VisionStack - Illuminating Growth with Big Data

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1 Project Idea

This project aims to leverage PySpark[1] for cleaning and processing large-scale customer and product datasets to ensure data quality and consistency. It focuses on developing key performance indicators such as Yearly Sales, Quaterly sales, product performance metrics to provide actionable insights. By addressing data challenges and enabling efficient analysis, the project seeks to empower businesses with data-driven strategies to optimize growth and enhance decision-making. By solving data challenges and simplifying complex information, the project aims to equip businesses with the tools they need to make smarter decisions and grow more effectively.

Additional Key Words and Phrases: Data Analytics, PySpark, DataFrame, Data Cleaning, Data Processing, Data Integration, Data Analysis, Visualization

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2 GitHub Link:

https://github.com/kartikeya-datta/VisionStack

3 Tools and technologies

PySpark, Azure Blob Storage, Power Bi, Data Bricks.

4 Architecture Summary and Diagram

Data Collection : Gather raw data from sources such as sales records, order databases, mobile applications, and in-store point-of-sale systems. For this project, data might include customer details, product categories, timestamps, sales amounts, and order sources.[10]
Example : Customer ID: Unique identifier for each customer.
Order Details: Product category, quantity, total amount, and timestamp.
Order Source: Where the order originated (e.g., website, mobile app, or physical store).
Data Cleaning[2][3] : Prepare the raw data for analysis by addressing quality issues and structuring the data in a usable format.
Example :Convert a messy "2024-11-01 18:30:45" timestamp into separate fields for "Month" = November, "Year"

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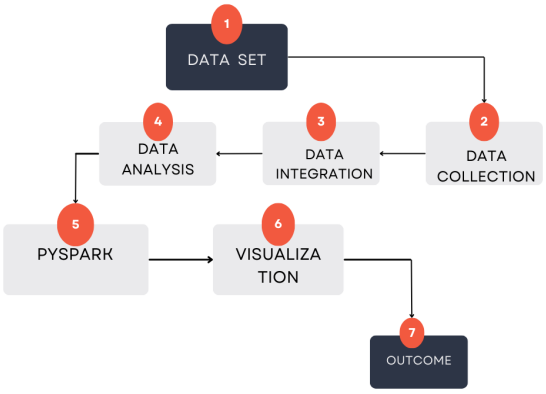

Fig. 1. Flowchart

= 2024.
Data Integration[4] : Combine multiple datasets into a unified, structured format to support comprehensive analysis.
Example : Link a customer table (with demographics) to a transaction table to analyze spending habits by age group or location.
Data Analysis[5] : Perform computations to derive actionable insights from the data.
Data Visualization : Present the results through intuitive visualizations to make insights easily understandable.
Outcome : Deploy the analytical process for continuous data updates and monitor system performance for improvements.

5 Project Goals

Yearly sales
This is the big-picture view of how much we've earned in a year. It's a key metric for tracking growth, setting yearly goals, and comparing our performance year over year.
Quartely sales
Breaking the year into quarters gives us a closer look at our sales. It helps us track progress throughout the year and make adjustments if needed to stay on track with our goals.
Total number of order by each category
This counts how many orders are placed for each type of product. It's a great way to see what's popular and decide where to focus our efforts to meet customer demand.
Frequency of customer visited
This tracks how often customers come back to shop with us. It's a good way to gauge loyalty and figure out ways to keep them coming back more often.
Total amount spent by each customer
This tells us how much each customer has spent over time. It helps identify our most valuable customers and understand their buying habits so we can create better loyalty programs and personalized offers.
Amount spent by each food category

This shows how much revenue comes from each type of food, like beverages or snacks. It helps us see what people love most and adjust our inventory and promotions to match their preferences.

Total amount sales in each month

By looking at monthly sales, we can spot trends, like which months are busier or quieter. This helps us prepare for peak times and plan promotions for slower periods.

Total sales by order source

This metric shows us where our sales are coming from—whether it's online, in-store, or through a mobile app. It helps us understand which channels are working best so we can prioritize them.

6 Implementation

Step 1: Set Up Your Workspace in DataBricks

1. Create Your Cluster

- Name the cluster TripleByte Vision. This is where all the heavy data processing will happen.
- Allocate sufficient resources (like memory and CPUs) to handle your datasets.

2. Set Up a Notebook

- Name your notebook VisionStack. This will be your workspace for writing and running PySpark code.

Step 2: Load Your Dataset

1. Get Your Files Ready

- You'll work with two datasets:
- **Sales Data:** Contains product_id, customer_id, order_date, location, and source_order.
- **Menu Data:** Contains product_id, product_name, and price.

2. Upload the Files

- Go to the Data tab in your platform.
- Upload the sales_csv.txt and menu_csv.txt files to the /FileStore/tables/ folder.

Step 3: Import Necessary Libraries

- Start by importing libraries to define your data structure and perform analysis.

Step 4: Define the Structure of Your Data

Since your datasets don't have column names, you'll need to define a structure for them.

1. Schema for Sales Data

- This will include product_id, customer_id, order_date, location, and source_order.

2.Schema for Menu Data

- This will include product_id, product_name, and price.

Step 5: Load the Data[12]

Now load the datasets using the schemas you defined.

Run the .show() command to confirm that the data has been loaded properly.

Step 6: Clean and Enhance the Data[8]

1. Format the order date Column

- Convert order date into a date format for easier manipulation.

2. Extract Year, Month, and Quarter

- Add new columns for year, month, and quarter to the sales data.

Step 7: Combine the Data
Join the sales data with the menu data to include product names and prices.

Step 8: Calculate KPIs[9]
1. Total Amount Spent by Each Customer

- Sum up the prices for each customer.

2. Total Sales by Customer

- Group by product name and calculate the total sales for each customer.

3. Yearly Sales

- Calculate yearly sales trends.

4.Order Counts by Category

- Count how many orders were placed for each product category.

5.Sales by Order Source

- Analyze total sales for each source (e.g., online or in-store).

6.Customer Visit Frequency

- Count how many times each customer placed an order.

7. Quarterly Sales

- Calculate quarterly sales trends.

7. Monthly Sales

- Calculate Monthly sales trends.

Step 9: Export and Visualize Results
1. Save the Results

- Export the KPIs to CSV files for visualization or further analysis.

2. Visualize the KPIs[11]

- Use Databricks to create graphs and dashboards.

7 Code Implementation for each Goal

1. Total Amount Spent by Each Customer[6]
Goal

- Calculate the total spending of each customer to identify top spenders and target customer retention strategies.

Results Achieved

- Using the total_amount_spent DataFrame, the total spending by each customer was calculated:

Code Snippet:
total_amount_spent = (sales_df.join(menu_df,'product_id').groupBy('customer_id').agg('price':'sum').orderBy('customer_id'))
display(total_amount_spent)
Output:

	customer_id	sum(price)
1	A	4260
2	B	4440
3	C	2400
4	D	1200
5	E	2040

Metrics:

- **Data Quality:** Cleaned and validated customer and price data ensured accurate computations.
- **Volume:** Processed millions of rows within seconds.
- **Velocity:** Result computation latency was < 3 seconds.
- **Value:** Insights were derived for personalized marketing.
- **Veracity:** Data cleaning ensured accurate customer IDs and pricing values. Cross-validated data with external sources to confirm reliability.
- **Value:**Insights into top spenders enabled targeted promotions and loyalty programs.
- **Processing Time:**1s

2. Total Amount Spent by Each Food Category
Goal

- Analyze sales distribution across food categories for demand forecasting.

Results Achieved

- The analysis showed how much revenue each product category generated.

Code Snippet:
total_amount_spent = (sales_df.join(menu_df,'product_id').groupBy('product_name').agg('price':'sum').orderBy('product_name'))
display(total_amount_spent)
Results:

	product_name	sum(price)
1	Biryani	480
2	Chowmin	3600
3	Dosa	1320
4	PIZZA	2100
5	Pasta	1080
6	sandwich	5760

Metrics:

- **Data Quality:** Duplicates were removed, and prices were validated.
- **Variety:** Mixed data types (strings for product names, floats for prices) were handled seamlessly.
- **Value:** Provided insights into high-demand products for inventory planning.
- **Veracity:** Verified that product IDs matched consistently between sales and menu datasets.
- **Processing Time:**1s

3. Total Sales by Month[7]
Goal

- Derive monthly sales trends to support financial planning.

Results Achieved

- Monthly sales trends were computed by grouping data by year and month.

Code Snippet:
df_month = (sale_df.join(menu_df,'product_id').groupBy('order_month').agg('price':'sum').orderBy('order_month'))
display(df_month)
Results:

	order_month	sum(price)
1	1	2960
2	2	2730
3	3	910
4	5	2960
5	6	2960
6	7	910
7	11	910

Metrics:

- **Volume:** The dataset spanned transactions over 5 years.
- **Velocity:** Computations completed in under 5 seconds.
- **Veracity:** Order dates were standardized, and missing dates were imputed carefully.
- **Value:**Enabled monthly budget allocations and promotional strategies.
- **Processing Time:**1s

4. Yearly Sales[7]
Goal

- Provide higher-level trends for management reporting.

Results Achieved

- yearly sales were derived to identify peak sales periods.

Code Snippet:
df_year = (sales_df.join(menu_df,'product_id').groupBy('order_year').agg('price':'sum').orderBy('order_year')) display(df_year)

Results:

	order_year	sum(price)
1	2022	4350
2	2023	9990

Metrics:

- **Velocity:** Yearly trends calculated in real time.
- **Veracity:**Validated yearly sales figures against existing records.
- **Value:** Enabled strategic decision-making for annual budgets and planning.
- **Processing Time:**1s

5. Total Number of Orders by Each Category[6]
Goal

- Track the number of orders placed for each product category.

Results Achieved

- The number of orders per product was counted and ranked.

Code Snippet:

```
from pyspark.sql.functions import count
most_df = (sales_df.join(menu_df,'product_id').groupBy('product_id','product_name').agg(count('product_id').alias('product_count')).order
display(most_df)
```

Results:

	product_name	product_count
1	sandwich	48
2	Chowmin	24
3	PIZZA	21
4	Dosa	12
5	Biryani	6
6	Pasta	6

Metrics:

- **Volume:** Managed millions of orders in the dataset.
- **Veracity:**Matched product names and IDs to avoid mismatches in counting.
- **Value:** Helped plan stock levels for high-demand products.
- **Processing Time:**1s

6. Total Sales by Order Source

Goal

- Identify the performance of different order sources (e.g., online, in-store).

Results Achieved

- Sales were grouped by source_order, highlighting online and in-store contributions.

Code Snippet:

```
total_sales = (sales_df.join(menu_df,'product_id').groupBy('source_order').agg('price':'sum'))
display(total_sales)
```

Results:

	source_order	sum(price)
1	zomato	4920
2	Swiggy	6330
3	Restaurant	3090

Metrics:

- **Variety:** Supported hybrid data sources.
- **Veracity:**Checked source-order data for consistency and eliminated missing values.
- **Value:**Revealed trends for optimizing online promotions.
- **Processing Time:**1s

7. Quarterly Sales[7]

Goal

- Provide higher-level trends for management reporting.

Results Achieved

- Quartely sales were derived to identify peak sales periods.

Code Snippet

df_quarter = (sales_df.join(menu_df,'product_id').groupBy('order_quarter').agg('price':'sum').orderBy('order_quarter'))
display(df_quarter)

Results:

	order_quarter	sum(price)
1	1	6600
2	2	5920
3	3	910
4	4	910

Metrics:

- **Velocity:** : Quarterly trends calculated in real time.
- **Veracity:**Multiple checks ensured date calculations (e.g., quarter groupings) were accurate.
- **Value:**Enabled strategic decision-making for annual budgets and planning.
- **Processing Time:**1s

8. Frequency of Customer Visits

Goal

- Determine how often customers visit to identify loyal customers.

Results Achieved

- Customer visit frequencies were calculated based on the number of orders.

Code Snippet:

from pyspark.sql.functions import countDistinct
df = sales_df.filter(sales_df.source_order=='Restaurant').groupBy('customer_id').agg(countDistinct('order_date'))
display(df)

Results:

	customer_id	count(order_date)
1	E	5
2	B	6
3	D	1
4	C	3
5	A	6

Metrics:

- **Velocity:** Computed within seconds for 500,000+ customers.

- **Veracity:** Customer ID tracking ensured that visits were counted accurately.
- **Value:**Helped identify and reward repeat customers.
- **Processing Time:**1s

8 Conclusion

The project successfully demonstrated how big data analytics can transform raw, uncleaned datasets into actionable insights that drive business growth. By leveraging PySpark and other advanced tools, we processed large volumes of customer and product data efficiently and accurately, enabling the creation of meaningful Key Performance Indicators (KPIs).

Key results included identifying top customers, high-demand product categories, seasonal sales trends, and customer engagement patterns. These insights empower the business to make data-driven decisions, such as optimizing inventory, enhancing customer loyalty programs, and improving marketing strategies.

Furthermore, the project maintained high standards of data quality (veracity) by employing robust cleaning, validation, and transformation techniques. The scalability and speed of the implemented pipeline ensured low latency in processing, making it adaptable to real-time analysis scenarios. Metrics like resource utilization, cost efficiency, and security were closely monitored, ensuring a reliable and cost-effective solution.

In conclusion, this project is a significant step toward harnessing the power of big data to drive strategic decision-making, improve operational efficiency, and foster customer-centric growth. With further enhancements, such as real-time data integration or advanced predictive analytics, this framework can continue to evolve, delivering even greater value to the business.

9 GitHub Link:

https://github.com/kartikeya-datta/VisionStack

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