization, including training-free similarity-based merging [185] and learnable saliency-driven merging [106], both designed to retain informative tokens while removing redundancy.

Specifically, TimeMarker [33], a versatile Video-LLM based on LLaMA3-8B, enables high-quality video-grounded dialogue with temporal localization. It introduces separator tokens to represent physical time, temporal separator tokens to enhance temporal awareness, and an AnyLength mechanism for dynamic frame sampling and adaptive token merging which adjusts the frames-per-second (FPS) and visual tokens to match the LLM’s context window and GPU budget. Similarly, Grounded-VideoLLM [209] augments the architecture with a temporal stream and discrete time tokens to enable explicit timestamp reasoning, trained through progressive video–language localization tasks. Seq2Time [49] advances this direction through sequential knowledge transfer, learning temporal grounding in a self-supervised manner by converting ordered image or clip sequences into time-annotated signals. Specifically, 10-second clips from Kinetics-700 are concatenated to simulate event progression in longer videos, each paired with a caption and positional index. The model learns to predict or align their sequential order, internalizing temporal structure without explicit timestamps.

Instruction-Aware Relative Temporal Localization. In contrast to temporally-anchored approaches that output absolute timestamps or time-interval tokens (e.g., “at 00:02:15”), the instruction-aware relative temporal localization focuses on answering relative temporal queries (e.g., “what happened after the second bell?”). Early studies typically combined video foundation models (e.g., Conv3D/I3D-style, two-stream, or transformer-based encoders) with text-only LLMs, but these systems relied on heavy pretraining and complex multi-module architectures.

RED-VILLM [84] shows that image-based LLMs can be efficiently extended to video understanding by introducing lightweight temporal adapters that align instruction semantics with temporal video features, avoiding full video-model retraining. Similarly, IVA-LLM [123] integrates a spatial feature interactor and a temporal frame selector within LLM blocks. The selector retrieves query-relevant frames, while the interactor focuses on salient regions or objects within those frames. This design enhances efficiency and visual fidelity under token aggregation while preserving strong temporal grounding aligned with natural language instructions.

Video Emotional Analysis. Video emotion analysis aims to infer affective states, social dynamics, and well-being from multimodal cues. As understanding and promoting well-being is crucial for long-term health and performance [158], traditional survey-based assessments are limited by their time-consuming nature and inability to capture the subtle, context-

dependent, and synchronized dynamics of visual, auditory, and textual signals.

To provide real-time feedback for behavior awareness, PERMA [158] predicts individual well-being during teamwork interactions. Panoramic videos are recorded, and for each person, nonverbal cues, including facial expressions, head pose, and 3D gaze, and environmental factors like scene brightness are extracted and summarized into 125 statistical features. These features are aligned with self-reported PERMA survey responses, and machine learning models predict each PERMA pillar as either classification or regression tasks, capturing discrete well-being states. Another system [90] assesses interview candidates by fusing multimodal cues. Faces are detected using HaarCascade classifiers [10], audio is represented via Mel-frequency cepstral coefficients, and visual and acoustic sequences are modeled with Inception-V3 and LSTM encoders. Textual data undergo standard NLP preprocessing before integration (e.g., tokenization, stop-word removal, sentiment features), enabling joint predictions of personality traits and performance from frame- and clip-level inputs.

Object Detection. Object detection identifies and classifies instances in images by assigning bounding boxes and category labels. In video analysis, it extends to maintain temporal consistency and track objects across frames.

Recent methods isolate region-level tokens and maintain object-specific trajectories over time. To capture fine-grained spatial and temporal details, VideoRefer [269] uses a spatial-temporal object encoder with adaptive temporal token merging to generate precise region representations for single- and multi-frame reasoning.

To enhance video analysis precision and efficiency, [48] uses YOLO-V8 for object detection and event-region segmentation, while Gemini-2.5-flash converts these visual cues into structured textual reports. An incident-context fusion pipeline aggregates temporal object trajectories and scene information before input to Gemini, producing summaries that preserve fine-grained entity details and overall context. By combining high-precision, anchor-free detection with multimodal reasoning, the framework reduces manual review while reliably capturing critical events. [181] proposes a three-stage pipeline for surveillance anomaly detection: (i) preprocessing with background subtraction and noise reduction, (ii) feature learning via an LSTM autoencoder of normal behavior trajectories, and (iii) anomaly detection using distribution-based regularity scoring with local minima analysis.

Gesture and Behavior Detection. Gesture and behavior detection aims to identify fine-grained body movements (e.g., hand gestures, nods) as well as higher-level behaviors (e.g., approach/avoidance, turn-taking), typically leveraging pose estimation, temporal classifiers, and interaction models.

Recently, MLLMs have been explored as tools for feature extraction in gesture and behavior detection. To explore how multimodal large language models (MLLMs) can be utilized as part of the multimodal learning analytics (MMLA) process, [235] employed MLLMs to automatically derive postural behavior indicators in a collaborative physics learning task, demonstrating that generative pipelines can reduce reliance on handcrafted annotations while preserving analytical depth. In this framework, MLLMs processed video data to extract features related to postural behaviors, leveraging their capac-

ity to interpret visual and spatial information. As a method to generate detailed quantitative measurements of 3D human behavior previously unattainable through manual efforts or 2D methods, HARMONI [234] integrates three-dimensional mesh estimation with spatial interaction modeling to analyze caregiver-child interactions in naturalistic environments. It first applies video tracking algorithms to isolate individual body trajectories, then employs a deep neural network to estimate 3D human mesh models for each frame, which are subsequently refined through optimization and temporal filtering.

Video Data for LLM. High-quality video-language datasets are critical for large language models (LLMs) to acquire temporal reasoning, multimodal alignment, and grounding capabilities beyond static images or text. Video inherently encodes temporal dynamics, causal relationships, and fine-grained nonverbal signals—all of which are essential for tasks such as action understanding, spatio-temporal reasoning, and multimodal planning which can boost the capability of VLMs. To enable LLMs to capture these capabilities, researchers have developed several complementary approaches to collect or generate video-language data. These approaches can be categorized into four parallel paradigms, each offering unique advantages in terms of annotation fidelity, scalability, and diversity.

- *Human Annotation.* Human-annotated video datasets offer the highest label fidelity and domain specificity, making them indispensable for tasks where nuanced human judgment is required.

Gesture and interaction datasets, such as [235] and [234] incorporate manual verification to ensure the accuracy and relevance of the labeled data. and curated gestures and interaction detection datasets. For emotion and behavior analysis, [158] and [90] combine human annotation with multimodal feature extraction—covering facial, audio, and textual cues—to produce rich, fine-grained annotations. Object detection-oriented datasets like [62] utilize staged annotation processes with multiple rounds of verification to guarantee consistency .

- *Human-in-the-Loop / Assisted Annotation.* Human-in-the-loop pipelines strike a balance between annotation quality and scalability by combining expert oversight with lightweight automation. This approach leverages lightweight automated modules to support annotators. Examples include the building process in TimeMarker’s temporal-separator tokens or the construction of VidThinker’s clip captions and key-frame selection modules. Additionally, annotation workflows often employ lightweight modules to assist human experts. For instance, temporal frame selection can be guided by models like VideoITG’s VidThinker[221], an automated pipeline for clip-level captioning, instruction-aware retrieval, and fine-grained frame localization, as demonstrated in [221] with the VideoITG-40K dataset. Such tools ensure fine-grained alignment across video frames by combining automated support with expert oversight.

- *Automated Curation & Filtering.* Fully automated curation pipelines prioritize scalability and efficiency, generating large datasets while employing built-in quality control mechanisms. These are end-to-end automated generation pipelines with built-in quality control, often implemented as multi-agent

engines with dedicated Reviewer agents, or via detection to LLM flows (such as YOLO-V8 to Gemini). For example, [269] employs a multi-agent engine to automatically curate fine-grained spatio-temporal object-level video instruction data for the VideoRefer-700K dataset, where a dedicated “Reviewer” agent filters erroneous or mismatched samples. As an example of detection to LLM flows, [48] implements a pipeline that begins with automated object detection using YOLO-V8, followed by the Gemini model to generate incident- and context-aware video summaries, thereby reducing the need for exhaustive manual review.

- **Synthetic Generation.** Synthetic data generation provides virtually unlimited scalability by creating aligned video–text pairs using generative models. Fully synthetic data generation produces aligned video–text pairs via text-to-video and domain-specific generators, offering high scalability. Models such as NUWA [237] employ a unified 3D transformer encoder–decoder architecture capable of handling text, images, and videos in a single framework for multimodal conditional generation. NUWA-Infinity extends this to arbitrarily long or high-resolution sequences using a hierarchical autoregressive “patch-over-patch” strategy with context caching and position control. Text2Video-Zero [100] demonstrates zero-shot text-to-video generation using Stable Diffusion without additional training, enriching latent codes with motion dynamics and reprogramming frame-level self-attention via cross-frame attention anchored to the first frame for temporally consistent, high-quality videos. Align Your Latents [26] converts an image-only latent diffusion model into a video generator by adding a temporal dimension to the latent space and finetuning only temporal components, enabling high-resolution, temporally coherent generation. Domain-specific generators such as SadTalker [278] and DreamTalk [149] synthesize talking-head videos from audio, while choreography-guided systems [222] produce human dance sequences from pose trajectories. High-fidelity text-to-video frameworks, including [74] and Make-A-Video [191], accelerate large-scale creation of scene-specific clips by extending powerful text-to-image backbones with spatial-temporal modules, substantially reducing the need for manual annotation. Collectively, these synthetic methods provide a scalable and automated alternative to traditional pipelines, delivering richly diverse, automatically aligned training data that accelerates the development of multimodal LLMs.

Takeaway: Through reformulating videos as structured token sequences containing temporal and visual evidence, LLMs can track and understand specific events in object level. **Complex Data Understanding (O1):** Processing spatial semantics and temporal dynamics, multi-modal cues for emotional analysis, and 3D human behavior [209, 234]. **NL-Based Interface (O2):** Driven through natural language using methods including adapters for instruction-conditioned reasoning [33, 123]. **Semantic Operators (O3):** Perform instruction-aware relative temporal localization to recognize conceptual relationships and contextual details [84, 48]. **Autonomous Evolution (O4):** Advance through adaptive methods like dynamic frame sampling and token merging [33, 269].

TABLE 3: Taxonomy of Multimodal Document Understanding Architectures.

Fusion Stage	Architecture	Example	Characteristics
Early Fusion	Single-stream Transformer	LayoutLM	Concatenated input, unified processing
	CNN + Transformer	Pipelines	Visual CNN, text Transformer, early concat
Intermediate Fusion	Dual-stream Transformer	LayoutLMv2 DocFormer	Parallel text/image streams, cross-attention
	Cross-Attention Transformer	VLCDoC	Inter-modal attention mechanisms
	Encoder-Decoder	OmniParser CREPE	Shared encoder, task-specific decoders
Late Fusion	Multi-head Networks	DLAFormer	Shared backbone, separate output heads
	Pipeline Integration	OCR+Layout	Independent modules, result combination
Unified Processing	Vision Transformer	ViLT	Patch-based, modality-agnostic processing

4.3 Documents

This section focuses on the challenges and techniques related to visually-rich document understanding, encompassing formats like PDFs, web pages, and scanned reports [253, 17]. Unlike plain text, these documents present information with complex, non-sequential layouts, incorporating visual elements such as tables, lists, figures, and footnotes alongside standard text. The primary challenge lies in parsing this intricate combination of structural, spatial, and semantic information into a coherent, machine-readable representation (e.g., vectors) [254, 86].

Core Challenges in Document Understanding. Document understanding is complicated. For short-form documents (e.g., invoices, web pages), a key bottleneck is form understanding [91], which involves tasks like accurate factual question answering by locating specific information amidst layout noise, generating concise summaries, and performing key-value extraction from structured content. For long-form documents (e.g., scientific papers, technical reports), the challenges escalate to integrative comprehension and cross-document synthesis, along with a robust capability for handling distractors. Finally, handling multilingual corpora requires not only high-fidelity translation but also complex downstream tasks like cross-lingual QA or summarization.

To tackle these challenges, the research community has developed several distinct technical paradigms. We categorize them into three primary approaches: (i) architecture designs ranging from unimodal to multimodal designs, with particular emphasis on fusion strategies and cross-modal interactions, (ii) retrieval-augmented methods for enhancing factual accuracy and context, and (iii) synthetic data generation techniques to address data scarcity and improve model training.

Architecture Design for Document Understanding. As shown in Table 3, the evolution of document understanding architectures reflects a fundamental shift from processing individual modalities in isolation to sophisticated multimodal integration. Early approaches treated text, layout, and visual elements as separate channels, which often led to suboptimal performance due to the loss of critical cross-modal relationships inherent in document structure. Unlike plain

text processing, document understanding inherently requires the simultaneous consideration of textual content, spatial layout, and visual appearance. This realization has driven the field toward multimodal architectures that can capture these complex interdependencies.

- *Transformer-Based Multimodal Architectures.* The transformer architecture has become the dominant paradigm for multimodal document understanding. Foundational models like LayoutLM [253] pioneer the integration of text, layout, and visual information within a unified transformer framework. Building upon this, LayoutLMv2 [254] introduces visual-textual attention mechanisms, while LayoutLMv3 [86] advances unified text-image masking for more effective pre-training. DocFormer [17] contributes multi-modal self-attention with separate attention heads for different modality pairs. Recent paradigm shifts emphasize efficiency and generalization. For example, DocLLM [208] represents layout-aware generative models that eliminate the need for raw visual encoders, significantly improving efficiency, whereas ViLT [101] takes this further by processing visual inputs in a convolution-free manner to concentrate computation on cross-modality interactions.

- *Multimodal Fusion Strategies.* The effectiveness of multimodal document understanding critically depends on how different modalities are integrated. Early fusion concatenates features at the input level; for example, LayoutLM [253] creates a single input representation for each token by combining textual embeddings with 1D sequential and 2D spatial position embeddings derived from bounding boxes. Intermediate fusion learns modality-specific representations separately before integrating them at deeper network layers, as exemplified by the dual-stream designs of LayoutLMv2 [254] and DocFormer [17]. By contrast, late fusion combines predictions from separately trained models; the shared-backbone, multi-head design of DLAFormer [211] can be viewed as a variant of this strategy.

- *Cross-Modal Interaction Designs.* Beyond fusion timing, cross-modal interaction mechanisms determine how effectively models capture fine-grained relationships. Attention-based designs such as VLCDoC [21] adopt a two-step “align-then-integrate” mechanism: Inter-Modality Cross-Attention (InterMCA) first establishes semantic links between modalities (e.g., using text queries to attend to visual keys and values to obtain visually enhanced text representations) followed by Intra-Modality Self-Attention (IntraMSA) to fuse the enriched representations with each modality’s own context. Prompt-guided methods like VisFocus [9] inject natural-language queries directly into the visual encoder, where cross-attention generates a weight map that highlights task-relevant regions. Coordinate-aware designs such as CREPE [164] further extend interaction by triggering a parallel coordinate-decoding head during autoregressive text generation, allowing the model to directly regress the bounding box of generated text when a special `</ocr>` token is emitted.

- *Specialized Architectural Innovations.* Recent work explores specialized designs to improve universality, efficiency, and reasoning capability. End-to-end unified frameworks like DLAFormer [211] jointly handle layout detection, role classification, and reading-order prediction as a single relation-prediction problem, taking a document image as input and

outputting detected objects with class and relation information. To address the need for task-agnostic solutions, OmniParser [206] proposes a universal framework that unifies outputs across tasks into three sequences (i.e., center points, polygonal shapes, and text contents) and decodes key-value pairs through a two-stage process that first predicts the center point of a value and then conditions on it to generate its boundary and text. Efficiency-oriented approaches such as Rationale Distillation [79] train a smaller model (e.g., Pix2Struct) to predict both final answers and intermediate reasoning steps of a larger model, optimizing a weighted combination of rationale and answer losses. Finally, multi-document reasoning systems like VisDoM [108] adopt a dual-pipeline RAG architecture, retrieving evidence separately from visual and textual sources and fusing them only when their consistency exceeds a predefined threshold.

- *Robustness to Modality Variations.* Real-world document understanding systems must remain effective when one or more modalities are missing or corrupted. To address this challenge, MissModal [148] introduces a missing-modality adaptation strategy that aligns representations across different modality combinations. By minimizing the distributional distance between features derived from complete data and those obtained from incomplete inputs, the model enforces consistency within a shared semantic space. Complementarily, MMP [85] explores masked-modality learning by training a projection function to generate “pseudo” representations for absent modalities (e.g., vision) using information from the remaining ones (e.g., text and audio). This dynamic projection enables the model to reconstruct missing signals during inference, thereby preserving performance even under severe modality dropouts.

RAG-Based Document Understanding. To address challenges of factual accuracy and external knowledge, RAG has emerged as a cornerstone architecture [110]. In document understanding, these systems can leverage different evidence modalities.

- *Text-Based RAG.* The most direct approach involves retrieving from the textual content of documents. More sophisticated methods like RAFT [277] focus on optimizing the retrieval and post-processing of text chunks.

- *Image-Based RAG.* Other systems leverage VLMs to perform retrieval directly on the visual content. M3DOCRAg [40] uses vision-language models to generate embeddings for each document page and computes cross-modal similarity with the query directly on these visual embeddings, completely bypassing OCR. SV-RAG [30] fine-tunes a VLM to first search for relevant page regions and then generate an answer from the retrieved visual evidence.

- *Dual-Modality RAG.* Hybrid approaches combine the strengths of both modalities. VisDoM [108], for example, implements parallel visual and textual retrieval branches and synthesizes evidence from both to formulate the final answer, improving reasoning by training models to focus on relevant retrieved context while ignoring distractors [277, 257].

Document Synthetic Generation for LLM. Beyond processing existing documents, a burgeoning area of research focuses on using generative models to synthesize them. For instance, [172] adopts transformer-based models to generate plausible scientific paper layouts. A particularly clever ap-

proach, *PosterLlama* [183], reformats the layout generation task as HTML code generation. Instead of outputting coordinates directly, it instructs an LLM to generate HTML and CSS code describing the document layout, leveraging the model’s inherent knowledge of web layout languages. To overcome one-shot generation limitations, *LayoutCoT* [186] uses Chain-of-Thought (CoT) prompting for iterative refinement, while *VASCAR* [274] introduces a visual self-correction loop. Meanwhile, diffusion models like *LayoutDM* [89] and *LDGM* [88] offer strong controllability. The frontier is moving towards aligning outputs with human aesthetic judgments, as exemplified by *AesthetiQ* [170], supported by new datasets like *SciPostLayout* [198] and metrics like *LTSim* [165].

Takeaway: LLM-based agents enhance document analysis by: **Complex Data Understanding (O1):** Leveraging multimodal architectures like *LayoutLM* [253] and *DocLLM* [208] to holistically integrate textual, spatial, and visual information from complex layouts. **NL-Based Interface (O2):** Enabling prompt-guided interaction where natural language queries direct visual analysis, as seen in methods like *VisFocus* [9]. **Semantic Operators (O3):** Employing advanced RAG systems to retrieve and synthesize information from both text and images, providing context-aware answers and summaries [110, 108]. **Autonomous Evolution (O4):** Utilizing iterative refinement and self-correction loops in synthetic data generation to progressively improve layout and content quality [186, 274].

4.4 Program Language Analysis

In this section we introduce LLMs for program analysis, focusing on code-task pairs. Unlike raw source code, this data explicitly links program artifacts to their semantic properties or desired outputs, forming the basis for sophisticated analysis tasks. Examples include code paired with vulnerability labels, formal proofs, or natural language summaries. We first survey the downstream applications that this data enables and then describe the core methodologies for synthesizing this specialized data. Table 4 summarizes the core applications and the synthesis techniques that enable them.

TABLE 4: Core Techniques in LLM-Based Program Analysis.

Application	Synthesis Methods	Key Techniques
ATP	Task-Specific Generation Iterative Refinement	Autoformalization Expert Iteration
Code Summarization	Few-Shot Learning RAG	Synthesized Data Pairs Example Retrieval
Repo-Level Completion	RAG	Adaptive/Iterative Retrieval Context Fusion

Automated Theorem Proving (ATP). As a frontier application, ATP requires models to generate formally verifiable mathematical proofs. Recent data synthesis pipelines combine three key techniques to reach state-of-the-art performance on challenging benchmarks. Autoformalization translates natural-language mathematical problems into formal, machine-verifiable statements in languages such as Lean4. For example, *DeepSeek-Prover* [246] automatically generates large-scale Lean4 proof data from mathematical competition

problems. Building on this foundation, expert iteration repeatedly tasks a model to solve a wide range of problems, collects all successful solutions as new training data, and then re-trains the model to become a stronger expert in the next round. Finally, reinforcement learning with verifier feedback allows models to explore proof strategies by generating candidate proofs and receiving binary correctness signals from formal verifiers (e.g., the Lean4 compiler), enabling learning through trial and error. The combination of autoformalization, iterative self-improvement, and verifier-guided reinforcement has empowered modern systems to generate entire, correct proofs in formal languages [246, 131, 162].

Code Summarization. By leveraging few-shot learning on synthesized code-summary pairs, LLMs significantly outperform traditional Seq2Seq models. Success relies on effective retrieval of similar code examples, using methods from token overlap to BM25, and enhancing prompts with semantic information like data flow to achieve state-of-the-art results [60, 11, 152].

Repository-Level Code Completion. LLMs are increasingly used to provide context-aware code completions by integrating information from an entire code repository. This task has progressed through a series of RAG techniques designed to resolve the so-called “Context–Latency Conundrum”, the trade-off between richer context and higher inference time. Early systems such as *RepoCoder* [272] adopt an *iterative retrieval-and-generation* pipeline, alternating between retrieving relevant code snippets and generating completions conditioned on the retrieved context. To reduce latency, *REPOFUSE* [128] introduces *efficient context fusion*, combining an “analogy context” from similar code and a “rationale context” from semantic relationships, and employing Rank Truncated Generation to condense this information. More advanced frameworks such as *Repoformer* [238] pursue *adaptive and selective retrieval*, allowing the model to self-assess when retrieval is actually beneficial and to skip it when unnecessary, thereby improving both robustness and inference speed. Pushing the conceptual boundary further, *FT2Ra* [63] proposes *fine-tuning-inspired retrieval*, treating each retrieval as a gradient-like update in which the retrieved document acts as a “gradient” and a tunable “learning rate” determines how strongly the retrieved information influences the evolving code representation. Together, these strategies illustrate a steady evolution toward repository-scale code completion that balances contextual richness with real-time responsiveness.

Data Synthesis for Code-Task Pairs. The ability to generate high-quality, large-scale datasets of code-task pairs is a primary driver of progress in this field. Two broad developmental paths characterize the evolution of code synthesis models. The **path of intrinsic structure** embeds formal grammars directly into model architectures to guarantee syntactic correctness. For example, early approaches such as *SVAE* [98] and *SD-VAE* [44] constrained the decoding process using explicit grammar rules, ensuring valid code outputs but limiting scalability due to structural rigidity. In contrast, the path of emergent capability leverages the powerful generalization ability of modern large language models through increasingly sophisticated data strategies. This trajectory advanced from scaling instruction diversity (*SELF-INSTRUCT* [228]), to systematically increasing instruction complexity (*EVOL-*

INSTRUCT [147]), and finally to harvesting real-world code diversity from open-source repositories (OSS-INSTRUCT [232]). The widespread adoption of functional-correctness metrics such as *pass@k* further catalyzed the development of genuine problem-solving abilities in these models.

- ***Core Synthesis Techniques.*** At the heart of data synthesis lies task-specific data generation, where initial datasets are created for targeted analysis tasks. A representative example is autoformalization in automated theorem proving, which translates natural-language mathematical problems into formal, machine-verifiable statements [246, 131]. Such task-driven pipelines provide the foundational training data needed to bootstrap powerful code models and to capture specialized reasoning patterns.

- ***Iterative Refinement and Self-Correction.*** Beyond one-shot generation, modern pipelines increasingly rely on iterative improvement strategies to enhance dataset quality. Expert iteration repeatedly tasks a strong model to solve large sets of problems, collects all successful solutions as new training data, and retrains the model to create progressively stronger experts [246, 131]. Complementing this, reinforcement learning with verifier feedback allows models to explore solution spaces by generating code, receiving binary correctness signals from external tools such as compilers, and refining their outputs through trial and error. In self-debugging variants [34], models go further by using execution feedback to explain errors and autonomously correct their own outputs, dramatically improving sample efficiency and final code quality.

Takeaway: In program analysis, LLM-based agents demonstrate significant capabilities by:

- Complex Data Understanding (O1):** Parsing entire code repositories with RAG techniques or translating natural language problems into formal code via autoformalization [238, 246].
- NL-Based Interface (O2):** Automating the translation of requirements expressed in natural language into formal, machine-verifiable proofs or concise code summaries [246, 60].
- Semantic Operators (O3):** Implementing adaptive retrieval mechanisms in repository-level code completion to find semantically relevant code snippets, going beyond simple keyword matching [272, 128].
- Autonomous Evolution (O4):** Employing techniques like expert iteration, reinforcement learning with verifier feedback, and self-debugging to continuously refine their problem-solving and code generation abilities [246, 34].

4.5 3D Models

3D models are digital representations of objects, scenes, or structures embedded in three-dimensional Euclidean space [236]. They are defined by explicit geometric data (e.g., point clouds, meshes, voxels, implicit surfaces) and may be further enriched with semantic or physical attributes (e.g., textures, materials, part-level annotations). Serving as a fundamental medium for spatial perception, reasoning, and interaction, 3D models provide the basis for computational systems to support tasks such as scene understanding, navigation, planning, and content creation.

Traditional 3D model analysis involves using 3D modeling software (e.g. Blender, 3ds Max, Maya) and need human input

for manipulation, annotation, and interpretation. As LLMs evolve, their integration with 3D spatial data enables unprecedented capabilities in understanding and interacting with physical environments. This section provides a comprehensive overview of methodologies that allow LLMs to process, interpret, and generate 3D data from point clouds to Neural Radiance Fields (NeRFs), and examines their applications in tasks such as scene understanding, captioning, question-answering, and dialogue. We further discuss the role of LLM-powered agents in spatial reasoning, planning, and navigation, highlighting their potential to bridge natural language with the inherent complexities of 3D spaces. As shown in Figure 9, the fusion of LLMs with 3D data primarily manifests in three key areas: 3D Language Fusion, which aligns 3D geometry with language descriptions; 3D-Derived Task Enhancement, which leverages 3D information to improve performance on downstream tasks; and Cross-Modal Capability Refinement, which uses existed experience on models (like 2-D image models) to refine 3D model’s understanding and generation abilities across different modalities.

3D-Language Fusion. Fusing three-dimensional data representations with the semantic space of natural language aims to establish a unified modality that enables models to seamlessly interpret, reason about, and generate grounded descriptions of physical 3D structures. This process faces several challenges, including the inherent sparsity and irregular nature of 3D data (like point clouds), the significant computational cost of processing large 3D models, and the difficulty of establishing a precise semantic alignment between geometric features and linguistic concepts. As shown in Figure 9, the process includes using a 3D-Encoder to capture spatial features and relationships at first, and then uses a projector to align 3D features with text space so that the 3D model features can be injected into LLM well.

- ***Fusion with Point Clouds.*** 3D-LLM [77] pioneered this by converting point clouds or scenes into multi-view renderings, extracting per-view visual tokens with a frozen vision-language encoder, and aggregating them into 3D-aware tokens that are fed to the LLM, which attaches 3D positional embeddings and outputs location tokens aligned with language. Scaling to direct point-cloud input, 3UR-LLM [250] proposes an end-to-end 3D multimodal large language model that ingests raw point clouds, fuses them with text instructions, and projects them into a compact set of vision tokens via a 3D Compressor, which utilizes a multi-layer Transformer architecture with learnable queries and cross-attention mechanisms to interlink visual and textual features, and a 3D Query Fusion mechanism, which selects high-confidence queries from the perception component based on objectness probability and integrates them with the original queries from the compressor.

- ***Domain-Specialized Fusions.*** For scientific domains, 3D-MoLM [119] equips an LLM with a dedicated 3D molecular encoder (typically a graph-based neural network that encodes atomic coordinates and conformations) and a learnable molecule-text projector (usually implemented as a lightweight MLP or transformer adapter) to encode atomic coordinates and conformations into language-context embeddings. The model is trained on a 3D molecule-text dataset to learn cross-modal retrieval, captioning, and open-ended QA.

TABLE 5: Overview of 3D-Language Fusion and Related Techniques.

Core Technical Objective	Sub-Objective	Details
3D-Language Fusion	Encoder-Projection Architecture	Dedicated 3D encoder + projection adapter; processes raw 3D data, and projects them into LLM-consumable feature space
	End-to-End Tokenization	Direct tokenization of 3D features; end-to-end fusion with text; no explicit projection layer
3D-Derived Task Enhancement	Geometric Reasoning	Textual abstraction of geometric problems; symbolic reasoning without computation; avoids direct spatial data exposure
	Textual Description Mediation	Converts 3D structures into textual descriptions; uses text-only model training/inference; avoids raw 3D input
	Multi-Agent Orchestration	LLM orchestrates specialized models; text-based API interaction; 3D data handled internally
Cross-modal Capability Refinement	Domain Adaptation	Cross-modal feature alignment; domain adversarial + contrastive learning; bridges 2D–3D gap
	Feature Enhancement Modules	Plug-in enhancement modules; addresses 3D perception weaknesses; preserves base architecture

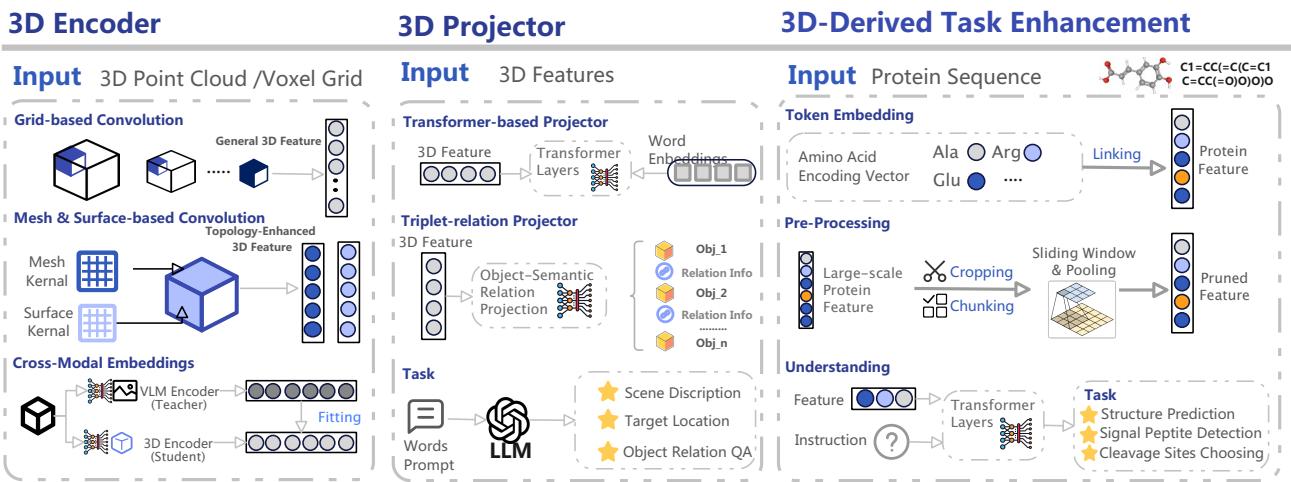


Fig. 9: Overview of 3D Model Analysis.

ProteinChat[61] is designed to enable ChatGPT-like conversational functionality centered on protein 3D structures. Its architecture follows a four-part blueprint: (i) a protein encoder that derives sequence and 3D embeddings; (ii) a Protein–Language Pretraining Transformer (PLP-former), a Transformer-based module trained with contrastive and self-supervised objectives to align protein and language representations; (iii) a projection adapter, typically a lightweight neural network trained jointly with the PLP-former while keeping the LLM frozen, which converts protein embeddings into prompts suitable for language generation; and (iv) a foundation LLM (Vicuna-13B) that generates language-grounded responses.

Building on the framework of [61], ProtChatGPT [207] extends ProteinChat by introducing a three-stage pipeline: 3D feature extraction, protein–language pretraining, and instruction tuning—to further enhance grounded question answering and explanatory capabilities for protein structures. This enhancement comes from its integration of both sequence- and structure-based protein encoders, contrastive pretraining that better aligns protein representations with textual descriptions, and instruction tuning that adapts the LLM for domain-specific reasoning, leading to more accurate and interpretable protein-grounded responses.

3D-Derived Task Enhancement Unlike 3D-Language Fusion which focuses on aligning spatial features with textual se-

mantics, 3D-derived task enhancement emphasizes leveraging structural representations to improve downstream tasks that inherently require geometric reasoning (e.g., spatial question answering) as shown in Figure 9. The central challenge lies in (i) achieving genuine structural understanding rather than relying on superficial correlations, and (ii) ensuring scalability, since incorporating high-dimensional 3D signals into large models can quickly lead to prohibitive memory and computation costs.

To evaluate LLMs’ understanding of geometric structures, GeomRel [225] identifies failure modes, including inaccurate identification of geometric relations, lack of structured reasoning in large language models (LLMs) by constructing a benchmark that isolates geometric relationship identification as a core subtask. To address this challenge, it encodes problems with structured relation pools (e.g., lines, angles, congruences) and labels target relations directly to facilitate accurate identification. For reasoning abilities, GeomRel introduces the Geometry Chain-of-Thought (GeoCoT), a two-stage prompting pipeline. The first stage forces enumeration and verification of candidate relations with reverse-checks for consistency, and the second stage performs rigorous reasoning over these relations. Ablations show that explicit supervision of relation identification helps LLMs learn spatial-structural semantics rather than producing numerically correct but conceptually hollow answers.

For molecular representation learning, GPT-MolBERTa [214] replaces compact SMILES [233] strings, which linearize molecular graphs into text sequences, with rich textual molecule descriptions. The model is pretrained on 326k molecules with natural language captions to learn embeddings that capture geometric cues and the biological co-evolution to predict the property of target protein.

At system levels, ProtChat [81] integrates specialized Protein Large Language Models (PLLMs) into practical workflows with a multi-agent orchestration framework. A high-capacity planner LLM (GPT-4) decomposes user instructions, dispatches domain-specific PLLMs (e.g., MASSA [80]), and aggregates their outputs for tasks such as protein property prediction and protein-drug interaction profiling. The system standardizes prompt-tool contracts, result formatting, uncertainty reporting, and error handling, enabling non-expert users to leverage 3D biological models through a single natural-language interface without writing complex scripts.

Cross-Modal Capability Refinement. As illustrated in Figure 9, cross-modal alignment seeks to establish a shared representational space that enables seamless interaction among heterogeneous modalities, such as 2D images, 3D assets, and natural language, by leveraging knowledge transferred from other modalities. However, several challenges arise in this process, including the semantic gap between low-level geometric features and high-level linguistic concepts, as well as differences in data formats (e.g., continuous 3D point clouds versus discrete textual tokens).

To handle the limitation of domain adaptation technique in learning discriminative features for target samples due to the lack of label information in target domain, Song et al. [194] improve image-mesh retrieval by combining adversarial domain alignment with self-supervised contrastive learning on unlabeled 3D data. The objective integrates (i) supervised discriminative learning on labeled 2D images, (ii) contrastive losses on multi-view 3D renderings that pull views of the same object together and push different objects apart, and (iii) adversarial terms to minimize domain gaps between 2D and 3D embeddings. An entropy-aware memory bank maintains representative negative samples and reduces false negatives, producing highly discriminative 3D embeddings and boosting retrieval accuracy.

To equip multimodal LLMs with 3D perception from single images, LLMI3D [259] augments a pretrained MLLM using parameter-efficient fine-tuning (PEFT) and three spatial reasoning modules including (i) Spatial-Enhanced Local Feature Mining sharpens object boundary and micro-geometry features via multi-scale attention with positional cues, (ii) 3D Query Token-Derived Info Decoding introduces explicit geometric-query tokens with regression heads for precise numeric output, and (iii) Geometry Projection-based Reasoning corrects for focal-length and perspective distortion by projecting features through differentiable camera models. The result shows that carefully designed spatial modules with PEFT can make general MLLMs competitive for 3D geometric reasoning without full-model retraining.

3D Data for LLM. Large language models have shown remarkable capabilities in reasoning over text and 2D imagery, but extending them to 3D domains introduces unique challenges. Unlike text or images, 3D data inherently en-

codes geometry, spatial relations, and multi-view consistency, which makes it both richer in information and more difficult to model. Recent research has therefore explored different paradigms for leveraging or directly generating 3D representations conditioned on language, aiming to unlock applications such as text-to-3D asset creation, embodied AI, and interactive design. Table 6 Existing methods can be broadly grouped into three categories: optimization-based approaches that adapt powerful 2D diffusion priors for 3D generation, feed-forward pipelines that prioritize speed and determinism, and emerging native 3D generative models that attempt to learn 3D distributions directly.

- *Optimization-Based.* This paradigm leverages pre-trained 2D diffusion models as supervisory signals to directly optimize a 3D representation (e.g., NeRF or mesh). A key technique here is Score Distillation Sampling (SDS), which transfers the generative prior of 2D diffusion models into the 3D domain. In details , SDS adds noise to images rendered from the current 3D representation, and then uses the diffusion model to predict the denoising direction conditioned on the text prompt, then distills this signal into a gradient that updates the 3D parameters. Over many iterations, the 3D asset is shaped so that its 2D projections from diverse viewpoints are judged as likely given the prompt.

The primary advantage of this approach is its high quality ceiling: it can synthesize novel, intricate textures and surfaces by tapping into the rich visual priors of 2D diffusion models . However, it suffers from two major drawbacks: slow per-instance optimization (often taking tens of minutes) and multi-view inconsistency. The latter arises because the 2D prior lacks an inherent understanding of 3D consistency, often providing conflicting guidance from different views and leading to artifacts like the “Janus head” problem.

To address such challenges, Fantasia3D [32] tackled the issue of blurred geometry in volumetric representations by explicitly disentangling geometry from appearance. It represents geometry with an explicit DMTet mesh and models appearance via a spatially-varying BRDF material model. During training, it separately optimizes geometry using normal map renderings and appearance using shaded renders via an SDS loss, resulting in high-fidelity, relightable assets. To combat the multi-view inconsistency problem, SweetDreamer [120] proposed innovating on the *prior itself* rather than just the optimizer. It fine-tunes a 2D diffusion model on Objaverse renderings to predict view-conditioned canonical coordinate maps, termed Aligned Geometric Priors. This embeds multi-view consistency directly into the diffusion model, leading to more stable SDS gradients and reduced failures. Building on this, RichDreamer [175] pushed prior specialization even further. Instead of relying on a single RGB diffusion model, it trains geometry-specific priors: one for normal maps, one for depth, and another for albedo (to factor out lighting). Applying SDS with these geometry-specific priors provides richer, higher-frequency supervisory signals, dramatically improving multi-view detail and surface fidelity compared to using a standard RGB-based SDS loss.

- *Feed-Forward Generation with Reconstruction.* This approach completely bypasses the slow, iterative SDS optimization process. Instead, it breaks the problem into two distinct, feed-forward stages: first, a multi-view synthesis model generates a set of coherent novel views from a single input image,

TABLE 6: Comparison of 3D Generation Methods across different paradigms.

Method	Year	Paradigm	Uses 2D Prior	Multi-view Consistency	Speed	Editable Output	Key Techniques
Fantasia3D	2023	Optimization-based	✓	Medium	Slow (minutes)	✓	SDS + DMTr mesh + BRDF
SweetDreamer	2023	Optimization-based	✓ (tuned)	High	Slow (minutes)	✓	SDS + Aligned Geometric Priors
RichDreamer	2024	Optimization-based	✓ (multi-prior)	High	Slow (minutes)	✓	SDS + Normal/Depth/Albedo Priors
Zero-1-to-3	2023	Feed-forward + Reconstruction	✓	Medium	Fast (seconds)	Limited	View-conditioned diffusion + NeuS
Hunyuan3D-1.0	2024	Feed-forward + Reconstruction	✓	High	Fast (seconds)	Limited	Multi-view diffusion + Sparse-view reconstructor
CraftsMan3D	2024	Native 3D Generation	—	High	Fast (seconds)	✓	3D latent diffusion
Direct3D	2024	Native 3D Generation	—	High	Fast (seconds)	✓	D3D-VAE + D3D-DiT
MeshAnything	2024	Native 3D Generation	—	High	Fast (seconds)	✓	VQ-VAE mesh codebook + transformer
LLaMA-Mesh	2024	Native 3D Generation	—	High	Fast (seconds)	✓	LLM autoregressive mesh tokens

and second, a fast 3D reconstruction network consumes these generated views to produce a 3D mesh in a single forward pass.

The key advantage is speed: generation time is reduced from minutes to seconds, offering deterministic behavior that is crucial for practical production pipelines. The trade-off is a loss of flexibility. The final output quality is bounded by the capabilities of the reconstruction network, and errors from the synthesis stage can propagate and accumulate in the reconstruction stage, potentially limiting the diversity and optimality of results.

This line of work focuses on improving the quality and coherence of the synthesized views to enable robust reconstruction. Zero-1-to-3 [137] laid a foundational stone by training a viewpoint-conditioned 2D diffusion model to generate novel views from a single image. These synthesized views, while not perfectly consistent, are sufficiently coherent to be fed into an off-the-shelf reconstruction network like NeuS[219] to produce a 3D mesh, all within seconds. Hunyuan3D-1.0 [262] follows this two-stage template but scales it into a robust, practical pipeline. It employs a powerful multi-view diffusion model that can generate a set of coherent RGB views from a single image in approximately four seconds. A key innovation is its learned sparse-view reconstructor, which is specifically trained to ingest these imperfect, AI-generated views (along with the original image) and predict high-quality geometry in a single, fast forward pass. This “synthesis-then-reconstruct” design prioritizes speed and determinism for rapid asset creation.

- **Native 3D Generation.** This emerging paradigm seeks to move beyond reliance on 2D diffusion priors altogether. The goal is to train generative models directly on large datasets of 3D assets, allowing them to learn the underlying distribution of 3D geometry and appearance natively. This requires designing efficient neural representations for 3D data, such as compact latent spaces or discrete tokens.

The primary advantage is inherent 3D consistency, eliminating multi-view issues from the root. It also promises fast generation and native support for 3D editing tasks. The main disadvantage is its heavy dependence on large-scale, high-quality 3D datasets for training, which are scarce compared to 2D image data. The technical complexity and computational cost of building these architectures are also currently very high.

Research is branching into different sub-architectures for native generation. One branch focuses on 3D diffusion. CraftsMan3D [121] performs diffusion directly in a latent space that represents both mesh and volumetric properties, enabling the generation of high-fidelity and editable meshes. To capture intricate geometry distributions, Direct3D [240] introduces an architecture comprising a D3D-VAE that encodes a 3D

asset into a compact latent representation, and a D3D-DiT (Diffusion Transformer) that learns to generate these latents, completely bypassing 2D priors and SDS. Another branch explores 3D tokenization, reframing 3D generation as a language modeling task. To optimize mesh extraction methods to no longer rely on dense faces and focus on geometric features, MeshAnything [35] learns a discrete codebook of mesh components using a VQ-VAE, allowing a transformer to then autoregressively decode a sequence of tokens into a high-quality mesh. LLaMA-Mesh [230] takes this concept to its logical extreme by fine-tuning a large language model (LLM) to directly output the vertices and faces of a mesh as a sequence of text tokens, effectively making the mesh a first-class citizen in language-conditioned generation and enabling fascinating applications like conversational mesh editing.

Takeaway: Reformulating 3D models using the 3D encoder and projector aligns the 3D space with the semantic space, enabling llms to understand spatial features. **Complex Data Understanding (O1):** Interpret point clouds and meshes using 3D encoders and projection adapters [77, 250], which fuses 3D spatial features with natural language semantics. **NL-Based Interface (O2):** LLMs function as high-capacity planners [81], decomposing tasks and orchestrating specialized models to interact with natural language. **Semantic Operators (O3):** LLMs perform geometric relation identification and structured reasoning via methods such as Geometry CoT [225], which translates complex 3D structures into textual descriptions [214]. **Autonomous Evolution (O4):** Learn 3D distributions directly bypassing 2D priors, and use techniques like mesh codebooks [35] to achieve inherently 3D-consistent content creation.

5 Heterogeneous Data Analysis

Heterogeneous data refers to the combination of diverse data types (e.g., relational data, semi-structured tables, document images) that exist in different formats. Effective analysis of such data requires the ability to capture both structural and semantic information, as well as the interrelationships among different modalities. Traditional approaches to heterogeneous data analysis focus on the construction of data lake systems for storage and retrieval. In these systems, analysts are responsible for writing retrieval queries and employing human-in-the-loop methods to conduct analyses, which are often labor-intensive and prone to error. Recent advances in LLMs and MLLMs offer new opportunities to analyze heterogeneous data through natural language interactions, thereby reducing human intervention. Current research primarily focuses on

modality alignment across diverse data types and the development of heterogeneous data analysis agents.

LLM for Modality Alignment. Modality alignment refers to the process of mapping heterogeneous data types into a shared representation space that preserves both structural and semantic information. The main challenge lies in bridging the semantic gap among modalities with inherently different formats and levels of abstraction, while minimizing information loss.

Unicorn [57] addresses the fundamental challenge of modality alignment, that determines whether two data objects convey the same semantic meaning. It employs DeBERTa [71] to encode serialized pairs (e.g., text, table columns, tuples, or knowledge graph entities), incorporates a Mixture-of-Experts (MoE) architecture for feature alignment, and leverages an MLP-based binary classifier to assess whether the two objects match. Symphony [38] introduces a novel approach from a natural language perspective. The framework offers question–answering capability tailored for heterogeneous data lakes encompassing text, databases, tables, and knowledge graph entities. It transforms data from diverse modalities into natural language summaries, which are subsequently encoded into vector representations. Questions are encoded within the same vector space, and cosine similarity is employed to measure their alignment with the data representations, thereby enabling the retrieval of relevant information for answer generation.

LLM for Heterogeneous Data Retrieval. Data retrieval focuses on extracting task-relevant or related information from underlying data sources. The core challenge in heterogeneous data settings lies in the identifying and understanding of relationships both within and across different modalities.

Early efforts primarily targeted text-based modalities. For example, LOTUS [168] introduces a declarative programming interface that supports operations such as top-k search over data columns and the construction of similarity indexes for individual data items. Similarly, Wang et al. [210] further abstract the retrieval process as a sequence of high-level APIs under a SQL-like paradigm, enabling operations such as selection, projection, join, and aggregation. While effective, these approaches remain confined to text data. Extending beyond this limitation, CAESURA [205] incorporates visual modalities by embedding visual question answering models into retrieval operations, thereby enabling multimodal queries such as counting the number of images relevant to a given query.

Heterogeneous Data Analysis Agents. A heterogeneous data analysis agent is an intelligent system that leverages LLMs or VLMs to automatically interpret, retrieve, and reason over heterogeneous data through natural language interaction. The key challenge is to ensure accurate, context-aware analysis while reducing reliance on human intervention, particularly in scenarios involving complex cross-modal reasoning.

XMODE [161] assumes that heterogeneous metadata is organized within a database and leverages LLMs to decompose natural language queries into subtasks such as text-to-SQL generation and image analysis. For instance, given the query “Plot the number of paintings that depict war in each century”, XMODE generates an operation sequence com-

prising: (i) retrieving painting metadata from the database via SQL, (ii) applying VLMs to determine whether each image depicts war, and (iii) producing visualization code. In practice, however, heterogeneous data is often disorganized. To address this challenge, Wang et al. [218] encode data objects using modality-specific models (e.g., BERT for text, CLIP for images) to construct an index. They further introduce a vector weight learning model that adaptively adjusts modality weights to better capture their relative importance in similarity measurement [217]. The user query is used to retrieve relevant data through semantic similarity for final answer generation.

Takeaway: Heterogeneous data analysis agents exhibit strong capabilities in the following aspects: **Complex Data Understanding (O1):** Capture both structural and semantic information across diverse modalities. **NL-Based Interface (O2):** Facilitate cross-modal alignment, retrieval, and reasoning through natural language interaction. **Semantic Operators (O3):** Combine LLM-driven semantic operations with cross-modal processing capabilities. **Autonomous Evolution (O4):** Enable self-designing and adaptive evolution of analysis pipelines in response to changes in data sources.

6 Challenges and Future Directions

6.1 Structured Data

Complex Analysis. Structured data encapsulates both semantic information (e.g., cell contents in tables) and structural information (e.g., key–value relationships in tables or edge connections in graphs). Effective analysis requires integrating these two dimensions. For simple tasks, LLMs can often derive answers directly from explicit semantic cues or straightforward structural patterns. However, complex tasks demand deeper comprehension and multi-hop reasoning across semantics and structure, which remain challenging for current LLMs. When LLMs alone fall short in handling such tasks end-to-end, multi-agent collaboration emerges as a promising direction. By decomposing a complex task into simpler subtasks, each agent can specialize in a narrower scope. Through prompt engineering or fine-tuning, LLMs can be tailored for specific subtasks, while intermediate outputs enhance both performance and interpretability.

Open World Task Adaptation. Structured data spans diverse domains with varying specifications and task requirements. LLMs trained for general-purpose analysis may fail to meet domain-specific needs. For instance, analyzing daily forms differs substantially from rigorous analyses in business or climate applications. Moreover, heterogeneity in system specifications, such as SQL dialects, poses additional adaptation challenges. To address these issues, domain adaptation through task-specific training or fine-tuning is essential. As manual annotation is often insufficient to support large-scale training, efficient automatic data generation methods warrant further exploration. In addition, techniques such as automatic query conversion and intermediate representations are crucial for bridging modality gaps, particularly between natural language and diverse SQL dialects.

6.2 Semi-Structured Data

Diverse Markup Language Formats. Markup languages encompass a wide spectrum, including HTML, XML, JSON, Markdown, LaTeX, and domain-specific standards such as Journal Article Tag Suite (JATS). However, most existing research remains concentrated on a few widely used formats, primarily including HTML, XML, and JSON which often derived from web-scraped data. This leaves domain-specific or less-studied markup languages, as well as proprietary formats in industry, underexplored. Addressing this gap requires the creation of specialized benchmarks for languages such as JATS, LaTeX, and Markdown to evaluate tasks like structure-aware question answering and format conversion. Moreover, model architectures must evolve towards structure-aware tokenization and training paradigms that explicitly leverage the hierarchical organization of markup, rather than treating markup as plain text sequences.

Understanding Table with Complex Structures. Semi-structured tables often exhibit irregular relationships and intricate nested structures, which remain difficult for current LLMs to fully capture. While recent approaches attempt to encode table structures and leverage the semantic reasoning capacity of LLMs, these methods are usually tailored to specific table types (e.g., financial tables). It is quite challenging to handle diverse semi-structured tables with complex structures. To address this, researchers have explored several directions. One line of work focuses on Structure-Aware Encodings, where the table’s hierarchical or graph-like organization (e.g., DOM trees for HTML tables or JSON schemas) is explicitly modeled and injected into LLMs. Another approach emphasizes Intermediate Representations, such as transforming semi-structured tables into canonical forms or domain-specific languages (DSLs) that better align with LLMs’ sequential reasoning ability. In addition, Retrieval-Augmented Methods leverage external knowledge bases or schema repositories to supplement missing semantics, enabling LLMs to ground their reasoning in richer contexts.

Large-Scale Table Comprehension. For both PLM- and LLM-based methods, efficiency and accuracy are constrained by token limitations and context window sizes. When processing large-scale tables, effectively compressing both structure and content while minimizing information loss remains an urgent challenge. Advances in hierarchical encoding, table summarization, and scalable retrieval-augmented mechanisms may provide promising directions for addressing this limitation.

6.3 Unstructured Data

High-Level Chart Understanding. While significant progress has been made in basic chart recognition and data extraction, critical higher-order tasks such as chart-based fact checking, detection of visual or statistical misrepresentations (e.g., truncated axes, inconsistent scales, or fabricated trends), and cross-modal chart data verification remain largely unaddressed. These tasks demand not only accurate perception of visual elements but also reasoning about data semantics, statistical validity, and alignment with external knowledge or textual assertions. The absence of standardized benchmarks and evaluation protocols for such tasks further

hinders systematic progress. We advocate for the development of comprehensive frameworks that support critical chart literacy—enabling systems to not just “read” charts, but to audit them. This includes creating datasets with annotated errors, factual inconsistencies, and deceptive visual practices, as well as designing models capable of joint visual-semantic reasoning to validate the integrity and truthfulness of the graph.

Inadequate Multimodal Reasoning for Diverse Chart Types.

Charts are inherently multimodal artifacts that fuse structured visual encodings (e.g., glyphs, spatial arrangements, color mappings) with natural language (titles, axis labels, captions). Current models often treat chart understanding as a vision-only or simplified vision-language problem, failing to capture the nuanced interplay between graphical conventions, domain-specific semantics, and contextual information. This limitation becomes especially pronounced when handling complex or non-standard chart types (e.g., small multiples, Sankey diagrams, or interactive dashboards). A holistic, end-to-end chart understanding pipeline that unifies low-level perception (e.g., element detection), mid-level parsing (e.g., data-value mapping), and high-level inference (e.g., trend interpretation or anomaly detection) is needed. Such a pipeline should be modular, chart-type-agnostic, and grounded in both visualization theory and real-world usage patterns, enabling robust performance across diverse downstream applications.

Computational Efficiency of Video Analysis. Video is long-form sequential data; fixed sampling or full-frame processing consumes large compute and wastes capacity. Compressing frames/tokens often sacrifices fine-grained temporal cues, hurting localization and detail recognition. To address this, we can develop representations that preserve fine-grained visual detail while offering controllable context length (e.g., temporal separator tokens, dynamic sampling, learnable token merging, temporal positional encodings). Integrate temporal modeling and token-aggregation objectives into training to achieve a better trade-off between efficiency and fidelity.

Video Temporal Localization with Semantic Coherence. Precise temporal localization requires detecting sparse, transient cues (e.g., action start/end, sudden events) and maintaining semantic consistency across long sequences. Current methods still struggle with event-boundary detection, timestamp reasoning, and preventing erroneous cross-time associations. To address this, we can improve fine-grained event detection and semantic continuity by incorporating temporally aware tokens and supervision objectives directly into LLM-friendly representations.

Video Multimodal Fusion and Scalability. Effectively time-aligning and fusing visual, audio, and textual streams is both modeling and engineering challenging; high-quality, fine-grained human annotation is costly and hard to scale. Domain-specific tasks (emotion, gesture, anomaly detection, etc.) often rely on specialized labels and bespoke pipelines, which limits generalization. To address this, we can combine modular architectures (lightweight temporal adapters, instruction-aware selectors), multi-agent data curation/reviewer pipelines, and large-scale synthetic video-text generation to improve annotation efficiency, domain adaptation, and instruction-conditioned reasoning. Encourage task-centered cooperative agents that decompose complex video-

understanding problems into simpler subtasks.

Generalizing Multimodal Understanding for Documents. A key challenge beyond OCR is achieving deep multimodal understanding—integrating text, layout, and visuals—across diverse domains and languages. General-purpose models often fail on specialized document structures, such as dense scientific layouts or non-linear historical manuscripts, and struggle with language-specific conventions like right-to-left scripts. Addressing this requires document-native architectures (e.g., DocLLM) that emphasize layout over costly visual encoding, combined with layout-aware instruction tuning to teach multi-granularity structural reasoning, supported by large-scale, multilingual datasets for robust generalization.

Efficiency in Large-Scale Document Processing. Processing large volumes of long-form documents, such as legal archives, presents a trade-off between computational efficiency and analytical depth. The limited context windows of most LLMs force chunking strategies that can sever long-range dependencies, while preserving fine-grained spatial details across thousands of pages remains a major technical hurdle. Future work should focus on adaptive context management and hierarchical document representations. Combining these with progressive reasoning strategies, where a model first builds a coarse understanding before focusing on details, can create a better balance between computational cost and high-fidelity analytical accuracy.

Accuracy and Robustness in Program Vulnerability Detection. While LLMs show promise in software vulnerability detection, the accuracy of state-of-the-art methods remains unsatisfactory, with reported success rates around 67.6% for detection and only 20% for automated repair. The number of vulnerabilities continues to grow, with over 25,000 new CVEs reported in 2024 alone. Moreover, the performance of deep learning-based methods has been shown to degrade significantly on rigorously validated datasets and in the face of simple code modifications. The development of novel frameworks that integrate Code Property Graphs (CPGs) with LLMs presents a promising path. Techniques like CPG-guided code slicing can reduce code size while preserving vulnerability-relevant context, leading to significant improvements in F1 scores for inter-procedural vulnerability detection.

Program Analysis Complexity and Scope Limitations. The inherent complexity of vulnerabilities poses a significant challenge, with inter-procedural flaws being substantially harder to detect than intra-procedural ones. LLMs often struggle with uncommon CWE types, and their performance degrades when vulnerabilities span multiple code units. Most current LLM-based solutions are limited to the function level, a narrow scope that questions their effectiveness for class-level or repository-level analysis. Future research should focus on developing LLM architectures that support multi-level code analysis, scaling from the function level to project and enterprise levels. Integrating Retrieval-Augmented Generation (RAG) techniques is crucial for effectively handling the vast contextual information present in large-scale codebases.

Reliability in Code Generation and Repair. Although LLMs offer advantages in generality and interpretability—providing intermediate reasoning for their findings—they still face significant challenges in terms of trust and accuracy,

particularly for automated code repair. Establishing mechanisms for trust and collaboration with developers is essential. LLMs should be designed to signal uncertainty rather than providing potentially inaccurate outputs. Furthermore, developing multi-agent collaborative frameworks, with specialized agents for code analysis, vulnerability detection, and repair, could lead to more robust and reliable systems.

High Quality 3D Modality Representation. 3D data, including point clouds, meshes, voxels, implicit fields, and NeRFs, vary in sampling, topology, and attributes. Converting them into LLM-ready inputs requires trade-offs, where aggressive simplification loses geometric detail, while token explosion exceeds context limits, leading to inconsistent cues and poor generalization. This can be mitigated with compact, trainable encoders that produce a small set of informative tokens, such as vector-quantized mesh tokens, learned point-feature aggregators, and geometry-aware positional encodings. Jointly training these encoders with lightweight adapters using multiview consistency, reprojection, and geometric-accuracy losses preserves topology and metric cues while staying within LLM context budgets.

Accurate 3D Geometric Grounding. LLMs lack native metric reasoning and struggle with coordinate frames, units, and precise spatial numerics. The scarcity of richly labeled 3D datasets limits supervised learning for distances, poses, and geometric constraints, so systems often produce plausible qualitative descriptions but fail on quantitative queries, affecting navigation, manipulation, simulation, and safety-critical tasks. This can be addressed using domain adapters that encode coordinate conventions, units, and regression heads for distances/poses, trained with metric supervision from simulators/renderers or differentiable-rendering losses, and evaluated on numerically grounded benchmarks to ensure quantitative fidelity.

6.4 Heterogeneous Data.

Pluggable Modality Extensibility. A key challenge for heterogeneous data agents is integrating new data types without redesigning or retraining the system. Traditional architectures are rigid, making it difficult to handle emerging modalities like audio, video, or sensor data. Future work should focus on modular and extensible frameworks with independent encoders or adapters, standardized integration interfaces, adaptive weighting for multiple modalities, and self-supervised alignment to ensure compatibility with existing representations. Such approaches will enhance scalability, maintainability, and robustness in increasingly complex and evolving data.

High-Level Heterogeneous Data Analysis. A key challenge for heterogeneous data agents is performing high-level analysis, encompassing reasoning, summarization, and cross-modal inference beyond simple retrieval. This requires understanding interrelationships among modalities, capturing context, and generating actionable insights. Existing systems, such as XMODE [161] and [218], offer partial solutions via step-wise query decomposition or adaptive modality weighting but still struggle with large-scale or disorganized datasets, limiting fully automated, context-aware analysis. Future research should develop agents capable of robust, end-to-end

reasoning across heterogeneous modalities. Promising directions include using multimodal embeddings for joint inference, integrating symbolic and neural reasoning for interpretability, and employing adaptive task planning to decompose complex queries and synthesize results across modalities for comprehensive real-world data analysis.

7 Conclusion

In this paper, we summarize the recent techniques on LLM/Agent for data analysis, organized from the perspective of diverse data types, including structured data, semi-structured data, unstructured data, and heterogeneous data. Five key design goals for intelligent data analysis agents are distilled from the technical evolution. We also outline several remaining research challenges and propose some insights and practical directions for advancing LLM/Agents-powered data analysis.

References

- [1] <https://blazegraph.com/>.
- [2] <https://github.com/neo4j/neo4j>.
- [3] <https://graphdb.ontotext.com/>.
- [4] <https://pymol.org/>.
- [5] <https://pytorch.org/>.
- [6] <https://www.mongodb.com/>.
- [7] Iceberg.
- [8] S. Abiteboul. Querying semi-structured data. In *Database Theory—ICDT’97: 6th International Conference Delphi, Greece, January 8–10, 1997 Proceedings 6*, pages 1–18. Springer, 1997.
- [9] O. Abramovich, N. Nayman, A. Levi, R. Magar, and J. Goldberger. VisFocus: Prompt-Guided Vision Encoders for OCR-Free Dense Document Understanding. *arXiv preprint arXiv:2407.12594*, 2024.
- [10] Y. Adepu, V. R. Boga, et al. Interviewee performance analyzer using facial emotion recognition and speech fluency recognition. In *2020 IEEE International Conference for Innovation in Technology (INOCON)*, pages 1–5. IEEE, 2020.
- [11] T. Ahmed, K. S. Pai, P. Devanbu, and E. Barr. Automatic semantic augmentation of language model prompts (for code summarization). In *Proceedings of the IEEE/ACM 46th International Conference on Software Engineering, ICSE ’24*, New York, NY, USA, 2024. Association for Computing Machinery.
- [12] M. Al-Shetairy, H. Hindy, D. Khattab, and M. M. Aref. Transformers utilization in chart understanding: A review of recent advances & future trends. *arXiv preprint arXiv:2410.13883*, 2024.
- [13] M. M. Alam, L. Torgo, and A. Bifet. A survey on spatio-temporal data analytics systems. *ACM Comput. Surv.*, 54(10s), Nov. 2022.
- [14] S. Alnegheimish, L. Nguyen, L. Berti-Equille, and K. Veeramachaneni. Can large language models be anomaly detectors for time series? In *2024 IEEE 11th International Conference on Data Science and Advanced Analytics (DSAA)*, pages 1–10. IEEE, 2024.
- [15] R. Angles. A comparison of current graph database models. In *2012 IEEE 28th International Conference on Data Engineering Workshops*, pages 171–177, 2012.
- [16] R. Angles and C. Gutierrez. Survey of graph database models. *ACM Comput. Surv.*, 40(1), Feb. 2008.
- [17] S. Appalaraju, B. Jasani, B. U. Kota, Y. Xie, and R. Manmatha. Docformer: End-to-end transformer for document understanding. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 993–1003, October 2021.
- [18] S. Arora, B. Yang, S. Eyuboglu, A. Narayan, A. Hojel, I. Trummer, and C. Ré. Language models enable simple systems for generating structured views of heterogeneous data lakes. *arXiv preprint arXiv:2304.09433*, 2023.
- [19] D. Atreja. Alas: Autonomous learning agent for self-updating language models, 2025.
- [20] X. Bai, S. Huang, C. Wei, and R. Wang. Collaboration between intelligent agents and large language models: A novel approach for enhancing code generation capability. *Expert Systems with Applications*, 269:126357, 2025.
- [21] S. Bakkali, Z. Ming, M. Coustaty, M. Rusinol, A. Fornes, and J. Lladós. Vlcdoc: Vision-language contrastive pre-training model for cross-modal document classification. *Pattern Recognition*, 137:109296, 2023.
- [22] C. Barboule, B. Piwowarski, and Y. Chabot. Survey on question answering over visually rich documents: Methods, challenges, and trends. *arXiv preprint arXiv:2501.02235*, 2025.
- [23] K. Batko and A. Ślęzak. The use of big data analytics in healthcare. *Journal of big Data*, 9(1):3, 2022.
- [24] D. Baviskar, S. Ahirrao, V. Potdar, and K. Kotecha. Efficient automated processing of the unstructured documents using artificial intelligence: A systematic literature review and future directions. *Ieee Access*, 9:72894–72936, 2021.
- [25] J. M. Blain. *The complete guide to Blender graphics: computer modeling & animation*. AK Peters/CRC Press, 2019.
- [26] A. Blattmann, R. Rombach, H. Ling, T. Dockhorn, S. W. Kim, S. Fidler, and K. Kreis. Align your latents: High-resolution video synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 22563–22575, 2023.
- [27] L. Cao. Ai in finance: challenges, techniques, and opportunities. *ACM Computing Surveys (CSUR)*, 55(3):1–38, 2022.
- [28] L. Cao. Tablemaster: A recipe to advance table understanding with language models, 2025.
- [29] C. Chang, W.-Y. Wang, W.-C. Peng, and T.-F. Chen. Llm4ts: Aligning pre-trained llms as data-efficient time-series forecasters. *ACM Transactions on Intelligent Systems and Technology*, 16(3):1–20, 2025.
- [30] J. Chen, R. Zhang, Y. Zhou, J. Gu, J. Kuen, C. Chen, and T. Sun. Sv-rag: Lora-contextualizing adaptation of mlms for long document understanding. *arXiv preprint arXiv:2411.01106*, 2024.
- [31] L. Chen, X. Zhao, Z. Zeng, J. Huang, L. Zheng, Y. Zhong, and L. Ma. Breaking the sft plateau: Multimodal structured reinforcement learning for chart-to-code generation, 2025.
- [32] R. Chen, Y. Chen, N. Jiao, and K. Jia. Fantasia3d: Disentangling geometry and appearance for high-quality text-to-3d content creation. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 22246–22256, 2023.
- [33] S. Chen, X. Lan, Y. Yuan, Z. Jie, and L. Ma. Timemarker: A versatile video-llm for long and short video understanding with superior temporal localization ability. *arXiv preprint arXiv:2411.18211*, 2024.
- [34] X. Chen, M. I. Lin, N. Schärlí, and D. Zhou. Teaching large language models to self-debug. In *The Eleventh International Conference on Learning Representations (ICLR 2023)*, 2023.
- [35] Y. Chen, T. He, D. Huang, W. Ye, S. Chen, J. Tang, X. Chen, Z. Cai, L. Yang, G. Yu, et al. Meshanything: Artist-created mesh generation with autoregressive transformers. *arXiv preprint arXiv:2406.10163*, 2024.
- [36] Y. Chen, Z. Li, C. Yang, X. Wang, and G. Xu. Large language models are few-shot multivariate time series classifiers. *arXiv preprint arXiv:2502.00059*, 2025.
- [37] Y. Chen and G. Medioni. Object modelling by registration of multiple range images. *Image and vision computing*, 10(3):145–155, 1992.
- [38] Z. Chen, Z. Gu, L. Cao, J. Fan, S. Madden, and N. Tang. Symphony: Towards natural language query answering over multi-modal data lakes. In *CIDR*, pages 1–7, 2023.
- [39] S. Cheng, Z. Zhuang, Y. Xu, F. Yang, C. Zhang, X. Qin, X. Huang, L. Chen, Q. Lin, D. Zhang, S. Rajmohan, and Q. Zhang. Call me when necessary: Llms can efficiently and faithfully reason over structured environments, 2024.
- [40] J. Cho, D. Mahata, O. Irsoy, Y. He, and M. Bansal. M3docrag: Multi-modal retrieval is what you need for multi-page multi-document understanding. *arXiv preprint arXiv:2411.04952*, 2024.
- [41] A. Chowdhery, S. Narang, J. Devlin, M. Bosma, G. Mishra, A. Roberts, P. Barham, H. W. Chung, C. Sutton, S. Gehrmann, P. Schuh, K. Shi, S. Tsvyashchenko, J. Maynez, A. Rao, P. Barnes, Y. Tay, N. Shazeer, V. Prabhakaran, E. Reif, N. Du, B. Hutchinson, R. Pope, J. Bradbury, J. Austin, M. Isard, G. Gur-Ari, P. Yin, T. Duke, A. Levskaya, S. Ghemawat, S. Dev, H. Michalewski, X. Garcia, V. Misra, K. Robinson, L. Fedus, D. Zhou, D. Ippolito, D. Luan, H. Lim, B. Zoph, A. Spiridonov, R. Sepassi, D. Dohan, S. Agrawal, M. Omernick, A. M. Dai, T. S. Pillai, M. Pellat, A. Lewkowycz, E. Moreira, R. Child, O. Polozov, K. Lee, Z. Zhou, X. Wang, B. Saeta, M. Diaz, O. Fırat, M. Catasta, J. Wei, K. Meier-Hellstern, D. Eck, J. Dean, S. Petrov, and N. Fiedel. Palm: Scaling language modeling with pathways, 2022.
- [42] E. F. Codd. A relational model of data for large shared data banks. *Commun. ACM*, 13(6):377–387, June 1970.
- [43] V. Crescenzi, G. Mecca, and P. Merialdo. Automatic web information extraction in the roadrunner system. In *International Conference on Conceptual Modeling*, pages 264–277. Springer, 2001.
- [44] H. Dai, Y. Tian, A. Sordoni, A. Courville, L.-P. St-Aubin, et al. Syntax-directed variational autoencoder for structured data. In *International Conference on Learning Representations*, 2018.
- [45] S. Darabi, P. Bigaj, D. Majchrowski, A. Kasymov, P. Morkisz, and A. Fit-Florea. A framework for large-scale synthetic graph dataset generation. *IEEE Transactions on Neural Networks and Learning Systems*, pages 1–11, 2025.
- [46] A. K. Das, M. Tarun, and K. Mueller. Charts-of-thought: Enhancing llm visualization literacy through structured data extraction, 2025.
- [47] T. K. Das and P. M. Kumar. Big data analytics: A framework for unstructured data analysis. *International Journal of Engineering Science & Technology*, 5(1):153, 2013.
- [48] U. De Silva, L. Fernando, K. Bandara, and R. Nawaratne. Video summarisation with incident and context information using generative ai. In *IECON 2024-50th Annual Conference of the IEEE Industrial Electronics Society*, pages 1–6. IEEE, 2024.

- [49] A. Deng, Z. Gao, A. Choudhuri, B. Planche, M. Zheng, B. Wang, T. Chen, C. Chen, and Z. Wu. Seq2time: Sequential knowledge transfer for video llm temporal grounding. In *Proceedings of the Computer Vision and Pattern Recognition Conference*, pages 13766–13775, 2025.
- [50] X. Deng, P. Shiralkar, C. Lockard, B. Huang, and H. Sun. Dom-lm: Learning generalizable representations for html documents. *arXiv preprint arXiv:2201.10608*, 2022.
- [51] S. Dernbach, K. Agarwal, A. Zuniga, M. Henry, and S. Choudhury. Glam: Fine-tuning large language models for domain knowledge graph alignment via neighborhood partitioning and generative subgraph encoding. In *Proceedings of the AAAI Symposium Series*, volume 3, pages 82–89, 2024.
- [52] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers)*, pages 4171–4186, 2019.
- [53] Y. Ding, S. C. Han, J. Lee, and E. Hovy. Deep learning based visually rich document content understanding: A survey. *arXiv preprint arXiv:2408.01287*, 2024.
- [54] H. Dong, Y. Hu, and Y. Cao. Reasoning and retrieval for complex semi-structured tables via reinforced relational data transformation. In *Proceedings of the 48th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR '25*, page 1382–1391, New York, NY, USA, 2025. Association for Computing Machinery.
- [55] H. Dong, J. Zhao, Y. Tian, J. Xiong, S. Xia, M. Zhou, Y. Lin, J. Cambronero, Y. He, S. Han, et al. Spreadsheetllm: encoding spreadsheets for large language models. *arXiv preprint arXiv:2407.09025*, 2024.
- [56] J. Fan, Z. Gu, S. Zhang, Y. Zhang, Z. Chen, L. Cao, G. Li, S. Madden, X. Du, and N. Tang. Combining small language models and large language models for zero-shot nl2sql. *Proceedings of the VLDB Endowment*, 17(11):2750–2763, 2024.
- [57] J. Fan, J. Tu, G. Li, P. Wang, X. Du, X. Jia, S. Gao, and N. Tang. Unicorn: a unified multi-tasking matching model. *ACM SIGMOD Record*, 53(1):44–53, 2024.
- [58] A. M. Farahani, P. Adibi, M. S. Ehsani, H.-P. Hutter, and A. Darvishy. Automatic chart understanding: a review. *IEEE Access*, 11:76202–76221, 2023.
- [59] M. Garland and P. S. Heckbert. Surface simplification using quadric error metrics. In *Proceedings of the 24th annual conference on Computer graphics and interactive techniques*, pages 209–216, 1997.
- [60] M. Geng, S. Wang, D. Dong, H. Wang, G. Li, Z. Jin, X. Mao, and X. Liao. Large language models are few-shot summarizers: Multi-intent comment generation via in-context learning, 2023.
- [61] H. Guo, M. Huo, R. Zhang, and P. Xie. Proteinchat: Towards achieving chatgpt-like functionalities on protein 3d structures. *Authorea Preprints*, 2023.
- [62] J. Guo, Z. Xu, L. Wu, F. Gao, W. Liu, and X. Wang. Xs-vid: An extremely small video object detection dataset. *arXiv preprint arXiv:2407.18137*, 2024.
- [63] Q. Guo, X. Li, D. Ye, J.-G. Lou, L. Bu, L.-M. Zhang, and Z. Zhao. FT2Ra: A fine-tuning-inspired approach to retrieval-augmented code completion. In *Proceedings of the 46th IEEE/ACM International Conference on Software Engineering (ICSE '24)*, 2024.
- [64] Z. Guo, Y. Yu, P. Lv, C. Zhang, H. Li, Z. Wang, K. Yao, J. Liu, and J. Wang. Trust: An accurate and end-to-end table structure recognizer using splitting-based transformers. *arXiv preprint arXiv:2208.14687*, 2022.
- [65] V. Gupta, P. Kandoi, M. B. Vora, S. Zhang, Y. He, R. Reinanda, and V. Srikumar. Temptabqa: Temporal question answering for semi-structured tables, 2023.
- [66] V. Gupta, M. Mehta, P. Nokhiz, and V. Srikumar. Infotabs: Inference on tables as semi-structured data. *arXiv preprint arXiv:2005.06117*, 2020.
- [67] H. T. Ha and A. Horák. Information extraction from scanned invoice images using text analysis and layout features. *Signal Processing: Image Communication*, 102:116601, 2022.
- [68] W. L. Hamilton, R. Ying, and J. Leskovec. Inductive representation learning on large graphs. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, NIPS'17, page 1025–1035, Red Hook, NY, USA, 2017. Curran Associates Inc.
- [69] Y. Han, C. Zhang, X. Chen, X. Yang, Z. Wang, G. Yu, B. Fu, and H. Zhang. Chartllama: A multimodal llm for chart understanding and generation. *arXiv preprint arXiv:2311.16483*, 2023.
- [70] M. A. Hardy and A. Bryman. Handbook of data analysis. 2004.
- [71] P. He, X. Liu, J. Gao, and W. Chen. Deberta: Decoding-enhanced bert with disentangled attention. *arXiv preprint arXiv:2006.03654*, 2020.
- [72] X. He, Y. Tian, Y. Sun, N. Chawla, T. Laurent, Y. LeCun, X. Bresson, and B. Hooi. G-retriever: Retrieval-augmented generation for textual graph understanding and question answering. *Advances in Neural Information Processing Systems*, 37:132876–132907, 2024.
- [73] J. Herzog, P. K. Nowak, T. Müller, F. Piccinno, and J. M. Eisenschlos. Tapas: Weakly supervised table parsing via pre-training. *arXiv preprint arXiv:2004.02349*, 2020.
- [74] J. Ho, W. Chan, C. Saharia, J. Whang, R. Gao, A. Gritsenko, D. P. Kingma, B. Poole, M. Norouzi, D. J. Fleet, et al. Imagen video: High definition video generation with diffusion models. *arXiv preprint arXiv:2210.02303*, 2022.
- [75] P. D. Hoff. Multilinear tensor regression for longitudinal relational data. *The annals of applied statistics*, 9(3):1169, 2015.
- [76] S. Hong, Y. Lin, B. Liu, B. Liu, B. Wu, C. Zhang, C. Wei, D. Li, J. Chen, J. Zhang, J. Wang, L. Zhang, L. Zhang, M. Yang, M. Zhuge, T. Guo, T. Zhou, W. Tao, X. Tang, X. Lu, X. Zheng, X. Liang, Y. Fei, Y. Cheng, Z. Gou, Z. Xu, and C. Wu. Data interpreter: An llm agent for data science, 2024.
- [77] Y. Hong, H. Zhen, P. Chen, S. Zheng, Y. Du, Z. Chen, and C. Gan. 3d-llm: Injecting the 3d world into large language models. *Advances in Neural Information Processing Systems*, 36:20482–20494, 2023.
- [78] H. Hoppe. View-dependent refinement of progressive meshes. In *Proceedings of the 24th annual conference on Computer graphics and interactive techniques*, pages 189–198, 1997.
- [79] C.-Y. Hsieh, C. Zhang, Y. Jiang, Y.-S. Lee, W.-L. Cheng, B. Li, J. Wu, A. Kembhavi, and A. Farhadi. Rationale Distillation for Efficient VLM Training. *arXiv preprint arXiv:2406.03182*, 2024.
- [80] F. Hu, Y. Hu, W. Zhang, H. Huang, Y. Pan, and P. Yin. A multimodal protein representation framework for quantifying transferability across biochemical downstream tasks. *Advanced Science*, 10(22):2301223, 2023.
- [81] H. Huang, X. Shi, H. Lei, F. Hu, and Y. Cai. Protchat: An ai multi-agent for automated protein analysis leveraging gpt-4 and protein language model. *Journal of Chemical Information and Modeling*, 65(1):62–70, 2024.
- [82] J. Huang, D. Guo, C. Wang, J. Gu, S. Lu, J. P. Inala, C. Yan, J. Gao, N. Duan, and M. R. Lyu. Contextualized data-wrangling code generation in computational notebooks. In *Proceedings of the 39th IEEE/ACM International Conference on Automated Software Engineering, ASE '24*, page 1282–1294. ACM, Oct. 2024.
- [83] M. Huang, H. Lai, X. Zhang, W. Wu, J. Ma, L. Zhang, and J. Liu. Evochart: A benchmark and a self-training approach towards real-world chart understanding. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 39, pages 3680–3688, 2025.
- [84] S. Huang, H. Zhang, L. Zhong, H. Chen, Y. Gao, Y. Hu, and Z. Qin. From image to video, what do we need in multimodal llms? *arXiv preprint arXiv:2404.11865*, 2024.
- [85] T.-Y. Huang, S.-Y. Chuang, L.-H. Sun, and M.-H. Chen. Mmp: Towards robust multi-modal learning with masked modality projection. *arXiv preprint arXiv:2410.03010*, 2024.
- [86] Y. Huang, T. Lv, L. Cui, Y. Lu, and F. Wei. Layoutlmv3: Pre-training for document ai with unified text and image masking, 2022.
- [87] V. Hudovernik. Relational data generation with graph neural networks and latent diffusion models. In *NeurIPS 2024 Third Table Representation Learning Workshop*, 2024.
- [88] M. Hui, Z. Zhang, X. Zhang, W. Xie, Y. Wang, and Y. Lu. Unifying layout generation with a decoupled diffusion model. *arXiv preprint arXiv:2303.05049*, 2023.
- [89] N. Inoue, K. Kikuchi, M. Otani, E. Simo-Serra, and K. Yamaguchi. Layoutdm: Discrete diffusion model for controllable layout generation. *arXiv preprint arXiv:2303.08137*, 2023.
- [90] A. Jadhav, R. Ghodake, K. Muralidharan, and G. T. Varma. Ai based multimodal emotion and behavior analysis of interviewee. 2023.
- [91] G. Jaume, H. K. Ekenel, and J.-P. Thiran. Funsd: A dataset for form understanding in noisy scanned documents. In *2019 International Conference on Document Analysis and Recognition Workshops (ICDARW)*, pages 1–6, 2019.
- [92] J. Jiang, K. Zhou, Z. Dong, K. Ye, W. X. Zhao, and J.-R. Wen. Structgpt: A general framework for large language model to reason over structured data, 2023.
- [93] J. Jiang, K. Zhou, W. X. Zhao, and J.-R. Wen. Unikgqa: Unified retrieval and reasoning for solving multi-hop question answering over knowledge graph, 2023.
- [94] Y. Jiang, W. Yu, G. Lee, D. Song, K. Shin, W. Cheng, Y. Liu, and H. Chen. Explainable multi-modal time series prediction with llm-in-the-loop. *arXiv preprint arXiv:2503.01013*, 2025.
- [95] R. L. J. X. Y. C. P. H. C. H. M. D. Z. Jie Tan, Kangfei Zhao and Y. Rong. Can large language models be query optimizer for relational databases? *CoRR*, abs/2502.05562, 2025.
- [96] M. Jin, S. Wang, L. Ma, Z. Chu, J. Y. Zhang, X. Shi, P. Chen, Y. Liang, Y. Li, S. Pan, and Q. Wen. Time-llm: Time series forecasting by reprogramming large language models. In *The Twelfth International Conference on Learning Representations, ICLR 2024, Vienna, Austria, May 7-11, 2024*. OpenReview.net, 2024.
- [97] N. Jin, J. Siebert, D. Li, and Q. Chen. A survey on table question answering: recent advances. In *China Conference on Knowledge Graph and Semantic Computing*, pages 174–186. Springer, 2022.
- [98] M. J. Johnson, D. Duvenaud, A. B. Wiltschko, R. P. Adams, and S. R. Datta. Composing graphical models with neural networks for structured representations and fast inference. In *Advances in neural information processing systems*, pages 2946–2954, 2016.
- [99] K. Kafle, B. Price, S. Cohen, and C. Kanan. Dvqa: Understanding

- data visualizations via question answering, 2018.
- [100] L. Khachatryan, A. Movsisyan, V. Tadevosyan, R. Henschel, Z. Wang, S. Navasardyan, and H. Shi. Text2video-zero: Text-to-image diffusion models are zero-shot video generators. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 15954–15964, 2023.
- [101] W. Kim, B. Son, and I. Kim. Vilt: Vision-and-language transformer without convolution or region supervision. In *International Conference on Machine Learning*, pages 5583–5594. PMLR, 2021.
- [102] T. N. Kipf and M. Welling. Semi-supervised classification with graph convolutional networks. In *Proceedings of the 5th International Conference on Learning Representations (ICLR)*, 2017. Published as a conference paper at ICLR 2017.
- [103] H. Klopries and A. Schwung. Itf-gan: Synthetic time series dataset generation and manipulation by interpretable features. *Knowledge-Based Systems*, 283:111131, 2024.
- [104] C. T. Lee. *Can an LLM find its way around a Spreadsheet?* PhD thesis, Virginia Tech, 2024.
- [105] G. Lee, W. Yu, K. Shin, W. Cheng, and H. Chen. Timecap: Learning to contextualize, augment, and predict time series events with large language model agents. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 39, pages 18082–18090, 2025.
- [106] S.-H. Lee, J. Wang, Z. Zhang, D. Fan, and X. Li. Video token merging for long-form video understanding. *arXiv preprint arXiv:2410.23782*, 2024.
- [107] F. Lei, X. Li, Y. Wei, S. He, Y. Huang, J. Zhao, and K. Liu. S3HQQA: A three-stage approach for multi-hop text-table hybrid question answering. In A. Rogers, J. Boyd-Graber, and N. Okazaki, editors, *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 1731–1740, Toronto, Canada, July 2023. Association for Computational Linguistics.
- [108] M. Lei, K. Karthikeyan, W. Liu, X. Chen, B. Li, Z. Xu, Y. K. L. Wang, and J. Gao. VisDoM: Multi-Document QA with Visually Rich Elements Using Multimodal Retrieval-Augmented Generation. *arXiv preprint arXiv:2412.10704*, 2024.
- [109] M. Lewis, Y. Liu, N. Goyal, M. Ghazvininejad, A. Mohamed, O. Levy, V. Stoyanov, and L. Zettlemoyer. BART: denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In D. Jurafsky, J. Chai, N. Schluter, and J. R. Tetreault, editors, *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020*, pages 7871–7880. Association for Computational Linguistics, 2020.
- [110] P. Lewis, E. Perez, A. Piktus, F. Petroni, V. Karpukhin, N. Goyal, H. Küttler, M. Lewis, W.-t. Yih, T. Rocktäschel, et al. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in Neural Information Processing Systems*, 33:9459–9474, 2020.
- [111] B. Li, Y. Luo, C. Chai, G. Li, and N. Tang. The dawn of natural language to sql: Are we fully ready? *Proceedings of the VLDB Endowment*, 17(11):3318–3331, July 2024.
- [112] F. Li, Y. Wang, Y. Liu, M. Huang, D. Hong, and J. Ma. Seed: A structural encoder for embedding-driven decoding in time series prediction with llms. *arXiv preprint arXiv:2506.20167*, 2025.
- [113] G. Li, X. Zhou, and X. Zhao. Llm for data management. *Proc. VLDB Endow.*, 17(12):4213–4216, Aug. 2024.
- [114] H. Li, J. Zhang, H. Liu, J. Fan, X. Zhang, J. Zhu, R. Wei, H. Pan, C. Li, and H. Chen. Codes: Towards building open-source language models for text-to-sql, 2024.
- [115] J. Li, B. Hui, G. Qu, and 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*, 36, 2024.
- [116] J. Li, Y. Xu, L. Cui, and F. Wei. Markuplm: Pre-training of text and markup language for visually-rich document understanding. *arXiv preprint arXiv:2110.08518*, 2021.
- [117] P. Li, Y. He, C. Yan, Y. Wang, and S. Chaudhuri. Auto-tables: Synthesizing multi-step transformations to relationalize tables without using examples, 2023.
- [118] P. Li, Y. He, D. Yashar, W. Cui, S. Ge, H. Zhang, D. R. Fainman, D. Zhang, and S. Chaudhuri. Table-gpt: Table-tuned gpt for diverse table tasks, 2023.
- [119] S. Li, Z. Liu, Y. Luo, X. Wang, X. He, K. Kawaguchi, T.-S. Chua, and Q. Tian. Towards 3d molecule-text interpretation in language models. *arXiv preprint arXiv:2401.13923*, 2024.
- [120] W. Li, R. Chen, X. Chen, and P. Tan. Sweetdreamer: Aligning geometric priors in 2d diffusion for consistent text-to-3d. *arXiv preprint arXiv:2310.02596*, 2023.
- [121] W. Li, J. Liu, H. Yan, R. Chen, Y. Liang, X. Chen, P. Tan, and X. Long. Craftsman3d: High-fidelity mesh generation with 3d native generation and interactive geometry refiner. *arXiv preprint arXiv:2405.14979*, 2024.
- [122] X. Li, Z. Wu, J. Wu, H. Cui, J. Jia, R.-H. Li, and G. Wang. Graph learning in the era of llms: A survey from the perspective of data, models, and tasks, 2024.
- [123] Y. Li, X. Chen, B. Hu, and M. Zhang. Llms meet long video: Advancing long video comprehension with an interactive visual adapter in llms. *arXiv preprint arXiv:2402.13546*, 3(7), 2024.
- [124] Y. Li, B. Wang, and X. Luan. Xpath agent: An efficient xpath programming agent based on llm for web crawler. *arXiv preprint arXiv:2502.15688*, 2024.
- [125] Z. Li, Y. Du, M. Zheng, and M. Song. Mimotable: A multi-scale spreadsheet benchmark with meta operations for table reasoning, 2024.
- [126] Z. Li, S. Fan, Y. Gu, X. Li, Z. Duan, B. Dong, N. Liu, and J. Wang. Flexkbqa: A flexible llm-powered framework for few-shot knowledge base question answering, 2024.
- [127] Z. Li, X. Wang, J. Zhao, S. Yang, G. Du, X. Hu, B. Zhang, Y. Ye, Z. Li, R. Zhao, and H. Mao. Pet-sql: A prompt-enhanced two-round refinement of text-to-sql with cross-consistency, June 2024.
- [128] M. Liang, X. Xie, Y. Li, H. Wang, Y. Liu, and G. Fan. REPOFUSE: Repository-level code completion with fused dual context. *arXiv preprint arXiv:2402.14275*, 2024.
- [129] Y. Liang, K. Tan, T. Xie, W. Tao, S. Wang, Y. Lan, and W. Qian. Aligning large language models to a domain-specific graph database for nl2gql. In *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management*, pages 1367–1377, 2024.
- [130] Y. Liang, T. Xie, G. Peng, Z. Huang, Y. Lan, and W. Qian. Natnl2gql: A novel multi-agent framework for translating natural language to graph query language, 2024.
- [131] Y. Lin, S. Tang, B. Lyu, J. Wu, H. Lin, K. Yang, J. Li, M. Xia, D. Chen, S. Arora, and C. Jin. Gödel-prover: A frontier model for open-source automated theorem proving. *arXiv preprint arXiv:2502.07640*, 2025.
- [132] C. Liu, Q. Xu, H. Miao, S. Yang, L. Zhang, C. Long, Z. Li, and R. Zhao. Timecma: Towards llm-empowered multivariate time series forecasting via cross-modality alignment. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 39, pages 18780–18788, 2025.
- [133] C. Liu, S. Zhou, Q. Xu, H. Miao, C. Long, Z. Li, and R. Zhao. Towards cross-modality modeling for time series analytics: A survey in the llm era. *arXiv preprint arXiv:2505.02583*, 2025.
- [134] H. Liu, C. Li, Y. Li, and Y. J. Lee. Improved baselines with visual instruction tuning, 2024.
- [135] M. Liu, D. Chen, Y. Li, G. Fang, and Y. Shen. Chartthinker: A contextual chain-of-thought approach to optimized chart summarization. *arXiv preprint arXiv:2403.11236*, 2024.
- [136] P. Liu, H. Guo, T. Dai, N. Li, J. Bao, X. Ren, Y. Jiang, and S.-T. Xia. Calf: Aligning llms for time series forecasting via cross-modal fine-tuning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 39, pages 18915–18923, 2025.
- [137] R. Liu, R. Wu, B. Van Hoorick, P. Tokmakov, S. Zakharov, and C. Vondrick. Zero-1-to-3: Zero-shot one image to 3d object. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 9298–9309, 2023.
- [138] X. Liu, S. Shen, B. Li, P. Ma, R. Jiang, Y. xin Zhang, J. Fan, G. Li, N. Tang, and Y. Luo. A survey of text-to-sql in the era of llms: Where are we, and where are we going? *IEEE Transactions on Knowledge and Data Engineering*, 37:5735–5754, 2024.
- [139] X. Liu, S. Shen, B. Li, P. Ma, R. Jiang, Y. Zhang, J. Fan, G. Li, N. Tang, and Y. Luo. A survey of nl2sql with large language models: Where are we, and where are we going?, 2025.
- [140] Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, O. Levy, M. Lewis, L. Zettlemoyer, and V. Stoyanov. Roberta: A robustly optimized bert pretraining approach, 2019.
- [141] Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, O. Levy, M. Lewis, L. Zettlemoyer, and V. Stoyanov. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019.
- [142] Z. Liu, Q. Liao, W. Gu, and C. Gao. Software vulnerability detection with gpt and in-context learning. In *2023 8th International Conference on Data Science in Cyberspace (DSC)*, pages 229–236, 2023.
- [143] L. Long, X. Gu, X. Sun, W. Ye, H. Wang, S. Wu, G. Chen, and J. Zhao. Bridging the semantic gap between text and table: A case study on nl2sql. In *The Thirteenth International Conference on Learning Representations*, 2025.
- [144] J. Lu, Y. Song, Z. Qin, H. Zhang, C. Zhang, and R. C.-W. Wong. Bridging the gap: Enabling natural language queries for nosql databases through text-to-nosql translation. *arXiv preprint arXiv:2502.11201*, 2025.
- [145] H. Luo, Y. Guo, Q. Lin, X. Wu, X. Mu, W. Liu, M. Song, Y. Zhu, L. A. Tuan, et al. Kbqa-o1: Agentic knowledge base question answering with monte carlo tree search. *arXiv preprint arXiv:2501.18922*, 2025.
- [146] Y. Luo, G. Li, J. Fan, C. Chai, and N. Tang. Natural language to sql: State of the art and open problems. *Proceedings of the VLDB Endowment*, 18(12):5466–5471, 2025.
- [147] Z. Luo, C. Xu, P. Zhao, Q. Sun, X. Geng, W. Hu, C. Tao, J. Ma, Q. Lin, and D. Jiang. Wizardcoder: Empowering code large language models with eval-instruct, 2023.
- [148] M. Ma, J. Ren, L. Zhao, S. Tulyakov, C. Wu, and X. Peng. Miss-modal: Increasing robustness to missing modality in multimodal sentiment analysis. *Transactions of the Association for Computational Linguistics*, 11:1606–1620, 2023.

- [149] Y. Ma, S. Zhang, J. Wang, X. Wang, Y. Zhang, and Z. Deng. Dreamtalk: When emotional talking head generation meets diffusion probabilistic models. *arXiv preprint arXiv:2312.09767*, 2023.
- [150] Z. Ma, B. Zhang, J. Zhang, J. Yu, X. Zhang, X. Zhang, S. Luo, X. Wang, and J. Tang. Spreadsheetbench: Towards challenging real world spreadsheet manipulation, 2024.
- [151] J. Maervoet, C. Vens, G. Vanden Berghe, H. Blockeel, and P. De Causmaecker. Outlier detection in relational data: A case study in geographical information systems. *Expert Systems with Applications*, 39(5):4718–4728, 2012.
- [152] Y. Mao, X. Li, W. Li, X. Wang, and L. Xie. Scla: Automated smart contract summarization via llms and semantic augmentation, 2024.
- [153] A. Masry, P. Kavehzaheh, X. L. Do, E. Hoque, and S. Joty. Unichart: A universal vision-language pretrained model for chart comprehension and reasoning. *arXiv preprint arXiv:2305.14761*, 2023.
- [154] A. Masry, D. X. Long, J. Q. Tan, S. Joty, and E. Hoque. Chartqa: A benchmark for question answering about charts with visual and logical reasoning, 2022.
- [155] A. Masry, M. Thakkar, A. Bajaj, A. Kartha, E. Hoque, and S. Joty. Chartgemma: Visual instruction-tuning for chart reasoning in the wild, 2024.
- [156] V. O. Mittal, J. D. Moore, G. Carenini, and S. Roth. Describing complex charts in natural language: A caption generation system. *Computational Linguistics*, 24(3):431–467, 1998.
- [157] F. Mu, S. Mo, and Y. Li. Snag: Scalable and accurate video grounding, 2024.
- [158] M. Müller, A. Dupuis, T. Zeulner, I. Vazquez, J. Hagerer, and P. A. Gloor. Predicting team well-being through face video analysis with ai. *Applied Sciences*, 14(3):1284, 2024.
- [159] L. Nan, C. Hsieh, Z. Mao, X. V. Lin, N. Verma, R. Zhang, W. Kryściński, H. Schoelkopf, R. Kong, X. Tang, et al. Fetaqa: Free-form table question answering. *Transactions of the Association for Computational Linguistics*, 10:35–49, 2022.
- [160] S. N. Z. Naqvi, S. Yfantidou, and E. Zimányi. Time series databases and influxdb. *Studienarbeit, Université Libre de Bruxelles*, 12:1–44, 2017.
- [161] F. Nooralahzadeh, Y. Zhang, J. Furst, and K. Stockinger. Explainable multi-modal data exploration in natural language via llm agent. *arXiv preprint arXiv:2412.18428*, 2024.
- [162] Numina and Kimi Team. Kimina-prover preview: Towards large formal reasoning models with reinforcement learning. *arXiv preprint arXiv:2504.11354*, 2025.
- [163] J. Obeid and E. Hoque. Chart-to-text: Generating natural language descriptions for charts by adapting the transformer model. In B. Davis, Y. Graham, J. Kelleher, and Y. Sripada, editors, *Proceedings of the 13th International Conference on Natural Language Generation*, pages 138–147, Dublin, Ireland, Dec. 2020. Association for Computational Linguistics.
- [164] Y. Okamoto, Y. Baek, G. Kim, R. Nakao, D. Kim, M. B. Yim, S. Park, and B. Lee. Crepe: Coordinate-aware end-to-end document parser. *arXiv preprint arXiv:2406.04093*, 2024.
- [165] M. Otani, N. Inoue, K. Kikuchi, and R. Togashi. Ltsim: Layout transportation-based similarity measure for evaluating layout generation. *arXiv preprint arXiv:2407.12356*, 2024.
- [166] Z. Pan, Y. Jiang, S. Garg, A. Schneider, Y. Nevyvaka, and D. Song. \$s\$2\$IP-LLM: Semantic space informed prompt learning with LLM for time series forecasting. In *Forty-first International Conference on Machine Learning*, 2024.
- [167] P. Pasupat and P. Liang. Compositional semantic parsing on semi-structured tables. *arXiv preprint arXiv:1508.00305*, 2015.
- [168] L. Patel, S. Jha, C. Guestrin, and M. Zaharia. Lotus: Enabling semantic queries with llms over tables of unstructured and structured data. *arXiv e-prints*, pages arXiv–2407, 2024.
- [169] S. Patnaik, H. Changwal, M. Aggarwal, S. Bhatia, Y. Kumar, and B. Krishnamurthy. Cabinet: Content relevance based noise reduction for table question answering, 2024.
- [170] S. Patnaik, R. Jain, B. Krishnamurthy, and M. Sarkar. Aesthetiq: Enhancing graphic layout design via aesthetic-aware preference alignment of multi-modal large language models. *arXiv preprint arXiv:2503.00591*, 2025.
- [171] Q. Pei, L. Wu, K. Gao, J. Zhu, Y. Wang, Z. Wang, T. Qin, and R. Yan. Leveraging biomolecule and natural language through multi-modal learning: A survey, 2024.
- [172] M. Pisaneschi, S. Appalaraju, and R. Manmatha. Automatic generation of scientific papers for data augmentation in document layout analysis. *Pattern Recognition Letters*, 167:87–94, 2023.
- [173] M. Pourreza and D. Rafiei. Din-sql: Decomposed in-context learning of text-to-sql with self-correction, 2023.
- [174] N. PP and A. P. N. Iyer. Hysem: A context length optimized llm pipeline for unstructured tabular extraction. *arXiv preprint arXiv:2408.09434*, 2024.
- [175] L. Qiu, G. Chen, X. Gu, Q. Zuo, M. Xu, Y. Wu, W. Yuan, Z. Dong, L. Bo, and X. Han. Richdreamer: A generalizable normal-depth diffusion model for detail richness in text-to-3d. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 9914–9925, 2024.
- [176] Qwen, ., A. Yang, B. Yang, B. Zhang, B. Hui, B. Zheng, B. Yu, C. Li, D. Liu, F. Huang, H. Wei, H. Lin, J. Yang, J. Tu, J. Zhang, J. Yang, J. Yang, J. Zhou, J. Lin, K. Dang, K. Lu, K. Bao, K. Yang, L. Yu, M. Li, M. Xue, P. Zhang, Q. Zhu, R. Men, R. Lin, T. Li, T. Tang, T. Xia, X. Ren, X. Ren, Y. Fan, Y. Su, Y. Zhang, Y. Wan, Y. Liu, Z. Cui, Z. Zhang, and Z. Qiu. Qwen2.5 technical report, 2025.
- [177] R. Rafailov, A. Sharma, E. Mitchell, S. Ermon, C. D. Manning, and C. Finn. Direct preference optimization: Your language model is secretly a reward model, 2024.
- [178] F. Rahmani and M. H. Fattahi. Association between forecasting models' precision and nonlinear patterns of daily river flow time series. *Modeling Earth Systems and Environment*, 8(3):4267–4276, 2022.
- [179] E. Reiter. An architecture for data-to-text systems. In S. Busemann, editor, *Proceedings of the Eleventh European Workshop on Natural Language Generation (ENLG 07)*, pages 97–104, Saarbrücken, Germany, June 2007. DFKI GmbH.
- [180] X. Ren, J. Tang, D. Yin, N. Chawla, and C. Huang. A survey of large language models for graphs. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pages 6616–6626, 2024.
- [181] E. Sengonul, R. Samet, Q. Abu Al-Haija, A. Alqahtani, R. A. Alsemeari, B. Alghamdi, B. Alturki, and A. A. Alsulami. Abnormal event detection in surveillance videos through lstm auto-encoding and local minima assistance. *Discover Internet of Things*, 5(1):32, 2025.
- [182] P. Senin. Dynamic time warping algorithm review. *Information and Computer Science Department University of Hawaii at Manoa Honolulu, USA*, 855(1–23):40, 2008.
- [183] J. Seol, S. Kim, and J. Yoo. Posterllama: Bridging design ability of language model to content-aware layout generation. *arXiv preprint arXiv:2404.00995*, 2024.
- [184] W. Shang and X. Huang. A survey of large language models on generative graph analytics: Query, learning, and applications. *arXiv preprint arXiv:2404.14809*, 2024.
- [185] L. Shen, T. Hao, T. He, S. Zhao, Y. Zhang, P. Liu, Y. Bao, and G. Ding. Tempme: Video temporal token merging for efficient text-video retrieval. *arXiv preprint arXiv:2409.01156*, 2024.
- [186] H. Shi, J. Su, R. Xu, and J. Gao. Layoutcot: Unleashing the deep reasoning potential of large language models for layout generation. *arXiv preprint arXiv:2504.10829*, 2025.
- [187] L. Shi, Z. Tang, N. Zhang, X. Zhang, and Z. Yang. A survey on employing large language models for text-to-sql tasks. *ACM Computing Surveys*, 2024.
- [188] L. Shi, Z. Tang, N. Zhang, X. Zhang, and Z. Yang. A survey on employing large language models for text-to-sql tasks. *ACM Computing Surveys*, 2024.
- [189] S. Siami-Namini, N. Tavakoli, and A. S. Namin. The performance of lstm and bilstm in forecasting time series. In *2019 IEEE International Conference on Big Data (Big Data)*, pages 3285–3292, 2019.
- [190] S. Siami-Namini, N. Tavakoli, and A. Siami Namin. A comparison of arima and lstm in forecasting time series. In *2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA)*, pages 1394–1401, 2018.
- [191] U. Singer, A. Polyak, T. Hayes, X. Yin, J. An, S. Zhang, Q. Hu, H. Yang, O. Ashual, O. Gafni, et al. Make-a-video: Text-to-video generation without text-video data. *arXiv preprint arXiv:2209.14792*, 2022.
- [192] A. Singh, A. Singh, P. Agarwal, Z. Huang, A. Singh, T. Yu, S. Kim, V. Bursztyn, N. K. Ahmed, P. Mathur, E. Learned-Miller, F. Dermoncourt, and R. A. Rossi. Figcaps-hf: A figure-to-caption generative framework and benchmark with human feedback, 2025.
- [193] A. V. Solatorio and O. Dupriez. Realtabformer: Generating realistic relational and tabular data using transformers. *arXiv preprint arXiv:2302.02041*, 2023.
- [194] D. Song, C.-M. Zhang, X.-Q. Zhao, T. Wang, W.-Z. Nie, X.-Y. Li, and A.-A. Liu. Self-supervised image-based 3d model retrieval. *ACM Transactions on Multimedia Computing, Communications and Applications*, 19(2):1–18, 2023.
- [195] A. Su, A. Wang, C. Ye, C. Zhou, G. Zhang, G. Chen, G. Zhu, H. Wang, H. Xu, H. Chen, H. Li, H. Lan, J. Tian, J. Yuan, J. Zhao, J. Zhou, K. Shou, L. Zha, L. Long, L. Li, P. Wu, Q. Zhang, Q. Huang, S. Yang, T. Zhang, W. Ye, W. Zhu, X. Hu, X. Gu, X. Sun, X. Li, Y. Yang, and Z. Xiao. Tablegpt2: A large multimodal model with tabular data integration, 2024.
- [196] Y. Suhara, J. Li, Y. Li, D. Zhang, Q. Demiralp, C. Chen, and W.-C. Tan. Annotating columns with pre-trained language models. In *Proceedings of the 2022 International Conference on Management of Data*, pages 1493–1503, 2022.
- [197] S. Talaei, M. Pourreza, Y.-C. Chang, A. Mirhoseini, and A. Saberi. Chess: Contextual harnessing for efficient sql synthesis, 2024.
- [198] S. Tanaka, H. Wang, and Y. Ushiku. Scipostlayout: A dataset for layout analysis and layout generation of scientific posters. *arXiv preprint arXiv:2407.19787*, 2024.
- [199] J. Tang, Y. Yang, W. Wei, L. Shi, L. Su, S. Cheng, D. Yin, and C. Huang. Graphgpt: Graph instruction tuning for large language models, 2024.
- [200] Y. Tang, J. Bi, S. Xu, L. Song, S. Liang, T. Wang, D. Zhang, J. An, J. Lin, R. Zhu, et al. Video understanding with large language

- models: A survey. *IEEE Transactions on Circuits and Systems for Video Technology*, 2025.
- [201] Z. Tang, B. Niu, X. Zhou, B. Li, W. Zhou, J. Wang, G. Li, X. Zhang, and F. Wu. St-raptor: Llm-powered semi-structured table question answering. *arXiv preprint arXiv:2508.18190*, 2025.
- [202] B. Taskar, E. Segal, and D. Koller. Probabilistic classification and clustering in relational data. In *International joint conference on artificial intelligence*, volume 17, pages 870–878. Lawrence Erlbaum Associates LTD, 2001.
- [203] S. Tickoo. *Autodesk Maya 2019: A Comprehensive Guide*. Cadcam Technologies, 2018.
- [204] J. Tu, J. Fan, N. Tang, P. Wang, G. Li, X. Du, X. Jia, and S. Gao. Unicorn: A unified multi-tasking model for supporting matching tasks in data integration. *Proc. ACM Manag. Data*, 1(1):84:1–84:26, 2023.
- [205] M. Urban and C. Binnig. Caesura: Language models as multi-modal query planners, 2023.
- [206] J. Wan, S. Song, W. Yu, Y. Liu, W. Cheng, F. Huang, X. Bai, C. Yao, and Z. Yang. Omniparser: A unified framework for text spotting, key information extraction and table recognition. In *2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 15641–15653, 2024.
- [207] C. Wang, H. Fan, R. Quan, and Y. Yang. Protchatgpt: Towards understanding proteins with large language models. *arXiv preprint arXiv:2402.09649*, 2024.
- [208] D. Wang, Z. Ma, A. Nourbakhsh, K. Mangalampani, and S. Shah. Docilm: A layout-aware generative language model for multimodal document understanding. *arXiv preprint arXiv:2401.00908*, 2024.
- [209] H. Wang, Z. Xu, Y. Cheng, S. Diao, Y. Zhou, Y. Cao, Q. Wang, W. Ge, and L. Huang. Grounded-videoilm: Sharpening fine-grained temporal grounding in video large language models. *arXiv preprint arXiv:2410.03290*, 2024.
- [210] J. Wang, Y. Feng, C. Shen, S. Rahman, and E. Kandogan. Towards operationalizing heterogeneous data discovery. *arXiv preprint arXiv:2504.02059*, 2025.
- [211] J. Wang, K. Hu, and Q. Huo. Dlaformer: An end-to-end transformer for document layout analysis. *arXiv preprint arXiv:2405.11757*, 2024.
- [212] J. Wang and G. Li. Aop: Automated and interactive llm pipeline orchestration for answering complex queries. CIDR, 2025.
- [213] J. Wang, R. Li, R. Li, B. Fu, and D. Z. Chen. Hmcrautoencoder: An interpretable deep learning framework for time series analysis. *IEEE Transactions on Emerging Topics in Computing*, 10(1):99–111, 2022.
- [214] J. Wang, H. Luo, R. Qin, M. Wang, X. Wan, M. Fang, O. Zhang, Q. Gou, Q. Su, C. Shen, et al. 3dsmiles-gpt: 3d molecular pocket-based generation with token-only large language model. *Chemical Science*, 16(2):637–648, 2025.
- [215] J. Wang, J. Wu, Y. Hou, Y. Liu, M. Gao, and J. McAuley. Instruct-graph: Boosting large language models via graph-centric instruction tuning and preference alignment, 2024.
- [216] L. Wang. Heterogeneous data and big data analytics. In *ACIS*, volume 3, pages 8–15, 2017.
- [217] M. Wang, X. Ke, X. Xu, L. Chen, Y. Gao, P. Huang, and R. Zhu. Must: An effective and scalable framework for multimodal search of target modality. In *2024 IEEE 40th International Conference on Data Engineering (ICDE)*. IEEE, 2024.
- [218] M. Wang, H. Wu, X. Ke, Y. Gao, X. Xu, and L. Chen. An interactive multi-modal query answering system with retrieval-augmented large language models, 2024.
- [219] P. Wang, L. Liu, Y. Liu, C. Theobalt, T. Komura, and W. Wang. Neus: Learning neural implicit surfaces by volume rendering for multi-view reconstruction. *arXiv preprint arXiv:2106.10689*, 2021.
- [220] Q. Wang, Y. Fang, A. Ravula, F. Feng, X. Quan, and D. Liu. Webformer: The web-page transformer for structure information extraction. In *Proceedings of the ACM Web Conference 2022*, pages 3124–3133, 2022.
- [221] S. Wang, G. Chen, D.-a. Huang, Z. Li, M. Li, G. Li, J. M. Alvarez, L. Zhang, and Z. Yu. Videointg: Multimodal video understanding with instructed temporal grounding. *arXiv preprint arXiv:2507.13353*, 2025.
- [222] T. Wang, L. Li, K. Lin, Y. Zhai, C.-C. Lin, Z. Yang, H. Zhang, Z. Liu, and L. Wang. Disco: Disentangled control for realistic human dance generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9326–9336, 2024.
- [223] X. Wang, M. Costa, J. Kovaceva, S. Wang, and F. C. Pereira. Plugging schema graph into multi-table qa: A human-guided framework for reducing llm reliance. *arXiv preprint arXiv:2506.04427*, 2025.
- [224] X. Wang, M. Feng, J. Qiu, J. Gu, and J. Zhao. From news to forecast: Integrating event analysis in llm-based time series forecasting with reflection. *Advances in Neural Information Processing Systems*, 37:58118–58153, 2024.
- [225] X. Wang, Y. Wang, W. Zhu, and R. Wang. Do large language models truly understand geometric structures? *arXiv preprint arXiv:2501.13773*, 2025.
- [226] Y. Wang and J. Hu. Detecting tables in html documents. In *International Workshop on Document Analysis Systems*, pages 249–260. Springer, 2002.
- [227] Y. Wang and H. A. Karimi. Exploring large language models for climate forecasting. *CoRR*, abs/2411.13724, 2024.
- [228] Y. Wang, Y. Kordi, S. Mishra, A. Liu, N. A. Smith, D. Khashabi, and H. Hajishirzi. Self-instruct: Aligning language models with self-generated instructions, 2022.
- [229] Z. Wang, H. Dong, R. Jia, J. Li, Z. Fu, S. Han, and D. Zhang. Tuta: Tree-based transformers for generally structured table pre-training. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, pages 1780–1790, 2021.
- [230] Z. Wang, J. Lorraine, Y. Wang, H. Su, J. Zhu, S. Fidler, and X. Zeng. Llama-mesh: Unifying 3d mesh generation with language models. *arXiv preprint arXiv:2411.09595*, 2024.
- [231] Z. Wang, H. Zhang, C.-L. Li, J. M. Eisenschlos, V. Perot, Z. Wang, L. Miculicich, Y. Fujii, J. Shang, C.-Y. Lee, and T. Pfister. Chain-of-table: Evolving tables in the reasoning chain for table understanding, 2024.
- [232] Y. Wei, Z. Wang, J. Liu, Y. Ding, and L. Zhang. Magicoder: Source code is all you need. *arXiv preprint arXiv:2312.02120*, 10, 2023.
- [233] D. Weininger. Smiles, a chemical language and information system. 1. introduction to methodology and encoding rules. *Journal of chemical information and computer sciences*, 28(1):31–36, 1988.
- [234] Z. Weng, L. Bravo-Sánchez, Z. Wang, C. Howard, M. Xenochristou, N. Meister, A. Kanazawa, A. Milstein, E. Bergelson, K. L. Humphreys, et al. Artificial intelligence-powered 3d analysis of video-based caregiver-child interactions. *Science Advances*, 11(8):eabd4422, 2025.
- [235] R. Whitehead, A. Nguyen, and S. Järvelä. Utilizing multimodal large language models for video analysis of posture in studying collaborative learning: A case study. *Journal of Learning Analytics*, 12(1):186–200, 2025.
- [236] Wikipedia contributors. 3d model, 2025. Accessed: 2025-09-08.
- [237] C. Wu, J. Liang, X. Hu, Z. Gan, J. Wang, L. Wang, Z. Liu, Y. Fang, and N. Duan. Nuwa-infinity: Autoregressive over autoregressive generation for infinite visual synthesis. *arXiv preprint arXiv:2207.09814*, 2022.
- [238] D. Wu, W. U. Ahmad, S. Li, and X. Ma. Repoformer: Selective retrieval for repository-level code completion. In *Proceedings of the 29th ACM International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS '24)*, 2024.
- [239] J. Wu, L. Yang, D. Li, Y. Ji, M. Okumura, and Y. Zhang. Mmq: Evaluating llms with multi-table multi-hop complex questions. In *The Thirteenth International Conference on Learning Representations*, 2025.
- [240] S. Wu, Y. Lin, F. Zhang, Y. Zeng, J. Xu, P. Torr, X. Cao, and Y. Yao. Direct3d: Scalable image-to-3d generation via 3d latent diffusion transformer. *Advances in Neural Information Processing Systems*, 37:121859–121881, 2024.
- [241] X. Wu, A. Ritter, and W. Xu. Tabular data understanding with llms: A survey of recent advances and challenges. *arXiv preprint arXiv:2508.00217*, 2025.
- [242] Y. Wu, L. Yan, L. Shen, Y. Wang, N. Tang, and Y. Luo. Chartinsights: Evaluating multimodal large language models for low-level chart question answering. *arXiv preprint arXiv:2405.07001*, 2024.
- [243] Y. Xiao, J. Liu, Y. Zheng, X. Xie, J. Hao, M. Li, R. Wang, F. Ni, Y. Li, J. Luo, S. Jiao, and J. Peng. Cellagent: An llm-driven multi-agent framework for automated single-cell data analysis, 2024.
- [244] X. Xie, G. Xu, L. Zhao, and R. Guo. Opensearch-sql: Enhancing text-to-sql with dynamic few-shot and consistency alignment. *Proc. ACM Manag. Data*, 3(3):194:1–194:24, 2025.
- [245] Z. Xie, Z. Li, X. He, L. Xu, X. Wen, T. Zhang, J. Chen, R. Shi, and D. Pei. Chatts: Aligning time series with llms via synthetic data for enhanced understanding and reasoning. *arXiv preprint arXiv:2412.03104*, 2024.
- [246] H. Xin, D. Guo, Z. Shao, Z. Ren, Q. Zhu, B. Liu, C. Ruan, W. Li, and X. Liang. Deepseek-prover: Advancing theorem proving in llms through large-scale synthetic data. *arXiv preprint arXiv:2405.14333*, 2024.
- [247] J. Xing, Y. He, M. Zhou, H. Dong, S. Han, L. Chen, D. Zhang, S. Chaudhuri, and H. Jagadish. Mmtu: A massive multi-task table understanding and reasoning benchmark. *arXiv preprint arXiv:2506.05587*, 2025.
- [248] G. Xiong, J. Bao, and W. Zhao. Interactive-kbqa: Multi-turn interactions for knowledge base question answering with large language models, 2024.
- [249] G. Xiong, H. Li, and W. Zhao. Mcts-kbqa: Monte carlo tree search for knowledge base question answering. *arXiv preprint arXiv:2502.13428*, 2025.
- [250] H. Xiong, Y. Zhuge, J. Zhu, L. Zhang, and H. Lu. 3ur-llm: An end-to-end multimodal large language model for 3d scene understanding. *IEEE Transactions on Multimedia*, 2025.
- [251] H. Xu, L. Chen, Z. Zhao, D. Ma, R. Cao, Z. Zhu, and K. Yu. Hierarchical multimodal pre-training for visually rich webpage understanding. In *Proceedings of the 17th ACM International Conference on Web Search and Data Mining*, pages 864–872, 2024.
- [252] K. Xu, G. Ganey, E. Joubert, R. Davison, O. Van Acker, and L. Robinson. Synthetic data generation of many-to-many datasets

- via random graph generation. In *The Eleventh International Conference on Learning Representations*, 2022.
- [253] Y. Xu, M. Li, L. Cui, S. Huang, F. Wei, and M. Zhou. Layoutlm: Pre-training of text and layout for document image understanding. *arXiv preprint arXiv:1912.13318*, 2020.
- [254] Y. Xu, Y. Xu, T. Lv, L. Cui, F. Wei, G. Wang, Y. Lu, D. Florencio, C. Zhang, W. Che, M. Zhang, and L. Zhou. Layoutlmv2: Multi-modal pre-training for visually-rich document understanding. pages 2579–2591, 2021.
- [255] Z. Xu, S. Du, Y. Qi, C. Xu, C. Yuan, and J. Guo. Chartbench: A benchmark for complex visual reasoning in charts, 2024.
- [256] Z. Xu, B. Qu, Y. Qi, S. Du, C. Xu, C. Yuan, and J. Guo. Chartmoe: Mixture of diversely aligned expert connector for chart understanding, 2025.
- [257] S.-Q. Yan, J.-C. Gu, Y. Zhu, and Z.-H. Ling. Corrective retrieval augmented generation. *arXiv preprint arXiv:2401.15884*, 2024.
- [258] C. Yang, C. Shi, Y. Liu, B. Shui, J. Wang, M. Jing, L. Xu, X. Zhu, S. Li, Y. Zhang, G. Liu, X. Nie, D. Cai, and Y. Yang. Chartmimic: Evaluating lmm’s cross-modal reasoning capability via chart-to-code generation, 2025.
- [259] F. Yang, S. Zhao, Y. Zhang, H. Chen, H. Chen, W. Tang, H. Lu, P. Xu, Z. Yang, J. Han, et al. Llmi3d: Empowering llm with 3d perception from a single 2d image. *arXiv preprint arXiv:2408.07422*, 2024.
- [260] J. Yang, A. Gupta, S. Upadhyay, L. He, R. Goel, and S. Paul. Tableformer: Robust transformer modeling for table-text encoding. *arXiv preprint arXiv:2203.00274*, 2022.
- [261] S. Yang, D. Wang, H. Zheng, and R. Jin. Timerag: Boosting llm time series forecasting via retrieval-augmented generation. In *ICASSP 2025-2025 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 1–5. IEEE, 2025.
- [262] X. Yang, H. Shi, B. Zhang, F. Yang, J. Wang, H. Zhao, X. Liu, X. Wang, Q. Lin, J. Yu, et al. Hunyuan3d 1.0: A unified framework for text-to-3d and image-to-3d generation. *arXiv preprint arXiv:2411.02293*, 2024.
- [263] Q. Ye, H. Xu, G. Xu, J. Ye, M. Yan, Y. Zhou, J. Wang, A. Hu, P. Shi, Y. Shi, C. Li, Y. Xu, H. Chen, J. Tian, Q. Qian, J. Zhang, F. Huang, and J. Zhou. mplug-owl: Modularization empowers large language models with multimodality, 2024.
- [264] R. Ye, C. Zhang, R. Wang, S. Xu, and Y. Zhang. Language is all a graph needs, 2024.
- [265] P. Yin, W.-D. Li, K. Xiao, A. Rao, Y. Wen, K. Shi, J. Howland, P. Bailey, M. Catasta, H. Michalewski, A. Polozov, and C. Sutton. Natural language to code generation in interactive data science notebooks, 2022.
- [266] T. Yu, M. Yasunaga, K. Yang, R. Zhang, D. Wang, Z. Li, and D. R. Radev. Syntaxsqlnet: Syntax tree networks for complex and cross-domain text-to-sql task. In E. Riloff, D. Chiang, J. Hockenmaier, and J. Tsujii, editors, *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018*, pages 1653–1663. Association for Computational Linguistics, 2018.
- [267] T. Yu, R. Zhang, K. Yang, M. Yasunaga, D. Wang, Z. Li, J. Ma, I. Li, Q. Yao, S. Roman, et al. Spider: A large-scale human-labeled dataset for complex and cross-domain semantic parsing and text-to-sql task. *arXiv preprint arXiv:1809.08887*, 2018.
- [268] X. Yu, Z. Chen, Y. Ling, S. Dong, Z. Liu, and Y. Lu. Temporal data meets llm-explainable financial time series forecasting. *arXiv preprint arXiv:2306.11025*, 2023.
- [269] Y. Yuan, H. Zhang, W. Li, Z. Cheng, B. Zhang, L. Li, X. Li, D. Zhao, W. Zhang, Y. Zhuang, et al. Videorefer suite: Advancing spatial-temporal object understanding with video llm. In *Proceedings of the Computer Vision and Pattern Recognition Conference*, pages 18970–18980, 2025.
- [270] F. P. Zadeh, J. Kim, J.-H. Kim, and G. Kim. Text2chart31: Instruction tuning for chart generation with automatic feedback, 2025.
- [271] C. Zhang, Y. Mao, Y. Fan, Y. Mi, Y. Gao, L. Chen, D. Lou, and J. Lin. Finsql: Model-agnostic llms-based text-to-sql framework for financial analysis, 2024.
- [272] F. Zhang, B. Chen, Y. Wang, Y. T. Lee, Z. Sui, and W. Chen. RepoCoder: Repository-level code completion through iterative retrieval and generation. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, 2023.
- [273] H. Zhang, J. Zhang, B. Srinivasan, Z. Shen, X. Qin, C. Faloutsos, H. Rangwala, and G. Karypis. Mixed-type tabular data synthesis with score-based diffusion in latent space. *arXiv preprint arXiv:2310.09656*, 2023.
- [274] J. Zhang, R. Yoshihashi, R. Kawakami, and Y. Nakashima. Vascar: Content-aware layout generation via visual-aware self-correction. *arXiv preprint arXiv:2412.04237*, 2024.
- [275] J. Zhang, X. Zhang, J. Yu, J. Tang, J. Tang, C. Li, and H. Chen. Subgraph retrieval enhanced model for multi-hop knowledge base question answering. In S. Muresan, P. Nakov, and A. Villavicencio, editors, *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 5773–5784, Dublin, Ireland, May 2022. Association for Computational Linguistics.
- [276] Q. Zhang, B. Wang, V. S.-J. Huang, J. Zhang, Z. Wang, H. Liang, C. He, and W. Zhang. Document parsing unveiled: Techniques, challenges, and prospects for structured information extraction. *arXiv preprint arXiv:2410.21169*, 2024.
- [277] T. Zhang, Z. Chen, W. Li, and D. Chen. RAFT: Retrieval augmented fine-tuning for language models. *arXiv preprint arXiv:2403.10131*, 2024.
- [278] W. Zhang, X. Cun, X. Wang, Y. Zhang, X. Shen, Y. Guo, Y. Shan, and F. Wang. Sadtalker: Learning realistic 3d motion coefficients for stylized audio-driven single image talking face animation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 8652–8661, 2023.
- [279] Y. Zhang, J. Henkel, A. Floratou, J. Cahoon, S. Deep, and J. M. Patel. Reactable: Enhancing react for table question answering, 2023.
- [280] W. Zhao, H. Feng, Q. Liu, J. Tang, S. Wei, B. Wu, L. Liao, Y. Ye, H. Liu, W. Zhou, H. Li, and C. Huang. Tabpedia: Towards comprehensive visual table understanding with concept synergy, 2024.
- [281] X. Zhao, X. Zhou, and G. Li. Chat2data: An interactive data analysis system with rag, vector databases and llms. *Proc. VLDB Endow.*, 17(12):4481–4484, Aug. 2024.
- [282] Y. Zhao, L. Chen, A. Cohan, and C. Zhao. TaPERA: Enhancing faithfulness and interpretability in long-form table QA by content planning and execution-based reasoning. In L.-W. Ku, A. Martins, and V. Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 12824–12840, Bangkok, Thailand, Aug. 2024. Association for Computational Linguistics.
- [283] L. Zheng, W.-L. Chiang, Y. Sheng, S. Zhuang, Z. Wu, Y. Zhuang, Z. Lin, Z. Li, D. Li, E. Xing, et al. Judging llm-as-a-judge with mt-bench and chatbot arena. *Advances in Neural Information Processing Systems*, 36:46595–46623, 2023.
- [284] M. Zheng, X. Feng, Q. Si, Q. She, Z. Lin, W. Jiang, and W. Wang. Multimodal table understanding, 2024.
- [285] W. Zhou, Y. Gao, X. Zhou, and G. Li. Cracking SQL Barriers: An llm-based dialect translation system. *Proc. ACM Manag. Data*, 3(3 (SIGMOD)), 2025.
- [286] W. Zhou, Y. Gao, X. Zhou, and G. Li. Cracksq: A hybrid sql dialect translation system powered by large language models. *arXiv Preprint*, 2025.
- [287] Y. Zhou, Y. He, S. Tian, Y. Ni, Z. Yin, X. Liu, C. Ji, S. Liu, X. Qiu, G. Ye, and H. Chai. r^3 -NL2GQL: A model coordination and knowledge edge graph alignment approach for NL2GQL. In Y. Al-Onaizan, M. Bansal, and Y.-N. Chen, editors, *Findings of the Association for Computational Linguistics: EMNLP 2024*, pages 13679–13692, Miami, Florida, USA, Nov. 2024. Association for Computational Linguistics.
- [288] F. Zhu, Z. Liu, F. Feng, C. Wang, M. Li, and T. S. Chua. Tat-llm: A specialized language model for discrete reasoning over financial tabular and textual data. In *Proceedings of the 5th ACM International Conference on AI in Finance, ICAIF ’24*, page 310–318, New York, NY, USA, 2024. Association for Computing Machinery.
- [289] J. Zhu, Y. Fu, J. Zhou, and D. Chen. A temporal knowledge graph generation dataset supervised distantly by large language models. *Scientific Data*, 12, 05 2025.
- [290] X. Zhu, Q. Li, L. Cui, and Y. Liu. Large language model enhanced text-to-sql generation: A survey. *arXiv preprint arXiv:2410.06011*, 2024.