Big Time Series Forecasting

Contents

Introduction

Time series forecasting is a key component in the automation and optimization of business processes. In recent years because of the availability of large, diverse time series data, forecasting techniques are becoming more data driven and automated.

This project explores methods to forecast Big Time Series using classical modeling of time series and Modern approaches.

Challenges

Some challenges related to processing Big time series and manual forecasting processes are as following:

`Lack of Automation` Manual, Error prone forecasting processes are common at many companies. This also leads to issues with scalability.

`Computation Time` Processing hundreds of thousands of time series using manual processes takes a lot of time which might cause issues with Business stakeholders.

`Lack of Resources` Creating forecasts for thousands of stores or SKUs could involve dedicated effort from several quantitative experts which might not be feasible for many companies.

`Bias/Accuracy Issues` Manual forecasting systems involving human interventions leads to more errors and biases in the forecasting process.

`Large/diverse data sources` How can we build statistical models to learn to forecast from large and diverse data sources? How can we leverage the statistical power of "similar" time series to improve forecasts in the case of limited observations?

Corporación Favorita

Brick-and-mortar grocery stores are always in a delicate dance with purchasing and sales forecasting. Predict a little over, and grocers are stuck with overstocked, perishable goods. Guess a little under, and popular items quickly sell out, leaving money on the table and customers fuming.

The problem becomes more complex as retailers add new locations with unique needs, new products, ever transitioning seasonal tastes, and unpredictable product marketing.

Corporación Favorita, a large Ecuadorian-based grocery retailer, knows this all too well. They operate hundreds of supermarkets, with over 200,000 different products on their shelves. They currently rely on subjective forecasting methods with very little data to back them up and very little automation to execute plans.

Data

The data is taken from Kaggle competition Corporación Favorita Grocery Sales Forecasting.

The training data includes dates, store and item information, whether that item was being promoted, as well as the unit sales. Additional files include supplementary information that may be useful in building your models.

File Descriptions and Data Field Information

`train.csv`

- Training data, which includes the target unit_sales by date, store_nbr, and item_nbr and a unique id to label rows.

- The target unit_sales can be integer (e.g., a bag of chips) or float (e.g., 1.5 kg of cheese). Negative values of unit_sales represent returns of that particular item.
- The onpromotion column tells whether that item_nbr was on promotion for a specified date and store_nbr.
- Approximately 16% of the onpromotion values in this file are NaN.
- NOTE: The training data does not include rows for items that had zero unit_sales for a store/date combination. There is no information as to whether or not the item was in stock for the store on the date, and teams will need to decide the best way to handle that situation. Also, there are a small number of items seen in the training data that aren't seen in the test data.

`stores.csv`

- Store metadata, including city, state, type, and cluster.
- cluster is a grouping of similar stores.

`items.csv`

- Item metadata, including family, class, and perishable.
- NOTE: Items marked as perishable have a score weight of 1.25; otherwise, the weight is 1.0.

`transactions.csv`

- The count of sales transactions for each date, store_nbr combination. Only included for the training data timeframe.

`oil.csv`

- Daily oil price. Includes values during both the train and test data timeframe. (Ecuador is an oil-dependent country and it's economical health is highly vulnerable to shocks in oil prices.)

`holidays_events.csv`

- Holidays and Events, with metadata
- NOTE: Pay special attention to the transferred column. A holiday that is transferred officially falls on that calendar day, but was moved to another date by the government. A transferred day is more like a normal day than a holiday. To find the day that it was actually celebrated, look for the corresponding row where type is Transfer. For example, the holiday Independencia de Guayaquilwas transferred from 2012-10-09 to 2012-10-12, which means it was celebrated on 2012-10-12. Days that are type Bridge are extra days that are added to a holiday (e.g., to extend the break across a long weekend). These are frequently made up by the type Work Day which is a day not normally scheduled for work (e.g., Saturday) that is meant to payback the Bridge.
- Additional holidays are days added a regular calendar holiday, for example, as typically happens around Christmas (making Christmas Eve a holiday).
- Additional Notes
- Wages in the public sector are paid every two weeks on the 15 th and on the last day of the month. Supermarket sales could be affected by this.
- A magnitude 7.8 earthquake struck Ecuador on April 16, 2016. People rallied in relief efforts donating water and other first need products which greatly affected supermarket sales for several weeks after the earthquake.

Approach

Tools

R, RStudio, R Markdown, AWS, tsfresh

Open source R forecasting Packages:

forecast: Rob Hyndman's R package is among the most popular packages. Contains implementations for many classic methods.

prophet: Facebook's Prophet package uses Stan behind the scences.

Exploratory analysis

Plot sample data. Are there consistent patterns? Is there a significant trend? Is seasonality important? Is there evidence of the presence of business cycles? Are there any outliers in the data that need to be explained by those with expert knowledge? How strong are the relationships among the variables available for analysis?

Forecasting Methods

Classical methods for Forecasting:

`Average method`

Here, the forecasts of all future values are equal to the average (or "mean") of the historical data. Average method is used as the baseline model for comparing accuracy metrics.

`ARIMA`

The auto.arima() function in R uses a variation of the Hyndman-Khandakar algorithm (Hyndman & Khandakar, 2008), which combines unit root tests, minimisation of the AICc and MLE to obtain an ARIMA model. The arguments to auto.arima() provide for many variations on the algorithm.

`Exponential Smoothing`

Exponential Smoothing State Space Model

`Prophet`

Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects.

Implementation code: src/process_fcast.R

Evaluation

Dataset will be split into train/test based on the date index. Test set will contain the last 16 days data.

Following accuracy measures were computed for all the time series:

Scale dependent accuracy measures - Mean absolute error: MAE, Root mean squared error: RMSE

Mean Absolute Percentage Error: MAPE

Mean Absolute Scaled Error: MASE

Mean RMSE of all the time series was used in this report as the Evaluation Metric to compare the forecasting methods.

For sample time series, the following plots will be shown:

(1) Predicted vs Actual scatterplot

(2) Predicted vs Residuals scatterplot

(3) Histogram of Residuals

Time Series forecasting

libraries

```
library('ggplot2')
library('dplyr')
library('readr')
library('data.table')
library('forecast')
library('prophet')
library('tibble')
library('tidyr')
library('stringr')
library('forcats')
library('lubridate')
```

Load data

training data is 4.7 GB in size with 126 million rows.

```
set.seed(32)
## reading train data
train_data_f <- fread('../data/raw/train.csv', skip = 36458909,
                col.names = c('id', 'date','store_nbr', 'item_nbr', 'unit_sales', 'onpromotion'))
```

Training data

```
summary(train_data_f)
```

```
##        id                 date              store_nbr        item_nbr
##  Min.   : 36458908   Length:89038132    Min.   : 1.00   Min.   :  96995
##  1st Qu.: 58718441   Class :character   1st Qu.:12.00   1st Qu.: 584188
##  Median : 80977974   Mode  :character   Median :28.00   Median :1089044
##  Mean   : 80977974                      Mean   :27.65   Mean   :1059528
##  3rd Qu.:103237506                      3rd Qu.:43.00   3rd Qu.:1459225
##  Max.   :125497039                      Max.   :54.00   Max.   :2127114
##    unit_sales        onpromotion
##  Min.   :-15372.00   Mode :logical
##  1st Qu.:     2.00   FALSE:81596506
##  Median :     4.00   TRUE :7441626
##  Mean   :     8.39
##  3rd Qu.:     9.00
##  Max.   : 89440.00
```

```
glimpse(train_data_f)
```

```
## Observations: 89,038,132
## Variables: 6
## $ id          <int> 36458908, 36458909, 36458910, 36458911, 36458912, ...
## $ date        <chr> "2014-12-02", "2014-12-02", "2014-12-02", "2014-12...
## $ store_nbr   <int> 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10...
## $ item_nbr    <int> 464336, 464339, 464374, 464906, 464940, 467808, 46...
## $ unit_sales  <dbl> 4, 5, 4, 1, 7, 34, 1, 7, 2, 4, 2, 1, 1, 3, 14, 5, ...
## $ onpromotion <lgl> FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, F...
```

time series data for a store,item

Top 2 stores by sales: 44, 45 Considering time series of store 44, Item 1503823

```
train_data_f[, ':='(
  date = ymd(date, tz = NULL),
  store_item = paste(store_nbr, item_nbr, sep="_")
)]

data_wide <- dcast(train_data_f, store_item ~ date, value.var = "unit_sales", fill = 0)
```

```
data_item <- data_wide %>%
    filter(store_item == "44_1503823")
```

```
  h <- 16
  frequency <- 7
  date_index_test <- tail(colnames(data_wide), 16)

  data_df <- melt(data_item, id.vars = c("store_item"))

  store_item_val <- data_df$store_item[1]
  data_df$store_item <- NULL
```

```
  colnames(data_df) <- c("ds", "y")

  # Date column handling
  data_ts <- data_df
  data_ts <- data_ts %>%
               select(-ds)


  test_index <- tail(rownames(data_ts), h) %>% as.numeric()
  test_data <- data_ts %>% slice(test_index) %>% `row.names<-`(test_index)
  train_data <- data_ts %>% slice(-test_index)

  # Converts train data to time.series object
  train_ts <- ts(train_data, frequency = frequency, start = 1)
```

Arima forcast

```
  fit_arima <- auto.arima(x = train_ts)
  fit_arima
```

```
## Series:
## ARIMA(2,0,2)(2,1,1)[7]
##
## Coefficients:
##          ar1     ar2      ma1      ma2    sar1    sar2     sma1
##       0.3031  0.5758  -0.0807  -0.4594  0.0364  0.0056  -0.7325
## s.e.  0.4367  0.4028   0.4347   0.3072  0.0536  0.0443   0.0429
##
## sigma^2 estimated as 33.24:  log likelihood=-3049.12
## AIC=6114.25   AICc=6114.4   BIC=6153.2
```

```
    forecast_arima <- forecast(fit_arima, h = h)
    forecast_arima
```

```
##          Point Forecast      Lo 80    Hi 80      Lo 95    Hi 95
## 139.4286       8.553684  1.1646239 15.94274 -2.7469083 19.85428
## 139.5714       5.866297 -1.7032683 13.43586 -5.7103539 17.44295
## 139.7143      13.390628  5.7001786 21.08108  1.6291004 25.15216
## 139.8571       6.916667 -0.8927458 14.72608 -5.0267993 18.86013
## 140.0000       7.404020 -0.4960974 15.30414 -4.6781671 19.48621
## 140.1429      18.893021 10.9105363 26.87551  6.6848642 31.10118
## 140.2857      14.822266  6.7730822 22.87145  2.5121015 27.13243
## 140.4286       8.914853  0.2462449 17.58346 -4.3426389 22.17234
## 140.5714       6.026591 -2.7526820 14.80586 -7.4001484 19.45333
## 140.7143      13.678302  4.8115573 22.54505  0.1177864 27.23882
## 140.8571       6.992968 -1.9515212 15.93746 -6.6864478 20.67238
## 141.0000       7.518037 -1.4904752 16.52655 -6.2592934 21.29537
## 141.1429      19.002492  9.9383615 28.06662  5.1401004 32.86488
## 141.2857      14.991184  5.8803567 24.10201  1.0573758 28.92499
## 141.4286       9.071390 -0.5071531 18.64993 -5.5777273 23.72051
## 141.5714       6.144710 -3.5159768 15.80540 -8.6300356 20.91946
```

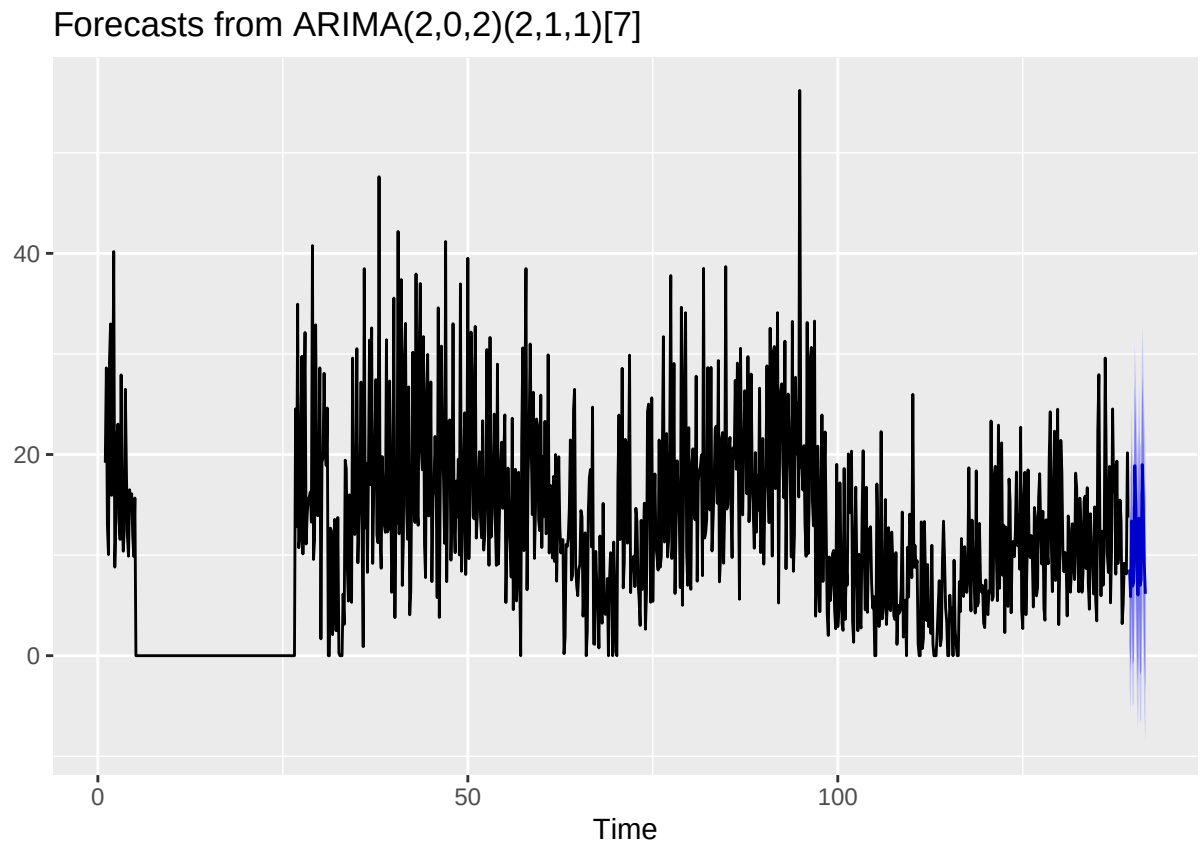
Accuracy Metrics (Arima)

```
    t_data <- test_data$y %>% as.numeric()
    accuracy_arima <- forecast::accuracy(forecast_arima, t_data)
    accuracy_arima
```

```
##                       ME     RMSE      MAE      MPE     MAPE      MASE
## Training set -0.06418749 5.723912 4.014630      NaN      Inf 0.5485505
## Test set      0.79180558 3.405526 2.719444 4.590383 23.82331 0.3715791
##                    ACF1
## Training set -0.01706721
## Test set              NA
```

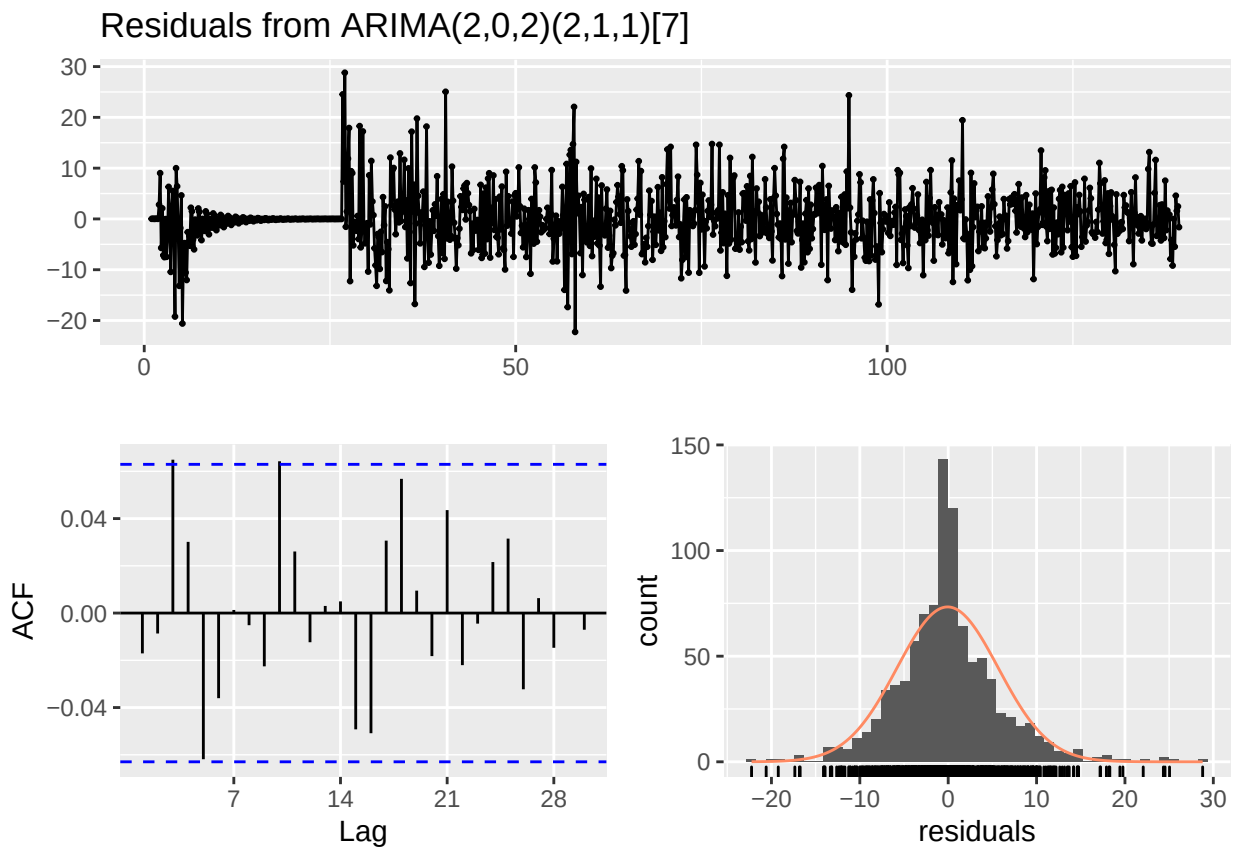
Arima forecast plot

```
autoplot(forecast_arima)
```



Arima residuals plot

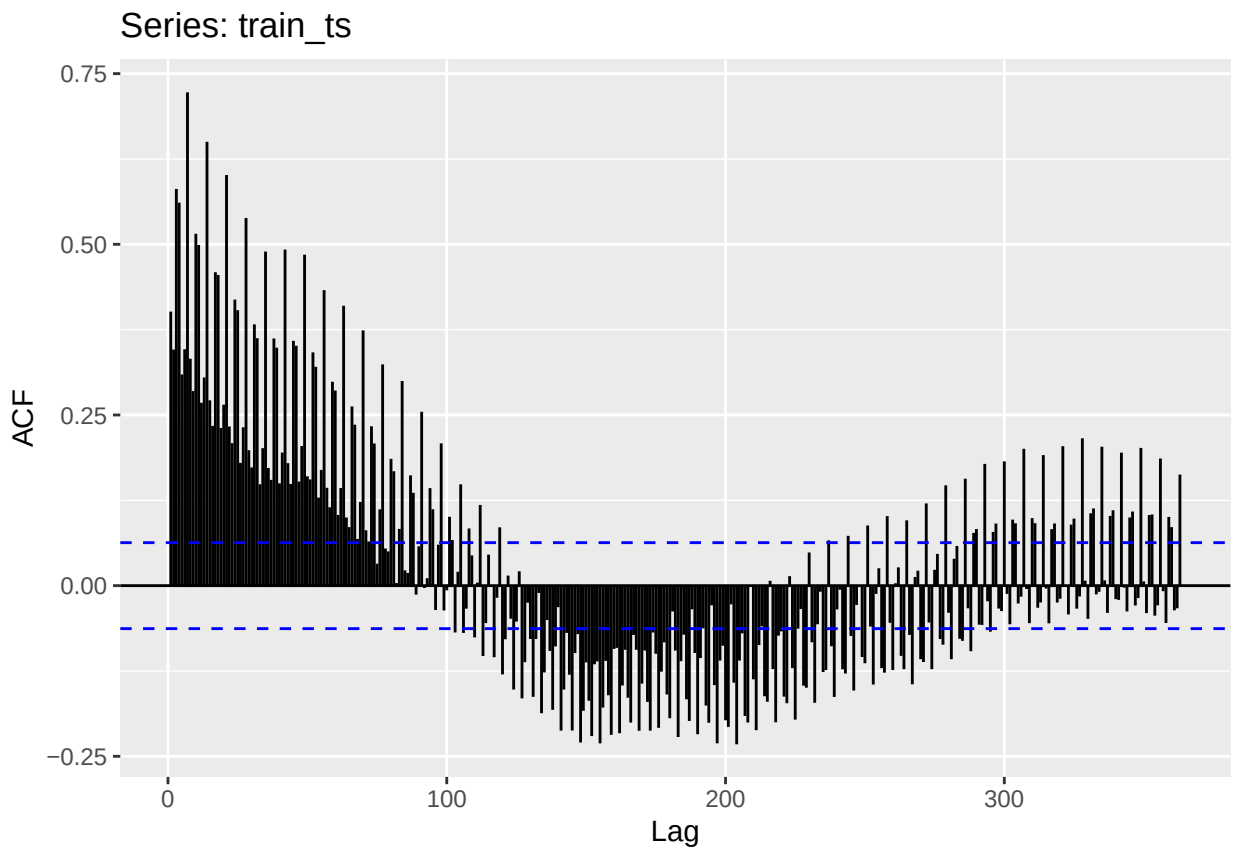
```
checkresiduals(fit_arima)
```



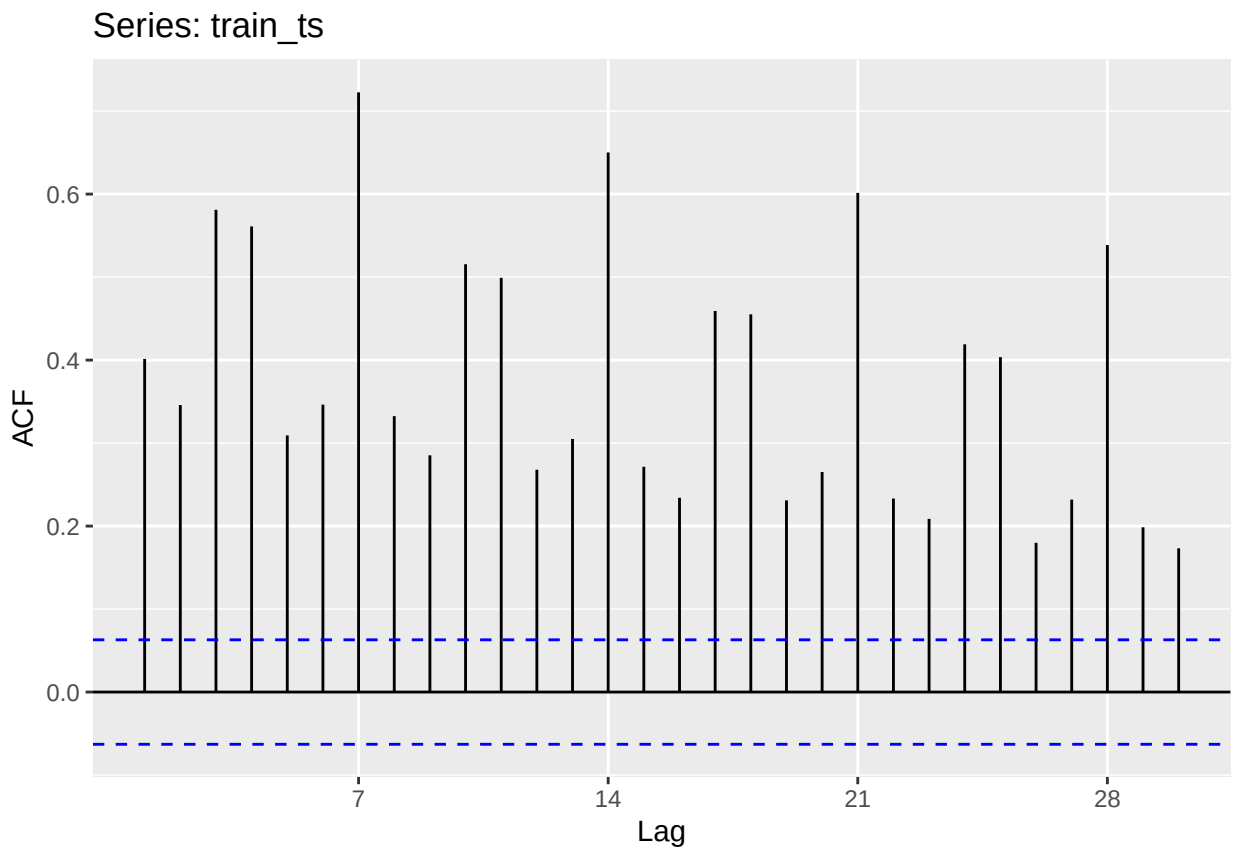

```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(2,0,2)(2,1,1)[7]
## Q* = 15.78, df = 7, p-value = 0.0272
##
## Model df: 7.   Total lags used: 14
```

##ACF plots

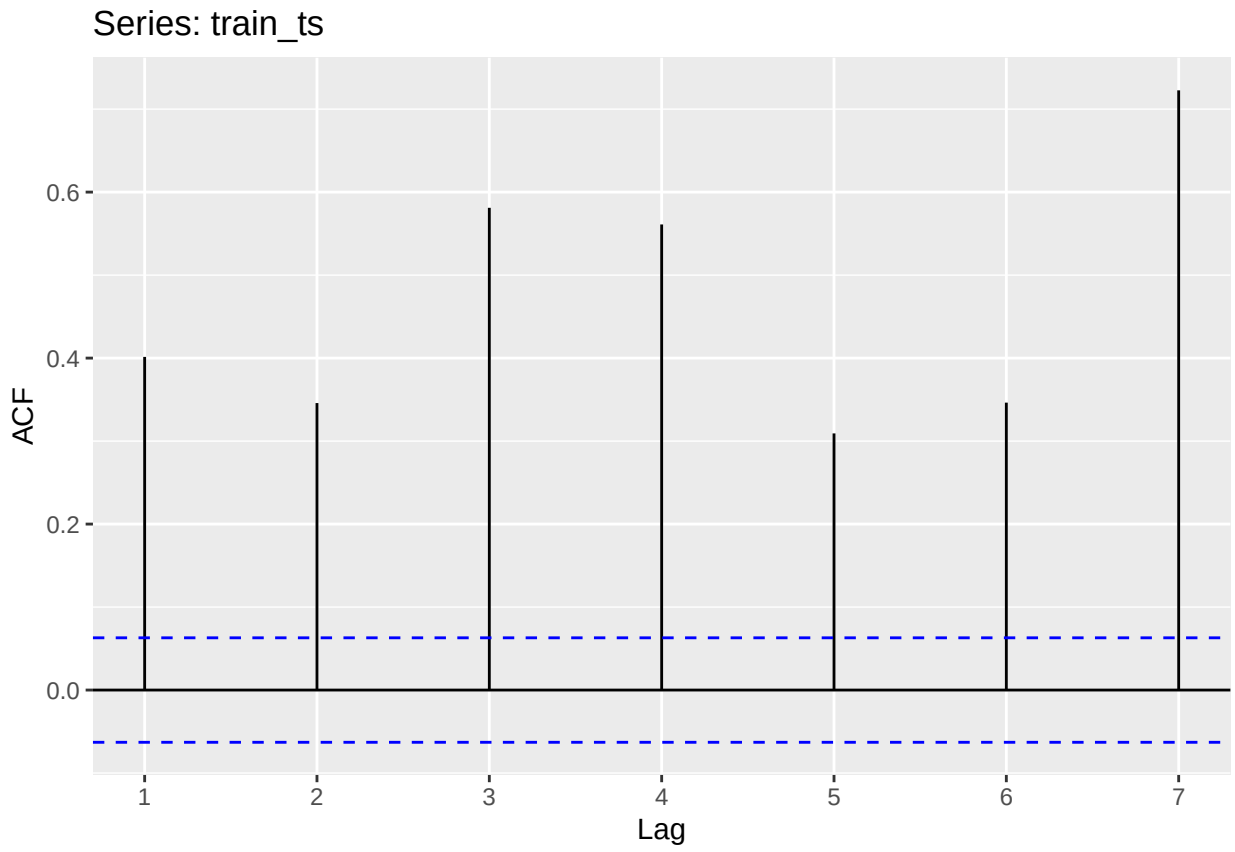
```
ggAcf(train_ts, lag = 363)
```




```
ggAcf(train_ts, lag = 30)
```




```
ggAcf(train_ts, lag = 7)
```



prophet

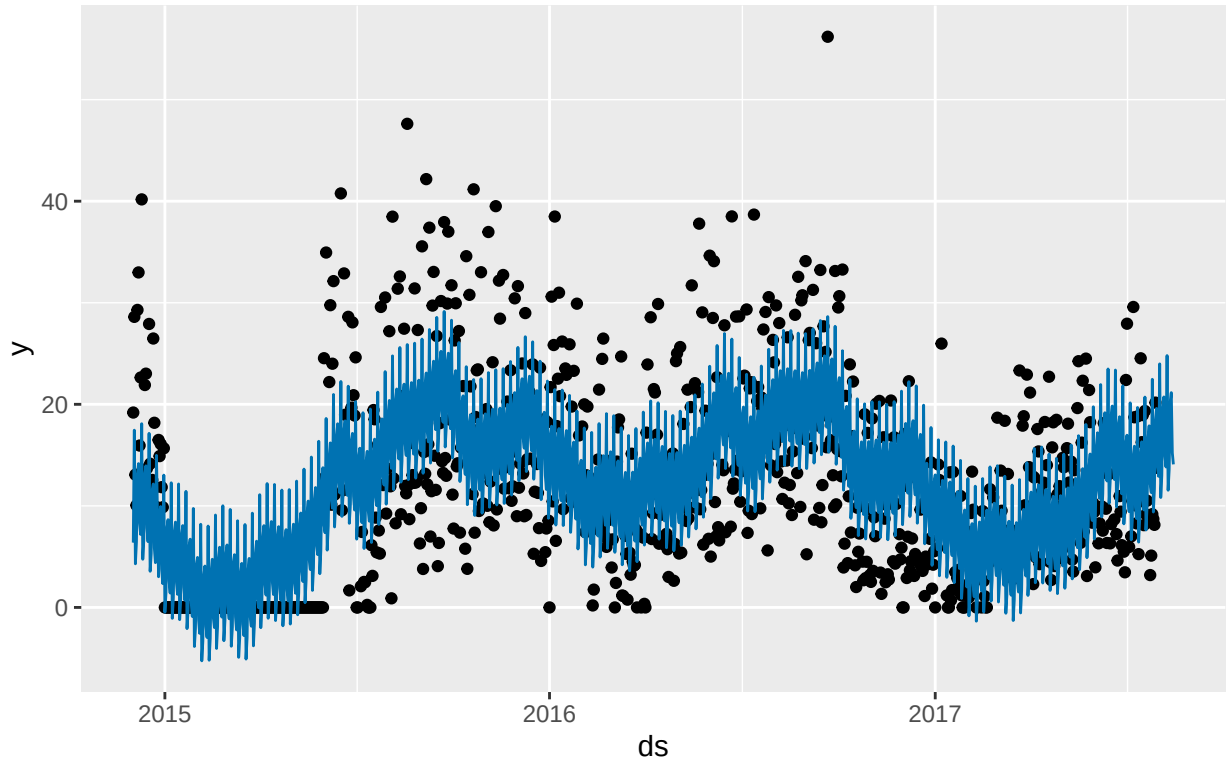
```
test_index <- tail(rownames(data_df), h) %>% as.numeric()
test_data <- data_df %>% slice(test_index) %>% `row.names<-`(test_index)
train_data <- data_df %>% slice(-test_index)


df = train_data
yearly.seasonality=TRUE
weekly.seasonality = TRUE
daily.seasonality=FALSE

fit_prophet <- prophet(df = train_data, yearly.seasonality=TRUE, weekly.seasonality = TRUE,
             daily.seasonality=FALSE)
future <- make_future_dataframe(fit_prophet, periods = 16)
forecast <- predict(fit_prophet, future)
forecast <- forecast[c('ds', 'yhat')]
forecast$store_item <- store_item_val
```

prophet forecast plot

```
plot(fit_prophet, forecast)
```

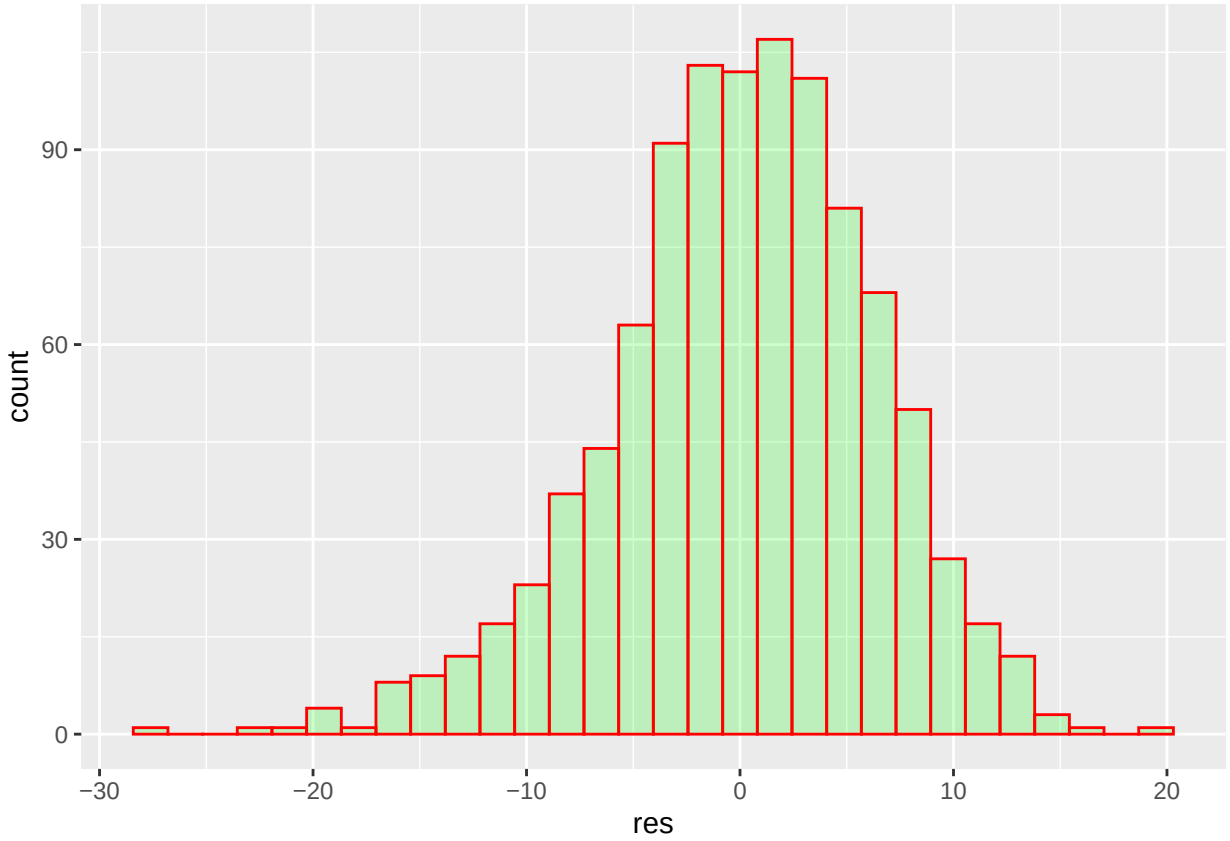


prophet residuals plot

```
  colnames(data_df) <- c("ds", "y")
  residuals_f = forecast['yhat'] - data_df['y']
  colnames(residuals_f) <- c("res")
  head(residuals_f)
```

```
##          res
## 1 -12.804108
## 2 -11.158240
## 3  -8.775529
## 4  -3.602418
## 5 -16.138064
## 6 -18.823040
```

```
  ggplot(residuals_f, aes(res)) +
  geom_histogram( col="red",
                  fill="green",
                  alpha=.2)
```




```
    forecast <- forecast[forecast$ds >= ymd("2017-07-30"),]

    t_data <- test_data$y %>% as.numeric()
    accuracy_prophet <- forecast::accuracy(forecast$yhat, t_data)
    accuracy_prophet
```

```
##                  ME     RMSE      MAE       MPE     MAPE
## Test set -5.559209 8.726081 7.045657 -74.55215 83.42445
```

Accuracy measures (Big Time Series)

Accuracy measures for the 18310 time series considering Top 5 store numbers (44, 45, 47, 3, 49) by total sales as the baseline for processing multiple time series are shown below. AWS EC2 Instance Type, c5.2xlarge was used for processing.

Method	Mean RMSE	Time
mean	7.45920546451115	40.76 mins
ets	8.0311892817118	48.55 mins
auto.arima	6.589306454993	7.83 hours
prophet	7.49642904779891	3.24 hours

Conclusions and Future Work

In this project we have explored use of classical time series models like Arima, ETS and prophet to forecast Big Time Series. From the accuracy measures above, Auto Arima was the best performing forecasting method.

Other approaches to consider for possible improvements:

1) Feature Engineering
2) Use Alternate Data
3) Multivariate - Machine Learning Techniques
4) Ensemble Models
5) Deep Learning Techniques
6) Tools like tsfresh, DataRobot, H2O, Amazon Forecast

Recommendations to the Client

Retailers face varying product demand due to diverse factors, such as weather or short-lived trends. Diverse variables influence demand and, consequently, product sales. Relevant data related to the below Demand Influencing factors of retail supply chains would help in improving the forecasting process.

Demand Forecast Categories	Influence Factors
Products	Quality Competitors, substitutes, complements Price
Consumer preferences	Fashions and trends
External factors	Buying behavior, Brand awareness and perception Weather Special events Seasonality Income level, economic outlook Local development Mega trends (demographics, technology, climate, etc.)
Marketing Factors	Promotions Advertisement
Shop Factors	Local competition Shop attractiveness Shop assortment and layout
Supply factors	Available products at point of sale Expiring products

Another recommendation - additional data related to business objectives and constraints will help in adding

a prescriptive analytics layer (i.e actions) on the top of forecasting process. This will help the decision-maker with the 'What if?' question: so I have a prediction, now what do I do?

References

1) Rob J Hyndman and George Athanasopoulos, Forecasting: Principles and Practice, (https://otexts.com/fpp2/)

2) Christos Faloutsos et al., Forecasting Big Time Series: Theory and Practice

3) Erik Hofmann, Emanuel Rutschmann, Big data analytics and demand forecasting in supply chains: a conceptual analysis

4) Christ, Kempa-Liehr, Feindt: Distributed and parallel time series feature extraction for industrial big data applications (https://arxiv.org/pdf/1610.07717.pdf)

5) https://aws.amazon.com/forecast/

6) https://www.datarobot.com/