FINAL PROJECT REPORT

Retail Sales Analytics

Uncovering Revenue Drivers, Category Performance & Discount Efficiency

Title	Retail Sales Analytics – DVA Capstone 1
Sector	Retail
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Team Members	Mayank | Archit | Manjeet | Jivit | Sushant | Akhilesh
Academic Year	2024-28

2. Executive Summary

This report presents our end-to-end data analytics project on Retail Sales, completed as part of the DVA Capstone 1 programme at Newton School of Technology. Our team of six analysed a multi-category retail transaction dataset spanning January 2022 to January 2025, covering 8 product categories and 2 sales channels (Online and In-store). The entire analysis pipeline — from raw data cleaning to dashboard creation — was executed in Google Sheets.

Problem

Organisation had three years of transactional sales data but no structured analytics framework. Without clear visibility into category-level revenue, channel performance, payment trends, and discount effectiveness, management was making decisions based on instinct rather than evidence — leading to missed growth opportunities and margin leakage.

Approach

We sourced the dataset from Kaggle, cleaned it in Google Sheets (handling missing values, duplicates, and format inconsistencies), built a KPI framework, constructed pivot tables, and developed an interactive dashboard with filters. We then performed trend, category, channel, and discount impact analysis before deriving actionable insights.

Key Insights

- Our dataset contains 11,362 transactions generating total revenue of ₹14,72,998.50 with 62,889 units sold.
- Month-over-month revenue growth is –0.97%, signalling near-stagnation that requires strategic intervention.
- Our Revenue Concentration Ratio of 0.51 reveals a significant dependency on just two product categories — posing a business continuity risk.
- Approximately 48% of transactions had a discount applied; while this drives volume, it compresses revenue per transaction.
- Online and In-store channels display distinctly different growth patterns and category preferences.

Key Recommendations

- Reduce revenue concentration by growing underperforming categories through targeted campaigns.
- Redesign discount policies with category-specific profit-floor thresholds to protect margins.
- Prioritise high-AOV categories (Furniture, Computers & Electronics) for online channel investment.
- Implement real-time dashboards to move from monthly retrospective reviews to weekly decision cycles.

3. Sector & Business Context

Sector Overview

We chose to work in the Retail sector — one of the most data-intensive and fast-moving industries in India and globally. Organised retail in India is growing rapidly, driven by increasing urbanisation, rising disposable incomes, digital payment proliferation, and the expansion of e-commerce. Retailers today operate across hybrid models — physical stores and online platforms — serving diverse customer segments across multiple product categories including food, beverages, household goods, electronics, and furniture.

Current Challenges in Retail

During our research and problem framing, we identified the following key challenges that retail businesses commonly face:

- Unstructured, siloed transaction data across channels makes consistent performance measurement difficult.
- Management lacks a unified KPI framework to compare performance across categories, time periods, and locations.
- Discount and promotional strategies are largely intuition-driven, resulting in revenue and margin leakage.
- Inventory decisions are made without adequate demand-side analytics, causing stockouts or overstocking.
- Static, delayed reports prevent timely interventions when sales trends deteriorate.

Why We Chose This Problem

We selected Retail Sales Analytics because it offered a rich, multi-dimensional dataset that allowed us to demonstrate the complete analytics lifecycle — from raw data wrangling to strategic business recommendations. The availability of transactional data spanning 37 months, 8 categories, and 2 channels gave us the depth needed to produce genuinely meaningful insights, while also aligning with real-world business problems that any retail manager would recognise and find valuable.

4. Problem Statement & Objectives

Formal Problem Definition

A retail business has accumulated 37 months of transaction-level sales data across 8 product categories and 2 sales channels but has no structured analytics framework to convert this data into actionable intelligence. The absence of KPI tracking, trend visibility, and discount effectiveness measurement results in suboptimal pricing, inefficient promotional spend, and missed revenue opportunities.

Project Scope

Our project covered the following analytical scope:

- Analyse sales performance across product categories, channels, payment methods, and time periods (2022–2025).
- Define, compute, and track a KPI framework covering revenue, volume, growth, and concentration risk.
- Build an interactive, filter-enabled Google Sheets dashboard for executive-level consumption.
- Identify 8–12 decision-relevant insights from the data.
- Provide business recommendations with impact estimates and feasibility ratings.

Success Criteria

Success Criterion	Definition
Data Completeness	≥95% of records usable after cleaning
KPI Coverage	Minimum 6 KPIs defined and computed from actual data
Insight Depth	8–12 insights, each directly linked to a business decision
Dashboard Usability	Interactive filters by category, channel, and date in Google Sheets
Recommendations	Each recommendation tied to a specific insight and estimated impact

5. Data Description

Exact Dataset Source & Access

Dataset Name: Retail Store Sales Dataset

Source Platform: Kaggle

Citation: Fares Ashraf (2024). Retail Store Sales. Kaggle.
https://www.kaggle.com/datasets/faresashraf1001/retail-store-sales

Our Working File (Google Sheets — Raw Data, Cleaned Data, Pivot Tables, Dashboard):

https://docs.google.com/spreadsheets/d/112HhLBUQNRM1SgkNvdGLBjG2Wk2nk5YADVmCigKOx2Q/edit?usp=sharing

Data Structure & Column Explanation

Column Name	Data Type	Description	Example Value
Transaction ID	String	Unique identifier for each transaction	TXN_6867343
Customer ID	String	Anonymised customer identifier (25 unique customers)	CUST_09
Category	String	Product category — 8 distinct categories	Patisserie
Item	String	Specific product SKU code within its category	Item_10_PAT
Price Per Unit	Decimal	Unit selling price in local currency	18.5
Quantity	Integer	Number of units purchased in the transaction	10
Total Spent	Decimal	Price Per Unit × Quantity (transaction revenue)	185.0
Payment Method	String	Mode of payment used by the customer	Digital Wallet
Location	String	Sales channel: Online or In-store	Online
Transaction Date	Date	Date of transaction (YYYY-MM-DD format)	2024-04-08
Discount Applied	Boolean	Whether a discount was applied (TRUE / FALSE)	TRUE

Data Size

Our dataset contained approximately 11,500 raw rows. After our cleaning process, we retained 11,362 valid transaction records. The data spans 37 months (January 2022 to January 2025) and covers 25 unique customers, 8 product categories, 3 payment methods (Cash, Credit Card, Digital Wallet), and 2 channels (Online, In-store).

Data Limitations

We identified the following limitations in our dataset before beginning analysis:

- Several rows had missing values in the Item, Price Per Unit, Quantity, and Discount Applied fields — requiring careful imputation.
- No Cost of Goods Sold (COGS) data is available, making true gross margin or profitability analysis impossible.
- Only 25 unique customers exist — this is a narrow base that may limit the generalisability of customer behaviour findings.
- No geographic or store-location granularity was available for location-based performance benchmarking.
- The Discount Applied field had blank entries that could not definitively be treated as either TRUE or FALSE.

6. Data Cleaning & Preparation

All primary cleaning and transformation steps were executed in Google Sheets, as per the capstone requirement. We performed our cleaning on the 'retail_store_sales_raw' sheet and maintained the cleaned output in the 'retail_store_sales_cleaned' sheet.

Cleaning Steps Performed

Issue Found	What We Did	Assumption Made	Tool Used
Raw Data Integrity	Copied retail_store_sales_raw into a new working sheet to preserve original dataset	Original raw data must remain unchanged for traceability	Manual sheet duplication in Google Sheets
Duplicate Records	Removed duplicate transaction entries to ensure uniqueness	Each Transaction ID should be unique	Remove Duplicates feature in Google Sheets
Null / Blank Values	Applied filters to detect blanks; removed rows where Column D was blank using FILTER formula	Rows with blank critical fields are invalid for analysis	=FILTER(retail_store_sales_raw!A:J, retail_store_sales_raw!D:D<>"")
Discount Value Inconsistency	Corrected discount lookup using XLOOKUP formula	If discount not found, treat as FALSE (no discount)	XLOOKUP + IF formula in Sheets
Numeric Format Inconsistency	Standardized number, currency, and date formats across columns	Formatting inconsistencies may cause calculation errors	Format → Number in Google Sheets
Data Type Standardization	Ensured consistent numeric and date data types across dataset	Consistent data types improve pivot accuracy	Manual formatting + validation
Date Information Not Structured	Extracted Transaction Year and Transaction Month from Transaction Date	Time-based fields improve trend analysis	Date extraction formulas (YEAR, MONTH)
Pivot Table Errors	Removed null-heavy rows causing pivot calculation errors	Pivot tables require clean, non-null structured data	Filtering + Formula correction

Feature Engineering

We engineered the following additional columns in our cleaned sheet to support analysis:

- Month-Year: Extracted from Transaction Date using =TEXT(date,"MMM-YYYY") for monthly trend analysis.
- Year: Extracted using =YEAR(date) for year-over-year comparisons.
- Revenue Band: Classified each transaction as Low (<₹100), Medium (₹100–₹300), or High (>₹300) for distribution analysis.
- Discount Flag: Standardised Discount Applied to show only TRUE/FALSE; blanks excluded from discount-specific pivot filters.

Assumptions

- We assumed the dataset represents real retail transactions and that no intentional data manipulation occurred at source.
- Imputed values are flagged in our Google Sheet and treated as estimates, not ground truth.
- All monetary values are assumed to be in the same local currency throughout (no FX conversion needed).

7. KPI & Metric Framework

We designed our KPI framework to directly map to our project objectives: measuring revenue performance, understanding volume, tracking growth, and quantifying concentration risk. Each KPI was computed in our Google Sheets pivot and displayed on our dashboard.

KPI Definitions, Formulas & Mapping

KPI	Formula (Google Sheets)	Why This KPI Matters	Objective Mapped To
Total Revenue	=SUM(Total_Spent)	The core measure of our business health across the study period	Revenue Measurement
Total Transactions	=COUNTA(Transaction_ID)	Measures overall business activity and customer engagement volume	Volume Tracking
Total Quantity Sold	=SUM(Quantity)	Indicates total demand and product movement across all categories	Demand Analysis
Average Order Value (AOV)	=Total Revenue ÷ Total Transactions	Reflects basket size; rising AOV = more value per customer visit	Profitability Proxy
Month-over-Month (MoM) Growth	=(Current Month Rev – Prev Month Rev) ÷ Prev Month Rev	Tracks near-real-time revenue trajectory; flags growth or decline early	Growth Monitoring
Revenue Concentration Ratio	=Top 2 Category Revenue ÷ Total Revenue	Quantifies business dependency risk on key product segments	Risk Management

Our Computed KPI Results

KPI	Our Computed Value
Total Revenue	₹14,72,998.50
Total Transactions	11,362
Total Quantity Sold	62,889 units
Average Order Value (AOV)	≈ ₹129.63
Month-over-Month Growth	–0.97%
Revenue Concentration Ratio	0.51

8. Exploratory Data Analysis (EDA)

We conducted our EDA directly in Google Sheets using pivot tables and charts. Below we present our findings across four key analytical dimensions: trends, comparisons, distributions, and correlations.

8.1 Trend Analysis – Monthly Revenue

We calculated monthly revenue using SUMIF across our Month-Year engineered column. Our analysis showed that revenue remained broadly stable across the 37-month period, ranging between approximately ₹30,000 and ₹55,000 per month. The near-flat MoM growth of –0.97% confirmed near-stagnation. We observed predictable seasonal upticks in mid-year (May–July) and year-end (November–December) — which we believe are driven by consumer spending patterns around summer and holiday seasons. These peaks are an exploitable opportunity for targeted promotional campaigns.

8.2 Distribution Analysis – Payment Methods & Revenue Bands

We found that all three payment methods — Cash, Credit Card, and Digital Wallet — were used in relatively balanced proportions across our dataset. Digital Wallet adoption was notably strong, consistent with India's broader digital payment growth trajectory between 2022 and 2025.

In our revenue band distribution, the majority of transactions (approximately 60–65%) fell in the Medium band (₹100–₹300), with a right-skewed long tail of high-value Furniture and Electronics transactions. This bimodal-like pattern confirms the need for separate customer journey designs for high-ticket vs. everyday purchase categories.

8.3 Correlation Analysis – Discounts vs. Revenue

We analysed discounted vs. non-discounted transactions side by side. Our pivot table showed that ~48% of all transactions in our dataset had a discount applied. Discounted transactions showed higher quantity sold on average — consistent with price elasticity — but lower average Total Spent per transaction. This is a clear indicator that while our discounts successfully drive volume, they come at a cost to per-transaction revenue quality. We also observed that certain categories (Patisserie, Furniture) had significantly higher discount rates than others, suggesting non-uniform discount deployment.

9. Advanced Analysis

9.1 Revenue Concentration & Risk Analysis

Our Revenue Concentration Ratio of 0.51 indicates that 51% of our total revenue comes from just two product categories. This level of concentration is a material strategic risk — if either of these categories faces supply disruption, demand contraction, or competitive pressure, more than half our revenue could be impacted. We used this finding to prioritise the recommendation to diversify revenue across underperforming categories.

9.2 Growth Pattern Analysis – Online vs. In-Store Channel

When we segmented transaction trends by channel across 2022, 2023, and 2024, we observed a clear divergence. Online channel transactions showed a gradual year-on-year increase, particularly for Furniture and Computers & Electronics — categories where customers research and compare before buying. In-store transactions were flat-to-declining year-on-year, concentrated in Food, Beverages, and Patisserie. This channel-level insight directly shaped our recommendation to invest in the online channel for high-AOV categories.

10. Dashboard Design

Dashboard Objective

Our dashboard was designed to give management and category managers a single-screen, interactive view of retail performance. We wanted the dashboard to answer the three most critical business questions at a glance: How much are we selling? What is selling? And where is it selling?

Implementation

Our dashboard was built entirely in the 'Dashboard' sheet of our Google Sheets file using pivot tables, SUMIF/COUNTIF formulas, and Google Sheets native charts. We used dropdown-driven Data Validation filters to enable dynamic interaction — no external BI tool or plugin was used, as required by the capstone guidelines.

Dashboard View Structure

Dashboard Panel	What It Shows & Why We Included It
KPI Summary Strip (Top Row)	Displays our 6 core KPIs: Total Revenue (₹14,72,998.50), Total Transactions (11,362), Quantity Sold (62,889), AOV (₹129.63), MoM Growth (–0.97%), Concentration Ratio (0.51) — gives instant health check
Revenue by Category (Bar Chart)	Horizontal bar chart showing each category's total revenue contribution — makes category-level prioritisation immediately visible
Monthly Revenue Trend (Line Chart)	Time-series line chart of monthly revenue from Jan 2022 to Jan 2025 — reveals seasonal patterns and the near-stagnation trend
Online vs. In-Store Channel Split (Donut Chart)	Proportional breakdown of revenue by channel — visual evidence for the online vs. in-store strategic divergence
Payment Method Distribution (Bar Chart)	Transaction count and revenue share by Cash, Credit Card, and Digital Wallet — supports payment infrastructure decisions
Discounted vs. Non-Discounted Revenue	Side-by-side comparison of revenue, quantity, and AOV for discounted vs. non-discounted transactions — directly supports our discount strategy findings

Filters & Drilldowns We Built

- Category Filter: Dropdown to view data for any single category or all categories combined.
- Location Filter: Toggle between Online, In-store, or All — immediately repaints all charts and KPIs.
- Year Filter: Allows year-level comparison between 2022, 2023, and 2024.
- Discount Toggle: Filters all views to show only discounted or only non-discounted transactions.

11. Insights Summary

Below are the 10 most important insights we derived from our analysis. We have written each insight in decision language — directly answering 'So what does this mean for the business?'

#	Insight Title	What It Means for the Business
1	Revenue Stagnation	Our MoM growth of –0.97% tells us that the current strategy is not working. Without a change in approach, revenue will continue to plateau or decline.
2	Concentration Risk is Real	51% of our revenue comes from just two categories. If either underperforms, the business feels it immediately. Diversification is not optional — it is necessary.
3	Online Channel is Growing	Year-on-year, our online transactions are increasing. The business must invest in its digital storefront before this window of advantage narrows.
4	Discounts Drive Volume But Hurt Revenue Quality	~48% discount rate is very high. Discounts are being applied too broadly — not targeted where they are most needed to drive incremental sales.
5	High-AOV Categories Are Underinvested	Furniture and Computers & Electronics generate the highest revenue per transaction but are receiving less marketing attention than Food and Beverages.
6	Seasonal Peaks Are Predictable and Exploitable	We consistently see revenue spikes in May–July and November–December. Pre-positioning inventory and running promotions ahead of these periods is a low-risk, high-reward move.
7	Digital Wallet Adoption Is Rising	Growing digital payment use creates an opportunity to integrate a loyalty programme that rewards wallet users, driving repeat purchase behaviour.
8	In-Store Food & Beverage Drive Footfall	Food and Beverage dominate in-store transactions. Cross-selling higher-margin products at the point of sale could materially increase average basket size.
9	Small but Loyal Customer Base	With only 25 unique customers making thousands of transactions, we have a highly repeat-purchase base. Deepening these relationships through CRM can unlock significant share-of-wallet.
10	No Real-Time Visibility	Our current dataset-based analysis is retrospective. The business needs a live dashboard connected to real-time transaction data to enable week-level interventions.

12. Recommendations

Each of our recommendations is directly mapped to a specific insight, with an assessment of expected business impact and implementation feasibility.

Our Recommendation	Insight #	Business Impact	Feasibility
Launch targeted growth campaigns for Butchers and Electric Household Essentials	2, 8	Reduces revenue concentration from 0.51; grows two underperforming segments	High — low cost, uses existing channels
Redesign discount policy with category-specific profit-floor thresholds	4	Protects per-transaction revenue; reduces unnecessary margin loss on non-price-sensitive buyers	Medium — requires pricing policy and approval process change
Prioritise Furniture and Electronics for online channel product pages and promotions	3, 5	Drives high-AOV purchases through the growing digital channel	Medium — requires investment in product content and online merchandising
Pre-position inventory before May–July and November–December peaks	6	Avoids stockouts during peak demand; maximises revenue capture in proven high-sale windows	High — based on consistent, predictable seasonal patterns in our data
Introduce a loyalty programme integrated with Digital Wallet payments	7, 9	Increases repeat purchase frequency and share-of-wallet from our existing loyal customer base	Medium — requires fintech integration and programme design investment
Deploy cross-sell strategies at in-store POS for food and beverage customers	8	Increases average basket value per in-store visit with minimal incremental cost	High — primarily training-based; no significant capital expenditure needed
Implement a real-time sales dashboard with weekly reporting cadence	10	Shifts management from reactive monthly reviews to timely, proactive weekly decisions	Medium — Google Data Studio or Sheets live API connection required

13. Impact Estimation

We have estimated the approximate business impact of our recommendations. We acknowledge these are directional estimates based on dataset analysis and retail industry benchmarks — actual results will depend on execution quality, market conditions, and customer response.

Impact Area	Estimated Gain / Saving	How It Will Be Achieved	Confidence Level
Cost Saving — Discount Optimisation	3–5% revenue uplift (~₹44,000–₹74,000 annually)	Removing blanket discounts from non-price-sensitive transactions while retaining targeted offers	Medium
Efficiency — Seasonal Inventory Pre-positioning	2–3% reduction in stockout revenue loss	Pre-ordering top-selling SKUs 6–8 weeks before identified peak windows	Medium-High
Revenue Improvement — High-AOV Category Push	5–8% AOV increase (~₹6.50–₹10.40 per transaction)	Shifting online product mix toward Furniture and Electronics categories	Medium
Service Improvement — Loyalty Programme	10–15% increase in repeat transaction frequency	Rewarding Digital Wallet users and loyal customer base with points or exclusive offers	Medium-Low
Revenue Improvement — In-store Cross-sell	₹15–₹25 incremental revenue per in-store visit	Training staff to suggest complementary products at checkout for food and beverage buyers	High
Risk Reduction — Revenue Diversification	Reduce concentration ratio from 0.51 to ≤0.40 over 12 months	Growing two underperforming categories through dedicated campaigns and shelf space	Medium

14. Limitations

Data Issues We Encountered

- No COGS data was available, so we could not compute true gross margins or profitability per category or transaction.
- Missing values in Item, Price Per Unit, Quantity, and Discount Applied fields required imputation, which introduces estimation uncertainty.
- Only 25 unique customers were in our dataset — findings about customer behaviour should not be generalised to larger retail populations without caution.
- No geographic or store-level granularity was present, preventing location-based performance benchmarking.

Assumption Risks

- Our imputed values (median price, modal item name) may introduce systematic bias if the pattern of missing data is non-random.
- Our scenario analysis assumes a specific price elasticity that may not hold uniformly across all categories.
- Treating blank Discount Applied entries as 'Unknown' (rather than FALSE) means our discount rate calculation may be understated.

What We Cannot Conclude from This Data

- We cannot determine true profit margins — only revenue and AOV proxies.
- We cannot establish causality between discount application and customer acquisition — discounts may only be changing transaction size, not bringing new customers.
- We cannot attribute revenue trends to specific business events, competitor actions, or macroeconomic factors using this dataset alone.
- We cannot perform customer lifetime value (LTV) analysis without customer demographic and acquisition cost data.

15. Future Scope

What More Analysis We Can Do

- Sales forecasting using time-series models (ARIMA, Facebook Prophet) to predict next-quarter revenue by category — this would allow proactive rather than reactive inventory and marketing planning.
- RFM (Recency, Frequency, Monetary) customer segmentation to identify high-value vs. at-risk customers and personalise retention strategies.
- Market Basket / Association Rule analysis to identify frequently co-purchased item pairs — directly enabling cross-sell product bundling.
- Predictive discount modelling to determine optimal discount depth by category and customer segment, replacing our current blanket approach.
- Year-over-year cohort analysis to track whether customer purchase frequency is improving or declining across the three-year period.

What New Data We Would Need

- Cost of Goods Sold (COGS) per SKU — to compute true gross margins and make profit-based category decisions.
- A larger, more diverse customer base (1,000+ customers) — for statistically robust segmentation and persona development.
- Store-level and regional data — to enable geographic performance benchmarking and location-specific strategy.
- Customer demographic data (age, location, income bracket) — to build persona-based marketing and loyalty models.
- Real-time transaction feeds — to power a live dashboard and enable week-level monitoring rather than retrospective monthly analysis.

16. Conclusion

Through this DVA Capstone project, our team successfully applied the complete data analytics lifecycle to a real-world retail transaction dataset — from raw data ingestion and cleaning to KPI design, exploratory and advanced analysis, dashboard development, and business recommendations.

Working with 11,362 transactions across 37 months, 8 product categories, and 2 sales channels, we uncovered 10 critical business insights. Our analysis revealed a business at an inflection point: revenue is stable but stagnating (–0.97% MoM growth), concentration risk is high (51% revenue from two categories), and the online channel is showing growth that is not yet being fully capitalised on. At the same time, our data exposed a discount strategy that is too broad and a set of high-AOV categories that are underinvested.

Our seven recommendations — grounded in data and assessed for feasibility — offer a clear, actionable roadmap for the business to recover growth momentum, protect margins, and reduce strategic risk. Our estimated combined impact across these recommendations could yield ₹50,000–₹1,00,000 in annual revenue improvement alongside meaningful margin protection and improved customer retention.

The Google Sheets dashboard we built ensures that these insights do not end with this report — management now has a self-service analytical tool to monitor the KPIs we defined on an ongoing basis. With the future enhancements we have outlined — particularly real-time data integration and predictive modelling — this framework can evolve into a fully operational retail intelligence platform.

This project reinforced for our team that the most valuable skill in data analytics is not just technical proficiency — it is the ability to translate numbers into business decisions. That is exactly what we have aimed to deliver here.

17. Appendix A

Data Structure & Column Explanation

Column Name	Data Type	Description	Example Value
Transaction ID	String	Unique identifier for each transaction	TXN_6867343
Customer ID	String	Anonymised customer identifier (25 unique customers)	CUST_09
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Location	String	Sales channel: Online or In-store	Online
Transaction Date	Date	Date of transaction (YYYY-MM-DD format)	2024-04-08
Discount Applied	Boolean	Whether a discount was applied (TRUE / FALSE)	TRUE

18. Contribution Matrix

This section documents each team member's contribution across all project stages. All contribution claims are verifiable through the Google Sheets Version History of our shared working file.

Team Member	Dataset & Sourcing	Cleaning	KPI & Analysis	Dashboard	Report Writing	PPT	Overall Role
Mayank		Yes		Yes			Dashboard Lead
Archit		Yes			Yes		Data Cleaning Lead
Manjeet	Yes		Yes				Analysis Lead
Jivit	Yes					Yes	Strategy Lead
Sushant	Yes				Yes		Project Lead
Akhilesh					Yes	Yes	PPT and Report Lead