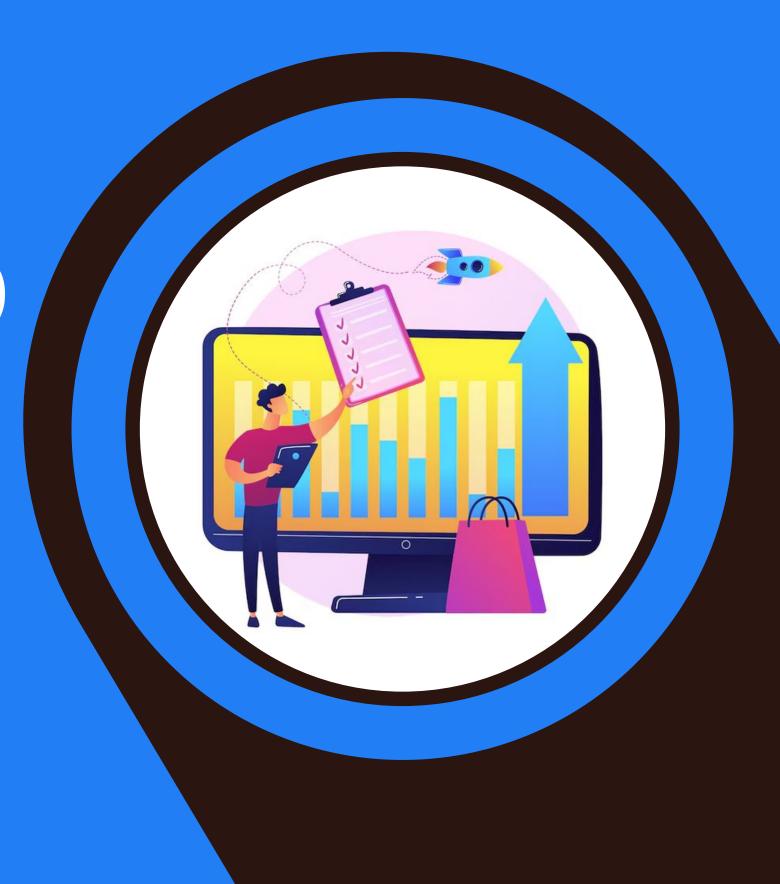
INVENTORY FORECAST DEMAND

Team Members:

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Overview

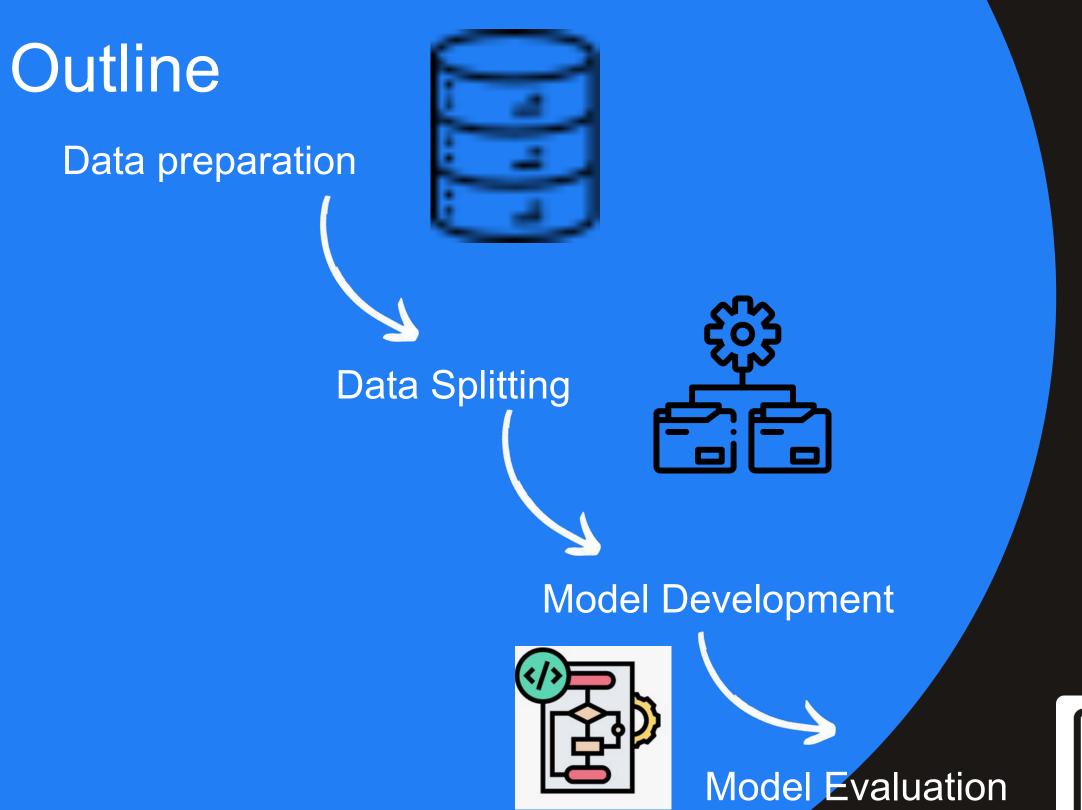
01 Outline 06 Experimental Results

02 Problem Statement 07 Result Analysis

03Introduction08Future Work

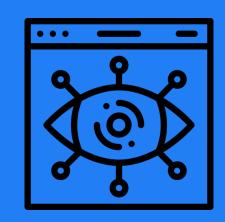
04 Model and Methods 09 Conclusion

05 Dataset Details





Visualisation



Problem Statement

Efficient inventory management is essential for businesses to meet customer demand effectively while minimizing costs. However, accurately predicting inventory needs presents a significant challenge



Stockouts

Running out of products leads to lost sales & unhappy customers.



Obsolete Inventory

Products becoming outdated result in financial losses



Supply Chain Disruptions

Unexpected events like delays or transportation issues disrupt inventory flow, affecting customer satisfaction



Excess Inventory

Holding too much stock ties up money and space, increasing costs.



Inaccurate Forecasts

Poor predictions lead to inefficient ordering and mismatched inventory levels.

Introduction

Welcome to the Retail Sales Prediction presentation. Today, the focus is on analyzing sales data from 2010 to 2012 to forecast demand for Walmart, a major U.S. retail chain. This presentation will cover



Project Overview Understanding

the goals.

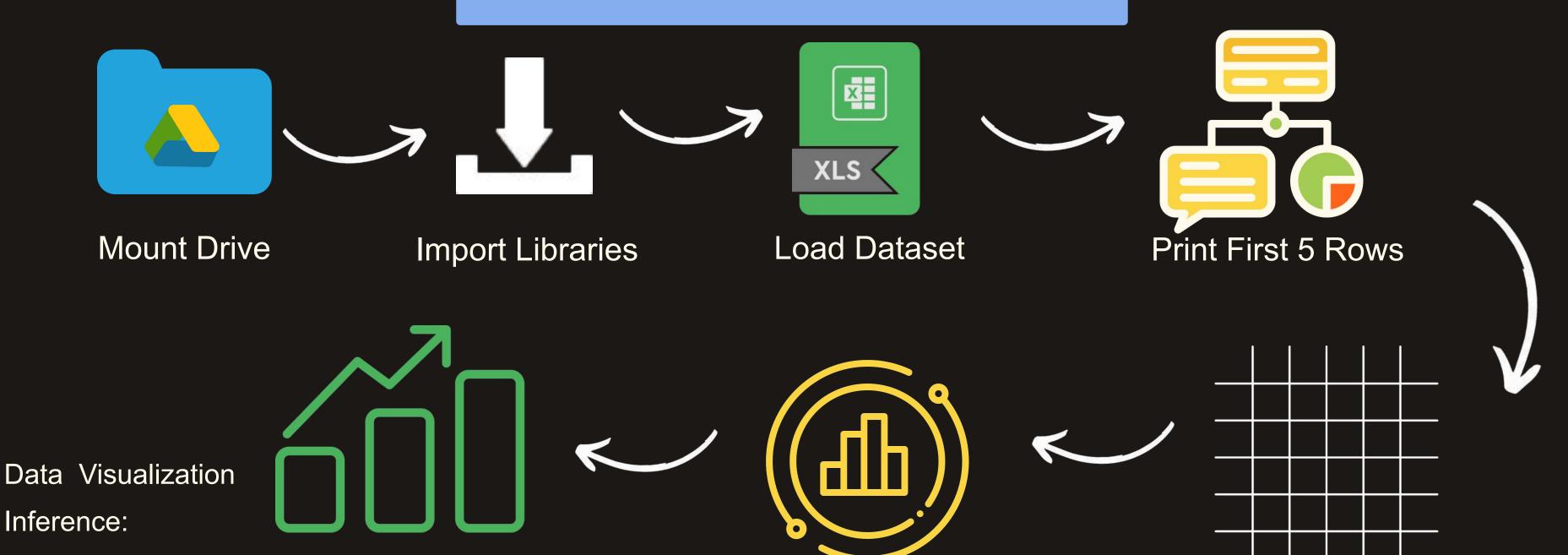


Modeling Techniques Predicting sales methods.







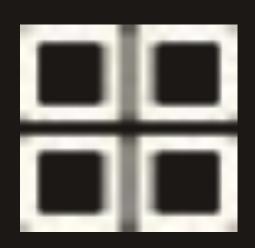


- 1. Best season summer
- 2. TOTAL SALES IN EACH YR 2011
- 3. TOTAL SALES IN EACH MONTH july
- 4. TOTAL SALES IN EACH WEEK week 51
- 5. HEAT MAP

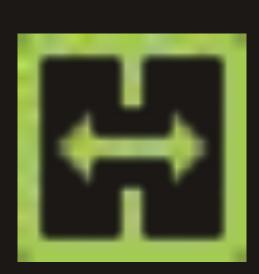
- **Data Pre-Processing**
- 1. Handling Missing values
 - 2. Feature Engineering

EDA
Patterns+anomalies=Hypothesis

After Data Visualization







Type Casting
Better Analysis

Data Transformation

Data splitting

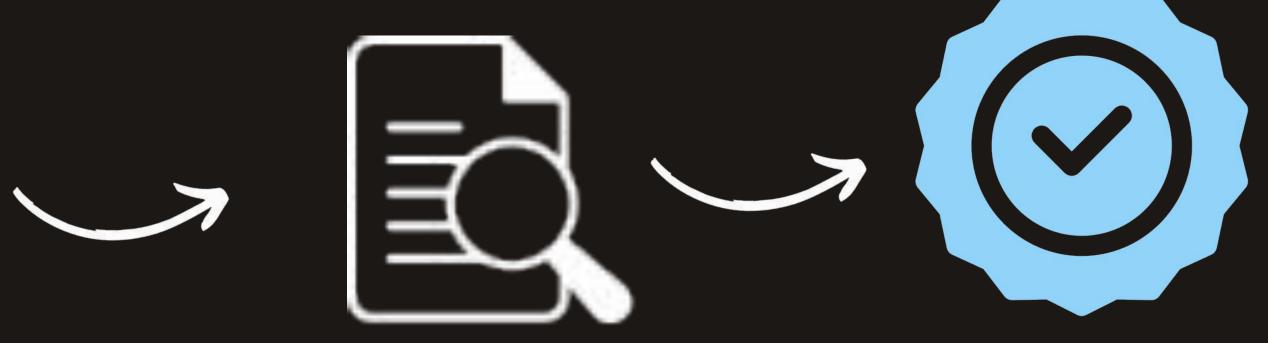
- 1. Copy code to df1
- 2. Numerical data to categorical (Explicit)
- 3. Store, holiday flag & week converted

- Numerical Features : ['Temperature', 'Fuel_Price 'CPI', 'Unemployment']
- 2. Categorical Features:['Store','Holiday_Flag', 'we

After Detecting And Removing
Outliers







Hyperparameter Tuning(GRID SEARCH Cross Validation + RANDOMISED SEARCH)

- 1. Z-Score
- 2. Total outliers: 675 when threshold = 3
- 3. 3 is standard deviation from mean is a common approach holding about 99.7% of data under a normal distribution
- 1. Small dataset
- 2. Few hyperparameters
- 3. Grid search > Random search for accuracy

Supervised Learning

Linear Regression

Global estimator

Regression

Non-linear Relationship

Polynomial

Random

Forest

Predictive

Ridge

Regression

Coefficient estimation

KNN

Regressor

Local estimation Lasso

Regression

Predictive

Accuracy

XGB

Regressor

Gradient Boosting

Individual predictions

Decision

Tree

accuracy

Unsupervised Learning

K Means

Clustering

Grouping unlabeled

datasets

Hierachical

Clustering

Organizing groups

based on similarities

Evaluation Metrics

Supervised & Deep

- Mean Absolute Error (MAE)
- Mean Squared Error (MSE)
- 3. Root Mean Squared Error (RMSE)

4 R Squared (R2)

Unsupervised

- 1. Silhouette score
- 2. index

Deep Learning

Multi-Layer

Perceptron

Interconnected

neural network

Visualization

Distribution Plot

Dataset Details

- Well-documented
- Learning purpose
- covers sales from 2010-02-05 to 2012-11-01
- In the dataset,
 - Store the store number
 - Date the week of sales
 - Weekly_Sales sales for the given store
 - Holiday_Flag whether the week is a special holiday week 1 Holiday week 0 Non-holiday week
 - Temperature Temperature on the day of sale
 - Fuel_Price Cost of fuel in the region
 - CPI Prevailing consumer price index
 - Unemployment Prevailing unemployment rate
 - Holiday Events
 - Super Bowl: 12-Feb-10, 11-Feb-11, 10-Feb-12, 8-Feb-13
 - Labour Day: 10-Sep-10, 9-Sep-11, 7-Sep-12, 6-Sep-13
 - Thanksgiving: 26-Nov-10, 25-Nov-11, 23-Nov-12, 29-Nov-13
 - Christmas: 31-Dec-10, 30-Dec-11, 28-Dec-12, 27-Dec-13
- One of the leading retail stores in the US, Walmart, would like to predict the sales and demand accurately. There are certain events and holidays which impact sales on each day. There are sales

Experimental Results

1	MODEL NAME	DATA	MAE	MSE	RMSE	R2
2		TRAINING	358406.76	204470961002.30	452184.65	31.08 %
3	LINEAR REGRESSION	TESTING	362471.07	210920722575.97	459261.06	31.86 %
4						
5		TRAINING	58374.79	6886879714.26	82987.23	97.68 %
6	POLY REGRESSION	TESTING	69004.3	9318364369.55	96531.68	96.99 %
7						
8	RIDGE REGRESSION GRID	TRAINING	358542.43	204480782446.65	452195.51	31.07 %
9	SEARCH	TESTING	362730.83	210893777737.26	459231.73	31.87 %
10						
11	RIDGE REGRESSION	TRAINING	358484.39	204474451017.80	452188.51	31.08 %
12	RANDOM SEARCH	TESTING	362622.14	210901978470.13	459240.65	31.86 %
13						
14	LASSO REGRESSION	TRAINING	358407.68	204470966370.87	452184.66	31.08 %
15	GRID SEARCH	TESTING	362472.09	210919193605.71	459259.4	31.86 %
16						
17	LASSO REGRESSION	TRAINING	358407.67	204470966241.68	452184.66	31.08 %
18	RANDOM SEARCH	TESTING	362472.07	210919212014.84	459259.42	31.86 %
19						
20	DECISION TREE GRID SEARCH	TRAINING	27113.33	2256760434.69	47505.37	99.24 %
21		TESTING	59095.59	8772553461.59	93661.91	97.17 %
22						
23	DECISION TREE RANDOM SEARCH	TRAINING	27000.89	2244776329.23	47379.07	99.24 %
24		TESTING	58738.8	8753530390.98	93560.3	97.17 %

Experimental Results

	А	В	С	D	E	F
1	MODEL NAME	DATA	MAE	MSE	RMSE	R2
26	RANDOM FOREST GRID	TRAINING	24055.94	1802225821.92	42452.63	99.39 %
27	SEARCH	TESTING	64607.3	13365236840.70	115608.12	95.68 %
28						
29	RANDOM FOREST	TRAINING	40365.92	5119646425.12	71551.7	98.27 %
30	RANDOM SEARCH	TESTING	65684.06	13874073317.90	117788.26	95.52 %
31						
32		TRAINING	0.0	0.00	0.0	100.0 %
33	KNN GRID SEARCH	TESTING	214115.04	79202332295.33	281429.09	74.41 %
34						
35		TRAINING E	246614.87	101506755882.72	318601.25	65.78 %
36		TESTING E	256808.54	110053791468.37	331743.56	64.45 %
37						
38		TRAINING	0.0	0.00	0.0	100.0 %
39	KNN RANDOM SEARCH	TESTING	291807.32	133755273840.64	365725.68	56.79 %
40						
41		TRAINING E	346471.61	178306750577.20	422263.84	39.9 %
42		TESTING E	358868.73	192819516586.96	439112.19	37.71 %
43						
44	XBG REGRESSOR GRID SEARCH	TRAINING	65424.52	9102237939	95405.65	96.93 %
45		TESTING	75429.65	12495116665.71	111781.56	95.96 %
46						
47	XBG REGRESSOR RANDOM SEARCH	TRAINING	94695.14	18516254405.49	136074.44	93.76 %
48		TESTING	103000.97	22844342401.63	151143.45	92.62 %

Experimental Results

	А	В	С	D	Е	F
1	MODEL NAME	DATA	MAE	MSE	RMSE	R2
49						
50						
51						
52		INERTIA	12026.7834735127			
53	K MEANS CLUSTERING	SILHOUSE SCORE	0.116711518227683			
54						
55	HIERACHICAL CLUSTERING	Cophenetic Correlation Coefficient	0.521065897267871			
56		SILHOUSE SCORE	0.159184013358915			
57						
58	NEURAL NETWORKS - MULTI LAYER PERCEPTRON (MLP)	TRAINING	391606.57	234613111059.68	484368.78	20.92 %
59		TESTING	395631.04	241326470551.12	491249.91	22.04 %
60						

Conclusion



- Best Supervised Model
 - Decision Tree with Random Search or Random Forest with Grid
 Search
 - Low MAE, MSE, RMSE
 - High R2 scores on training and testing data
- Best Unsupervised Model
 - Hierarchical clustering
 - Moderate cophenetic correlation
 - Higher silhouette score

Polynomial Regression achieves highest score

- Deep Learning Model (MLP)
- High errors
- Low R2 values
- Model Analysis
- Polynomial Regression, Random Forest, and XGB Regressor outperform others
- Best scores
- Generalization capability
- Avoiding overfitting
- 8 8



Future Works

Feature Engineering Refinement

Further exploration and engineering of features to capture more nuanced patterns and relationships in the data

Ensemble Methods Exploration

Investigate the effectiveness of ensemble methods such as stacking or blending to combine the strengths of multiple models and improve overall performance

Hyperparameter Fine-Tuning

Conduct thorough hyperparameter tuning for the selected models to optimize performance further and achieve even better results

Incorporate External Data

Explore the integration of additional external datasets, such as economic indicators or demographic information, to enhance the predictive capabilities of the models.

Deep Learning Architectures

Experiment with more complex deep learning architectures or pre-trained models to leverage the potential of neural networks for improved forecasting



Thank You