Time-Series Forecasting of Retail Company Sales

MIE1628 Final Project Report

Group 10

Yonghao Li

1004905668

Abstract

For this group project, we chose to use the department store sales data from Kaggle. This data includes multiple features along with weekly retail sales figures and their corresponding timestamps. We used a time-series approach for this project because we wanted to forecast into the near future beyond what the dataset has provided for us. Our statistical model (simple and moving average, SMA) and several machine learning models (linear regression, decision tree, random forest, and gradient boosted regression) produced low SMAPE scores when predicting sales in the test set with different prediction horizons. However, we would need further data processing and model improvement before implementation with real data.

Introduction

Out of the several project options offered, we chose this topic because time series analysis is intriguing, challenging, and very applicable to real-life situations such as financial forecasting, pattern recognition, and quality control. To analyze, interpret, and fully understand a time-series model can be difficult, which I believe provided an opportunity for us to learn a lot in the process. Also, a couple of our group members have previous experience with stock market analysis, which could be beneficial to our project. Company sales analysis also seems more relevant to us compared to other dataset options (population, exoplanet, GBatteries, etc.).

The retail sales data consists of three separate datasets in CSV format on Kaggle (https://www.kaggle.com/manjeetsingh/retaildataset?select=stores+data-set.csv):

- “Features data” includes features such as store number, dates, temperature, fuel price, markdown (levels of discount), CPI, unemployment, and a holiday indicator (True or False). The size of this dataset is (8190, 12);
- “Sales data” includes store and department numbers, dates, weekly sales figures, and the holiday indicator. The size of this dataset is (421570, 5);
- “Stores data” includes store number, store type, and store size. The size of this dataset is (45,3).

Our goal is to predict company-wide sales figures in the near future, hence I preprocessed the data by merging the 3 datasets and aggregating the weekly sales numbers across all stores and departments while eliminating duplicate columns. Since the data only exists within a 2-year-and-10-month period, the weekly aggregate data only has 143 rows. To combat the shortage of samples, we decided to use linear interpolation for the expansion of the dataset (see Methodology for details). As a result, our target label has become the daily total sales figures which are large and fluctuate between 4e7 to 8e7. Most of the time sales are very close to 4e7, except around the holiday seasons. If we look at the histogram plot of sales amount versus their repetitions, we would see a highly right-skewed (positive skew) distribution in which the mean sales amount can be much larger than the median. The distribution of total sales has obvious seasonality and is non-stationary, which are issues that we addressed and will be discussed in-depth under the methodology section.

To determine whether to use the external features (such as CPI, unemployment, or holiday indicator) or not, we constructed correlation matrices to systematically check for correlations between each feature and the company sales figures. Initially, I calculated and created the correlation table in Scala, however, since Scala and Spark lack graphical capabilities, we exported the relevant data and plotted using Python. (See Fig. 1 in Appendices.) Contrary to our initial assumption that these features could be highly correlated to sales figures, the correlation matrix proved that they actually have relatively low influence. Thus we only use the target label and timestamp columns for further time-series analysis.

Literature Review

Generally, there are multiple approaches when analyzing a time series problem. In this paper from 2012 (Hejase & Assi), they looked at solar radiation data in a time-series manner, while using stochastic regression models (ARMA) validated with multiple validation parameters (R-squared deterministic coefficients, RMSE, MAPE, MBE, and MABE). This study provided a baseline statistical approach to time-series analysis, and it shows us that such a model has the potential to be implemented in real-world forecasting situations.

Regarding time series regression (TSR), rather than only exploring its mathematical background (W. William, 2011), another paper reviews and discusses techniques for TSR in environmental epidemiology (Imai, C. at al., 2015). Using influenza and cholera datasets, this study provides a systematic view of time series regression and its many aspects. In addition to mathematical and statistical concepts, the authors also look at logarithmic autocorrelation control, lag estimation analysis, seasonality removal, and quasi-Poisson distributions. The authors claim that some of these TSR approaches can be augmented or replaced by alternative models such as ARIMA or wavelet analysis.

In addition to using linear regression alone, another study suggests an interesting alternative method where they implement segmentation of “the input time series into groups and simultaneously optimizing both the average loss of each group and the variance of the loss between groups” (Ristanoski, Liu, & Bailey, 2013) Instead of using regular least squares loss function, their distributed segmentation method utilizes quadratic mean based loss function for optimization (QMReg). By comparing RMSE results, the paper shows that the QM method performs much better than the LS or ARIMA approach, similar to robust regression and SVM. This study introduces a novel segmentation regression approach to time series analysis which seems to be more robust than the regular approach.

Besides academic papers, some highly-regarded online websites also have intriguing articles regarding time-series analysis. One article provides an introduction to using Random Forest for time series in the form of a tutorial (Brownlee, 2020). By first explaining the concepts behind ensemble modeling, bootstrapping, and bagging, the author gives a good overview of the benefits of using RF. in the later pages, he also provides some sample codes and plots specifically for time series analysis using RF. This article shows us what to expect when dealing with a similar project while providing a sample workflow for us to compare ours to. Another journal article illustrates how to leverage the advantages of decision tree regression, random forest regression, and gradient boosted regression for time-series prediction (Jakhotia, 2019).

Methodology

Interpolation

As mentioned in the introduction section, our dataset has been condensed into only 143 rows after preprocessing due to its short timeline. We tried training a random forest model with this weekly-total-sales data, however, the prediction errors were very high due to the lack of samples in both train and test sets. As an attempt to solve this issue before proceeding to build other models, we implemented interpolation. Since the target data point at one time is highly correlated with its neighbors in time-series analysis, we used a linear interpolation (data population) method to expand our dataset:

- Calculate differences between two consecutive weekly sales figures;
- Evenly distribute the difference across 7 days in between two data points;
- Increment the dates and sales amount accordingly for each day.

Time-series split function

This function was created to manually split train-validation-test sets by percentage. If we used the train-test split package, it will randomly assign data points into different sets, causing data leakage (future data mixing with past data). With our function, the sets are split by a percentage while maintaining the original order, hence keeping the timeline intact (train set is always before validation or test set).

Feature engineering and seasonal differencing

In our project, feature engineering is done separately for each of the five prediction windows (1-day, 1-week, 2-weeks, 3-weeks, and 1-month). Within each prediction window, both train and test sets undergo similar feature engineering steps such that they can be compatible during fitting and transformation within model development. For each train-test pair, we introduced lags that are equal to or greater than the prediction horizon. As an example, if the prediction window is 1-week, then both train and test set will have features such as "lag 1 week, lag 2 weeks". Additionally, feature engineering includes calculating moving averages and standard deviations of the minimally-lagged value over a rolling window. These features also conform to the rule that the lag time must be equal to or larger than the prediction horizon time. At the same time, this process also includes leading the target such that the corresponding target label (total sales amount) for each row is ahead of the current time point by a leading time specified by the prediction horizon.

Along with feature engineering, we also applied seasonal differencing to the data by subtracting the sales amount on the same day a year ago from the one on the same day this year. (See Fig. 2 & 3 in Appendices.) After detrending to remove some of the seasonality of the data, we can proceed to explore the underlying distribution. However, since our data has a rather short longitudinal range, further removal of seasonality was difficult to accomplish without risking more information loss. (Note: the seasonal differences will be added back into the prediction and label within each corresponding test set for reconstruction before computing SMAPE.)

To ensure no data leakage between the train set and the test set, we also created a gap between each train-test set. (See Fig. 4 in Appendices.) This gap varies in size among different train-test sets created for different prediction windows (due to having different features) and is subtracted from the tail of each corresponding train set. The size of the gap equals the number of rows led by the target plus the number of rows corresponding to the max lagged value. For example, if the prediction horizon is 1 week, then the gap size would be the sum of:

- Leading target label by one week → 7 rows;
- Max lag is 4 weeks → 28 rows;
- Gap = 7 + 28 = 35 rows.

Rolling K-Fold Cross-Validation (Increasing Train Set)

This function was written so that we can use cross-validation during model optimization. The idea is to ensure the integrity of the timeline while keeping future data separated from the past data. Within this function, we use RMSE as the loss function. (See Fig. 5 in Appendices.)

Models and Rationale

Simple Moving Average (SMA)

SMA is a statistical model that calculates the unweighted average sales amount based on a predefined rolling window. A Larger rolling window leads to smoother SMA lines. SMA is good for analyzing long-term trends because it does not get influenced by small fluctuations, but it might not accurately reflect trends that are more recent (rapid changes). We tried using SMA for prediction by recursively predicting on a day-by-day basis, but it was time-consuming to run on Databricks and the results were neither generalizable nor good for visualization. Hence, we only use the SMA results as baseline references for other machine learning algorithms.

Linear Regression (LR)

As a simple and naive supervised machine learning algorithm, linear regression is easy to train and interpret, while having a relatively low time complexity. We use linear regression as a benchmark model so that we can compare this to the results of other more complex machine learning models. In time-series analysis, since the generated features and the target label have a linear relationship, we can implement multivariate linear regression. LR is sensitive to outliers and is prone to overfitting (which is manageable using regularization).

Decision Tree Regression (DT)

Decision tree is a reliable and versatile supervised machine learning model that can handle both categorical and numerical data. In time-series analysis, we use it for regression tree construction. Compared to other machine learning algorithms, DT does not require normalization or scaling of the data before training, which means that it requires much less data preparation in general. Since it generates a tree-based model, DT results can be easy for interpretation and visualization. However, DT is sensitive to small changes within the data and is easy to overfit. To prevent overfitting, we need to make sure that its hyperparameters are reasonably tuned.

Random Forest Regression (RF)

Random forest is a bagging machine learning method containing many decision trees. It supports both classification and regression. The voting mechanism included within the RF model helps it to be more reliable and robust than a single decision tree. For multivariate time-series regression, RF creates a range of decision trees in parallel and averages the results before prediction. In general, the random forest model is more flexible, accurate, and less likely to overfit than a decision tree model due to its randomness. However, if the RF model is set to have too much depth, it can lead to overfitting. Also, it is computationally more complex and time-consuming to train. Results can be hard to interpret.

Gradient Boosted Tree Regression (GBT)

Similar to the random forest model, gradient boosted tree regression also contains many weaker tree models. Instead of pooling and averaging the results, GBT builds tree models consecutively, where each tree is built to help model the errors made by the previous one. GBT is an advanced, powerful learning algorithm, but it can be computationally expensive to train. It is sensitive to noisy data, and the hyperparameters can be hard to tune.

Reconstruction

After building each model (fitting train set and transforming test set), we applied reconstruction to both prediction column and the label column by adding back the corresponding seasonal differences that were subtracted before. With the reconstructed predictions and labels, we proceeded to calculate the SMAPE score for each model with different prediction windows.

SMAPE

The metric we use for the evaluation of our time-series ml models is the symmetric mean absolute percentage error. (See Fig. 6 in Appendices.) The absolute difference between At and Ft is divided by half the sum of absolute values of the actual value At and the forecasted value Ft. The value of this calculation is summed for every point t and divided by the number of points n. We use SMAPE because it scales the errors, normalizes them by the actual amplitude of the signal, sums them up, and averages them to provide a relative measure. SMAPE limits outlier effects.

Results

Feature Importance

When calculating feature importance within each pair of the train-test set, we used a standard random forest model to fit the train data, transform the test data, and extract the importance scores from the "feature importance" parameter. For the 1-day and 1-week datasets, we can see that the moving averages and standard deviations calculated over 3 or 4 weeks window have the highest importance scores (see Appendices). In a more general sense, features containing moving averages or standard deviations have more influence than the features that simply contain lagged values. Another observation is that within the model for each prediction window, the features generated with a larger rolling window have higher importance than the other ones.

Hyperparameter Tuning

With rolling k-fold cross-validation, below are a list of hyperparameters that we were able to tune for each machine learning model:

- LR: RegParam (0, 0.1, 0.5) and ElasticNetParam (0, 0.1, 0.5). The regularization parameter (lambda) defines the trade-off between minimizing training error and minimizing model complexity (to avoid overfitting). Elastic Net is a combination of L1 and L2 regularizations. This parameter is within the range from 0 to 1. For alpha = 0, the penalty is an L2 penalty. For alpha = 1, it is an L1 penalty.
- DT: MaxDepth (5, 7, 10) and MaxBins (20, 25, 30). Max depth defines the maximum depth of the tree that can be created (max length of the path from the root node to a leaf node). If the max depth is too high, the model easily overfits. Max bins define the number of bins allowed to use when discretizing continuous features, and a larger number means that the model can make more accurate split decisions. However, larger max bins will lead to more training time as it increases computational complexity.
- RF: NumTrees (5, 10, 15) and MaxBins (28, 30, 32). NumTrees specifies how many trees the RF model can use for training. In general, more trees means a more robust model with better results, but it comes with a much longer training time and higher complexity. If the data contains high variance, a larger number of trees might decrease performance.
- GBT: MaxDepth, MaxBins, and MaxIteration. Since GBT creates tree models sequentially, the MaxIteration parameter defines the number of decision trees to grow. Higher number of iterations can lead to overfitting.

The results for cross-validation vary across different models and prediction horizons (see Appendices).

SMAPE Results

As shown in the table below, we can see that the SMAPE scores generated by models using a 1-day prediction horizon are significantly lower than the results from longer time periods. There is a clear trend of increasing SMAPE (decreasing accuracy) as the prediction window becomes larger. We use the SMAPE scores produced by SMA as references. Since LR is a naive algorithm, its overall performance is worse than the more advanced models. Among the tree-based models, we can see that GBT has best performance within the 1-day and 2-weeks prediction windows, while RF has a more consistent overall performance that is better than DT.

SMAPE Summary Table

(Calculated using original weekly data)

Model / Prediction Window	1-day	1-week	2-weeks	3-weeks	1-month
SMA	N/A	1.4477	2.1174 (3.2855)	2.5212 (3.5817)	2.5934 (3.3261)
LR	0.5562	2.4552	3.0125	4.5267	5.3629
DT	0.5103	2.1280	2.5853	4.4684	3.1903
RF	0.6322	1.8343	2.3636	2.0982	2.4604
GBT	0.4785	2.4828	1.8691	4.4718	3.2513

Discussions

During the process of completing this project, we did run into several challenges. One of the issues when using Databricks is the low cluster core numbers and low memory overhead. With the community edition that is free-of-charge, running functions such as rolling cross-validation or recursive prediction would take up a massive amount of time. If we had access to better environment configurations, we might be able to tune more hyperparameters for each model, introduce more rolling times within cross-validation, and perhaps get more consistent results. Another potential issue is the limited libraries and packages for time-series support in Scala. Although we were able to complete the project with a lot of hard-code functions, if we could have access to some more advanced packages, the workflow would be smoother and the results might be better. In terms of the data, we have a rather limited number of time-series samples (only 2 years and 10 months). The longitudinal range of our data is considered very short in the realm of time series analysis. This made it very difficult for us to remove non-stationarity completely. In our results, the low SMAPE scores might be due to the relatively small test sets and the fact that the distributions of the year-by-year data are extremely similar to each other (which makes it easier for models to predict).

One recommendation that I would make is to consider including some of the external attributes. However, this would lead to a change of interpolation strategy because a linear method would not make sense when implemented over some of the other features. Additionally, I also highly recommend that we look for similar data that spans a longer period of time or incorporate other related datasets. A longer timeline would give us a better chance to improve seasonality removal, model training, and hyperparameter tuning results. If we have better resources, we could further tune hyperparameters for each model with a more sophisticated rolling CV. Also, we can try to modify the target variable into categories, which would enable us to experiment with other classification machine learning models that Spark has to offer.

References

Hejase, H. A. N., & Assi, A. H. (2012, April 11). Time-Series Regression Model for Prediction of Mean Daily Global Solar Radiation in Al-Ain, UAE. Hindawi. https://www.hindawi.com/journals/isrn/2012/412471/#abstract

Imai, C. et al. (2015, October 1). Time series regression model for infectious disease and weather. ScienceDirect. https://www.sciencedirect.com/science/article/pii/S0013935115300128

Wei, William. (2011). Time Series Regression. International Encyclopedia of Statistical Science. 1607-1609. 10.1007/978-3-642-04898-2_596.

Brownlee, J. (2020, October 31). Random Forest for Time Series Forecasting. Machine Learning Mastery. https://machinelearningmastery.com/random-forest-for-time-series-forecasting/

Ristanoski, Goce & Liu, Wei & Bailey, James. (2013). Time Series Forecasting using Distribution Enhanced Linear Regression. 10.13140/2.1.3300.9921.

Jakhotia, P. (2019, May 31). Using Decision Trees, Random Forest, and Gradient Boosting for Time Series Prediction. Medium. https://medium.com/@jakhotiaprerana21/using-decision-trees-random-forest-and-gradient-boosting-for-time-series-prediction-6d6064e3f270

Appendices

Relevant Plots

Fig. 1 External Feature vs. Sales Correlation

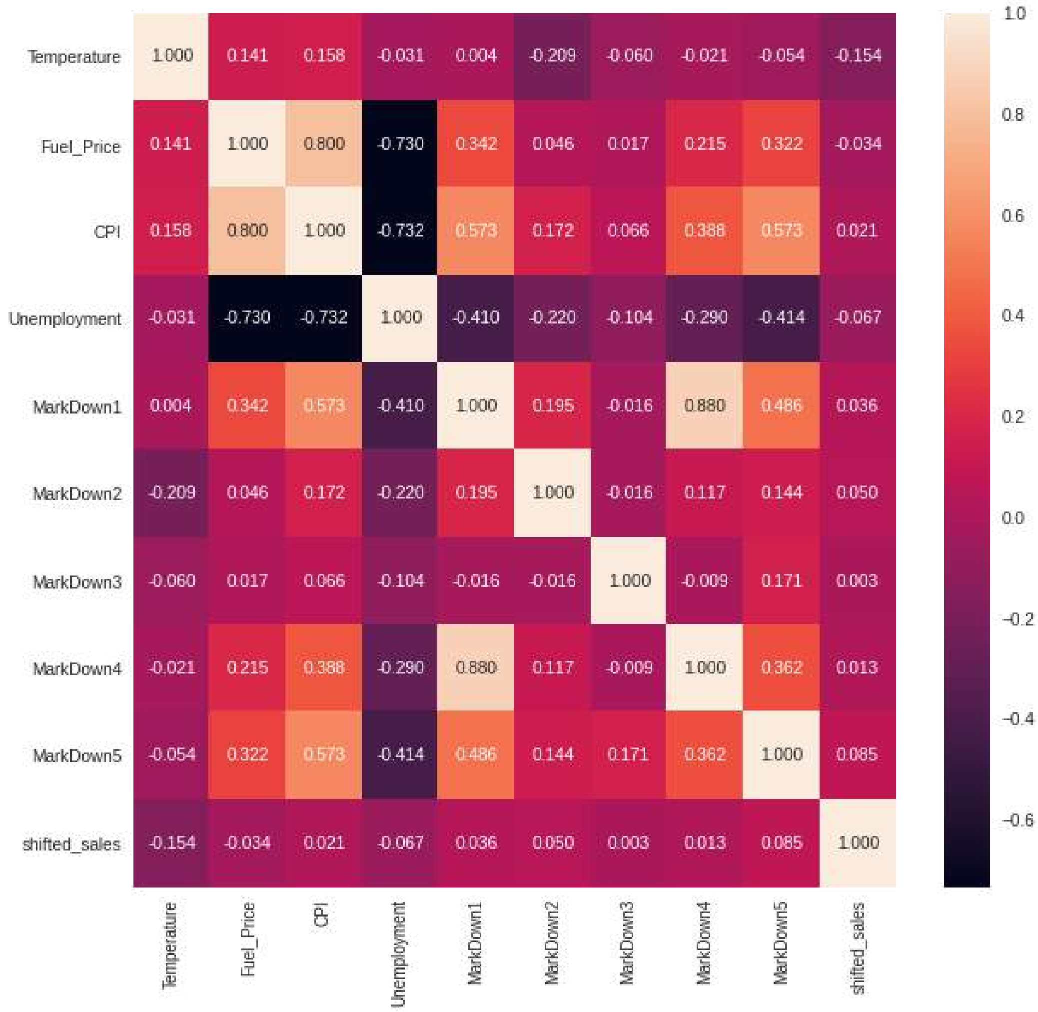


Fig. 2 Original Sales Distribution

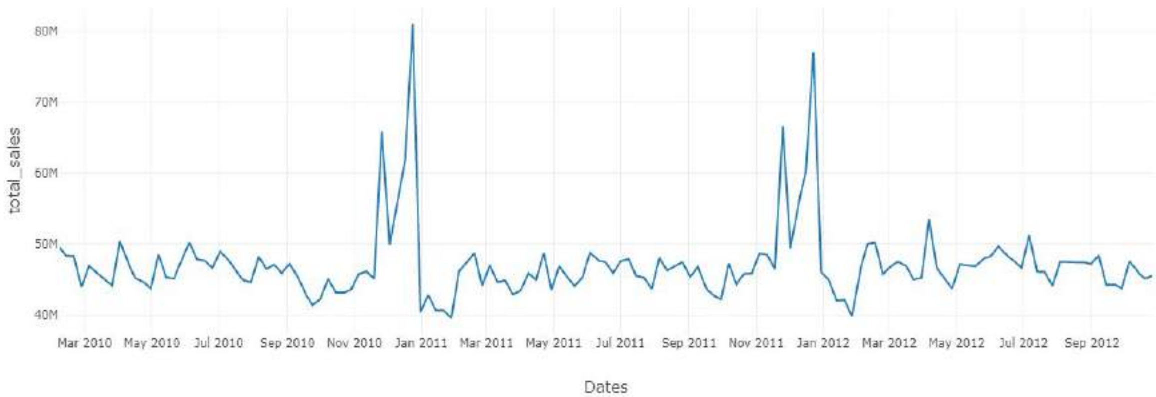


Fig. 3 After Seasonal Differencing

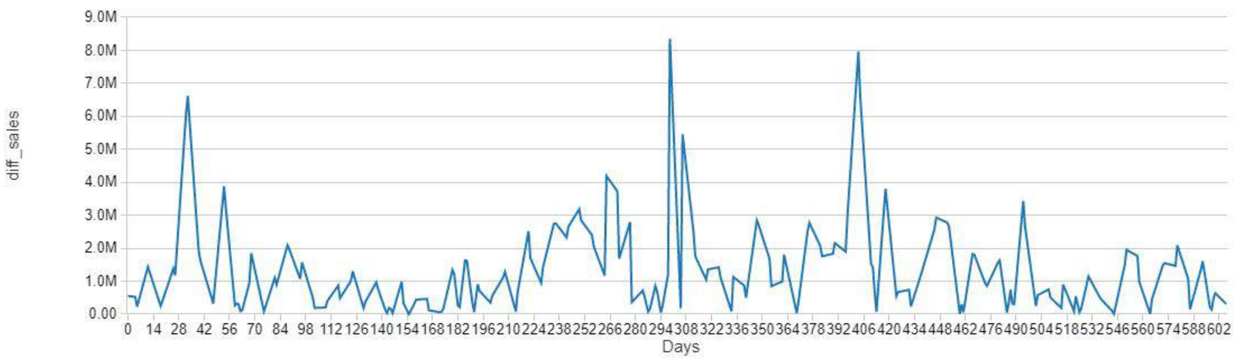


Fig. 4 Creating a Gap Between Each Train-Test Pair

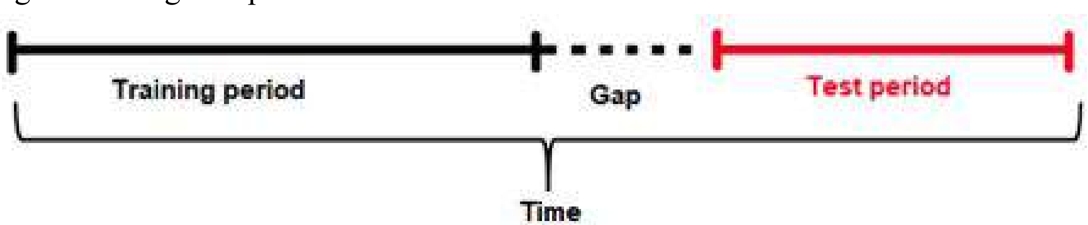


Fig. 5 Time-Series Rolling CV

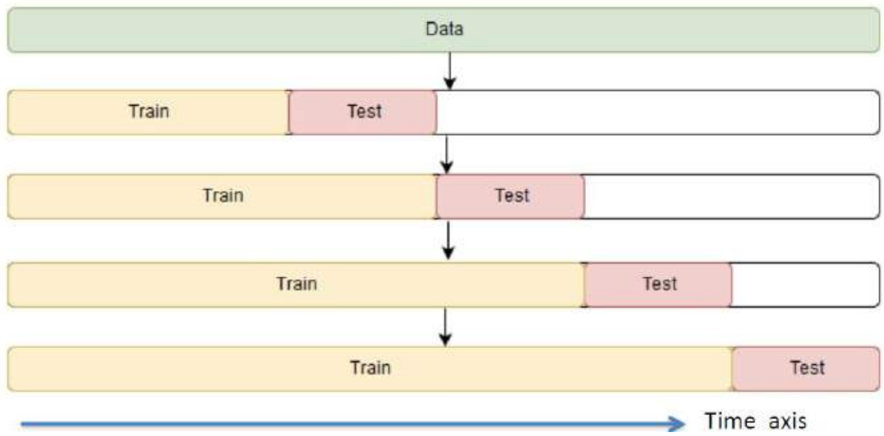


Fig. 6 SMAPE

$$\text{SMAPE} = \frac{100\%}{n} \sum_{t=1}^{n} \frac{|F_t - A_t|}{(|A_t| + |F_t|)/2}$$

where A_t is the actual value and F_t is the forecast value.

Feature Importance

1-day

```
-----------------------------------
std_4weeks -> 0.48060663788531005
diff_sales -> 0.20541242033194065
lag_3weeks -> 0.05996095489797325
ma_2weeks -> 0.02911517425551858
month -> 0.02636373331084928
std_1week -> 0.0254821371096213
lag_1day -> 0.023996190781759626
ma_1week -> 0.02299645822053426
ma_3weeks -> 0.022664348038718793
std_2weeks -> 0.020879240449779866
day -> 0.019281562052471505
std_3weeks -> 0.018497651159507272
ma_4weeks -> 0.017157458672051297
lag_2weeks -> 0.012598757073451606
lag_5days -> 0.009642874413557783
lag_1week -> 0.004671448769726507
year -> 6.729525772282224E-4
-----------------------------------
```

1-week

```
------------------------------------
ma_3weeks -> 0.14297118005146908
std_4weeks -> 0.11531770637488058
ma_4weeks -> 0.10983726573915151
std_3weeks -> 0.08312879700344797
ma_2weeks -> 0.07877991485282489
std_1week -> 0.07132787062176611
day -> 0.0656406692045842
std_2weeks -> 0.06134166428920447
lag_2weeks -> 0.045426546768668856
lag_1week -> 0.0419079827888783
ma_1week -> 0.0377768375249901
diff_sales -> 0.03698123003983979
lag_3weeks -> 0.036123782021939894
lag_4weeks -> 0.031870373446634834
month -> 0.026683155693142144
year -> 0.014885023578577324
------------------------------------
```

2-weeks

```
------------------------------------
std_2weeks -> 0.12014393168914063
std_4weeks -> 0.11224311104748723
month -> 0.11149736753773483
std_3weeks -> 0.1010823833998608
std_5weeks -> 0.0943050119063537
ma_3weeks -> 0.07536959152335206
lag_2weeks -> 0.0741888280443994
lag_5weeks -> 0.06874577445768497
ma_4weeks -> 0.04604026893232798
diff_sales -> 0.0430117643564103
ma_5weeks -> 0.04292575164265888
day -> 0.04100093498460487
lag_3weeks -> 0.024817185814592174
ma_2weeks -> 0.01927680473618801
year -> 0.013071106755248236
lag_4weeks -> 0.012280183171955896
------------------------------------
```

3-weeks

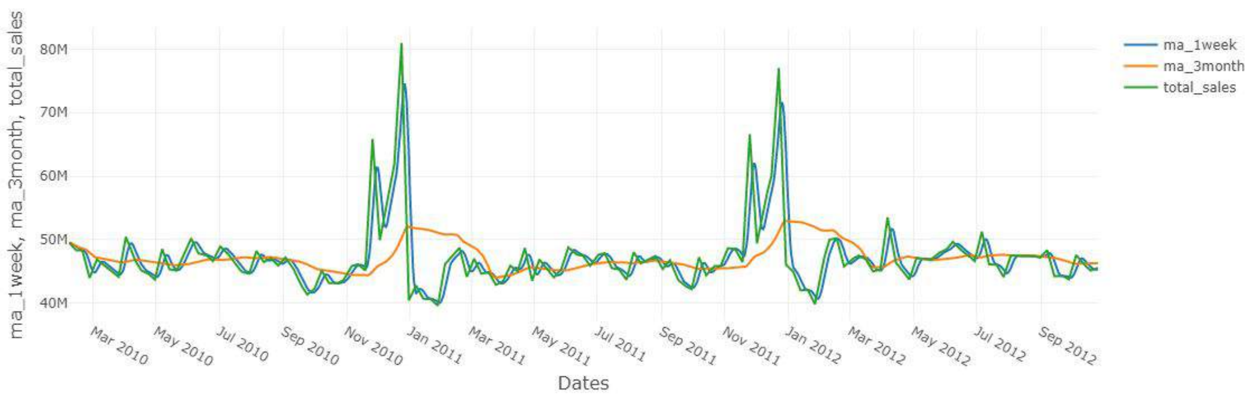
```
-----------------------------------
ma_5weeks -> 0.13760178957748456
std_5weeks -> 0.12346492078430375
month -> 0.12264478979745258
day -> 0.08979584121057345
diff_sales -> 0.074325864511961
std_6weeks -> 0.07180492238726471
lag_6weeks -> 0.06952304944491863
lag_4weeks -> 0.04831830808648697
ma_4weeks -> 0.048018921649250125
ma_3weeks -> 0.04295242716980618
std_3weeks -> 0.04203999859962835
std_4weeks -> 0.03863833689847181
ma_6weeks -> 0.0294089955792176
lag_5weeks -> 0.027140143955199095
year -> 0.01939556239743649
lag_3weeks -> 0.014926127950544578
-----------------------------------
```

1-month

```
------------------------------------
ma_7weeks -> 0.1741215473552611
month -> 0.10868264617311027
diff_sales -> 0.09121351572812682
std_6weeks -> 0.08713885371589519
ma_6weeks -> 0.08292119712732847
std_7weeks -> 0.0723971257137345
std_4weeks -> 0.06638631355713298
ma_4weeks -> 0.06032910040294176
lag_6weeks -> 0.05535892082906385
ma_5weeks -> 0.05247840018408913
day -> 0.03516064153188055
std_5weeks -> 0.03248197169560493
year -> 0.029019676012196134
lag_7weeks -> 0.025055989537776793
lag_4weeks -> 0.01750026659448341
lag_5weeks -> 0.009753833841374184
------------------------------------
```

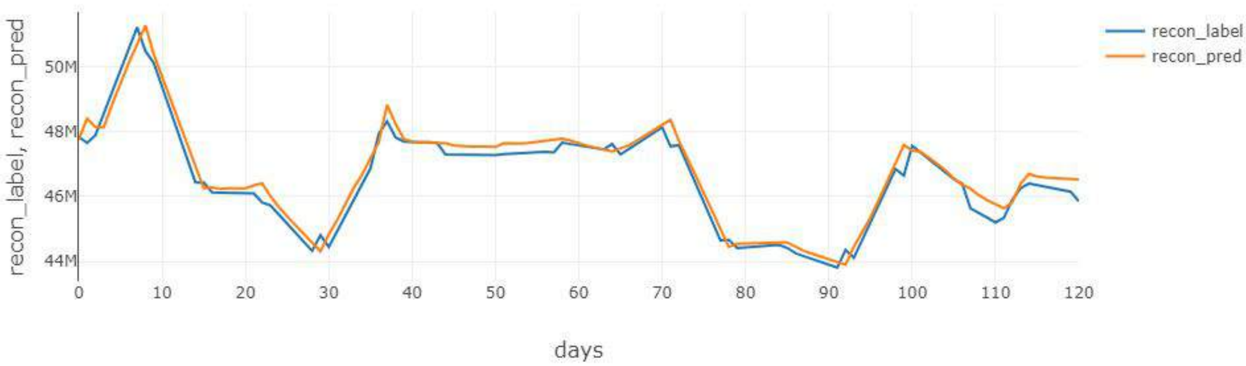
Model Results (Plots and Hyperparameters)

SMA

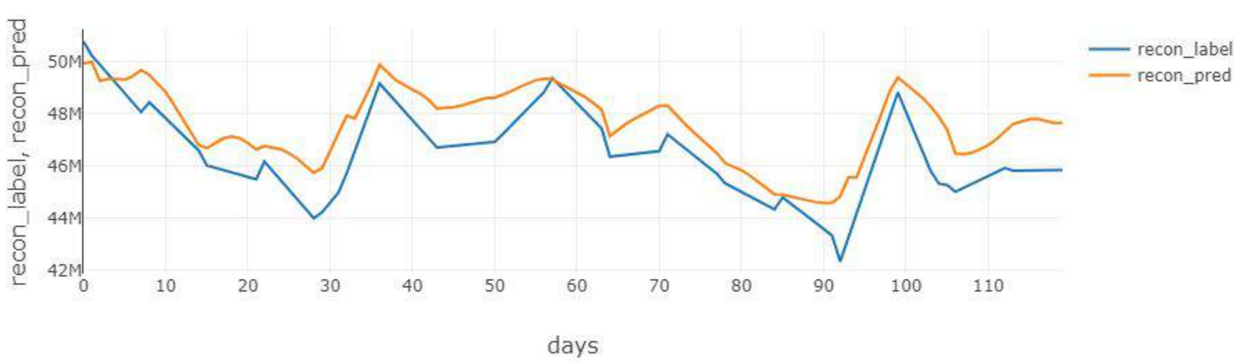


Linear Regression Model

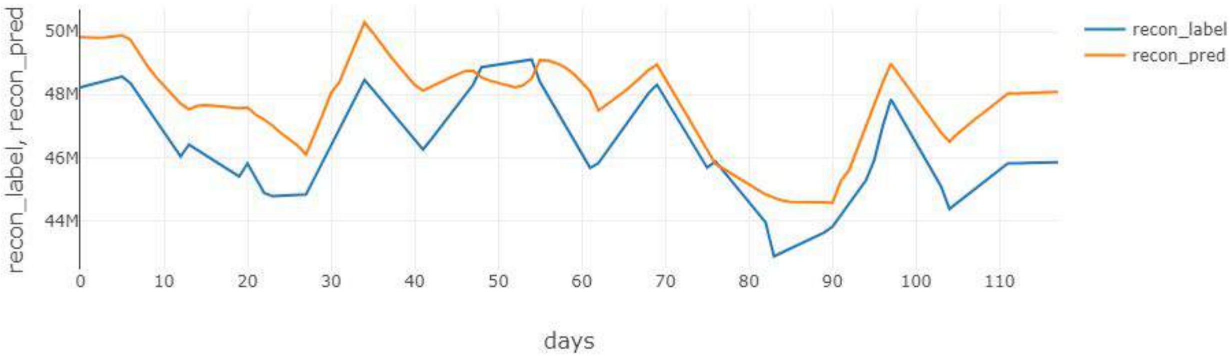
1-day hyperparameters: RegParam = 0.1, ElasticNetParam = 0.1



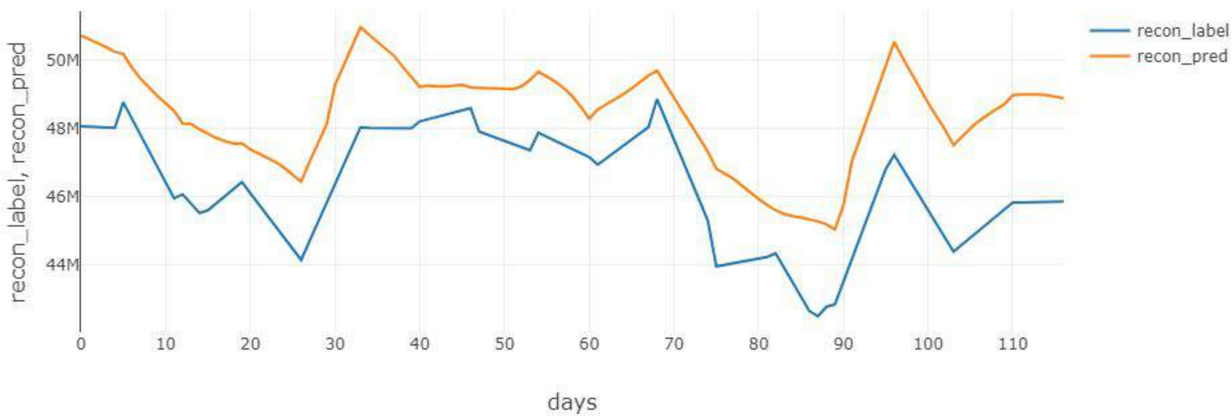
1-week hyperparameters: RegParam = 0.5, ElasticNetParam = 0.5



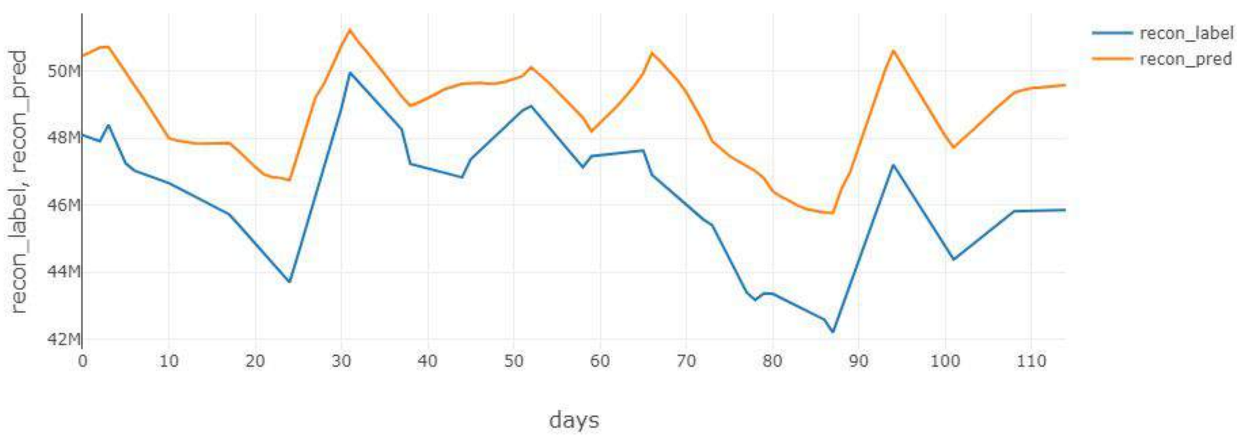
2-weeks hyperparameters: RegParam = 0.5, ElasticNetParam = 0.5



3-weeks hyperparameters: RegParam = 0.5, ElasticNetParam = 0.5

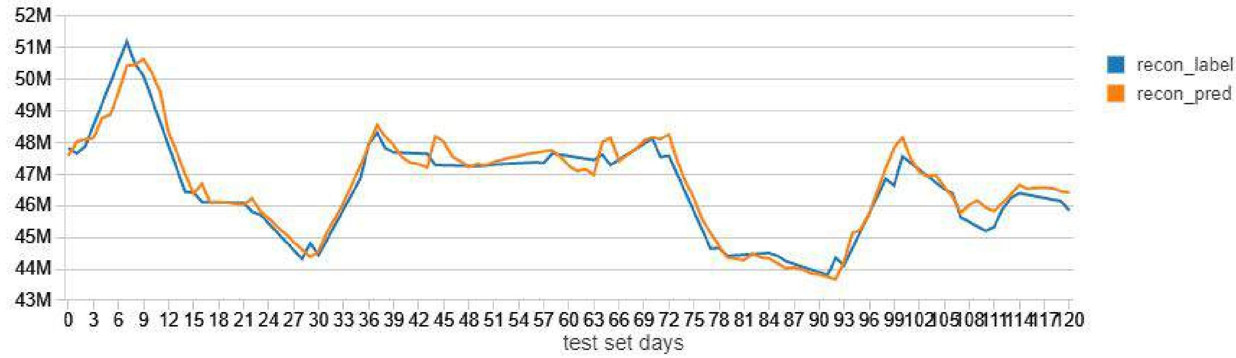


1-month hyperparameters: RegParam = 0.5, ElasticNetParam = 0.1

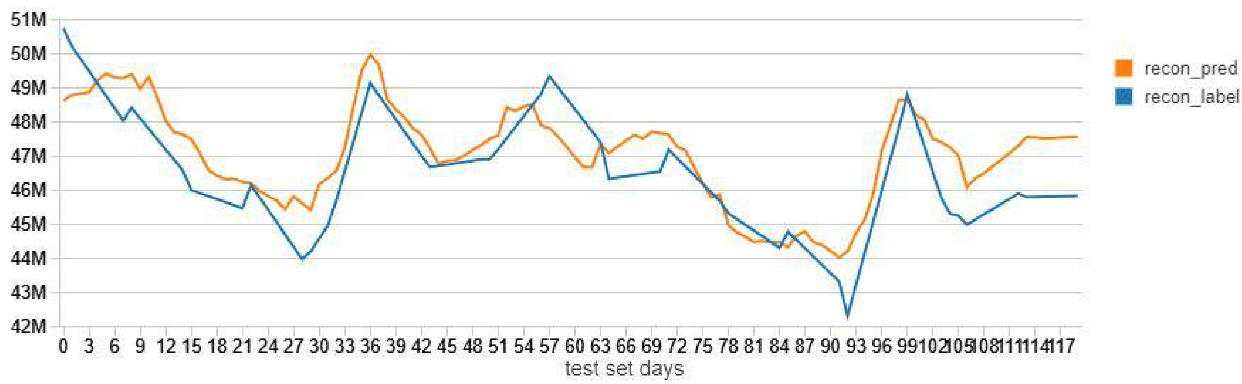


Random Forest Model

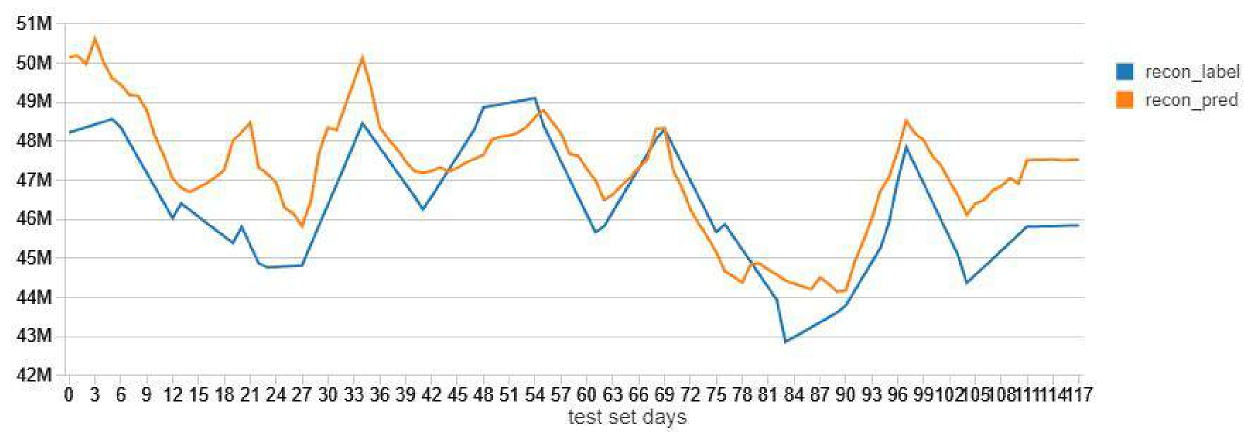
1-day hyperparameters: NumTrees = 10, MaxBins = 32



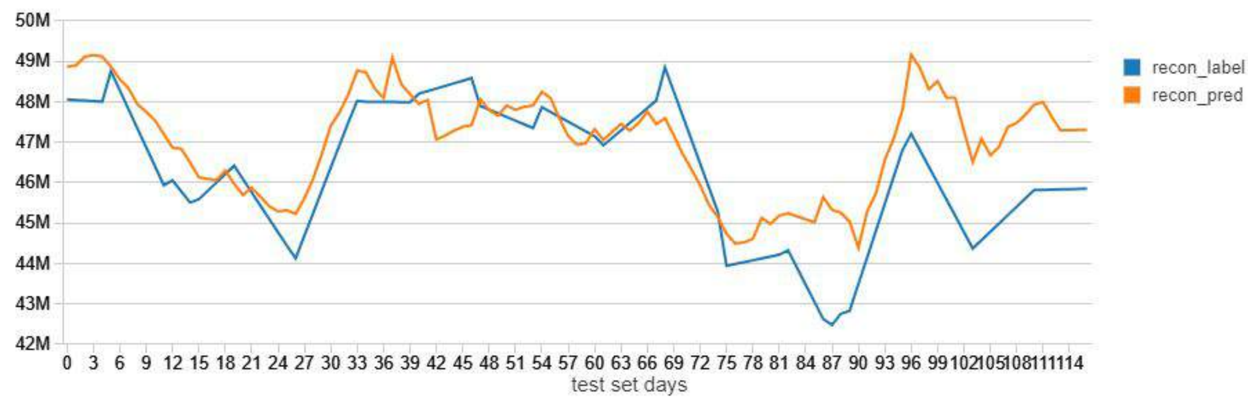
1-week hyperparameters: NumTrees = 10, MaxBins = 32



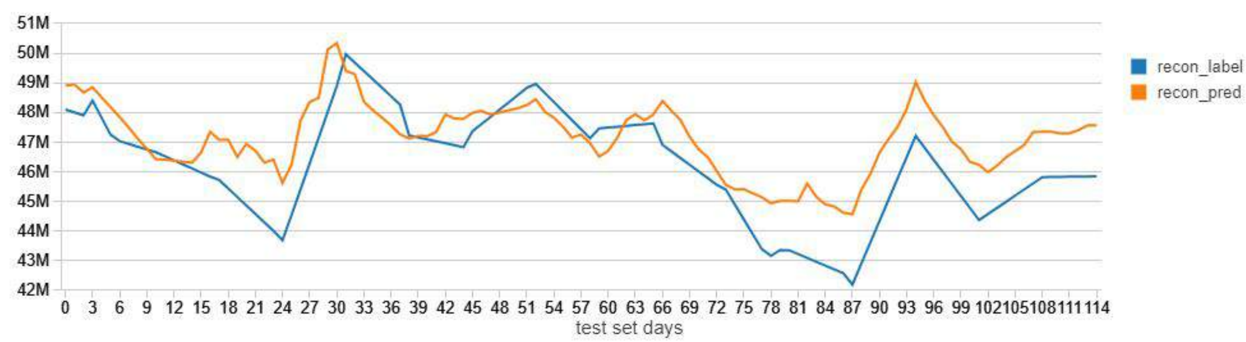
2-weeks hyperparameters: NumTrees = 10, MaxBins = 32



3-weeks hyperparameters: NumTrees = 10, MaxBins = 30

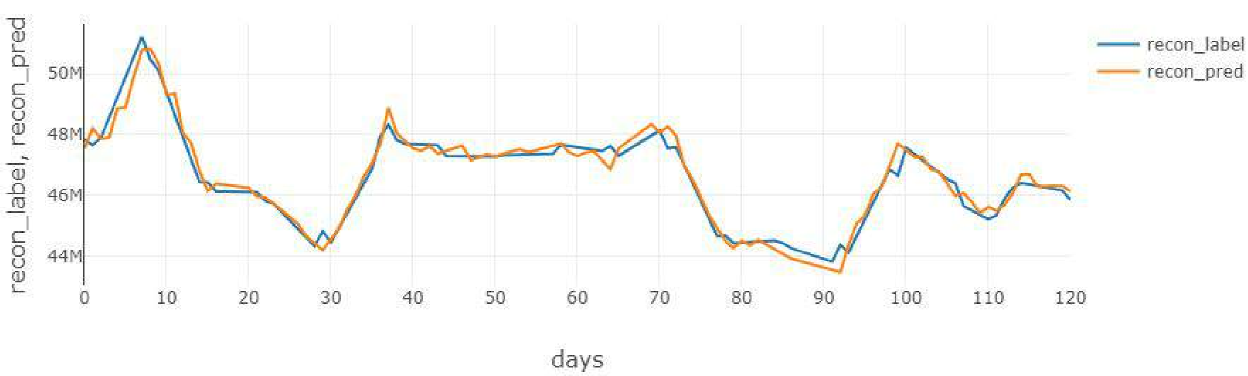


1-month hyperparameters: NumTrees = 10, MaxBins = 32

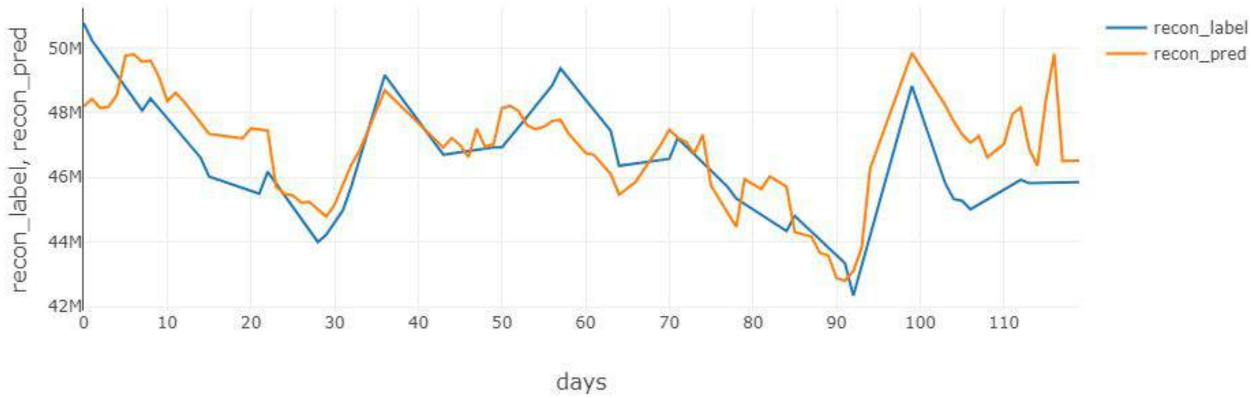


Decision Tree Model

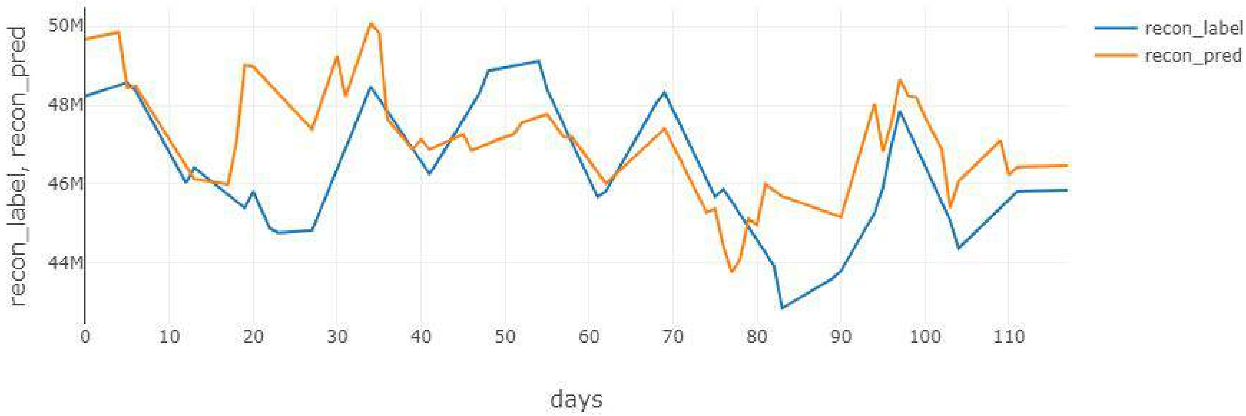
1-day hyperparameters: MaxDepth = 5, MaxBins = 30



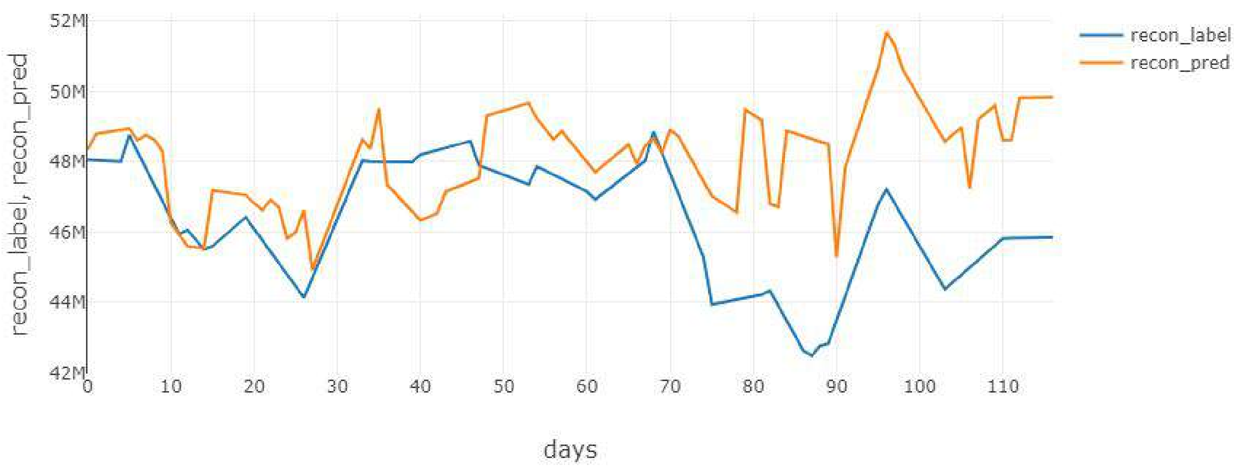
1-week hyperparameters: MaxDepth = 10, MaxBins = 25



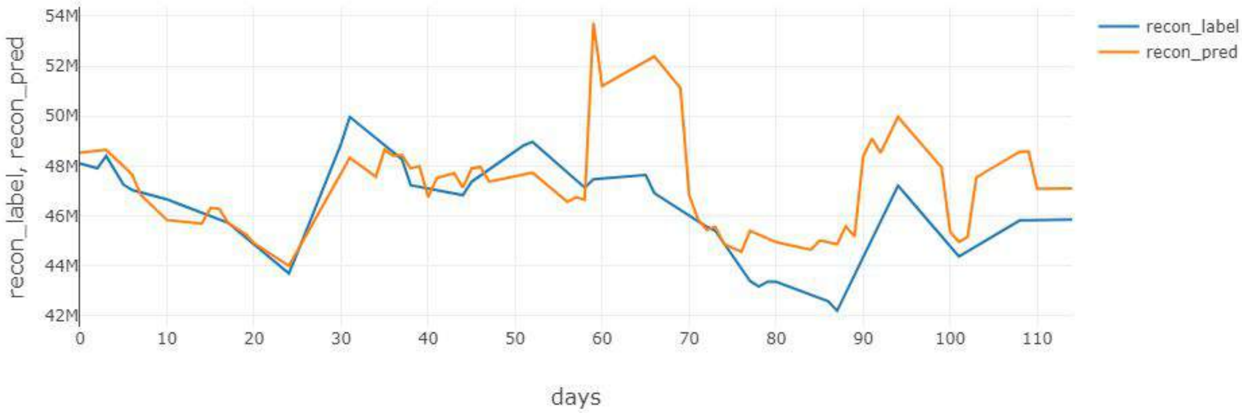
2-weeks hyperparameters: MaxDepth = 7, MaxBins = 30



3-weeks hyperparameters: MaxDepth = 10, MaxBins = 30

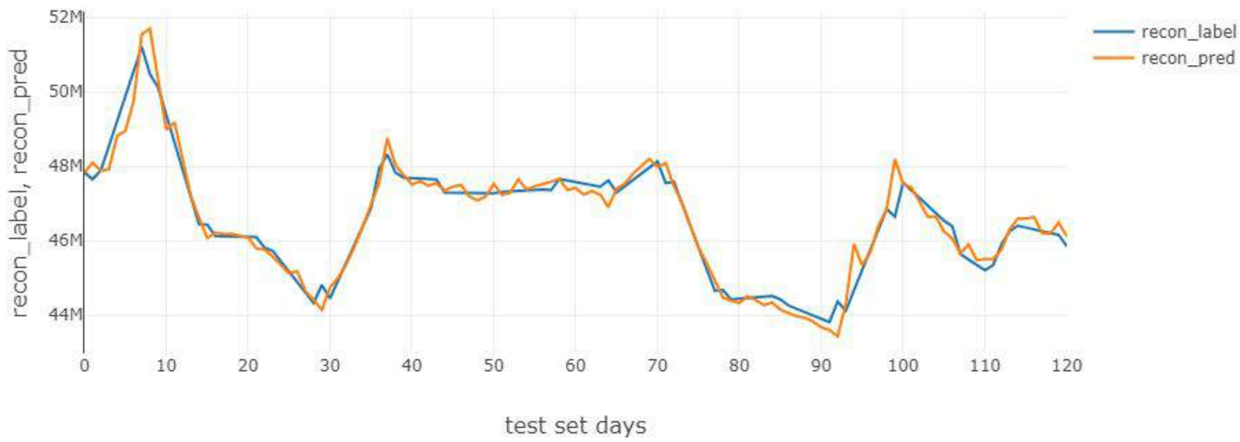


1-month hyperparameters: MaxDepth = 7, MaxBins = 25



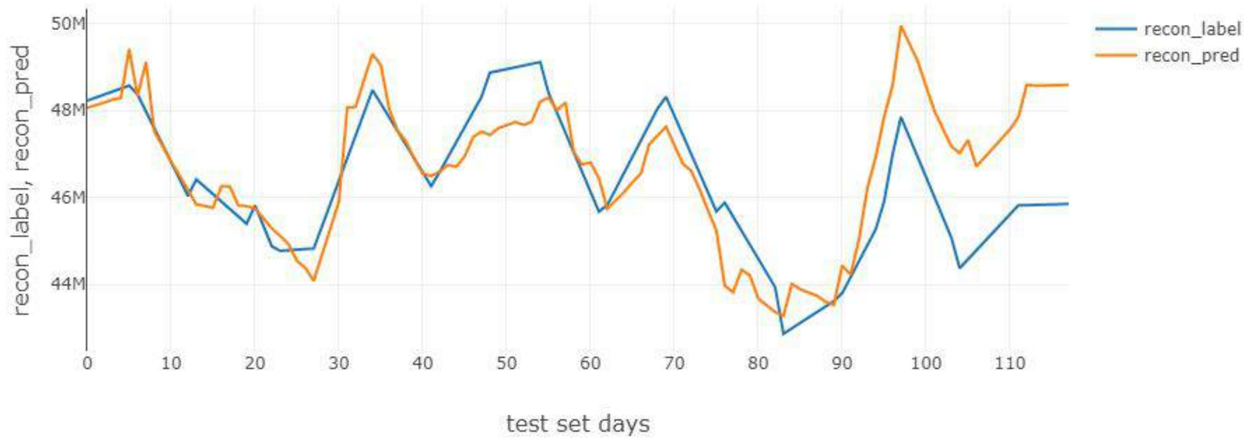
Gradient Boosted Trees Model

1-day hyperparameters: MaxIter = 5, MaxDepth = 6, MaxBins = 23



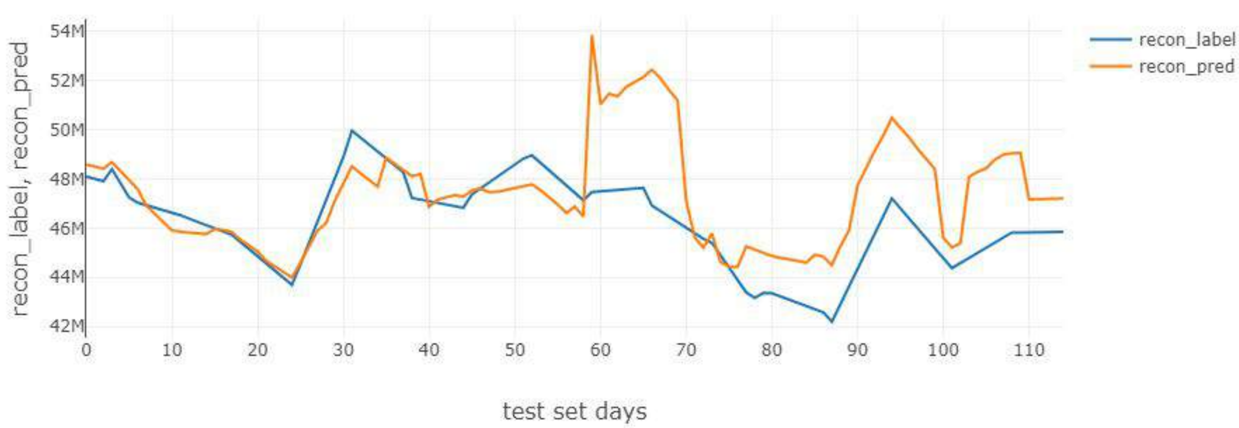
1-week hyperparameters: MaxIter = 5, MaxDepth = 6, MaxBins = 25

2-weeks hyperparameters: MaxIter = 4, MaxDepth = 10, MaxBins = 27



3-weeks hyperparameters: MaxIter = 5, MaxDepth = 8, MaxBins = 30

1-month hyperparameters: MaxIter = 5, MaxDepth = 6, MaxBins = 25



(Codes start at the next page.)

```scala
import org.apache.spark.sql.functions._
import org.apache.spark.sql.types
import org.apache.spark.sql.Column
import org.apache.spark.sql.{DataFrame, Row, SaveMode}
import org.apache.spark.ml.linalg.{Matrix, Vectors}
import org.apache.spark.mllib.linalg.{Vector, Vectors}
import org.apache.spark.ml.stat.Correlation
import org.apache.spark.sql.Row
import spark.implicits._
import scala.util.Random
import org.apache.spark.sql.expressions.Window
import java.util.Date
import java.sql.Timestamp
import java.text.SimpleDateFormat
import java.time.{ZoneId, ZonedDateTime}
import org.apache.spark.sql.types.DoubleType
import org.apache.spark.sql.{DataFrame, SparkSession}
import org.apache.spark.mllib.stat.Statistics
import org.apache.spark.ml.feature.VectorAssembler
import org.apache.spark.ml.tuning.{CrossValidator, ParamGridBuilder}
import org.apache.spark.sql.functions.col
import org.apache.spark.sql.types.DoubleType
import org.apache.spark.sql.{Column, SparkSession}
import org.apache.spark.ml.Pipeline
import org.apache.spark.ml.evaluation.RegressionEvaluator
import org.apache.spark.ml.feature.VectorIndexer
import org.apache.spark.ml.regression.{RandomForestRegressionModel, RandomForestRegressor}
```

```
import org.apache.spark.sql.functions._
import org.apache.spark.sql.types
import org.apache.spark.sql.Column
import org.apache.spark.sql.{DataFrame, Row, SaveMode}
import org.apache.spark.ml.linalg.{Matrix, Vectors}
import org.apache.spark.mllib.linalg.{Vector, Vectors}
import org.apache.spark.ml.stat.Correlation
import org.apache.spark.sql.Row
import spark.implicits._
import scala.util.Random
import org.apache.spark.sql.expressions.Window
import java.util.Date
import java.sql.Timestamp
import java.text.SimpleDateFormat
import java.time.{ZoneId, ZonedDateTime}
import org.apache.spark.sql.types.DoubleType
import org.apache.spark.sql.{DataFrame, SparkSession}
import org.apache.spark.mllib.stat.Statistics
import org.apache.spark.ml.feature.VectorAssembler
import org.apache.spark.ml.tuning.{CrossValidator, ParamGridBuilder}
import org.apache.spark.sql.functions.col
```

```scala
// Import tables
val features_data = spark.table("features_data_set_csv").withColumnRenamed("Date", "Dates")
val sales_data = spark.table("sales_data_set_csv").withColumnRenamed("IsHoliday", "IsHolidays")
val stores_data = spark.table("stores_data_set_csv").withColumnRenamed("Store", "Store_num")
```

```
features_data: org.apache.spark.sql.DataFrame = [Store: int, Dates: string ... 10 more fields]
sales_data: org.apache.spark.sql.DataFrame = [Store: int, Dept: int ... 3 more fields]
stores_data: org.apache.spark.sql.DataFrame = [Store_num: int, Type: string ... 1 more field]
```

```scala
// Check table content
features_data.show(10)
sales_data.show(10)
stores_data.show(10)
```

```
+-----+----------+-----------+----------+---------+---------+---------+---------+---------+---------+------------+---------+
|Store|     Dates|Temperature|Fuel_Price|MarkDown1|MarkDown2|MarkDown3|MarkDown4|MarkDown5|      CPI|Unemployment|IsHoliday|
+-----+----------+-----------+----------+---------+---------+---------+---------+---------+---------+------------+---------+
|    1|05/02/2010|      42.31|     2.572|     null|     null|     null|     null|     null|211.09636|       8.106|    false|
|    1|12/02/2010|      38.51|     2.548|     null|     null|     null|     null|     null|211.24217|       8.106|     true|
|    1|19/02/2010|      39.93|     2.514|     null|     null|     null|     null|     null|211.28914|       8.106|    false|
|    1|26/02/2010|      46.63|     2.561|     null|     null|     null|     null|     null|211.31964|       8.106|    false|
|    1|05/03/2010|       46.5|     2.625|     null|     null|     null|     null|     null|211.35014|       8.106|    false|
|    1|12/03/2010|      57.79|     2.667|     null|     null|     null|     null|     null|211.38065|       8.106|    false|
|    1|19/03/2010|      54.58|      2.72|     null|     null|     null|     null|     null|211.21564|       8.106|    false|
|    1|26/03/2010|      51.45|     2.732|     null|     null|     null|     null|     null|211.01804|       8.106|    false|
|    1|02/04/2010|      62.27|     2.719|     null|     null|     null|     null|     null|210.82045|       7.808|    false|
|    1|09/04/2010|      65.86|      2.77|     null|     null|     null|     null|     null|210.62286|       7.808|    false|
+-----+----------+-----------+----------+---------+---------+---------+---------+---------+---------+------------+---------+
only showing top 10 rows

+-----+----+----------+------------+----------+
|Store|Dept|      Date|Weekly_Sales|IsHolidays|
+-----+----+----------+------------+----------+
|    1|   1|05/02/2010|     24924.5|     false|
|    1|   1|12/02/2010|    46039.49|      true|
```

```scala
// Check sizes
println((features_data.count(), features_data.columns.size))
println((sales_data.count(), sales_data.columns.size))
println((stores_data.count(), stores_data.columns.size))
```

```
(8190,12)
(421570,5)
(45,3)
```

Preprocessing and Data Cleaning

```scala
//Merging three tables
val store = sales_data.join(stores_data, sales_data("Store") === stores_data("Store_num"))
  .drop("Store")
  .drop("IsHolidays")
val sales = features_data.join(store, features_data("Dates") === store("Date") &&
                              features_data("Store") === store("Store_num"))
  .drop("Date")
  .withColumn("Date", to_date($"Dates", "dd/MM/yyyy"))
  .drop("Dates")
```

```
store: org.apache.spark.sql.DataFrame = [Dept: int, Date: string ... 4 more fields]
sales: org.apache.spark.sql.DataFrame = [Store: int, Temperature: float ... 15 more fields]
```

```scala
//Converting T/F values in the IsHoliday column into 1/0
//Transforming original DF into new DF grouped by week
val total_sales_hms = sales
  .groupBy("Date")
  .agg(sum("Weekly_Sales").as("total_sales"))
  .orderBy(col("Date"))
  .select("Date", "total_sales")
  .withColumn("Week", monotonically_increasing_id)
  .withColumn("Dates",concat(col("Date"), lit(" 00:00:00")))
  .drop("Date")
```

```
total_sales_hms: org.apache.spark.sql.DataFrame = [total_sales: double, Week: bigint ... 1 more field]
```

```
display(total_sales_hms)
```

	total_sales	Week	Dates
1	49750740.48903691	0	2010-02-05 00:00:00
2	48336677.65355365	1	2010-02-12 00:00:00
3	48276993.8119329	2	2010-02-19 00:00:00
4	43968571.08629376	3	2010-02-26 00:00:00
5	46871470.31031599	4	2010-03-05 00:00:00
6	45925396.47580373	5	2010-03-12 00:00:00
7	44988974.64017445	6	2010-03-19 00:00:00
8	44133961.00393582	7	2010-03-26 00:00:00
9	50423831.31450006	8	2010-04-02 00:00:00
10	47365290.4499662	9	2010-04-09 00:00:00
11	45183667.11180175	10	2010-04-16 00:00:00
12	44734452.60229535	11	2010-04-23 00:00:00
13	43705126.69820616	12	2010-04-30 00:00:00
14	48503243.52487117	13	2010-05-07 00:00:00
15	45330080.23340504	14	2010-05-14 00:00:00
16	45120108.02918173	15	2010-05-21 00:00:00
17	47757502.58156212	16	2010-05-28 00:00:00
18	50188543.14000124	17	2010-06-04 00:00:00
19	47826546.68921248	18	2010-06-11 00:00:00

S g all 143 rows.

Interpolation (Data Population)

```
// Function for data population (interpolation)
def tsInterpolate(tsPattern: String) = udf{

  (ts1: String, ts2: String, amt1: Double, amt2: Double) =>
    import java.time.LocalDateTime
    import java.time.format.DateTimeFormatter

    val timeFormat = DateTimeFormatter.ofPattern(tsPattern)

    val perdaysTS = if (ts1 == ts2) Vector(ts1) else {
      val ldt1 = LocalDateTime.parse(ts1, timeFormat)
      val ldt2 = LocalDateTime.parse(ts2, timeFormat)
      Iterator.iterate(ldt1.plusDays(1))(_.plusDays(1)).
        takeWhile(! _.isAfter(ldt2)).
        map(_.format(timeFormat)).
        toVector
    }

    val perdaysAmt = for {
      i <- 1 to perdaysTS.size
    } yield amt1 + ((amt2 - amt1) * i / perdaysTS.size)

    perdaysTS zip perdaysAmt
}

// Populate the original data (becomes estimated daily data)
val df = total_sales_hms.select("Week", "total_sales","Dates")

val tsPattern = "yyyy-MM-dd HH:mm:ss"
val win = Window.orderBy(col("Week"))

val df_sales = df.
  withColumn("datePrev", when(row_number.over(win) === 1, $"Dates").
    otherwise(lag($"Dates", 1).over(win))).
  withColumn("salePrev", when(row_number.over(win) === 1, $"Dates").
    otherwise(lag($"total_sales", 1).over(win))).
  withColumn("interpolatedList",
    tsInterpolate(tsPattern)($"datePrev", $"Dates", $"salePrev", $"total_sales")
  ).
  withColumn("interpolated", explode($"interpolatedList")).
  select( $"interpolated._1".as("Dates"), round($"interpolated._2", 2).as("total_sales")
  )
```

```
tsInterpolate: (tsPattern: String)org.apache.spark.sql.expressions.UserDefinedFunction
df: org.apache.spark.sql.DataFrame = [Week: bigint, total_sales: double ... 1 more field]
tsPattern: String = yyyy-MM-dd HH:mm:ss
win: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@4b554242
df_sales: org.apache.spark.sql.DataFrame = [Dates: string, total_sales: double]
```

```
display(df_sales)
```

	Dates	total_sales
1	2010-02-06 00:00:00	49548731.51
2	2010-02-07 00:00:00	49346722.54
3	2010-02-08 00:00:00	49144713.56
4	2010-02-09 00:00:00	48942704.58
5	2010-02-10 00:00:00	48740695.61
6	2010-02-11 00:00:00	48538686.63
7	2010-02-12 00:00:00	48336677.65
8	2010-02-13 00:00:00	48328151.39
9	2010-02-14 00:00:00	48319625.13
10	2010-02-15 00:00:00	48311098.86
11	2010-02-16 00:00:00	48302572.6
12	2010-02-17 00:00:00	48294046.34
13	2010-02-18 00:00:00	48285520.08
14	2010-02-19 00:00:00	48276993.81
15	2010-02-20 00:00:00	47661504.85
16	2010-02-21 00:00:00	47046015.89
17	2010-02-22 00:00:00	46430526.93
18	2010-02-23 00:00:00	45815037.97

S g all 994 rows.

Convert Timestamp into 3 Columns (Year, Month, Day)

```
// extract dates into year, month and day
val df_sale1 = df_sales.withColumn("year", year(to_timestamp($"Dates", "yyyy-MM-dd HH:mm:ss")))
                       .withColumn("month", month(to_timestamp($"Dates", "yyyy-MM-dd HH:mm:ss")))
                       .withColumn("day", dayofmonth(to_timestamp($"Dates", "yyyy-MM-dd HH:mm:ss")))
df_sale1.show
```

```
+-------------------+------------+----+-----+---+
|              Dates| total_sales|year|month|day|
+-------------------+------------+----+-----+---+
|2010-02-06 00:00:00|4.954673151E7|2010|    2|  6|
|2010-02-07 00:00:00|4.934672254E7|2010|    2|  7|
|2010-02-08 00:00:00|4.914471356E7|2010|    2|  8|
|2010-02-09 00:00:00|4.894270458E7|2010|    2|  9|
|2010-02-10 00:00:00|4.874069561E7|2010|    2| 10|
|2010-02-11 00:00:00|4.853868663E7|2010|    2| 11|
|2010-02-12 00:00:00|4.833667765E7|2010|    2| 12|
|2010-02-13 00:00:00|4.832815139E7|2010|    2| 13|
|2010-02-14 00:00:00|4.831962513E7|2010|    2| 14|
|2010-02-15 00:00:00|4.831109886E7|2010|    2| 15|
|2010-02-16 00:00:00| 4.83025726E7|2010|    2| 16|
|2010-02-17 00:00:00|4.829404634E7|2010|    2| 17|
|2010-02-18 00:00:00|4.828552008E7|2010|    2| 18|
|2010-02-19 00:00:00|4.827699381E7|2010|    2| 19|
|2010-02-20 00:00:00|4.766150485E7|2010|    2| 20|
|2010-02-21 00:00:00|4.704601589E7|2010|    2| 21|
|2010-02-22 00:00:00|4.643052693E7|2010|    2| 22|
|2010-02-23 00:00:00|4.581503797E7|2010|    2| 23|
```

Time-Series Train-Test Split

```scala
// Function for timeseries train-test split
def ts_split(split_pct: Double, df: DataFrame) : (DataFrame, DataFrame) =  {
  /**
    * Returns two dataframe based on the given split percentage
    * The two dataframe can be used as train and test dataset
    *
    */
  val breakpoint = math.ceil(df.count() * split_pct)

  val df_id = df.withColumn("id", monotonically_increasing_id)
  val first = df_id.where($"id" < breakpoint).drop("id")
  val second = df_id.where($"id" >= breakpoint).drop("id")

  return (first, second)
}
```

```
ts_split: (split_pct: Double, df: org.apache.spark.sql.DataFrame)(org.apache.spark.sql.DataFrame, org.apache.spark.sql.DataFrame)
```

Time-Series Seasonality Differencing and Feature Engineering for Different Prediction Horizons

```scala
val w = Window.orderBy(col("Dates"))
val weekly_win = Window.orderBy(col("Dates")).rowsBetween(-7, 0)
val biweekly_win = Window.orderBy(col("Dates")).rowsBetween(-14, 0)
val triweekly_win = Window.orderBy(col("Dates")).rowsBetween(-21, 0)
val monthly_win = Window.orderBy(col("Dates")).rowsBetween(-28, 0)
val week5_win = Window.orderBy(col("Dates")).rowsBetween(-35, 0)
val week6_win = Window.orderBy(col("Dates")).rowsBetween(-42, 0)
val week7_win = Window.orderBy(col("Dates")).rowsBetween(-49, 0)

// Prediction horizon: 1 day
val df_1day1 = df_sale1
  .withColumn("lag_1year", lag("total_sales", 365, 0).over(w))
  .where($"lag_1year">0)
  .withColumn("diff_sales", abs($"total_sales" - $"lag_1year"))
  .withColumn("lag_1day", lag("diff_sales", 1, 0).over(w))
  .withColumn("lag_5days", lag("diff_sales", 5, 0).over(w))
  .withColumn("lag_1week", lag("diff_sales", 7, 0).over(w))
  .withColumn("lag_2weeks", lag("diff_sales", 14, 0).over(w))
  .withColumn("lag_3weeks", lag("diff_sales", 21, 0).over(w))
  .where($"lag_3weeks">0)
  .withColumn("ma_1week", avg("lag_1day").over(weekly_win))
  .withColumn("ma_2weeks", avg("lag_1day").over(biweekly_win))
  .withColumn("ma_3weeks", avg("lag_1day").over(triweekly_win))
  .withColumn("ma_4weeks", avg("lag_1day").over(monthly_win))
  .withColumn("std_1week", stddev("lag_1day").over(weekly_win))
  .withColumn("std_2weeks", stddev("lag_1day").over(biweekly_win))
  .withColumn("std_3weeks", stddev("lag_1day").over(triweekly_win))
  .withColumn("std_4weeks", stddev("lag_1day").over(monthly_win))
  .where($"std_4weeks">0)
  .withColumn("label", lead("diff_sales", 1, 0).over(w))
  .na.drop
  .drop("Dates", "total_sales")
//   .withColumn("Days", monotonically_increasing_id)

val season_diff_1day = df_1day1.select("lag_1year")

val df_1day = df_1day1.drop("lag_1year")

//Prediction horizon: 1 week
val df_1week1 = df_sale1
  .withColumn("lag_1year", lag("total_sales", 365, 0).over(w))
  .where($"lag_1year">0)
  .withColumn("diff_sales", abs($"total_sales" - $"lag_1year"))
  .withColumn("lag_1week", lag("diff_sales", 7, 0).over(w))
  .withColumn("lag_2weeks", lag("diff_sales", 14, 0).over(w))
  .withColumn("lag_3weeks", lag("diff_sales", 21, 0).over(w))
  .withColumn("lag_4weeks", lag("diff_sales", 28, 0).over(w))
  .where($"lag_4weeks">0)
  .withColumn("ma_1week", avg("lag_1week").over(weekly_win))
  .withColumn("ma_2weeks", avg("lag_1week").over(biweekly_win))
  .withColumn("ma_3weeks", avg("lag_1week").over(triweekly_win))
  .withColumn("ma_4weeks", avg("lag_1week").over(monthly_win))
  .withColumn("std_1week", stddev("lag_1week").over(weekly_win))
  .withColumn("std_2weeks", stddev("lag_1week").over(biweekly_win))
  .withColumn("std_3weeks", stddev("lag_1week").over(triweekly_win))
  .withColumn("std_4weeks", stddev("lag_1week").over(monthly_win))
  .where($"std_4weeks">0)
  .withColumn("label", lead("diff_sales", 7, 0).over(w))
  .na.drop
  .drop("Dates", "total_sales")

val season_diff_1week = df_1week1.select("lag_1year")

val df_1week = df_1week1.drop("lag_1year")

// Prediction horizon: 2 weeks
val df_2weeks1 = df_sale1
  .withColumn("lag_1year", lag("total_sales", 365, 0).over(w))
  .where($"lag_1year">0)
  .withColumn("diff_sales", abs($"total_sales" - $"lag_1year"))
  .withColumn("lag_2weeks", lag("diff_sales", 14, 0).over(w))
  .withColumn("lag_3weeks", lag("diff_sales", 21, 0).over(w))
  .withColumn("lag_4weeks", lag("diff_sales", 28, 0).over(w))
  .withColumn("lag_5weeks", lag("diff_sales", 35, 0).over(w))
  .where($"lag_5weeks">0)
  .withColumn("ma_2weeks", avg("lag_2weeks").over(biweekly_win))
  .withColumn("ma_3weeks", avg("lag_2weeks").over(triweekly_win))
  .withColumn("ma_4weeks", avg("lag_2weeks").over(monthly_win))
  .withColumn("ma_5weeks", avg("lag_2weeks").over(week5_win))
  .withColumn("std_2weeks", stddev("lag_2weeks").over(biweekly_win))
  .withColumn("std_3weeks", stddev("lag_2weeks").over(triweekly_win))
```

```
  .withColumn("std_4weeks", stddev("lag_2weeks").over(monthly_win))
  .withColumn("std_5weeks", stddev("lag_2weeks").over(week5_win))
  .where($"std_5weeks">0)
  .withColumn("label", lead("diff_sales", 14, 0).over(w))
  .na.drop
  .drop("Dates", "total_sales")

val season_diff_2weeks = df_2weeks1.select("lag_1year")

val df_2weeks = df_2weeks1.drop("lag_1year")

// Prediction horizon: 3 weeks
val df_3weeks1 = df_sale1
  .withColumn("lag_1year", lag("total_sales", 365, 0).over(w))
  .where($"lag_1year">0)
  .withColumn("diff_sales", abs($"total_sales" - $"lag_1year"))
  .withColumn("lag_3weeks", lag("diff_sales", 21, 0).over(w))
  .withColumn("lag_4weeks", lag("diff_sales", 28, 0).over(w))
  .withColumn("lag_5weeks", lag("diff_sales", 35, 0).over(w))
  .withColumn("lag_6weeks", lag("diff_sales", 42, 0).over(w))
  .where($"lag_6weeks">0)
  .withColumn("ma_3weeks", avg("lag_3weeks").over(triweekly_win))
  .withColumn("ma_4weeks", avg("lag_3weeks").over(monthly_win))
  .withColumn("ma_5weeks", avg("lag_3weeks").over(week5_win))
  .withColumn("ma_6weeks", avg("lag_3weeks").over(week6_win))
  .withColumn("std_3weeks", stddev("lag_3weeks").over(triweekly_win))
  .withColumn("std_4weeks", stddev("lag_3weeks").over(monthly_win))
  .withColumn("std_5weeks", stddev("lag_3weeks").over(week5_win))
  .withColumn("std_6weeks", stddev("lag_3weeks").over(week6_win))
  .where($"std_6weeks">0)
  .withColumn("label", lead("diff_sales", 21, 0).over(w))
  .na.drop
  .drop("Dates", "total_sales")

val season_diff_3weeks = df_3weeks1.select("lag_1year")

val df_3weeks = df_3weeks1.drop("lag_1year")

// Prediction horizon: 1 month
val df_1month1 = df_sale1
  .withColumn("lag_1year", lag("total_sales", 365, 0).over(w))
  .where($"lag_1year">0)
  .withColumn("diff_sales", abs($"total_sales" - $"lag_1year"))
  .withColumn("lag_4weeks", lag("diff_sales", 28, 0).over(w))
  .withColumn("lag_5weeks", lag("diff_sales", 35, 0).over(w))
  .withColumn("lag_6weeks", lag("diff_sales", 42, 0).over(w))
  .withColumn("lag_7weeks", lag("diff_sales", 49, 0).over(w))
  .where($"lag_7weeks">0)
  .withColumn("ma_4weeks", avg("lag_4weeks").over(monthly_win))
  .withColumn("ma_5weeks", avg("lag_4weeks").over(week5_win))
  .withColumn("ma_6weeks", avg("lag_4weeks").over(week6_win))
  .withColumn("ma_7weeks", avg("lag_4weeks").over(week7_win))
  .withColumn("std_4weeks", stddev("lag_4weeks").over(monthly_win))
  .withColumn("std_5weeks", stddev("lag_4weeks").over(week5_win))
  .withColumn("std_6weeks", stddev("lag_4weeks").over(week6_win))
  .withColumn("std_7weeks", stddev("lag_4weeks").over(week7_win))
  .where($"std_7weeks">0)
  .withColumn("label", lead("diff_sales", 28, 0).over(w))
  .na.drop
  .drop("Dates", "total_sales")

val season_diff_1month = df_1month1.select("lag_1year")

val df_1month = df_1month1.drop("lag_1year")
```

```
w: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@1902da1a
weekly_win: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@1d80b113
biweekly_win: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@2a63769d
triweekly_win: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@33bd28ab
monthly_win: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@3ce8eecc
week5_win: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@24f8486a
week6_win: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@151815f7
week7_win: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@4ff4c786
df_1day1: org.apache.spark.sql.DataFrame = [year: int, month: int ... 17 more fields]
season_diff_1day: org.apache.spark.sql.DataFrame = [lag_1year: double]
df_1day: org.apache.spark.sql.DataFrame = [year: int, month: int ... 16 more fields]
df_1week1: org.apache.spark.sql.DataFrame = [year: int, month: int ... 16 more fields]
season_diff_1week: org.apache.spark.sql.DataFrame = [lag_1year: double]
df_1week: org.apache.spark.sql.DataFrame = [year: int, month: int ... 15 more fields]
df_2weeks1: org.apache.spark.sql.DataFrame = [year: int, month: int ... 16 more fields]
season_diff_2weeks: org.apache.spark.sql.DataFrame = [lag_1year: double]
df_2weeks: org.apache.spark.sql.DataFrame = [year: int, month: int ... 15 more fields]
df_3weeks1: org.apache.spark.sql.DataFrame = [year: int, month: int ... 16 more fields]
season_diff_3weeks: org.apache.spark.sql.DataFrame = [lag_1year: double]
df_3weeks: org.apache.spark.sql.DataFrame = [year: int, month: int ... 15 more fields]
df_1month1: org.apache.spark.sql.DataFrame = [year: int, month: int ... 16 more fields]
```

```
// Split train-test sets from dataframes (80/20)
val (train_set_1day_a, test_set_1day) = ts_split(0.8, df_1day)
val (train_set_1week_a, test_set_1week) = ts_split(0.8, df_1week)
val (train_set_2weeks_a, test_set_2weeks) = ts_split(0.8, df_2weeks)
val (train_set_3weeks_a, test_set_3weeks) = ts_split(0.8, df_3weeks)
val (train_set_1month_a, test_set_1month) = ts_split(0.8, df_1month)
```

```
train_set_1day_a: org.apache.spark.sql.DataFrame = [year: int, month: int ... 16 more fields]
test_set_1day: org.apache.spark.sql.DataFrame = [year: int, month: int ... 16 more fields]
train_set_1week_a: org.apache.spark.sql.DataFrame = [year: int, month: int ... 15 more fields]
test_set_1week: org.apache.spark.sql.DataFrame = [year: int, month: int ... 15 more fields]
train_set_2weeks_a: org.apache.spark.sql.DataFrame = [year: int, month: int ... 15 more fields]
test_set_2weeks: org.apache.spark.sql.DataFrame = [year: int, month: int ... 15 more fields]
train_set_3weeks_a: org.apache.spark.sql.DataFrame = [year: int, month: int ... 15 more fields]
test_set_3weeks: org.apache.spark.sql.DataFrame = [year: int, month: int ... 15 more fields]
train_set_1month_a: org.apache.spark.sql.DataFrame = [year: int, month: int ... 15 more fields]
test_set_1month: org.apache.spark.sql.DataFrame = [year: int, month: int ... 15 more fields]
```

```
// Create gap between train and test sets to ensure no data leakage
val train_set_1day = train_set_1day_a.limit(464)
val train_set_1week = train_set_1week_a.limit(445)
val train_set_2weeks = train_set_2weeks_a.limit(426)
val train_set_3weeks = train_set_3weeks_a.limit(406)
val train_set_1month = train_set_1month_a.limit(387)
```

```
train_set_1day: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [year: int, month: int ... 16 more fields]
train_set_1week: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [year: int, month: int ... 15 more fields]
train_set_2weeks: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [year: int, month: int ... 15 more fields]
train_set_3weeks: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [year: int, month: int ... 15 more fields]
train_set_1month: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [year: int, month: int ... 15 more fields]
```

```
// Split the seasonal differences using the same ratio
// Only use "test_diff" later for reconstruction
val (train_diff_1day, test_diff_1day) = ts_split(0.8, season_diff_1day)
val (train_diff_1week, test_diff_1week) = ts_split(0.8, season_diff_1week)
val (train_diff_2weeks, test_diff_2weeks) = ts_split(0.8, season_diff_2weeks)
val (train_diff_3weeks, test_diff_3weeks) = ts_split(0.8, season_diff_3weeks)
val (train_diff_1month, test_diff_1month) = ts_split(0.8, season_diff_1month)
```

```
train_diff_1day: org.apache.spark.sql.DataFrame = [lag_1year: double]
test_diff_1day: org.apache.spark.sql.DataFrame = [lag_1year: double]
train_diff_1week: org.apache.spark.sql.DataFrame = [lag_1year: double]
```

```
test_diff_1week: org.apache.spark.sql.DataFrame = [lag_1year: double]
train_diff_2weeks: org.apache.spark.sql.DataFrame = [lag_1year: double]
test_diff_2weeks: org.apache.spark.sql.DataFrame = [lag_1year: double]
train_diff_3weeks: org.apache.spark.sql.DataFrame = [lag_1year: double]
test_diff_3weeks: org.apache.spark.sql.DataFrame = [lag_1year: double]
train_diff_1month: org.apache.spark.sql.DataFrame = [lag_1year: double]
test_diff_1month: org.apache.spark.sql.DataFrame = [lag_1year: double]
```

Convert Features into Dense Vectors

```
// Vectorize the features

// Prediction horizon: 1 day
val vectorAssembler_1day = new VectorAssembler()
  .setInputCols(Array("year","month","day","lag_1day","lag_5days","lag_1week","lag_2weeks","lag_3weeks",
                      "ma_1week","ma_2weeks","ma_3weeks","ma_4weeks","std_1week","std_2weeks",
                     "std_3weeks","std_4weeks","diff_sales"))
  .setOutputCol("features")

val train_1day = vectorAssembler_1day.transform(train_set_1day)
  .drop("year","month","day","lag_1day","lag_5days","lag_1week","lag_2weeks","lag_3weeks",
        "ma_1week","ma_2weeks","ma_3weeks","ma_4weeks","std_1week","std_2weeks",
        "std_3weeks","std_4weeks","diff_sales")

val test_1day = vectorAssembler_1day.transform(test_set_1day)
  .drop("year","month","day","lag_1day","lag_5days","lag_1week","lag_2weeks","lag_3weeks",
        "ma_1week","ma_2weeks","ma_3weeks","ma_4weeks","std_1week","std_2weeks",
        "std_3weeks","std_4weeks","diff_sales")

// Prediction horizon: 1 week
val vectorAssembler_1week = new VectorAssembler()
  .setInputCols(Array("year","month","day","lag_1week","lag_2weeks","lag_3weeks","lag_4weeks","ma_1week",
                      "ma_2weeks","ma_3weeks","ma_4weeks","std_1week","std_2weeks","std_3weeks","std_4weeks",
                      "diff_sales"))
  .setOutputCol("features")

val train_1week = vectorAssembler_1week.transform(train_set_1week)
  .drop("year","month","day","lag_1week","lag_2weeks","lag_3weeks","lag_4weeks","ma_1week",
        "ma_2weeks","ma_3weeks","ma_4weeks","std_1week","std_2weeks","std_3weeks","std_4weeks",
       "diff_sales")

val test_1week = vectorAssembler_1week.transform(test_set_1week)
  .drop("year","month","day","lag_1week","lag_2weeks","lag_3weeks","lag_4weeks","ma_1week",
        "ma_2weeks","ma_3weeks","ma_4weeks","std_1week","std_2weeks","std_3weeks","std_4weeks",
        "diff_sales")

// Prediction horizon: 2 weeks
val vectorAssembler_2weeks = new VectorAssembler()
  .setInputCols(Array("year","month","day","lag_2weeks","lag_3weeks","lag_4weeks","lag_5weeks",
                      "ma_2weeks","ma_3weeks","ma_4weeks","ma_5weeks","std_2weeks","std_3weeks",
                      "std_4weeks","std_5weeks","diff_sales"))
  .setOutputCol("features")

val train_2weeks = vectorAssembler_2weeks.transform(train_set_2weeks)
  .drop("year","month","day","lag_2weeks","lag_3weeks","lag_4weeks","lag_5weeks","ma_2weeks",
        "ma_3weeks","ma_4weeks","ma_5weeks","std_2weeks","std_3weeks","std_4weeks","std_5weeks",
        "diff_sales")

val test_2weeks = vectorAssembler_2weeks.transform(test_set_2weeks)
  .drop("year","month","day","lag_2weeks","lag_3weeks","lag_4weeks","lag_5weeks","ma_2weeks",
        "ma_3weeks","ma_4weeks","ma_5weeks","std_2weeks","std_3weeks","std_4weeks","std_5weeks",
        "diff_sales")

// Prediction horizon: 3 weeks
val vectorAssembler_3weeks = new VectorAssembler()
  .setInputCols(Array("year","month","day","lag_3weeks","lag_4weeks","lag_5weeks","lag_6weeks",
                      "ma_3weeks","ma_4weeks","ma_5weeks","ma_6weeks","std_3weeks","std_4weeks",
                      "std_5weeks","std_6weeks","diff_sales"))
  .setOutputCol("features")

val train_3weeks = vectorAssembler_3weeks.transform(train_set_3weeks)
  .drop("year","month","day","lag_3weeks","lag_4weeks","lag_5weeks","lag_6weeks","ma_3weeks",
        "ma_4weeks","ma_5weeks","ma_6weeks","std_3weeks","std_4weeks","std_5weeks","std_6weeks",
        "diff_sales")

val test_3weeks = vectorAssembler_3weeks.transform(test_set_3weeks)
  .drop("year","month","day","lag_3weeks","lag_4weeks","lag_5weeks","lag_6weeks","ma_3weeks",
        "ma_4weeks","ma_5weeks","ma_6weeks","std_3weeks","std_4weeks","std_5weeks","std_6weeks",
        "diff_sales")

// Prediction horizon: 1 month
val vectorAssembler_1month = new VectorAssembler()
  .setInputCols(Array("year","month","day","lag_4weeks","lag_5weeks","lag_6weeks","lag_7weeks",
                      "ma_4weeks","ma_5weeks","ma_6weeks","ma_7weeks","std_4weeks","std_5weeks",
                      "std_6weeks","std_7weeks","diff_sales"))
  .setOutputCol("features")

val train_1month = vectorAssembler_1month.transform(train_set_1month)
  .drop("year","month","day","lag_4weeks","lag_5weeks","lag_6weeks","lag_7weeks","ma_4weeks",
        "ma_5weeks","ma_6weeks","ma_7weeks","std_4weeks","std_5weeks","std_6weeks","std_7weeks",
        "diff_sales")

val test_1month = vectorAssembler_1month.transform(test_set_1month)
  .drop("year","month","day","lag_4weeks","lag_5weeks","lag_6weeks","lag_7weeks","ma_4weeks",
        "ma_5weeks","ma_6weeks","ma_7weeks","std_4weeks","std_5weeks","std_6weeks","std_7weeks",
        "diff_sales")
```

```
vectorAssembler_1day: org.apache.spark.ml.feature.VectorAssembler = VectorAssembler: uid=vecAssembler_379495da5b16, handleInvalid=error, numInputCols=17
train_1day: org.apache.spark.sql.DataFrame = [label: double, features: vector]
test_1day: org.apache.spark.sql.DataFrame = [label: double, features: vector]
vectorAssembler_1week: org.apache.spark.ml.feature.VectorAssembler = VectorAssembler: uid=vecAssembler_90d7efcc70a8, handleInvalid=error, numInputCols=16
train_1week: org.apache.spark.sql.DataFrame = [label: double, features: vector]
test_1week: org.apache.spark.sql.DataFrame = [label: double, features: vector]
vectorAssembler_2weeks: org.apache.spark.ml.feature.VectorAssembler = VectorAssembler: uid=vecAssembler_de7e8fbe08d1, handleInvalid=error, numInputCols=16
train_2weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector]
test_2weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector]
vectorAssembler_3weeks: org.apache.spark.ml.feature.VectorAssembler = VectorAssembler: uid=vecAssembler_63259d30c297, handleInvalid=error, numInputCols=16
train_3weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector]
test_3weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector]
vectorAssembler_1month: org.apache.spark.ml.feature.VectorAssembler = VectorAssembler: uid=vecAssembler_6da3c6a53487, handleInvalid=error, numInputCols=16
train_1month: org.apache.spark.sql.DataFrame = [label: double, features: vector]
test_1month: org.apache.spark.sql.DataFrame = [label: double, features: vector]
```

Feature Importance (5 different prediction window dataframes)

```
// train a new random forest model
val rf = new RandomForestRegressor()

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(rf))

// Train model
val model = pipeline.fit(train_1day)

// Make predictions.
```

```scala
val predictions = model.transform(test_1day)

// extract feature importance from rf model
val importances = model // this would be your trained model
  .stages(0)
  .asInstanceOf[RandomForestRegressionModel]
  .featureImportances

val features = train_set_1day.columns.filterNot(Set("Date", "label"))

val printImportance = importances.toArray zip features

println("----------------------------------------")
printImportance.sortBy(-_._1).foreach(x => println(x._2 + " -> " + x._1))
println("----------------------------------------")
```

```
----------------------------------------
std_4weeks -> 0.48860663788531085
diff_sales -> 0.20541242833194065
lag_3weeks -> 0.05996895489797325
ma_2weeks -> 0.02911517425551858
month -> 0.02636373331084928
std_1week -> 0.0254821371096213
lag_1day -> 0.02399619078175962
ma_1week -> 0.02299845822053420
ma_3weeks -> 0.02266434803871879
std_2weeks -> 0.02887924844977986
day -> 0.019281562052471505
std_3weeks -> 0.018497651159587272
ma_4weeks -> 0.017157458672051297
lag_2weeks -> 0.012598757873451606
lag_5days -> 0.009642874413557783
lag_1week -> 0.004671448765726587
year -> 6.729525772282224E-4
----------------------------------------
rf: org.apache.spark.ml.regression.RandomForestRegressor = rfr_73dd29f89ef6
pipeline: org.apache.spark.ml.Pipeline = pipeline_b0cc7823e867
```

```scala
// train a new random forest model
val rf = new RandomForestRegressor()

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(rf))

// Train model
val model = pipeline.fit(train_1week)

// Make predictions.
val predictions = model.transform(test_1week)

// extract feature importance from rf model
val importances = model // this would be your trained model
  .stages(0)
  .asInstanceOf[RandomForestRegressionModel]
  .featureImportances

val features = train_set_1week.columns.filterNot(Set("Date", "label"))

val printImportance = importances.toArray zip features

println("----------------------------------------")
printImportance.sortBy(-_._1).foreach(x => println(x._2 + " -> " + x._1))
println("----------------------------------------")
```

```
----------------------------------------
ma_3weeks -> 0.14297118085146988
std_4weeks -> 0.11531770837488858
ma_4weeks -> 0.10983726573915151
std_3weeks -> 0.08312879788344797
ma_2weeks -> 0.07877991485282489
std_1week -> 0.07132787062176611
day -> 0.06564066928458842
std_2weeks -> 0.061341664289280447
lag_2weeks -> 0.045426546768668856
lag_1week -> 0.04198798278887883
ma_1week -> 0.03777683752499801
diff_sales -> 0.03698123883983979
lag_3weeks -> 0.036123782021939894
lag_4weeks -> 0.031870373446634834
month -> 0.02668315569314214
year -> 0.014885023578577324
----------------------------------------
rf: org.apache.spark.ml.regression.RandomForestRegressor = rfr_10ef4f97297e
pipeline: org.apache.spark.ml.Pipeline = pipeline_7188d97736a9
model: org.apache.spark.ml.PipelineModel = pipeline_7188d97736a9
```

```scala
// train a new random forest model
val rf = new RandomForestRegressor()

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(rf))

// Train model
val model = pipeline.fit(train_2weeks)

// Make predictions.
val predictions = model.transform(test_2weeks)

// extract feature importance from rf model
val importances = model // this would be your trained model
  .stages(0)
  .asInstanceOf[RandomForestRegressionModel]
  .featureImportances

val features = train_set_2weeks.columns.filterNot(Set("Date", "label"))

val printImportance = importances.toArray zip features

println("----------------------------------------")
printImportance.sortBy(-_._1).foreach(x => println(x._2 + " -> " + x._1))
println("----------------------------------------")
```

```
----------------------------------------
std_2weeks -> 0.12814393168914063
std_4weeks -> 0.11224311104748723
month -> 0.11149736753773483
std_3weeks -> 0.10188238339986088
std_5weeks -> 0.09430501196683537
ma_3weeks -> 0.07538959152235206
lag_2weeks -> 0.07418882884439904
lag_5weeks -> 0.06874577445766497
ma_4weeks -> 0.04684026893232798
diff_sales -> 0.04381176435641083
ma_5weeks -> 0.04292575164265888
day -> 0.04108093498460487
lag_3weeks -> 0.024817185814592174
ma_2weeks -> 0.01927680473618801
year -> 0.01287110675524823
lag_4weeks -> 0.012288183171955896
----------------------------------------
```

```
rf: org.apache.spark.ml.regression.RandomForestRegressor = rfr_788a85aa1c97
pipeline: org.apache.spark.ml.Pipeline = pipeline_a6859af0b329
model: org.apache.spark.ml.PipelineModel = pipeline_a6859af0b329
```

```
// train a new random forest model
val rf = new RandomForestRegressor()

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(rf))

// Train model
val model = pipeline.fit(train_3weeks)

// Make predictions.
val predictions = model.transform(test_3weeks)

// extract feature importance from rf model
val importances = model // this would be your trained model
  .stages(0)
  .asInstanceOf[RandomForestRegressionModel]
  .featureImportances

val features = train_set_3weeks.columns.filterNot(Set("Date", "label"))

val printImportance = importances.toArray zip features

println("-----------------------------------------")
printImportance.sortBy(-_._1).foreach(x => println(x._2 + " -> " + x._1))
println("-----------------------------------------")
```

```
-----------------------------------------
ma_5weeks -> 0.13768178957748456
std_5weeks -> 0.12346492878430375
month -> 0.12264478979745258
day -> 0.08979584121057345
diff_sales -> 0.07432586451196 1
std_6weeks -> 0.07180492238726471
lag_6weeks -> 0.06952384944491863
lag_4weeks -> 0.04831830888648697
ma_4weeks -> 0.04881892164925012 5
ma_3weeks -> 0.04295242716980618
std_3weeks -> 0.04283998659962835
std_4weeks -> 0.03863833688847181
ma_6weeks -> 0.0294689965792176
lag_5weeks -> 0.027148143955199095
year -> 0.019395562397436 45
lag_3weeks -> 0.014926127958544578
-----------------------------------------
rf: org.apache.spark.ml.regression.RandomForestRegressor = rfr_955aa5a165b3
pipeline: org.apache.spark.ml.Pipeline = pipeline_358eac7578ca
model: org.apache.spark.ml.PipelineModel = pipeline_358eac7578ca
```

```
// train a new random forest model
val rf = new RandomForestRegressor()

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(rf))

// Train model
val model = pipeline.fit(train_1month)

// Make predictions.
val predictions = model.transform(test_1month)

// extract feature importance from rf model
val importances = model // this would be your trained model
  .stages(0)
  .asInstanceOf[RandomForestRegressionModel]
  .featureImportances

val features = train_set_1month.columns.filterNot(Set("Date", "label"))

val printImportance = importances.toArray zip features

println("-----------------------------------------")
printImportance.sortBy(-_._1).foreach(x => println(x._2 + " -> " + x._1))
println("-----------------------------------------")
```

```
-----------------------------------------
ma_7weeks -> 0.1741215473552611
month -> 0.1086826461731102 7
diff_sales -> 0.09121351572812682
std_6weeks -> 0.08713885371589519
ma_6weeks -> 0.08292119712732847
std_7weeks -> 0.0723971267137346
std_4weeks -> 0.06638631355713298
ma_4weeks -> 0.06032918040294176
lag_6weeks -> 0.05535892882906385
ma_5weeks -> 0.05247840018408913
day -> 0.03516064153188055
std_5weeks -> 0.03248197169560493
year -> 0.02981967681219613 4
lag_7weeks -> 0.025855989537776793
lag_4weeks -> 0.017568265594483 41
lag_5weeks -> 0.009753833841374184
-----------------------------------------
rf: org.apache.spark.ml.regression.RandomForestRegressor = rfr_6b5518f7342d
pipeline: org.apache.spark.ml.Pipeline = pipeline_7c87b48698da
model: org.apache.spark.ml.PipelineModel = pipeline_7c87b48698da
```

Simple & Moving Average (SMA)

```
// def getLastRow(df: DataFrame): DataFrame = {
//   val with_id = df.withColumn("_id", monotonically_increasing_id())
//   val i = with_id.select(max("_id")).first()(0)
// //   val i = with_id.count().toInt - 1
//   return with_id.where(col("_id") === i).drop("_id")
// }
```

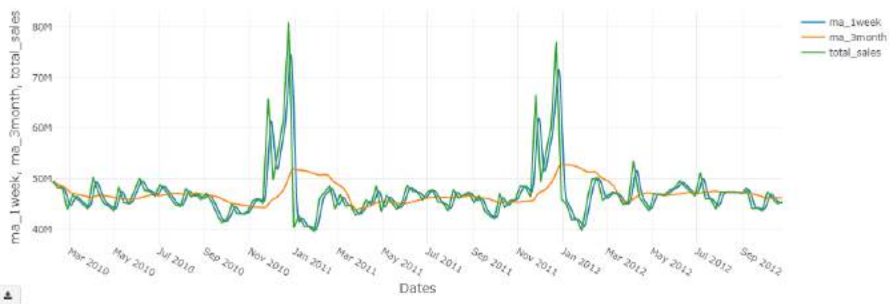
```
// def SMA_predict(df: DataFrame, prediction_len: Int, win_num: Int): DataFrame = {
//   /**
//   * df contains cols: Dates & total_sales
//   */
//   val clean_df: DataFrame = df.select("Dates","total_sales")

//   val w = Window.orderBy(col("Dates")).rowsBetween(-win_num, -1)

// //   val newRow1 = Seq((clean_df.tail(1)(0)(0) + 1, 0)).toDF("Dates","total_sales")
//   val newRow1 = getLastRow(clean_df).withColumn("Dates", date_add($"Dates", 1)).withColumn("total_sales", lit(0))

//   val df_apended = clean_df.union(newRow1)
```

```
//   var ma_1: DataFrame = df_apended.withColumn("ma_1", avg("total_sales").over(w))

//   ma_1 = ma_1.withColumn("total_sales", when(df_apended.col("total_sales") === 0, ma_1.tail(2)(0)(2)).
//              otherwise(df_apended.col("total_sales")))

//   println(df_apended.count().toInt)

//   if(df_apended.count().toInt >= prediction_len) {
//     return ma_1
//   } else {
//     SMA_predict(ma_1, prediction_len, win_num)
//   }

// }
```

```
val week_w = Window.orderBy(col("Dates")).rowsBetween(-7, -1)
val biweekly_w = Window.orderBy(col("Dates")).rowsBetween(-14, -1)
val triweekly_w = Window.orderBy(col("Dates")).rowsBetween(-21, -1)
val monthly_w = Window.orderBy(col("Dates")).rowsBetween(-28, -1)
val trimonth_w = Window.orderBy(col("Dates")).rowsBetween(-84, -1)
```

```
week_w: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@21712a30
biweekly_w: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@41b499b5
triweekly_w: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@4711620e
monthly_w: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@7590e6af
trimonth_w: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@5d186287
```

```
// Create a comparison dataframe to show 1-week SMA versus 3-month SMA
val compare_ma = df_sale1
  .withColumn("ma_1week", avg("total_sales").over(week_w))
  .withColumn("ma_3month", avg("total_sales").over(trimonth_w))

display(compare_ma)
```




```
// Splitting the original data to get test set before calculating SMA
val (train_set_wma, test_set_wma) = ts_split(0.8, total_sales_hms)
```

```
train_set_wma: org.apache.spark.sql.DataFrame = [total_sales: double, Week: bigint ... 1 more field]
test_set_wma: org.apache.spark.sql.DataFrame = [total_sales: double, Week: bigint ... 1 more field]
```

```
val df_sales_wid = df_sales
  .withColumn("Day", monotonically_increasing_id)

display(df_sales_wid)
```

	Dates	total_sales	Day
1	2010-02-06 00:00:00	49648731.51	0
2	2010-02-07 00:00:00	49346722.54	1
3	2010-02-08 00:00:00	49144713.56	2
4	2010-02-09 00:00:00	48942704.58	3
5	2010-02-10 00:00:00	48740695.61	4
6	2010-02-11 00:00:00	48538686.63	5
7	2010-02-12 00:00:00	48336677.65	6
8	2010-02-13 00:00:00	48328151.39	7

Showing all 994 rows.

```
// Splitting the interpolated data to get test set before calculating SMA
val (train_set_dma, test_set_dma) = ts_split(0.8, df_sales_wid)
```

```
train_set_dma: org.apache.spark.sql.DataFrame = [Dates: string, total_sales: double ... 1 more field]
test_set_dma: org.apache.spark.sql.DataFrame = [Dates: string, total_sales: double ... 1 more field]
```

```
// Using interpolated data to calculate SMA
val ma_1week = test_set_dma
  .withColumn("ma_1week", avg("total_sales").over(week_w))
  .where("id > 802")
  .drop("Dates")

ma_1week.
  withColumn("diff_abs", abs($"ma_1week" - $"total_sales")).
  withColumn("demo", (abs($"ma_1week") + abs($"total_sales")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / ma_1week.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|1.4477|
+-------+

ma_1week: org.apache.spark.sql.DataFrame = [total_sales: double, Day: bigint ... 1 more field]
```

```
val ma_2weeks = test_set_dma
  .withColumn("ma_2weeks", avg("total_sales").over(biweekly_w))
  .where("id > 809")
  .drop("Dates")

ma_2weeks.
  withColumn("diff_abs", abs($"ma_2weeks" - $"total_sales")).
  withColumn("demo", (abs($"ma_2weeks") + abs($"total_sales")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / ma_2weeks.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
```

```
| SMAPE|
+-------+
|2.1174|
+-------+

ma_2weeks: org.apache.spark.sql.DataFrame = [total_sales: double, Day: bigint ... 1 more field]
```

```
val ma_3weeks = test_set_dma
  .withColumn("ma_3weeks", avg("total_sales").over(triweekly_w))
  .where("id > 816")
  .drop("Dates")

ma_3weeks.
  withColumn("diff_abs", abs($"ma_3weeks" - $"total_sales")).
  withColumn("demo", (abs($"ma_3weeks") + abs($"total_sales")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / ma_3weeks.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|2.5212|
+-------+

ma_3weeks: org.apache.spark.sql.DataFrame = [total_sales: double, Day: bigint ... 1 more field]
```

```
val ma_1month = test_set_dma
  .withColumn("ma_1month", avg("total_sales").over(monthly_w))
  .where("id > 823")
  .drop("Dates")

ma_1month.
  withColumn("diff_abs", abs($"ma_1month" - $"total_sales")).
  withColumn("demo", (abs($"ma_1month") + abs($"total_sales")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / ma_1month.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|2.5934|
+-------+

ma_1month: org.apache.spark.sql.DataFrame = [total_sales: double, Day: bigint ... 1 more field]
```

```
val twoweek_w = Window.orderBy(col("Week")).rowsBetween(-2, -1)
val threeweek_w = Window.orderBy(col("Week")).rowsBetween(-3, -1)
val onemonth_w = Window.orderBy(col("Week")).rowsBetween(-4, -1)
```

```
twoweek_w: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@3ec6ce32
threeweek_w: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@1c632d6
onemonth_w: org.apache.spark.sql.expressions.WindowSpec = org.apache.spark.sql.expressions.WindowSpec@64bb1378
```

```
// Using original data to calculate SMA
val ma_2w = test_set_wma
  .drop("Dates")
  .withColumn("ma_2weeks", avg("total_sales").over(twoweek_w))
  .where("Week > 115")

ma_2w.
  withColumn("diff_abs", abs($"ma_2weeks" - $"total_sales")).
  withColumn("demo", (abs($"ma_2weeks") + abs($"total_sales")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / ma_2w.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|3.2866|
+-------+

ma_2w: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [total_sales: double, Week: bigint ... 1 more field]
```

```
val ma_3w = test_set_wma
  .drop("Dates")
  .withColumn("ma_3weeks", avg("total_sales").over(threeweek_w))
  .where("Week > 116")

ma_3w.
  withColumn("diff_abs", abs($"ma_3weeks" - $"total_sales")).
  withColumn("demo", (abs($"ma_3weeks") + abs($"total_sales")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / ma_3w.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|3.5817|
+-------+

ma_3w: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [total_sales: double, Week: bigint ... 1 more field]
```

```
val ma_1m = test_set_wma
  .drop("Dates")
  .withColumn("ma_1month", avg("total_sales").over(onemonth_w))
  .where("Week > 117")

ma_1m.
  withColumn("diff_abs", abs($"ma_1month" - $"total_sales")).
  withColumn("demo", (abs($"ma_1month") + abs($"total_sales")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / ma_1m.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|3.3261|
+-------+

ma_1m: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [total_sales: double, Week: bigint ... 1 more field]
```

Random Forest Models Predictions, Reconstructions, and SMAPE

```
def rolling_cv_tuning(initial_train_obs: Int, shift: Int, assembled_df: DataFrame, hyper_params: Map[String, String]): Double = {
  /**
    * Returns the average rmse for the whole rolling process
```

```
  * For example, if we have 143 rows in total,
  * we set the initial train as 43, and 10 more rolling forward, then
  * train first 43, test 44 - 53
  * train first 53, test 54 - 64
  * ...
  * train first 133, test 134 - 143
  * the function will roll 9 times in this case, and we calculate the rmse for each time / 9, and return the value
  */

 val total_rows = assembled_df.count()
 val rolling_space = total_rows - initial_train_obs
 val fold_num = (rolling_space / shift).toInt


 var total_rmse = 0.0

 for (i <- 1 to fold_num) {

   // define rolling frame
   var total_select = initial_train_obs + shift * i
   var train_pct = initial_train_obs.toFloat / total_select

   // train test split
   val (train_set, test_set) = ts_split(train_pct, assembled_df.limit(total_select.toInt))

   /*******************REPLACE TO OTHER MODEL START *********************/
   // Initiate model object
   val rf = new RandomForestRegressor().
     setMaxBins(hyper_params("MaxBins").toInt).
     setNumTrees(hyper_params("NumTrees").toInt)

   // Setup Pipeline.
   val pipeline = new Pipeline().setStages(Array(rf))

   // Train model
   val model = pipeline.fit(train_set)

   // Make predictions.
   val predictions = model.transform(test_set)

   // Select (prediction, true label) and compute test error.
   val evaluator = new RegressionEvaluator()
     .setMetricName("rmse")

   val rmse = evaluator.evaluate(predictions)

   // trained model
   val rfModel = model.stages(0).asInstanceOf[RandomForestRegressionModel]
   /*******************REPLACE TO OTHER MODEL END *********************/

   total_rmse += rmse

   println(s"Hyper params: $hyper_params; rolling times: $i ($total_select/$total_rows); rmse: $rmse")
 }

 return total_rmse / fold_num

}

rolling_cv_tuning: (initial_train_obs: Int, shift: Int, assembled_df: org.apache.spark.sql.DataFrame, hyper_params: Map[String,String])Double
```

```
// Setting up for rolling cv
val param_grid = Map(
  "NumTrees" -> Seq("5","10","15"),
  "MaxBins" -> Seq("28","30","32")
)

// transform arrays into lists with values paired with map key
val pairedWithKey = param_grid.map { case (k,v) => v.map(i => k -> i).toList }

val accumulator = pairedWithKey.head.map(x => Vector(x))

val params_combination = pairedWithKey.tail.foldLeft(accumulator)( (acc, elem) =>
  for { x <- acc; y <- elem } yield x :+ y
)

param_grid: scala.collection.immutable.Map[String,Seq[String]] = Map(NumTrees -> List(5, 10, 15), MaxBins -> List(28, 30, 32))
pairedWithKey: scala.collection.immutable.Iterable[List[(String, String)]] = List(List((NumTrees,5), (NumTrees,10), (NumTrees,15)), List((MaxBins,28), (MaxBins,30), (MaxBins,32)))
accumulator: List[scala.collection.immutable.Vector[(String, String)]] = List(Vector((NumTrees,5)), Vector((NumTrees,10)), Vector((NumTrees,15)))
params_combination: List[scala.collection.immutable.Vector[(String, String)]] = List(Vector((NumTrees,5), (MaxBins,28)), Vector((NumTrees,5), (MaxBins,30)), Vector((NumTrees,5), (MaxBins,32)), Vector((NumTrees,10), (MaxBins,28)), Vector((N
umTrees,10), (MaxBins,30)), Vector((NumTrees,10), (MaxBins,32)), Vector((NumTrees,15), (MaxBins,28)), Vector((NumTrees,15), (MaxBins,30)), Vector((NumTrees,15), (MaxBins,32)))
```

Prediction Window = 1 day

```
//1 day rolling cv
var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  val avg_rmse = rolling_cv_tuning(64, 200, train_1day, hyper_params) //train1day has 464 rows, use 64 as train and every 200 for cv

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}
// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")
```

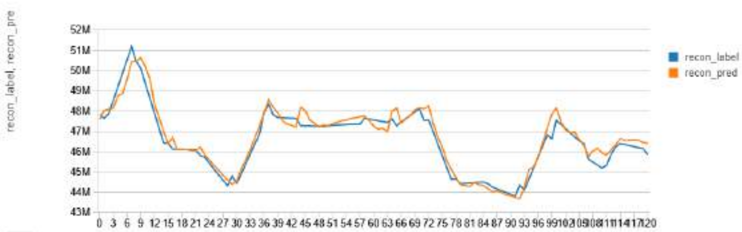
```
Hyper params: Map(NumTrees -> 5, MaxBins -> 28); rolling times: 1 (264/464); rmse: 620859.0754262772
Hyper params: Map(NumTrees -> 5, MaxBins -> 28); rolling times: 2 (464/464); rmse: 857982.2917266886
Hyper params: Map(NumTrees -> 5, MaxBins -> 30); rolling times: 1 (264/464); rmse: 560581.3740698683
Hyper params: Map(NumTrees -> 5, MaxBins -> 30); rolling times: 2 (464/464); rmse: 814843.2950235651
Hyper params: Map(NumTrees -> 5, MaxBins -> 32); rolling times: 1 (264/464); rmse: 609296.9982348494
Hyper params: Map(NumTrees -> 5, MaxBins -> 32); rolling times: 2 (464/464); rmse: 905066.6611920457
Hyper params: Map(NumTrees -> 10, MaxBins -> 28); rolling times: 1 (264/464); rmse: 494907.88525327433
Hyper params: Map(NumTrees -> 10, MaxBins -> 28); rolling times: 2 (464/464); rmse: 849945.4559216195
Hyper params: Map(NumTrees -> 10, MaxBins -> 30); rolling times: 1 (264/464); rmse: 494641.3242002952
Hyper params: Map(NumTrees -> 10, MaxBins -> 30); rolling times: 2 (464/464); rmse: 759748.9666059434
Hyper params: Map(NumTrees -> 10, MaxBins -> 32); rolling times: 1 (264/464); rmse: 479925.5526462603
Hyper params: Map(NumTrees -> 10, MaxBins -> 32); rolling times: 2 (464/464); rmse: 728874.2480037136
Hyper params: Map(NumTrees -> 15, MaxBins -> 28); rolling times: 1 (264/464); rmse: 509672.02343818216
Hyper params: Map(NumTrees -> 15, MaxBins -> 28); rolling times: 2 (464/464); rmse: 772947.8542815864
Hyper params: Map(NumTrees -> 15, MaxBins -> 30); rolling times: 1 (264/464); rmse: 488671.9334075607
Hyper params: Map(NumTrees -> 15, MaxBins -> 30); rolling times: 2 (464/464); rmse: 806515.7239681443
Hyper params: Map(NumTrees -> 15, MaxBins -> 32); rolling times: 1 (264/464); rmse: 485204.08841444645
Hyper params: Map(NumTrees -> 15, MaxBins -> 32); rolling times: 2 (464/464); rmse: 778674.9187805974
_____________________________________________
Best Hyper Parameter is:
Some((604399.9003249869,Map(NumTrees -> 10, MaxBins -> 32)))
```

```
// Using best parameters from CV
// Best hyperparameters found: NumTrees = 10, MaxBins = 32
val rf = new RandomForestRegressor()
```

```
    .setFeaturesCol("features")
    .setNumTrees(10)
    .setMaxBins(32)

// Setup Pipeline
val pipeline = new Pipeline().setStages(Array(rf))

// Train model
val model = pipeline.fit(train_1day)

// Make predictions.
val predictions = model.transform(test_1day)

// Reconstruction of predictions with seasonal differences
val diff_1day = test_diff_1day.withColumn("id", monotonically_increasing_id())
val pred_1day = predictions.withColumn("id", monotonically_increasing_id())
val merged_1day = pred_1day.join(diff_1day, diff_1day.col("id") === pred_1day.col("id"), "left_outer").drop("id")
val recon_predictions_1day = merged_1day.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("test set days", monotonically_increasing_id())

// Compute SMAPE
recon_predictions_1day.
//   limit(120).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_1day.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|0.6322|
+-------+

rf: org.apache.spark.ml.regression.RandomForestRegressor = rfr_b64e5c3b5ced
pipeline: org.apache.spark.ml.Pipeline = pipeline_80d2a3b65ba2
model: org.apache.spark.ml.PipelineModel = pipeline_80d2a3b65ba2
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_1day: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_1day: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_1day: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_1day: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

```
display(recon_predictions_1day)
```



Prediction Window = 1 week

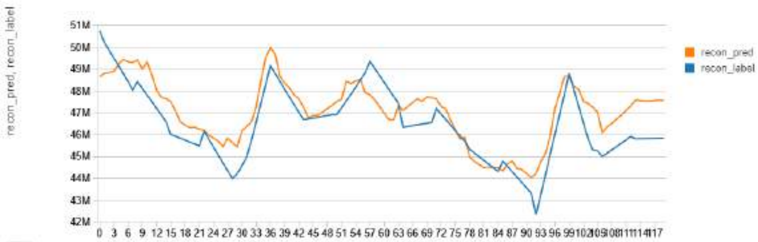
```
// 1 week rolling cv
var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  val avg_rmse = rolling_cv_tuning(65, 190, train_1week, hyper_params) //train1week has 445 rows, use 65 as train and every 190 for cv

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}
// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")
```

```
Hyper params: Map(NumTrees -> 5, MaxBins -> 28); rolling times: 1 (255/445); rmse: 1626974.9174286106
Hyper params: Map(NumTrees -> 5, MaxBins -> 28); rolling times: 2 (445/445); rmse: 1658955.2154388255
Hyper params: Map(NumTrees -> 5, MaxBins -> 30); rolling times: 1 (255/445); rmse: 1624233.0207597497
Hyper params: Map(NumTrees -> 5, MaxBins -> 30); rolling times: 2 (445/445); rmse: 1708655.5801281407
Hyper params: Map(NumTrees -> 5, MaxBins -> 32); rolling times: 1 (255/445); rmse: 1528737.765905241
Hyper params: Map(NumTrees -> 5, MaxBins -> 32); rolling times: 2 (445/445); rmse: 1718527.9479596484
Hyper params: Map(NumTrees -> 10, MaxBins -> 28); rolling times: 1 (255/445); rmse: 1630032.38157273
Hyper params: Map(NumTrees -> 10, MaxBins -> 28); rolling times: 2 (445/445); rmse: 1633162.5329673588
Hyper params: Map(NumTrees -> 10, MaxBins -> 30); rolling times: 1 (255/445); rmse: 1513333.598161624
Hyper params: Map(NumTrees -> 10, MaxBins -> 30); rolling times: 2 (445/445); rmse: 1639287.2683525262
Hyper params: Map(NumTrees -> 10, MaxBins -> 32); rolling times: 1 (255/445); rmse: 1468493.6879179259
Hyper params: Map(NumTrees -> 10, MaxBins -> 32); rolling times: 2 (445/445); rmse: 1683034.319464999
Hyper params: Map(NumTrees -> 15, MaxBins -> 28); rolling times: 1 (255/445); rmse: 1584928.8369688813
Hyper params: Map(NumTrees -> 15, MaxBins -> 28); rolling times: 2 (445/445); rmse: 1657170.957488294
Hyper params: Map(NumTrees -> 15, MaxBins -> 30); rolling times: 1 (255/445); rmse: 1536626.840784858
Hyper params: Map(NumTrees -> 15, MaxBins -> 30); rolling times: 2 (445/445); rmse: 1682869.162096915
Hyper params: Map(NumTrees -> 15, MaxBins -> 32); rolling times: 1 (255/445); rmse: 1650624.9049826586
Hyper params: Map(NumTrees -> 15, MaxBins -> 32); rolling times: 2 (445/445); rmse: 1660664.3179522834
_____________________________________________
Best Hyper Parameter is:
Some((684399.9083249869,Map(NumTrees -> 10, MaxBins -> 32)))
```

```
// Using best parameters from CV
// Best hyperparameters found: NumTrees = 10, MaxBins = 32
val rf = new RandomForestRegressor()
    .setFeaturesCol("features")
    .setNumTrees(10)
    .setMaxBins(32)

// Setup Pipeline
val pipeline = new Pipeline().setStages(Array(rf))

// Train model
val model = pipeline.fit(train_1week)

// Make predictions.
val predictions = model.transform(test_1week)

// Reconstruction of predictions with seasonal differences
val diff_1week = test_diff_1week.withColumn("id", monotonically_increasing_id())
val pred_1week = predictions.withColumn("id", monotonically_increasing_id())
val merged_1week = pred_1week.join(diff_1week, diff_1week.col("id") === pred_1week.col("id"), "left_outer").drop("id")
```

```
val recon_predictions_1week = merged_1week.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("test set days", monotonically_increasing_id())

// Compute SMAPE
recon_predictions_1week.
//   limit(113).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_1week.count() * 100, 4) as "SMAPE").
  show()

+-------+
| SMAPE|
+-------+
|1.8343|
+-------+

rf: org.apache.spark.ml.regression.RandomForestRegressor = rfr_fbf2f545df91
pipeline: org.apache.spark.ml.Pipeline = pipeline_f51db3666d8f
model: org.apache.spark.ml.PipelineModel = pipeline_f51db3666d8f
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_1week: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_1week: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_1week: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_1week: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

```
display(recon_predictions_1week)
```



Prediction Window = 2 weeks

```
// 2 weeks rolling cv
var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  val avg_rmse = rolling_cv_tuning(66, 180, train_2weeks, hyper_params) //train2weeks has 426 rows, use 66 as train and every 180 for cv

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}
// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")
```

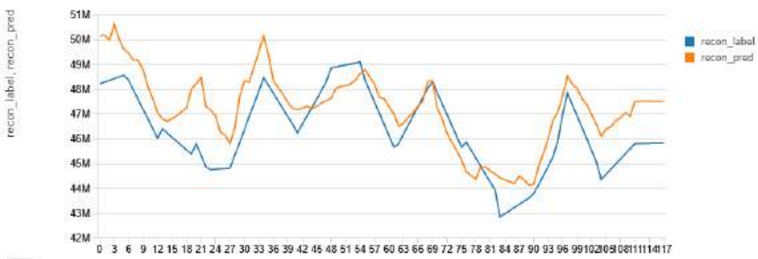
```
Hyper params: Map(NumTrees -> 5, MaxBins -> 28); rolling times: 1 (246/426); rmse: 2832996.0583821538
Hyper params: Map(NumTrees -> 5, MaxBins -> 28); rolling times: 2 (426/426); rmse: 1838348.8104556703
Hyper params: Map(NumTrees -> 5, MaxBins -> 30); rolling times: 1 (246/426); rmse: 2191152.188600683
Hyper params: Map(NumTrees -> 5, MaxBins -> 30); rolling times: 2 (426/426); rmse: 1966826.683888683
Hyper params: Map(NumTrees -> 5, MaxBins -> 32); rolling times: 1 (246/426); rmse: 2297145.5881749785
Hyper params: Map(NumTrees -> 5, MaxBins -> 32); rolling times: 2 (426/426); rmse: 2823931.515368753
Hyper params: Map(NumTrees -> 10, MaxBins -> 28); rolling times: 1 (246/426); rmse: 1942923.4221352485
Hyper params: Map(NumTrees -> 10, MaxBins -> 28); rolling times: 2 (426/426); rmse: 1880295.2516126814
Hyper params: Map(NumTrees -> 10, MaxBins -> 30); rolling times: 1 (246/426); rmse: 2184564.140242831
Hyper params: Map(NumTrees -> 10, MaxBins -> 30); rolling times: 2 (426/426); rmse: 1896566.7272125285
Hyper params: Map(NumTrees -> 10, MaxBins -> 32); rolling times: 1 (246/426); rmse: 2288697.8665068676
Hyper params: Map(NumTrees -> 10, MaxBins -> 32); rolling times: 2 (426/426); rmse: 1955388.8539766665
Hyper params: Map(NumTrees -> 15, MaxBins -> 28); rolling times: 1 (246/426); rmse: 2134689.8167023167
Hyper params: Map(NumTrees -> 15, MaxBins -> 28); rolling times: 2 (426/426); rmse: 1917168.7944642229
Hyper params: Map(NumTrees -> 15, MaxBins -> 30); rolling times: 1 (246/426); rmse: 2235689.4116415083
Hyper params: Map(NumTrees -> 15, MaxBins -> 30); rolling times: 2 (426/426); rmse: 1966338.6331891166
Hyper params: Map(NumTrees -> 15, MaxBins -> 32); rolling times: 1 (246/426); rmse: 2142918.2009635773
Hyper params: Map(NumTrees -> 15, MaxBins -> 32); rolling times: 2 (426/426); rmse: 1937638.3321122394
_____________________________________________
Best Hyper Parameter is:
Some((684399.9083249869,Map(NumTrees -> 10, MaxBins -> 32)))
```

```
// Using best parameters from CV
// Best hyperparameters found: NumTrees = 10, MaxBins = 32
val rf = new RandomForestRegressor()
    .setFeaturesCol("features")
    .setNumTrees(10)
    .setMaxBins(32)

// Setup Pipeline
val pipeline = new Pipeline().setStages(Array(rf))

// Train model
val model = pipeline.fit(train_2weeks)

// Make predictions.
val predictions = model.transform(test_2weeks)

// Reconstruction of predictions with seasonal differences
val diff_2weeks = test_diff_2weeks.withColumn("id", monotonically_increasing_id())
val pred_2weeks = predictions.withColumn("id", monotonically_increasing_id())
val merged_2weeks = pred_2weeks.join(diff_2weeks, diff_2weeks.col("id") === pred_2weeks.col("id"), "left_outer").drop("id")
val recon_predictions_2weeks = merged_2weeks.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("test set days", monotonically_increasing_id())

// Compute SMAPE
recon_predictions_2weeks.
//   limit(184).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_2weeks.count() * 100, 4) as "SMAPE").
  show()

+-------+
| SMAPE|
+-------+
```

```
|2.3636|
+-------+
```

```
rf: org.apache.spark.ml.regression.RandomForestRegressor = rfr_dc619575cb77
pipeline: org.apache.spark.ml.Pipeline = pipeline_a1803a898d64
model: org.apache.spark.ml.PipelineModel = pipeline_a1803a898d64
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_2weeks: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_2weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_2weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_2weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

```
display(recon_predictions_2weeks)
```



Prediction Window = 3 weeks

```
// 3 weeks rolling cv
var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  val avg_rmse = rolling_cv_tuning(60, 173, train_3weeks, hyper_params) //train3weeks has 406 rows, use 60 as train and every 173 for cv

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}
// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")
```

```
Hyper params: Map(NumTrees -> 5, MaxBins -> 28); rolling times: 1 (233/406); rmse: 1115504.9406277166
Hyper params: Map(NumTrees -> 5, MaxBins -> 28); rolling times: 2 (406/406); rmse: 1535782.0316438603
Hyper params: Map(NumTrees -> 5, MaxBins -> 30); rolling times: 1 (233/406); rmse: 1105164.2764877197
Hyper params: Map(NumTrees -> 5, MaxBins -> 30); rolling times: 2 (406/406); rmse: 1528492.7466532318
Hyper params: Map(NumTrees -> 5, MaxBins -> 32); rolling times: 1 (233/406); rmse: 1108105.211926883
Hyper params: Map(NumTrees -> 5, MaxBins -> 32); rolling times: 2 (406/406); rmse: 1534134.4808604405
Hyper params: Map(NumTrees -> 10, MaxBins -> 28); rolling times: 1 (233/406); rmse: 1078664.262309281
Hyper params: Map(NumTrees -> 10, MaxBins -> 28); rolling times: 2 (406/406); rmse: 1436895.1768718448
Hyper params: Map(NumTrees -> 10, MaxBins -> 30); rolling times: 1 (233/406); rmse: 1053052.7050338648
Hyper params: Map(NumTrees -> 10, MaxBins -> 30); rolling times: 2 (406/406); rmse: 1440302.3802055777
Hyper params: Map(NumTrees -> 10, MaxBins -> 32); rolling times: 1 (233/406); rmse: 1075363.8156288454
Hyper params: Map(NumTrees -> 10, MaxBins -> 32); rolling times: 2 (406/406); rmse: 1442199.136047611
Hyper params: Map(NumTrees -> 15, MaxBins -> 28); rolling times: 1 (233/406); rmse: 1076536.883586533
Hyper params: Map(NumTrees -> 15, MaxBins -> 28); rolling times: 2 (406/406); rmse: 1469019.1180838281
Hyper params: Map(NumTrees -> 15, MaxBins -> 30); rolling times: 1 (233/406); rmse: 1081980.3755640795
Hyper params: Map(NumTrees -> 15, MaxBins -> 30); rolling times: 2 (406/406); rmse: 1460872.401785882
Hyper params: Map(NumTrees -> 15, MaxBins -> 32); rolling times: 1 (233/406); rmse: 1061357.8648553052
Hyper params: Map(NumTrees -> 15, MaxBins -> 32); rolling times: 2 (406/406); rmse: 1444741.8417268263
_____________________________________________
Best Hyper Parameter is:
Some((1246677.5426193213,Map(NumTrees -> 10, MaxBins -> 30)))
```

```
// Using best parameters from CV
// Best hyperparameters found: NumTrees = 10, MaxBins = 30
val rf = new RandomForestRegressor()
    .setFeaturesCol("features")
    .setNumTrees(10)
    .setMaxBins(30)

// Setup Pipeline
val pipeline = new Pipeline().setStages(Array(rf))

// Train model
val model = pipeline.fit(train_3weeks)

// Make predictions.
val predictions = model.transform(test_3weeks)

// Reconstruction of predictions with seasonal differences
val diff_3weeks = test_diff_3weeks.withColumn("id", monotonically_increasing_id())
val pred_3weeks = predictions.withColumn("id", monotonically_increasing_id())
val merged_3weeks = pred_3weeks.join(diff_3weeks, diff_3weeks.col("id") === pred_3weeks.col("id"), "left_outer").drop("id")
val recon_predictions_3weeks = merged_3weeks.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("test set days", monotonically_increasing_id())

// Compute SMAPE
recon_predictions_3weeks.
//    limit(96).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_3weeks.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|2.0982|
+-------+
```

```
rf: org.apache.spark.ml.regression.RandomForestRegressor = rfr_5b05fe442cc6
pipeline: org.apache.spark.ml.Pipeline = pipeline_0c409cc38886
model: org.apache.spark.ml.PipelineModel = pipeline_0c409cc38886
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_3weeks: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_3weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_3weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_3weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

```
display(recon_predictions_3weeks)
```

Prediction Window = 1 month

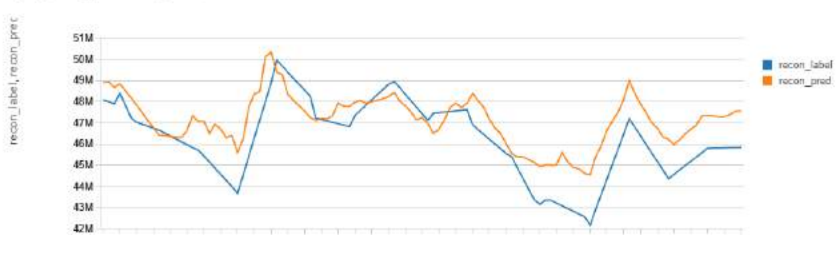
```
// 1 month rolling cv
var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  val avg_rmse = rolling_cv_tuning(57, 165, train_1month, hyper_params) //train1month has 387 rows, use 57 as train and every 165 for cv

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}
// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")
```

```
Hyper params: Map(NumTrees -> 5, MaxBins -> 28); rolling times: 1 (222/387); rmse: 1159546.6602385603
Hyper params: Map(NumTrees -> 5, MaxBins -> 28); rolling times: 2 (387/387); rmse: 1526076.7899672586
Hyper params: Map(NumTrees -> 5, MaxBins -> 30); rolling times: 1 (222/387); rmse: 1122838.9837959273
Hyper params: Map(NumTrees -> 5, MaxBins -> 30); rolling times: 2 (387/387); rmse: 1500109.7446752638
Hyper params: Map(NumTrees -> 5, MaxBins -> 32); rolling times: 1 (222/387); rmse: 1118729.0687340582
Hyper params: Map(NumTrees -> 5, MaxBins -> 32); rolling times: 2 (387/387); rmse: 1499796.6365522865
Hyper params: Map(NumTrees -> 10, MaxBins -> 28); rolling times: 1 (222/387); rmse: 1082351.9674277033
Hyper params: Map(NumTrees -> 10, MaxBins -> 28); rolling times: 2 (387/387); rmse: 1490172.5704682488
Hyper params: Map(NumTrees -> 10, MaxBins -> 30); rolling times: 1 (222/387); rmse: 1113978.523655878
Hyper params: Map(NumTrees -> 10, MaxBins -> 30); rolling times: 2 (387/387); rmse: 1501554.8941543547
Hyper params: Map(NumTrees -> 10, MaxBins -> 32); rolling times: 1 (222/387); rmse: 1083058.9504865713
Hyper params: Map(NumTrees -> 10, MaxBins -> 32); rolling times: 2 (387/387); rmse: 1486557.509188841
Hyper params: Map(NumTrees -> 15, MaxBins -> 28); rolling times: 1 (222/387); rmse: 1125069.5345799893
Hyper params: Map(NumTrees -> 15, MaxBins -> 28); rolling times: 2 (387/387); rmse: 1509942.821196458
Hyper params: Map(NumTrees -> 15, MaxBins -> 30); rolling times: 1 (222/387); rmse: 1087929.164532966
Hyper params: Map(NumTrees -> 15, MaxBins -> 30); rolling times: 2 (387/387); rmse: 1490559.4320668967
Hyper params: Map(NumTrees -> 15, MaxBins -> 32); rolling times: 1 (222/387); rmse: 1134376.8155988576
Hyper params: Map(NumTrees -> 15, MaxBins -> 32); rolling times: 2 (387/387); rmse: 1515116.5705763726
_____________________________________________
Best Hyper Parameter is:
Some((1284808.2298337063,Map(NumTrees -> 10, MaxBins -> 32)))
```

```
// Using best parameters from CV
// Best hyperparameters found: NumTrees = 10, MaxBins = 32
val rf = new RandomForestRegressor()
    .setFeaturesCol("features")
    .setNumTrees(10)
    .setMaxBins(32)

// Setup Pipeline
val pipeline = new Pipeline().setStages(Array(rf))

// Train model
val model = pipeline.fit(train_1month)

// Make predictions.
val predictions = model.transform(test_1month)

// Reconstruction of predictions with seasonal differences
val diff_1month = test_diff_1month.withColumn("id", monotonically_increasing_id())
val pred_1month = predictions.withColumn("id", monotonically_increasing_id())
val merged_1month = pred_1month.join(diff_1month, diff_1month.col("id") === pred_1month.col("id"), "left_outer").drop("id")
val recon_predictions_1month = merged_1month.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("test set days", monotonically_increasing_id())

// Compute SMAPE
recon_predictions_1month.
//   limit(87).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_1month.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|2.4684|
+-------+

rf: org.apache.spark.ml.regression.RandomForestRegressor = rfr_1a2439fe4077
pipeline: org.apache.spark.ml.Pipeline = pipeline_6da9b6a9301f
model: org.apache.spark.ml.PipelineModel = pipeline_6da9b6a9301f
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_1month: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_1month: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_1month: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_1month: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

```
display(recon_predictions_1month)
```



0 3 6 9 12 15 18 21 24 27 30 33 36 39 42 45 48 51 54 57 60 63 66 69 72 75 78 81 84 87 90 93 96 99 102105108111114

Linear Regression Models Predictions, Reconstructions, and SMAPE

```
import org.apache.spark.ml.regression.LinearRegression
import org.apache.spark.ml.regression.LinearRegressionModel
def rolling_cv_tuning(initial_train_obs: Int, shift: Int, assembled_df: DataFrame, hyper_params: Map[String, String]): Double = {

  val total_rows = assembled_df.count()
  val rolling_space = total_rows - initial_train_obs
  val fold_num = (rolling_space / shift).toInt


  var total_rmse = 0.0

  for (i <- 1 to fold_num) {

    // define rolling frame
    var total_select = initial_train_obs + shift * i
    var train_pct = initial_train_obs.toFloat / total_select

    // train test split
    val (train_set, test_set) = ts_split(train_pct, assembled_df.limit(total_select.toInt))

    /******************REPLACE TO OTHER MODEL START ********************/
    // Initiate model object
    val lr = new LinearRegression()
      .setRegParam(hyper_params("RegParam").toFloat)
      .setElasticNetParam(hyper_params("ElasticNetParam").toFloat)
      .setLabelCol("label")
      .setFeaturesCol("features")

    // Setup Pipeline.
    val pipeline = new Pipeline().setStages(Array(lr))

    // Train model
    val model = pipeline.fit(train_set)

    // Make predictions.
    val predictions = model.transform(test_set)

    // Select (prediction, true label) and compute test error.
    val evaluator = new RegressionEvaluator()
      .setMetricName("rmse")

    val rmse = evaluator.evaluate(predictions)

    // trained model
    val lrModel = model.stages(0).asInstanceOf[LinearRegressionModel]
    /******************REPLACE TO OTHER MODEL END ********************/

    total_rmse += rmse

    println(s"Hyper params: $hyper_params; rolling times: $i ($total_select/$total_rows); rmse: $rmse")
  }

  return total_rmse / fold_num

}
```

```
import org.apache.spark.ml.regression.LinearRegression
import org.apache.spark.ml.regression.LinearRegressionModel
rolling_cv_tuning: (initial_train_obs: Int, shift: Int, assembled_df: org.apache.spark.sql.DataFrame, hyper_params: Map[String,String])Double
```

```
// Setting up for rolling cv
val param_grid = Map(
  "RegParam" -> Seq("0","0.1","0.5"),
  "ElasticNetParam" -> Seq("0","0.1","0.5")
)

// transform arrays into lists with values paired with map key
val pairedWithKey = param_grid.map { case (k,v) => v.map(i => k -> i).toList }

val accumulator = pairedWithKey.head.map(x => Vector(x))

val params_combination = pairedWithKey.tail.foldLeft(accumulator)( (acc, elem) =>
  for { x <- acc; y <- elem } yield x :+ y
)
```

```
param_grid: scala.collection.immutable.Map[String,Seq[String]] = Map(RegParam -> List(0, 0.1, 0.5), ElasticNetParam -> List(0, 0.1, 0.5))
pairedWithKey: scala.collection.immutable.Iterable[List[(String, String)]] = List(List((RegParam,0), (RegParam,0.1), (RegParam,0.5)), List((ElasticNetParam,0), (ElasticNetParam,0.1), (ElasticNetParam,0.5)))
accumulator: List[scala.collection.immutable.Vector[(String, String)]] = List(Vector((RegParam,0)), Vector((RegParam,0.1)), Vector((RegParam,0.5)))
params_combination: List[scala.collection.immutable.Vector[(String, String)]] = List(Vector((RegParam,0), (ElasticNetParam,0)), Vector((RegParam,0), (ElasticNetParam,0.1)), Vector((RegParam,0), (ElasticNetParam,0.5)), Vector((RegParam,0.
1), (ElasticNetParam,0)), Vector((RegParam,0.1), (ElasticNetParam,0.1)), Vector((RegParam,0.1), (ElasticNetParam,0.5)), Vector((RegParam,0.5), (ElasticNetParam,0)), Vector((RegParam,0.5), (ElasticNetParam,0.1)), Vector((RegParam,0.5), (Ela
sticNetParam,0.5)))
```

Prediction Window = 1 day

```
//1 day rolling cv + tuning
var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  val avg_rmse = rolling_cv_tuning(64, 200, train_1day, hyper_params) //train1day has 464 rows, use 64 as train and every 200 for cv

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}
// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")
```

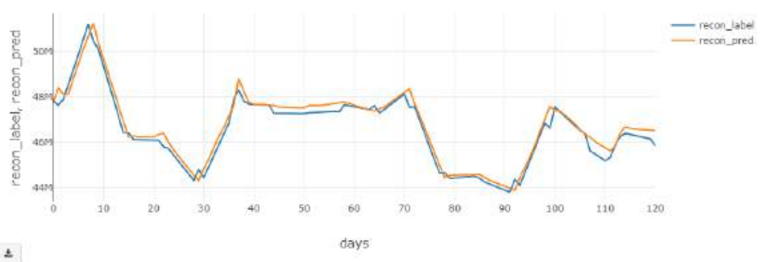
```
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0); rolling times: 1 (264/464); rmse: 5533072.812463968
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0); rolling times: 2 (464/464); rmse: 4690550.726433968
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.1); rolling times: 1 (264/464); rmse: 5533072.812463968
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.1); rolling times: 2 (464/464); rmse: 4690558.726433968
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.5); rolling times: 1 (264/464); rmse: 5533072.812463968
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.5); rolling times: 2 (464/464); rmse: 4690558.726433968
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0); rolling times: 1 (264/464); rmse: 6867715.245882469
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0); rolling times: 2 (464/464); rmse: 6043765.306474306
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.1); rolling times: 1 (264/464); rmse: 1928471.2935608719
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.1); rolling times: 2 (464/464); rmse: 1875698.1585265783
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.5); rolling times: 1 (264/464); rmse: 2075276.1680215451
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.5); rolling times: 2 (464/464); rmse: 1966781.0584926462
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0); rolling times: 1 (264/464); rmse: 6863676.577312397
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0); rolling times: 2 (464/464); rmse: 6040384.562850681
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.1); rolling times: 1 (264/464); rmse: 2075257.4787815535
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.1); rolling times: 2 (464/464); rmse: 1966768.7587371665
```

```
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.5); rolling times: 1 (264/464); rmse: 2075262.472327159
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.5); rolling times: 2 (464/464); rmse: 1908719.1272153175
------------------------------------------------
Best Hyper Parameter is:
Some((1902084.7220437252,Map(RegParam -> 0.1, ElasticNetParam -> 0.1)))
```

```
//1 day best cv settings
//best hyperparameters found: RegParam = 0.1, ElasticNetParam = 0.1
val lr = new LinearRegression()
      .setRegParam(0.1)
      .setElasticNetParam(0.1)

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(lr))

// Train model
val model = pipeline.fit(train_1day)

// Make predictions.
val predictions = model.transform(test_1day)
// Reconstruction of predictions with seasonal differences
val diff_1day = test_diff_1day.withColumn("id", monotonically_increasing_id())
val pred_1day = predictions.withColumn("id", monotonically_increasing_id())
val merged_1day = pred_1day.join(diff_1day, diff_1day.col("id") === pred_1day.col("id"), "left_outer").drop("id")
val recon_predictions_1day = merged_1day.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("days",monotonically_increasing_id())

// Compute sMAPE
recon_predictions_1day.
//   limit(120).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_1day.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|0.5562|
+-------+

lr: org.apache.spark.ml.regression.LinearRegression = linReg_4ef17f32e3c9
pipeline: org.apache.spark.ml.Pipeline = pipeline_4b44af41446a
model: org.apache.spark.ml.PipelineModel = pipeline_4b44af41446a
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_1day: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_1day: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_1day: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_1day: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

```
//1 day prediction horizon
display(recon_predictions_1day)
```



Prediction Window = 1 week

```
//1 week rolling cv + tuning
var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  val avg_rmse = rolling_cv_tuning(65, 190, train_1week, hyper_params) //train1week has 445 rows, use 65 as train and every 190 for cv

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}
// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")
```

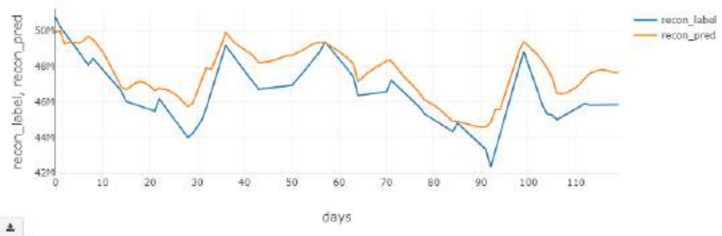
```
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0); rolling times: 1 (255/445); rmse: 2.912203394643107E7
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0); rolling times: 2 (445/445); rmse: 2.3725557232651394E7
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.1); rolling times: 1 (255/445); rmse: 2.912283394643107E7
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.1); rolling times: 2 (445/445); rmse: 2.3725557232651394E7
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.5); rolling times: 1 (255/445); rmse: 2.912283394643107E7
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.5); rolling times: 2 (445/445); rmse: 2.3725557232651394E7
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0); rolling times: 1 (255/445); rmse: 3.1017546188208353E7
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0); rolling times: 2 (445/445); rmse: 3.301334427882443E7
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.1); rolling times: 1 (255/445); rmse: 1.3958809519878759E7
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.1); rolling times: 2 (445/445); rmse: 1.1083859288961306E7
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.5); rolling times: 1 (255/445); rmse: 1.3958013474273804E7
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.5); rolling times: 2 (445/445); rmse: 1.1247185563229848E7
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0); rolling times: 1 (255/445); rmse: 3.0994190466953594E7
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0); rolling times: 2 (445/445); rmse: 3.29876164728273E7
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.1); rolling times: 1 (255/445); rmse: 1.3957799350224935E7
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.1); rolling times: 2 (445/445); rmse: 1.1247006793170353E7
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.5); rolling times: 1 (255/445); rmse: 1.1713489868719868E7
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.5); rolling times: 2 (445/445); rmse: 1.2786400532825679E7
------------------------------------------------
Best Hyper Parameter is:
Some((1.1249945200772773E7,Map(RegParam -> 0.5, ElasticNetParam -> 0.5)))
```

```
//1 week best cv settings
//best hyperparameters found: RegParam = 0.5 ,ElasticNetParam = 0.5
val lr = new LinearRegression()
      .setRegParam(0.5)
      .setElasticNetParam(0.5)

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(lr))
```

```
// Train model
val model = pipeline.fit(train_1week)

// Make predictions.
val predictions = model.transform(test_1week)
// Compute sMAPE
// Reconstruction of predictions with seasonal differences
val diff_1week = test_diff_1week.withColumn("id", monotonically_increasing_id())
val pred_1week = predictions.withColumn("id", monotonically_increasing_id())
val merged_1week = pred_1week.join(diff_1week, diff_1week.col("id") === pred_1week.col("id"), "left_outer").drop("id")
val recon_predictions_1week = merged_1week.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("days",monotonically_increasing_id())

// Compute sMAPE
recon_predictions_1week.
//   limit(113).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_1week.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|2.4552|
+-------+

lr: org.apache.spark.ml.regression.LinearRegression = linReg_e75dd4a9e1ce
pipeline: org.apache.spark.ml.Pipeline = pipeline_2d39b17bffe4
model: org.apache.spark.ml.PipelineModel = pipeline_2d39b17bffe4
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_1week: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_1week: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_1week: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 3 more fields]
recon_predictions_1week: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

```
//1 week prediction horizon
display(recon_predictions_1week)
```



Prediction Window = 2 weeks

```
// 2 weeks rolling cv + tuning
var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  val avg_rmse = rolling_cv_tuning(66, 180, train_2weeks, hyper_params) //train2weeks has 426 rows, use 66 as train and every 180 for cv

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}
// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")
```

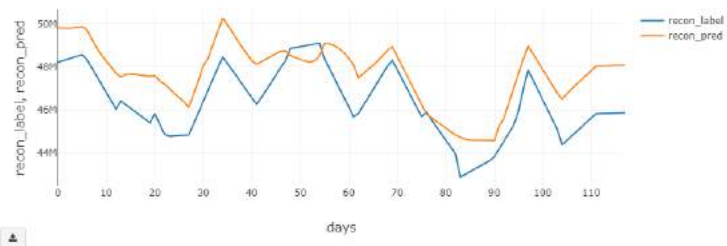
```
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0); rolling times: 1 (246/426); rmse: 4.101761186896301E7
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0); rolling times: 2 (426/426); rmse: 3.617825804620921E7
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.1); rolling times: 1 (246/426); rmse: 4.101761186896301E7
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.1); rolling times: 2 (426/426); rmse: 3.617825804620921E7
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.5); rolling times: 1 (246/426); rmse: 4.101761186896301E7
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.5); rolling times: 2 (426/426); rmse: 3.617825804620921E7
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0); rolling times: 1 (246/426); rmse: 4.528310733711362E7
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0); rolling times: 2 (426/426); rmse: 3.95191021964172E7
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.1); rolling times: 1 (246/426); rmse: 4490290.7512706965
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.1); rolling times: 2 (426/426); rmse: 3943785.1335564437
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.5); rolling times: 1 (246/426); rmse: 4759192.251733424
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.5); rolling times: 2 (426/426); rmse: 4185647.1932266937
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0); rolling times: 1 (246/426); rmse: 4.525984206484188E7
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0); rolling times: 2 (426/426); rmse: 3.949881850886161E7
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.1); rolling times: 1 (246/426); rmse: 4759171.528772669
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.1); rolling times: 2 (426/426); rmse: 4185625.461447741
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.5); rolling times: 1 (246/426); rmse: 4224149.074380541
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.5); rolling times: 2 (426/426); rmse: 3681338.317918476
_____________________________________________
Best Hyper Parameter is:
Some((3952743.6961495885,Map(RegParam -> 0.5, ElasticNetParam -> 0.5)))
```

```
//2 week best cv settings
//best hyperparameters found: RegParam = 0.5, ElasticNetParam = 0.5
val lr = new LinearRegression()
      .setRegParam(0.5)
      .setElasticNetParam(0.5)

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(lr))

// Train model
val model = pipeline.fit(train_2weeks)

// Make predictions.
val predictions = model.transform(test_2weeks)
// Compute sMAPE
// Reconstruction of predictions with seasonal differences
val diff_2weeks = test_diff_2weeks.withColumn("id", monotonically_increasing_id())
val pred_2weeks = predictions.withColumn("id", monotonically_increasing_id())
val merged_2weeks = pred_2weeks.join(diff_2weeks, diff_2weeks.col("id") === pred_2weeks.col("id"), "left_outer").drop("id")
val recon_predictions_2weeks = merged_2weeks.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("days",monotonically_increasing_id())

// Compute sMAPE
recon_predictions_2weeks.
//   limit(184).
```

```
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_2weeks.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|3.0125|
+-------+

lr: org.apache.spark.ml.regression.LinearRegression = linReg_a14b80090d68
pipeline: org.apache.spark.ml.Pipeline = pipeline_c1f5146ff99f
model: org.apache.spark.ml.PipelineModel = pipeline_c1f5146ff99f
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_2weeks: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_2weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_2weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_2weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

```
// 2 weeks prediction horizon
display(recon_predictions_2weeks)
```



Prediction Window = 3 weeks

```
//3 weeks rolling cv + tuning
var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  val avg_rmse = rolling_cv_tuning(60, 173, train_3weeks, hyper_params) //train3weeks has 406 rows, use 60 as train and every 173 for cv

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}
// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")
```

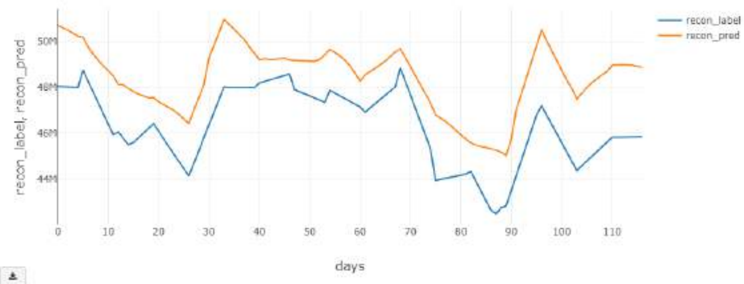
```
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0); rolling times: 1 (233/406); rmse: 4889257.446063449
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0); rolling times: 2 (406/406); rmse: 4084532.277841278
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.1); rolling times: 1 (233/406); rmse: 4889257.446063449
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.1); rolling times: 2 (406/406); rmse: 4084532.277841278
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.5); rolling times: 1 (233/406); rmse: 4889257.446063449
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.5); rolling times: 2 (406/406); rmse: 4084532.277841278
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0); rolling times: 1 (233/406); rmse: 8682838.66718464
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0); rolling times: 2 (406/406); rmse: 7545833.671581693
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.1); rolling times: 1 (233/406); rmse: 1124544.6339932622
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.1); rolling times: 2 (406/406); rmse: 3190521.8145924374
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.5); rolling times: 1 (233/406); rmse: 1133699.8460338216
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.5); rolling times: 2 (406/406); rmse: 3233872.5414895597
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0); rolling times: 1 (233/406); rmse: 8542441.45863956
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0); rolling times: 2 (406/406); rmse: 7398198.509162538
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.1); rolling times: 1 (233/406); rmse: 1133699.8860809744
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.1); rolling times: 2 (406/406); rmse: 3233830.4842536886
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.5); rolling times: 1 (233/406); rmse: 1401330.7248813548
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.5); rolling times: 2 (406/406); rmse: 2322996.00965402
_____________________________________________
Best Hyper Parameter is:
Some((1862163.3672276875,Map(RegParam -> 0.5, ElasticNetParam -> 0.5)))
```

```
//3 week best cv settings
//best hyperparameters found: RegParam = 0.5, ElasticNetParam = 0.5
val lr = new LinearRegression()
      .setRegParam(0.5)
      .setElasticNetParam(0.5)

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(lr))

// Train model
val model = pipeline.fit(train_3weeks)

// Make predictions.
val predictions = model.transform(test_3weeks)
// Reconstruction of predictions with seasonal differences
val diff_3weeks = test_diff_3weeks.withColumn("id", monotonically_increasing_id())
val pred_3weeks = predictions.withColumn("id", monotonically_increasing_id())
val merged_3weeks = pred_3weeks.join(diff_3weeks, diff_3weeks.col("id") === pred_3weeks.col("id"), "left_outer").drop("id")
val recon_predictions_3weeks = merged_3weeks.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("days",monotonically_increasing_id())

// Compute sMAPE
recon_predictions_3weeks.
//   limit(96).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_3weeks.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|4.5267|
+-------+

lr: org.apache.spark.ml.regression.LinearRegression = linReg_96857c586173
pipeline: org.apache.spark.ml.Pipeline = pipeline_f1b136e1ab7e
model: org.apache.spark.ml.PipelineModel = pipeline_f1b136e1ab7e
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_3weeks: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
```

```
pred_3weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_3weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_3weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

```
// 3 weeks prediction horizon
display(recon_predictions_3weeks)
```



Prediction Window = 1 month

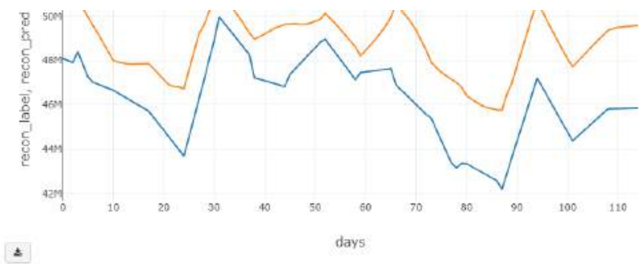
```
//1 month rolling cv + tuning
var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  val avg_rmse = rolling_cv_tuning(57, 165, train_1month, hyper_params) //train1month has 387 rows, use 57 as train and every 165 for cv

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}
// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")
```

```
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0); rolling times: 1 (222/387); rmse: 8734023.88804814
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0); rolling times: 2 (387/387); rmse: 8981644.323251298
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.1); rolling times: 1 (222/387); rmse: 8734023.88804814
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.1); rolling times: 2 (387/387); rmse: 8981644.323251298
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.5); rolling times: 1 (222/387); rmse: 8734023.88804814
Hyper params: Map(RegParam -> 0, ElasticNetParam -> 0.5); rolling times: 2 (387/387); rmse: 8981644.323251298
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0); rolling times: 1 (222/387); rmse: 9785693.585711866
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0); rolling times: 2 (387/387); rmse: 1.484284622551187E7
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.1); rolling times: 1 (222/387); rmse: 7101804.927184899
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.1); rolling times: 2 (387/387); rmse: 6914711.79728566
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.5); rolling times: 1 (222/387); rmse: 7016881.7671507756
Hyper params: Map(RegParam -> 0.1, ElasticNetParam -> 0.5); rolling times: 2 (387/387); rmse: 6785889.453951162
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0); rolling times: 1 (222/387); rmse: 9382911.871718205
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0); rolling times: 2 (387/387); rmse: 1.3282975391361763E7
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.1); rolling times: 1 (222/387); rmse: 7016669.382083226
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.1); rolling times: 2 (387/387); rmse: 6784866.105927593
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.5); rolling times: 1 (222/387); rmse: 7282447.848357576
Hyper params: Map(RegParam -> 0.5, ElasticNetParam -> 0.5); rolling times: 2 (387/387); rmse: 6963676.744125272
_____________________________________________
Best Hyper Parameter is:
Some((6900767.744010409,Map(RegParam -> 0.5, ElasticNetParam -> 0.1)))
```

```
//1 month best cv settings
//best hyperparameters found: RegParam = 0.5, ElasticNetParam = 0.1
val lr = new LinearRegression()
      .setRegParam(0.5)
      .setElasticNetParam(0.1)

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(lr))

// Train model
val model = pipeline.fit(train_1month)

// Make predictions.
val predictions = model.transform(test_1month)
// Reconstruction of predictions with seasonal differences
val diff_1month = test_diff_1month.withColumn("id", monotonically_increasing_id())
val pred_1month = predictions.withColumn("id", monotonically_increasing_id())
val merged_1month = pred_1month.join(diff_1month, diff_1month.col("id") === pred_1month.col("id"), "left_outer").drop("id")
val recon_predictions_1month = merged_1month.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("days",monotonically_increasing_id())

// Compute sMAPE
recon_predictions_1month.
//   limit(87).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_1month.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|5.3629|
+-------+

lr: org.apache.spark.ml.regression.LinearRegression = linReg_44a5786f4ff4
pipeline: org.apache.spark.ml.Pipeline = pipeline_7a30dc51cda5
model: org.apache.spark.ml.PipelineModel = pipeline_7a30dc51cda5
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_1month: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_1month: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_1month: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_1month: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

```
// 1 month prediction horizon
display(recon_predictions_1month)
```



Decision Tree Models Predictions, Reconstructions, and SMAPE

```
import org.apache.spark.ml.regression.DecisionTreeRegressor
import org.apache.spark.ml.regression.DecisionTreeRegressionModel

def rolling_cv_tuning(initial_train_obs: Int, shift: Int, assembled_df: DataFrame, hyper_params: Map[String, String]): Double = {

  val total_rows = assembled_df.count()
  val rolling_space = total_rows - initial_train_obs
  val fold_num = (rolling_space / shift).toInt


  var total_rmse = 0.0

  for (i <- 1 to fold_num) {

    // define rolling frame
    var total_select = initial_train_obs + shift * i
    var train_pct = initial_train_obs.toFloat / total_select

    // train test split
    val (train_set, test_set) = ts_split(train_pct, assembled_df.limit(total_select.toInt))

    /*******************REPLACE TO OTHER MODEL START ********************/
    // Initiate model object
    val dt = new DecisionTreeRegressor()
      .setMaxDepth(hyper_params("MaxDepth").toInt)
      .setMaxBins(hyper_params("MaxBins").toInt)
      .setLabelCol("label")
      .setFeaturesCol("features")

    // Setup Pipeline.
    val pipeline = new Pipeline().setStages(Array(dt))

    // Train model
    val model = pipeline.fit(train_set)

    // Make predictions.
    val predictions = model.transform(test_set)

    // Select (prediction, true label) and compute test error.
    val evaluator = new RegressionEvaluator()
      .setMetricName("rmse")

    val rmse = evaluator.evaluate(predictions)

    // trained model
    val dtModel = model.stages(0).asInstanceOf[DecisionTreeRegressionModel]
    /*******************REPLACE TO OTHER MODEL END ********************/

    total_rmse += rmse

    println(s"Hyper params: $hyper_params; rolling times: $i ($total_select/$total_rows); rmse: $rmse")
  }

  return total_rmse / fold_num

}
```

```
import org.apache.spark.ml.regression.DecisionTreeRegressor
import org.apache.spark.ml.regression.DecisionTreeRegressionModel
rolling_cv_tuning: (initial_train_obs: Int, shift: Int, assembled_df: org.apache.spark.sql.DataFrame, hyper_params: Map[String,String])Double
```

```
// Setting up for rolling cv
val param_grid = Map(
  "MaxDepth" -> Seq("5","7","10"),
  "MaxBins" -> Seq("20","25","30")
)

// transform arrays into lists with values paired with map key
val pairedWithKey = param_grid.map { case (k,v) => v.map(i => k -> i).toList }

val accumulator = pairedWithKey.head.map(x => Vector(x))

val params_combination = pairedWithKey.tail.foldLeft(accumulator)( (acc, elem) =>
  for { x <- acc; y <- elem } yield x :+ y
)
```

```
param_grid: scala.collection.immutable.Map[String,Seq[String]] = Map(MaxDepth -> List(5, 7, 10), MaxBins -> List(20, 25, 30))
pairedWithKey: scala.collection.immutable.Iterable[List[(String, String)]] = List(List((MaxDepth,5), (MaxDepth,7), (MaxDepth,10)), List((MaxBins,20), (MaxBins,25), (MaxBins,30)))
accumulator: List[scala.collection.immutable.Vector[(String, String)]] = List(Vector((MaxDepth,5)), Vector((MaxDepth,7)), Vector((MaxDepth,10)))
params_combination: List[scala.collection.immutable.Vector[(String, String)]] = List(Vector((MaxDepth,5), (MaxBins,20)), Vector((MaxDepth,5), (MaxBins,25)), Vector((MaxDepth,5), (MaxBins,30)), Vector((MaxDepth,7), (MaxBins,20)), Vector((Ma
xDepth,7), (MaxBins,25)), Vector((MaxDepth,7), (MaxBins,30)), Vector((MaxDepth,10), (MaxBins,20)), Vector((MaxDepth,10), (MaxBins,25)), Vector((MaxDepth,10), (MaxBins,30)))
```

Prediction Window = 1 day

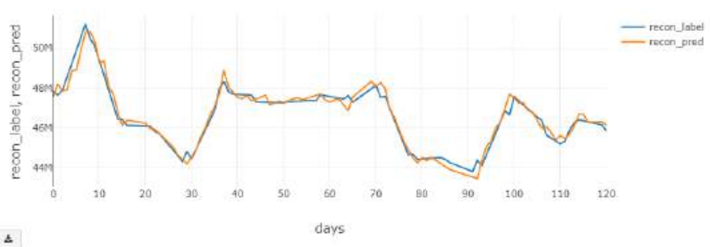
```
// 1 day rolling cv + tuning
var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  val avg_rmse = rolling_cv_tuning(64, 200, train_1day, hyper_params) //train1day has 464 rows, use 64 as train and every 200 for cv

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}
// print best hyper-parameter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")
```

```
Hyper params: Map(MaxDepth -> 5, MaxBins -> 20); rolling times: 1 (264/464); rmse: 513285.5844499546
Hyper params: Map(MaxDepth -> 5, MaxBins -> 20); rolling times: 2 (464/464); rmse: 911753.7618601996
Hyper params: Map(MaxDepth -> 5, MaxBins -> 25); rolling times: 1 (264/464); rmse: 581663.2069489224
Hyper params: Map(MaxDepth -> 5, MaxBins -> 25); rolling times: 2 (464/464); rmse: 874428.628511769
Hyper params: Map(MaxDepth -> 5, MaxBins -> 30); rolling times: 1 (264/464); rmse: 587244.3449378127
Hyper params: Map(MaxDepth -> 5, MaxBins -> 30); rolling times: 2 (464/464); rmse: 899194.7157377745
Hyper params: Map(MaxDepth -> 7, MaxBins -> 20); rolling times: 1 (264/464); rmse: 538367.9637294344
Hyper params: Map(MaxDepth -> 7, MaxBins -> 20); rolling times: 2 (464/464); rmse: 922883.8155846416
Hyper params: Map(MaxDepth -> 7, MaxBins -> 25); rolling times: 1 (264/464); rmse: 614947.4379434711
Hyper params: Map(MaxDepth -> 7, MaxBins -> 25); rolling times: 2 (464/464); rmse: 896892.9087471683
Hyper params: Map(MaxDepth -> 7, MaxBins -> 30); rolling times: 1 (264/464); rmse: 512133.6989652199
Hyper params: Map(MaxDepth -> 7, MaxBins -> 30); rolling times: 2 (464/464); rmse: 912643.6062029466
Hyper params: Map(MaxDepth -> 10, MaxBins -> 20); rolling times: 1 (264/464); rmse: 545409.464234261
Hyper params: Map(MaxDepth -> 10, MaxBins -> 20); rolling times: 2 (464/464); rmse: 923466.3838981276
Hyper params: Map(MaxDepth -> 10, MaxBins -> 25); rolling times: 1 (264/464); rmse: 611479.3568314801
Hyper params: Map(MaxDepth -> 10, MaxBins -> 25); rolling times: 2 (464/464); rmse: 897145.0625249345
Hyper params: Map(MaxDepth -> 10, MaxBins -> 30); rolling times: 1 (264/464); rmse: 516782.4732766299
Hyper params: Map(MaxDepth -> 10, MaxBins -> 30); rolling times: 2 (464/464); rmse: 912972.2891411836
---------------------------------------------
Best Hyper Parameter is:
Some((783219.5383373936,Map(MaxDepth -> 5, MaxBins -> 30)))
```

```
//1 day best cv settings
//best hyperparameters found: MaxDepth = 5, MaxBins = 30
val dt = new DecisionTreeRegressor()
  .setLabelCol("label")
  .setFeaturesCol("features")
  .setMaxDepth(5)
  .setMaxBins(30)

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(dt))

// Train model
val model = pipeline.fit(train_1day)

// Make predictions.
val predictions = model.transform(test_1day)

// Reconstruction of predictions with seasonal differences
val diff_1day = test_diff_1day.withColumn("id", monotonically_increasing_id())
val pred_1day = predictions.withColumn("id", monotonically_increasing_id())
val merged_1day = pred_1day.join(diff_1day, diff_1day.col("id") === pred_1day.col("id"), "left_outer").drop("id")
val recon_predictions_1day = merged_1day.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("days",monotonically_increasing_id())

// Compute sMAPE
recon_predictions_1day.
//   limit(120).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_1day.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|0.5183|
+-------+

dt: org.apache.spark.ml.regression.DecisionTreeRegressor = dtr_67fec2860b10
pipeline: org.apache.spark.ml.Pipeline = pipeline_9b6bbd1e2c3b
model: org.apache.spark.ml.PipelineModel = pipeline_9b6bbd1e2c3b
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_1day: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_1day: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_1day: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_1day: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

```
// 1 day prediction horizon
display(recon_predictions_1day)
```



Prediction Window = 1 week

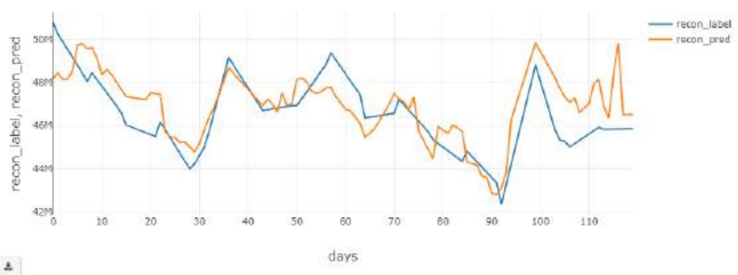
```
//1 week rolling cv + tuning
var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  val avg_rmse = rolling_cv_tuning(65, 190, train_1week, hyper_params) //train1week has 445 rows, use 65 as train and every 190 for cv

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}
// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")
```

```
Hyper params: Map(MaxDepth -> 5, MaxBins -> 20); rolling times: 1 (255/445); rmse: 1849506.777300283
Hyper params: Map(MaxDepth -> 5, MaxBins -> 20); rolling times: 2 (445/445); rmse: 1952464.0839697993
Hyper params: Map(MaxDepth -> 5, MaxBins -> 25); rolling times: 1 (255/445); rmse: 1678071.8927188322
Hyper params: Map(MaxDepth -> 5, MaxBins -> 25); rolling times: 2 (445/445); rmse: 1864044.4240888797
Hyper params: Map(MaxDepth -> 5, MaxBins -> 30); rolling times: 1 (255/445); rmse: 1942724.4218595957
Hyper params: Map(MaxDepth -> 5, MaxBins -> 30); rolling times: 2 (445/445); rmse: 1972019.9857668884
Hyper params: Map(MaxDepth -> 7, MaxBins -> 20); rolling times: 1 (255/445); rmse: 1835924.2251680898
Hyper params: Map(MaxDepth -> 7, MaxBins -> 20); rolling times: 2 (445/445); rmse: 1968348.1805602352
Hyper params: Map(MaxDepth -> 7, MaxBins -> 25); rolling times: 1 (255/445); rmse: 1667901.527659439
Hyper params: Map(MaxDepth -> 7, MaxBins -> 25); rolling times: 2 (445/445); rmse: 1878810.7871175914
Hyper params: Map(MaxDepth -> 7, MaxBins -> 30); rolling times: 1 (255/445); rmse: 1974659.3762598883
Hyper params: Map(MaxDepth -> 7, MaxBins -> 30); rolling times: 2 (445/445); rmse: 2003463.9170115897
Hyper params: Map(MaxDepth -> 10, MaxBins -> 20); rolling times: 1 (255/445); rmse: 1832240.7471404963
Hyper params: Map(MaxDepth -> 10, MaxBins -> 20); rolling times: 2 (445/445); rmse: 1964442.8658798576
```

```
Hyper params: Map(MaxDepth -> 10, MaxBins -> 25); rolling times: 1 (255/445); rmse: 1666887.8388545294
Hyper params: Map(MaxDepth -> 10, MaxBins -> 25); rolling times: 2 (445/445); rmse: 1860597.0690116843
Hyper params: Map(MaxDepth -> 10, MaxBins -> 30); rolling times: 1 (255/445); rmse: 1986668.8927004575
Hyper params: Map(MaxDepth -> 10, MaxBins -> 30); rolling times: 2 (445/445); rmse: 2064819.8469928981
_____________________________________________
Best Hyper Parameter is:
Some((1763702.4539331067,Map(MaxDepth -> 10, MaxBins -> 25)))
```

```
//1 week best cv settings
//best hyperparameters found: MaxDepth -> 10, MaxBins -> 25
val dt = new DecisionTreeRegressor()
  .setLabelCol("label")
  .setFeaturesCol("features")
  .setMaxDepth(10)
  .setMaxBins(25)

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(dt))

// Train model
val model = pipeline.fit(train_1week)

// Make predictions.
val predictions = model.transform(test_1week)

// Reconstruction of predictions with seasonal differences
val diff_1week = test_diff_1week.withColumn("id", monotonically_increasing_id())
val pred_1week = predictions.withColumn("id", monotonically_increasing_id())
val merged_1week = pred_1week.join(diff_1week, diff_1week.col("id") === pred_1week.col("id"), "left_outer").drop("id")
val recon_predictions_1week = merged_1week.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("days",monotonically_increasing_id())

// Compute sMAPE
recon_predictions_1week.
//   limit(113).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_1week.count() * 100, 4) as "SMAPE").
  show()

+------+
|SMAPE|
+------+
|2.128|
+------+

dt: org.apache.spark.ml.regression.DecisionTreeRegressor = dtr_ba45258cbf08
pipeline: org.apache.spark.ml.Pipeline = pipeline_42e1697d9688
model: org.apache.spark.ml.PipelineModel = pipeline_42e1697d9688
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_1week: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_1week: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_1week: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_1week: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

```
// 1 week prediction horizon
display(recon_predictions_1week)
```



Prediction Window = 2 weeks

```
// 2 week rolling cv + tuning
var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  val avg_rmse = rolling_cv_tuning(66, 180, train_2weeks, hyper_params) //train2weeks has 426 rows, use 66 as train and every 180 for cv

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}
// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")
```

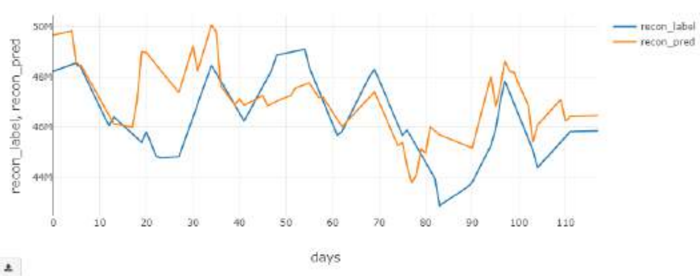
```
Hyper params: Map(MaxDepth -> 5, MaxBins -> 20); rolling times: 1 (246/426); rmse: 2714688.9595595673
Hyper params: Map(MaxDepth -> 5, MaxBins -> 20); rolling times: 2 (426/426); rmse: 2254383.397492816
Hyper params: Map(MaxDepth -> 5, MaxBins -> 25); rolling times: 1 (246/426); rmse: 2697096.8430075366
Hyper params: Map(MaxDepth -> 5, MaxBins -> 25); rolling times: 2 (426/426); rmse: 2263045.6187261216
Hyper params: Map(MaxDepth -> 5, MaxBins -> 30); rolling times: 1 (246/426); rmse: 2628529.2689621806
Hyper params: Map(MaxDepth -> 5, MaxBins -> 30); rolling times: 2 (426/426); rmse: 2195475.9712490453
Hyper params: Map(MaxDepth -> 7, MaxBins -> 20); rolling times: 1 (246/426); rmse: 2694682.7641937514
Hyper params: Map(MaxDepth -> 7, MaxBins -> 20); rolling times: 2 (426/426); rmse: 2264272.119201382
Hyper params: Map(MaxDepth -> 7, MaxBins -> 25); rolling times: 1 (246/426); rmse: 2694832.4337504855
Hyper params: Map(MaxDepth -> 7, MaxBins -> 25); rolling times: 2 (426/426); rmse: 2271571.7148781777
Hyper params: Map(MaxDepth -> 7, MaxBins -> 30); rolling times: 1 (246/426); rmse: 2612918.284682655
Hyper params: Map(MaxDepth -> 7, MaxBins -> 30); rolling times: 2 (426/426); rmse: 2183792.4655912844
Hyper params: Map(MaxDepth -> 10, MaxBins -> 20); rolling times: 1 (246/426); rmse: 2699353.936871885
Hyper params: Map(MaxDepth -> 10, MaxBins -> 20); rolling times: 2 (426/426); rmse: 2260284.751785886
Hyper params: Map(MaxDepth -> 10, MaxBins -> 25); rolling times: 1 (246/426); rmse: 2696536.578118588
Hyper params: Map(MaxDepth -> 10, MaxBins -> 25); rolling times: 2 (426/426); rmse: 2274261.5358228874
Hyper params: Map(MaxDepth -> 10, MaxBins -> 30); rolling times: 1 (246/426); rmse: 2614652.938674883
Hyper params: Map(MaxDepth -> 10, MaxBins -> 30); rolling times: 2 (426/426); rmse: 2183033.1265034927
_____________________________________________
Best Hyper Parameter is:
Some((2398355.3751389296,Map(MaxDepth -> 7, MaxBins -> 30)))
```

```
// 2 weeks best cv settings
// best hyperparameters found:MaxDepth -> 7, MaxBins -> 30
val dt = new DecisionTreeRegressor()
```

```
  .setLabelCol("label")
  .setFeaturesCol("features")
  .setMaxDepth(7)
  .setMaxBins(30)

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(dt))

// Train model
val model = pipeline.fit(train_2weeks)

// Make predictions.
val predictions = model.transform(test_2weeks)

// Reconstruction of predictions with seasonal differences
val diff_2weeks = test_diff_2weeks.withColumn("id", monotonically_increasing_id())
val pred_2weeks = predictions.withColumn("id", monotonically_increasing_id())
val merged_2weeks = pred_2weeks.join(diff_2weeks, diff_2weeks.col("id") === pred_2weeks.col("id"), "left_outer").drop("id")
val recon_predictions_2weeks = merged_2weeks.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("days",monotonically_increasing_id())

// Compute sMAPE
recon_predictions_2weeks.
//   limit(184).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_2weeks.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|2.5853|
+-------+

dt: org.apache.spark.ml.regression.DecisionTreeRegressor = dtr_e12723083e7e
pipeline: org.apache.spark.ml.Pipeline = pipeline_cd41cde210be
model: org.apache.spark.ml.PipelineModel = pipeline_cd41cde210be
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_2weeks: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_2weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_2weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_2weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

```
// 2 weeks prediction horizon
display(recon_predictions_2weeks)
```



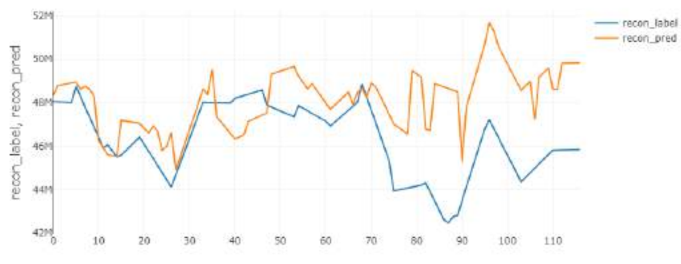
Prediction Window = 3 weeks

```
// 3 week rolling cv + tuning
var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  val avg_rmse = rolling_cv_tuning(60, 173, train_3weeks, hyper_params) //train3weeks has 486 rows, use 60 as train and every 173 for cv

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}
// print best hyper-paramter and its average rmse
println("_______________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_______________________________________________")
```

```
Hyper params: Map(MaxDepth -> 5, MaxBins -> 20); rolling times: 1 (233/486); rmse: 1199202.5806906673
Hyper params: Map(MaxDepth -> 5, MaxBins -> 20); rolling times: 2 (406/486); rmse: 1532512.843073247
Hyper params: Map(MaxDepth -> 5, MaxBins -> 25); rolling times: 1 (233/486); rmse: 1266471.3647186894
Hyper params: Map(MaxDepth -> 5, MaxBins -> 25); rolling times: 2 (406/486); rmse: 1505178.6386685888
Hyper params: Map(MaxDepth -> 5, MaxBins -> 30); rolling times: 1 (233/486); rmse: 1233395.3204438135
Hyper params: Map(MaxDepth -> 5, MaxBins -> 30); rolling times: 2 (406/486); rmse: 1542982.7757184973
Hyper params: Map(MaxDepth -> 7, MaxBins -> 20); rolling times: 1 (233/486); rmse: 1184516.914212882
Hyper params: Map(MaxDepth -> 7, MaxBins -> 20); rolling times: 2 (406/486); rmse: 1538308.637144782
Hyper params: Map(MaxDepth -> 7, MaxBins -> 25); rolling times: 1 (233/486); rmse: 1269829.189395284
Hyper params: Map(MaxDepth -> 7, MaxBins -> 25); rolling times: 2 (406/486); rmse: 1519418.89425426
Hyper params: Map(MaxDepth -> 7, MaxBins -> 30); rolling times: 1 (233/486); rmse: 1208806.023783766
Hyper params: Map(MaxDepth -> 7, MaxBins -> 30); rolling times: 2 (406/486); rmse: 1523333.1805032704
Hyper params: Map(MaxDepth -> 10, MaxBins -> 20); rolling times: 1 (233/486); rmse: 1189317.898879421
Hyper params: Map(MaxDepth -> 10, MaxBins -> 20); rolling times: 2 (406/486); rmse: 1537831.5572623226
Hyper params: Map(MaxDepth -> 10, MaxBins -> 25); rolling times: 1 (233/486); rmse: 1265708.8893758317
Hyper params: Map(MaxDepth -> 10, MaxBins -> 25); rolling times: 2 (406/486); rmse: 1613683.8687987186
Hyper params: Map(MaxDepth -> 10, MaxBins -> 30); rolling times: 1 (233/486); rmse: 1194305.6464969213
Hyper params: Map(MaxDepth -> 10, MaxBins -> 30); rolling times: 2 (406/486); rmse: 1515794.230379794
-----------------------------------------------
Best Hyper Parameter is:
Some((1355049.9384383578,Map(MaxDepth -> 10, MaxBins -> 30)))
```

```
//3 week  best cv settings
//best hyperparameters found:MaxDepth -> 10, MaxBins -> 30
val dt = new DecisionTreeRegressor()
  .setLabelCol("label")
  .setFeaturesCol("features")
  .setMaxDepth(10)
  .setMaxBins(30)

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(dt))

// Train model
val model = pipeline.fit(train_3weeks)

// Make predictions.
```

```
val predictions = model.transform(test_3weeks)

// Reconstruction of predictions with seasonal differences
val diff_3weeks = test_diff_3weeks.withColumn("id", monotonically_increasing_id())
val pred_3weeks = predictions.withColumn("id", monotonically_increasing_id())
val merged_3weeks = pred_3weeks.join(diff_3weeks, diff_3weeks.col("id") === pred_3weeks.col("id"), "left_outer").drop("id")
val recon_predictions_3weeks = merged_3weeks.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("days",monotonically_increasing_id())

// Compute sMAPE
recon_predictions_3weeks.
// limit(96).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_3weeks.count() * 100, 4) as "SMAPE").
  show()

+-------+
| SMAPE|
+-------+
|4.4684|
+-------+

dt: org.apache.spark.ml.regression.DecisionTreeRegressor = dtr_276a78c096b1
pipeline: org.apache.spark.ml.Pipeline = pipeline_83c5c3ea4bf9
model: org.apache.spark.ml.PipelineModel = pipeline_83c5c3ea4bf9
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_3weeks: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_3weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_3weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_3weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]


// 3 weeks prediction horizon
display(recon_predictions_3weeks)
```



Prediction Window = 1 month

```
//1month rolling cv + tuning
var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  val avg_rmse = rolling_cv_tuning(57, 165, train_1month, hyper_params) //train1month has 387 rows, use 57 as train and every 165 for cv

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}
// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")
```

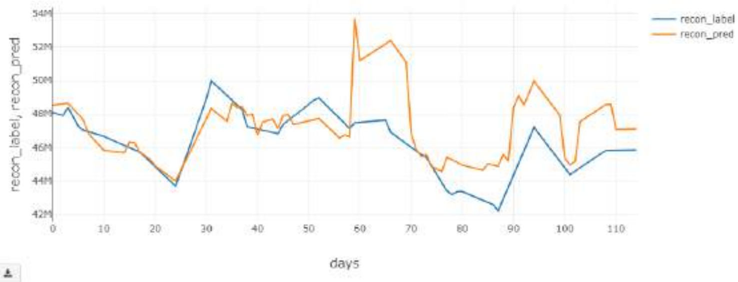
```
Hyper params: Map(MaxDepth -> 5, MaxBins -> 20); rolling times: 1 (222/387); rmse: 1872602.0542204771
Hyper params: Map(MaxDepth -> 5, MaxBins -> 20); rolling times: 2 (387/387); rmse: 1521489.7763248696
Hyper params: Map(MaxDepth -> 5, MaxBins -> 25); rolling times: 1 (222/387); rmse: 1873211.7138925483
Hyper params: Map(MaxDepth -> 5, MaxBins -> 25); rolling times: 2 (387/387); rmse: 1498831.8794757624
Hyper params: Map(MaxDepth -> 5, MaxBins -> 30); rolling times: 1 (222/387); rmse: 1148326.4820893845
Hyper params: Map(MaxDepth -> 5, MaxBins -> 30); rolling times: 2 (387/387); rmse: 1522817.6786206134
Hyper params: Map(MaxDepth -> 7, MaxBins -> 20); rolling times: 1 (222/387); rmse: 1814877.187655846
Hyper params: Map(MaxDepth -> 7, MaxBins -> 20); rolling times: 2 (387/387); rmse: 1497697.3527624656
Hyper params: Map(MaxDepth -> 7, MaxBins -> 25); rolling times: 1 (222/387); rmse: 1028459.4878591116
Hyper params: Map(MaxDepth -> 7, MaxBins -> 25); rolling times: 2 (387/387); rmse: 1482176.0999556913
Hyper params: Map(MaxDepth -> 7, MaxBins -> 30); rolling times: 1 (222/387); rmse: 1098455.481658053
Hyper params: Map(MaxDepth -> 7, MaxBins -> 30); rolling times: 2 (387/387); rmse: 1498624.1123454452
Hyper params: Map(MaxDepth -> 10, MaxBins -> 20); rolling times: 1 (222/387); rmse: 1016557.6021465559
Hyper params: Map(MaxDepth -> 10, MaxBins -> 20); rolling times: 2 (387/387); rmse: 1495719.8290728402
Hyper params: Map(MaxDepth -> 10, MaxBins -> 25); rolling times: 1 (222/387); rmse: 1036976.1335293652
Hyper params: Map(MaxDepth -> 10, MaxBins -> 25); rolling times: 2 (387/387); rmse: 1484681.8435539752
Hyper params: Map(MaxDepth -> 10, MaxBins -> 30); rolling times: 1 (222/387); rmse: 1084689.3146357497
Hyper params: Map(MaxDepth -> 10, MaxBins -> 30); rolling times: 2 (387/387); rmse: 1496892.9711915753
---------------------------------------------
Best Hyper Parameter is:
Some((1255317.7939874814,Map(MaxDepth -> 7, MaxBins -> 25)))
```

```
//1 month  best cv settings
//best hyperparameters found: MaxDepth -> 7, MaxBins -> 25
val dt = new DecisionTreeRegressor()
  .setLabelCol("label")
  .setFeaturesCol("features")
  .setMaxDepth(7)
  .setMaxBins(25)

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(dt))

// Train model
val model = pipeline.fit(train_1month)

// Make predictions.
val predictions = model.transform(test_1month)

// Reconstruction of predictions with seasonal differences
val diff_1month = test_diff_1month.withColumn("id", monotonically_increasing_id())
val pred_1month = predictions.withColumn("id", monotonically_increasing_id())
val merged_1month = pred_1month.join(diff_1month, diff_1month.col("id") === pred_1month.col("id"), "left_outer").drop("id")
val recon_predictions_1month = merged_1month.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("days",monotonically_increasing_id())

// Compute sMAPE
```

```
recon_predictions_1month.
//   limit(87).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_1month.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|3.1983|
+-------+

dt: org.apache.spark.ml.regression.DecisionTreeRegressor = dtr_78fce4c6da48
pipeline: org.apache.spark.ml.Pipeline = pipeline_7cfad423c98f
model: org.apache.spark.ml.PipelineModel = pipeline_7cfad423c98f
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_1month: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_1month: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_1month: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_1month: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

```
// 1 month prediction horizon
display(recon_predictions_1month)
```



Gradient Boosted Tree Models Predictions, Reconstructions, and SMAPE

```
import org.apache.spark.ml.Pipeline
import org.apache.spark.ml.evaluation.RegressionEvaluator
import org.apache.spark.ml.regression.{GBTRegressionModel, GBTRegressor}
import org.apache.spark.sql.DataFrame
import org.apache.spark.ml.feature.VectorAssembler

def rolling_cv_tuning(initial_train_obs: Int, shift: Int, assembled_df: DataFrame, hyper_params: Map[String, String]): Double = {
  /**
    * Returns the average rmse for the whole rolling process
    * For example, we have 143 rows in total,
    * we set the initial train as 43, and 10 more rolling forward, then
    * train first 43, test 44 - 53
    * train first 53, test 54 - 64
    * ...
    * train first 133, test 134 - 143
    * the function will roll 9 times in this case, and we calculate the rmse for each time / 9, and return the value
    */

  val total_rows = assembled_df.count()
  val rolling_space = total_rows - initial_train_obs
  val fold_num = (rolling_space / shift).toInt


  var total_rmse = 0.0

  for (i <- 1 to fold_num) {

    // define rolling frame
    var total_select = initial_train_obs + shift * i
    var train_pct = initial_train_obs.toFloat / total_select

    // train test split
    val (train_set, test_set) = ts_split(train_pct, assembled_df.limit(total_select.toInt))

    // Initiate model object

    val gbt = new GBTRegressor()
      .setMaxIter(hyper_params("Iteration").toInt)
      .setMaxBins(hyper_params("MaxBins").toInt)
      .setMaxDepth(hyper_params("MaxDepth").toInt)

    // Setup Pipeline.
    val pipeline = new Pipeline().setStages(Array(gbt))

    // Train model
    val model = pipeline.fit(train_set)

    // Make predictions.
    val predictions = model.transform(test_set)

    // Select (prediction, true label) and compute test error.
    val evaluator = new RegressionEvaluator()
      .setMetricName("rmse")

    val rmse = evaluator.evaluate(predictions)

    // trained model
    val gbtModel = model.stages(0).asInstanceOf[GBTRegressionModel]

    total_rmse += rmse

    println(s"Hyper params: $hyper_params; rolling times: $i ($total_select/$total_rows); rmse: $rmse")
  }

  return total_rmse / fold_num

}
```

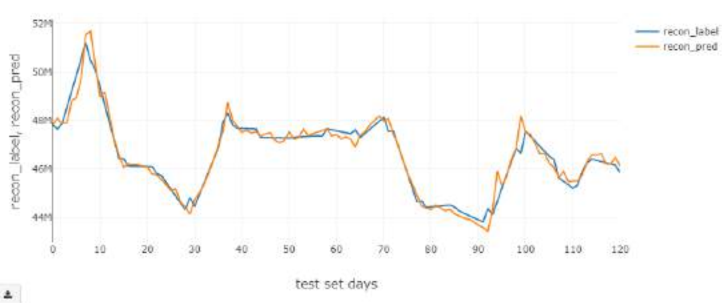
```
import org.apache.spark.ml.Pipeline
import org.apache.spark.ml.evaluation.RegressionEvaluator
import org.apache.spark.ml.regression.{GBTRegressionModel, GBTRegressor}
import org.apache.spark.sql.DataFrame
import org.apache.spark.ml.feature.VectorAssembler
rolling_cv_tuning: (initial_train_obs: Int, shift: Int, assembled_df: org.apache.spark.sql.DataFrame, hyper_params: Map[String,String])Double
```

Prediction Window = 1 day

```
val param_grid = Map(
  "Iteration" -> Seq("5","7","10"),
  "MaxBins" -> Seq("23","25","27"),
  "MaxDepth" -> Seq("6","8","10")
)

// transform arrays into lists with values paired with map key
val pairedWithKey = param_grid.map { case (k,v) => v.map(i => k -> i).toList }

val accumulator = pairedWithKey.head.map(x => Vector(x))

val params_combination = pairedWithKey.tail.foldLeft(accumulator)( (acc, elem) =>
  for { x <- acc; y <- elem } yield x :+ y
)

var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  // how to set the initial value (first param), and shift value (second param)?
  // In train_1day, we have 464 total rows, I set 64 as the initial, and 200 for each rolling forward
  // this means we will roll 2 times in total for each combination of hyper-params: (464 - 64) / 200 = 2
  // *the smaller the shift, the more rolling times, and the longer time we need to run this function
  val avg_rmse = rolling_cv_tuning(64, 200, train_1day, hyper_params)

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}

// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")



// use best hyper parameter to train a new model, and apply to the test set
//Hyper params: Map(MaxDepth -> 6, MaxBins -> 23, Iteration -> 5); rolling times: 1 (264/464); rmse: 581392.48469468766
//Hyper params: Map(MaxDepth -> 6, MaxBins -> 23, Iteration -> 5); rolling times: 2 (464/464); rmse: 1085183.6056703655
// GBT model set-up using the tuned hyperparemeter.

val gbt = new GBTRegressor()
    .setFeaturesCol("features")
    .setMaxIter(5)
    .setMaxBins(23)
    .setMaxDepth(6)

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(gbt))

// Train model
val model = pipeline.fit(train_1day)

// Make predictions.
val predictions = model.transform(test_1day)

// Reconstruction of predictions with seasonal differences
val diff_1day = test_diff_1day.withColumn("id", monotonically_increasing_id())
val pred_1day = predictions.withColumn("id", monotonically_increasing_id())
val merged_1day = pred_1day.join(diff_1day, diff_1day.col("id") === pred_1day.col("id"), "left_outer").drop("id")
val recon_predictions_1day = merged_1day.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("test set days", monotonically_increasing_id())

// Compute SMAPE
recon_predictions_1day.
//   limit(120).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_1day.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|0.4785|
+-------+

gbt: org.apache.spark.ml.regression.GBTRegressor = gbtr_6e86693009c5
pipeline: org.apache.spark.ml.Pipeline = pipeline_c7943b8b3374
model: org.apache.spark.ml.PipelineModel = pipeline_c7943b8b3374
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_1day: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_1day: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_1day: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_1day: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

```
display(recon_predictions_1day)
```



Prediction Window = 1 week

```
val param_grid = Map(
  "Iteration" -> Seq("5","7","10"),
  "MaxBins" -> Seq("25","27","30"),
  "MaxDepth" -> Seq("4","6","8")
)
// transform arrays into lists with values paired with map key
val pairedWithKey = param_grid.map { case (k,v) => v.map(i => k -> i).toList }

val accumulator = pairedWithKey.head.map(x => Vector(x))
```

```
val params_combination = pairedWithKey.tail.foldLeft(accumulator)( (acc, elem) =>
  for { x <- acc; y <- elem } yield x :+ y
)

var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  // how to set the initial value (first param), and shift value (second param)?
  // In train_1week, we have 445 total rows, I set 65 as the initial, and 190 for each rolling forward
  // this means we will roll 2 times in total for each combination of hyper-params: (445 - 65) / 190 = 2
  // +the smaller the shift, the more rolling times, and the longer time we need to run this function
  val avg_rmse = rolling_cv_tuning(65, 190, train_1week, hyper_params)

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}

// print best hyper-paramter and its average rmse
println("__________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("__________________________________________")


// use best hyper parameter to train a new model, and apply to the test set
// GBT model set-up
// Hyper params: Map(MaxDepth -> 6, MaxBins -> 25, Iteration -> 5); rolling times: 1 (255/445); rmse: 1546186.490863489
// Hyper params: Map(MaxDepth -> 6, MaxBins -> 26, Iteration -> 5); rolling times: 2 (445/445); rmse: 1826336.0653840875

val gbt = new GBTRegressor()
    .setFeaturesCol("features")
    .setMaxIter(5)
    .setMaxBins(25)
    .setMaxDepth(6)


// Train model
val model = pipeline.fit(train_1week)

// Make predictions.
val predictions = model.transform(test_1week)

// Reconstruction of predictions with seasonal differences
val diff_1week = test_diff_1week.withColumn("id", monotonically_increasing_id())
val pred_1week = predictions.withColumn("id", monotonically_increasing_id())
val merged_1week = pred_1week.join(diff_1week, diff_1week.col("id") === pred_1week.col("id"), "left_outer").drop("id")
val recon_predictions_1week = merged_1week.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("test set days", monotonically_increasing_id())

// Compute SMAPE
recon_predictions_1week.
//   limit(113).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_1week.count() * 100, 4) as "SMAPE").
  show()

+-------+
| SMAPE|
+-------+
|2.4828|
+-------+

gbt: org.apache.spark.ml.regression.GBTRegressor = gbtr_63bd9a93bd0a
model: org.apache.spark.ml.PipelineModel = pipeline_c7943b8b3374
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_1week: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_1week: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_1week: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_1week: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]


display(recon_predictions_1week)
```

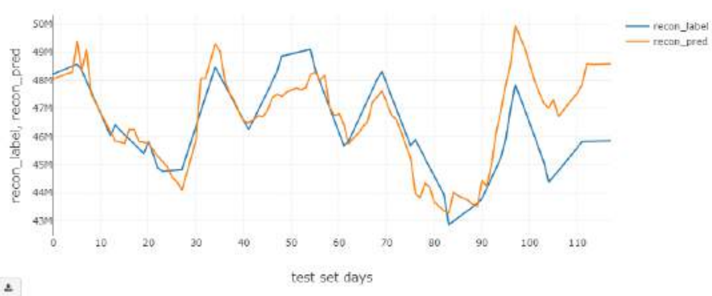
Prediction Window = 2 weeks

```
val param_grid = Map(
  "Iteration" -> Seq("5","7","10"),
  "MaxBins" -> Seq("25","27","30"),
  "MaxDepth" -> Seq("4","6","8")
)
// transform arrays into lists with values paired with map key
val pairedWithKey = param_grid.map { case (k,v) => v.map(i => k -> i).toList }

val accumulator = pairedWithKey.head.map(x => Vector(x))

val params_combination = pairedWithKey.tail.foldLeft(accumulator)( (acc, elem) =>
  for { x <- acc; y <- elem } yield x :+ y
)

var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

   // In train_2weeks, we have 426 total rows, I set 66 as the initial, and 180 for each rolling forward
  // this means we will roll 2 times in total for each combination of hyper-params: (426 - 66) / 180 = 2
  // +the smaller the shift, the more rolling times, and the longer time we need to run this function
  val avg_rmse = rolling_cv_tuning(66, 180, train_2weeks, hyper_params)
```

```scala
  result_collector = result_collector :+ (avg_rmse, hyper_params)

}

// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")


//Hyper params: Map(MaxDepth -> 4, MaxBins -> 27, Iteration -> 10); rolling times: 1 (246/426); rmse: 1755331.4325966472
//Hyper params: Map(MaxDepth -> 4, MaxBins -> 27, Iteration -> 10); rolling times: 2 (426/426); rmse: 1718890.8777430

val gbt = new GBTRegressor()
    .setFeaturesCol("features")
    .setMaxIter(4)
    .setMaxBins(27)
    .setMaxDepth(10)

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(gbt))


// Train model
val model = pipeline.fit(train_2weeks)

// Make predictions.
val predictions = model.transform(test_2weeks)

// Reconstruction of predictions with seasonal differences
val diff_2weeks = test_diff_2weeks.withColumn("id", monotonically_increasing_id())
val pred_2weeks = predictions.withColumn("id", monotonically_increasing_id())
val merged_2weeks = pred_2weeks.join(diff_2weeks, diff_2weeks.col("id") === pred_2weeks.col("id"), "left_outer").drop("id")
val recon_predictions_2weeks = merged_2weeks.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("test set days", monotonically_increasing_id())

// Compute SMAPE
recon_predictions_2weeks.
//   limit(104).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_2weeks.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|1.8691|
+-------+

gbt: org.apache.spark.ml.regression.GBTRegressor = gbtr_e9cb27a6d7af
pipeline: org.apache.spark.ml.Pipeline = pipeline_53944efcab17
model: org.apache.spark.ml.PipelineModel = pipeline_53944efcab17
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_2weeks: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_2weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_2weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_2weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

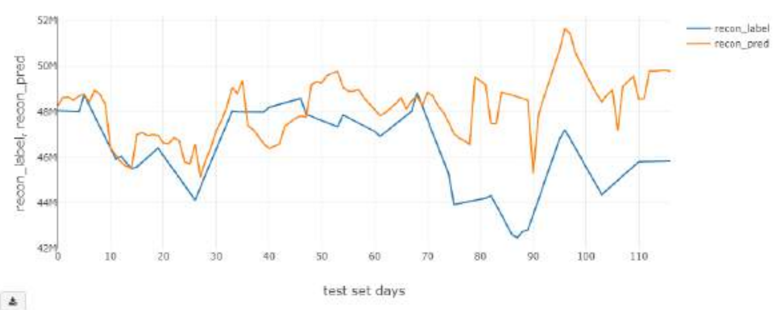
```scala
display(recon_predictions_2weeks)
```



Prediction Window = 3 weeks

```scala
val param_grid = Map(
  "Iteration" -> Seq("5","7","10"),
  "MaxBins" -> Seq("25","27","30"),
  "MaxDepth" -> Seq("4","6","8")
)
// transform arrays into lists with values paired with map key
val pairedWithKey = param_grid.map { case (k,v) => v.map(i => k -> i).toList }

val accumulator = pairedWithKey.head.map(x => Vector(x))

val params_combination = pairedWithKey.tail.foldLeft(accumulator)( (acc, elem) =>
  for { x <- acc; y <- elem } yield x :+ y
)

var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  // how to set the initial value (first param), and shift value (second param)?
  // In train_3weeks, we have 406 total rows, I set 60 as the initial, and 173 for each rolling forward
  // this means we will roll 2 times in total for each combination of hyper-params: (406 - 60) / 173 = 2
  // *the smaller the shift, the more rolling times, and the longer time we need to run this function
  val avg_rmse = rolling_cv_tuning(60, 173, train_3weeks, hyper_params)

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}

// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")


//Hyper params: Map(MaxDepth -> 8, MaxBins -> 30, Iteration -> 5); rolling times: 1 (233/406); rmse: 1196415.9887087953
```

```
//Hyper params: Map(MaxDepth -> 8, MaxBins -> 30, Iteration -> 6); rolling times: 2 (406/406); rmse: 1529967.9947142881

val gbt = new GBTRegressor()
    .setFeaturesCol("features")
    .setMaxIter(5)
    .setMaxBins(30)
    .setMaxDepth(8)

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(gbt))

// Train model
val model = pipeline.fit(train_3weeks)

// Make predictions.
val predictions = model.transform(test_3weeks)

// Reconstruction of predictions with seasonal differences
val diff_3weeks = test_diff_3weeks.withColumn("id", monotonically_increasing_id())
val pred_3weeks = predictions.withColumn("id", monotonically_increasing_id())
val merged_3weeks = pred_3weeks.join(diff_3weeks, diff_3weeks.col("id") === pred_3weeks.col("id"), "left_outer").drop("id")
val recon_predictions_3weeks = merged_3weeks.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("test set days", monotonically_increasing_id())

// Compute SMAPE
recon_predictions_3weeks.
//   limit(96).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_3weeks.count() * 100, 4) as "SMAPE").
  show()

+-------+
| SMAPE|
+-------+
|4.4718|
+-------+

gbt: org.apache.spark.ml.regression.GBTRegressor = gbtr_c64895a153f4
pipeline: org.apache.spark.ml.Pipeline = pipeline_a80f8ee3f5c2
model: org.apache.spark.ml.PipelineModel = pipeline_a88f8ee3f5c2
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_3weeks: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_3weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_3weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_3weeks: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]


display(recon_predictions_3weeks)
```



Prediction Window = 1 month

```
val param_grid = Map(
  "Iteration" -> Seq("5","7","10"),
  "MaxBins" -> Seq("25","27","30"),
  "MaxDepth" -> Seq("4","6","8")
)
// transform arrays into lists with values paired with map key
val pairedWithKey = param_grid.map { case (k,v) => v.map(i => k -> i).toList }

val accumulator = pairedWithKey.head.map(x => Vector(x))

val params_combination = pairedWithKey.tail.foldLeft(accumulator)( (acc, elem) =>
  for { x <- acc; y <- elem } yield x :+ y
)

var result_collector : List[(Double,Map[String, String])] = List()

for (comb <- params_combination) {

  val hyper_params = comb.groupBy(_._1).map { case (k,v) => (k,v.map(_._2).head)}

  // how to set the initial value (first param), and shift value (second param)?
  // In train_1month, we have 387 total rows, I set 57 as the initial, and 165 for each rolling forward
  // this means we will roll 2 times in total for each combination of hyper-params: (387 - 57) / 165 = 2
  // *the smaller the shift, the more rolling times, and the longer time we need to run this function
  val avg_rmse = rolling_cv_tuning(57, 165, train_1month, hyper_params)

  result_collector = result_collector :+ (avg_rmse, hyper_params)

}

// print best hyper-paramter and its average rmse
println("_____________________________________________")
println("Best Hyper Parameter is: ")
println(result_collector.sortBy(_._1).lift(0))
println("_____________________________________________")


//Hyper params: Map(MaxDepth -> 6, MaxBins -> 25, Iteration -> 5); rolling times: 1 (222/387); rmse: 997349.6312181305
//Hyper params: Map(MaxDepth -> 6, MaxBins -> 25, Iteration -> 5); rolling times: 2 (387/387); rmse: 1451547.3269248738
val gbt = new GBTRegressor()
    .setFeaturesCol("features")
    .setMaxIter(5)
    .setMaxBins(25)
    .setMaxDepth(6)

// Setup Pipeline.
val pipeline = new Pipeline().setStages(Array(gbt))

// Train model
val model = pipeline.fit(train_1month)

// Make predictions.
```

```scala
val predictions = model.transform(test_1month)

// Reconstruction of predictions with seasonal differences
val diff_1month = test_diff_1month.withColumn("id", monotonically_increasing_id())
val pred_1month = predictions.withColumn("id", monotonically_increasing_id())
val merged_1month = pred_1month.join(diff_1month, diff_1month.col("id") === pred_1month.col("id"), "left_outer").drop("id")
val recon_predictions_1month = merged_1month.withColumn("recon_label", $"label"+$"lag_1year")
  .withColumn("recon_pred", $"prediction"+$"lag_1year")
  .withColumn("test set days", monotonically_increasing_id())

// Compute SMAPE
recon_predictions_1month.
//   limit(87).
  withColumn("diff_abs", abs($"recon_pred" - $"recon_label")).
  withColumn("demo", (abs($"recon_pred") + abs($"recon_label")) / 2).
  withColumn("division", $"diff_abs" / $"demo").
  agg(round(sum($"division") / recon_predictions_1month.count() * 100, 4) as "SMAPE").
  show()
```

```
+-------+
| SMAPE|
+-------+
|3.2513|
+-------+

gbt: org.apache.spark.ml.regression.GBTRegressor = gbtr_8cc1c94e872e
pipeline: org.apache.spark.ml.Pipeline = pipeline_57378a98503d
model: org.apache.spark.ml.PipelineModel = pipeline_57378a98503d
predictions: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 1 more field]
diff_1month: org.apache.spark.sql.DataFrame = [lag_1year: double, id: bigint]
pred_1month: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
merged_1month: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 2 more fields]
recon_predictions_1month: org.apache.spark.sql.DataFrame = [label: double, features: vector ... 5 more fields]
```

```scala
display(recon_predictions_1month)
```