Tidymodels Approach to Time Series Forecasting: modeltime methods

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Content

In this topic, we are going to explore the tidymodels approach in time series forecasting.

- import and wrangling time-series data by using appropriate tidyverse methods,
- visualise and analyse time-series data,
- calibrate time-series forecasting models by using exponential smoothing and ARIMA techniques, and
- compare and evaluate the performance of forecasting models.

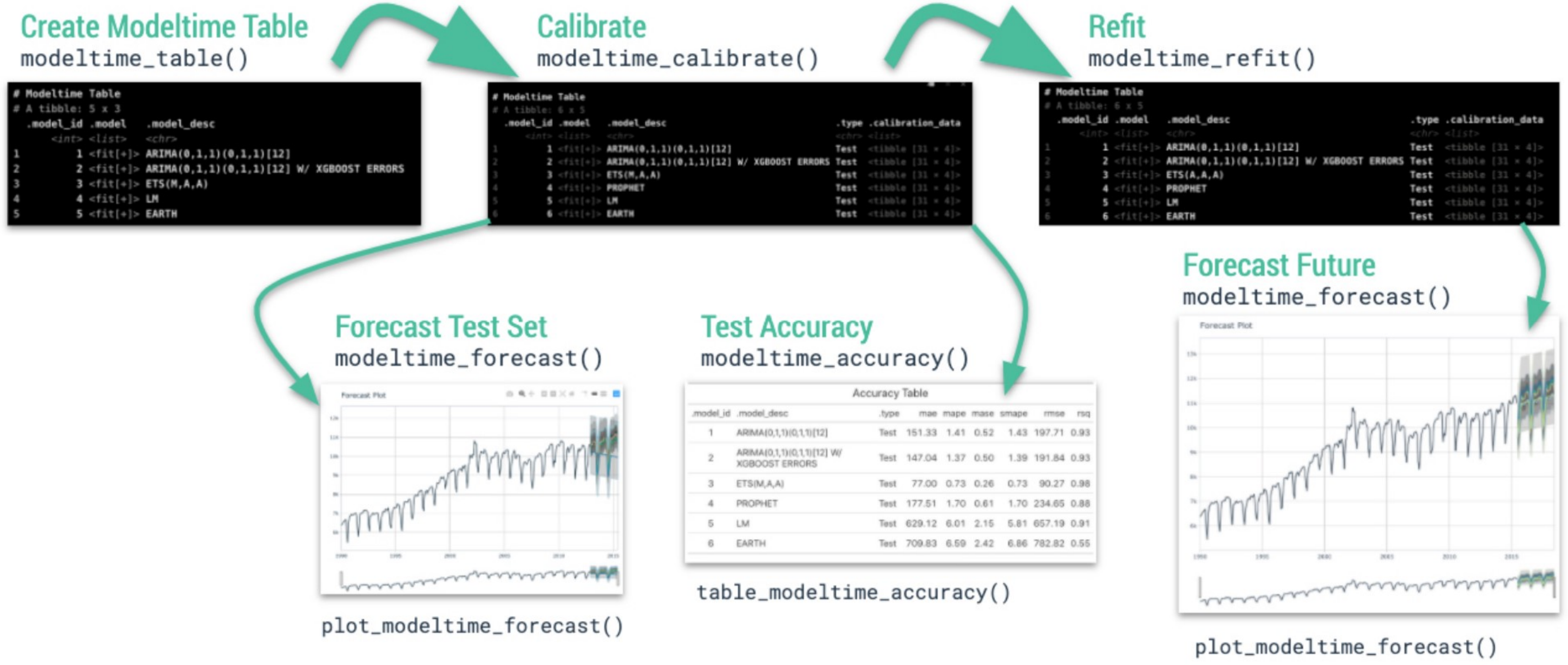
Setting Up R Environment

For the purpose of this hands-on exercise, the following R packages will be used.

```
pacman::p_load(tidyverse, tidymodels,
               timetk, modeltime)
```

- **tidyverse** provides a collection of commonly used functions for importing, wrangling and visualising data. In this hands-on exercise the main packages used are readr, dplyr, tidyr and ggplot2.
- **modeltime** a new time series forecasting package designed to speed up model evaluation, selection, and forecasting. modeltime does this by integrating the **tidymodels** machine learning ecosystem of packages into a streamlined workflow for tidyverse forecasting.

Introducing modeltime workflow



```
# Modeltime Table
# A tibble: 5 x 3
  .model_id .model     .model_desc
      <int> <list>     <chr>
1         1 <fit[+]> ARIMA(0,1,1)(0,1,1)[12]
2         2 <fit[+]> ARIMA(0,1,1)(0,1,1)[12] W/ XGBOOST ERRORS
3         3 <fit[+]> ETS(M,A,A)
4         4 <fit[+]> LM
5         5 <fit[+]> EARTH
```

```
# Modeltime Table
# A tibble: 6 x 5
  .model_id .model   .model_desc                               .type .calibration_data
      <int> <list>   <chr>                                     <chr> <list>
1         1 <fit[+]> ARIMA(0,1,1)(0,1,1)[12]                   Test  <tibble [31 × 4]>
2         2 <fit[+]> ARIMA(0,1,1)(0,1,1)[12] W/ XGBOOST ERRORS Test  <tibble [31 × 4]>
3         3 <fit[+]> ETS(M,A,A)                                Test  <tibble [31 × 4]>
4         4 <fit[+]> PROPHET                                   Test  <tibble [31 × 4]>
5         5 <fit[+]> LM                                        Test  <tibble [31 × 4]>
6         6 <fit[+]> EARTH                                     Test  <tibble [31 × 4]>
```

```
# Modeltime Table
# A tibble: 6 x 5
  .model_id .model   .model_desc                               .type .calibration_data
      <int> <list>   <chr>                                     <chr> <list>
1         1 <fit[+]> ARIMA(0,1,1)(0,1,1)[12]                   Test  <tibble [31 × 4]>
2         2 <fit[+]> ARIMA(0,1,1)(0,1,1)[12] W/ XGBOOST ERRORS Test  <tibble [31 × 4]>
3         3 <fit[+]> ETS(A,A,A)                                Test  <tibble [31 × 4]>
4         4 <fit[+]> PROPHET                                   Test  <tibble [31 × 4]>
5         5 <fit[+]> LM                                        Test  <tibble [31 × 4]>
6         6 <fit[+]> EARTH                                     Test  <tibble [31 × 4]>
```

Accuracy Table

.model_id	.model_desc	.type	mae	mape	mase	smape	rmse	rsq
1	ARIMA(0,1,1)(0,1,1)[12]	Test	151.33	1.41	0.52	1.43	197.71	0.93
2	ARIMA(0,1,1)(0,1,1)[12] W/ XGBOOST ERRORS	Test	147.04	1.37	0.50	1.39	191.84	0.93
3	ETS(M,A,A)	Test	77.00	0.73	0.26	0.73	90.27	0.98
4	PROPHET	Test	177.51	1.70	0.61	1.70	234.65	0.88
5	LM	Test	629.12	6.01	2.15	5.81	657.19	0.91
6	EARTH	Test	709.83	6.59	2.42	6.86	782.82	0.55

Source: Getting Started with Modeltime

The data

In this sharing, **Store Sales - Time Series Forecasting: Use machine learning to predict grocery sales** from Kaggle competition will be used. For the purpose of this sharing, the main data set used is *train.csv*. It consists of six columns. They are:

- *id* contains unique id for each records.
- *date* gives the sales dates.
- *store_nbr* identifies the store at which the products are sold.
- *family* identifies the type of product sold.
- *sales* gives the total sales for a product family at a particular store at a given date. Fractional values are possible since products can be sold in fractional units (1.5 kg of cheese, for instance, as opposed to 1 bag of chips).
- *onpromotion* gives the total number of items in a product family that were being promoted at a store at a given date.

For the purpose of this sharing, I will focus of grocery sales instead of all products. Code chunk below is used to extract grocery sales from *train.csv* and saved the output into an rds file format for subsequent used.

```r
store_sales <- read_csv(
  "data/store_sales/train.csv") %>%
  filter(family == "GROCERY I") %>%
  write_rds("data/store_sales/grocery.rds")
```

Time Series Forecasting Process

- Collect data and split into training and test sets
- Create & Fit Multiple Models
- Add fitted models to a Model Table
- Calibrate the models to a testing set.
- Perform Testing Set Forecast & Accuracy Evaluation
- Refit the models to Full Dataset & Forecast Forward

Step 1: Data Import and Sampling

In the code chunk below, `read_rds()` of **readr** package is used to import both data sets into R environment.

```
grocery <- read_rds(
  "data/store_sales/grocery.rds") %>%
  mutate(across(c(1, 3, 4),
                as.factor)) %>%
  group_by(family, date) %>%
  summarise(sum_sales = sum(sales)) %>%
  ungroup()
```

Optionally, you can also import the rest of the data sets provided at Kaggle by usign the code chunk below.

```
holidays_events <- read_csv(
  "data/store_sales/holidays_events.csv")
oil <- read_csv(
  "data/store_sales/oil.csv")
stores <- read_csv(
  "data/store_sales/stores.csv")
transactions <- read_csv(
  "data/store_sales/transactions.csv")
```

Step 1: Data Import and Sampling

grocery tibble data frame consists of 1684 days of daily sales data starts from 1st January 2013. We will split the data set into training and hold-out data sets by using `initial_time_split()` of **rsample** package, a member of the tidymodels family.

```
splits <- grocery %>%
  initial_time_split(prop = 0.955)
```

For checking purposes, the code chunk below can be used save the split sample data sets into *training* and *holdout* tibble data tables respectively.

```
training <- training(splits)
holdout <- testing(splits)
```

Step 2: Create & Fit Multiple Models

In this step, we will build and fit four models using the code chunks below:

Model 1: Exponential Smoothing (Modeltime)

An Error-Trend-Season (ETS) model by using `exp_smoothing()`.

```
model_fit_ets <- exp_smoothing() %>%
    set_engine(engine = "ets") %>%
    fit(sum_sales ~ `date`,
        data = training(splits))
```

Model 2: Auto ARIMA (Modeltime)

An auto ARIMA model by using `arima_reg()`.

```
model_fit_arima <- arima_reg() %>%
  set_engine(engine = "auto_arima") %>%
  fit(sum_sales ~ `date`,
      data = training(splits))
```

Model 3: Boosted Auto ARIMA (Modeltime)

An Boosted auto ARIMA model by using `arima_boost()`.

```
model_fit_arima_boosted <- arima_boost(
  min_n = 2,
  learn_rate = 0.015) %>%
  set_engine(
    engine = "auto_arima_xgboost") %>%
  fit(sum_sales ~ `date`,
      data = training(splits))
```

Model 4: prophet (Modeltime)

A prophet model using `prophet_reg()`.

```
model_fit_prophet <- prophet_reg() %>%
  set_engine(engine = "prophet") %>%
  fit(sum_sales ~ `date`,
      data = training(splits))
```

Step 3: Add fitted models to a Model Table

Next, modeltime_table() of modeltime package is used to add each of the models to a Modeltime Table.

```
models_tbl <- modeltime_table(
  model_fit_ets,
  model_fit_arima,
  model_fit_arima_boosted,
  model_fit_prophet)

models_tbl
```

```
## # Modeltime Table
## # A tibble: 4 × 3
##   .model_id .model   .model_desc
##       <int> <list>   <chr>
## 1         1 <fit[+]> ETS(M,N,M)
## 2         2 <fit[+]> ARIMA(3,0,0)(1,1,2)[7]
## 3         3 <fit[+]> ARIMA(1,0,3)(2,1,2)[7]
## 4         4 <fit[+]> PROPHET
```

Step 4 - Calibrate the model to a testing set

In the code chunk below, `modeltime_caibrate()` is used to add a new column called *.calibrate_data* into the newly *created models_tbl* tibble data table.

```
calibration_tbl <- models_tbl %>%
    modeltime_calibrate(new_data = testing(splits))

calibration_tbl
```

```
## # Modeltime Table
## # A tibble: 4 × 5
##   .model_id .model   .model_desc             .type .calibration_data
##       <int> <list>   <chr>                   <chr> <list>
## 1         1 <fit[+]> ETS(M,N,M)              Test  <tibble [76 × 4]>
## 2         2 <fit[+]> ARIMA(3,0,0)(1,1,2)[7]  Test  <tibble [76 × 4]>
## 3         3 <fit[+]> ARIMA(1,0,3)(2,1,2)[7]  Test  <tibble [76 × 4]>
## 4         4 <fit[+]> PROPHET                 Test  <tibble [76 × 4]>
```

Note that Calibration Data is simply forecasting predictions and residuals that are calculated from the hold-out data (also know as test data in machine learning)

Step 5: Model Accuracy Assessment

In general, there are two ways to assess accuracy of the models. They are by means of accuracy metrics or visualisation.

In the code chunk below, `modeltime_accuracy()` of modeltime package is used compute the accuracy metrics. Then, `table_modeltime_accuracy()` is used to present the accuracy metrics in tabular form.

```
calibration_tbl %>%
  modeltime_accuracy %>%
  table_modeltime_accuracy(
    .interactive = FALSE)
```

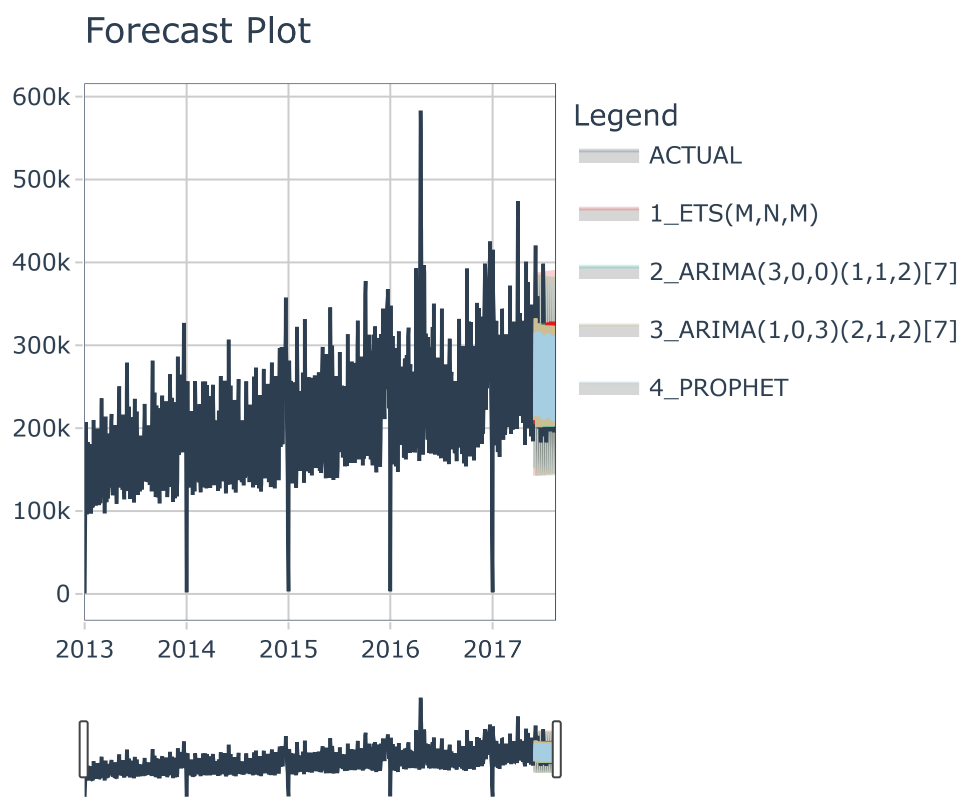
Accuracy Table

.model_id	.model_desc	.type	mae	mape	mase	smape	rmse	rsq
1	ETS(M,N,M)	Test	25250.52	9.86	0.65	9.61	31554.80	0.64
2	ARIMA(3,0,0)(1,1,2)[7]	Test	23087.67	8.90	0.59	8.79	29863.72	0.66
3	ARIMA(1,0,3)(2,1,2)[7]	Test	23049.21	8.89	0.59	8.78	29829.18	0.66
4	PROPHET	Test	22386.78	8.56	0.58	8.61	30521.01	0.66

Step 5: Model Accuracy Assessment

Visualizing the Test Error is easy to do using the interactive plotly visualization (just toggle the visibility of the models using the Legend).

```
calibration_tbl %>%
  modeltime_forecast(
    new_data = testing(splits),
    actual_data = grocery) %>%
  plot_modeltime_forecast(
    .legend_max_width = 25,
    .interactive = TRUE,
    .plotly_slider = TRUE)
```



Step 6 - Refit to Full Dataset & Forecast Forward

The final step is to refit the models to the full dataset using `modeltime_refit()` and forecast them forward.

The code chunk below uses modeltime_refit() to refit the forecasting models with the full data.

```
refit_tbl <- calibration_tbl %>%
    modeltime_refit(data = grocery)
```

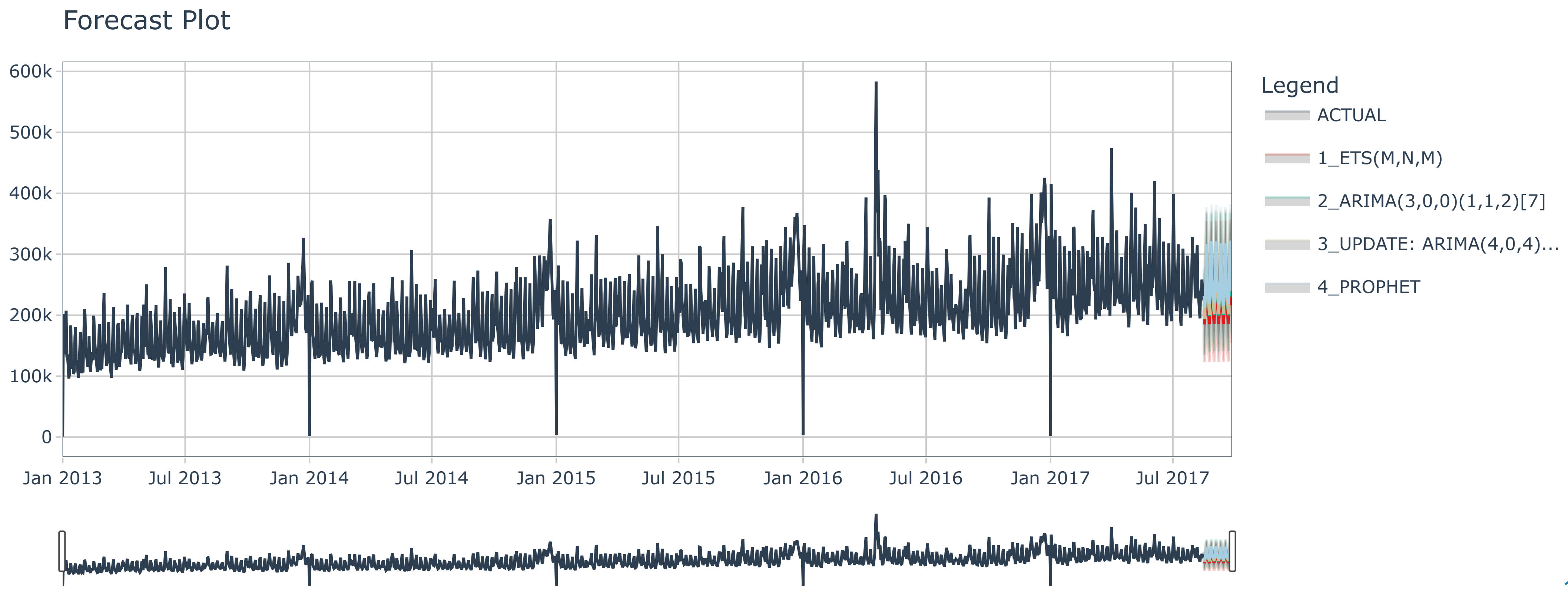
Then, `modeltime_forecast()` is used to forecast to a selected future time period, in this example 6 weeks.

```
forecast_tbl <- refit_tbl %>%
  modeltime_forecast(
    h = "6 weeks",
    actual_data = grocery,
    keep_data = TRUE)
```

Notice that this newly derived *forecast_tbl* consists of 1852 rows (1684 rows for the original grocery sales data plus 7 days x 6 weeks x 4 models forecasted data)

Step 6 - Refit to Full Dataset & Forecast Forward

```
forecast_tbl %>%
  plot_modeltime_forecast(
    .legend_max_width = 25,
    .interactive = TRUE,
    .plotly_slider = TRUE)
```



Step 6 - Refit to Full Dataset & Forecast Forward

Let us also examine the model accuracy metrics after refitting the full data set.

```
refit_tbl %>%
  modeltime_accuracy() %>%
  table_modeltime_accuracy(
    .interactive = FALSE)
```

Accuracy Table

.model_id	.model_desc	.type	mae	mape	mase	smape	rmse	rsq
1	ETS(M,N,M)	Test	25250.52	9.86	0.65	9.61	31554.80	0.64
2	ARIMA(3,0,0)(1,1,2)[7]	Test	23087.67	8.90	0.59	8.79	29863.72	0.66
3	UPDATE: ARIMA(4,0,4)(1,1,2)[7] WITH DRIFT	Test	23049.21	8.89	0.59	8.78	29829.18	0.66
4	PROPHET	Test	22386.78	8.56	0.58	8.61	30521.01	0.66