

A survey of ML Based sales prediction

Team: Hinton's Heuristics

Members:

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Course Instructor:

Prof. Preethi Jyothi

Task Description

Aim:

- Predict Walmart's sales for the next **28 days** using the **M5** dataset.

Dataset:

- **6 years** of Walmart sales data across **3 states**.

Method:

- Incorporate events, holidays, and promotions into the forecast.

Focus:

- Evaluate **Linear Regression**, **LSTM** and **LightGBM** models.

Evaluation:

- The RMSSE formula from the M5 competition is the following:

$$RMSSE = \sqrt{\frac{1}{h} \frac{\sum_{t=n+1}^{n+h} (Y_t - \hat{Y}_t)^2}{\frac{1}{n-1} \sum_{t=2}^n (Y_t - Y_{t-1})^2}},$$

Dataset Details

Calendar

Holiday,
Promotion
etc details

215 MB

1969x14

Sales_train

Per day
sales, item
wise

452 MB

30490x18

Sell Prices

Item wise
sale prices

208 MB

6841121x
4

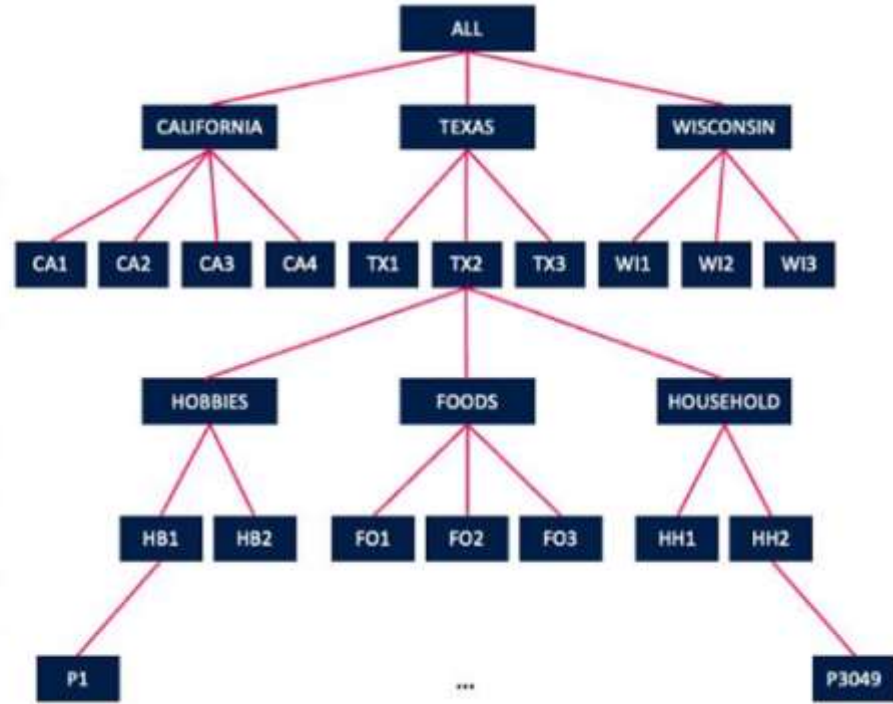
3 states

10 stores

3 product
categories

7 product
sub-categories

3049
products



Data Preprocessing

Memory Optimization with Down casting

- **Purpose:** large data types (**float64**) into smaller ones (**float32**) w/o losing precision.
- **Implementation:** Dynamically using NumPy.
- **Impact:** Optimized data storage and faster processing
- **Result:** Reduction in size upto 45% *.

Data Normalization with Min-Max Scaling

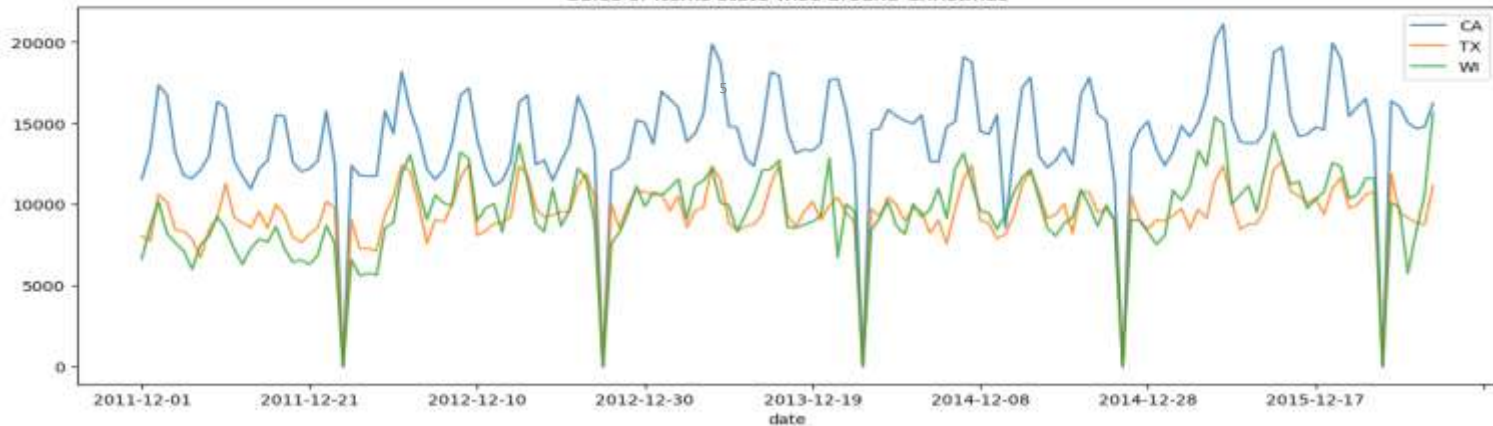
- **Purpose:** Standardize numeric data to a common scale (-1 to 1 in this case).
- **Implementation:** Utilizes **MinMaxScaler** while preserving the proportionality in features
- **Impact:** training stability and convergence for features with varying scales.

EDA

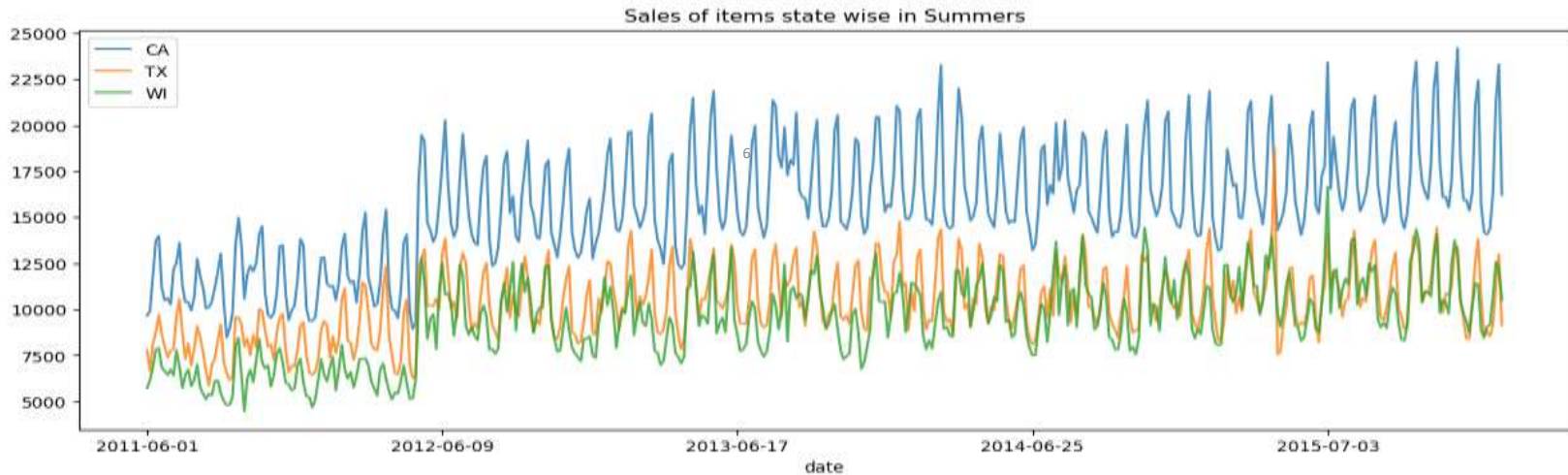
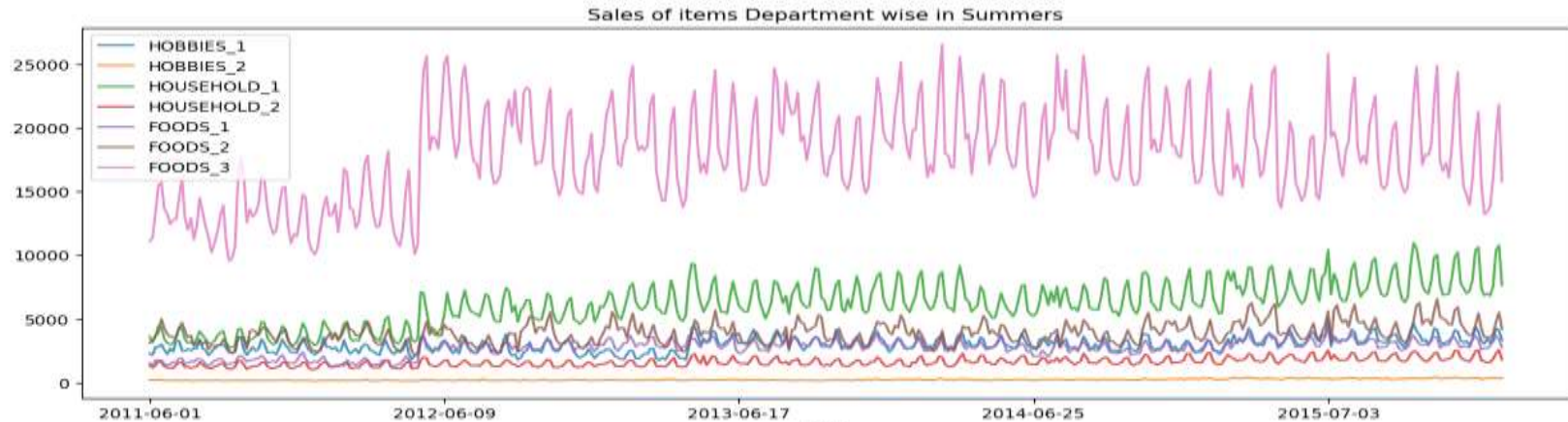
Sales of items category wise during Christmas



Sales of items state wise around Christmas



EDA



Linear Regression: Ridge regression model

Salient Features:

Tailored Predictions: Models can be optimized for specific category patterns and trends.

Reduced Noise: Less diverse data leads to better focus on relevant features.

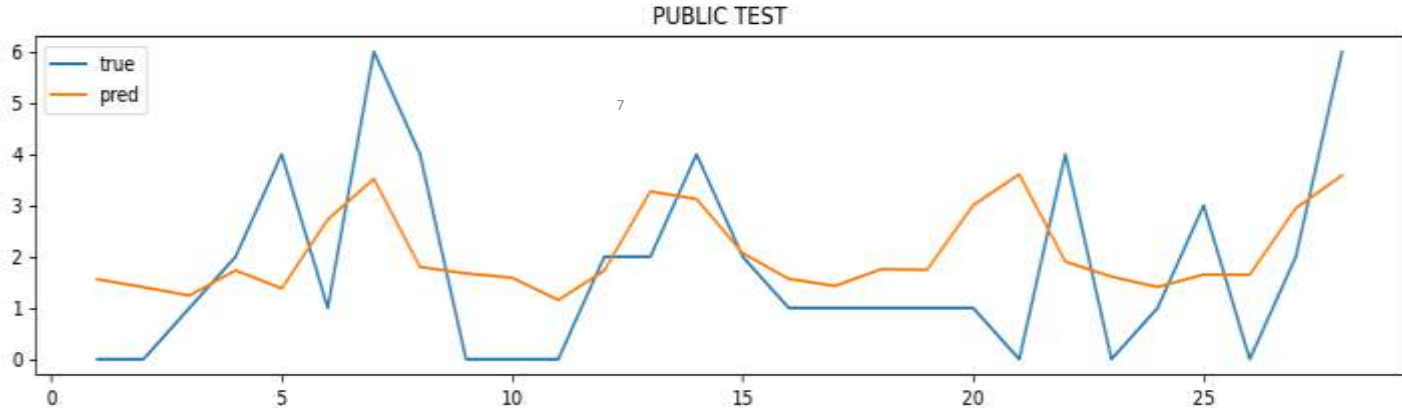
Faster Training and Inference: Smaller datasets accelerate model training and prediction.

Improved Interpretability: Insights from individual models can inform targeted strategies.

Enhanced Accuracy: Specialized models can yield more accurate predictions.

RMSSE Score - 0.69725

Sample Prediction for HOBBIES 1 004 CA 1



LSTM

Key Training Parameters

Number of Epochs: 500

Number of Layers: 4

Learning Rate: 1×10^{-3}

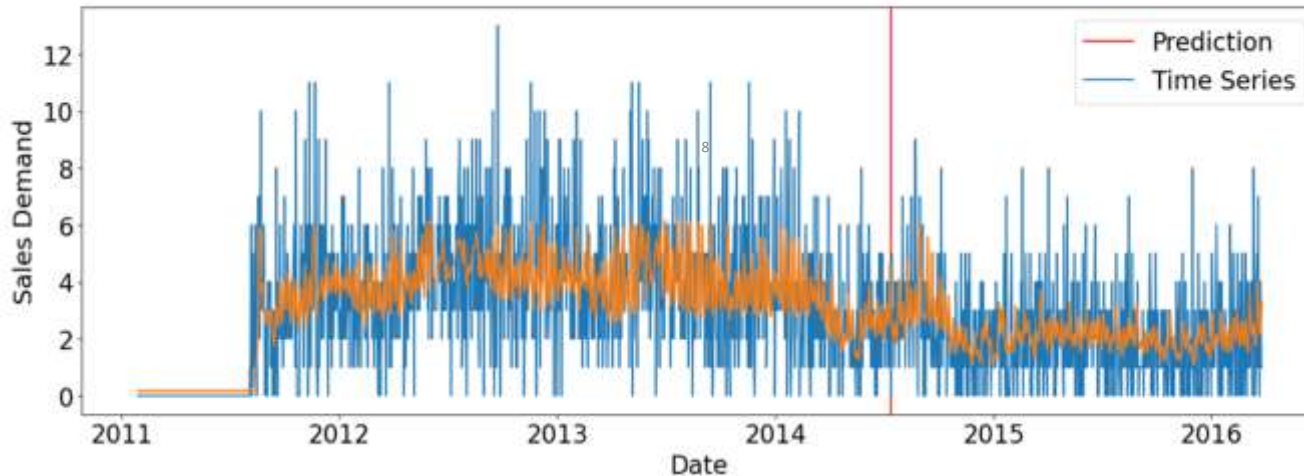
Optimizer: Adam with L2 Regularization

Hidden Size: 512

Learning Rate Scheduler: patience = 50, factor = 0.5

RMSSE - 0.76605

Time-Series Prediction Entire Set



LIGHTGBM

Purpose: To understand LightGBM and explore its features

Approach Taken:

Reduced the dataset from 6 years to 2 years
Prediction carried out for random item selected from the dataset for next 28 days

Evaluation Methodology:

Generated forecast for random items and compare it with proven prediction from kaggle

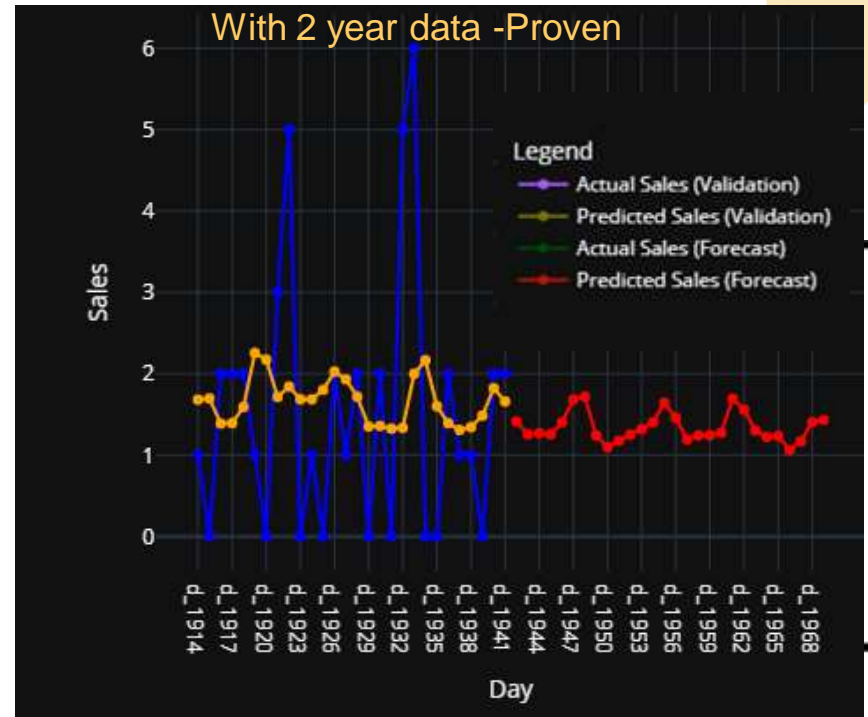
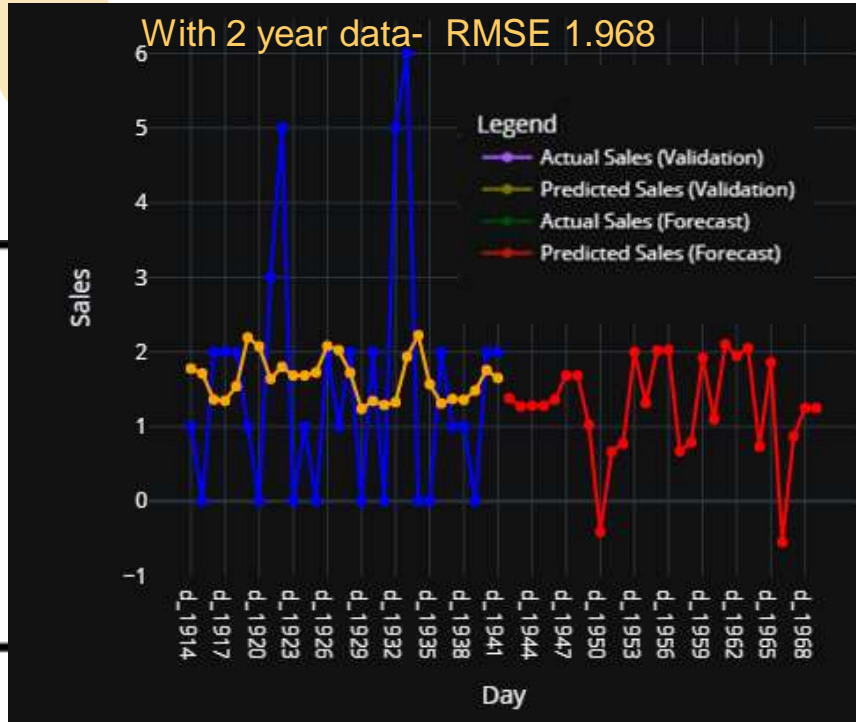
Feature Engineering:

Merging relevant features of three dataset into one
Lag and rolling mean for last 7 days and 28 days

Model Parameters:

```
lgb_params = (  
    'objective': 'regression',  
    'metric': 'rmse',  
    'boosting_type': 'gbdt',  
    'num_leaves': 31,  
    'learning_rate': 0.1,  
    'feature_fraction': 0.5,  
    'seed' : 2000  
)
```

LIGHTGBM-Results



Possible Reasons for difference in results:

1. Tweedie Regression objective function and other parameters considered for tuning
2. Recursive prediction

TEAM TASK ALLOTMENT

Sr.	Task	Executed By
1	Data Preprocessing	Prashik
2	EDA	Team
3	LSTM	Shoaib
4	Linear Regression	Prashik
5	LGBM	JatinKumar

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Mr Ambuj Nayan(24M0003) has not participated in any project activity for unknown reasons.



Thank
You