

Forecasting Process (with External Regressors)

Want to apply this workflow to a *real business analysis*?
Then take the [High-Performance Forecasting Course](#) through
Business Science University.

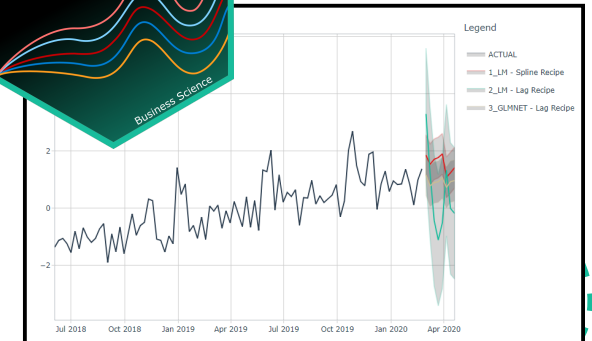
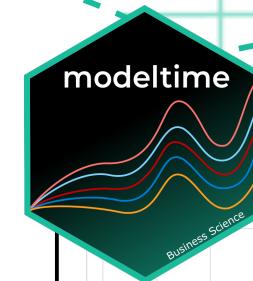
The Modeltime Ecosystem:

- [Timetk](#) (Time Series)
- [Modeltime](#) (Forecasting)
- [Modeltime Ensemble](#) (Blending)
- [Modeltime GluonTS](#) (Deep Learning)
- [Modeltime H2O](#) (AutoML)
- [Modeltime Resample](#) (Backtesting)

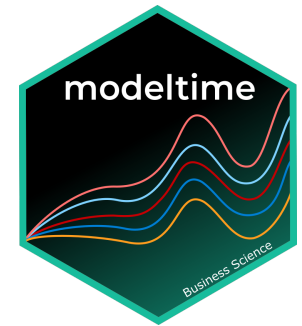


Business Science University
university.business-science.io

5-Course R-Track
The Ultimate Online Data Science Program



MODELTIME Workflow



Create Modeltime Table

`modeltime_table()`

```
# 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
```

Calibrate

`modeltime_calibrate()`

```
# 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 x 4]>
2 2 <fit(+)> ARIMA(0,1,1)(0,1,1)[12] W/ XGBOOST ERRORS Test <tibble [31 x 4]>
3 3 <fit(+)> ETS(M,A,A) Test <tibble [31 x 4]>
4 4 <fit(+)> PROPHET Test <tibble [31 x 4]>
5 5 <fit(+)> LM Test <tibble [31 x 4]>
6 6 <fit(+)> EARTH Test <tibble [31 x 4]>
```

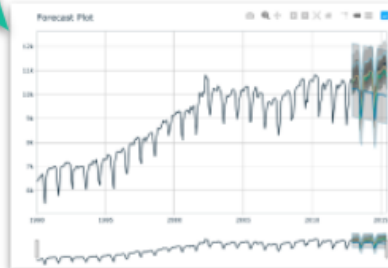
Refit

`modeltime_refit()`

```
# 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 x 4]>
2 2 <fit(+)> ARIMA(0,1,1)(0,1,1)[12] W/ XGBOOST ERRORS Test <tibble [31 x 4]>
3 3 <fit(+)> ETS(A,A,A) Test <tibble [31 x 4]>
4 4 <fit(+)> PROPHET Test <tibble [31 x 4]>
5 5 <fit(+)> LM Test <tibble [31 x 4]>
6 6 <fit(+)> EARTH Test <tibble [31 x 4]>
```

Forecast Test Set

`modeltime_forecast()`



`plot_modeltime_forecast()`

Test Accuracy

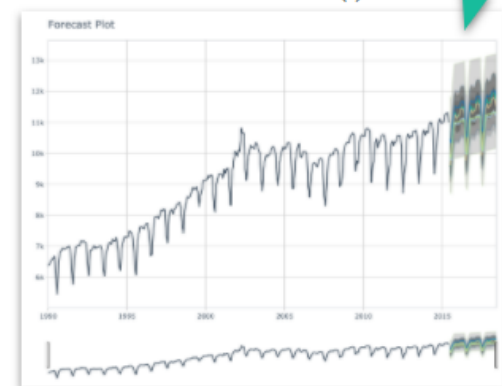
`modeltime_accuracy()`

Accuracy Table								
.model_id	.model_desc	.type	mae	mape	mase	smape	rmse	r
1	ARIMA(0,1,1)(0,1,1)[12]	Test	161.33	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

`table_modeltime_accuracy()`

Forecast Future

`modeltime_forecast()`



`plot_modeltime_forecast()`

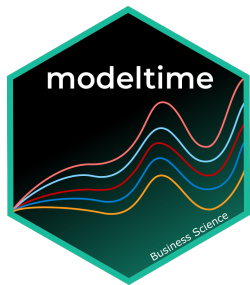
Resources:

- This workflow is covered in depth in the [High-Performance Time Series Course \(Modules 7 to 18\)](#)
- A beginner tutorial is available here: [Getting Started with Modeltime](#)
- The ["Global Forecasting Workflow"](#) is used to create scalable high-performance model(s) that forecast many time series
- This is NOT the "Iterative Forecasting Process" (Nested Workflow), which is used to forecast iteratively. The Iterative Forecasting Procedure is shown on Page 5.



Business Science University
university.business-science.io

5-Course **R**-Track
The Ultimate Online Data Science Program



1. Cross Validation Plan

Can be used for more
than 1 model

START
Cross Validation

Sequential
Time Series CV
`time_series_cv()`

Ex. Arima Boost

Non-Sequential
10-Fold CV
`vfold_cv()`

Ex. Prophet Boost

2. Identify Tuning Parameters

Specific to Each Model

Model Spec & Recipe
Identify Parameters
`tune(id)`

3. Make Grid for Parameters

Specific to Each Model

Grid Spec
`grid_latin_hypercube(
param_set
)`

4. Hyperparameter Tune

Specific to Each Model

Use Parallel Processing
to Speed Up

Tune Grid
`tune_grid(
resamples,
grid,
metrics,
control
)`

Review Parameters
Adjust & Re-Tune
(if necessary)

`autoplot()`

Model
Parameters,
Residuals, &
Confidence

Model
Parameters,
Residuals, &
Confidence

Hyperparameter Tuning & Cross-Validation for Time Series

Cross-Validation and Hyperparameter Tuning are absolutely critical for Machine Learning algorithms.

Additional Resources:

- [The NEW Hyperparameter Tuning & Parallel Processing Process](#)



MODELTIME ENSEMBLE

Multi-Level Stacking



Level 3: Weighted Stack

`ensemble_weighted()`
`ensemble_average()`

$$w1*m1 + w2*m2 + w3*m3 + \dots$$

Level 2: Stacking Algorithms

`ensemble_model_spec()`
`modeltime_fit_resamples()`

Linear Stack

Tree Stack

Level 1: Sub-Models

ARIMA

GLMNET

SVM

XGBoost

`arima_reg()`

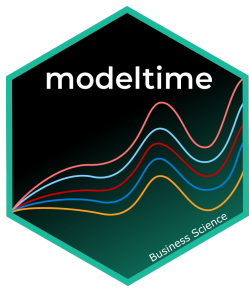
`linear_reg()`

`svm_rbf()`

`boost_tree()`

Additional Resources:

- The Modeltime Ensemble process is covered in-depth in the [High-Performance Time Series Course Module 14](#)
- The [Lost Time Series Module 5](#) shows how to use Ensembles to improve *Hierarchical Forecasting Performance*
- Additional Resource: [Getting Started with Modeltime Ensemble](#)



Iterative Forecasting (Nested Workflow)

Used to make individual models for many time series. Can be more accurate than Global Forecasting, but is less scalable.

- This process is covered in-depth in the **Lost Time Series Modules (Module 2 - Iterative Forecasting at Scale) and (Module 3 - Recursive Iterative Forecasting)**
- Additional Resource: [Getting Started with Nested Forecasting](#).

Nested Time Series Data

```
extend_timeseries()
nest_timeseries()
split_nested_timeseries()
```

```
# A tibble: 7 x 5
  id      .actual_data .future_data .splits
  <fct> <list>          <list>          <list>
1 1_1    <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]>
2 1_3    <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]>
3 1_8    <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]>
4 1_13   <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]>
5 1_38   <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]>
6 1_93   <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]>
7 1_95   <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]>
```

Many Models



`modeltime_nested_fit()`

Nested Modeltime Table

```
# Nested Modeltime Table
Trained on: .splits | Model Errors: [0]
# A tibble: 7 x 5
  id      .actual_data .future_data .splits .modeltime_tables
  <fct> <list>          <list>          <list> <list>
1 1_1    <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]> <mdl_time_tbl [2 x 5]>
2 1_3    <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]> <mdl_time_tbl [2 x 5]>
3 1_8    <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]> <mdl_time_tbl [2 x 5]>
4 1_13   <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]> <mdl_time_tbl [2 x 5]>
5 1_38   <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]> <mdl_time_tbl [2 x 5]>
6 1_93   <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]> <mdl_time_tbl [2 x 5]>
7 1_95   <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]> <mdl_time_tbl [2 x 5]>
```

Core Functions | Nested Forecasting

1: Nested Fitting

`modeltime_nested_fit()`

- Trains** each model on training split
- Logs** test accuracy, test forecast with confidence intervals on testing split
- Logs** additional information including error reports

2: Select Best

`modeltime_nested_select_best()`

- Selects best model** using accuracy metric
- Filters** test forecasts to just those of best models
- Logs** best models

3: Nested Refitting

`modeltime_nested_refit()`

- Retrains** selected models on actual data
- Logs** future forecast on future data

Extracting Nested Modeltime Table Logs

Nested Modeltime Table

```
# Nested Modeltime Table
Trained on: .actual_data | Model Errors: [0]
# A tibble: 7 x 5
  id      .actual_data .future_data .splits .modeltime_tables
  <fct> <list>          <list>          <list> <list>
1 1_1    <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]> <mdl_time_tbl [1 x 5]>
2 1_3    <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]> <mdl_time_tbl [1 x 5]>
3 1_8    <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]> <mdl_time_tbl [1 x 5]>
4 1_13   <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]> <mdl_time_tbl [1 x 5]>
5 1_38   <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]> <mdl_time_tbl [1 x 5]>
6 1_93   <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]> <mdl_time_tbl [1 x 5]>
7 1_95   <tibble [104 x 2]> <tibble [52 x 2]> <split [52/52]> <mdl_time_tbl [1 x 5]>
```

Contains
Logged
Attributes
for fast
extraction

Test Accuracy

`extract_nested_test_accuracy()`

id	model_id	model_desc	error_desc
1_1	1	PROPHET	Time series forecast error: 0.00
1_3	2	HGBOOST	Time series forecast error: 0.00
1_8	1	PROPHET	Time series forecast error: 0.00
1_13	2	HGBOOST	Time series forecast error: 0.00
1_38	1	PROPHET	Time series forecast error: 0.00
1_93	2	HGBOOST	Time series forecast error: 0.00
1_95	1	PROPHET	Time series forecast error: 0.00

Test Forecast

`extract_nested_test_forecast()`



Error Reporting

`extract_nested_error_report()`

```
# A tibble: 4 x 4
  id      .model_id .model_desc .error_desc
  <fct>      <int>      <chr>      <chr>
1 1_1        2 BOOST_TREE "'data' has class 'character' and length 52.\n 'data...'
2 1_3        2 BOOST_TREE "'data' has class 'character' and length 52.\n 'data...'
3 1_8        1 BOOST_TREE "'x' should be an 'rsplit' object"
4 1_8        2 BOOST_TREE "'x' should be an 'rsplit' object"
```



Business Science University
university.business-science.io

5-Course **R**-Track
The Ultimate Online Data Science Program