FishBiasLens: Integrating Large Language Models and Visual Analytics for Bias Detection

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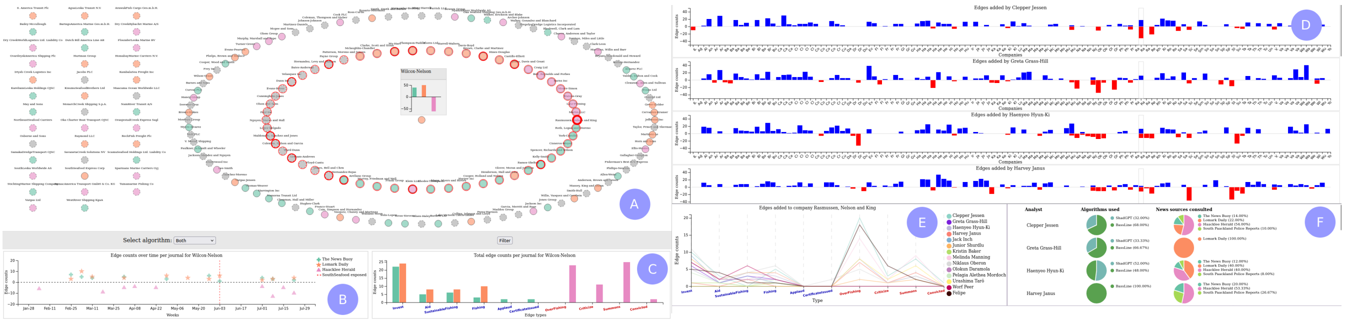

Figure 1: Overview of our visualization system: The left panels (A–C) display companies and temporal journal reports—(A) Company Graph, (B) Journal Bias Timeline, (C) Journal Bias Breakdown. The right panels (D–F) focus on journal and analyst bias analysis—(D) Analyst Bias Summary, (E) Parallel Coordinates of Analyst Bias, (F) Analyst Information Sources.

Abstract

Identifying unreliable sources is crucial for preventing misinformation and making informed decisions. CatchNet, the Oceanus Knowledge Graph, contains biased perspectives that threaten its credibility. We use Large Language Models (LLMs) and interactive visualization systems to identify these biases. By analyzing police reports and using GPT-3.5 to extract information from articles, we establish the ground truth for our analysis. Our visual analytics system detects anomalies, revealing unreliable news sources such as The News Buoy and biased analysts such as Harvey Janus and Junior Shurdlu.

Index Terms: GPT, Visualization, Knowledge Graph, Bias detection, LLM

1 Introduction

Since 2023, the VAST Challenge has released a dataset called Fisheye, which contains detailed information on seafood and aims to explore the social, political, and economic forces driving the illegal fishing trade. Within this context, VAST has created three mini-challenges using these data. We focus on Mini Challenge 1 (MC1), which employs a knowledge graph representing various interactions between companies and organizations in Oceanus.

The MC1 Knowledge Graph is a directed multi-graph with 215 nodes and 16,231 edges, primarily consisting of one large connected component. It includes various types of nodes, such as organizations, regions, commodities, and individuals, with edges representing events like aid, fishing, transactions, and ownership. The metadata fields track details such as the last editor, the date added, and the data source. Additionally, the challenge provides 338 text files containing raw news article text, although the graph may also include information from sources not covered in these articles.

The knowledge graph may accumulate biased information as the information passes through various layers — source articles, extraction algorithms, and human analysts. Recent studies [1] show that the spread of misinformation complicates enforcement and misleads people about the real environmental and economic impacts. The primary task is to identify bias and its sources, which may originate from journals, LLM algorithms used for extraction, or human analysts.

2 Methodology

We divide our methodology into two main steps: data preprocessing and visual analytics.

2.1 Data preprocessing

Classifying edges: We organize edges by type and isolate ownership-related edges (Event.Owns.PartiallyOwns) while removing duplicates. We classify the edges as **Positive** (Invest, Aid, SustainableFishing, Applaud, CertificateIssued), **Neutral** (Conference, Transaction, PartiallyOwns, Fishing), or **Negative** (OverFishing, Criticize, Summons, Convicted). This classification facilitates the comparison of the data provided by each journal.

LLM-analyst: The use of LLMs in visual analytics shows promising results. For instance, a study [2] highlights that a systematic approach augmented with GPT improves problem understanding, data processing, and results analysis. In our approach, we use GPT 3.5 to extract relationships from raw articles. We also inspect the police reports to verify their mention in the source articles. The goal is to uncover missing information in journals and analysts' reports that benefits companies.

2.2 Visual Analytics System

We employ two views (see Figure 1). The first view identifies potential biases in journals and algorithms, while the second focuses on detecting analyst bias.

2.2.1 First View

Company Graph (A): Each node represents a company, with color indicating the journal reporting the most positive news; uncolored nodes lack journal information. A straight border shows the most positive edges, while a dotted border indicates negative ones. Hovering over a node displays a bar chart of aggregated edges by journal and highlights transaction-linked companies with red borders.

Figure 2: Clear bias is observed in Lonmark Daily and The News Buoy, which report only positive edges for the top three companies with the most unreported police records.

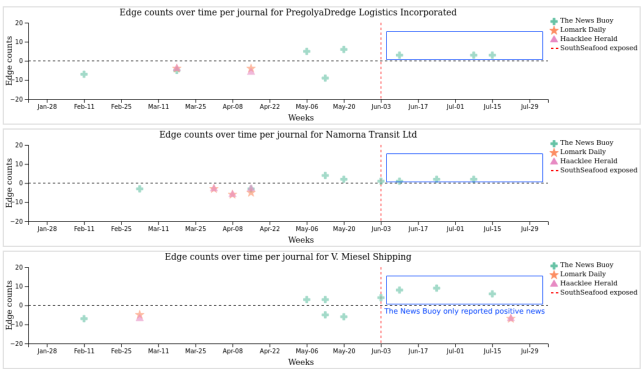

Figure 3: Clear bias is observed in The News Buoy, which reports only positive edges for Conti family companies.

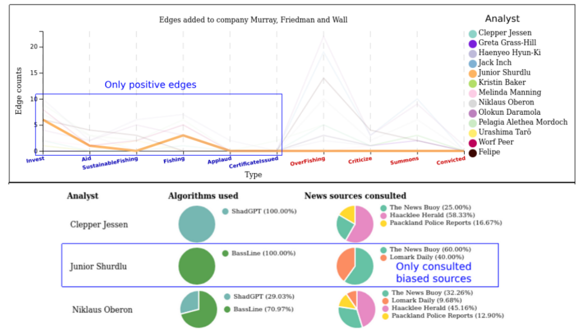

Figure 4: Junior Shurdlu shows clear bias, adding only positive edges from biased journals (Lonmark Daily and The News Buoy).

Clicking a node rearranges the layout into two circles: companies with transactions in the inner circle and others in the outer circle. Companies without transactions are placed separately on the left. Clicking also activates components (B) and (C).

Journal Bias Timeline (B): A scatterplot displays the number of positive and negative edges added over time, with positive edges above the x-axis (weekly) and negative edges below. Users can compare multiple companies simultaneously with their data stacked vertically. A red dotted line marks the Southseafood incident. Users can filter by algorithm, including our LLM extractor, "OwnExtraction," by selecting the algorithm name from a dropdown menu.

Journal Bias Breakdown (C): This component shows the number of edges by type and journal in a bar chart, helping users identify which edge types contribute to bias in each journal. A dropdown menu above allows for further filtering.

2.2.2 Second View

Analyst Bias Summary (D): Bar charts display the number of edges added by each analyst for all companies, with positive edges shown as blue bars above the x-axis and negative edges as red bars below. This component helps identify discrepancies in the edge classifications by analysts. Clicking on any bar activates components (E) and (F).

Analyst Bias Parallel Coordinates (E): A Parallel Coordinates plot visualizes the types of edges each analyst adds. Hovering over an analyst's name highlights their corresponding line in the plot. Positive edge types are arranged on the left, and negative edges are on the right. We include a new analyst called "Felipe" to represent our extracted information for additional comparison.

Analyst Information Sources (F): The final component displays pie charts showing the algorithms used and news sources consulted by each analyst, along with their corresponding percentages.

3 Results and Findings

This section details our findings and provides visual evidence of unreliable actors.

Bias in Journals and Police Records: For companies like "Murray, Friedman and Wall", "Rasmussen, Nelson and King", and "Wilcox-Nelson", we observe that only one journal, the Haacklee Herald, reports news consistent with available police records. In contrast, the other two journals report only positive news. This omission clearly indicates bias (see Figure 2).

Bias in the Conti Family: A similar pattern emerges in four companies owned by a Conti family member. Using ownership information and our visual analytics system, we discover that "The News Buoy" reports only positive news after the SouthSeafood incident, suggesting a bias toward the Conti family. In contrast, the other two journals report negative news (see Figure 3).

Analyst Bias We identify a suspicious pattern among analysts Harvey Janus, Junior Shurdlu, Kristin Baker, and Nikalus Oberon (see Figure 4). For SouthSeafood, only Harvey Janus adds positive information, revealing his bias. Additionally, discrepancies between the `_date_added` and the `_last_edited_date` suggest potential data manipulation by Janus.

4 Conclusion

Our approach effectively identifies biases within CatchNet. Integrating LLM improves our ability to gather and compare information, and our visual analytics system provides strong evidence of bias. The advanced integration of LLMs with real-time data sources could improve bias detection. Expanding the analysis to include more datasets or exploring different domains could help generalize the findings and refine the detection techniques.

References

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