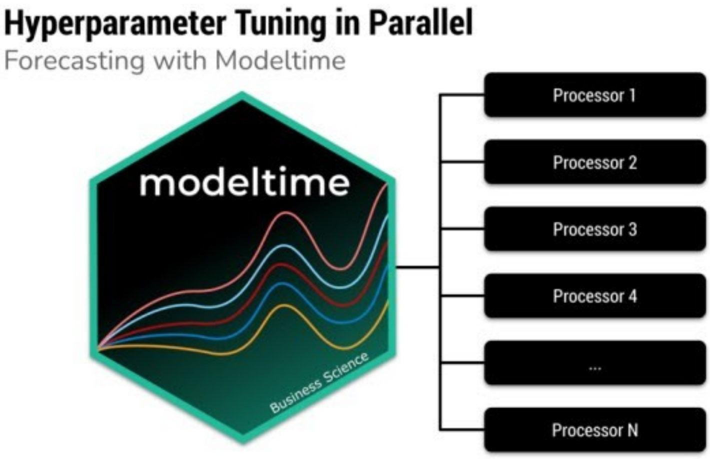
Speed up forecasting with `modeltime`'s new built-in parallel processing.

Fitting many time series models can be an expensive process. To help speed up computation, `modeltime` now includes **parallel processing**, which is support for high-performance computing by spreading the model fitting steps across multiple CPUs or clusters.

Highlights

- We now have a new workflow for forecast model fitting with parallel processing that is **much faster** when creating many forecast models.
- With 2-cores we got an immediate **30%-40% boost** in performance. With more expensive processes and more CPU cores we get even more performance.
- It's perfect for **hyperparameter tuning.** See `create_model_grid()` for filling model specs with hyperparameters.
- The workflow is **simple.** Just use `parallel_start(6)` to fire up 6-cores. Just use `control_fit_workflowsets(allow_par = TRUE)` to tell the `modeltime_fit_workflowset()` to run in parallel.

Forecast Hyperparameter Tuning Tutorial
Speed up forecasting



Speed up forecasting using multiple processors

In this tutorial, we go through a common **Hyperparameter Tuning** workflow that shows off the `modeltime` parallel processing integration and support for `workflowsets` from the tidymodels ecosystem. Hyperparameter tuning is an expensive process that can benefit from parallelization.

If you like what you see, I have an Advanced Time Series Course where you will learn the foundations of the growing Modeltime Ecosystem.

Time Series Forecasting Article Guide:

This article is part of a series of software announcements on the Modeltime Forecasting Ecosystem.

1. (**Start Here**) Modeltime: Tidy Time Series Forecasting using Tidymodels
2. Modeltime H2O: Forecasting with H2O AutoML
3. Modeltime Ensemble: Time Series Forecast Stacking
4. Modeltime Recursive: Tidy Autoregressive Forecasting
5. Hyperparameter Tuning Forecasts in Parallel with Modeltime
6. Time Series Forecasting Course: Now Available

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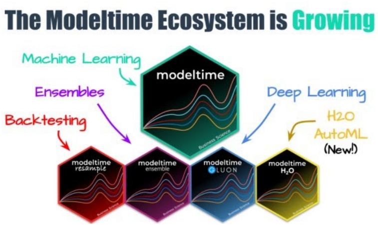
on new cutting-edge R software like `modeltime`.

What is Modeltime?
A **growing** ecosystem for tidymodels forecasting



Modeltime is a **growing** ecosystem of forecasting packages used to develop scalable forecasting systems for your business.

The Modeltime Ecosystem **extends** `tidymodels`, which means any machine learning algorithm can now become a forecasting algorithm.

The Modeltime Ecosystem **includes**:

- Modeltime (Machine Learning, Forecasting Workflow)
- Modeltime H2O (Forecasting with AutoML)
- Modeltime GluonTS (Deep Learning)
- Modeltime Ensemble (Blending Forecasts)
- Modeltime Resample (Backtesting)
- Timetk (Data Transformation, Feature Engineering, Time Series Visualization)

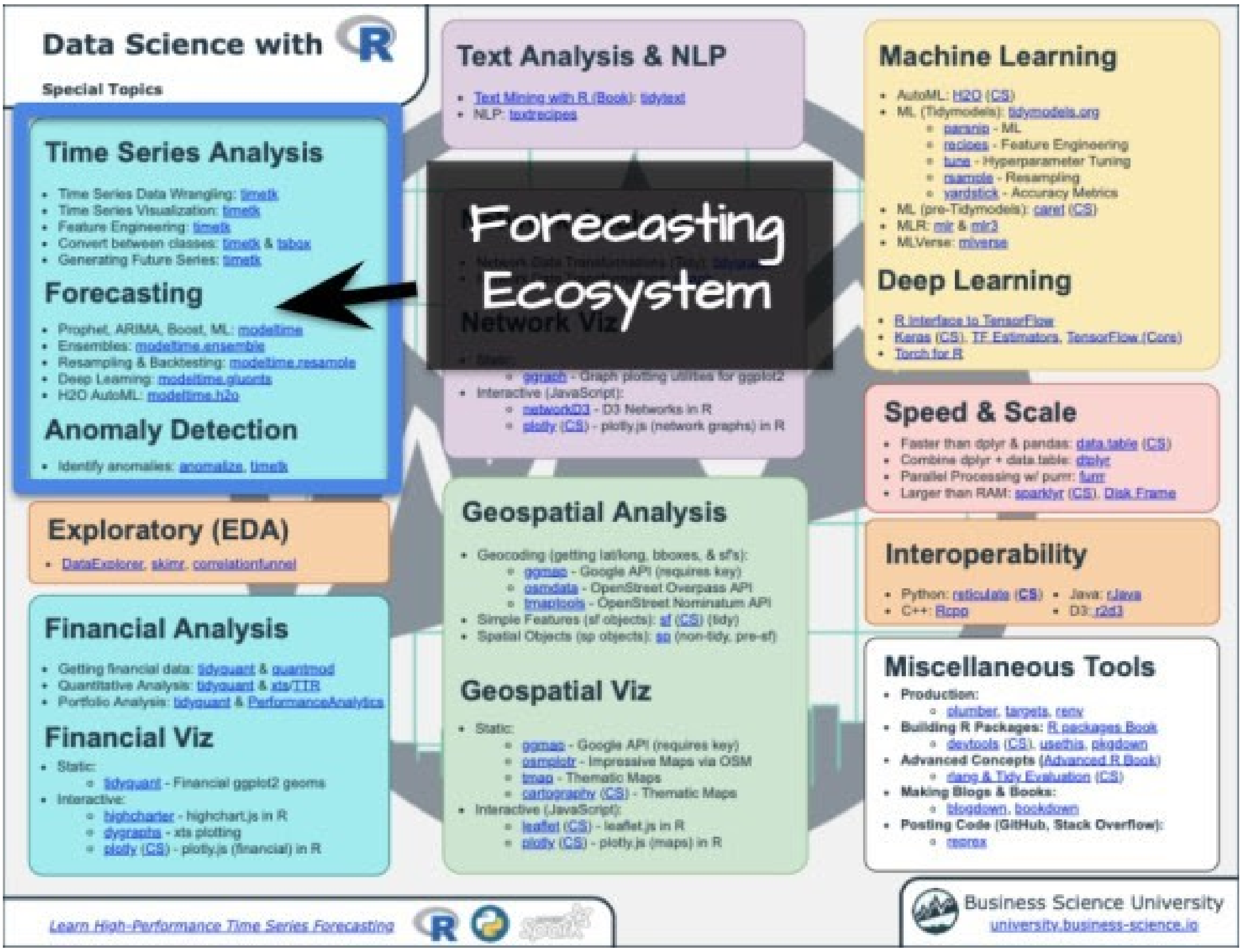
Out-of-the-Box
Parallel Processing Functionality Included

The newest feature of the `modeltime` package is **parallel processing functionality.** Modeltime comes with:

- Use of `parallel_start()` and `parallel_stop()` to simplify the parallel processing setup.
- Use of `create_model_grid()` to help generate `parsnip` model specs from `dials` parameter grids.
- Use of `modeltime_fit_workflowset()` for initial fitting many models in parallel using `workflowsets` from the `tidymodels` ecosystem.
- Use of `modeltime_refit()` to refit models in parallel.
- Use of `control_fit_workflowset()` and `control_refit()` for controlling the fitting and refitting of many models.

Download the Cheat Sheet

As you go through this tutorial, it may help to use the Ultimate R Cheat Sheet. Page 3 covers the *Modeltime Forecasting Ecosystem* with links to key documentation.



Forecasting Ecosystem Links (Ultimate R Cheat Sheet)

How to Use Parallel Processing

Let's go through a common **Hyperparameter Tuning** workflow that shows off the `modeltime` **parallel processing integration** and support for `workflowsets` from the tidymodels ecosystem.

Libraries

Load the following libraries. Note that the new parallel processing functionality is available in Modeltime 0.6.1 (or greater).

```
# Machine Learning
library(modeltime) # Requires version >= 0.6.1
library(tidymodels)
library(workflowsets)

# Core
library(tidyverse)
library(timetk)
```

Setup Parallel Backend

I'll set up this tutorial to use two (2) cores.

- To simplify creating clusters, `modeltime` includes `parallel_start()`. We can simply supply the number of cores we'd like to use.
- To detect how many physical cores you have, you can run `parallel::detectCores(logical = FALSE)`.

```
parallel_start(2)
```

Load Data

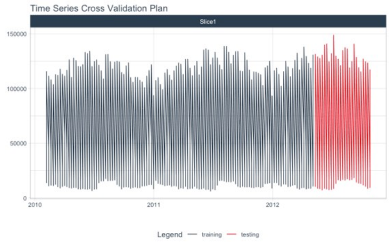
We'll use the `walmart_sales_weeekly` dataset from `timetk`. It has seven (7) time series that represent weekly sales demand by department.

```
dataset_tbl <- walmart_sales_weekly %>%
  select(id, Date, Weekly_Sales)

dataset_tbl %>%
  group_by(id) %>%
  plot_time_series(
    .date_var    = Date,
    .value       = Weekly_Sales,
    .facet_ncol  = 2,
    .interactive = FALSE
  )
```

Train / Test Splits

Use `time_series_split()` to make a temporal split for all seven time series.

```
splits <- time_series_split(
  dataset_tbl,
  assess     = "6 months",
  cumulative = TRUE
)

splits %>%
  tk_time_series_cv_plan() %>%
  plot_time_series_cv_plan(Date, Weekly_Sales, .interactive = F)
```



Recipe

Make a preprocessing recipe that generates time series features.

```
recipe_spec_1 <- recipe(Weekly_Sales ~ ., data = training(splits)) %>%
  step_timeseries_signature(Date) %>%
  step_rm(Date) %>%
  step_normalize(Date_index.num) %>%
  step_zv(all_predictors()) %>%
  step_dummy(all_nominal_predictors(), one_hot = TRUE)
```

Model Specifications

We'll make 6 `xgboost` model specifications using `boost_tree()` and the "xgboost" engine. These will be combined with the `recipe` from the previous step using a `workflow_set()` in the next section.

The general idea

We can vary the `learn_rate` parameter to see it's effect on forecast error.

```
# XGBOOST MODELS
model_spec_xgb_1 <- boost_tree(learn_rate = 0.001) %>%
  set_engine("xgboost")

model_spec_xgb_2 <- boost_tree(learn_rate = 0.010) %>%
  set_engine("xgboost")

model_spec_xgb_3 <- boost_tree(learn_rate = 0.100) %>%
  set_engine("xgboost")

model_spec_xgb_4 <- boost_tree(learn_rate = 0.350) %>%
  set_engine("xgboost")

model_spec_xgb_5 <- boost_tree(learn_rate = 0.500) %>%
  set_engine("xgboost")

model_spec_xgb_6 <- boost_tree(learn_rate = 0.650) %>%
  set_engine("xgboost")
```

A faster way

You may notice that this is a lot of repeated code to adjust the `learn_rate`. To simplify this process, we can use `create_model_grid()`.

```
model_tbl <- tibble(
  learn_rate = c(0.001, 0.010, 0.100, 0.350, 0.500, 0.650)
) %>%
  create_model_grid(
    f_model_spec = boost_tree,
    engine_name  = "xgboost",
    mode         = "regression"
  )

model_tbl
```

```
## # A tibble: 6 x 2
##   learn_rate .models
##        <dbl> <list>
## 1      0.001 <spec[+]>
## 2      0.01  <spec[+]>
## 3      0.1   <spec[+]>
## 4      0.35  <spec[+]>
## 5      0.5   <spec[+]>
## 6      0.65  <spec[+]>
```

Extracting the model list

We can extract the model list for use with our `workflowset` next. This is the same result if we would have placed the manually generated 6 model specs into a `list()`.

```
model_list <- model_tbl$.models

model_list
```

```
## [[1]]
## Boosted Tree Model Specification (regression)
##
## Main Arguments:
##   learn_rate = 0.001
##
## Computational engine: xgboost
##
##
## [[2]]
## Boosted Tree Model Specification (regression)
##
## Main Arguments:
##   learn_rate = 0.01
##
## Computational engine: xgboost
##
##
## [[3]]
## Boosted Tree Model Specification (regression)
##
## Main Arguments:
##   learn_rate = 0.1
##
## Computational engine: xgboost
##
##
## [[4]]
## Boosted Tree Model Specification (regression)
##
## Main Arguments:
##   learn_rate = 0.35
##
## Computational engine: xgboost
##
##
## [[5]]
## Boosted Tree Model Specification (regression)
##
## Main Arguments:
##   learn_rate = 0.5
##
## Computational engine: xgboost
##
##
## [[6]]
## Boosted Tree Model Specification (regression)
##
## Main Arguments:
##   learn_rate = 0.65
##
## Computational engine: xgboost
```

Workflowsets

With the `workflow_set()` function, we can combine the 6 xgboost models with the 1 recipe to return six (6) combinations of recipe and model specifications. These are currently untrained (unfitted).

```
model_wfset <- workflow_set(
  preproc = list(
    recipe_spec_1
  ),
  models = model_list,
  cross = TRUE
)
```

```
model_wfset
```

```
## # A workflow set/tibble: 6 x 4
##   wflow_id            info             option      result
##   <chr>               <list>           <list>      <list>
## 1 recipe_boost_tree_1 <tibble [1 × 4]> <wrkflw__ > <list [0]>
## 2 recipe_boost_tree_2 <tibble [1 × 4]> <wrkflw__ > <list [0]>
## 3 recipe_boost_tree_3 <tibble [1 × 4]> <wrkflw__ > <list [0]>
## 4 recipe_boost_tree_4 <tibble [1 × 4]> <wrkflw__ > <list [0]>
## 5 recipe_boost_tree_5 <tibble [1 × 4]> <wrkflw__ > <list [0]>
## 6 recipe_boost_tree_6 <tibble [1 × 4]> <wrkflw__ > <list [0]>
```

Parallel Training (Fitting)

We can train each of the combinations in parallel.

Controlling the Fitting Proces

Each fitting function in `modeltime` has a “control” function:

- `control_fit_workflowset()` for `modeltime_fit_workflowset()`
- `control_refit()` for `modeltime_refit()`

The control functions help the user control the verbosity (adding remarks while training) and set up parallel processing. We can see the output when `verbose = TRUE` and `allow_par = TRUE`.

- **allow_par:** Whether or not the user has indicated that parallel processing should be used.
  - If the user has set up parallel processing externally, the clusters will be reused.
  - If the user has not set up parallel processing, the fitting (training) process will set up parallel processing internally and shutdown. Note that this is more expensive, and usually costs around 10-15 seconds to set up.
- **verbose:** Will return important messages showing the progress of the fitting operation.
- **cores:** The cores that the user has set up. Since we've already set up `doParallel` to use 2 cores, the control recognizes this.
- **packages:** The packages are packages that will be sent to each of the workers.

```
control_fit_workflowset(
  verbose   = TRUE,
  allow_par = TRUE
)
```

```
## workflowset control object
## --------------------------
## allow_par : TRUE
## cores     : 2
## verbose   : TRUE
## packages  : modeltime parsnip dplyr stats lubridate tidymodels timetk forcats stringr readr
tidyverse yardstick workflowsets workflows tune tidyr tibble rsample recipes purrr modeldata
infer ggplot2 dials scales broom graphics grDevices utils datasets methods base
```

Fitting Using Parallel Backend

We use the `modeltime_fit_workflowset()` and `control_fit_workflowset()` together to train the unfitted workflowset in parallel.

```
model_parallel_tbl <- model_wfset %>%
  modeltime_fit_workflowset(
    data    = training(splits),
    control = control_fit_workflowset(
      verbose   = TRUE,
      allow_par = TRUE
    )
  )
```

```
## Using existing parallel backend with 2 clusters (cores)...
##  Beginning Parallel Loop | 0.006 seconds
##  Finishing parallel backend. Clusters are remaining open. | 12.458 seconds
##  Close clusters by running: `parallel_stop()`.
##  Total time | 12.459 seconds
```

This returns a modeltime table.

```
model_parallel_tbl
```

```
## # Modeltime Table
## # A tibble: 6 x 3
##   .model_id .model     .model_desc
##       <int> <list>     <chr>
## 1         1 <workflow> XGBOOST
## 2         2 <workflow> XGBOOST
## 3         3 <workflow> XGBOOST
## 4         4 <workflow> XGBOOST
## 5         5 <workflow> XGBOOST
## 6         6 <workflow> XGBOOST
```

Comparison to Sequential Backend

We can compare to a sequential backend. We have a slight perfomance boost. Note that this performance benefit increases with the size of the training task.

```
model_sequential_tbl <- model_wfset %>%
  modeltime_fit_workflowset(
    data    = training(splits),
    control = control_fit_workflowset(
      verbose   = TRUE,
      allow_par = FALSE
    )
  )
```

```
## i Fitting Model: 1
## ✓ Model Successfully Fitted: 1
## i Fitting Model: 2
## ✓ Model Successfully Fitted: 2
## i Fitting Model: 3
## ✓ Model Successfully Fitted: 3
## i Fitting Model: 4
## ✓ Model Successfully Fitted: 4
## i Fitting Model: 5
## ✓ Model Successfully Fitted: 5
## i Fitting Model: 6
## ✓ Model Successfully Fitted: 6
## Total time | 15.781 seconds
```

Accuracy Assessment

We can review the forecast accuracy. We can see that Model 5 has the lowest MAE.

```
model_parallel_tbl %>%
  modeltime_calibrate(testing(splits)) %>%
  modeltime_accuracy() %>%
  table_modeltime_accuracy(.interactive = FALSE)
```

Accuracy Table

.model_id	.model_desc	.type	mae	mape	mase	smape	rmse	rsq
1	XGBOOST	Test	55572.50	98.52	1.63	194.17	66953.92	0.96
2	XGBOOST	Test	48819.23	86.15	1.43	151.49	58992.30	0.96
3	XGBOOST	Test	13426.89	21.69	0.39	25.06	17376.53	0.98
4	XGBOOST	Test	3699.94	8.94	0.11	8.68	5163.37	0.98
5	XGBOOST	Test	3296.74	7.30	0.10	7.37	5166.48	0.98
6	XGBOOST	Test	3612.70	8.15	0.11	8.24	5308.19	0.98

Forecast Assessment

We can visualize the forecast.

```
model_parallel_tbl %>%
  modeltime_forecast(
    new_data    = testing(splits),
    actual_data = dataset_tbl,
    keep_data   = TRUE
  ) %>%
  group_by(id) %>%
  plot_modeltime_forecast(
    .facet_ncol  = 3,
    .interactive = FALSE
  )
```

Closing Clusters

We can close the parallel clusters using `parallel_stop()`.

```
parallel_stop()
```

It gets better

You've just scratched the surface, here's what's coming…

The Modeltime Ecosystem functionality is much more feature-rich than what we've covered here (I couldn't possibly cover everything in this post). 😀

Here's what I didn't cover:

- **Feature Engineering:** We can make this forecast much more accurate by including features from competition-winning strategies
- **Ensemble Modeling:** We can stack H2O Models with other models not included in H2O like GluonTS Deep Learning.
- **Deep Learning:** We can use GluonTS Deep Learning for developing high-performance, scalable forecasts.

So how are you ever going to learn time series analysis and forecasting?

You're probably thinking:

- There's so much to learn
- My time is precious
- I'll never learn time series

I have good news that will put those doubts behind you.

You can learn time series analysis and forecasting in hours with my state-of-the-art time series forecasting course. 👇

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