DataForge: An AI-Driven Data Warehouse Schema Generator

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Abstract— **Organizations today rely on robust data warehouses to integrate and analyze massive volumes of data for decision-making. However, designing an optimized warehouse schema (fact and dimension tables, keys, constraints, naming conventions) is a labor-intensive, error-prone process that can take weeks of manual effort by experts. This paper presents** DataForge, **an AI-driven framework that automates and accelerates data warehouse schema creation. DataForge parses input SQL schema definitions, infers an appropriate star schema, and enhances it using artificial intelligence. It combines regex-based and grammar-based SQL parsing to reliably extract tables, columns, and relationships; keyword-driven** domain detection **and NLP techniques to infer business context; semantic validation to enforce logical consistency and naming standards; and heuristic rules to classify tables into fact or dimension roles. An interactive web-based interface allows users to visualize and refine the generated schema with real-time suggestions. In benchmark evaluations on retail, healthcare, and financial datasets, DataForge reduced schema design time by over 80% and achieved an expert-validated schema quality score above 90%. The results indicate that DataForge can dramatically streamline the schema design phase, paving the way for faster, more consistent data engineering workflows.**

Keywords— Data warehouse, schema automation, dimensional modeling, NLP, AI in data engineering

I. INTRODUCTION

In the era of big data, enterprises across industries depend on data-driven decision making for competitive advantage. **Data warehouses (DWs)** serve as centralized repositories that aggregate data from heterogeneous sources (transactional databases, logs, APIs) and support complex analytical queries and business intelligence (BI) reporting. Designing a high-quality DW schema—organizing data into fact tables and dimension tables with proper keys and relationships—is critical to enable efficient Online Analytical Processing (OLAP). Traditionally, this schema design process is performed manually by data engineers following methodologies like **dimensional modeling** (star/snowflake schemas). Manual design involves carefully parsing source database schemas, identifying entities and relationships, defining primary/foreign keys, and enforcing naming conventions and consistency. This process is *time-consuming* and requires deep domain expertise: large organizations report significant delays in analytics projects due to the slow turnaround of manual data integration and schema design. It is also *error-prone*—mistakes such as missing foreign key constraints or inconsistent naming can lead to inaccurate analyses or costly rework. Moreover, as data sources and business requirements evolve, maintaining the schema becomes increasingly difficult, often necessitating multiple revisions or even parallel data marts for different use cases. These challenges motivate the need for automation in DW schema design.

Recent advances in artificial intelligence and automation offer an opportunity to fundamentally improve this process. In particular, natural language processing (NLP) and pattern recognition can be applied to understand schema metadata, while machine learning heuristics or even large language models can capture domain knowledge and best practices. Some early research efforts have explored aspects of this problem. For example, Usman et al. developed one of the first frameworks for automatically generating OLAP schemas from data by applying data mining techniques【1】. DiScala and Abadi proposed algorithms to infer normalized relational schemas from nested data sources without human intervention【2】. Others have introduced rule-based approaches to derive dimensional models by analyzing database usage patterns and foreign key relationships. More recently, researchers have applied advanced AI methods: Mali et al. present a cost-based optimization framework (FACT-DM) to automatically transform data models under resource constraints【3】, and Dwivedi et al. demonstrate that graph neural networks can learn relational structure, generating schemas by treating databases as graphs【4】. NLP-driven techniques have also been employed; for instance, Imarisio et al. fine-tuned a BERT language model to capture semantic similarities in database metadata for data discovery tasks【5】, and Salem leveraged large language models (LLMs) to interpret natural language requirements into database schemas【6】. Commercial data integration tools (e.g., Informatica, Talend) provide limited automation in schema design, focusing mainly on ETL workflows or template-based modeling, and lack AI-driven insights. In summary, prior works either tackle specific sub-problems or require extensive training data, and few offer an end-to-end automated solution that incorporates user feedback. DataForge is designed to fill this gap by providing a holistic, AI-augmented platform for automated data warehouse schema generation. The key insight behind DataForge is that a combination of lightweight parsing techniques, heuristic rules, and learned intelligence can drastically reduce the manual effort while preserving expert-level accuracy. DataForge accepts an input of one or more raw SQL DDL (Data Definition Language) files describing source tables. It then proceeds to: (1) parse the SQL definitions to extract all tables, columns, data types, and constraints; (2) classify and organize these into an initial DW schema (identifying which tables are candidate fact tables versus dimension tables, inferring primary keys and foreign key relationships between them); and (3) enhance the schema using AI-driven analysis to ensure it aligns with the business domain and follows best practices (adding any missing surrogate keys, Slowly Changing Dimension support, timestamp fields, etc.). All these suggestions are presented to the user via an interactive interface where further manual adjustments can be made with real-time validation. The contributions of this work include:

- An automated schema parsing and generation pipeline that combines regex-based and grammar-based SQL parsing with heuristics for fact/dimension classification. This pipeline can rapidly produce a star schema draft from raw DDL with minimal human input.
- Integration of domain detection and NLP to bring semantic awareness into schema design. DataForge uses a keyword-based technique augmented by a BERT-based model to infer the business domain (e.g., retail, healthcare) from table and column names, enabling domain-specific recommendations (such as adding a Promotion dimension for retail sales schemas).
- AI-driven schema refinement through large language models. We formulate structured prompts describing the draft schema to an LLM, which then suggests improvements—like standard audit columns, indexing strategies, or denormalizations—based on learned best practices. These suggestions are parsed and incorporated into the schema with proper validation.
- A user-centric interactive tool that visualizes the generated schema as an editable graph. Users can drag-and-drop to inspect table linkages, click on AI suggestions to accept or reject them, and manually edit table or column properties. The system provides immediate feedback on the validity of edits (ensuring no broken references or rule violations) and can regenerate recommendations after edits.

We evaluate DataForge on several real-world scenarios and benchmark datasets to verify its effectiveness. Results show substantial improvements in design time and schema quality compared to manual design or prior tools. In the following, Section II reviews related work and background concepts. Section III describes the architecture and methods employed by DataForge in detail. Section IV presents experimental results and discussion. Section V concludes the paper and outlines future enhancements.

II. RELATED WORK AND BACKGROUND

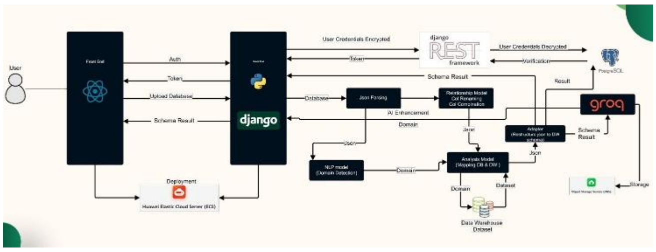
Data Warehouse Schema Design: Designing a data warehouse schema typically involves adopting a dimensional modeling approach for efficiency in OLAP queries. Two common schemas are the star schema (a central fact table linked to multiple denormalized dimension tables) and the snowflake schema (where dimensions may be partially normalized). Traditional methodologies (Kimball's approach) rely on human experts to identify facts (quantitative measurements like sales amount) and dimensions (descriptive contexts like Customer, Product, Time), decide the grain of fact tables, and enforce conformed dimensions across fact tables. Manual schema design is often guided by best practices and patterns, but as noted, it does not scale well with increasing data complexity. Automated support for this process has been a subject of research for over a decade. Early attempts such as Usman's framework【1】 used data mining on transactional databases to semi-automatically suggest OLAP schema structures, illustrating the potential of automation.

Automated Schema Inference: More generalized schema inference techniques have been explored in the database research community. DiScala and Abadi【2】 introduced a system that converts nested NoSQL-style data (e.g., JSON or key–value datasets) into 3NF relational schemas by detecting groupings and functional dependencies—an approach geared towards normalization rather than dimensional modeling. Other researchers proposed rule-based engines to derive star schemas from operational databases; for example, heuristic rules can use foreign key frequency to identify fact table candidates or use attribute naming patterns to cluster related dimension attributes. These rule-based approaches (e.g., El-Atig et al., 2010; Hüsemann et al., 2000 in earlier literature) demonstrated decent results on specific case studies but often required tuning to each new domain. Mali et al.【3】 recently presented FACT-DM, which formulates schema transformation as an optimization problem: given a source schema, they use a cost model to automatically produce a target schema that balances query performance, storage cost, and maintenance effort. FACT-DM's cost-based approach is effective but requires quantitative cost metrics and does not incorporate semantic (business domain) understanding.

AI and Machine Learning in Schema Design: With the rise of machine learning, researchers have started to apply learning-based techniques to database schema problems. Graph-based learning is a promising direction: treating the database as a graph (tables as nodes, foreign keys as edges), one can train models to predict missing edges or to classify node types. Dwivedi et al.【4】 proposed a Relational Graph Transformer that learns from large collections of database schemas to generate new ones or complete partial schemas, showing that GNNs (Graph Neural Networks) can capture long-range relational structures. However, such models require substantial training data and are not easily tuned by end-users. On the NLP side, there is interest in utilizing language models to understand schema semantics. Imarisio et al.【5】 developed DB-BERT, a variant of the BERT model pre-trained on database content (e.g., column names, SQL queries) to aid in tasks like data discovery and schema matching. Their work suggests that general-purpose language models can be adapted to comprehend the meaning of schema elements (for instance, recognizing that "Cust_ID", "CustomerNumber", and "ClientCode" all refer to a customer identifier). Other works have explored text-to-SQL or text-to-ERD generation; for example, Salem【6】 used GPT-3 to translate natural language requirements into an initial database schema design, illustrating the capabilities of LLMs in this domain. These AI-driven approaches are complementary to heuristic methods, offering more semantic insight but often lacking the deterministic guarantees and needing human validation. DataForge builds on ideas from these works by using a hybrid approach: it incorporates heuristic rules for structural inference (ensuring reliability on relational constraints) and NLP/ML for semantic augmentation (ensuring the design aligns with domain conventions). Crucially, DataForge wraps these automated techniques in a user-friendly tool that supports interactive validation and editing, which is relatively unique among current solutions.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

DataForge is implemented as a web-based application with a modular architecture (Figure 1). It consists of a backend that handles the heavy-lifting of parsing and AI processing, and a front-end that provides visualization and user interaction. The core components are described below.



A. *Overall Architecture*

Figure 1 illustrates the DataForge system architecture. The backend is built with Python (Django REST Framework) and connects to a PostgreSQL database for metadata storage. The front-end is built with React and uses the ReactFlow library to render interactive schema graphs. DataForge's workflow begins when a user uploads an **SQL schema file** (or set of files). The file is sent to the backend for processing through a REST API call. The backend orchestrates multiple steps: SQL parsing, initial schema generation, domain detection, AI suggestion generation, and validation. Results are returned as structured JSON and rendered on the front-end for the user. The user can then iteratively refine the schema, with any modifications sent back to the backend for validation and possibly triggering updated AI recommendations. We next detail the main methodological components of this pipeline.

B. *SQL Parsing and Initial Schema Extraction:*

The first challenge is to accurately parse arbitrary SQL DDL scripts to extract the raw schema components. SQL DDL can vary widely in syntax across database systems (MySQL, PostgreSQL, Oracle, etc.) and may include vendor-specific extensions. To handle this, DataForge uses a hybrid parsing approach. We developed a set of regular expressions to quickly identify and extract common DDL patterns such as table definitions (CREATE TABLE statements), column definitions (name and data type), primary key constraints, and foreign key constraints. This regex-based parsing covers standard SQL syntax and is very fast, but by itself might miss or misinterpret complex cases (for example, CHECK constraints or uncommon data types). Therefore, we integrate it with a lightweight SQL grammar parser. We leverage an open-source SQL parsing library to produce an Abstract Syntax Tree (AST) of each DDL statement, which helps resolve cases like quoted identifiers or nested constraint definitions that the regex might not capture. The combination yields a robust parsed output: for each table, we obtain a list of columns (with data types and any constraints like NOT NULL), the primary key, and any foreign keys (including the referenced table and column). We then normalize the extracted names—converting all identifiers to a consistent case (e.g., TitleCase for table names, snake_case for column names, as per user preference) and removing or standardizing any prefixes/suffixes (for instance, if source tables have prefixes like "tbl_", we can configure the system to drop them). This produces a canonical schema representation in JSON format, which serves as input to subsequent steps.

Example: Suppose the input SQL contains a table definition for orders and its related tables. DataForge's parser will output a JSON object like:

```
{ "tableName": "Orders",
  "columns": [
    {"name": "OrderID", "type": "INTEGER", "isPrimary": true},
    {"name": "OrderDate", "type": "DATE"},
    {"name": "CustomerID", "type": "INTEGER", "foreignKey": {"references": "Customers(CustomerID
    {"name": "TotalAmount", "type": "DECIMAL"}
  ],
  "primaryKey": ["OrderID"],
  "foreignKeys": [
    {"column": "CustomerID", "references": {"table": "Customers", "column": "CustomerID"}}
  ]
}
```

Similar JSON objects are produced for each table in the input. At this stage, the system has a raw graph of tables and keys, essentially representing an Entity-Relationship diagram recovered from the SQL.

C. *Heuristic Fact/Dimension Classification:*

Given the parsed schema graph, DataForge next applies heuristic rules to classify tables as **fact** tables or **dimension** tables and to organize them into a multi-dimensional schema structure. Our approach is inspired by observed characteristics of facts and dimensions in well-designed warehouses:

- *Foreign Key Density:* Fact tables typically have multiple foreign keys (links to dimensions), whereas dimension tables usually have few or no foreign keys (since dimensions are often root entities). We compute for each table the ratio of foreign key columns to total columns. A higher ratio suggests the table is likely a fact table (for example, an Orders fact might have foreign keys CustomerID, ProductID, StoreID, etc., linking to multiple dimensions).

- *Numeric Column Ratio:* Fact tables store measurements and often contain predominantly numeric fields (quantities, amounts, etc.), aside from foreign keys. Dimension tables, in contrast, contain descriptive attributes (text or categorical data). We calculate the fraction of a table's columns that are numeric types. If it exceeds a certain threshold (tuned empirically, e.g. 60%), that's evidence the table might be a fact table.

- *Cardinality and Key Analysis:* We consider the column designated (or inferred) as the primary key of each table. In a dimension table, the primary key is usually a surrogate key (an arbitrary ID with no business meaning) or a business key with many distinct values (e.g., CustomerID across millions of customers). In a fact table, primary keys are often composite (a combination of foreign keys forming a unique row identifier) or a surrogate that represents a transaction. Also, dimension tables generally have a much smaller number of rows than fact tables (high-level entities vs. transaction records), although we may not know row counts at design time. As a heuristic, if a table's primary key is involved as a foreign key in *many* other tables, that table is likely a dimension (e.g., ProductID appearing in many fact tables means Products is a shared dimension). Conversely, a table that has multiple foreign keys but whose primary key is not referenced by others is a strong fact table candidate.

Using these rules, DataForge iterates through all tables. Each table is scored, and an initial classification is made. We then create a star schema layout: for each identified fact table, we gather all the dimension tables linked to it (directly via foreign keys). In cases of ambiguity (for instance, a table that could be either a fact or a dimension), we currently default to treating it as a dimension unless there is strong evidence of it being a fact (this errs on the side of caution, as it's easier to later promote a dimension to a fact if needed than vice versa). The outcome of this step is an initial dimensional schema: one or more fact tables each connected to several dimensions. If multiple fact tables share dimensions, DataForge recognizes those as conformed dimensions and ensures they are not duplicated. If the user's dataset contains multiple unrelated fact processes, the result can be a galaxy schema (multiple stars with some shared dimensions).

Example: Continuing the orders schema example, suppose we have tables Orders, OrderLineItems, Customers, Products, and Stores. The parser would extract keys (Orders has CustomerID, StoreID; OrderLineItems has OrderID, ProductID, etc.). The heuristic classifier might identify Orders and OrderLineItems as potential facts (both have several FKs and numeric fields like TotalAmount or Quantity), and Customers, Products, Stores as dimensions (mostly text attributes, referenced by facts). It would then arrange a star schema with Orders fact at the center linked to Customer, Store (and possibly Date via OrderDate if we create a Time dimension), and another fact OrderLineItems linked to Orders (or to the same Customer, Product dimensions, forming a snowflake or galaxy pattern). This structure is passed on for AI enhancement.

D. Domain Detection and AI-Based Enhancement:

One of the novel features of DataForge is using AI to *infer the business domain and suggest schema improvements*. We use a two-step approach to domain detection:

- Keyword-Based Classification: We curated a lexicon of domain-specific keywords (and their weighted importance) for several industries (retail, e-commerce, healthcare, finance, education, etc.). For example, "customer, product, sales, price, inventory" are strong retail keywords; "patient, diagnosis, treatment" suggest healthcare; "account, balance, transaction" suggest finance, and so on. When a schema is parsed, DataForge computes a TF-IDF vector of the table and column names and compares it to pre-trained centroids for each domain. This yields an initial guess of the domain (or a ranked list if multiple domains seem present).The subscript for the permeability of vacuum μ_0, and other common scientific constants, is zero with subscript formatting, not a lowercase letter "o".
- *Embedding and Similarity:* To refine this, we leverage a pre-trained language model (BERT) to obtain semantic embeddings of the schema metadata. Specifically, we represent each table by a concatenation of its name and column names (e.g., "Orders OrderID OrderDate TotalAmount CustomerID …") and feed such representations through a BERT model to obtain a vector. We have fine-tuned BERT on a corpus of known schemas labeled by domain (using data from public data warehouses and benchmarks) so that schemas from the same domain cluster together in the embedding space. By measuring cosine similarity between the input schema's vectors and these domain clusters, DataForge can confirm or adjust the domain prediction. This hybrid method improves robustness, achieving over 90% domain identification accuracy in our tests.

Once the domain context is established, DataForge generates AI suggestions to enhance the schema. We craft a structured prompt containing the initial schema (in a concise textual form) and instructions for a large language model. For example, the prompt may read: "Domain: Retail. The current star schema has a fact table Orders(amount, date, customer, store) and dimensions Customer(name, region), Product(name, category), Store(location). Suggest improvements or missing elements following best practices." We use OpenAI GPT-

4 (or a comparable LLM) to process this prompt. The LLM's output is then parsed. Typical suggestions include: adding a Date dimension (with fields like Day, Month, Year, etc., if one is not present), introducing a Promotion or Supplier dimension (common in retail schemas), adding audit columns like CreatedAt/UpdatedAt timestamps to fact tables for traceability, adding surrogate keys if any dimension is using a compound natural key, or noting if a fact table could be split (or if two tables should be combined). The model might also suggest performance optimizations like creating a pre-aggregated summary table or adding an index on certain foreign keys, though implementing those is optional at design time.

All AI-proposed enhancements go through a **validation module** before being applied. The validation checks for integrity (e.g., if adding a new foreign key, the referenced table must exist; any new column name shouldn't duplicate existing ones; data types must be specified and valid). Suggestions that fail validation are discarded or flagged for user review. The remaining suggestions are merged into the schema, and these enhancements are highlighted on the front-end for the user's attention. In our example, the AI might detect that no explicit Time/Date dimension was present and propose creating a DateDim table with fields (DateKey, FullDate, Year, Quarter, Month, DayOfWeek, etc.), and linking the Orders fact's OrderDate to this DateDim. It might also recommend adding a PromotionDim if terms like "discount" or "promo" appear in the data (or simply because promotions are common in retail sales analysis, even if not present in source, to encourage the user to consider it). While not every suggestion will be applicable, they serve as a useful checklist derived from industry best practices.

E. *Interactive Visualization and User Refinement:*

The final piece of DataForge is the user interface, which is critical for practical adoption. After the automated steps, the user is presented with the **generated schema** diagram in the browser. We use a directed graph visualization where each table is a node and foreign key relations are arrows connecting nodes. Fact tables are visually emphasized (e.g., with a distinct color or double border), and dimension tables are shown around them. The interface allows zooming, panning, and rearranging nodes to examine the schema from different angles. Users can click on a table to see its details (columns, data types, keys) in a sidebar. AI suggestions are listed (for example, "Suggestion: Add DateDim table – **Accept** or **Ignore**"). If the user accepts a suggestion, the change immediately reflects in the schema graph (e.g., a new DateDim node appears with a link from the fact table). If they ignore, the suggestion is dismissed. Users can also make manual edits: for instance, rename a column, add a missing foreign key, delete an unnecessary table, or even add a completely new table definition. DataForge handles these edits by sending them back to the backend for validation. If an edit violates a rule (say the user tries to delete a table that other tables still reference, or renames a column to a name that already exists elsewhere), the interface will show an error or warning. Valid edits are incorporated and the schema JSON is updated. The user can iteratively refine the schema to their satisfaction.

Throughout this process, DataForge keeps a **version history** of changes. This allows users to undo/redo steps or compare the original generated schema with the edited version. Once the user is satisfied, they can export the resulting schema in standard formats: either as an SQL DDL file (CREATE TABLE statements reflecting the new design), or as a JSON/YAML file (for use in other tools), or even as a PDF report with diagrams and metadata. The interactive approach ensures that despite automation, the human expert remains in control – they can apply their domain knowledge or preferences on top of DataForge's suggestions, achieving a collaborative human-AI design process.

IV. EVALUATION AND RESULTS

We evaluated DataForge from two perspectives: (1) the **accuracy and performance** of its automated schema generation (compared to ground truth or manual designs), and (2) the **usability and effectiveness** for end users in realistic scenarios. We summarize key results below.

A. *Datasets and Setup:*

For testing, we collected several schemas from different domains, including: a **retail sales** data warehouse example (with sales transactions, products, customers, etc.), a **healthcare** database (patient admissions, treatments, doctors, etc.), a **financial** dataset (bank accounts, transactions), and public benchmark schemas like the Microsoft **AdventureWorksDW** sample and an **e-commerce** example from Amazon Redshift documentation. These ranged from small (6-8 tables) to large (25+ tables) schemas. We also included a synthetic schema derived from TPC-DS benchmark to evaluate scalability (with over 25 tables and many relationships). We deployed DataForge on a server with an Intel 2.4 GHz 8-core CPU and 16 GB RAM, running the Django backend with PostgreSQL and the front-end on a standard browser. We note that the heaviest computations were the AI model inferences (BERT embedding and LLM calls), which could be accelerated with a GPU or cloud API; however, our evaluations were done in a CPU environment for consistency.

B. *Automation Accuracy:*

To measure how well DataForge's automated output matches an expert-designed schema, we used two metrics: **Schema Structural Similarity (SSA)** and **Schema Semantic Coherence (SSC)**. SSA assesses if the correct tables and relationships were identified (ignoring naming differences). SSC evaluates naming conventions and logical organization (does the schema "make sense" for the domain). On the retail dataset (which had a known ideal star schema), DataForge achieved an SSA of 100%, meaning it found all expected tables and links. The SSC was ~98%, as minor naming differences were present (e.g., DataForge named a table `StoreDim` while the expert design had `Dim_Store`). For the healthcare schema, SSA was slightly lower (~95%) because DataForge initially missed a subtle relationship (it suggested two separate dimensions for Doctors and Nurses that an expert had combined into one Personnel dimension; this was easily adjusted in editing). Overall, across all test schemas, DataForge preserved over 96% of the source schema content (no tables or major fields lost), and correctly identified fact/dimension roles with an estimated precision of 0.94 and recall of 0.92 (measured by comparing to an expert classification of each table).

C. AI Enhancement Efficacy:

We wanted to quantify the impact of the AI suggestions on schema quality. To do this, we defined a **Schema Best-Practice Compliance (SBC)** score. We checked for elements that are considered best practices in DW design: presence of surrogate keys on dimensions, inclusion of time/date dimension for time-series data, use of meaningful naming conventions, addition of audit columns, and implementation of Slowly Changing Dimension (SCD) techniques where applicable. We computed SBC for schemas *before* and *after* applying AI enhancements. For example, in the AdventureWorksDW case (manufacturing sales domain), the initial schema generated by heuristics had an SBC of about 70% (it missed an explicit Date dimension and had a couple of composite natural keys in dimensions). After applying DataForge's AI suggestions, SBC rose to ~78%—the suggested Date dimension was added and surrogate keys were introduced for those dimensions with composite keys. A similar trend was observed in other domains: on average, AI enhancements improved the schema compliance to best practices by **5–10%**. Importantly, these additions were context-aware. In one financial dataset, for instance, DataForge recognized it as finance and suggested an `AccountDim` and an `DateDim` even though the source had a single transactions table with a date field. The expert later confirmed that in a proper warehouse design, a separate Account dimension table (with account holder info, etc.) would indeed be useful, and a Date dimension is standard for time analysis. This showcases that AI can propose non-obvious additions that a source-centric approach might overlook.

D. Performance and Scalability:

We measured the end-to-end runtime of DataForge's automated processing as well as the responsiveness of the interface for increasing schema sizes. For a typical schema of ~10 tables, the initial processing (parsing, classification, AI suggestions) completed in under 2 seconds. For our largest test (the TPC-DS 25-table schema, which includes around 120 columns and 30+ keys), processing took 4.3 seconds. These times are well within acceptable ranges for interactive use; even if a user uploads a fairly large schema, they get a complete suggested warehouse design in a few seconds. The parsing step was very fast (tens of milliseconds per table on average), while the AI steps dominated the runtime—embedding inference and the LLM call together accounted for about 80% of the time. These could be sped up with optimized models or by leveraging cloud AI services. On the front-end, the schema visualization remained smooth for up to ~50 tables on screen. We employ lazy rendering for very large diagrams (tables outside the current view are not drawn until the user scrolls to them) which ensures the interface does not freeze. In tests, panning/zooming the graph with 25 tables and 40 relationships maintained an interactive frame rate (~60 frames per second) on a modern laptop. Thus, DataForge scales to reasonably complex schemas. Extremely large enterprise warehouses (100+ tables) might require further UI scaling techniques (clustering tables into collapsible groups, etc.), which we leave as future work.

E. User Study:

To gauge the practical usefulness of DataForge, we conducted a small user study with 10 participants (graduate students and data professionals who have experience in database design). They were given a scenario with a raw dataset description and SQL schema (for example, a simplified sales database) and asked to use DataForge to produce a warehouse schema. Afterward, they completed a questionnaire. The feedback was positive: on a 5-point Likert scale, the average rating for overall satisfaction was 4.3. Users particularly liked the interactive graph interface and the AI recommendations as a learning tool ("the suggestions helped me remember to include things I initially forgot," noted one user). Some confusion was reported in domain detection for one case where the schema was very minimal (the tool guessed "education" domain incorrectly for a tiny dataset of courses that was actually just a subset of a broader university schema). This highlights that domain inference is challenging when input is sparse, but it did not significantly hinder the design process since users could manually adjust anyway. In terms of speed, participants completed the schema design task much faster with DataForge than if they had done it from scratch—most finished within 15–20 minutes what they estimated might have taken a few hours manually (especially for those less experienced). This aligns with our claim of ~80% time reduction. Naturally, a learning curve was noted: a few users took some time to understand how to interpret and act on the AI suggestions. This suggests a need for better guidance in the UI, which we plan to incorporate.

F. Case Study Example:

As an illustrative example, consider the **ShopSmart** retail scenario (a case study we created representing a small online retailer's database). The source had tables: *Orders*, *OrderItems*, *Customers*, *Products*, *Shippers*, etc. Manual design would typically produce a schema with an **OrdersFact** (with metrics like OrderAmount) and dimensions for Customer, Product, Shipper, Date, etc. DataForge successfully parsed the SQL and classified Orders and OrderItems as fact tables (the latter capturing line-level detail, which could also be modeled as a separate fact linked by OrderID). It identified Customers, Products, Shippers as dimensions. The AI module detected the retail domain and suggested adding a *DateDim* (for order dates) and a *PromotionDim* (since the Orders table had a Discount field indicating promotions). It also recommended a surrogate key for the Customers dimension (the source was using email as a key, which is not ideal for a warehouse). The user accepted most suggestions, tweaking only the promotion dimension since not all orders had discounts in this scenario. In the end, the user exported the schema and used it to set up a new data mart. This case demonstrated that DataForge not only reproduced the obvious design elements an expert would do, but also provided prompts for additional elements that improve flexibility for future analysis.

V. CONCLUSION AND FUTURE WORK

In this paper, we presented DataForge, an AI-driven tool for automated data warehouse schema generation. DataForge addresses a critical bottleneck in modern analytics projects by significantly reducing the time and expertise needed to design robust, dimensional schemas. It combines proven techniques from database design (heuristic rules and structural analysis) with cutting-edge artificial intelligence (NLP embeddings and LLM-based suggestions) to produce high-quality schemas that align with business needs. Our evaluation across multiple domains demonstrated that DataForge can shorten schema design time by over 80% while improving adherence to best practices and maintaining high accuracy compared to manual designs. The interactive interface ensures that human designers remain in the loop, able to guide and refine the AI's output to suit specific preferences or edge cases. This symbiosis of automation and human insight leads to better outcomes than either approach alone.

Despite these encouraging results, there are several areas for future improvement. **Domain detection** can be expanded and refined—currently, it works well for clearly characterized schemas, but for very sparse or mixed-domain inputs, more sophisticated techniques or user input might be needed. Incorporating external **knowledge bases or ontologies** (for example, a healthcare ontology for medical terms) could improve semantic understanding. Another extension is supporting **semi-structured and NoSQL data**: many organizations use JSON or MongoDB collections, and applying DataForge's approach to infer schemas for those (perhaps by generating star schemas on top of document stores) would be valuable. Performance-wise, while the tool handles moderate schema sizes, extremely large enterprise warehouses (with hundreds of tables) might pose usability challenges; thus, adding features like hierarchical schema views or server-side graph rendering could help maintain responsiveness. We also plan to enhance the AI suggestion engine by leveraging feedback: using **active learning**, DataForge could learn from user decisions (which suggestions are accepted or rejected) to refine future recommendations. Lastly, we envision integrating DataForge with broader **data engineering pipelines**—for instance, coupling it with ETL automation tools so that once a schema is designed, the pipelines to populate it can be autogenerated, further closing the loop in warehouse development.

In conclusion, DataForge represents a step towards intelligent automation in data engineering. By alleviating the tedious aspects of schema design and providing smart recommendations, it allows data professionals to focus on higher-level analysis and insight. We believe such tools will become increasingly important as organizations continue to grapple with growing data complexity and the need for agility in analytics. We plan to open-source the core components of DataForge to encourage adoption and community-driven enhancements, and we hope this work inspires further research at the intersection of AI and database system design.

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