Needles in the ‘Sheet’stack: Augmented Analytics to get Insights from Spreadsheets

Medha Atre, Anand Deshpande, Reshma Godse, Pooja Deokar, Sandip Moharir
Dhruva Ray, Akshay Chitlangia, Trupti Phadnis, Yugansh Goyal
Persistent Systems
Pune, India
firstname.lastname@persistent.com

ABSTRACT

Business intelligence (BI) tools for database analytics have come a long way and nowadays also provide ready insights or visual query explorations, e.g., QuickInsights by Microsoft Power BI, SpotIQ by ThoughtSpot, Zenvisage, etc. In this demo, we focus on providing insights by examining periodic spreadsheets of different reports (aka views), without prior knowledge of the schema of the database or reports, or data information. Such a solution is targeted at users without the familiarity with the database schema or resources to conduct analytics in the contemporary way.

1. INTRODUCTION

Business Intelligence (BI) tools built on top of database systems provide excellent data analytics capabilities. E.g., trends of revenues of different companies over the past six months, or different departmental store products’ sales comparison over the past three months etc. However, user needs a fair bit of knowledge of the underlying database schema and acquaintance with the BI dashboard. This can be particularly challenging for users and organizations that are not tech savvy or do not have time and resources to do so. A recent BI tools survey highlights that despite the market presence of a large variety of BI tools, about 38% of the users continue to use spreadsheets as the main reporting and analytics tool. The use of BI tools remains low at an average of 10-15% of the users. While spreadsheet tools like Microsoft Excel provide advanced analytics abilities, e.g., pivot tables, visual charts, ready-to-use functions etc, they still have the bottleneck that the user requires learning about these techniques and knowledge of the database and spreadsheet schema. Also it is our observation that spreadsheet reports are often generated targeting a wide variety of audiences within the organization making them bulky with tens of columns and thousands of rows.

Augmented analytics proposes to take this learning effort off the user’s shoulder, with the help of machine learning techniques for automated data cleaning, preparation, and insight discovery. For example, if a user wants to find the sharpest sales trend (rising or falling) among thousands of departmental store products, an augmented analytics tool can provide such insights automatically. Existing BI tools have indeed started moving in this direction, such as QuickInsights by Microsoft Power BI, SpotIQ by ThoughtSpot etc. These tools, in their present form, are tightly coupled with an existing BI dashboard interface and a backend database. However, as we noted above, a sizable percent of users still use spreadsheets as the main reporting and analytics tool.

Our main contributions through this demo proposal are:

1. Finding insights from a series of spreadsheets of a report, without requiring pre-training or prior knowledge of the spreadsheet schema.

2. Allowing users to interact with the systems using a chatbot and semi-structured English commands to set individual preferences, and give personalized insights from the same spreadsheets there onward for different users.

For instance, CEO and marketing manager of a company can both get different personalized insights from the same series of spreadsheets. Our goal is to build a system similar to the modern social media, where different newsfeeds are generated for different users from the same underlying data. Our system’s focus is on the personalized newsfeed of insights generated from the same spreadsheets of organization reports, consumed over emails, chatbots, RSS etc.

2. ARCHITECTURE

Figure 1 shows the high level architecture of our system. Insights Generator runs continuously accepting spreadsheets of different reports. In Figure 1, R1, R2, R3 are three different types of reports, e.g., R1 can be product sales report, R2 new joinee and attrition report, and R3 bug report. R1, R2... represent periodic spreadsheets of report type R1 and so on. The engine does not impose any limit on the types of reports, the number of spreadsheets of each report, or their periodicity. It treats each report type and its spreadsheets independently.

The insight generator has three main components – (1) backend analysis unit, (2) frontend for insights delivery and

https://bi-survey.com/bi-deployment

https://www.gartner.com/en/documents/3773164
user interaction through chatbot, (3) a middle layer for communicating backend insights in JSON format to the frontend. Frontend in turn consists of two subcomponents – (a) an insight delivery mechanism (currently through email), and (b) user interaction and personalization through chatbot using semi-structured English language commands. Note that through this personalization we enable different users to get different insights in the successive spreadsheets of the same report type. We have deployed components of our engine using Microsoft Azure framework, but they can be deployed on any other suitable cloud or independent architecture.

2.1 Data Cleaning and Preparation

Our insight generator consumes reports in the spreadsheet format, which may not be strictly structured, and may have free text in the top rows or leftmost columns. We extract the most significant table from such sheets as follows – from the top of the sheet, designate the first row with maximum non-empty columns as the header, discard any leftmost empty columns from this header, and extract the table under.

Without losing generality, let the spreadsheets of a report type \( R1 \) have columns \( c_1, c_2, c_3, \ldots \). We categorize these into four mutually exclusive sets – (1) primary key attributes (K), (2) categorical attributes (C), (3) numeric attributes (N), and (4) all others. Presently we disregard \#4 all other attributes. Due to space constraints, we briefly describe our method of identifying these four attribute types using heuristic measures.

For primary key attributes (K), we assume that typically they appear in the first five columns of a spreadsheet, and identify them by considering the total number of unique values in these columns and the total number of rows in the spreadsheet. In case if no such attribute or combination of them exist, we keep primary key attributes empty. We identify categorical attributes (C) using heuristic measures of the data-type of the column and the ratio of total non-empty rows in that column to the unique values in it \((\#\text{nonemptyrows}/\#\text{unique})\). If the spreadsheet has more than five categorical attributes we sort all the categorical attributes in the descending order of \((\#\text{nonemptyrows}/\#\text{unique})\), and uniformly pick five attributes from this sorted order. From these five categorical attributes, we create \( (\binom{5}{2}) = 15 \) attribute combinations for analysis. Note that our engine allows end user to change this choice or combination for future analysis as elaborated later. We consider all the numeric attributes (N) without discarding any.

Timseries: Let us consider \( R_1, R_2, \ldots R_n \) spreadsheets of report \( R_1 \), where \( R_1 \) has the oldest timestamp and \( R_n \) the latest. We first choose \( R_1 \), and consider each primary key (composite) value \( k_i \) of \( K \) attributes. This is a composite key if \( K \) has more than one attribute. We consider each numeric attribute \( n_j \in N \), and create a timeseries key \((k_i, n_j)\) (key-attribute KA pair). E.g., if \( R_1 \) has Product-ID as the primary key, with \( Sales \) as a numeric attribute, the timeseries key for product with ID P1234 is \((P1234, Sales)\). Let the value of \( Sales \) for P1234 in \( R_1 \) be \( y_1 \), in \( R_2 \) be \( y_2 \) and so on. Thus from \( R_1 \ldots R_n \) spreadsheets, we form a time series for key \((P1234, Sales)\) \( \rightarrow [(t_1, y_1), (t_2, y_2) \ldots (t_n, y_n)] \), where \( t_1 \ldots t_n \) are the timestamps of the spreadsheets. A spreadsheet, say \( R_4 \), may not have the specific key P1234, in which case we do not enter \((t_4, y_4)\) value in the timeseries, thus accommodating for disappearing and reappearing entities. This is done for each unique primary key value and unique numeric attribute in all the spreadsheets. We call these timeseries numeric attribute timeseries or NTS.

Next, for each spreadsheet \( R_1 \ldots R_n \), we consider each numeric column \( n_j \in N \), and order \( n_j \)’s values corresponding to each primary key value and add a numeric column of these ranks, we call this \( n_j \)-rank. E.g., within the Sales column in \( R_1 \), let \( P1234 \) be \$1000, \( P2345 \) be \$500, and \( P3456 \) be \$1200, then the relative ascending order of \( P1234, P2345, P3456 \) for \( Sales \) column is 2, 1, 3 and we add a column \( Sales-rank \). Using the same procedure described above for NTS timeseries, we create rank timeseries RTS for each hybrid timeseries key \((k_i, n_j-rank)\) \( \rightarrow [(t_1, r_1), (t_2, r_2) \ldots (t_n, r_n)] \), where \( r_1 \ldots r_n \) are the values corresponding to \( k_i \) in \( n_j-rank \) column of each spreadsheet. In all we get \( 2\times\bigcup_{R_1 \ldots R_n} \text{uniq}(K)\times N \) NTS and RTS timeseries over all the spreadsheets.

Recall that we pick five categorical attributes, if more than five are present, and prepare maximum fifteen combinations of them. For each spreadsheet, we consider each \( c_k \) categorical attribute combination of these maximum 15 combinations. We compute the total number of rows \( u \) for a unique value \( v_1 \in c_k \). This is a composite value if \( c_k \) has two categorical attributes. We do this for each spreadsheet, and form a timeseries for \((v_1, c_k)\) \( \rightarrow [(t_1, u_1), (t_2, u_2) \ldots (t_n, u_n)] \) for each \((v_1, c_k)\) value-attribute (VA) pair across all the spreadsheets. We call these categorical attribute timeseries or CTS. Thus given timestamp ordered spreadsheets of a particular report, we form three types of timeseries – NTS, RTS, CTS.

2.2 Analytics

For the analytical processing, we consider only timeseries that have more than five points in them. Shorter timeseries are discussed after this under “LT5 Mean, Variance”.

Linear Regression: Recall that our engine neither assumes any information about the spreadsheet schema and data domain, nor is it pre-trained on any existing corpus of schemas such as \texttt{schema.org}. We use unsupervised learning methods based on – (1) trend analysis (linear regression), (2) mean squared error (MSE) of the fitted trend line, and (3) outlier scores of data points within the fitted trend, i.e., Cook’s Distance\footnote{\url{https://en.wikipedia.org/wiki/Cook's_distance}}. As given in Section 2.1, we form NTS, RTS, CTS consisting of several timeseries based on the unique values of primary keys and categorical attributes.
in the spreadsheets. For each timeseries in RTS, NTS, CTS, we do linear regression and fit a trend line. We compute the mean squared error (MSE) of this fit, and compute Cook’s Distance of each data point \((t_i,y_i), (t_i,r_i),\) and \((t_i,u_i)\) in each time series. For each time series, we pick the data point with highest Cook’s Distance. Thus at the end of this exercise, each timeseries in NTS, RTS, and CTS has a \((1)\) line equation with slope \(m\) and intercept \(b\), \((2)\) MSE \(mse\), and \((3)\) a point with maximum Cook’s Distance \(mcd\). We use these three features for deciding relative ranking of timeseries within each of NTS, RTS, CTS as follows. The procedure is applied same way for each of NTS, RTS, CTS group timeseries and hence we do not mention group names explicitly. We sort timeseries in the \((1)\) descending order of \(m^2\) (sharpness of the slope irrespective of whether the slope is rising or falling), \((2)\) descending order of \(mse\), and \((3)\) descending order of \(mcd\). In all, we get three orderings of timeseries, three each for NTS, RTS, CTS.

**LT5 Mean, Variance:** When the length of a timeseries is less than or equal to five, we only compute the mean and variance of the timeseries points, for each timeseries in NTS, RTS, CTS. Thus for each shorter timeseries in NTS, RTS, CTS we compute – \((1)\) mean \(\mu\), and \((2)\) variance \(\sigma^2\).

**Diff of the latest two:** We consider only the latest two spreadsheets of a report type, and compute the difference between them. This is achieved by using timeseries of NTS, RTS, CTS, and considering the last two points within them, if their timestamps correspond to the latest two reports. E.g., if a timeseries within NTS group is \((k_i,n_j) = (t_1,y_1), (t_2,y_2), (t_{10},y_{10})\), then we compute \((y_{10} - y_{2})^2\) for \((k_i,n_j)\) value, if \(t_{10}\) is of the latest spreadsheet. We repeat the same process for RTS and CTS timeseries.

**New Entities and Attributes:** Considering only the latest spreadsheet of a report type, say \(R1\), we compute if there are any new primary key values or attributes added to it. In our observation, the report schema can undergo slight changes over time. Our procedure of timeseries composition outlined above can accommodate such changes, because we form timeseries for each unique key-attribute (KA) or value-attribute (VA) pair. From these various metrics computed on timeseries and spreadsheets, we compute *insights* (the most significant observations) as described in Section 2.3.

### 2.3 Insights

We generate insights in four categories – \((1)\) Overall highlight, \((2)\) most significant sharp and flat trends, \((3)\) most significant outlier, \((4)\) most significant difference of the latest two spreadsheets (Delta).

**Highlight:** Recall from Section 2.2 that after linear regression we sort timeseries by \(m^2\), \(mse\), and \(mcd\) to get three sorted orders of timeseries in NTS, RTS, CTS each. Within the NTS timeseries, we compute a composite sorted order of each timeseries by multiplying sorted indices of it in each of the three sorted orders, \(o_{m^2}\), \(o_{mse}\), and \(o_{mcd}\). The composite rank is \(o_{m^2} \times o_{mse} \times o_{mcd}\), where \(o_{m^2}\), \(o_{mse}\), \(o_{mcd}\) are indices of \((k_i,n_j)\) in the sorted orders of \(m^2\), \(mse\), \(mcd\) respectively. From the composite rank we pick the top one. In case of a tie, we pick one randomly. We repeat this process for RTS, CTS group of timeseries too, and pick the timeseries with the top composite rank. Intuitively, the highlighted insight from NTS, RTS, CTS are timeseries that have sharp trend (rising or falling), have high fluctuations, and an outlier with relatively higher residual error.

**Trend:** Disregarding the timeseries picked in the Highlight (to avoid redundancy), next we pick the top timeseries from the \(m^2\) sorted order for each of the NTS, RTS, CTS group. Additionally we also pick the last timeseries from \(m^2\) order. Thus the Trend insights have sharp rising or falling and the flattest trends.

**Outlier:** Next, disregarding the timeseries picked in Highlight and Trend, we pick the top timeseries from the sorted order of \(mcd\) (Cook’s Distance) for NTS, RTS, CTS each.

**Delta:** Considering the ‘Diff of the latest two’ as given in Section 2.2 we pick the timeseries that shows the maximum change (Delta) in the latest two reports.

Note that we compute relative order of *all* the timeseries formed over *all* the numeric and selected categorical attributes (ref. Section 2.2), and pick the top ones for insights. However, different users might be interested in focusing on different attributes. For this we provide a user interaction interface for *personalization* as given in Section 2.3.

### 2.4 User Interaction

In spreadsheets with tens of columns and thousands of rows, the number of timeseries can run in several thousands, e.g., when we tested with Stock Exchange archive spreadsheets [2], each spreadsheet has several numeric attributes and a couple of thousand rows, making around 20,000 timeseries. Since our engine does not assume any prior knowledge of schema or data domain, we treat all of them at par and choose the top insights. But user-1 may be interested in insights from specific attributes, which may get overshadowed in the ranking from other insights. Hence we let user interact with the engine and set personalized configuration and preferences using chatbot. Through this, for the next round of insights, each user will get insights according to their previously set preferences.

### 2.5 Moving Window

Recall from Figure 4 that our engine can continuously churn periodically arriving spreadsheets, and generate a fresh set of insights after every new spreadsheet. We surmise that a typical user is most interested in finding out insights from the latest few spreadsheets. Thus we provide a configurable option to have a moving window over spreadsheets sorted by their timestamp. E.g., for report \(R1\), a user wants to consider only the latest 10 spreadsheets for insight generation. Thus when a new spreadsheet of \(R1\) arrives, we move the window by discarding the 10th *oldest* spreadsheet and adding the latest in the window.

### 3. SETUP

Our engine’s three main components (1) analysis or spreadsheet processing, (2) frontend for insight delivery and user feedback, (3) middle layer for communicating insights from analysis to the frontend using JSON, are implemented using Python 3.0. Currently our setup is deployed using Microsoft Azure infrastructure and works as follows.

We assume that a spreadsheet of a report is sent to several people in the organization over email. In addition to these people, the spreadsheet is also sent to an email robot listening service for our engine, e.g., *insightalias@persistent.com*.

\[\text{Such a Cook’s Distance always tends to order time series elements with large numbers first. But this can be configured to consider normalized numbers, for a fair treatment to the smaller numbers.}\]
Treating the subject of the email as the report type, the service creates a separate storage for each report, runs the procedure given in sections 2.1, 2.2, and 2.3, and sends the first set of insights to all the recipients of the report over an email, without any inputs or configuration asked from the user. In Figure 2 and 3, we have shown example of such insights generated on COVID-19 data acquired from [1]. Figure 2 shows top insights generated on the spreadsheets between February 1–12 and Figure 3 shows insights for March 1–15. Comparing the two, we can note that for February, all the top insights came from the Chinese provinces, whereas by March when COVID-19 spread in other countries, and its spread in China started dampening (due to the lock-down), the top insights started coming from Italy and Spain.

Note: these insights were generated by our engine without prior knowledge of the data, schema, or user inputs.

Clicking the ‘Explore’ button opens a Microsoft Teams chatbot. Users can interact with the engine using simple semi-structured English commands, personalize the configuration by choosing only some attributes according to their preference, and instantaneously get updated insights. The user can save this personal configuration. When the new spreadsheet arrives, the next insights are personalized using individual user’s configuration.

4. RELATED WORK

Microsoft Power BI’s QuickInsights [4], ThoughtSpot’s SpotIQ [3], and other augmented analytics tools offered by the BI tools come closest to our system. However, all those systems are integrated with an existing BI tool, and thus require access to the customer database. In comparison, our tool is lightweight which can work with spreadsheets without access to the full database or its schema. SeeDB [8], Zenvisage [5], and their successor systems [6] mainly focus on insightful visualizations of the underlying data. While their focus is on insightful visualizations, our focus is on insights presented in the English language. These systems expect knowledge of the underlying database schema to be able to identify the dimension and measure attributes. Since our system is targeted at users without the knowledge or resources to provide this information, we use heuristics to identify these attributes in the spreadsheets.

5. FUTURE WORK

In the ongoing enhancements, we are working on providing insights into identifying attribute correlations, to be able to provide insights into correlated outliers, e.g., a sudden fall or rise in the sales of particular products due to the change in the store staff attendance (e.g., COVID-19 pandemic or weather patterns). Attributes which are dependent on other attributes will have similar timeseries, and generate redundant insights. Similar timeseries can be identified using a variety of techniques such as Earth Mover’s Distance, Euclidean Distance, Dynamic Time Warp etc., and they can be clustered so as to efficiently provide unique insights. We plan to analyse semantics of attributes using NLP techniques, so as to make better decisions in deciding how to process them. Finally, while we keep the focus of the insights on the latest moving window, we intend to give a historical perspective for a particular timeseries.

6. REFERENCES

[1] COVID-19 Surveillance Dashboard by Univ. of Virginia. http://nssac.bii.virginia.edu/covid-19/dashboard/
[2] National Stock Exchange of India Ltd. https://www1.nseindia.com/products/content/equities/equities/archieve_eq.htm.
[3] SpotIQ by ThoughtSpot https://www.thoughtspot.com/spotiq.
[4] R. Ding, S. Han, Y. Xu, H. Zhang, and D. Zhang. Quickinsights: Quick and automatic discovery of insights from multi-dimensional data. In SIGMOD, 2019.
[5] T. Siddiqui, A. Kim, and A. Parameswaran. Zenvisage: Effortless visual data exploration. In SIGMOD, 2016.
[6] T. Siddiqui, P. Luh, Z. Wang, K. Karahalios, and A. Parameswaran. Shapesearch: flexible pattern-based querying of trend line visualizations. PVLDB, 11(12), 2018.
[7] B. Tang, S. Han, M. L. Yuu, R. Ding, and D. Zhang. Extracting top-k insights from multi-dimensional data. In SIGMOD, 2017.
[8] M. Vartak, S. Rahman, S. Madden, A. Parameswaran, and N. Polyzotis. Seedb: Efficient data-driven visualization recommendations to support visual analytics. In PVLDB, volume 8, 2015.

---

6 *Presently we do not describe insights from RTS timeseries, that work is in progress.*