Retail Data Analysis
CS109a Project

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Walmart

Background

Motivation & Context

- Walmart, one of the top retail chains in the US, wants to estimate sales and profits for earnings forecasts, which is of concern to investors and stakeholders
- Fluctuations in demand is a hurdle for the company make sales projections unstable, especially in an unpredictable macro climate

Description of the Data

- Weekly sales data for 45 Walmart locations nationwide in many geographies from 2010-02-05 to 2012-11-01.
- Also includes variables such as temperature, gasoline prices, holidays, the unemployment rate, and shifts in consumer price indices.

- Store: the store number
- Date: the week of sales
- Weekly_Sales: weekly 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

Description of the Data

First 5 rows:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
0	1	05-02-2010	1643690.90	0	42.31	2.572	211.096358	8.106
1	1	12-02-2010	1641957.44	1	38.51	2.548	211.242170	8.106
2	1	19-02-2010	1611968.17	0	39.93	2.514	211.289143	8.106
3	1	26-02-2010	1409727.59	0	46.63	2.561	211.319643	8.106
4	1	05-03-2010	1554806.68	0	46.50	2.625	211.350143	8.106

Summary of data:

	Store	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
count	6435.000000	6.435000e+03	6435.000000	6435.000000	6435.000000	6435.000000	6435.000000
mean	23.000000	1.046965e+06	0.069930	60.663782	3.358607	171.578394	7.999151
std	12.988182	5.643666e+05	0.255049	18.444933	0.459020	39.356712	1.875885
min	1.000000	2.099862e+05	0.000000	-2.060000	2.472000	126.064000	3.879000
25%	12.000000	5.533501e+05	0.000000	47.460000	2.933000	131.735000	6.891000
50%	23.000000	9.607460e+05	0.000000	62.670000	3.445000	182.616521	7.874000
75%	34.000000	1.420159e+06	0.000000	74.940000	3.735000	212.743293	8.622000
max	45.000000	3.818686e+06	1.000000	100.140000	4.468000	227.232807	14.313000

Project Question

To what extent can we predict Walmart's sales performance across 45 representative U.S. stores from macroeconomic and external factors?

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Exploratory Data Analysis

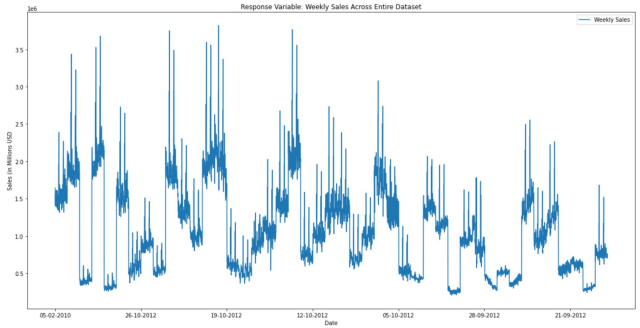
Data Quality

- Mix of continuous, categorical, & binary variables
- No null or duplicate values
- Distributions all within reason

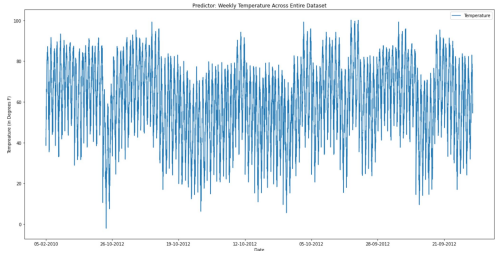
	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
count	6.435000e+03	6435.000000	6435.000000	6435.000000	6435.000000	6435.000000
mean	1.046965e+06	0.069930	60.663782	3.358607	171.578394	7.999151
std	5.643666e+05	0.255049	18.444933	0.459020	39.356712	1.875885
min	2.099862e+05	0.000000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

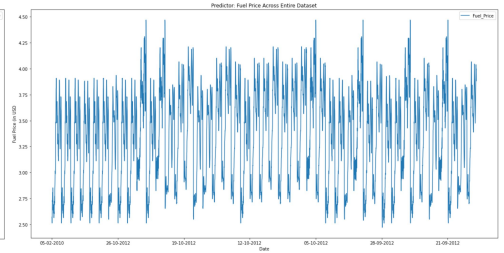
Response and Predictors

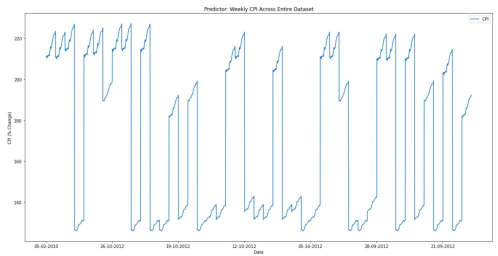
- All exhibit roughly annual seasonality
- Response variable (sales):

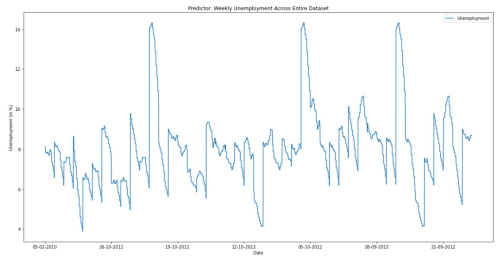


- Predictors:



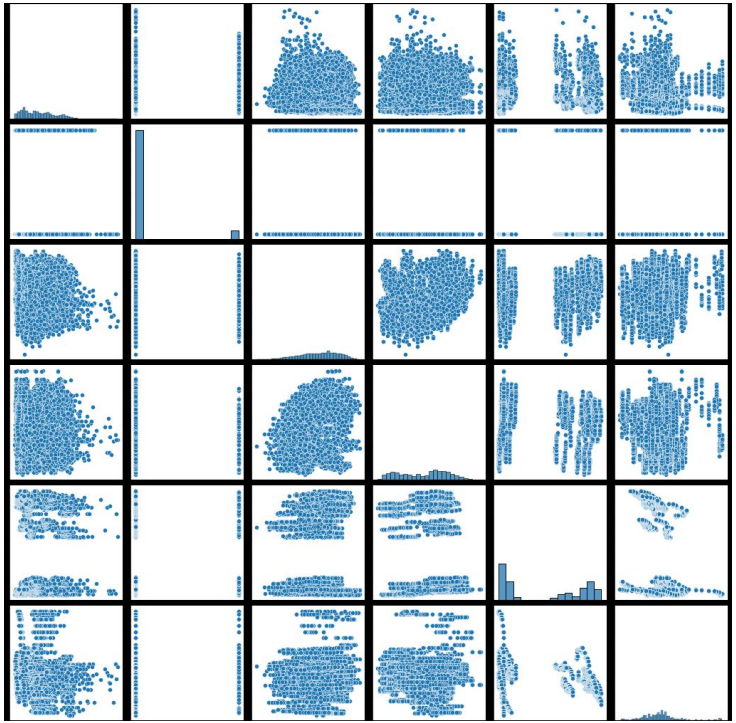






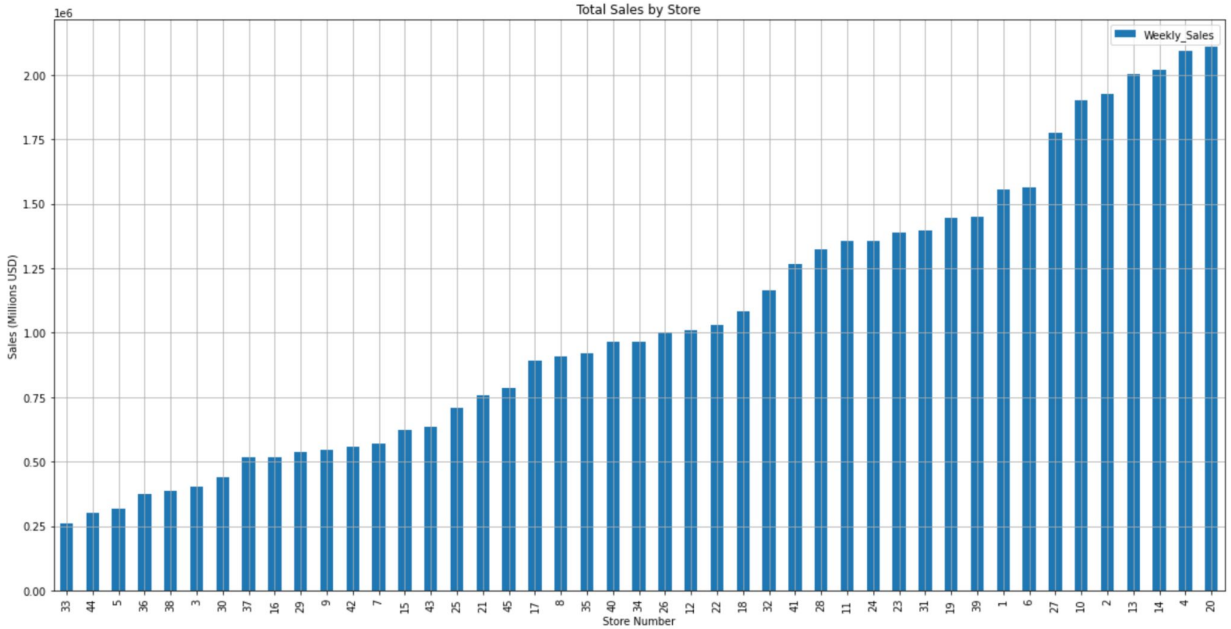
Pairplot

No immediately obvious correlations or relationships between variables



Store-Specific

Large variation in relative total sales of 45 individual stores



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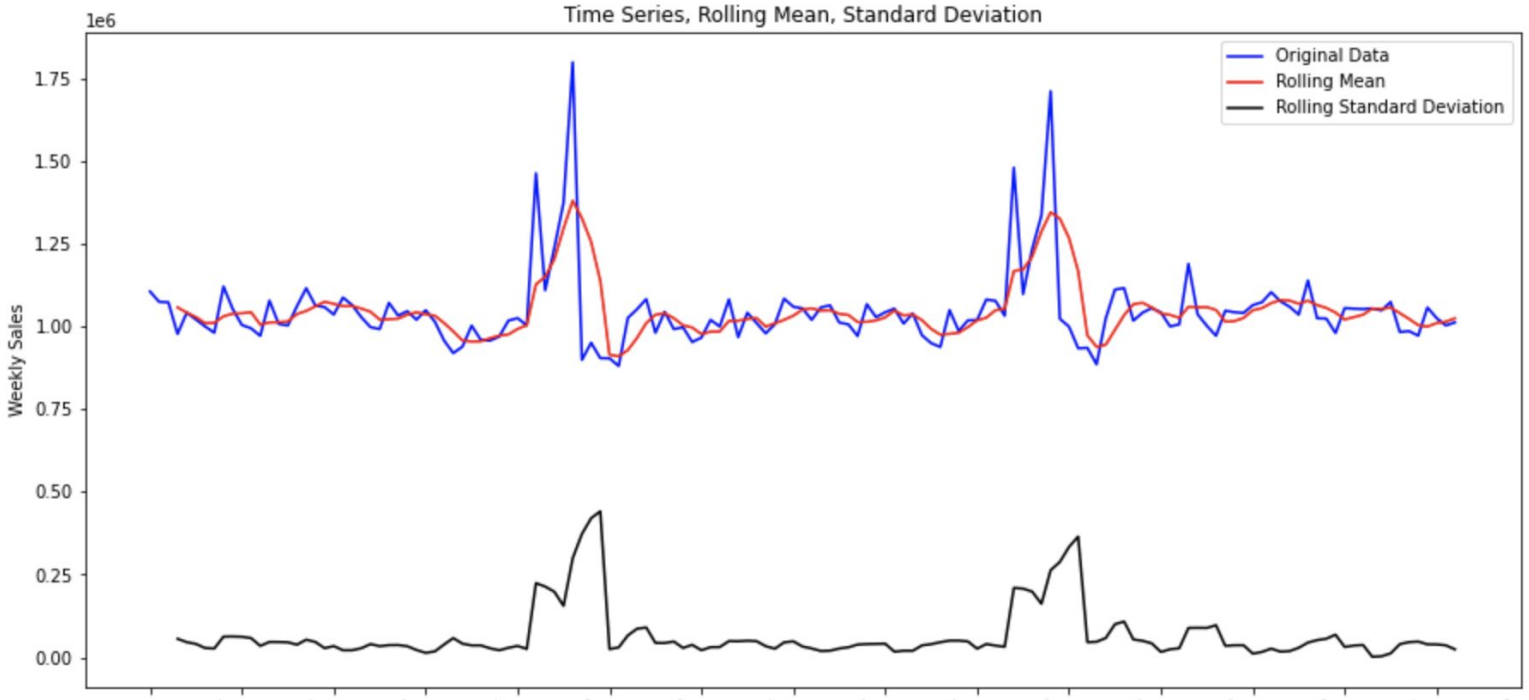
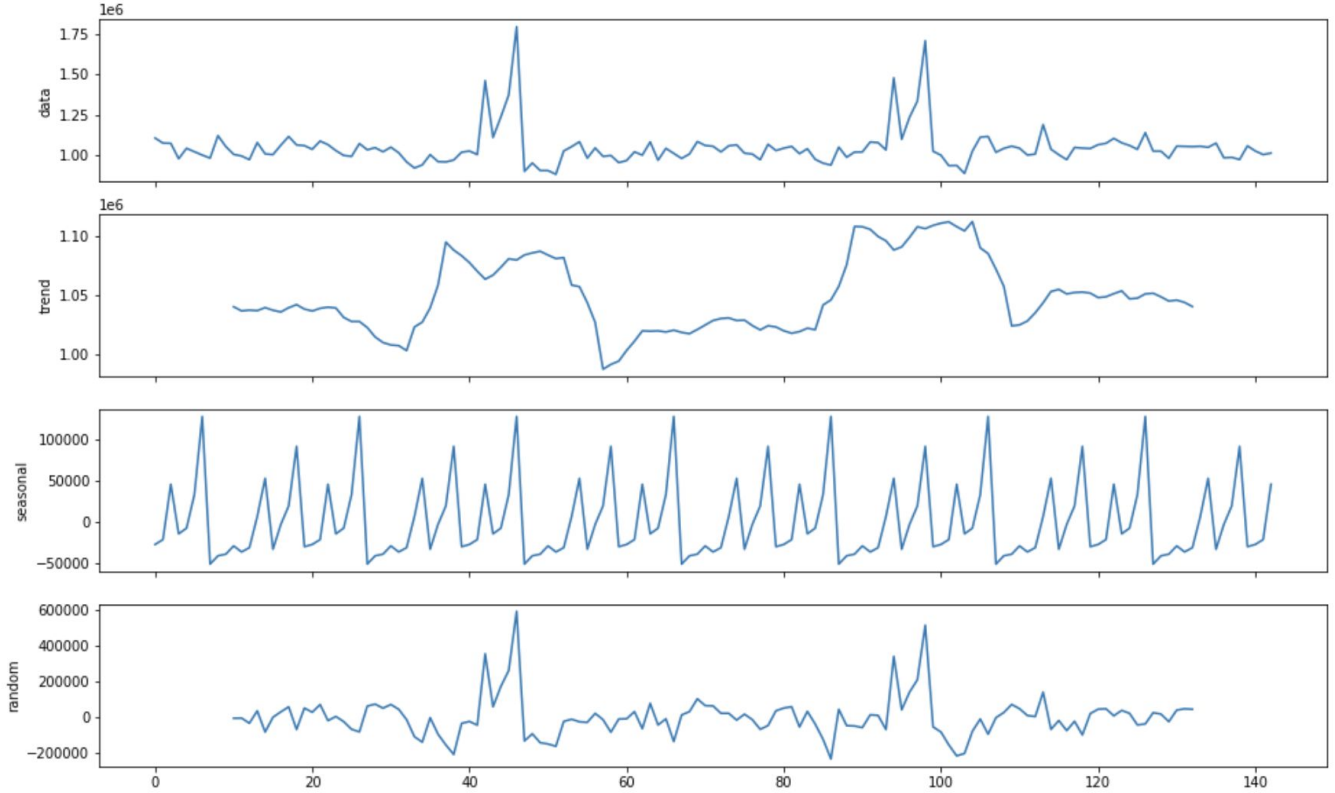
Baseline Model

Stationary Test

	Values	Metric
0	-5.908298e+00	Test Statistics
1	2.675979e-07	p-value
2	4.000000e+00	No. of lags used
3	1.380000e+02	Number of observations used
4	-3.478648e+00	critical value (1%)
5	-2.882722e+00	critical value (5%)
6	-2.578065e+00	critical value (10%)



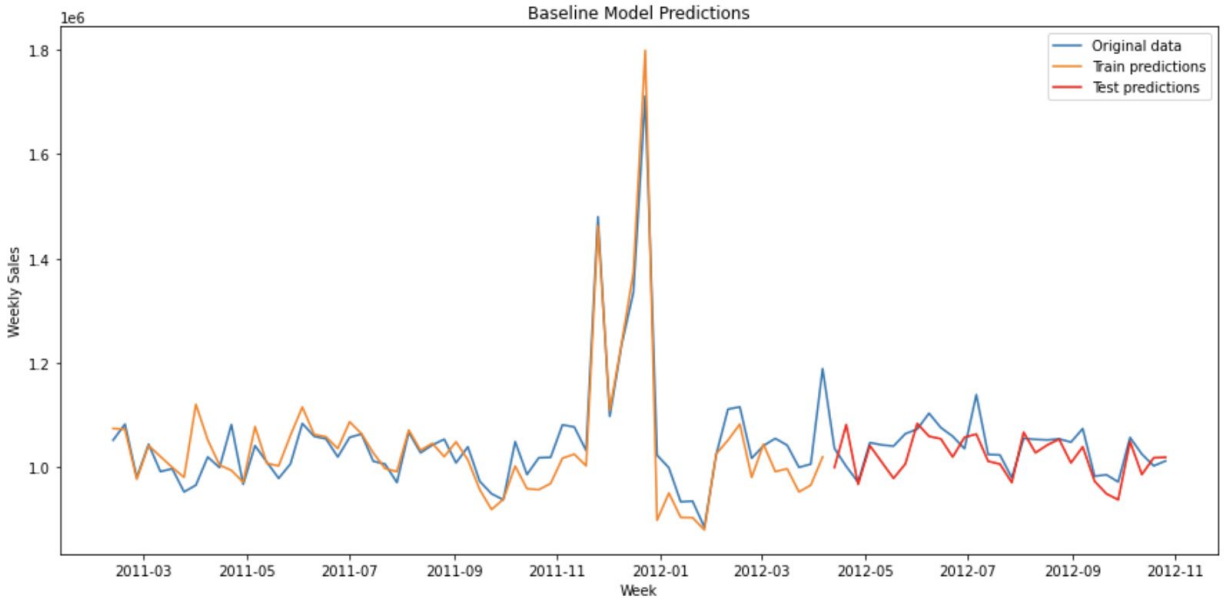
Seasonal Decompose



Baseline Model

Date	t-52	t
2012-04-13	9.994073e+05	1.036206e+06
2012-04-20	1.081704e+06	1.001612e+06
2012-04-27	9.673341e+05	9.714844e+05
2012-05-04	1.041377e+06	1.047204e+06
2012-05-11	1.009914e+06	1.042797e+06

	MAPE
train	0.031124
test	0.026532



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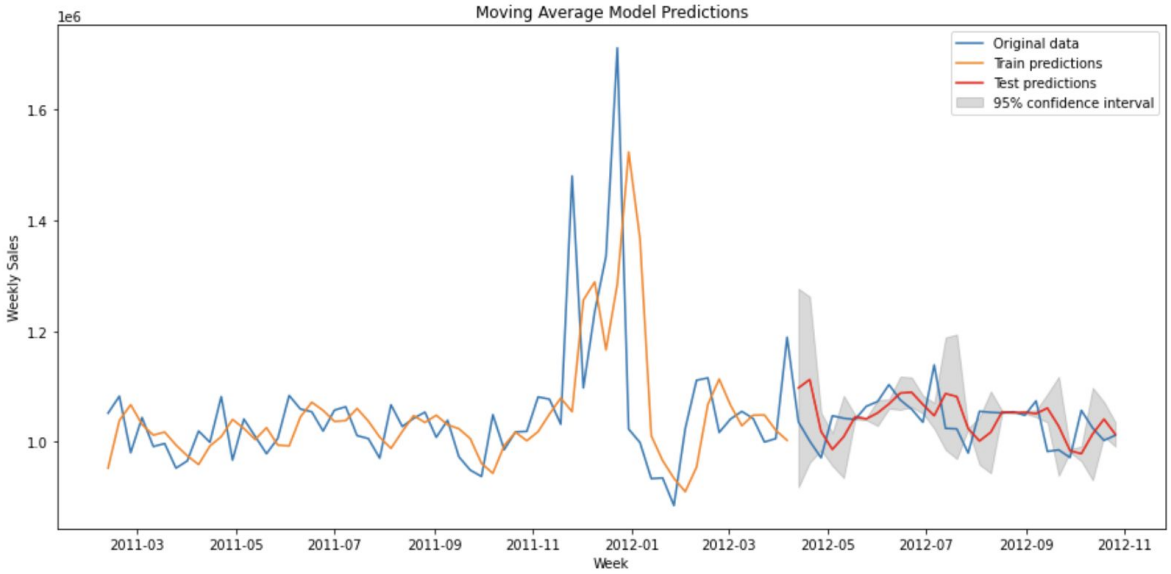
Moving Average Models

Moving Average Model

Date	rolling_mean	rolling_std	t
2012-04-13	1.097502e+06	129313.391618	1.036206e+06
2012-04-20	1.112573e+06	107999.631470	1.001612e+06
2012-04-27	1.018909e+06	24461.677601	9.714844e+05
2012-05-04	9.865481e+05	21303.255684	1.047204e+06
2012-05-11	1.009344e+06	53542.110387	1.042797e+06

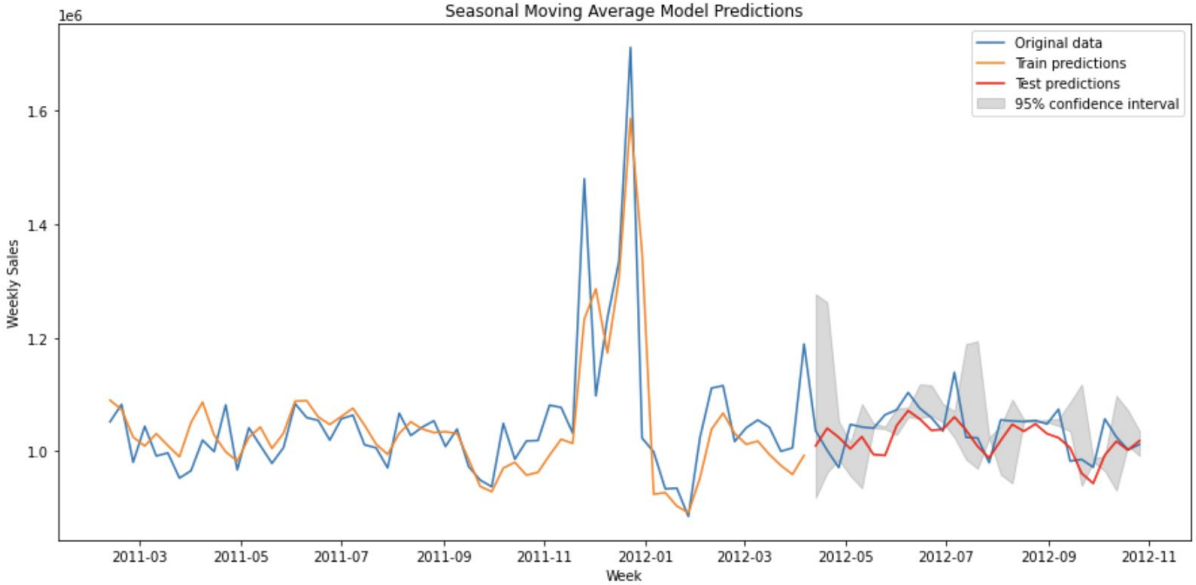
	MAPE
train	0.065877
test	0.037029



Seasonal Moving Average Model

Date	diff_rolling_mean	t
2012-04-13	1.009564e+06	1.036206e+06
2012-04-20	1.040556e+06	1.001612e+06
2012-04-27	1.024519e+06	9.714844e+05
2012-05-04	1.004355e+06	1.047204e+06
2012-05-11	1.025646e+06	1.042797e+06

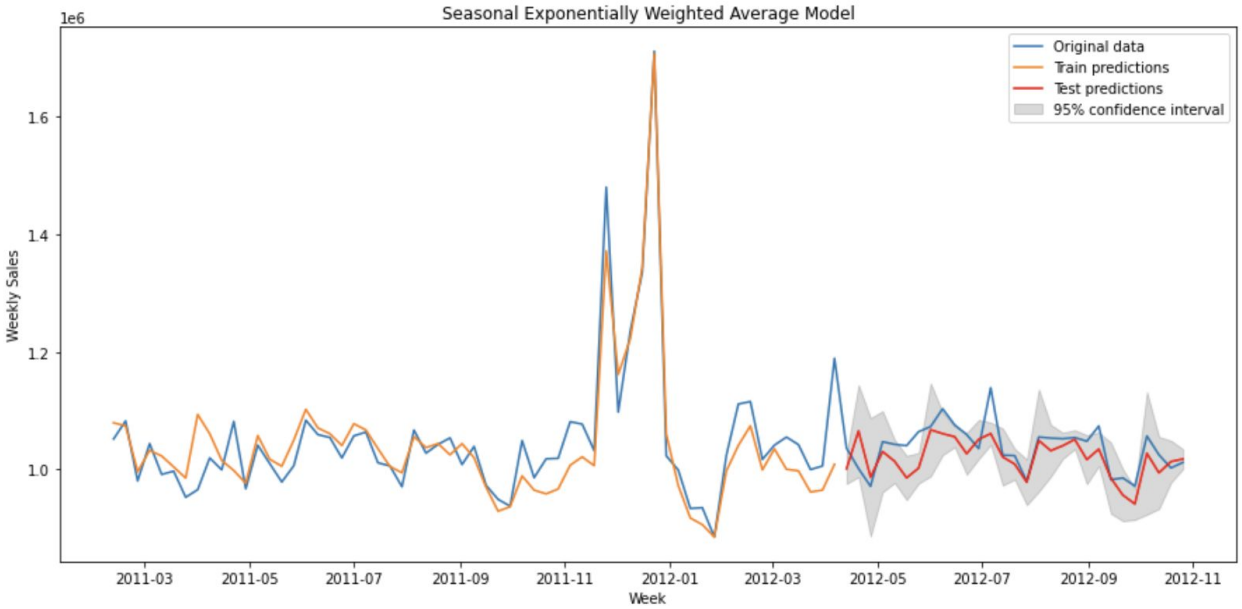
	MAPE
train	0.044108
test	0.026440



Seasonal Exponentially Weighted Model

Date	rolling_ewm	t
2012-04-13	1.001280e+06	1.036206e+06
2012-04-20	1.065619e+06	1.001612e+06
2012-04-27	9.869911e+05	9.714844e+05
2012-05-04	1.030500e+06	1.047204e+06
2012-05-11	1.014031e+06	1.042797e+06

	MAPE
train	0.029934
test	0.024380



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SARIMA Model

SARIMA Parameter Search

```
Performing stepwise search to minimize aic
 ARIMA(1,0,1)(0,1,1)[15] intercept   : AIC=2677.570, Time=1.14 sec
 ARIMA(0,0,0)(0,1,0)[15] intercept   : AIC=2699.629, Time=0.09 sec
 ARIMA(1,0,0)(1,1,0)[15] intercept   : AIC=2682.396, Time=0.81 sec
 ARIMA(0,0,1)(0,1,1)[15] intercept   : AIC=2688.614, Time=0.93 sec
 ARIMA(0,0,0)(0,1,0)[15]             : AIC=2698.666, Time=0.07 sec
 ARIMA(1,0,1)(0,1,0)[15] intercept   : AIC=2691.319, Time=0.24 sec
 ARIMA(1,0,1)(1,1,1)[15] intercept   : AIC=2679.164, Time=0.76 sec
 ARIMA(1,0,1)(0,1,2)[15] intercept   : AIC=2679.292, Time=1.43 sec
 ARIMA(1,0,1)(1,1,0)[15] intercept   : AIC=2680.570, Time=0.51 sec
 ARIMA(1,0,1)(1,1,2)[15] intercept   : AIC=inf, Time=3.43 sec
 ARIMA(1,0,0)(0,1,1)[15] intercept   : AIC=2680.914, Time=0.39 sec
 ARIMA(2,0,1)(0,1,1)[15] intercept   : AIC=2679.132, Time=0.74 sec
 ARIMA(1,0,2)(0,1,1)[15] intercept   : AIC=2679.679, Time=0.86 sec
 ARIMA(0,0,0)(0,1,1)[15] intercept   : AIC=2697.932, Time=0.43 sec
 ARIMA(0,0,2)(0,1,1)[15] intercept   : AIC=2684.157, Time=0.75 sec
 ARIMA(2,0,0)(0,1,1)[15] intercept   : AIC=2676.627, Time=0.60 sec
 ARIMA(2,0,0)(0,1,0)[15] intercept   : AIC=2691.338, Time=0.12 sec
 ARIMA(2,0,0)(1,1,1)[15] intercept   : AIC=2678.475, Time=0.58 sec
 ARIMA(2,0,0)(0,1,2)[15] intercept   : AIC=2678.494, Time=1.09 sec
 ARIMA(2,0,0)(1,1,0)[15] intercept   : AIC=2680.807, Time=0.38 sec
 ARIMA(2,0,0)(1,1,2)[15] intercept   : AIC=2679.672, Time=2.00 sec
 ARIMA(3,0,0)(0,1,1)[15] intercept   : AIC=2678.851, Time=0.62 sec
 ARIMA(3,0,1)(0,1,1)[15] intercept   : AIC=2678.472, Time=1.26 sec
 ARIMA(2,0,0)(0,1,1)[15]             : AIC=2673.460, Time=0.53 sec
 ARIMA(2,0,0)(0,1,0)[15]             : AIC=2689.452, Time=0.11 sec
 ARIMA(2,0,0)(1,1,1)[15]             : AIC=2675.407, Time=0.48 sec
 ARIMA(2,0,0)(0,1,2)[15]             : AIC=2675.385, Time=1.06 sec
```

```
Best model:  ARIMA(3,0,2)(0,1,1)[15]
Total fit time: 71.008 seconds
```

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	114
Model:	SARIMAX(3, 0, 2)x(0, 1, [1], 15)	**Log Likelihood**	-1323.956
Date:	Sat, 10 Dec 2022	**AIC**	2661.913
Time:	20:56:51	**BIC**	2680.078
Sample:	02-05-2010	**HQIC**	2669.263
	- 04-06-2012		

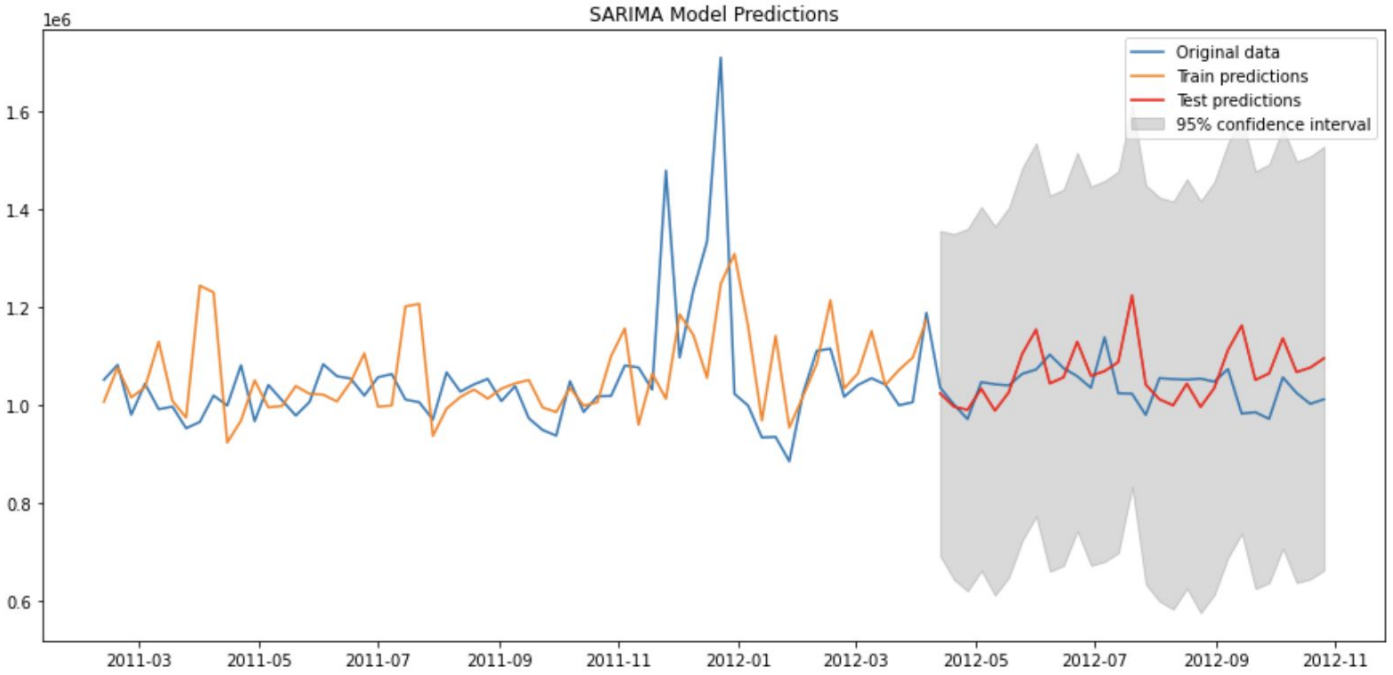
Covariance Type: opg

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.5690	0.322	1.770	0.077	-0.061	1.199
ar.L2	0.7861	0.360	2.186	0.029	0.081	1.491
ar.L3	-0.3699	0.132	-2.799	0.005	-0.629	-0.111
ma.L1	-0.2087	0.358	-0.583	0.560	-0.911	0.493
ma.L2	-0.6549	0.332	-1.971	0.049	-1.306	-0.004
ma.S.L15	-0.7346	0.210	-3.496	0.000	-1.146	-0.323
sigma2	2.868e+10	1.81e-11	1.58e+21	0.000	2.87e+10	2.87e+10

Ljung-Box (L1) (Q):	1.09	**Jarque-Bera (JB):**	43.93
Prob(Q):	0.30	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.69	**Skew:**	0.73
Prob(H) (two-sided):	0.29	**Kurtosis:**	5.92

SARIMA Model

	MAPE
train	0.077369
test	0.055078



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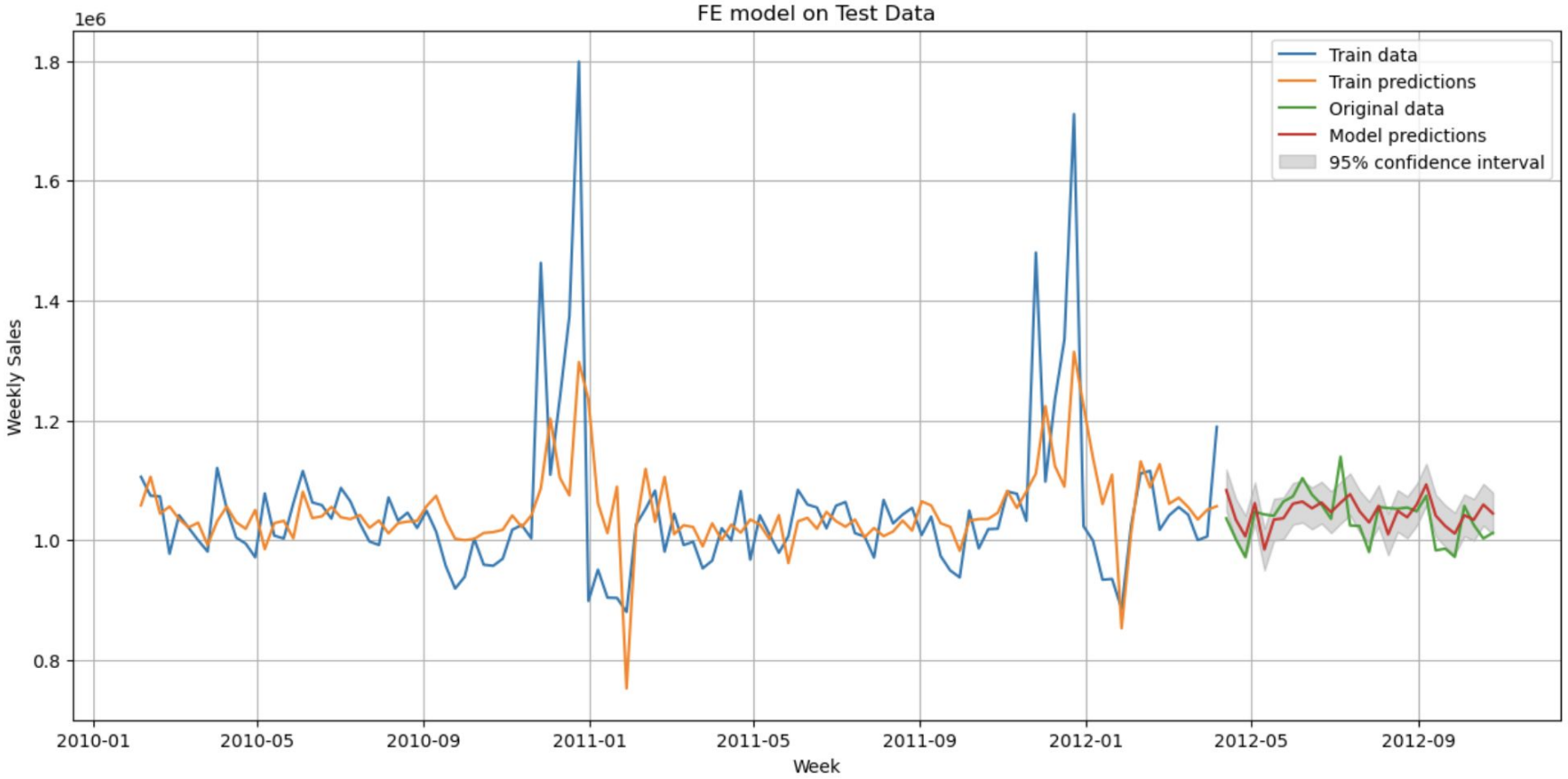
Fixed and Random Effects

MAPE : 0.028


FE model on Test Data
1e6
1.8
1.6
1.4
1.2
1.0
0.8
Weekly Sales
2010-01
2010-05
2010-09
2011-01
2011-05
2011-09
2012-01
2012-05
2012-09
Week
Train data
Train predictions
Original data
Model predictions
95% confidence interval

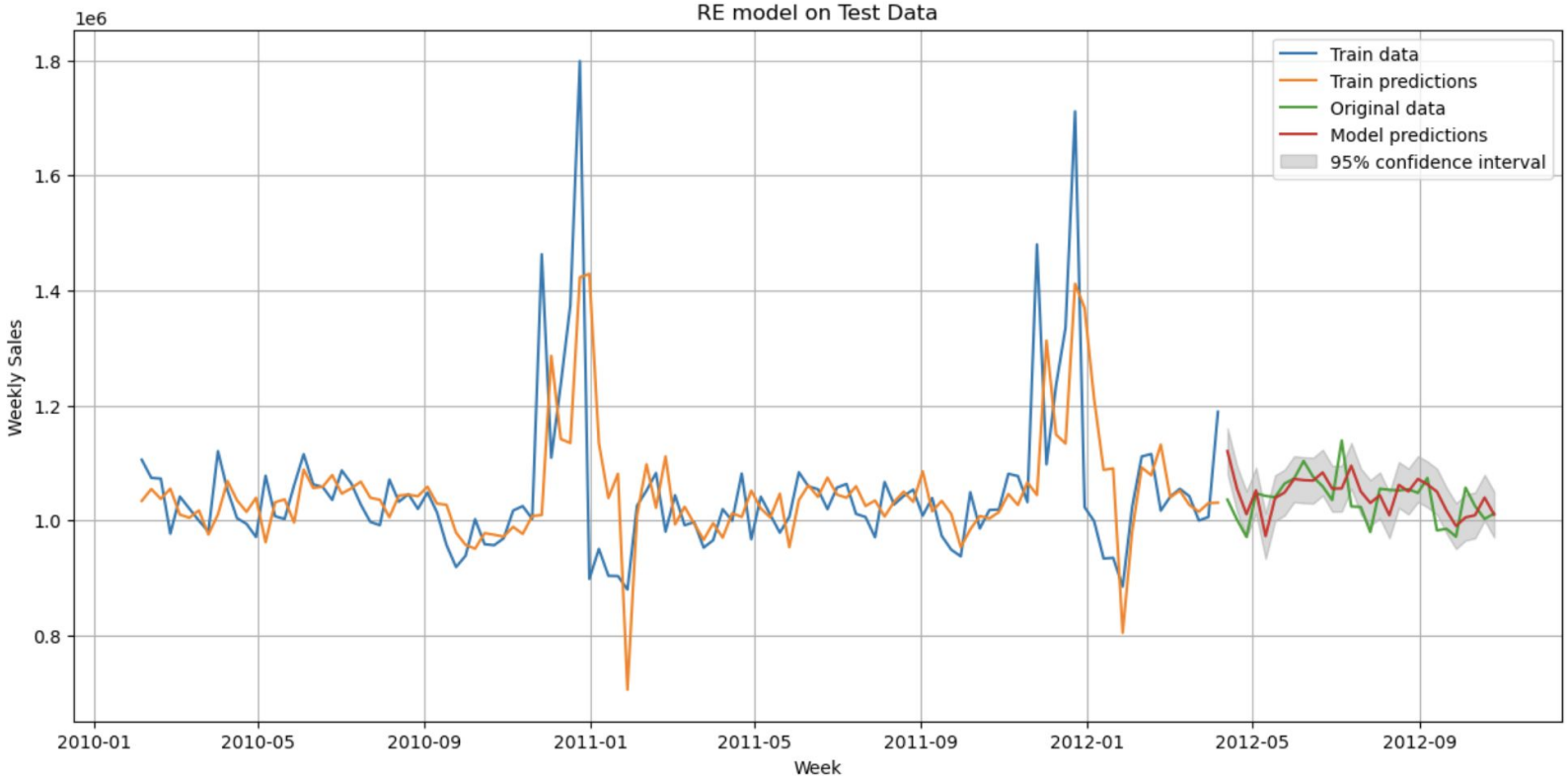
PanelOLS Estimation Summary

Dep. Variable:	Weekly_Sales	R-squared:	0.2623
Estimator:	PanelOLS	R-squared (Between):	0.3792
No. Observations:	5119	R-squared (Within):	0.2623
Date:	Sun, Dec 11 2022	R-squared (Overall):	0.3673
Time:	05:35:10	Log-likelihood	-6.829e+04
Cov. Estimator:	Unadjusted		
		F-statistic:	112.43
Entities:	45	P-value	0.0000
Avg Obs:	113.76	Distribution:	F(16,5058)
Min Obs:	103.00		
Max Obs:	114.00	F-statistic (robust):	112.43
		P-value	0.0000
Time periods:	114	Distribution:	F(16,5058)
Avg Obs:	44.904		
Min Obs:	44.000		
Max Obs:	45.000		

Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	7.266e+05	1.713e+04	42.407	0.0000	6.93e+05	7.602e+05
Holiday_Flag	4.965e+04	8850.3	5.6102	0.0000	3.23e+04	6.7e+04
Temperature	-8461.9	2679.3	-3.1583	0.0016	-1.371e+04	-3209.3
Fuel_Price	-1.448e+04	3544.1	-4.0859	0.0000	-2.143e+04	-7532.8
CPI	1.681e+05	5.424e+04	3.0991	0.0020	6.176e+04	2.744e+05
Unemployment	-4.115e+04	1.154e+04	-3.5652	0.0004	-6.378e+04	-1.852e+04
Lagged_1	0.3399	0.0138	24.666	0.0000	0.3129	0.3670
Lagged_2	0.0630	0.0145	4.3546	0.0000	0.0346	0.0913
Lagged_3	-0.0747	0.0145	-5.1603	0.0000	-0.1030	-0.0463
Lagged_4	0.2851	0.0145	19.721	0.0000	0.2568	0.3135
Lagged_5	-0.3384	0.0149	-22.650	0.0000	-0.3677	-0.3091
Lagged_6	0.0108	0.0158	0.6806	0.4962	-0.0203	0.0418
Lagged_7	0.0604	0.0154	3.9122	0.0001	0.0301	0.0907
Lagged_8	-0.0566	0.0143	-3.9602	0.0001	-0.0846	-0.0286

MAPE: 0.03


RE model on Test Data
1e6
1.8
1.6
1.4
1.2
1.0
0.8
Weekly Sales
2010-01
2010-05
2010-09
2011-01
2011-05
2011-09
2012-01
2012-05
2012-09
Week
Train data
Train predictions
Original data
Model predictions
95% confidence interval

RandomEffects Estimation Summary

Dep. Variable:	Weekly_Sales	R-squared:	0.9055
Estimator:	RandomEffects	R-squared (Between):	0.9980
No. Observations:	5119	R-squared (Within):	0.0111
Date:	Sun, Dec 11 2022	R-squared (Overall):	0.9055
Time:	05:36:27	Log-likelihood	-6.909e+04
Cov. Estimator:	Unadjusted		
		F-statistic:	3054.1
Entities:	45	P-value	0.0000
Avg Obs:	113.76	Distribution:	F(16,5102)
Min Obs:	103.00		
Max Obs:	114.00	F-statistic (robust):	3054.1
		P-value	0.0000
Time periods:	114	Distribution:	F(16,5102)
Avg Obs:	44.904		
Min Obs:	44.000		
Max Obs:	45.000		

Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	2.432e+04	5477.6	4.4403	0.0000	1.358e+04	3.506e+04
Holiday_Flag	7569.0	1.015e+04	0.7454	0.4561	-1.234e+04	2.748e+04
Temperature	3800.1	2634.9	1.4422	0.1493	-1365.5	8965.6
Fuel_Price	1805.9	2524.2	0.7154	0.4744	-3142.7	6754.5
CPI	-3934.7	2727.2	-1.4428	0.1491	-9281.1	1411.8
Unemployment	-3738.7	2689.3	-1.3902	0.1645	-9010.9	1533.6
Lagged_1	0.6154	0.0142	43.322	0.0000	0.5875	0.6432
Lagged_2	0.1726	0.0166	10.415	0.0000	0.1401	0.2050
Lagged_3	-0.0268	0.0168	-1.5941	0.1110	-0.0597	0.0062
Lagged_4	0.3375	0.0168	20.127	0.0000	0.3046	0.3703
Lagged_5	-0.3513	0.0174	-20.206	0.0000	-0.3853	-0.3172
Lagged_6	0.0627	0.0184	3.4162	0.0006	0.0267	0.0987
Lagged_7	0.1333	0.0179	7.4652	0.0000	0.0983	0.1683
Lagged_8	-0.0384	0.0166	-2.3095	0.0210	-0.0710	-0.0058
Lagged_9	0.1035	0.0168	6.1626	0.0000	0.0706	0.1364

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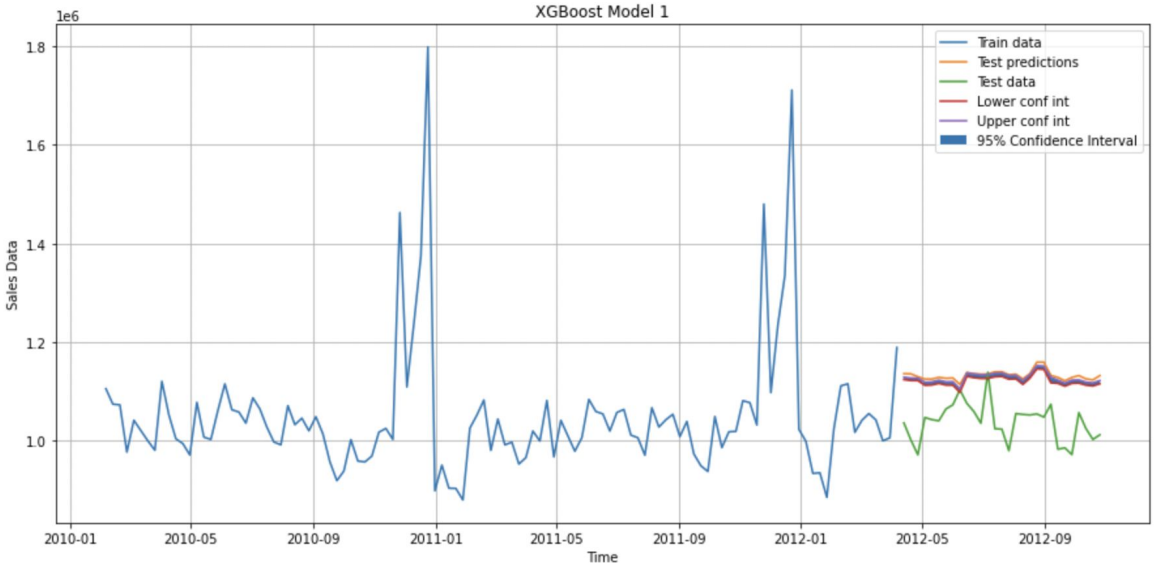
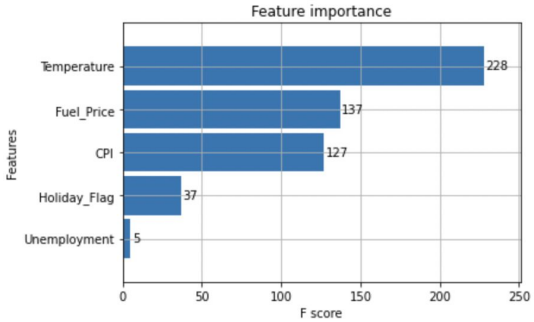
Gradient Boosted Trees

XGBoost Model 1

Simple model using XGBRegressor.

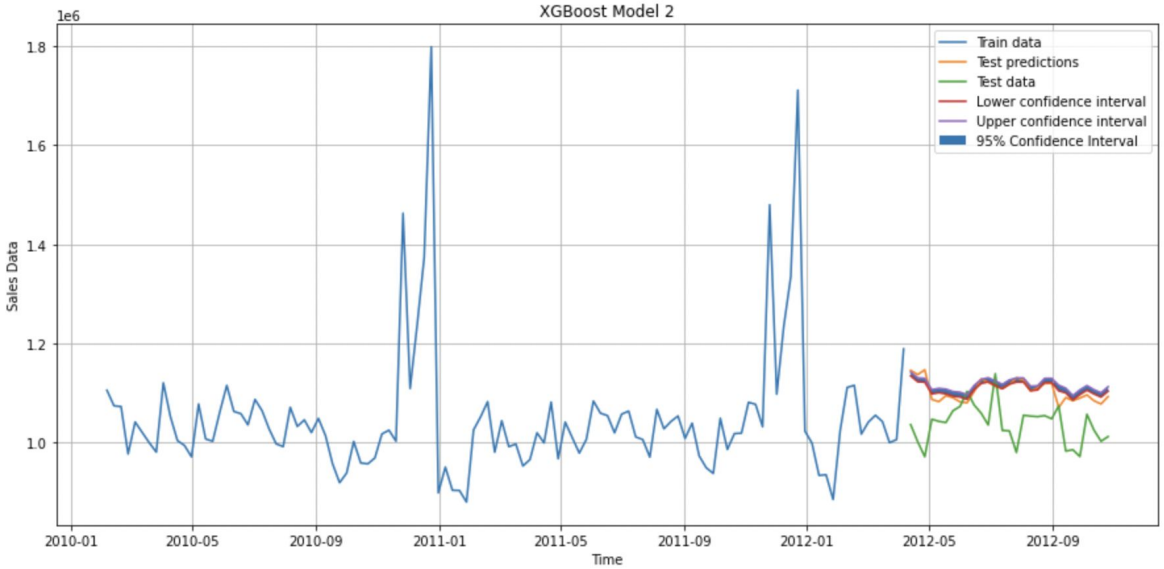


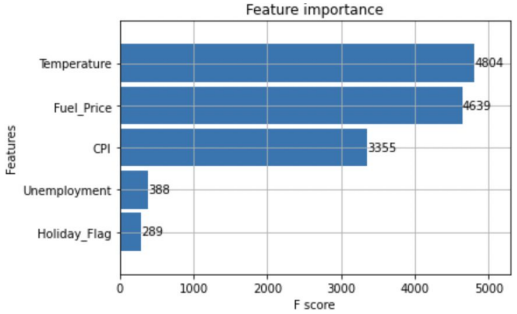



```
MAPE = 0.11378282760159741
```

XGBoost Model 2

XGBRegressor with hyperparameter-tuning using GridSearchCV()





MAPE = 0.06937198322581578

Walmart

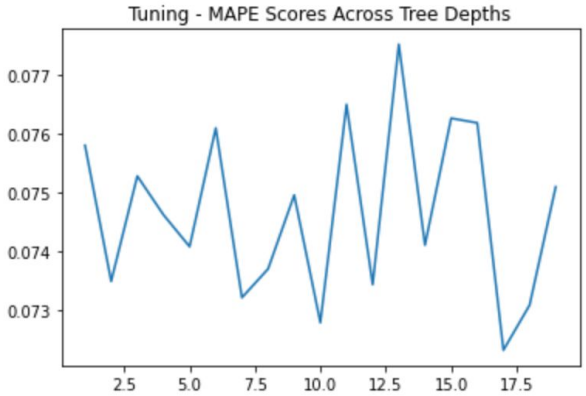
Random Forest Models

Random Forest - Tuning

- Initial performance:

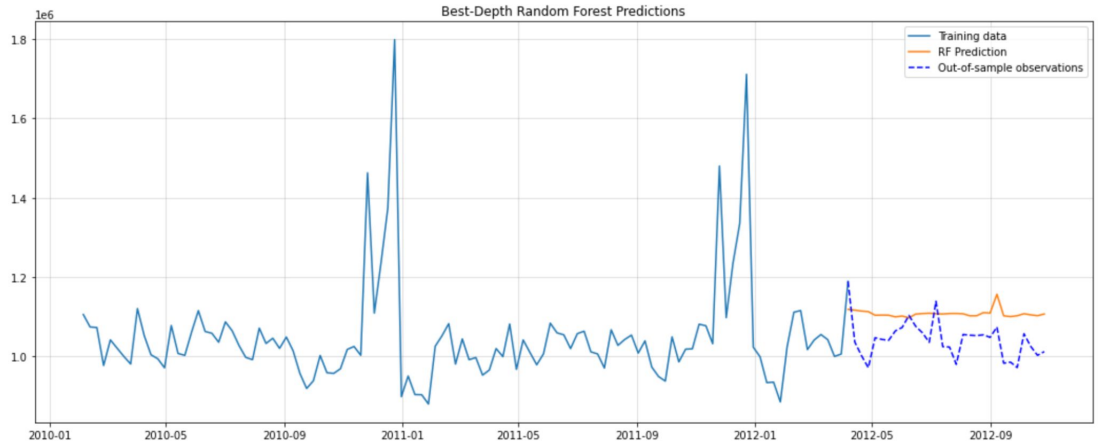
```
The random forest of depth-5 and 1000 trees achieves the following MAPE scores:

        train   0.0354
        TEST    0.0727
```

- Hyperparameter tuning for optimal tree depth:

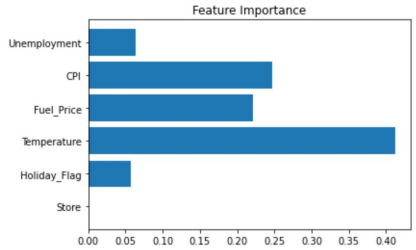


Random Forest - Results

- Tuned model performance
  - MAPE: 0.072



- Feature Importance:

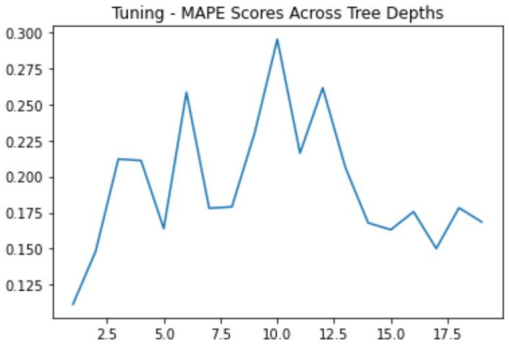


Random Forest - Autoregressive

- New model trained not on features, but past weekly sales
- Initial performance:

```
The ARF model with depth 5 gives a MAPE of 0.164
```

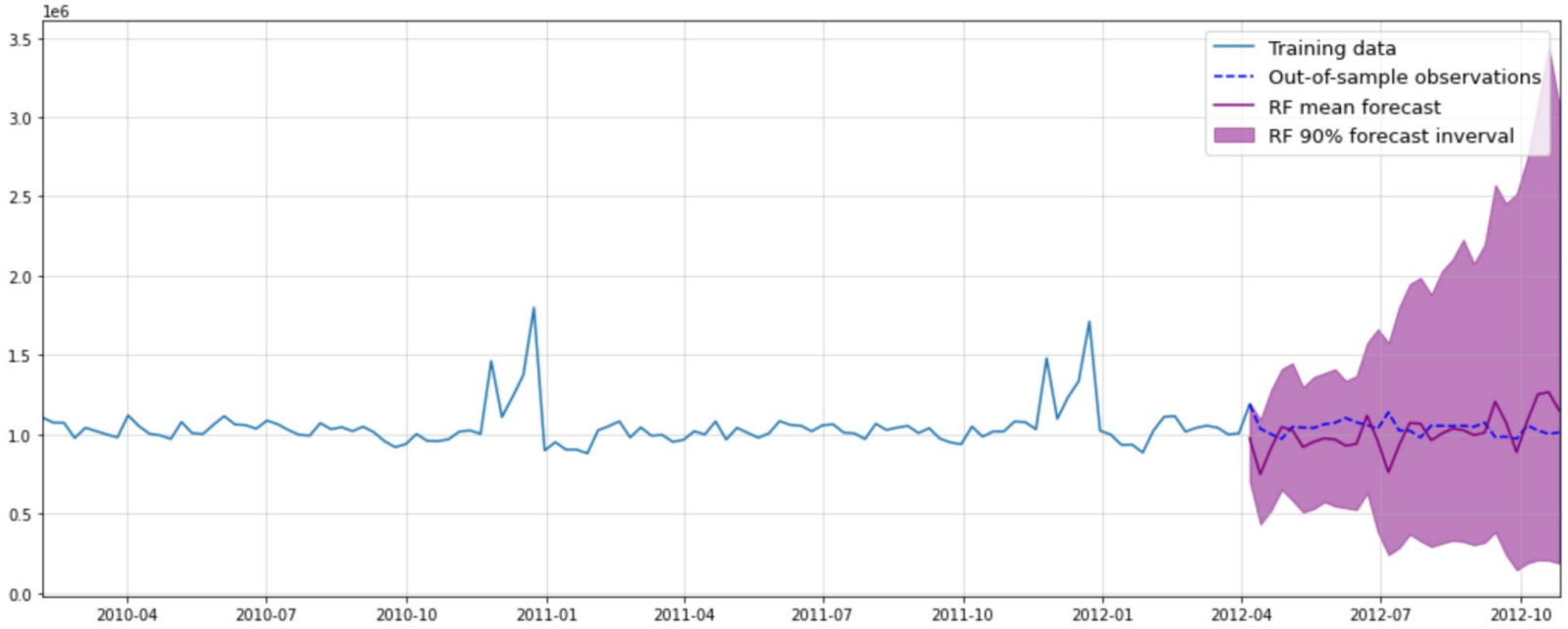
- Tuning:



- Performs best at depth of 1, makes sense since only fitting on one feature

Random Forest - Autoregressive Results

- Tuned model performance
  - MAPE: 0.11



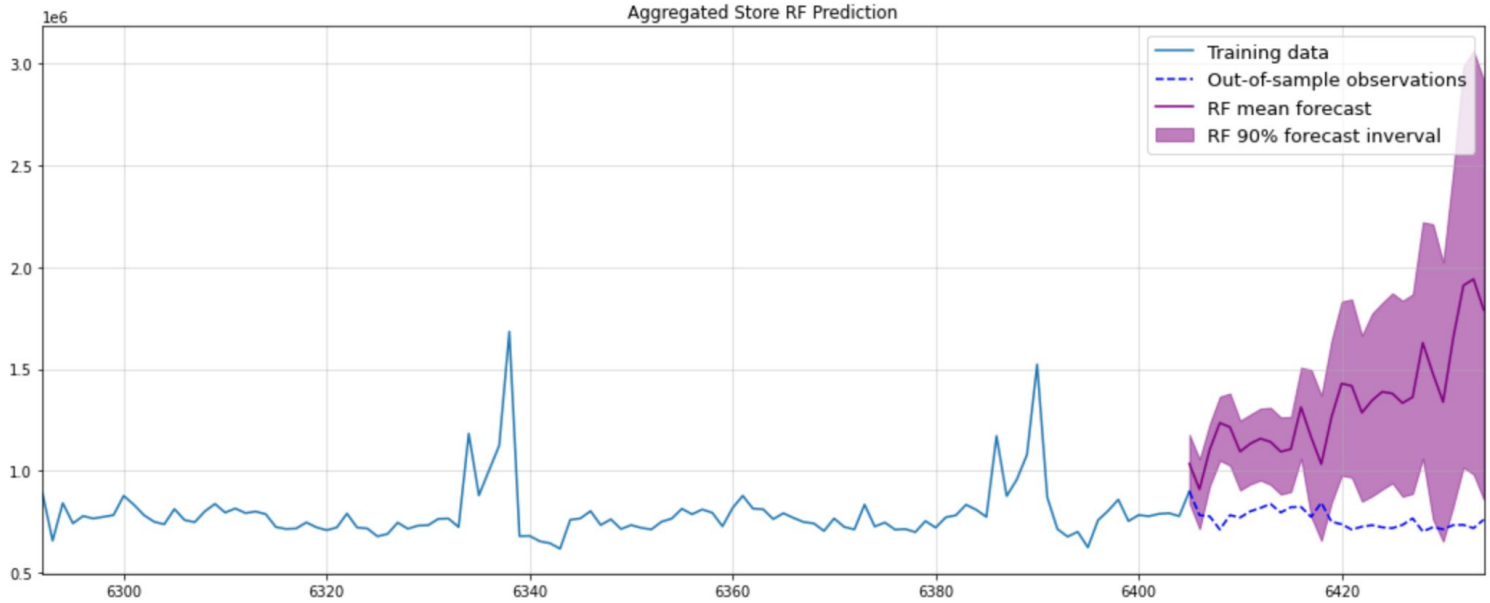
Random Forest - By Store

- Last attempt to fit RF: fit each store to its own model
- MAPEs across stores vary widely:

	store	MAPE
0	1	0.229820
1	2	0.356865
2	3	0.621875
3	4	0.442872
4	5	0.617666
5	6	0.439791
6	7	0.823693
7	8	0.549803
8	9	0.681451
9	10	0.990992

Random Forest - By Store Results

- Aggregated performance of by-store models
- Significant overestimation
  - Likely due to the model being an even worse fit for higher-revenue stores



Walmart

Overall Results

Comparison of Errors

Model	Mean Absolute % Error
Baseline (Seasonal Lag)	**0.026**
Moving Average	0.037
Seasonal Moving Average	0.026
Seasonal Exponentially Weighted	0.024
SARIMA	0.055
Fixed Effects	0.028
Random Effects	0.030
XGBoost	0.069
Random Forest	0.072

Conclusions

- To begin with, the baseline performs extremely well, indicating average weekly sales is driven largely by annual seasonal patterns in this period, and seasonal differencing renders the data extremely stationary
- The seasonal exponentially weighted average model is the best model, it accounts for annual seasonality and further weighs more recent observations more heavily
- Simplicity is king – the simplest prediction models performed much better than more complex models like trees and forests, which makes sense in the context of limited data
- Complex models need more data to train on to capture all relevant patterns and make inferences; over longer horizons they should outperform simple models

Future Work

Recommended Future Work

- Collect more data over a longer period for fitting more complex models – outside of 2010-2012, the seasonality regime is unlikely to hold
- Tune and test more by-store prediction models, ideally with more store-specific features relevant to location and products available
    - It is possible that more “luxury” products are correlated with macroeconomic factors, as opposed to “commodity” products
- Consider regularization strategies to prevent more complex models from overfitting on training data
- Aggregate Walmart data with alternative data on other comparable retail chains such as Target, Costco, etc. to identify correlations