Analyzing Walmart Sales

Data Science Programming

How do outside factors like unemployment and weather impact Walmart's sales?

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Agenda

What we'll discuss today

01 Background & EDA

02 Feature Engineering & Data Splitting

03 Our Models

04 Analysis/Takeaways

05 Conclusion

Background

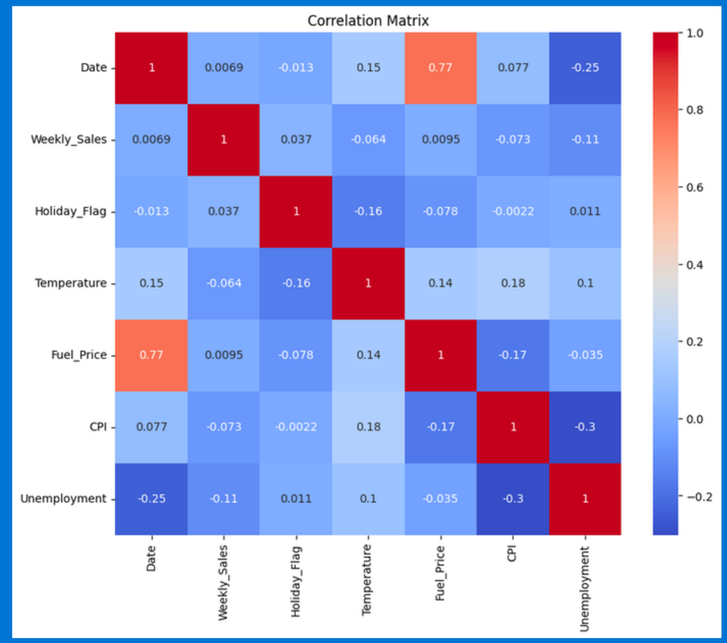
- **Dataset Information:** "Walmart Dataset (Retail)" by Rutu Patel from Kaggle
- **Variables Include:** Store, Date, Weekly_Sales, Holiday_Flag, Temperature, Fuel_Price, CPI, Unemployment
- **Research Objective:** Identify patterns in Walmart’s weekly sales influenced by factors like weather and national economic conditions.
- **Store-Specific Analysis:** Explore patterns specific to different store locations based on the stratified data.

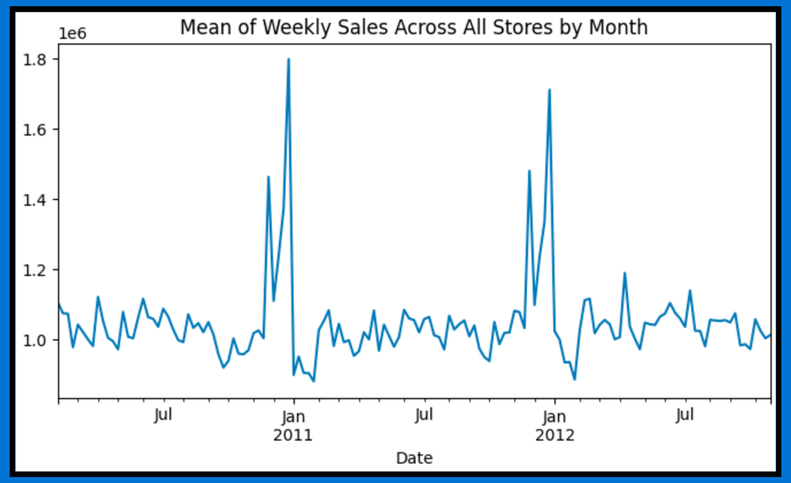
https://www.kaggle.com/datasets/rutuspatel/walmart-dataset-retail

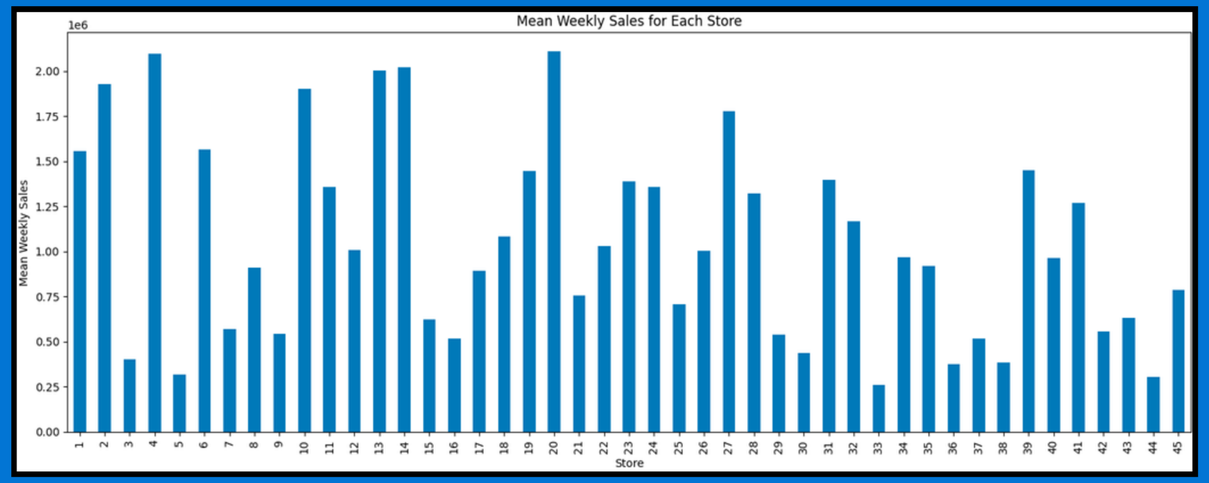
	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
count	6435	6.435000e+03	6435.000000	6435.000000	6435.000000	6435.000000	6435.000000
unique	143	NaN	NaN	NaN	NaN	NaN	NaN
top	5/2/2010	NaN	NaN	NaN	NaN	NaN	NaN
freq	45	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	1.046965e+06	0.069930	60.663782	3.358607	171.578394	7.999151
std	NaN	5.643666e+05	0.255049	18.444933	0.459020	39.356712	1.875885
min	NaN	2.099862e+05	0.000000	-2.060000	2.472000	126.064000	3.879000
25%	NaN	5.533501e+05	0.000000	47.460000	2.933000	131.735000	6.891000
50%	NaN	9.607460e+05	0.000000	62.670000	3.445000	182.616521	7.874000
75%	NaN	1.420159e+06	0.000000	74.940000	3.735000	212.743293	8.622000
max	NaN	3.818686e+06	1.000000	100.140000	4.468000	227.232807	14.313000

Exploratory Data Analysis

- Seasonality (holiday spikes)
- Significant variation in weekly sales depending on store number
- Correlations
  - Fuel price & date
  - Unemployment & date
  - CPI & unemployement







Feature Engineering & Data Splitting

1

Distance variables

Difference between individual store observations & store averages

Difference between individual store observations & national averages

2

Log Terms

Transformed weekly sales response variables into log terms to reduce skewness given wide range

3

One-Hot Encoding

Converted each unique store from a categorical variable into a dummy variable

4

Test-Train Split

Applied 80-20 split

Resulted in MSE in billions...

Reevaluate!

5

Revise Train/Test Split

Recoded train/set split to ensure inclusion of all store numbers in test set that were represented in train set

Multiple Regression

OLS Regression Results

Dep. Variable:	Weekly_Sales	R-squared:	0.958
Model:	OLS	Adj. R-squared:	0.958
Method:	Least Squares	F-statistic:	2367.
Date:	Sat, 10 Aug 2024	Prob (F-statistic):	0.00
Time:	16:21:03	Log-Likelihood:	3598.1
No. Observations:	5112	AIC:	-7096.
Df Residuals:	5062	BIC:	-6769.
Df Model:	49		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.5503	0.002	709.394	0.000	1.546	1.555
Holiday_Flag	0.0573	0.007	8.540	0.000	0.044	0.070
Temperature	0.0027	0.000	13.530	0.000	0.002	0.003
Fuel_Price	2.9887	0.003	995.883	0.000	2.983	2.995
CPI	0.0107	4.54e-05	235.082	0.000	0.011	0.011
Unemployment	0.0105	0.001	9.804	0.000	0.008	0.013
temp_distance	-0.0029	0.000	-13.075	0.000	-0.003	-0.003
fuel_price_distance	-1.5088	0.003	-475.468	0.000	-1.515	-1.503
cpi_distance	-0.0041	0.000	-9.506	0.000	-0.005	-0.003
unemployment_distance	-0.0139	0.002	-7.312	0.000	-0.018	-0.010
fuel_price_distance_national_avg	-1.5088	0.003	-475.468	0.000	-1.515	-1.503
cpi_distance_national_avg	-0.0041	0.000	-9.506	0.000	-0.005	-0.003
unemployment_distance_national_avg	-0.0139	0.002	-7.312	0.000	-0.018	-0.010
Store_1	0.5067	0.011	44.710	0.000	0.484	0.529
Store_2	0.7257	0.011	64.583	0.000	0.704	0.748
Store_3	-0.8815	0.011	-79.179	0.000	-0.903	-0.860

Root Mean Squared Error: 184,783
R-squared: 0.90

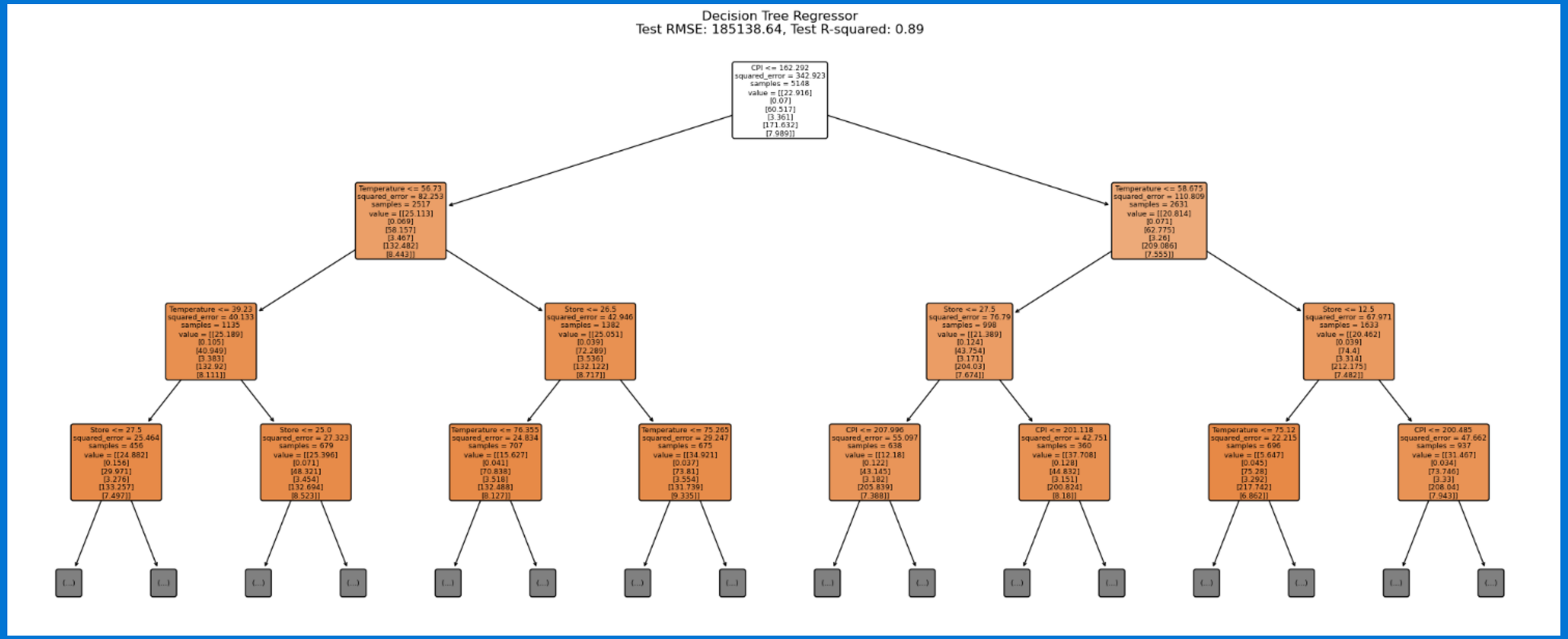
90% of variability in weekly sales is explained by the predictors

- We also tried LASSO, but gave worse result. So, we decided to leave that model out.

Regression Tree

Root Mean Squared Error: 185,139
R-squared: 0.89

89% of variability in weekly sales is explained by the predictors


Decision Tree Regressor
Test RMSE: 185138.64, Test R-squared: 0.89
CPI <= 162.292
squared_error = 342.923
samples = 5148
value = [[22.916]
[0.07]
[60.517]
[3.361]
[171.632]
[7.989]]
Temperature <= 56.73
squared_error = 82.253
samples = 2517
value = [[25.113]
[0.069]
[58.157]
[3.467]
[132.482]
[8.443]]
Temperature <= 58.675
squared_error = 110.809
samples = 2631
value = [[20.814]
[0.071]
[62.775]
[3.26]
[209.086]
[7.555]]
Temperature <= 39.23
squared_error = 40.133
samples = 1135
value = [[25.189]
[0.105]
[40.949]
[3.383]
[132.92]
[8.111]]
Store <= 26.5
squared_error = 42.946
samples = 1382
value = [[25.051]
[0.039]
[72.289]
[3.536]
[132.122]
[8.717]]
Store <= 27.5
squared_error = 76.79
samples = 998
value = [[21.389]
[0.124]
[43.754]
[3.171]
[204.03]
[7.674]]
Store <= 12.5
squared_error = 67.971
samples = 1633
value = [[20.462]
[0.039]
[74.4]
[3.314]
[212.175]
[7.482]]
Store <= 27.5
squared_error = 25.464
samples = 456
value = [[24.882]
[0.156]
[29.971]
[3.276]
[133.257]
[7.497]]
Store <= 25.0
squared_error = 27.323
samples = 679
value = [[25.396]
[0.071]
[48.321]
[3.454]
[132.694]
[8.523]]
Temperature <= 76.355
squared_error = 24.834
samples = 707
value = [[15.627]
[0.041]
[70.838]
[3.518]
[132.488]
[8.127]]
Temperature <= 75.265
squared_error = 29.247
samples = 675
value = [[34.921]
[0.037]
[73.81]
[3.554]
[131.739]
[9.335]]
CPI <= 207.996
squared_error = 55.097
samples = 638
value = [[12.18]
[0.122]
[43.145]
[3.182]
[205.839]
[7.388]]
CPI <= 201.118
squared_error = 42.751
samples = 360
value = [[37.708]
[0.128]
[44.832]
[3.151]
[200.824]
[8.18]]
Temperature <= 75.12
squared_error = 22.215
samples = 696
value = [[5.647]
[0.045]
[75.28]
[3.292]
[217.742]
[6.862]]
CPI <= 200.485
squared_error = 47.662
samples = 937
value = [[31.467]
[0.034]
[73.746]
[3.33]
[208.04]
[7.943]]
(...)
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Random Forest

MAE: 113,643

RMSE: 196,575

R-squared: 0.89

89% of variability in weekly sales is explained by the predictors

Gradient Boosting

```
param_grid = {
    'learning_rate': [0.01, 0.05, 0.1],
    'n_estimators': [100, 300, 500],
    'subsample': [0.8, 1.0],
    'max_depth': [3, 5, 7],
    'alpha': [0.1, 0.2, 0.3]
}
```

Root Mean Squared Error: 130,876
R-squared: 0.94

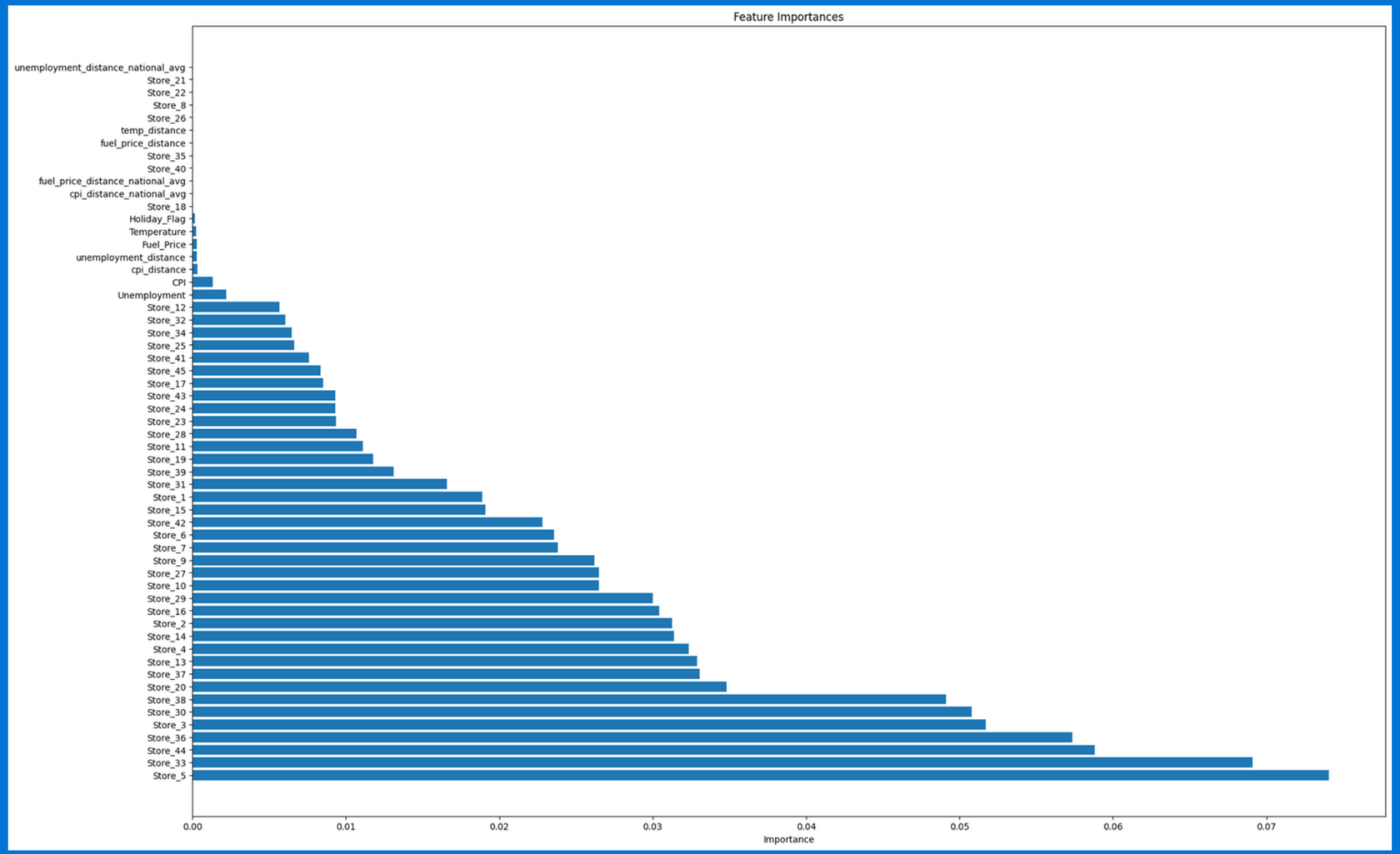
94% of variability in weekly sales is explained by the predictors

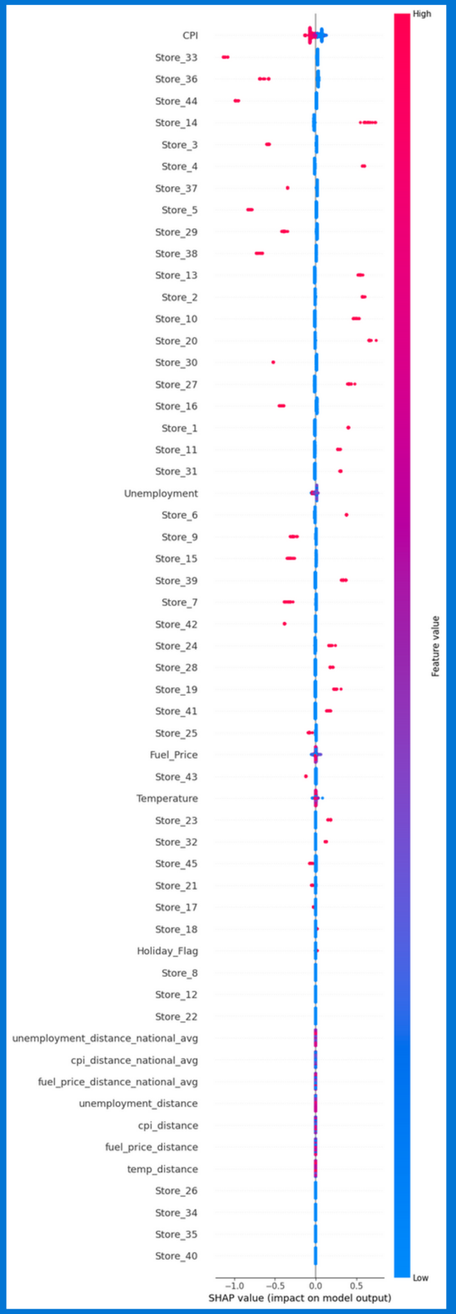
Xgboost

Root Mean Squared Error: 222,087
R-squared: 0.86

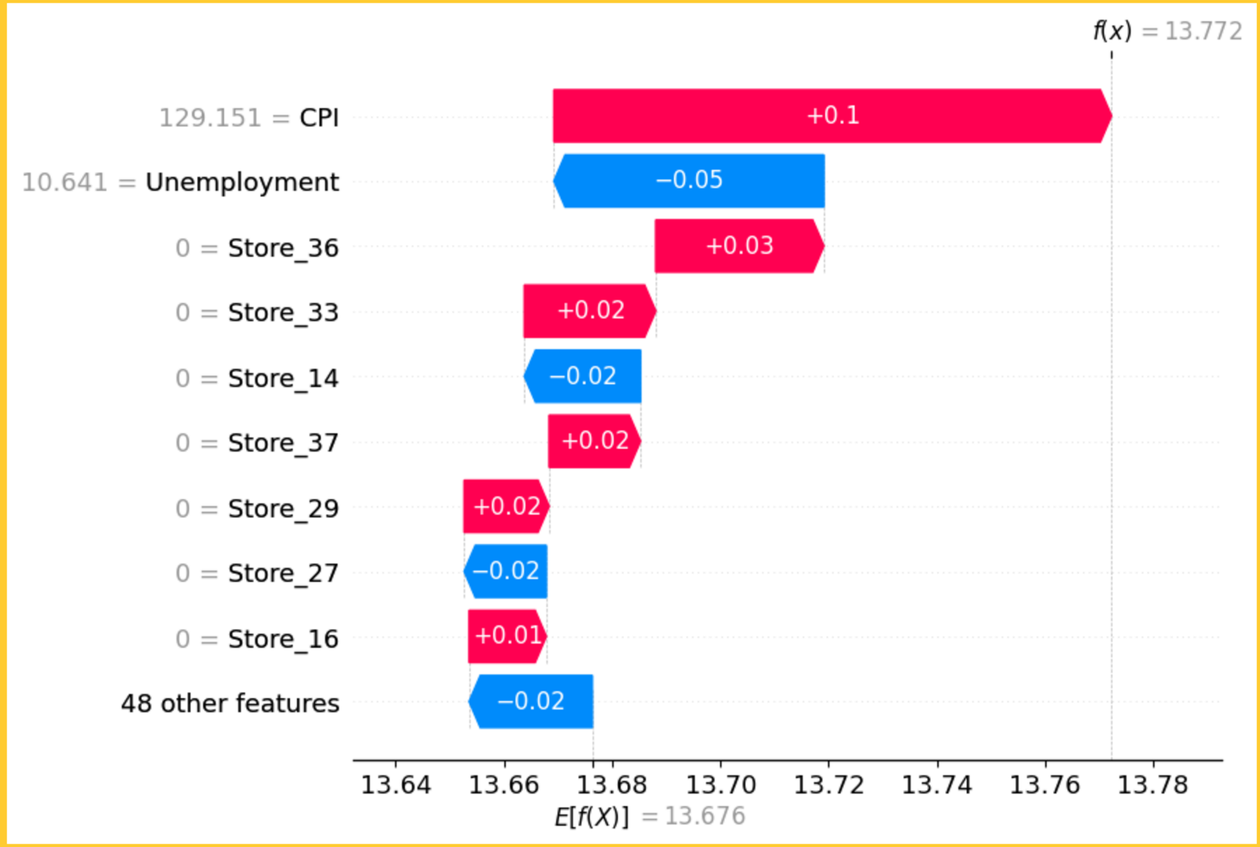
86% of variability in weekly sales is explained by the predictors

Feature Importance

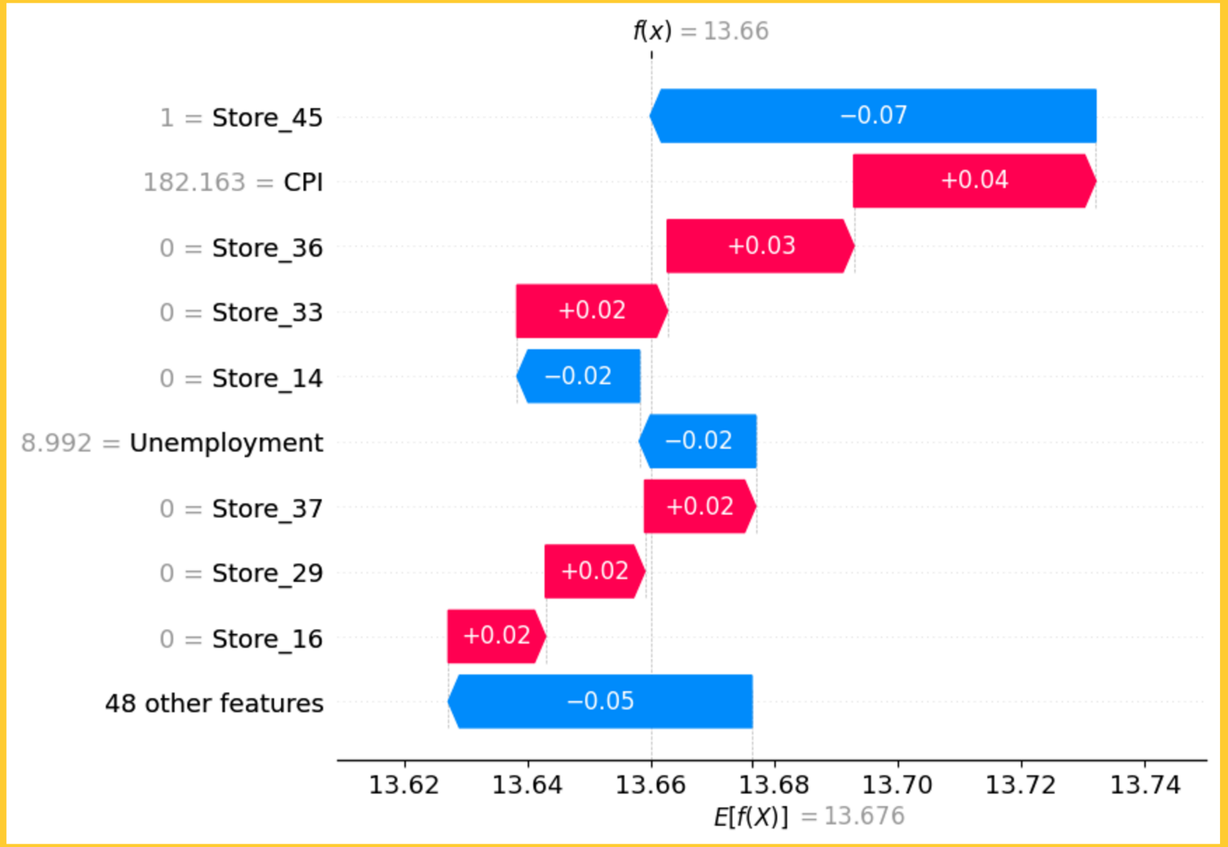




Shapley Waterfall Plots



Store 34, 7/22/11



Store 45, 3/12/10

Model Type	RMSE ($)	R-squared
Multiple Regression	184,783	0.90
Regression Tree	185,139	0.89
Random Forest	196,575	0.89
Gradient Boosting	**130,876**	**0.94**
Xgboost	222,087	0.86

Takeaways

- **Best Model:** Gradient boosting
- **Key Finding:** All models heavily relied on the store number
- **Implication:** External factors related to unique store locations, such as population density and median income, might better capture the underlying drivers of Walmart sales.
- **Important Metrics:** CPI and unemployment were identified as the most significant factors beyond store numbers, directly influencing consumer behavior and spending power.
- **Recommendation:** Walmart should prioritize hyperlocal trends over national macroeconomic measures to improve accurately capture the factors driving sales, considering the significant variation across different stores

THANK YOU