

# Boosting Text-to-Chart Retrieval through Training with Synthesized Semantic Insights

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## Abstract

Charts are crucial for data analysis and decision-making. Text-to-chart retrieval systems have become increasingly important for Business Intelligence (BI), where users need to find relevant charts that match their analytical needs. These needs can be categorized into precise queries that are well-specified and fuzzy queries that are more exploratory – both require understanding the semantics and context of the charts. However, existing text-to-chart retrieval solutions often fail to capture the semantic content and contextual information of charts, primarily due to the lack of comprehensive metadata (or semantic insights). To address this limitation, we propose a training data development pipeline that automatically synthesizes hierarchical semantic insights for charts, covering visual patterns (visual-oriented), statistical properties (statistics-oriented), and practical applications (task-oriented), which produces 207,498 semantic insights for 69,166 charts. Based on these, we train a CLIP-based model named ChartFinder to learn better representations of charts for text-to-chart retrieval. Our method leverages rich semantic insights during the training phase to develop a model that understands both visual and semantic aspects of charts. To evaluate text-to-chart retrieval performance, we curate *the first* benchmark, CRBench, for this task with 21,862 charts and 326 text queries from real-world BI applications, with ground-truth labels verified by the

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Conference acronym 'XX, Woodstock, NY'

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crowd workers. Experiments show that ChartFinder significantly outperforms existing methods in text-to-chart retrieval tasks across various settings. For precise queries, ChartFinder achieves up to 66.9% NDCG@10, which is **11.58%** higher than state-of-the-art models. In fuzzy query tasks, our method also demonstrates consistent improvements, with an average increase of 5% across nearly all metrics.

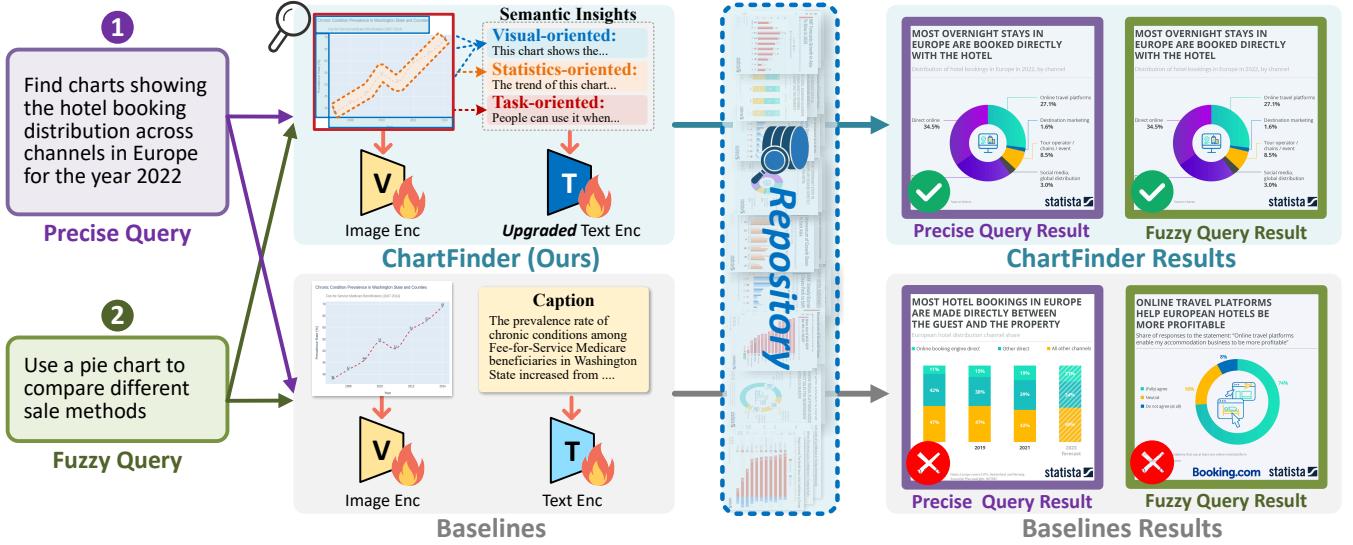
## 1 Introduction

Visualization charts (charts for short) are essential for various fields, including data analysis and business decision-making [19, 29, 33, 43]. In particular, Business Intelligence (BI) systems heavily rely on charts to present complex data in ways that provide users with intuitive and actionable insights [23, 32]. Most charts are carefully designed to serve specific analytical tasks, with considerations for visual design, chart types, and data relationships.

Given their quality and versatility, these well-crafted charts are valuable resources that can be reused across different tasks and contexts. Given a user-provided text query and a chart repository, the ***text-to-chart retrieval*** task is to find a set of charts that align with the user's query. This process requires understanding both the ***visual characteristics*** of the charts and the ***semantic content of the user query***, ensuring that the retrieved charts are not only relevant but also contextually suitable for the user's analytical task.

**Text-to-Chart Retrieval in Real-world BI Systems.** Through collaboration with a leading BI company X [Redacted], we analyzed real-world user behavior and identified two primary categories of user queries for chart retrieval: precise queries and fuzzy queries. These categories reflect the diverse needs of users, ranging from specific, data-driven queries to more exploratory or stylistic tasks.

**Precise queries** are characterized by data-driven intent and focus on specific analytical targets. These queries aim to retrieve charts that present well-defined information, such as trends, comparisons,



**Figure 1: ChartFinder integrates both visual and semantic aspects of charts to improve text-to-chart retrieval.**

or aggregated data points, to answer a clear analytical question. For example, as shown in Figure 1, a user may ask, “Find charts showing the hotel booking distribution across channels in Europe for the year 2022.” Such queries demand high semantic alignment to ensure the retrieved charts align closely with the user’s specific requirements. To achieve this, retrieval systems must effectively leverage both the data context and the visual features of chart images to establish strong semantic relationships between the query and the chart.

**Fuzzy queries**, on the other hand, are more open-ended and often focus on exploratory tasks and abstract information. These queries are less constrained and may emphasize stylistic or structural elements of charts rather than specific data content. For example, a user might query, “Use a pie chart to compare different sale methods”, as shown in Figure 1. Addressing such queries requires a retrieval system capable of understanding a broader intent and contextual flexibility inherent in exploratory tasks.

**Limitations of Existing Methods.** Text-to-image retrieval has seen remarkable advancements, leveraging state-of-the-art Multi-modal Large Language Models (MLLMs) [16]. These approaches have demonstrated effectiveness in general image retrieval tasks by efficiently capturing visual features from images. However, when being directly adapted to text-to-chart retrieval, these methods face several challenges in addressing the unique aspects of charts.

First, existing methods *fail to capture the semantic depth of charts*. Unlike natural images, which primarily convey visual information, charts encode complex data relationships, trends, and comparisons. Existing methods that focus solely on visual features often retrieve charts that are visually similar but semantically irrelevant. For example, two charts may share visual characteristics (e.g., both being bar charts) but represent entirely different datasets, topics, or analytical purposes. This limitation is particularly problematic for *precise queries*, which require high semantic alignment between the query and the retrieved chart to meet data-driven needs.

Second, current approaches *fail to address both precise and fuzzy queries* effectively. For precise queries, existing methods that prioritize visual features lack the ability to connect queries with the underlying data or analytical intent, leading to poor retrieval performance. For fuzzy queries, existing methods struggle to interpret broader user intents, such as stylistic preferences or exploratory goals, as they lack mechanisms to capture design elements of charts.

**Key Idea.** To improve text-to-chart retrieval, it is essential to capture both the visual and semantic aspects of charts. Our *key idea* is to extract semantic insights from chart metadata (e.g., source code) and combine this with the chart images. By training a model that incorporates both the charts (*in the form of images*) and the semantic insights (*in the form of text*), we aim to develop a system that comprehensively understands and bridges the gap between visual representation and the underlying semantic meaning of charts.

However, implementing this idea presents several **challenges**.

First, manually annotating semantic insights for charts is costly and time-consuming. Thus, we need to develop an efficient and scalable method to derive these semantic insights from chart metadata automatically. Once semantic insights are generated, the second challenge is to effectively integrate them with the visual features of the charts. We need an effective model architecture and training strategy that can seamlessly combine these two modalities, *i.e.*, semantic insights and visual features, to generate more accurate representations of the charts. Third, there is currently no readily available corpus containing text queries and their corresponding charts to evaluate the performance of text-to-chart retrieval.

**Our Proposal.** We propose ChartFinder, a new text-to-chart retrieval model that leverages contrastive learning techniques to align both the visual features and semantic insights of charts, based on the *Contrastive Language-Image Pre-Training* architecture [30, 48]. Specifically, our model is trained with both chart images (visual content) and their corresponding semantic insights (textual content), as shown in Figure 1. It is important to note that ChartFinder does not require synthesized semantic insights during the retrieval

phase. Instead, it relies solely on text queries and candidate charts to perform the retrieval. The semantic insights are utilized exclusively during the training phase, where they help the model better align chart images with their semantic meaning, thus enhancing its ability to retrieve relevant charts from a repository based on textual descriptions.

Once trained, ChartFinder accepts a user query and a chart repository as input, retrieving the top- $k$  most relevant charts by calculating the embedding distance between the text query and the charts.

To train the model effectively, we have developed a *training data generation pipeline* that automatically generates a large number of charts along with their corresponding semantic insights. Inspired by techniques in automatic data visualization [19] and insight generation [24], which create insightful charts from raw data, our pipeline synthesizes three key levels of semantic insights: (1) *Visual-oriented Insight*: a high-level summary of the chart, capturing the overall pattern and visual trends; (2) *Statistics-oriented Insights*: an in-depth analysis of the trends, comparisons, and relationships within the data, highlighting statistical patterns and anomalies; and (3) *Task-oriented Insights*: contextual information on how the chart can be applied for suitable data analysis tasks.

To evaluate the performance of the text-to-chart retrieval task, we introduce CRBench, the first text-to-chart retrieval benchmark sourced from real-world BI scenarios. CRBench contains 326 queries and 21,862 chart images. All query-chart labels are verified by crowd workers in order to capture the diversity of user needs.

**Contributions.** We make the following contributions:

(1) **A Semantic Insights Synthesis Pipeline for Charts.** We develop an automatic pipeline for generating semantic insights from chart metadata, synthesizing three levels of semantic insights, *i.e.*, visual-oriented, statistics-oriented, and task-oriented insights, *as training data*. This approach addresses the challenge of manual annotation by automating the process, enabling the creation of diverse insights that enrich the model's ability to comprehensively understand charts (Section 3).

(2) **ChartFinder Model.** We propose ChartFinder, a novel text-to-chart retrieval model that combines contrastive learning with the CLIP architecture to align visual features and semantic insights of charts. The model leverages the synthesized training data to improve retrieval accuracy, making it more context-aware in handling both precise and fuzzy queries (Section 4).

(3) **CRBench: A New Benchmark.** We curate CRBench, the first benchmark for evaluating text-to-chart retrieval sourced from *real-world BI scenarios*. It includes 326 text queries and 21,862 charts, with query-chart labels verified by crowd workers to capture the diversity of real user needs (Section 5).

(4) **Extensive Experiments.** Our experiments show that the synthesized training data pipeline significantly enhances the performance of ChartFinder, outperforming existing methods across multiple benchmarks. This includes demonstrating improved performance in zero-shot scenarios. The results validate the effectiveness of both the training data synthesis pipeline and the ChartFinder model in real-world text-to-chart retrieval tasks (Section 6).

## 2 Preliminaries

**Charts.** A *chart*  $C$  is a visual representation of data in the form of rasterized images designed to communicate patterns, trends, or comparisons across one or more variables.

**Chart Metadata.** Let  $M = (T, X, Y, CT, D, E)$  be the associated metadata of a chart, where:

- $T$  is the title of the chart,
- $X$  and  $Y$  are the labels for the x-axis and y-axis, respectively,
- $CT \in \{\text{line, bar, scatter, pie, ...}\}$  is the chart type,
- $D = \{(x_i, y_i)\}_{i=1}^n$  denotes the underlying data, where  $(x_i, y_i)$  are data points, and  $n$  is the number of data points,
- $E$  represents additional elements such as the legend, data labels, or annotations.

**Semantic Insights of Charts.** As shown in Figure 1 ( $\mathcal{O}$  area), the information content of a typical chart can be divided into three key components: (1) the visual representation of the data, (2) the statistical features embedded in the data, and (3) the application or contextual value the chart provides. These components correspond to the visual expression, numerical basis, and purpose of the chart, respectively. To ensure that the model fully understands the chart's semantics, we have designed three types of semantic insights. Given a chart  $C$  and its metadata  $M$ , we define three levels of semantic insights  $I = (I^v, I^t, I^s)$ , as follows.

- $I^v$  represents *Visual-oriented Insights*: These insights are derived from visual patterns, trends, or relationships observed in the chart. For example, trends shown in the chart may reveal increasing or decreasing patterns over time
- $I^t$  denotes *Task-oriented Insights*: These insights relate to the practical applications of the chart in specific tasks or decision-making processes. For example, a chart illustrating healthcare trends could help policymakers identify areas of resource allocation.
- $I^s$  represents *Statistics-oriented Insights*: These are quantitative analyses and statistical observations derived from the data. For example, identifying correlations, distributions, or outliers in the dataset used for the chart.

The process of deriving semantic insights is represented as  $f : (C, M) \rightarrow I$ , where  $f$  analyzes the chart  $C$  and its metadata  $M$  to produce the insights  $I$ . Please refer to Section 3 for details.

**EXAMPLE 1. (Example of Chart, Metadata, and Semantic Insights.)** As shown in Figure 2, the line chart  $C$  is rendered using the Plotly visualization library. The metadata for this chart is the source code used by Plotly, which contains the title, axis labels, data points, chart type, and other relevant information. We utilize the LLaMA-3.1 model to analyze this metadata and generate semantic insights.

**Text-to-Chart Retrieval.** Let  $C = \{C_1, C_2, \dots, C_n\}$  denote a repository of charts and a textual query  $Q$  provided by a user. The objective of the text-based chart retrieval problem is to retrieve a ranked list of  $k$  charts,  $C_k = \{C_{r_1}, C_{r_2}, \dots, C_{r_k}\} \subseteq C$ , where  $k \ll n$  and  $C_{r_i}$  represents the  $i$ -th most relevant chart to the query  $Q$ .

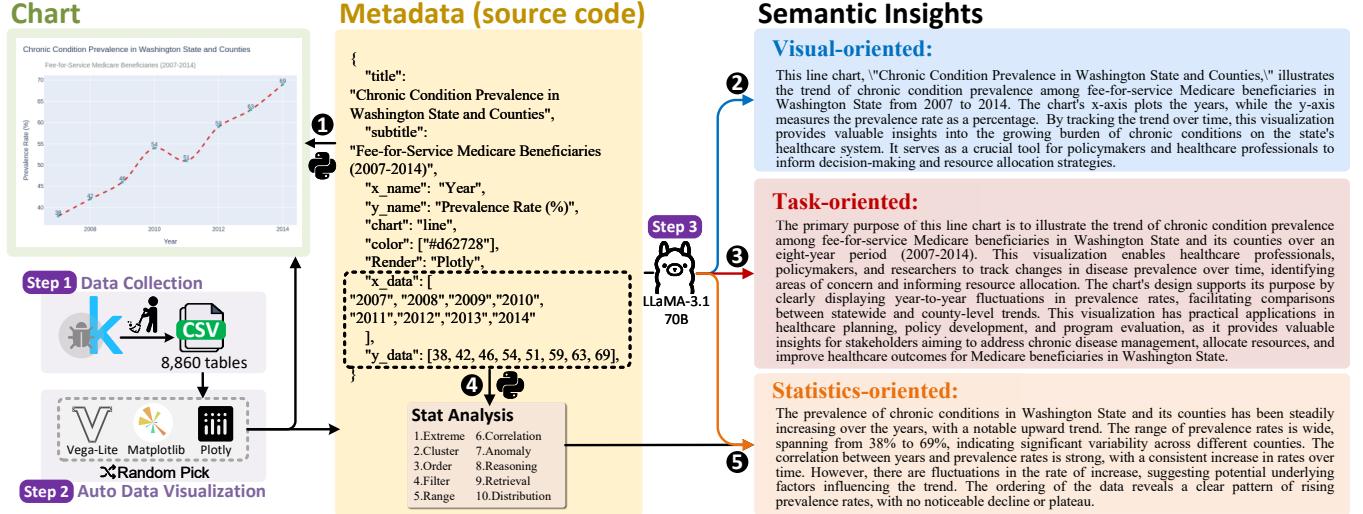


Figure 2: An overview of the semantic insights synthesis pipeline.

### 3 Semantic Insights Synthesis Pipeline

Manually annotating charts to generate semantic insights is time-consuming and inefficient. To address this, we propose a training data development pipeline that automatically synthesizes semantic insights from raw data, ensuring the data's effectiveness in supporting the training of text-to-chart retrieval models. This synthesized training data should enable the model to perform well across various benchmarks and improve its generalization ability.

Figure 2 shows our proposed pipeline, which consists of three key steps: data collection, automatic data visualization, and semantic insights generation based on the metadata (Figure 2: ❶–❸).

#### 3.1 Data Collection and Visualization

**Step-1: Data Collection.** The first step in generating high-quality semantic insights is selecting a reliable source of datasets. To meet the above criteria, we select datasets from Kaggle, which offers several advantages: many datasets are derived from real-world applications or competitions. In addition, Kaggle provides a scoring system for datasets, with those receiving a score of 10 typically offering comprehensive content and high data quality.

We crawled 9,003 datasets with a score of 10 from Kaggle and performed local preprocessing, including removing missing values. After cleaning, we retained **8,860 high-quality tables** (in CSV format), completing the data preparation for subsequent steps.

**Step-2: Automatic Data Visualization.** The second step is to create meaningful charts from the collected 8,860 tables. Specifically, we used DeepEye [19], an automatic data visualization system, to generate a variety of charts, including bar charts, pie charts, line charts, scatter plots, grouped line charts, stacked bar charts, and grouped bar charts, covering widely-used chart types [18]. In our implementation, DeepEye automatically visualized these 8,860 tables, resulting in a total of 69,166 generated charts. For each visualization, we also derived its chart specification in JSON format, which includes details like axis labels, chart titles, and data points. To enhance the visual diversity of the charts, we re-rendered

them using three popular visualization libraries: Matplotlib, Plotly, and Vega-Lite. For each chart, one of these libraries was randomly selected for re-rendering (see Figure 2: ❶).

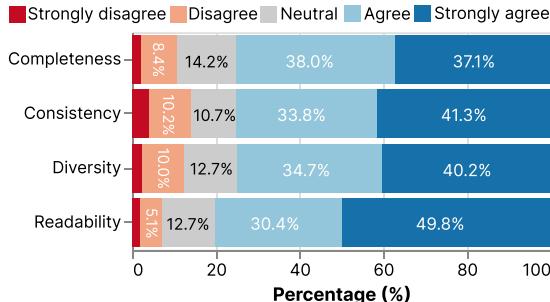
We further enriched the charts by randomizing various visualization parameters. For example, in line charts, we varied the line style between solid and dashed; in scatter plots, we alternated marker shapes (circular vs. diamond). Additionally, we introduced further variations, such as transforming a line chart into an area chart or converting a pie chart into a donut chart by adjusting a single parameter. These adjustments significantly increased the diversity of the generated charts.

Note that DeepEye[19] provides the metadata for each chart, which can be derived from its chart specification. We also store this metadata in the source code of the visualization, as shown in Figure 2. This metadata is essential for deriving semantic insights in Step 3. In total, we generated **69,166 charts** using Matplotlib, Plotly, or Vega-Lite, along with their corresponding *metadata*.

#### 3.2 Semantic Insights Synthesis

The third step is to generate detailed chart semantic insights based on the metadata of the charts. To comprehensively interpret the charts, we design three levels of semantic insights: from the apparent visual patterns observed in the chart, to data-driven statistical insights that uncover trends, comparisons, and relationships, to task-oriented insights that provide context on how the chart can be applied in real-world scenarios for decision-making and resource allocation. This layered approach allows for a holistic interpretation of each chart, supporting diverse user queries and enhancing the retrieval process. As illustrated in Figure 2 (❷–❸), the semantic insights *I* are computed through the following steps:

**Visual-oriented Insight Generation (Figure 2-❷).** In this step, we generate visual-oriented insights by analyzing the chart's visual patterns and trends. This insight summarizes the chart's overall visual presentation, such as identifying significant trends, distributions, and patterns in the data. For instance, we would identify



**Figure 3: Evaluation of caption quality on four aspects**

whether the chart shows a clear upward or downward trend, highlighting its most significant visual characteristics.

**Task-oriented Insight Generation (Figure 2-❸).** Next, we use both the metadata and the visual insights to derive task-oriented insights. This step contextualizes the chart for practical applications, helping users understand how the chart can be used in real-world scenarios. For example, a chart depicting healthcare data might be interpreted in terms of how it could inform resource allocation or support decision-making in healthcare planning.

**Statistics-oriented Insight Generation (Figure 2-❹).** First, we apply a set of 10 statistical analysis tasks [43] on the chart’s metadata (e.g., the X/Y-axes), as shown in Figure 2-❹. These tasks help identify statistical properties such as trends, correlations, and anomalies within the data. In the second step, we generate statistics-oriented insights by summarizing this statistical information. These insights provide an in-depth understanding of the chart’s data, focusing on aspects such as correlations, distributions, outliers, and other statistical relationships. This provides a deeper understanding of the data patterns and their significance.

After all the processes, we got a total of **69,166 charts** and corresponding **207,498 semantic insights**.

### 3.3 The Quality of Semantic Insights

After generating the semantic insights, we validated their quality through a crowdsourcing experiment. We randomly selected 50 captions and invited 100 crowd workers to rate them across four dimensions: completeness, consistency, diversity, and readability, using a 5-point scale (from Strongly Disagree to Strongly Agree).

The results are shown in Figure 3. Specifically, the majority of crowd workers rated the captions highly. Specifically, for completeness, 38% agreed and 37.1% strongly agreed; for consistency, 33.8% agreed and 41.3% strongly agreed; for diversity, 34.7% agreed and 40.2% strongly agreed; and for readability, 30.4% agreed and 49.8% strongly agreed. Overall, less than 5% of workers rated the semantic insights as Strongly Disagree, confirming their high quality.

These high-quality captions are used to train our text-to-chart retrieval model. If our model performs well and generalizes effectively on other text-to-chart retrieval benchmarks, it further validates the effectiveness of the training data generated by our pipeline.

## 4 ChartFinder: A Text-to-Chart Retrieval Model

In this section, we first describe the architecture of ChartFinder, followed by the training details. Finally, we outline how the model performs text-to-chart retrieval with ChartFinder.

### 4.1 Model Architecture

The design of ChartFinder is driven by the need to effectively retrieve relevant charts based on a user’s text query. This is a cross-modal retrieval task, where the goal is to align the textual queries with the charts’ visual and semantic features. Specifically, the challenge is to bridge the two modalities: the chart images (*visual content*) and the corresponding semantic insights (*textual content*). Our model should learn a shared embedding space where both visual and textual information can be effectively aligned.

To achieve this, we adopt a CLIP-based framework [30], which has demonstrated success in cross-modal tasks by aligning visual features with natural language supervision [2, 15, 26]. Since the semantic insights associated with charts can be long and detailed, we utilize Long-CLIP [48] to process these insights. Unlike the original CLIP model, which is limited to encoding short captions (up to 77 tokens), Long-CLIP extends the token limit to 248 tokens, allowing it to handle the longer and more complex textual descriptions required for charts. For encoding the chart images, we use the Vision Transformer (ViT) [4], which produces dense visual embeddings. ViT has shown strong performance in various image-related tasks, making it ideal for encoding the visual features of charts.

Together, the ViT-based image encoder and the Long-CLIP text encoder form the core of ChartFinder. To further explore the model’s scalability, we introduce two variants: ChartFinder and ChartFinder-B. Both versions utilize the same Long-CLIP text encoder but differ in their visual encoder. ChartFinder employs the larger ViT-L/14, while ChartFinder-B uses the smaller ViT-B/16.

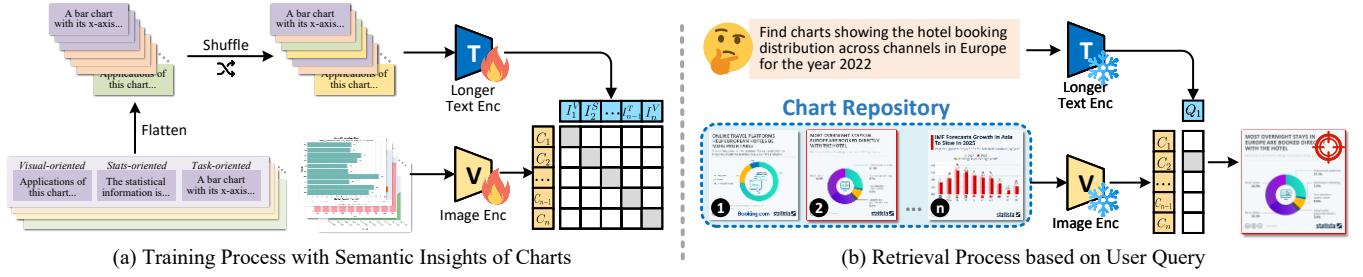
### 4.2 Training Details

As depicted in Figure 4(a), for each chart  $C_i$ , we associate three distinct semantic insights:  $I_i^v$  (visual-oriented insights),  $I_i^t$  (task-oriented insights), and  $I_i^s$  (statistical-oriented insights). The objective is for the model to learn to match the chart  $C_i$  with all three semantic insights in a unified embedding space. To achieve this, we experimented with two different strategies for training:

One approach was to maintain a similarity matrix for the three different insights during training and compute the average loss across them. However, experiments showed that this method was ineffective in learning meaningful representations.

After further analysis, we decided to *flatten* the semantic insights corresponding to all charts and then *shuffle* them, as illustrated in Figure 4(a). This approach ensures that the model learns to match each chart with its corresponding semantic insights without the interference of rigid similarity constraints. Subsequently, we apply *contrastive learning* based on the *CLIP framework* to optimize the model. The contrastive loss function is defined as:

$$L_i = -\log \frac{\exp^{(\text{sim}(C_i, I_i)/\tau)}}{\sum_{j=1}^N \exp^{(\text{sim}(C_i, I_j)/\tau)}}, \quad I_i, I_j \in [I^v, I^t, I^s]$$



**Figure 4: (a) ChartFinder is trained using both chart images and their corresponding semantic insights. (b) ChartFinder takes a query and a set of chart images as input, retrieving the most relevant charts based on embedding similarity.**

We trained ChartFinder using 4 A800 GPUs with a learning rate of  $1e-6$  for 20 epochs. For the base version of the model, we set the batch size to 512, while for the larger version, we reduced the batch size to 256 due to the increased memory usage associated with the larger model.

### 4.3 Text-to-Chart Retrieval with ChartFinder

Text-to-chart retrieval is a cross-modal task where the goal is to retrieve the most relevant charts from a repository  $C = \{C_1, C_2, \dots, C_n\}$  based on a textual query  $Q$  provided by the user. As shown in Figure 4(b), this process involves encoding both the text query and the chart images using text and image encoders, respectively.

Let  $\vec{Q}$  represent the embedding of the query, and  $\vec{C} = \{\vec{C}_1, \vec{C}_2, \dots, \vec{C}_n\}$  represent the set of chart embeddings, which are generated by the ChartFinder model. These embeddings capture both the visual content of the charts and the semantic insights associated with them. Once the embeddings are generated, the retrieval process involves computing the similarity scores between the query embedding  $\vec{Q}$  and all chart embeddings  $\vec{C}$ . We calculate the similarity using a suitable similarity function, such as cosine similarity:  $\text{sim}(Q, C_i) = \frac{\vec{Q} \cdot \vec{C}_i}{\|\vec{Q}\| \|\vec{C}_i\|}$ .

Finally, based on these similarity scores, we retrieve the top- $k$  most relevant charts  $\{C_{r_1}, C_{r_2}, \dots, C_{r_k}\}$ , where  $\{C_{r_1}, C_{r_2}, \dots, C_{r_k}\}$  are the charts with the highest similarity to the query  $Q$ . These top- $k$  charts are presented to the user as the most relevant results based on the provided textual query.

## 5 CRBench Benchmark

In this section, we first discuss the motivation behind the creation of a text-to-chart retrieval benchmark (Section 5.1), followed by an introduction to the benchmark curation process (Section 5.2). Finally, we provide an overview of the key characteristics of the first text-to-chart benchmark CRBench (Section 5.3).

### 5.1 Motivation and Design Consideration

Text-to-chart retrieval requires retrieving relevant charts from a repository based on a user's textual query, which involves aligning both the visual features of charts and the semantic insights embedded within the chart images. Unlike traditional image-based

retrieval, which focuses solely on visual content, text-to-chart retrieval must also account for the semantic context conveyed by textual descriptions.

While datasets like *VisText* [40] and *Chart-to-Text* [8] exist, they primarily focus on chart captioning and description generation, rather than the full text-to-chart retrieval task. These datasets aim to generate textual descriptions of charts but do not directly address the challenge of retrieving the appropriate chart based on textual queries, which is central to our work.

As a result, there is currently no benchmark for evaluating the performance of the text-to-chart retrieval task, which involves the alignment of both textual queries and chart visual content. This gap highlights the need for a benchmark that can evaluate the performance of models on this task.

**Design Consideration.** To fill this gap, we aim to propose a real-world dataset designed for text-to-chart retrieval, enabling the fair comparison of retrieval models across a variety of use cases. Several key factors were considered, as outlined below:

(1) *Precise and Fuzzy Queries*: As discussed in Section 1, user queries in real-world BI applications can be both precise (focused on specific details) and fuzzy (more general). Our benchmark includes both types of queries to reflect real-world user behavior and better evaluate model performance across different query complexities.

(2) *Diversity of Chart Types*: To reflect the variety of data visualizations encountered in real-world applications, the benchmark includes a broad range of chart types, testing model performance across various chart structures.

(3) *Real-world Charts*: The charts included in the benchmark should be sourced from real-world applications, ensuring their applicability in addressing actual user needs and scenarios.

### 5.2 Benchmark Construction

To build a benchmark that meets the aforementioned considerations, we first collected a large set of charts from real-world BI applications. Next, we used a chart embedding model to map the relevant charts to a given text query. We then employed crowdsourcing to perform preliminary annotations based on these text-chart pairs. Next, GPT-4o was used to generate text queries based on the predefined templates. Finally, we conducted a second round of crowdsourcing to validate the accuracy and relevance of the model-generated text queries.

The prompt for GPT-4o to generate queries.

**System Prompt:** You are a user searching for visualizations in a database. You will see 5 visualizations, but you should ONLY focus on the FIRST image when generating queries. The other four images are very similar to the first one, make sure your queries CAN NOT match any of the other four images. Generate two meaningful queries (10-15 words each):

**1. Precise Query:** Generate a query about specific content in the FIRST visualization that includes:

- Meaningful combination of axis labels/categories
- Important data values or time ranges
- Key categories or measurements
- If image contains time, you should include the time range in the query because it is important for the user to search for the specific time range and distinguish from other similar visualizations.
- When cover time range, do not direct use the initial time range in the chart. For example, if the initial time range in the x-axis is 2012-2019, you can use 2014 - 2018 or 2013 - 2016. Make sure the time range in your query is included in the initial time range.
- You don't need to cover very specific time range like specific months or days unless you need this to distinguish from other similar visualizations.
- Do not use comma in your query.
- Do not directly use the initial text in the image as the query, always find similar words or phrases to describe the content of the image. For example, if the title contains "weekly", you should use every 7 days in the query.

**Example:** "global temperature change 1990-2020 in the United States" (good, time and location are included)

**Bad example:** "global temperature change" (bad, no time and location to distinguish from other similar visualizations).

**2. Fuzzy Query:** Generate a query about the visualization purpose that includes:

- Line charts: trend analysis or comparison over time
- Bar charts: value comparison or ranking purpose
- Pie/stacked charts: distribution analysis or proportion comparison
- Scatter plots: correlation or pattern analysis

**Example:** "annual economic growth comparison between countries" (enough information to distinguish from other similar visualizations)

**Bad example:** "growth comparison" (too little information)

Format your response as:

{ "Precise query": "<10-15 word query about content>", "Fuzzy query": "<10-15 word query about purpose>" }

Remember:

- ONLY consider the FIRST image
- Include relevant context
- Be specific and meaningful
- Articles (a, an, the) and prepositions count as words

**Figure 5: The prompt for GPT-4o to generate precise queries and fuzzy queries.**

**5.2.1 Charts Collection from Real-world Applications.** To ensure CRBench reflects real-world chart retrieval scenarios, we collected charts from reliable sources widely used in business intelligence and data analysis: (i) *Tableau*: A leading data visualization platform for charting and business analytics [39]. (ii) *Statista*: A platform providing statistical data across various sectors [36]. (iii) *Pew Research Center*: A non-profit organization focusing on social science research [31]. (iv) *Our World in Data*: An open-access platform researching global challenges through charts on topics like economics, health, and society [25].

From these sources, we gathered 21,862 charts covering various domains, including finance, business, e-commerce, technology, and more. These fields are closely related to BI applications.

**5.2.2 Text Query Generation and Annotation.** After collecting charts that meet the BI scenario, our next step is to generate and annotate text queries based on the chart repository.

**Step 1: Similar Charts Selection.** In the real world, for example, when searching for charts in a BI system, the number of charts should be much larger than the number of queries. Moreover, each query will correspond to many similar charts. Based on this setting, the first step in annotating a query is to find similar charts. Calculating the similarity of rasterized charts is rather difficult. Thus,

we encode the charts into different embeddings and compare their representation similarity.

We use a pre-trained ViT model to encode chart  $C_i$ :  $\vec{C}_i = ViT(C_i), i \in [1, 21862]$ .  $\vec{C}_i$  is the embedding vector of the  $i$ -th chart, with dimension  $1 \times 768$ . Next, we concatenate all the single embeddings and have all the tensors  $T$ :  $T = \text{Concat}[\vec{C}_1; \vec{C}_2; \dots; \vec{C}_{21862}]$ .  $T$  shapes like  $21862 \times 768$ . After we get all the embedding tensors, we calculate the similarity matrices between these tensors with cosine similarity:  $\text{sim} = \cos(T, T^T)$ . Based on the similarity matrix, we can now easily get the similarity score of candidate  $C_j$  and the target  $C_i$ :  $S_{ij} = \text{sim}(C_i, C_j), i, j \in [1, 21862]$ . Afterward, we will set  $\theta$  as the similarity threshold. Only if  $S_{ik} > \theta, \forall k \in [j_1, j_2, j_3, j_4]$ . Then, we combine all four candidate charts and the target chart as one chart group:  $\text{Group}_a = (C_{a1}, C_{a2}, C_{a3}, C_{a4}, C_{a5}), a \in [1, 274]$ .

In this step, we set the threshold as 0.90 and produced 247 groups of similar charts.

**Step 2: Text Query Annotation by Crowdsourcing.** We collect text queries through the Appen [17] crowdsourcing platform based on groups of similar charts collected in Step 1. In this step, we ask workers to write both precise and fuzzy queries for each chart. To ensure the relevance of the text queries, we provide each worker not only with the chart in question but also with the four most

similar charts to the first chart. These additional charts serve as references, ensuring that the queries are contextually aligned with the chart’s content and not influenced by unrelated charts.

In the first round of crowdsourcing experiments, we assign five workers to annotate queries for each grouped chart. However, due to the inherent variability of crowdsourcing and the complexity of the task, we found that some queries were completely unrelated to the chart. Specifically, we observed that 2 or 3 responses in each group of submissions were irrelevant.

**Step 3: Text Query Generation by GPT-4o.** Building on the query patterns identified in the first 50 crowdsourcing experiments, we used them to generate high-quality prompt words for GPT-4o. The initial crowdsourcing data was found to have significant variability and low quality, which made it less reliable for further use. To improve the query quality, we turned to GPT-4o to generate queries.

Following the method outlined in *Step 2*, we show GPT-4o five charts at a time and instruct it to generate two types of queries. Specifically, we use a carefully designed prompt, which is shown in Figure 5, to guide GPT-4o to generate precise queries and fuzzy queries for only one of the five similar charts. We specifically ensure that the precise query contains enough details and constraints to make it accurately match only the target chart, not other charts. This method ensures that the queries generated are tailored to each chart’s characteristics and use case, addressing the challenges of crowdsourcing quality and providing more relevant and precise queries for chart retrieval.

**Step 4: Text Query Annotation by Crowdsourcing.** After generating a complete set of 247 precise and fuzzy queries, we noticed that, despite clear instructions to ensure the generated queries were relevant to the first chart and distinct from the other charts in the set, some queries still applied to multiple charts. To address this issue, we conducted a second round of crowdsourcing experiments.

In this round, we showed the generated queries along with their corresponding five charts to nine workers. We asked the workers to select the chart that they believed best matched the query. If five or more workers selected the same chart as the target, we considered the query to be unambiguous. After this crowdsourcing screening process, we retained 195 precise queries and 131 fuzzy queries.

### 5.3 CRBench Overview

In this section, we compare CRBench with two existing benchmarks, Chart-to-Text [8] and VisText [40], both of which focus on chart-related tasks like caption generation and description. While these benchmarks are useful for evaluating chart captioning and description generation, they do not address the text-to-chart retrieval task. In our study, we repurpose the captions in these benchmarks as queries for retrieval tasks, enabling us to compare their effectiveness with CRBench in retrieving relevant charts based on text queries. Specifically, in VisText, each chart is paired with two types of captions: L1 captions (e.g., basic properties) and L2+L3 captions (e.g., trends and statistics). This results in a chart-to-query ratio of 1:2. In contrast, Chart-to-Text pairs each chart with a single caption, resulting in a 1:1 ratio. In CRBench, however, the ratio is much higher (67:1), meaning the number of charts significantly exceeds

the number of queries, which is more representative of real-world scenarios where charts vastly outnumber queries.

Table 1 shows the distribution of query lengths in each benchmark. In VisText, the query lengths for L1 and L2+L3 captions typically range from 100 to 400 characters. Chart-to-Text features a wider range of query lengths, with some queries reaching up to 2400 characters. CRBench, however, features more concise queries, with both 195 precise and 131 fuzzy queries generally ranging from 0 to 100 characters, better reflecting how queries are typically structured in real-world applications.

Moreover, we compared examples of similar charts across the benchmarks. In VisText, similar charts show strong visual resemblance but often differ significantly in semantic content. In Chart-to-Text, charts deemed similar tend to align well semantically but differ visually. On the other hand, CRBench ensures that similar charts are closely aligned both visually and semantically, resulting in a more holistic and accurate comparison.

Overall, CRBench presents a more challenging and realistic benchmark for evaluating text-to-chart retrieval models.

## 5.4 Discussion

We discuss the quality and potential limitations of CRBench.

**Crowdsourcing and Query Generation.** While crowdsourcing was used to generate queries, we addressed quality issues through a second round of crowdsourcing and GPT-4o. This process helped ensure the relevance and clarity of the queries, resulting in a high-quality set of precise and fuzzy queries.

**Limitations.** Despite careful curation, crowdsourcing variability and the evolving landscape of data visualizations may require periodic updates to CRBench to maintain its relevance and accuracy.

## 6 Experiments

In this section, we conduct a set of experiments to evaluate whether the synthesized semantic insights can enhance text-to-chart retrieval performance across multiple benchmarks and settings. We also assess whether the ChartFinder model achieves state-of-the-art performance in text-to-chart retrieval tasks.

### 6.1 Experimental Settings

**Datasets.** We conduct experiments using three benchmarks: CRBench, VisText [40], and Chart-to-Text [8]. We compare the retrieval performance of different models on CRBench and perform *zero-shot* experiments on VisText and Chart-to-Text to evaluate the generalization of our model. The characteristics of these benchmarks are summarized in Table 1.

**Metrics.** To evaluate the effectiveness of the model in text-to-chart retrieval, we use the following metrics: Recall@1, Recall@5, Recall@10, MRR@10, and NDCG@10. These metrics are widely adopted in information retrieval tasks [29].

**Methods.** We evaluate 10 methods in our experiments: (1) VISTA [51], (2) Univl-dr [16], (3) MARVEL [52], (4) CLIP [30], (5) CLIP-DPR [16], (6) EVA-CLIP [38], (7) CoCa [3], (8) Jina-CLIP-v2 [9], (9) Long-CLIP [48] (with Long-CLIP-B for the Base version and Long-CLIP-L for the Large version, which differ by the size

**Table 1: Comparison of Existing Benchmarks.** The statistics for Chart-to-Text and VisText are from the respective test sets. The column “C/Q” indicates the ratio for charts (C) and text queries (Q). The column “Dist. of Query Len.” Shows the distribution of lengths of text queries in characters. The column “CT” means the types of charts.

| Datasets          | CT | #-Charts | #-Queries | C/Q | Difficulty | Dist. of Query Len. | Samples of Similar Charts |
|-------------------|----|----------|-----------|-----|------------|---------------------|---------------------------|
| VisText [40]      | 3  | 882      | 1764      | 0.5 | Easy       |                     |                           |
| Chart-to-Text [8] | 6  | 1393     | 1393      | 1   | Easy       |                     |                           |
| CRBench (ours)    | 11 | 21,862   | 326       | 67  | Hard       |                     |                           |

**Table 2: Performance Comparison of Text-to-Chart Retrieval Models on CRBench Benchmark.**

| Models               | #Param | Precise Query |              |              |              |              | Fuzzy Query  |              |              |              |              |
|----------------------|--------|---------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
|                      |        | R@1           | R@5          | R@10         | MRR@10       | NDCC@10      | R@1          | R@5          | R@10         | MRR@10       | NDCC@10      |
| VISTA [51]           | 196M   | 8.21          | 20.00        | 27.18        | 13.15        | 16.42        | 9.16         | 19.08        | 24.43        | 13.16        | 15.8         |
| Univl-DR [16]        | 151M   | 4.10          | 12.82        | 15.38        | 7.84         | 9.65         | 3.82         | 10.69        | 14.50        | 6.90         | 8.70         |
| MARVEL [52]          | 310M   | 1.54          | 5.13         | 7.69         | 3.08         | 4.63         | 0.00         | 0.76         | 1.53         | 0.46         | 2.23         |
| CLIP [30]            | 151M   | 12.31         | 26.15        | 33.33        | 19.01        | 22.43        | 10.69        | 21.37        | 25.95        | 15.69        | 18.15        |
| CLIP-DPR [16]        | 151M   | 9.74          | 18.46        | 23.59        | 13.60        | 15.95        | 5.34         | 13.74        | 16.79        | 8.51         | 10.48        |
| EVA-CLIP [38]        | 149M   | 5.13          | 19.49        | 24.10        | 11.08        | 14.21        | 3.05         | 9.92         | 13.74        | 6.40         | 8.14         |
| CoCa [3]             | 151M   | 8.72          | 21.54        | 25.1         | 14.11        | 16.76        | 3.05         | 8.40         | 9.92         | 5.19         | 6.33         |
| Jina-CLIP-v2 [9]     | 865M   | 4.10          | 16.92        | 25.13        | 10.01        | 13.58        | 3.05         | 10.69        | 14.50        | 5.84         | 7.87         |
| Long-CLIP-B [48]     | 149M   | 26.67         | 53.85        | 62.56        | 37.99        | 43.90        | 22.90        | 40.46        | 51.91        | 30.29        | 35.33        |
| <b>ChartFinder-B</b> | 149M   | 38.97         | 62.05        | 70.26        | 49.30        | 61.30        | 29.77        | 50.38        | 61.83        | 38.96        | 44.41        |
| Long-CLIP-L [48]     | 427M   | 41.03         | 75.90        | 79.49        | 55.32        | 55.32        | 38.93        | 67.18        | 74.81        | 50.99        | 56.77        |
| <b>ChartFinder</b>   | 427M   | <b>47.18</b>  | <b>80.00</b> | <b>84.10</b> | <b>61.23</b> | <b>66.90</b> | <b>41.98</b> | <b>75.57</b> | <b>80.15</b> | <b>55.31</b> | <b>61.40</b> |

of the vision encoder used). (10) Our Method: **ChartFinder** and **ChartFinder-B**: Both versions use the same Long-CLIP text encoder but differ in their visual encoder. *ChartFinder uses the larger ViT-L/14, while ChartFinder-B uses the smaller ViT-B/16.*

All methods encode the query and candidate charts into embeddings, with retrieval performed using cosine similarity via FAISS [7].

**Implementation Details.** Many CLIP-based models apply center cropping during preprocessing to focus on the central part of the image. However, we observed that this operation often crops out crucial chart information, such as the title and axis labels ( $x$ -axis and  $y$ -axis names). This can negatively impact retrieval performance, introducing bias in the model’s ability to understand key chart features. To address this, we removed the center crop operation during testing and instead resized the images directly to a shape suitable for the model’s vision encoder input. This adjustment ensures that important chart elements remain intact, reducing potential bias and improving the retrieval process. We applied this image processing strategy consistently across all methods we evaluated.

## 6.2 Exp-1: Overall Results on CRBench

The purpose of this experiment is to evaluate and compare the performance of different models in precise and fuzzy query tasks.

Experimental results are shown in Table 2. From the experimental results, it can be seen that ChartFinder and ChartFinder-B perform best in both query tasks, and multiple metrics are ahead of other methods by more than 5% or even 10%. For example, in the precise query task, ChartFinder’s R@1, R@5, and R@10 are 47.18%, 80.00%, and 84.10%, respectively, significantly higher than the second-place Long-CLIP-L’s 41.03%, 75.90%, and 79.49%. In the fuzzy query task, ChartFinder also surpasses Long-CLIP-L, with R@1, R@5, and R@10 being 3.05%, 8.39%, and 5.34% higher, respectively. In comparison, although Jina-CLIP-v2 (865M) has the largest number of parameters, it performs poorly in both types of tasks. The R@1 in the precise query task is only 4.10%, and the R@1 in the fuzzy query task is also only 3.05%.

Overall, ChartFinder and ChartFinder-B perform significantly better in precise and fuzzy query tasks than all the other models, leading other methods by more than 5% or 10% in multiple metrics.

**Table 3: Performance Comparison of Text-to-Chart Retrieval Models on VisText Benchmark.**

| Models               | L1 Caption   |              |              |              |              | L2+L3 Caption |              |              |              |              |
|----------------------|--------------|--------------|--------------|--------------|--------------|---------------|--------------|--------------|--------------|--------------|
|                      | R@1          | R@5          | R@10         | MRR@10       | NDCG@10      | R@1           | R@5          | R@10         | MRR@10       | NDCG@10      |
| VISTA [51]           | 75.85        | 87.76        | 89.80        | 79.85        | 82.27        | 44.56         | 63.95        | 70.86        | 37.61        | 41.80        |
| Univl-DR [16]        | 63.72        | 81.75        | 86.62        | 71.57        | 75.22        | 34.58         | 52.83        | 60.77        | 42.61        | 46.93        |
| MARVEL [52]          | 47.51        | 66.55        | 72.79        | 55.61        | 59.73        | 24.04         | 39.80        | 48.64        | 31.25        | 35.37        |
| CLIP [30]            | 77.44        | 89.46        | 92.74        | 83.05        | 85.41        | 48.41         | 68.25        | 74.83        | 56.81        | 61.14        |
| CLIP-DPR [16]        | 74.26        | 88.10        | 90.93        | 80.59        | 83.14        | 45.01         | 64.74        | 72.11        | 53.51        | 57.97        |
| EVA-CLIP [38]        | 71.77        | 87.07        | 89.68        | 78.50        | 81.26        | 31.86         | 49.43        | 57.26        | 39.39        | 43.64        |
| CoCa [3]             | 75.62        | 84.35        | 87.87        | 79.69        | 81.65        | 44.22         | 58.96        | 66.44        | 50.54        | 54.30        |
| Jina-CLIP-v2 [9]     | 79.71        | 90.93        | 94.67        | 84.85        | 87.23        | 54.20         | 74.49        | 80.50        | 62.72        | 67.01        |
| Long-CLIP-B [48]     | 90.48        | 94.78        | 95.35        | 81.88        | 83.50        | 60.20         | 78.12        | 83.45        | 67.99        | 71.73        |
| <b>ChartFinder-B</b> | 93.20        | 97.85        | 98.75        | 95.17        | 96.05        | 62.59         | 79.48        | 84.01        | 69.64        | 73.11        |
| Long-CLIP-L [48]     | 93.20        | 98.07        | 99.09        | 95.21        | 96.15        | 66.55         | 82.99        | 88.66        | 73.43        | 77.09        |
| <b>ChartFinder</b>   | <b>96.15</b> | <b>99.43</b> | <b>99.66</b> | <b>96.90</b> | <b>97.44</b> | <b>67.80</b>  | <b>84.58</b> | <b>89.12</b> | <b>75.20</b> | <b>78.78</b> |

**Table 4: Experimental Results on Chart-to-Text Benchmark.**

| Models               | R@1          | R@5          | R@10         | MRR@10       | NDCG@10      |
|----------------------|--------------|--------------|--------------|--------------|--------------|
| VISTA [51]           | 51.72        | 68.46        | 73.20        | 58.94        | 62.39        |
| Univl-DR [16]        | 49.61        | 67.91        | 73.08        | 57.60        | 61.35        |
| MARVEL [52]          | 21.68        | 38.19        | 46.30        | 28.97        | 33.08        |
| CLIP [30]            | 74.01        | 88.16        | 92.03        | 80.25        | 83.11        |
| CLIP-DPR [16]        | 66.04        | 82.56        | 85.86        | 73.09        | 76.21        |
| EVA-CLIP [38]        | 68.05        | 83.42        | 87.80        | 74.73        | 77.90        |
| CoCa [3]             | 67.98        | 83.92        | 87.65        | 74.49        | 77.92        |
| Jina-CLIP-v2 [9]     | 65.83        | 83.78        | 88.23        | 73.51        | 77.08        |
| Long-CLIP-B [48]     | 90.81        | 98.28        | 98.85        | 94.18        | 95.35        |
| <b>ChartFinder-B</b> | 94.90        | 99.07        | 99.43        | 96.89        | 97.53        |
| Long-CLIP-L [48]     | 94.97        | 99.35        | 99.78        | 97.06        | 97.75        |
| <b>ChartFinder</b>   | <b>97.06</b> | <b>99.86</b> | <b>99.86</b> | <b>98.41</b> | <b>98.80</b> |

Finding 1: ChartFinder significantly outperforms existing methods on both precise and fuzzy queries. The performance gain is consistent across all the metrics.

### 6.3 Exp-2: ChartFinder in the Zero-Shot Setting

In this experiment, we evaluate the performance of ChartFinder in a zero-shot setting, where the model is tasked with retrieving relevant charts without any prior fine-tuning on the target dataset. This setup tests the model’s ability to generalize across different datasets, assessing how well ChartFinder can perform text-to-chart retrieval when exposed to new, unseen data.

**6.3.1 Experiments on VisText Benchmark.** We use the test set of VisText [40], comprising 882 charts with each chart corresponding to two captions mentioned in Section 5.3, to conduct this group of experiments. We take the two-level caption as the query, and the annotated chart as the retrieval target to perform text-to-chart retrieval tasks.

**Overall Results.** As shown in Table 3, ChartFinder performs best in all metrics in L1 caption, significantly ahead of other models. For example, Recall@1 reaches 96.15%, far exceeding other models. Recall@10 reaches 99.66%, close to a full match. MRR@10 and NDCG@10 are 96.90% and 97.44%, respectively, further verifying their advantage in ranking quality. ChartFinder-B still achieves

excellent performance with fewer parameters. Recall@1 reaches 93.20%, which is comparable to Long-CLIP-L (93.20%) and about 3 percentage points higher than Long-CLIP-B. On Recall@10, ChartFinder-B reaches 98.85%, surpassing all models with similar parameter scales. L2+L3 captions are more inclined to detailed analytical descriptions. Thus, the retrieval difficulty is significantly higher than the L1 task, and the overall metrics have declined. ChartFinder still leads in this task with R@1 reaching 67.80%, R@10 reaching 89.12%, MRR@10 and NDCG@10 reaching 75.20% and 78.78%, respectively.

**Finding 2:** The results of all models decreased when L2+L3 was used as the query. We believe that the abstract data information, like a trend, cannot be fully understood by the model.

**6.3.2 Experiments on Chart-to-Text Benchmark.** We use the Chart-to-Text dataset [8] to conduct this experiment. Specifically, this dataset has 1,393 text and chart pairs in the test set. We use the same metrics as the Section 6.3.1.

**Overall Results.** As shown in Table 4, ChartFinder significantly outperforms other models in all metrics. For example, Recall@1 reaches 97.06%, 2.09% higher than the second-best model (Long-CLIP-L, 94.97%). Recall@10 reaches 99.86%, almost close to the full score, showing the excellent performance of the model in the top- $k$  retrieval task. MRR@10 and NDCG@10 are 98.41% and 98.80%, respectively, further verifying the effectiveness of ChartFinder in ranking quality. ChartFinder-B also demonstrates obvious performance, surpassing Long-CLIP-B in all metrics, especially in Recall@1 (94.90% vs. 90.81%) and NDCG@10 (97.53% vs. 95.35%). The above results further prove the effectiveness of ChartFinder.

**Finding 3:** When we use long captions as the query, the accuracy of all models is improved compared to CRBench. This also shows that in real BI scenarios, retrieval is more difficult when the query is shorter and more brief..

## 6.4 Exp-3: Ablation Study on the Combination of Synthesized Semantic Insights

**Experiment Settings.** To verify the necessity and synergy of the three semantic insights we proposed, we designed a series of ablation experiments. We used ChartFinder-B as the base model and arranged and combined the three semantic insights to obtain a total of 7 training configurations (including the initial model). Table 5 shows the performance of each configuration in the two scenarios of precise query and fuzzy query, and the evaluation indicators include R@10, MRR@10, and NDCG@10.

**Overall Results.** The experimental results reveal several key findings: First, the introduction of any semantic insights can significantly improve the performance of the baseline model, among which statistics-oriented insights perform best with an overall performance of 48.35%, slightly better than task-oriented (48.20) and visual-oriented (46.67) insights.

In the dual combination, the combination of visual-oriented and task-oriented insights has the most outstanding effect (50.81). It is worth noting that although statistics-oriented insights perform best when used alone, they have limited benefits when combined with other types, which clearly shows that there are obstacles to information integration between different types of insights: the abstract numerical analysis provided by statistical insights is difficult to directly establish an effective connection with visual patterns or application scenarios.

However, when we use the three insights together, we get the best result (54.34). We believe that this is because the three types of insights form a complete information processing chain: from visual perception (visual-oriented) to statistical verification (statistics-oriented) to application transformation (task-oriented). When one link is missing, it is difficult for the model to establish an effective semantic connection, resulting in reduced information utilization efficiency.

In summary, the experimental results strongly support our hypothesis: efficient chart-to-text retrieval models need to comprehensively utilize multi-dimensional semantic insights rather than simply superimposing features.

Finding 4: The best result (54.34%) was achieved by combining all three multiple semantic insights because they form a complete information processing chain from visual perception to statistical verification to application conversion. Using one insight alone or combining only two insights has a limited effect, indicating that there are information integration barriers between different types of insights. This proves the effectiveness of the three semantic insights we proposed.

## 6.5 Exp-4: The Generalizability of Synthesized Semantic Insights

**Experiment Settings.** To verify the versatility of the three designed semantic insights, we apply them to train different types of CLIP-based models to observe their impact on model performance. In this experiment, we select CLIP-DPR and UniVL-DR as base models and compare them with fine-tuned versions (FT-CLIP-DPR and FT-UniVL-DR) that incorporate semantic insights. All models

are evaluated on the CRBench dataset, using two test scenarios: exact query and fuzzy query. Evaluation metrics include R@10 and MRR@10.

**Overall Results.** As shown in Table 6, the introduction of semantic insights has brought significant performance improvements to different models. For the CLIP-DPR, in the precise query scenario, R@10 and MRR@10 increased by 4.62 and 4.18 percentage points, respectively; in the fuzzy query scenario, the improvement was more significant, with R@10 increasing by 8.39 percentage points. The UniVL-DR achieved greater performance gains after the introduction of semantic insights, especially in the fuzzy query scenario, with R@10 increasing by 10.69 percentage points and MRR@10 increasing by 8.82 percentage points. This result fully proves that the semantic insights we designed have good versatility and can effectively enhance the performance of retrieval models with different architectures, especially showing stronger robustness when processing fuzzy queries. This further verifies the universal value of multi-dimensional semantic insights for chart retrieval tasks.

Finding 5: We found that fine-tuning other models using semantic insights can also significantly improve their retrieval capabilities, proving the generalizability of the three semantic insights.

## 6.6 Exp-5: The Impact of Center Crop Strategy

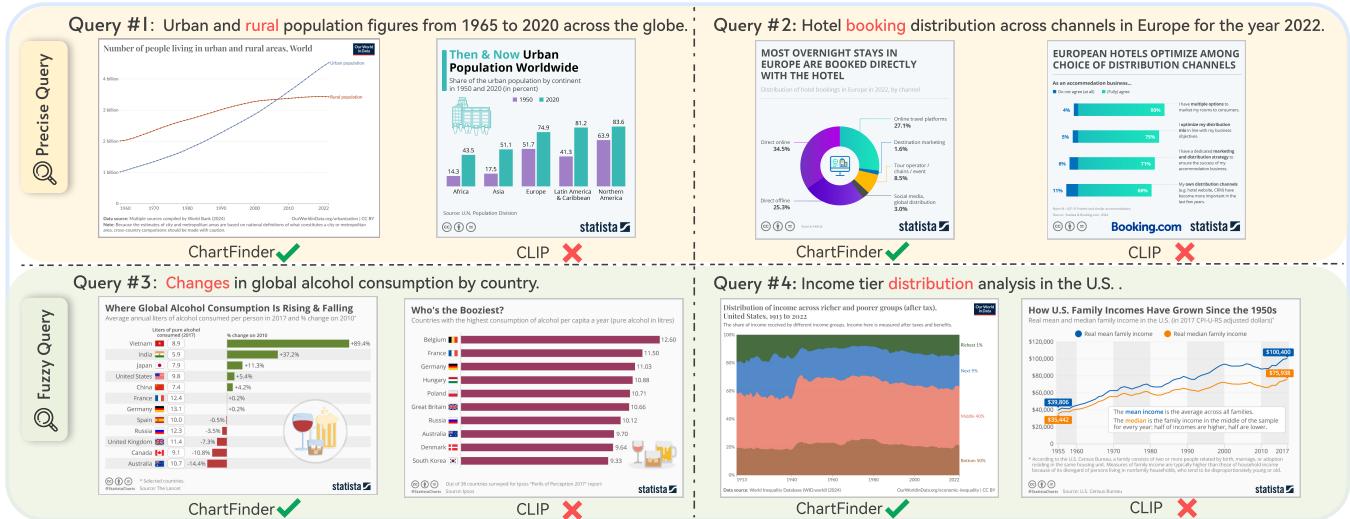
**Experiment Settings.** We mentioned in Section 6.1 that for the text-to-chart retrieval task, we replaced the traditional center crop preprocessing method in the CLIP-based models with a direct resize strategy. To verify the necessity of this modification, we selected Long-CLIP-B and Long-CLIP-L as the base models and conducted comparative tests on the urban1k and Chart-to-Text datasets, respectively. Urban1k [48] is a retrieval dataset containing natural images of urban scenes, which contains a variety of urban buildings, streets, and landscapes, representing a typical natural image retrieval task.

**Overall Results.** The results in Table 7 show that the preprocessing strategies have very different effects on different retrieval tasks. On the Urban1k dataset, direct resize caused a slight decrease in model performance, with Long-CLIP-B and Long-CLIP-L decreasing by 0.9 and 1.5 percentage points on average, respectively. However, on the Chart-to-Text dataset, the same strategy brought significant improvements, with the two models gaining approximately 12.3 and 13.1 percentage points in performance, respectively. This shows that in chart retrieval tasks, retaining the complete structure of the chart (including edge axis labels, legends, etc.) is more important than maintaining precise proportions, proving that our adjustments to chart-specific preprocessing strategies are necessary and effective.

Finding 6: In natural images, a lot of important semantic information is often in the center of the image, so the center crop processing allows the model to pay more attention to the query target. However, in the chart, important information such as the title, x-axis, and y-axis names are all around the chart, which makes it easy for the center crop to cut out important information.

**Table 5: The Effectiveness of ChartFinder on CRBench by Incorporating Different Semantic Insights.**

| Models        | Visual-o | Statistics-o | Task-o | Precise Query |        |         | Fuzzy Query |        |         | Overall |
|---------------|----------|--------------|--------|---------------|--------|---------|-------------|--------|---------|---------|
|               |          |              |        | R@10          | MRR@10 | NDCG@10 | R@10        | MRR@10 | NDCG@10 |         |
| ChartFinder-B | ✓        | ✓            | ✓      | 62.56         | 37.99  | 43.90   | 51.91       | 30.29  | 35.33   | 43.66   |
|               |          |              |        | 69.64         | 44.39  | 48.69   | 56.28       | 27.27  | 34.29   | 46.67   |
|               |          |              |        | 66.15         | 45.18  | 50.18   | 57.25       | 32.75  | 38.60   | 48.35   |
|               | ✓        | ✓            | ✓      | 65.64         | 44.44  | 49.52   | 58.78       | 32.24  | 38.59   | 48.20   |
|               |          |              |        | 71.79         | 44.96  | 51.40   | 60.31       | 35.24  | 41.17   | 50.81   |
|               | ✓        | ✓            | ✓      | 66.15         | 43.26  | 48.74   | 54.96       | 32.20  | 37.66   | 47.16   |
|               | ✓        | ✓            | ✓      | 65.64         | 43.53  | 48.87   | 54.96       | 30.44  | 36.23   | 46.61   |
|               | ✓        | ✓            | ✓      | 70.26         | 49.30  | 61.30   | 61.83       | 38.96  | 44.41   | 54.34   |

**Figure 6: Case study on Top-1 Text-to-Chart Retrieval Results of the ChartFinder and CLIP.****Table 6: The Impact of Training with Semantic Insights.**

| Models                     | Precise Query |        | Fuzzy Query |        |
|----------------------------|---------------|--------|-------------|--------|
|                            | R@10          | MRR@10 | R@10        | MRR@10 |
| CLIP-DPR [16]              | 20.00         | 8.90   | 10.69       | 6.60   |
| w/ three semantic insights | 24.62         | 13.08  | 19.08       | 10.97  |
|                            | ↑4.62         | ↑4.18  | ↑8.39       | ↑4.37  |
| UniVL-DR [16]              | 17.44         | 6.59   | 9.92        | 6.26   |
| w/ three semantic insights | 26.15         | 13.25  | 20.61       | 15.08  |
|                            | ↑8.71         | ↑6.66  | ↑10.69      | ↑8.82  |

## 6.7 Exp-6: Case Study

Figure 6 compares the top-1 retrieval performance of our model and CLIP on CRBench. In Query #1, ChartFinder successfully retrieves a chart that includes both *urban* and *rural population*, while CLIP retrieves a chart focusing only on *urban population*, failing to meet the query requirements. In Query #2, ChartFinder correctly aligns with the semantic meaning of *booking distribution*, retrieving a pie chart about hotel booking channels. In contrast, CLIP retrieves a chart about optimizing distribution channels, which does not match the query's focus. In Query #3, ChartFinder captures the keyword *change* and retrieves a chart showing trends in alcohol consumption.

**Table 7: Ablation Study on Center Crop. W/ direct resize means we directly resize the image to the required size instead of cropping the chart to the target size.**

| Models           | R@5    | R@10  | MRR@5  | MRR@10 | NDCG@10 |
|------------------|--------|-------|--------|--------|---------|
| Urban1k          |        |       |        |        |         |
| Long-CLIP-B      | 94.1   | 97.4  | 85.3   | 85.8   | 88.6    |
| w/ direct resize | 93.2   | 96.1  | 84.7   | 85.1   | 87.8    |
|                  | ↓0.9   | ↓1.3  | ↓0.6   | ↓0.7   | ↓0.8    |
| Long-CLIP-L      | 96.7   | 98.2  | 90.5   | 90.7   | 92.6    |
| w/ direct resize | 95.1   | 97.5  | 88.5   | 88.9   | 90.9    |
|                  | ↓1.6   | ↓0.7  | ↓2.0   | ↓1.8   | ↓1.5    |
| Chart-to-Text    |        |       |        |        |         |
| Long-CLIP-B      | 87.29  | 90.38 | 79.46  | 79.87  | 82.44   |
| w/ direct resize | 98.28  | 98.85 | 94.10  | 94.18  | 95.35   |
|                  | ↑10.99 | ↑8.47 | ↑14.64 | ↑14.31 | ↑12.91  |
| Long-CLIP-L      | 88.51  | 91.03 | 80.87  | 81.20  | 83.61   |
| w/ direct resize | 99.35  | 99.78 | 97.00  | 97.06  | 97.75   |
|                  | ↑10.84 | ↑8.75 | ↑16.13 | ↑15.86 | ↑14.14  |

In contrast, CLIP retrieves a chart ranking alcohol consumption, ignoring the notion of *change*. In Query #4, ChartFinder identifies *distribution* and retrieves a stacked area chart illustrating income

distribution. In contrast, CLIP retrieves a chart focusing on income growth trends, failing to address the *distribution* aspect.

## 7 Related Work

**Text-to-Chart Retrieval.** Previous work on text-to-chart chart retrieval has primarily focused on two approaches: visualization recommendation systems [27, 28, 42, 46] and natural language interfaces [20–22, 33, 41]. In the context of natural language interfaces, systems like Olio [32] and BOLT [35] allow users to express their analytical intents or design exploration using natural language for chart retrieval. On the other hand, visualization recommendation systems such as SlopeSeeker [1] and Snowy [34] focus on guiding users in exploring and discovering interesting patterns and charts within the data. Although much progress has been made in these two approaches, they still struggle to understand the user’s query intent. We believe embedding the query and charts into the same latent space will shine a light on Text-to-Chart Retrieval. With the development of MLLM [12, 13, 44, 47] models, we can see text-to-chart as a cross-modal retrieval task, which has been driven by large-scale image-text paired datasets and pre-trained models like CLIP [30]. Several variants have enhanced CLIP’s performance, such as EVA-CLIP [38], which improves retrieval by using EVA [6] as the visual encoder, and Jina-CLIP-v2 [9, 45] which enhances the text encoder [37] for better retrieval. Other approaches, like UniVL-DR [16], MagicLens [49], VISTA [51], and MARVEL [52], fine-tune CLIP on large, diverse datasets to improve model’s retrieval abilities. However, MLLM-based methods have limited research focused on chart retrieval. This paper addresses this gap by injecting semantic insights into ChartFinder based on contrastive learning.

**Chart Captions with Semantic Insights.** Studies show that rich captions can significantly enhance CLIP-based models’ performance [14]. For instance, VeCLIP [10] boosts performance by injecting extra visual information into captions, while DreamLIP [50] achieves the same effect as CLIP 300M data using just one-tenth of the long caption data. Another approach to enrich semantic information is to use multiple captions for the same image. Llip [11] suggests that each image should have captions from various angles. VisText [40] introduces a dataset for statistical charts with two levels of semantic information per chart. We extend this idea by proposing three levels of semantic insights to reflect the semantic depth of charts. Moreover, while VisText’s manually annotated data is limited, we generate semantic insights using Llama 3.1 [5] 70B based on metadata, ensuring both quality and quantity.

## 8 Conclusion

In this paper, we introduced ChartFinder, a novel text-to-chart retrieval model that combines contrastive learning with the CLIP architecture to align both visual and semantic features of charts. By leveraging synthesized semantic insights of charts, our model effectively retrieves relevant charts based on a user’s textual query. We also presented CRBench, the first benchmark for text-to-chart retrieval in real-world BI scenarios. Experiments show that ChartFinder outperforms existing methods, achieving significant improvements in both precise (up to 66.9% NDCG@10) and fuzzy query tasks on CRBench.

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