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# Walmart Sales Forecast Using ARIMA and Machine Learning

August 7, 2020

# WHY RETAIL SALES FORECASTING

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- Mass retailing is a high volume / low margin business
- Retailing is a seasonal and cyclical business
- Upfront investments in merchandise and stores
- Fixed costs in store maintenance
- Sales forecasting is a business critical factor
  - Overstocking results in markdowns and less profit
  - Under stocking results in loss sales, lower customer satisfactions

# DATA PREPARATION

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Variables	17
Observations	421570
Store	Factor, 45 levels
Dept	Factor, 81 levels
Type	Factor, 3 levels
Size	Interger
Date	Date, format"2010-02-05"
IsHoliday	Logic
Weekly_Sales	Numeric
MarkDown1	Numeric, anonymous
MarkDown 2	Numeric, anonymous
MarkDown 3	Numeric, anonymous
MarkDown 4	Numeric, anonymous
MarkDown 5	Numeric, anonymous
CPI	Numeric
Unemployment	Numeric
Temperature	Numeric
Fuel_Price	Numeric
Week	Numeric

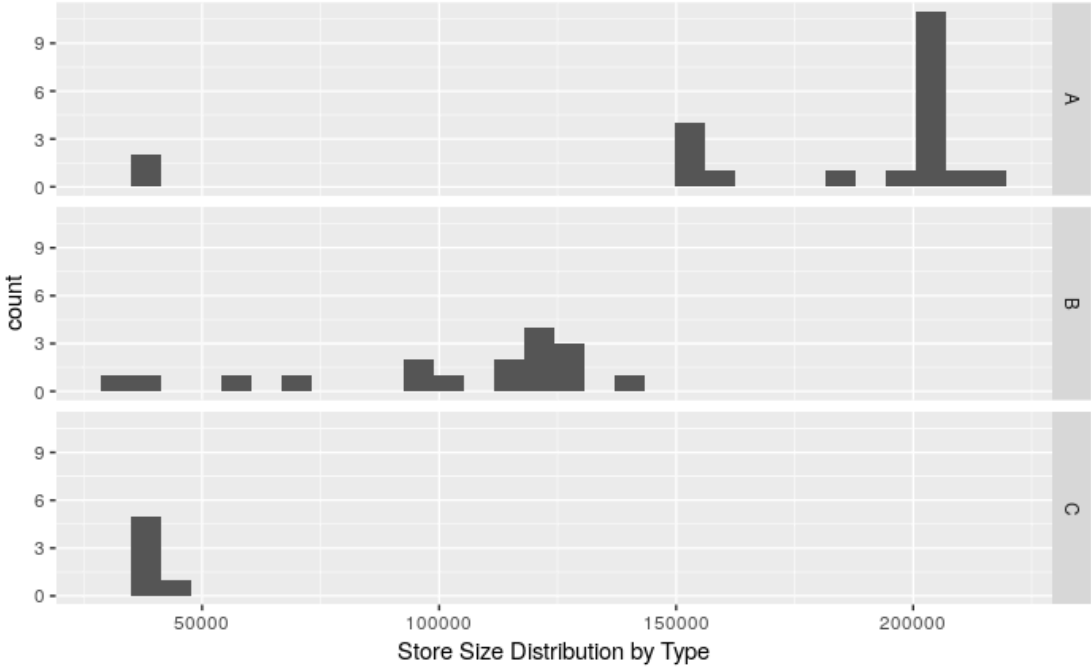
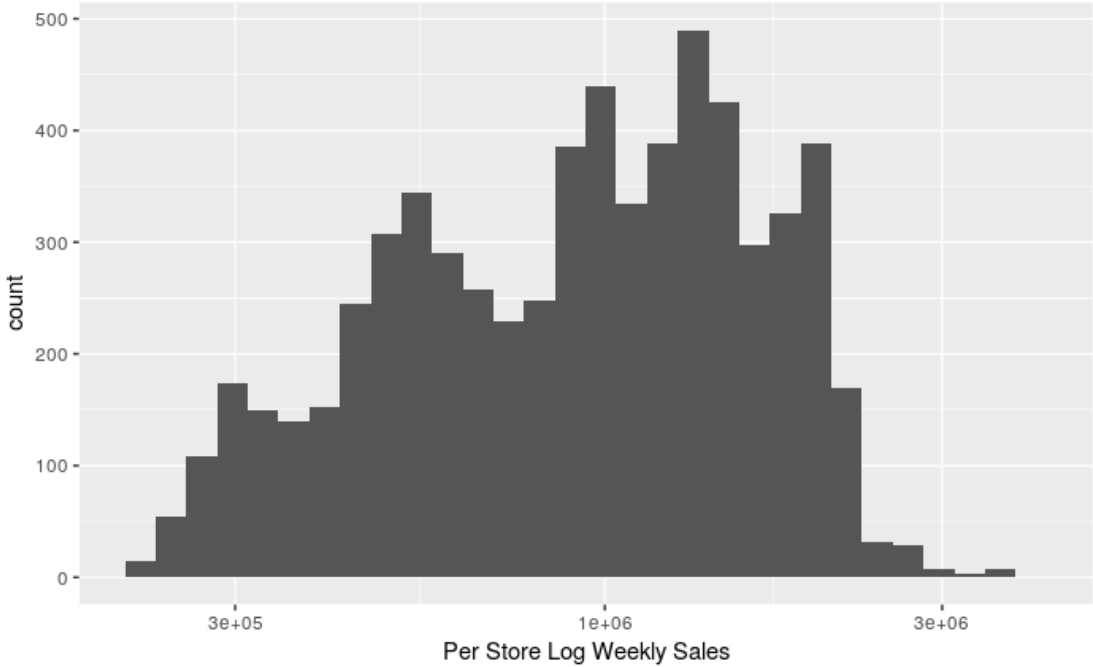
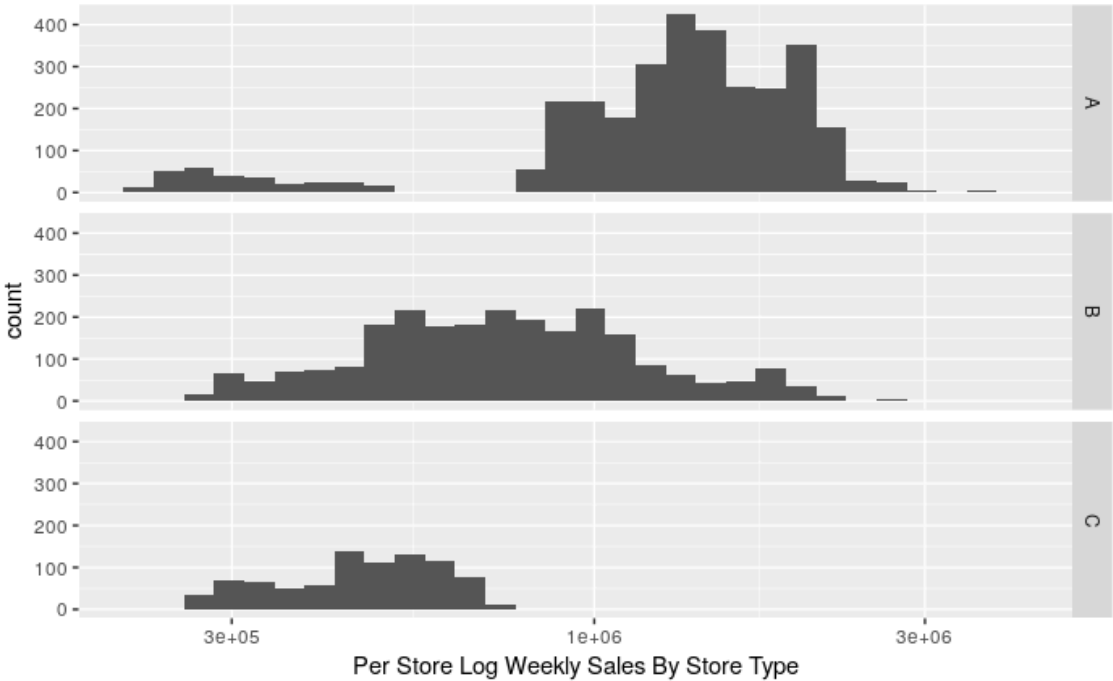
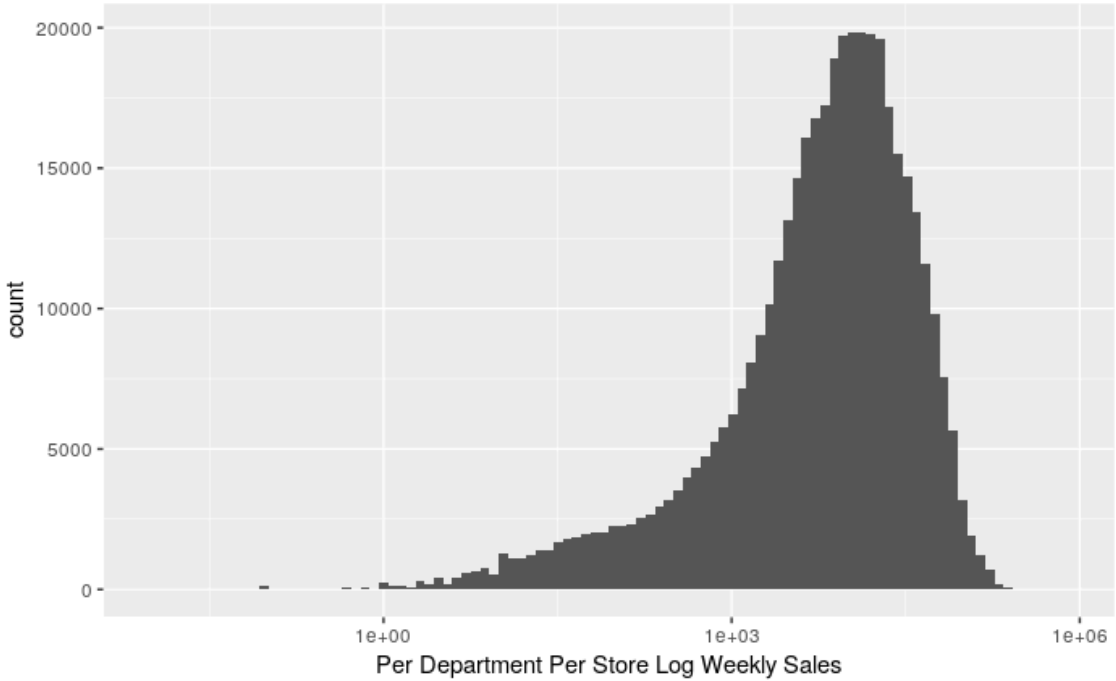
## Data background:

- A Kaggle recruiting competition in 2014
- Test set is withheld
- Time period: weekly sales data from 2010-02-05 to 2012-10-26 (143 weeks)

## Initial Data Cleaning

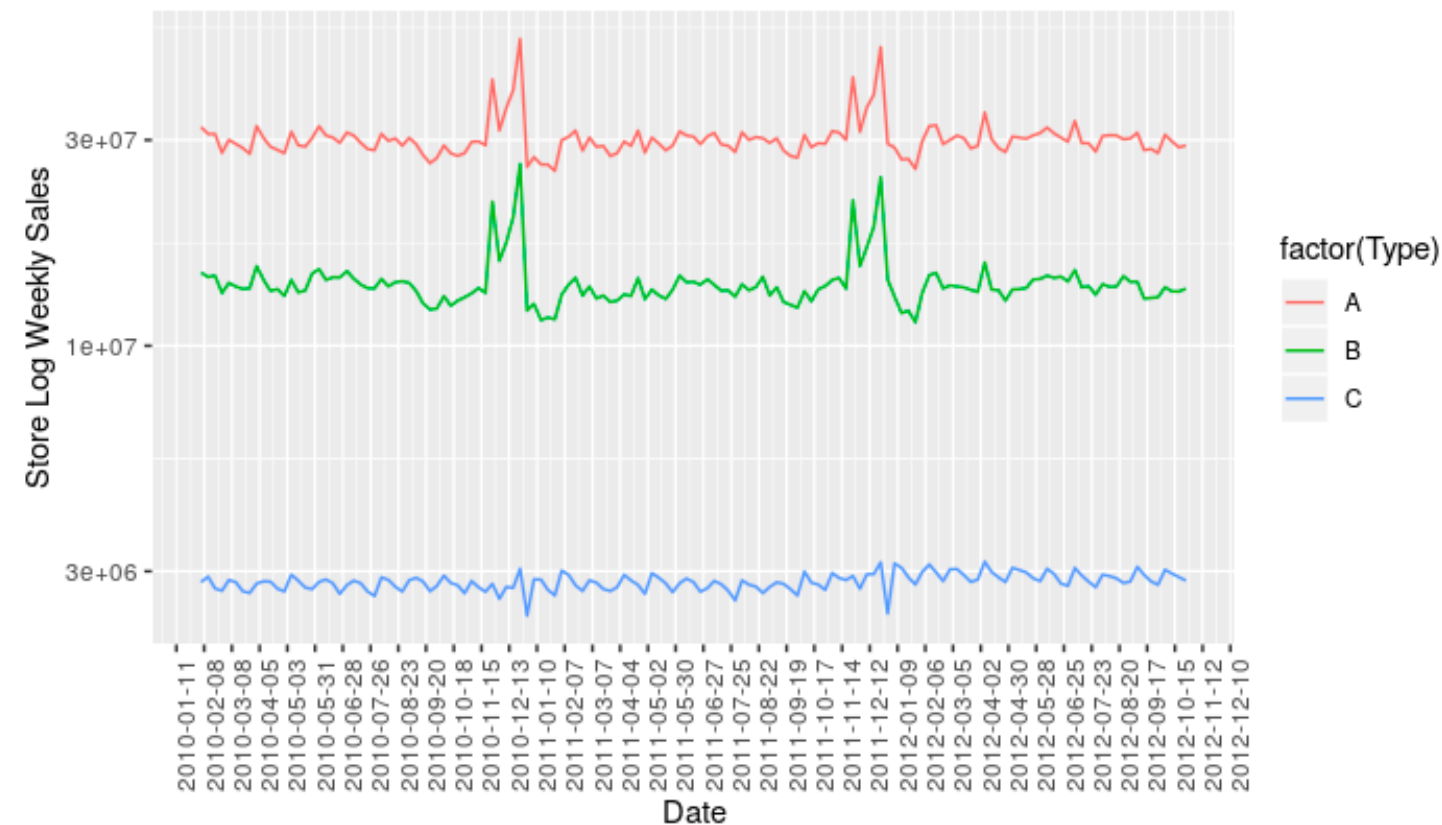
- Change “Store”, “Dept” from Integer to Factor
- Change “Date” from Integer to Factor
- Add “Week” variable with isoweek()
- Missing values: missing values only exist in 5 MarkDown variables, accounting for 64% - 74% of variable observations respectively
- Small numbers of negative “Weekly\_Sales”

# DATA PREPARATION



# DATA PREPARATION

Store Sales Time Series by Type



➤ Time series plotting shows strong seasonality

➤ Four holidays:

Super Bowl

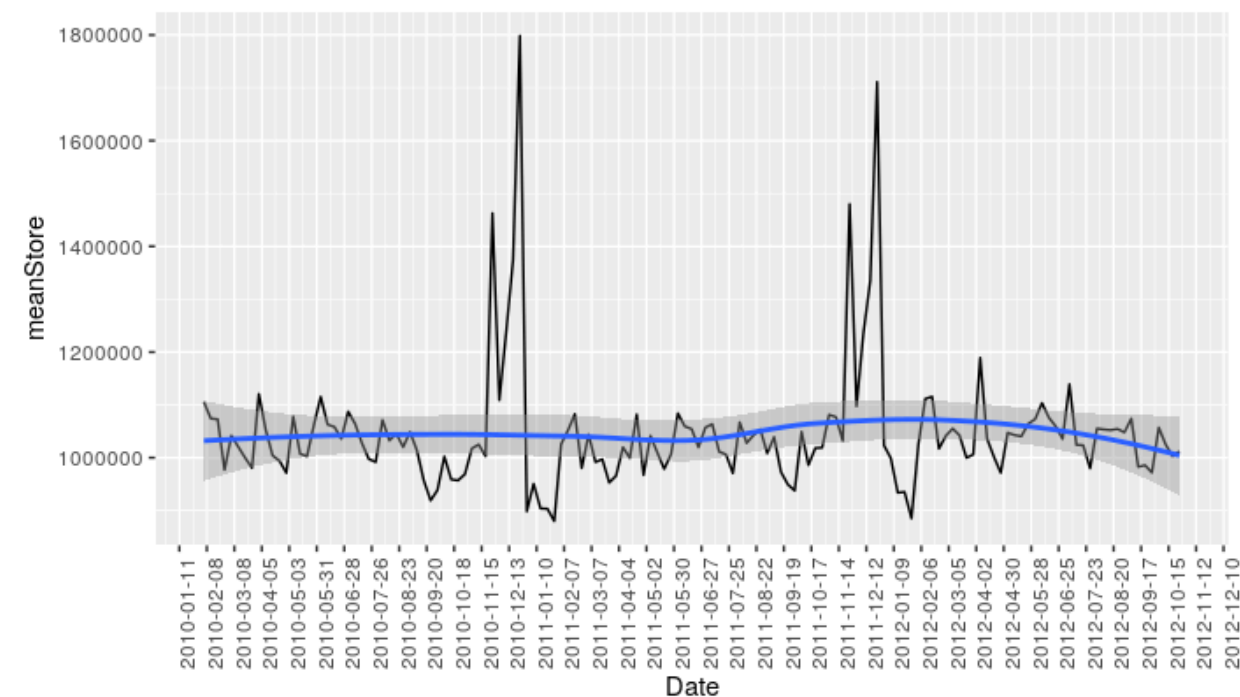
Labor Day

Thanksgiving

Christmas

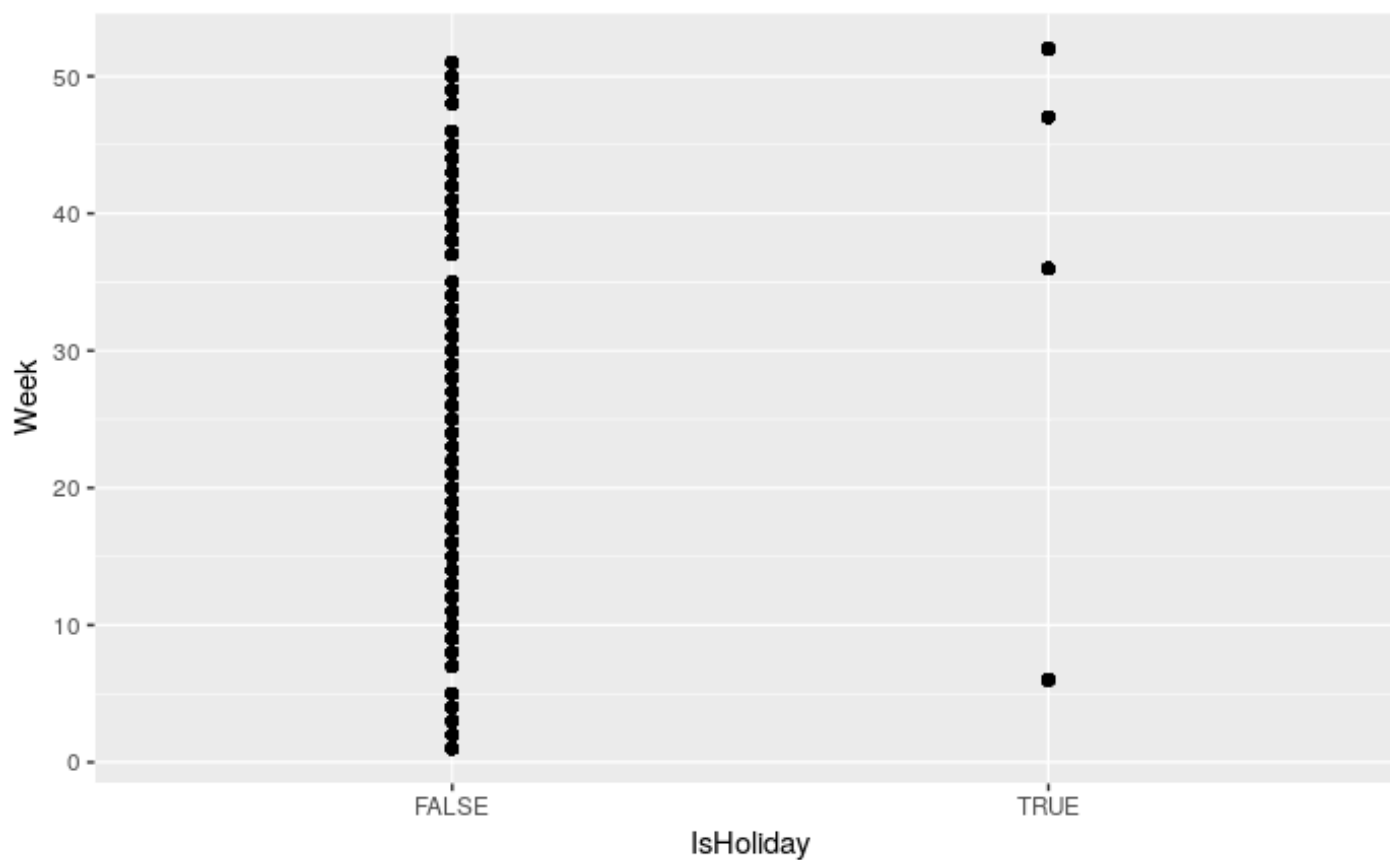
➤ Sales are dominated by Thanksgiving and Christmas holidays

Mean Store Weekly Sales Time Series



# DATA PREPARATION

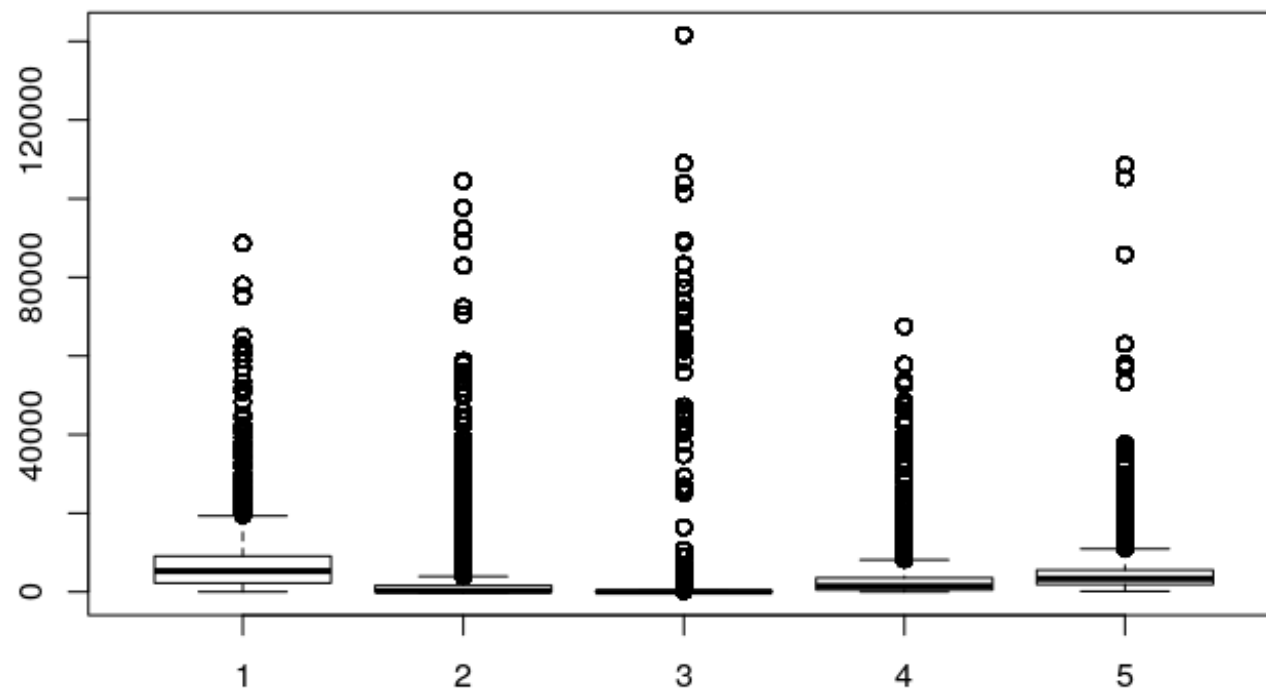
- Four holidays all appear on the same week of the year
- Super Bowl: week 6, Labor Day: week 36, Thanksgiving: week 47, Christmas: week 52



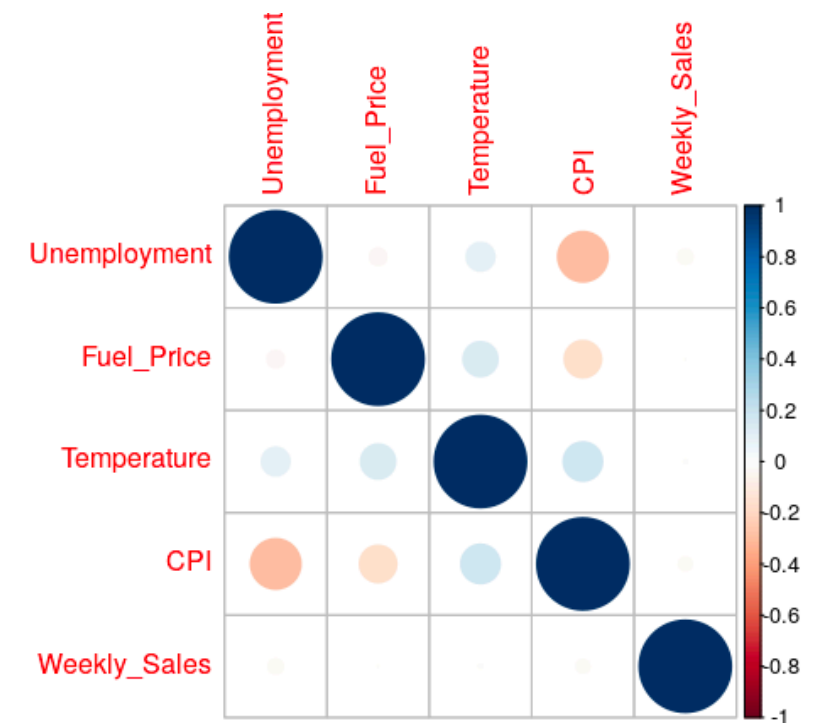
Date	IsHoliday <lgl>	Week <dbl>
2010-02-12	TRUE	6
2010-09-10	TRUE	36
2010-11-26	TRUE	47
2010-12-31	TRUE	52
2011-02-11	TRUE	6
2011-09-09	TRUE	36
2011-11-25	TRUE	47
2011-12-30	TRUE	52
2012-02-10	TRUE	6

# DATA PREPARATION

- Five markdown features are skewed by outliers
- External indices have almost zero correlation with Weekly\_Sales
- Drop Markdown and external indices features



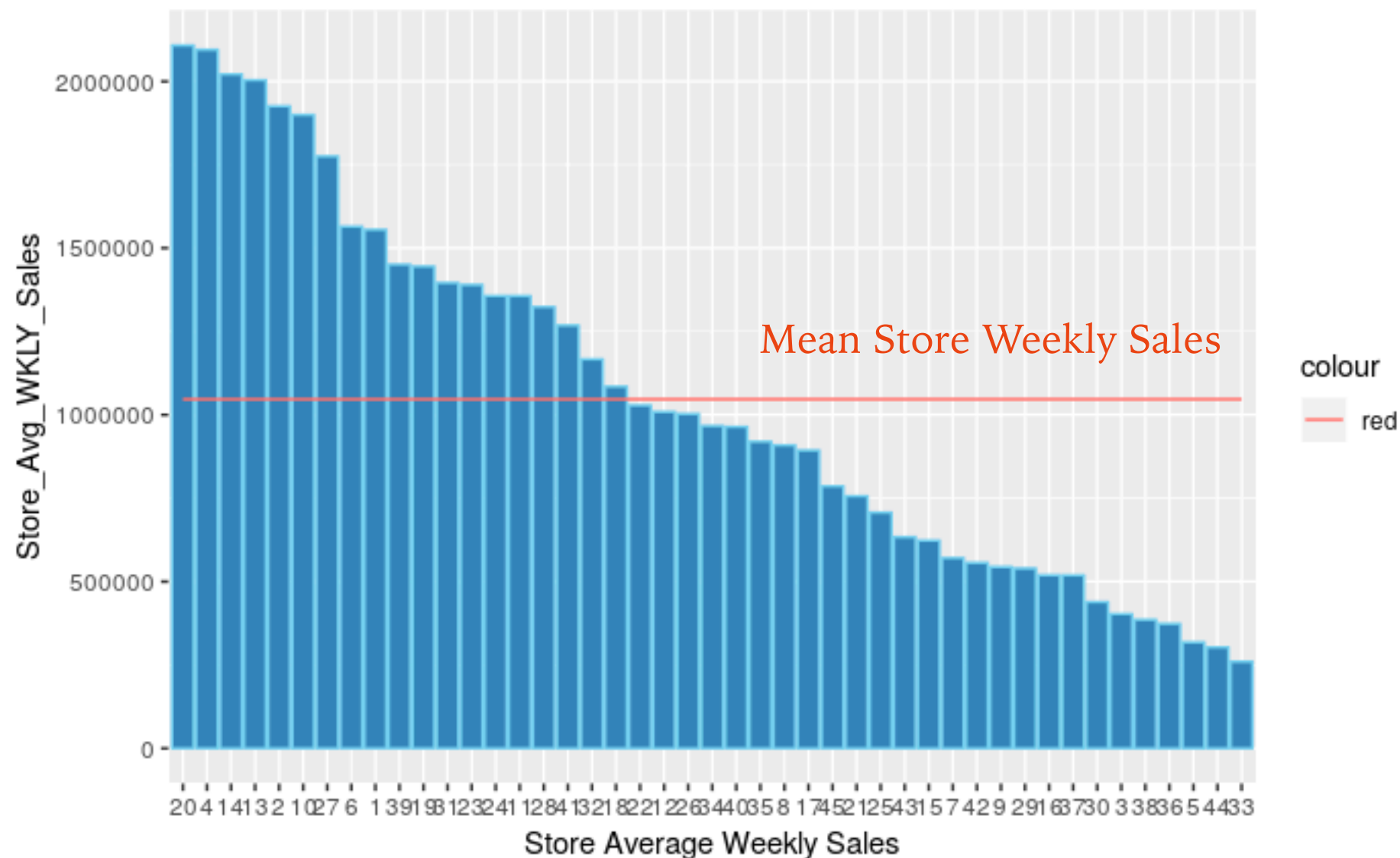
5 Markdown Features Box Plot



Correlations Matrix

# DATA PREPARATION

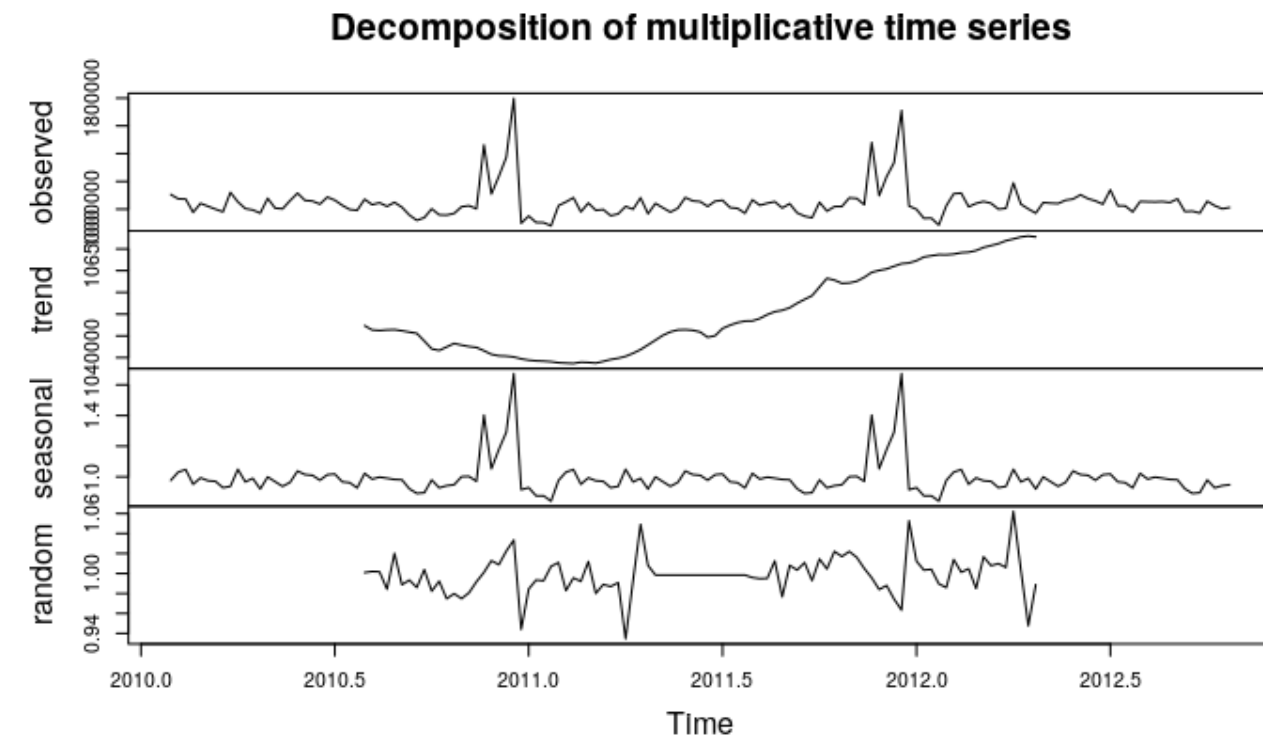
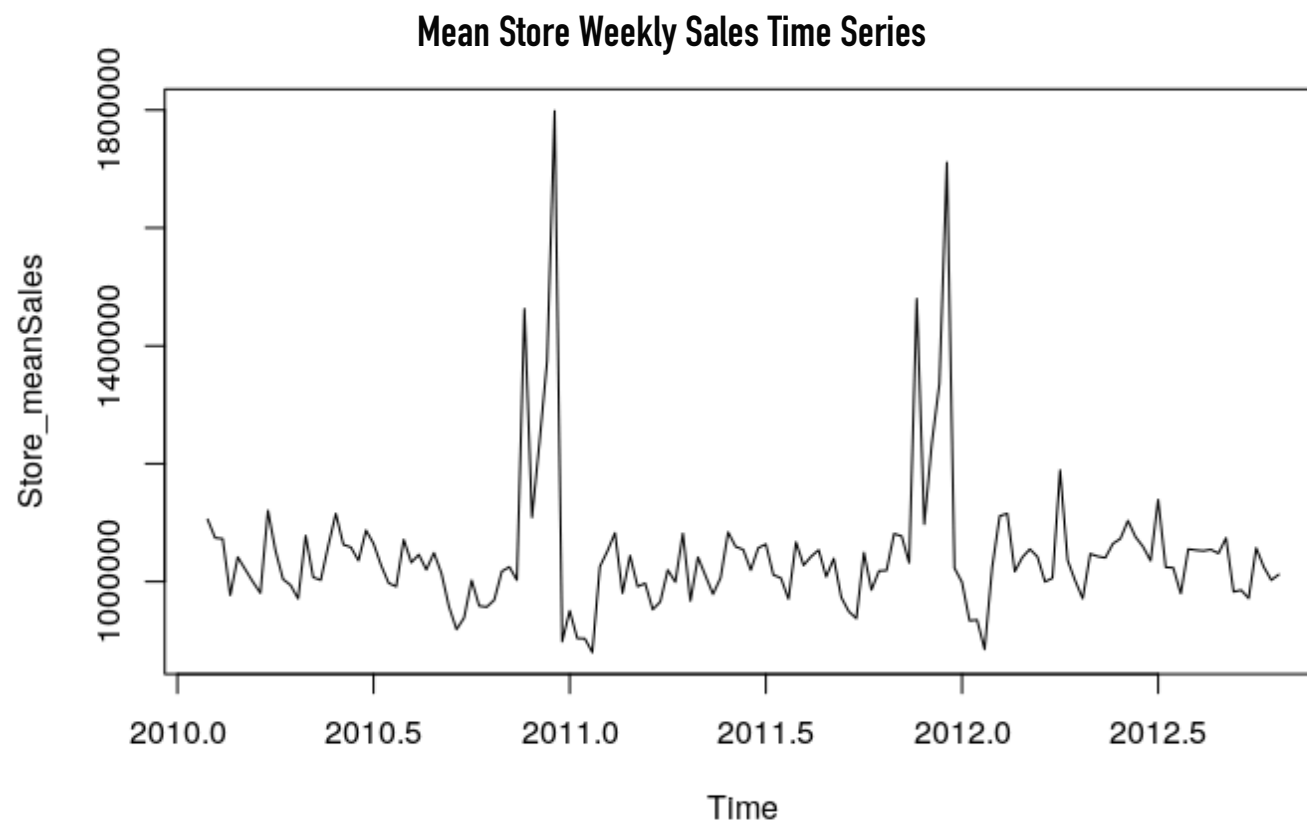
- 3331 Dept-Store ID: use paste() to create ID for every department in every store
- Expensive to compute: 3331 factors X 143 weeks
- This analysis focuses on forecasting 45 stores' aggregated weekly sales



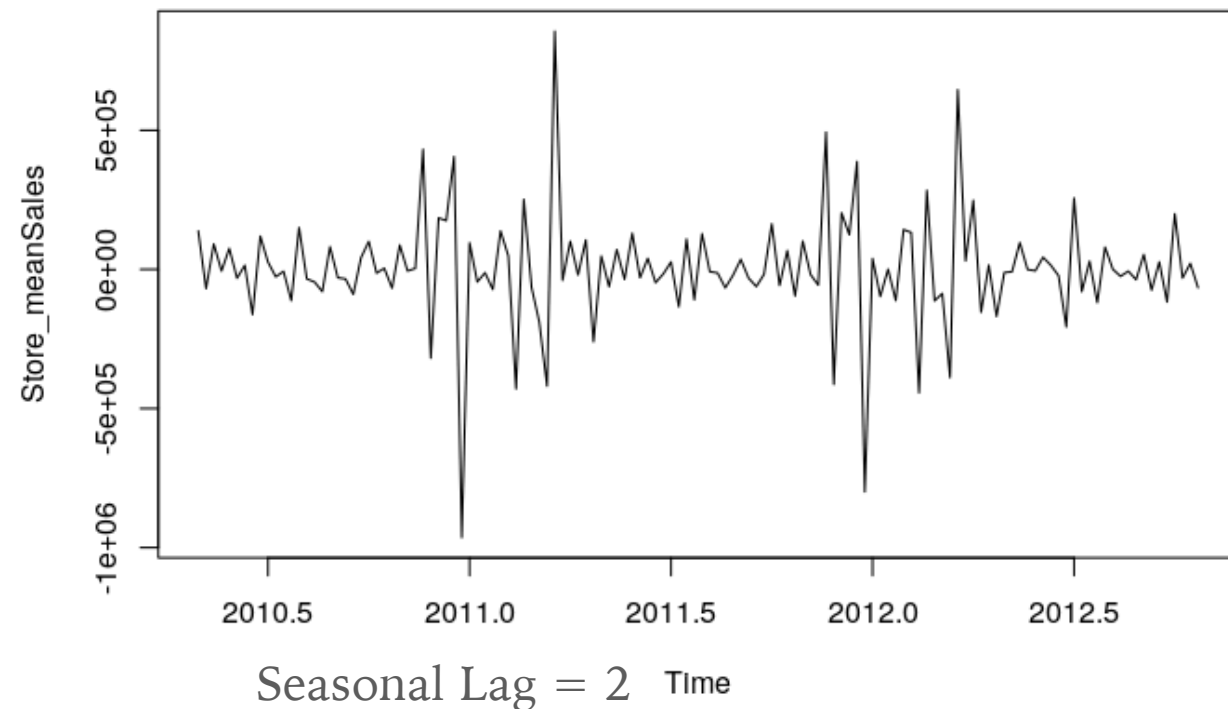
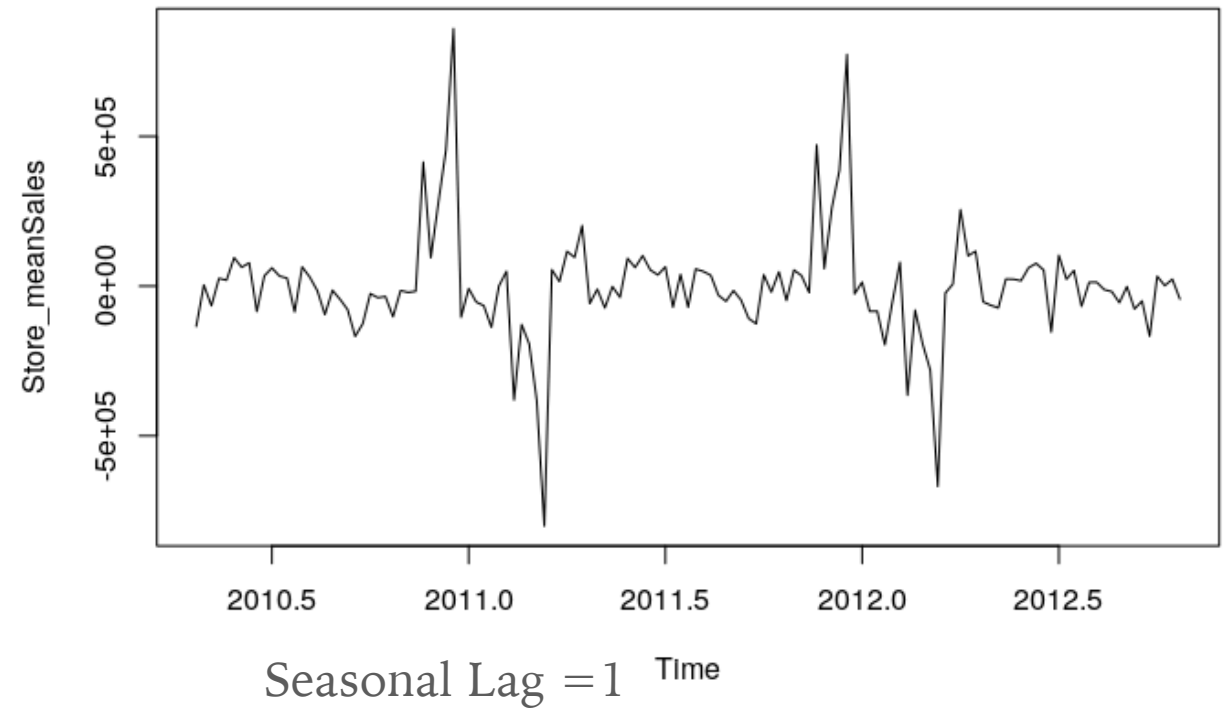
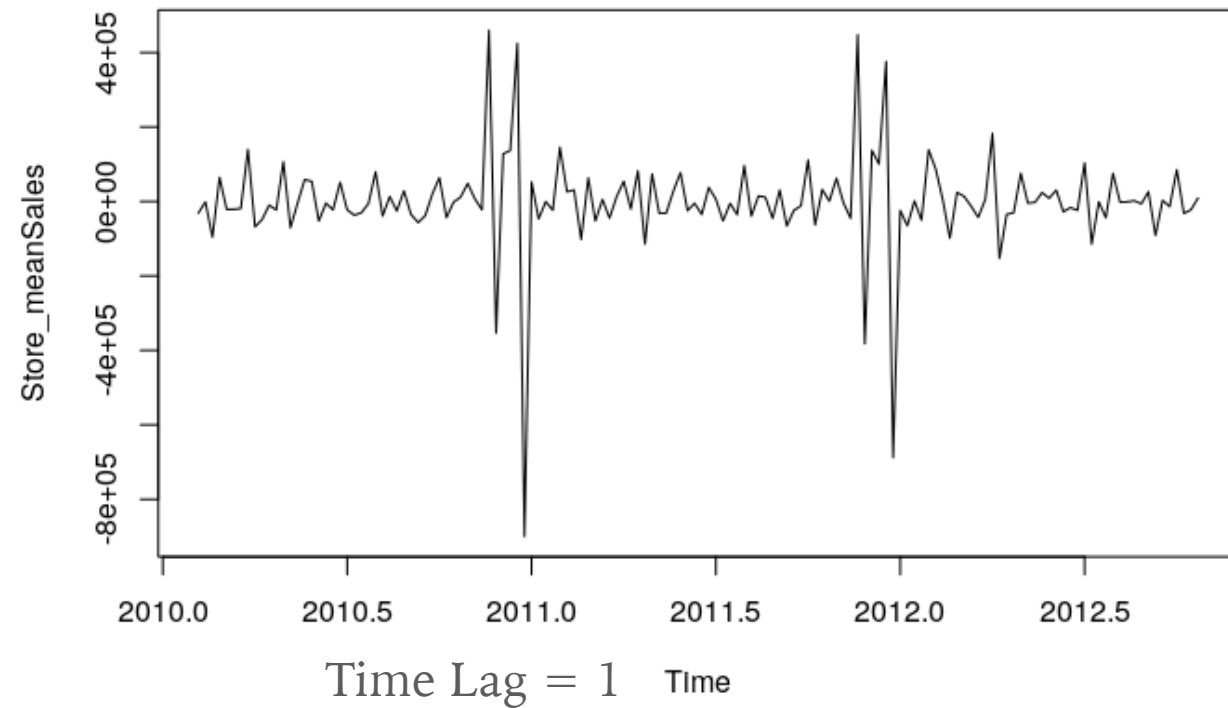


# DECOMPOSITION OF MULTIPLICATIVE TIME SERIES

- Decompose mean store weekly sales time series
- Results: strong trend, seasonal components; random component shows randomness



# DIFFERENCING TIME SERIES



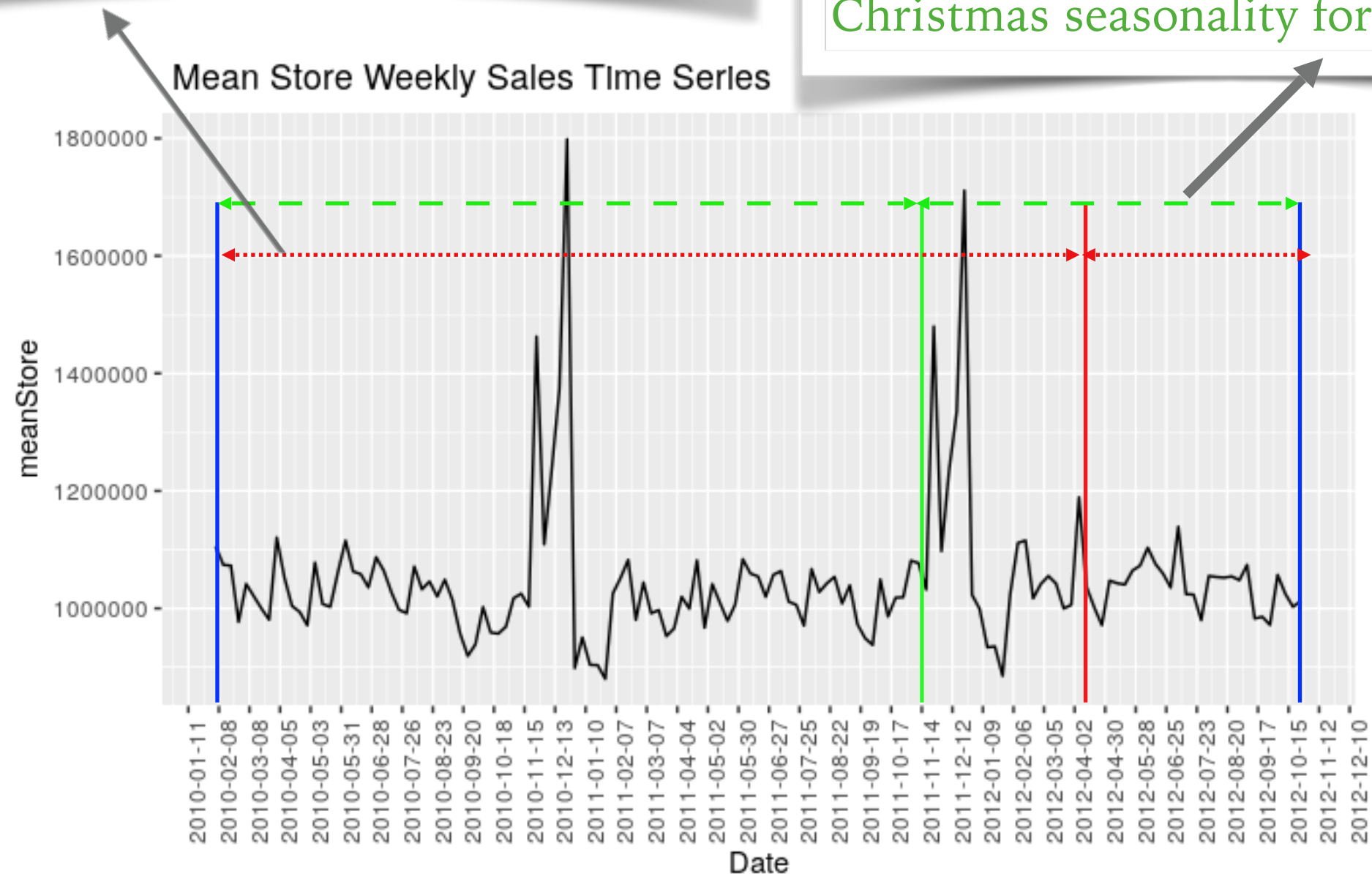
- Differencing removes seasonality in mean store weekly sales time series

# TIME SERIES TRAINING / TEST SETS SELECTION

Training/Test option 1: 80/20 split  
falls on 2012-04-06/2012-04-13

Training/Test option 1: 65/35 split  
falls on 2011-11-11/2011-11-18

Benefit: include Thanksgiving and  
Christmas seasonality for test set



# TIMES SERIES FORECASTING

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## Methods:

- Seasonal ARIMA
- Random Forests Regression
- XG Boosted Trees
- Neural Networks Regression

## Results Diagnostics:

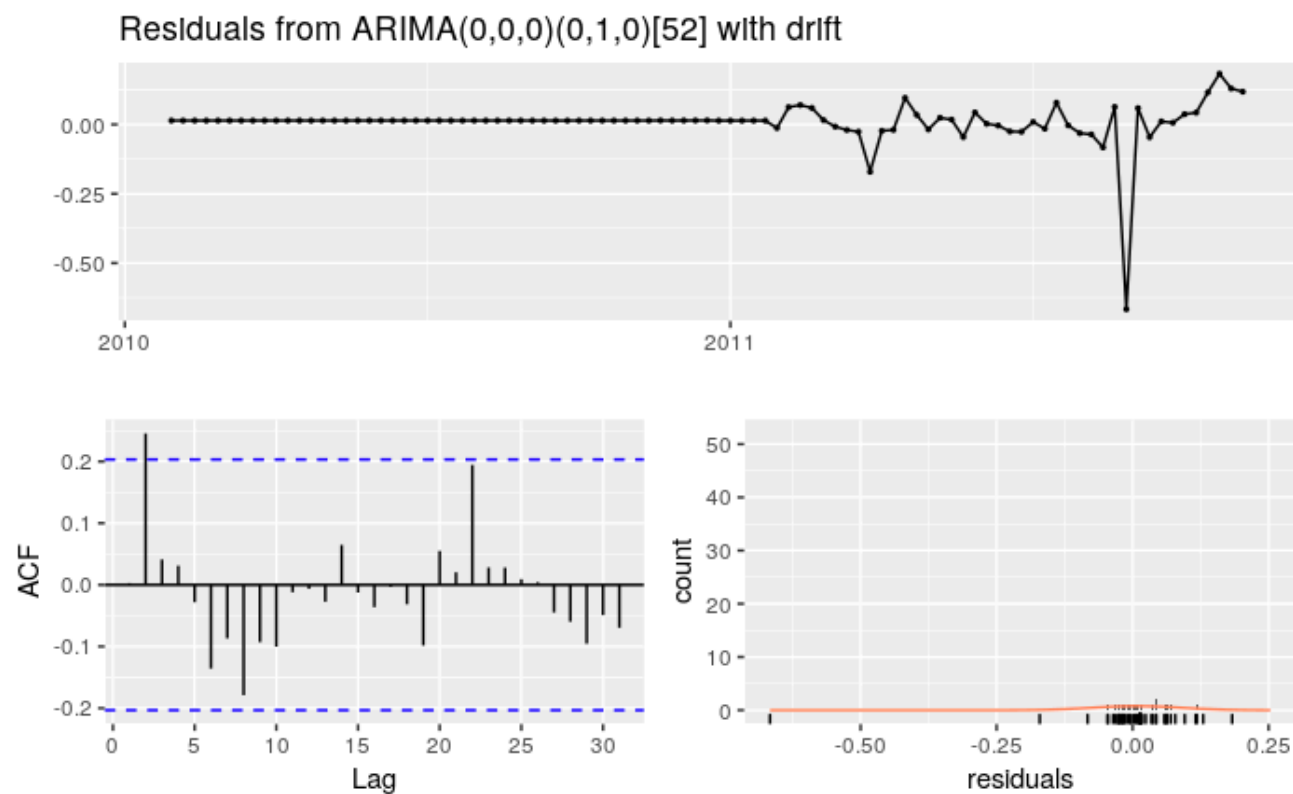
- MAE: scale dependent
- RMSE: scale dependent
- MAPE: non scale dependent

# SEASONAL ARIMA MODEL

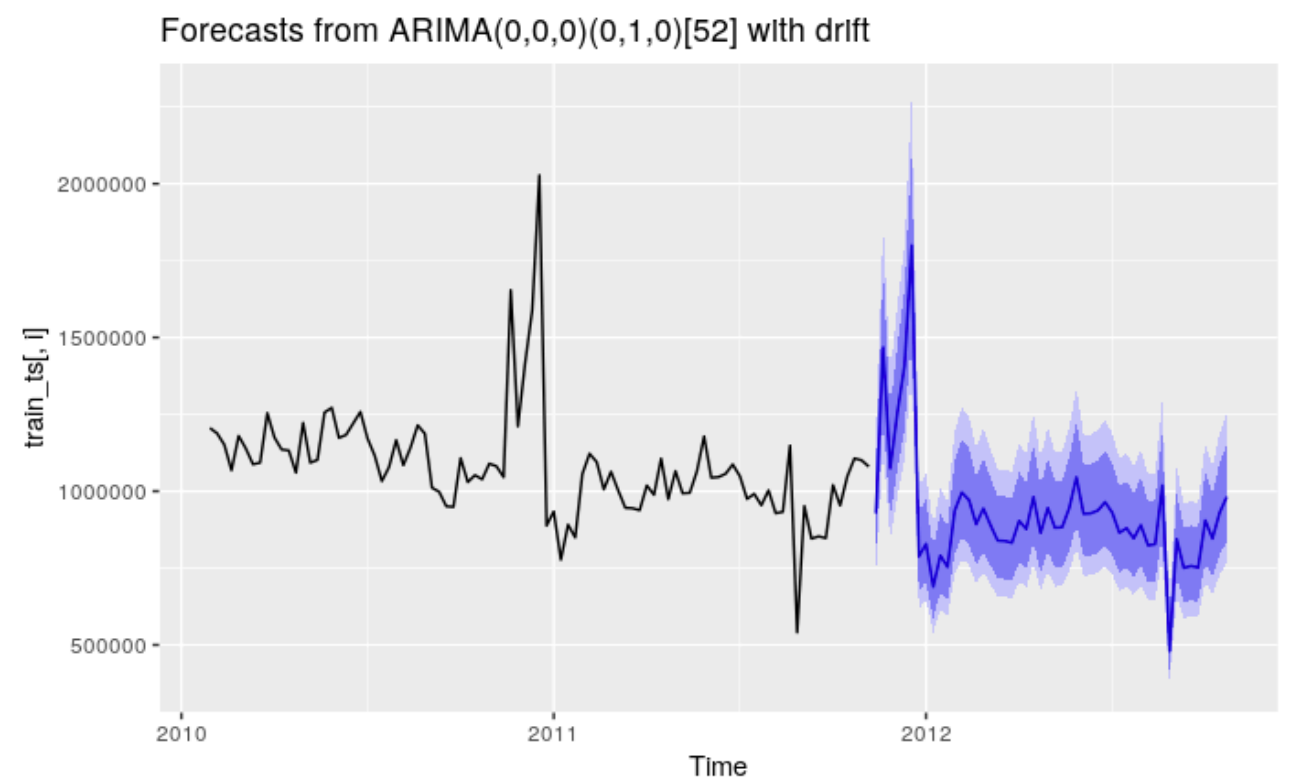
## Challenges:

- Shorter time periods constraint seasonal lag to 1
- Iterate over 45 time series using for() loop, resulting in slower speed

Residual Plots for Store #18, 65/35 Temporal Split



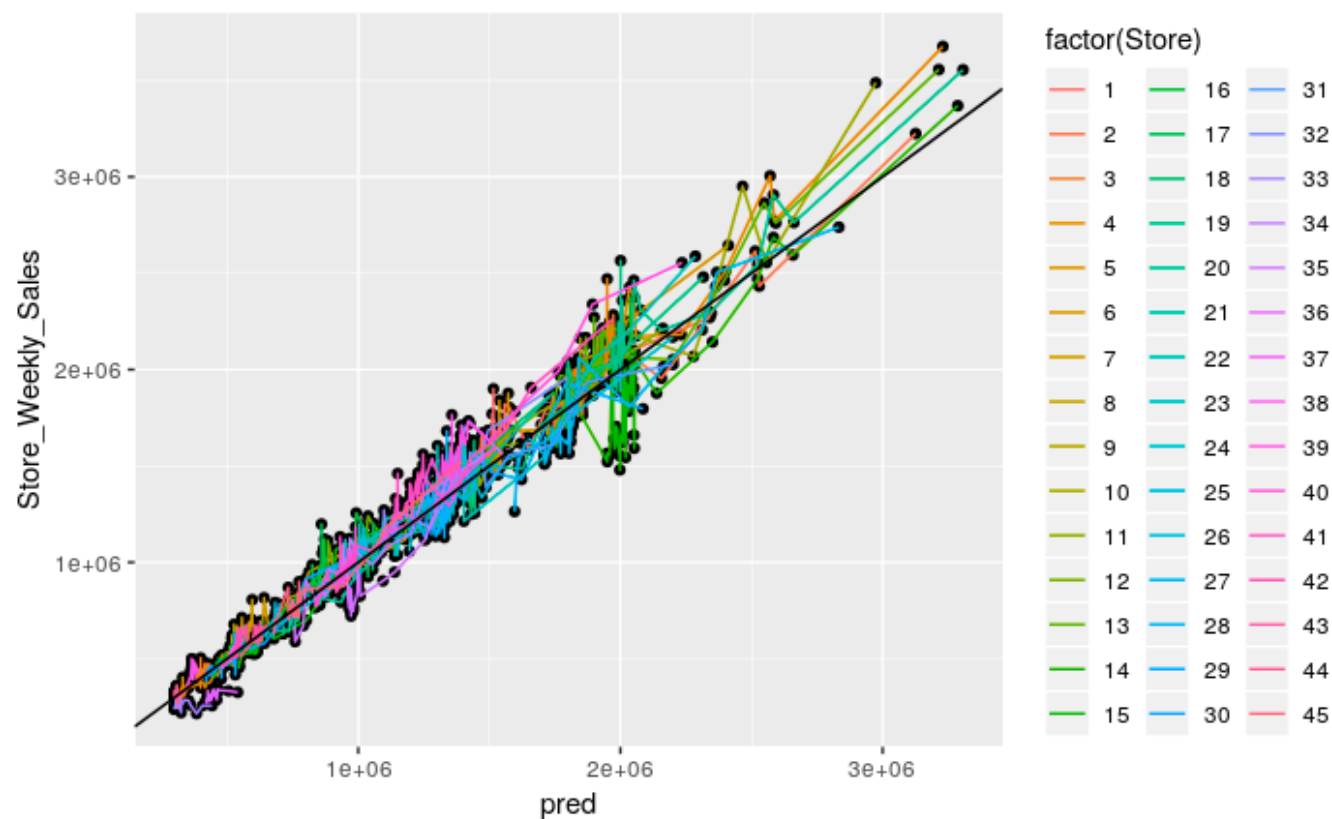
Forecasts Plot for Store #18, 65/35 Temporal Split



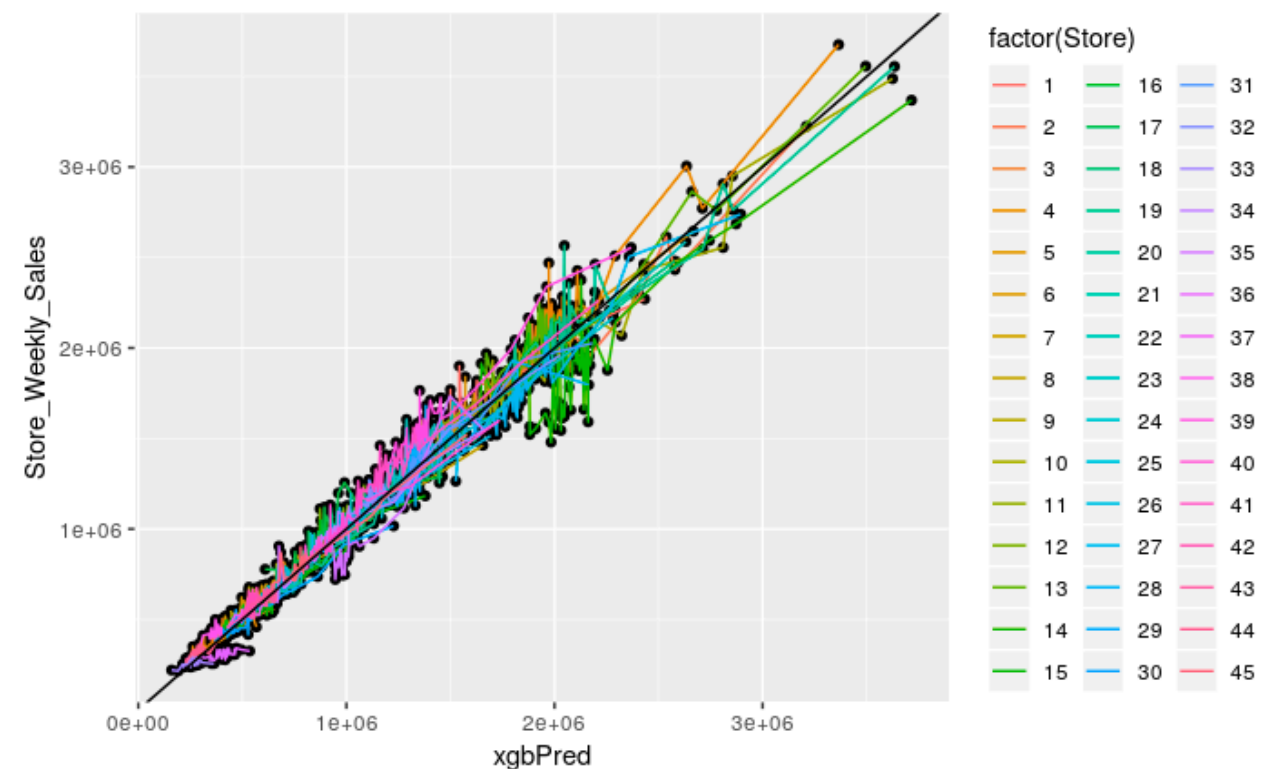
# RANDOM FORESTS VS. XG BOOSTED TREES

XG Boosted Tress has considerably improved prediction accuracy as compared with Random Forests

Random Forests, 65/35 Temporal Split



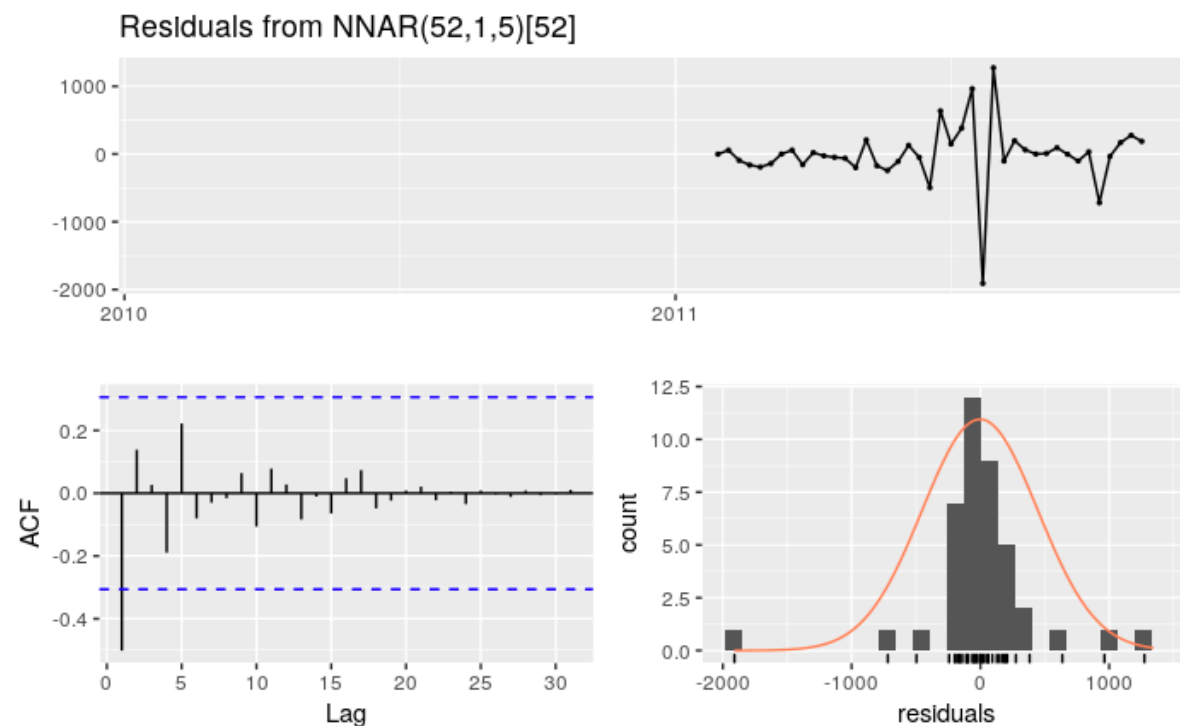
XG Boosted Trees, 65/35 Temporal Split



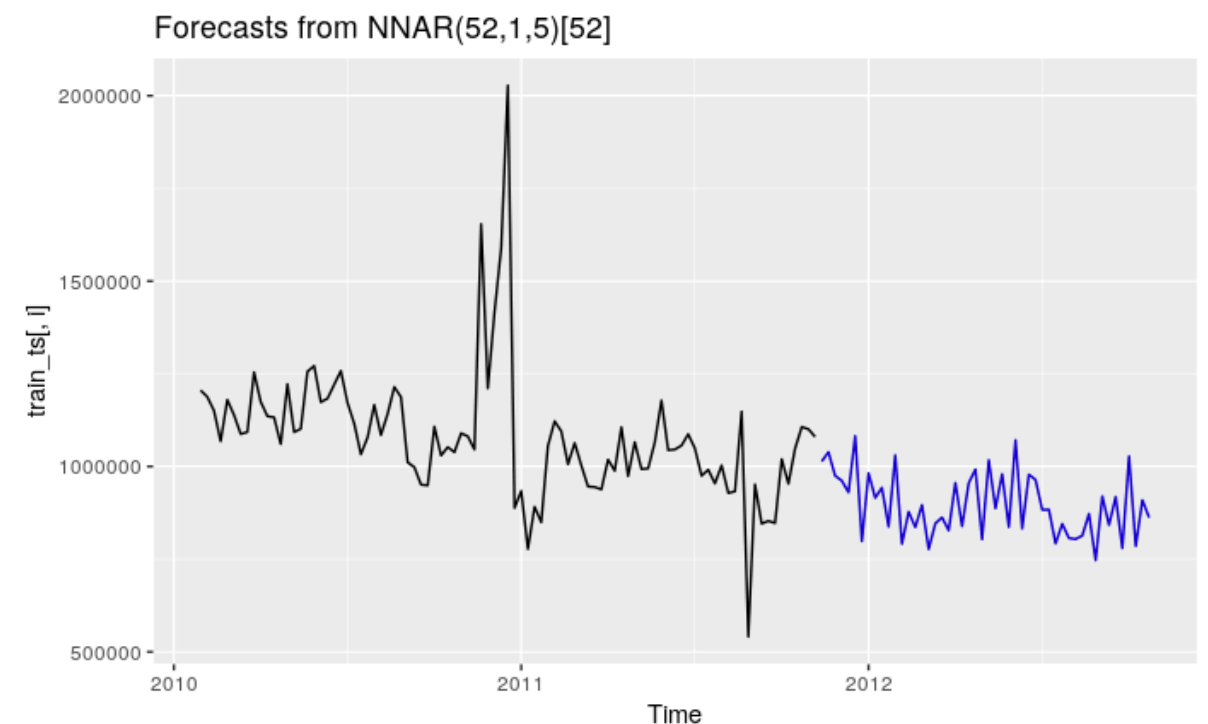
# NEURAL NETWORKS

- Feed forward `nnetar()` model with one hidden layer
- 5 neurons in hidden layer, repeat 20 times
- $\text{Lambda} = 0$ , no initial data transformation

Residuals Plots for Store # 18, 65/35 Temporal Split



Forecast Plot for Store # 18, 65/35 Temporal Split



# MODEL DIAGNOSTICS

- Seasonal ARIMA model outperforms in both time split cases
- XG Boost improves tree prediction accuracy notably
- Neural Networks can capture non-linearity better in 65/35 split

80/20 Temporal Split on 2012-04-13

	MAE	RMSE	MAPE
ARIMA	57517	71755	5.53
Random Forests	65746	77079	7.04
Xgboost	63740	73969	6.75
Neural Networks	116660	137922	10.49

65/35 Temporal Split on 2011-11-18

	MAE	RMSE	MAPE
ARIMA	61988	78263	5.76
Random Forests	70209	86753	7.29
Xgboost	66535	80961	6.92
Neural Networks	98224	152123	8.37



# SHORTCOMINGS

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- Lack of true test set data penalizes machine learning models
- Abnormally large missing values force to drop Markdown features
- Model diagnostics are equal-weight store accuracy statistics
- Overweighting holiday prediction errors should be explored