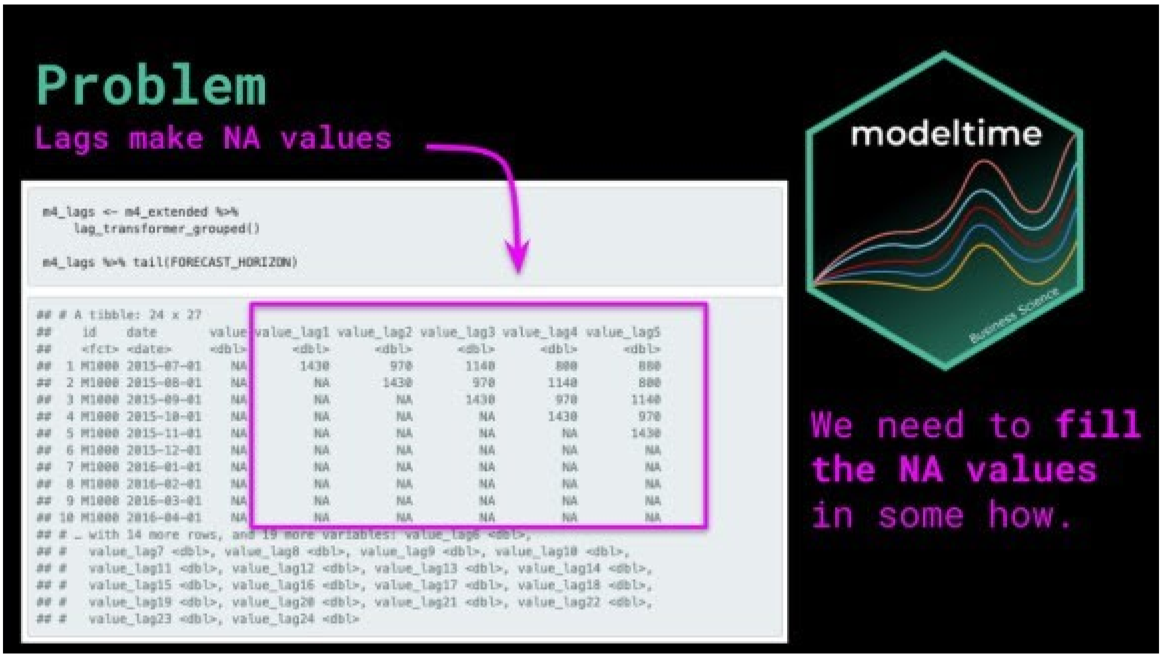
The Problem with Autoregressive Forecasting: Lags make Missing Values

Forecasting with autoregressive features is a challenge. The problem is that Lags make missing values that show up as `NA`.



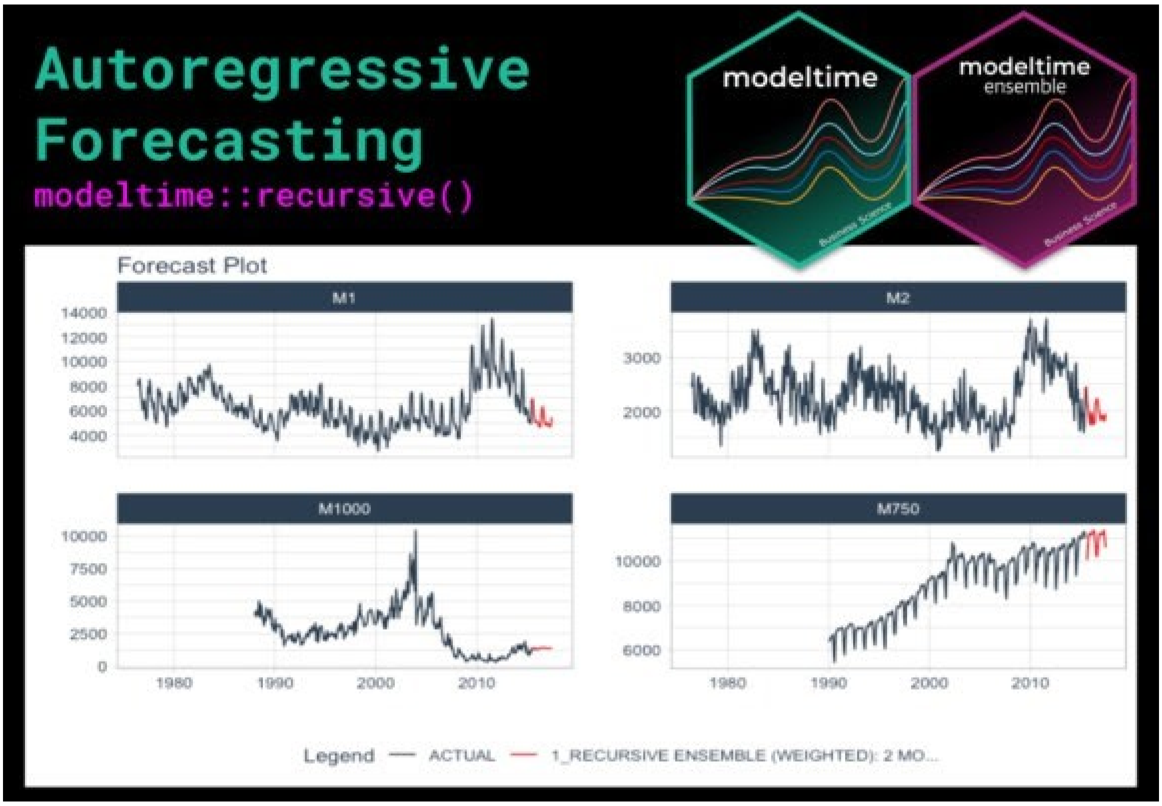
This isn't a new problem. Algorithms like ARIMA have been managing this internally for one time series at a time for decades. But, they've only been doing it for one time series at a time forcing us to loop through every time series for prediction. **This iterative approach is not scalable with modern machine learning.**

The new challenge is how do we manage this for multiple time series? If you have more than one time series, this quickly becomes a forecasting nightmare that will make your head spin. Then multiply this by the number of different modeling algorithms you want to experiment with, and, well, you get the picture…

Enter `modeltime::recursive()`: A new function that is capable of turning **any Tidymodels regression algorithm into an autoregressive forecaster.**

> It's a *Lag Management Tool* that handles the lagged predictions on one or more time series.

Solution: `modeltime::recursive()` Autoregressive forecasting with **lag management.**



Modeltime 0.5.0 includes a new and improved `modeltime::recursive()` function that turns any `tidymodels` regression algorithm into an autoregressive forecaster.

✅ Hassle-Free

Recursive is a new way to manage lagged regressors used in autoregressive forecasting.

✅ Any Tidymodel can become Autoregressive.

Recursive can be used with any regression model that is part of the tidymodels ecosystem (e.g. XGBoost, Random Forest, GLMNET).

✅ Works with Multiple Time Series.

Recursive works on single time series and multiple time series (panel data).

✅ Works with Ensembles.

Recursive can also be used in Ensembles (Recursive Ensembles) with `modeltime.ensemble` 0.4.0 (just released, yay! 🎉).

What do you need to do to get Recursive?

Simply upgrade to `modeltime` and `modeltime.ensemble`. Both were just released to CRAN.

```
install.packages(c('modeltime', 'modeltime.ensemble'))
```

This version of the tutorial uses the “development version” of both packages. We are improving this software a lot as we **grow the Modeltime Ecosystem.** If you’d like to install the development version with the latest features:

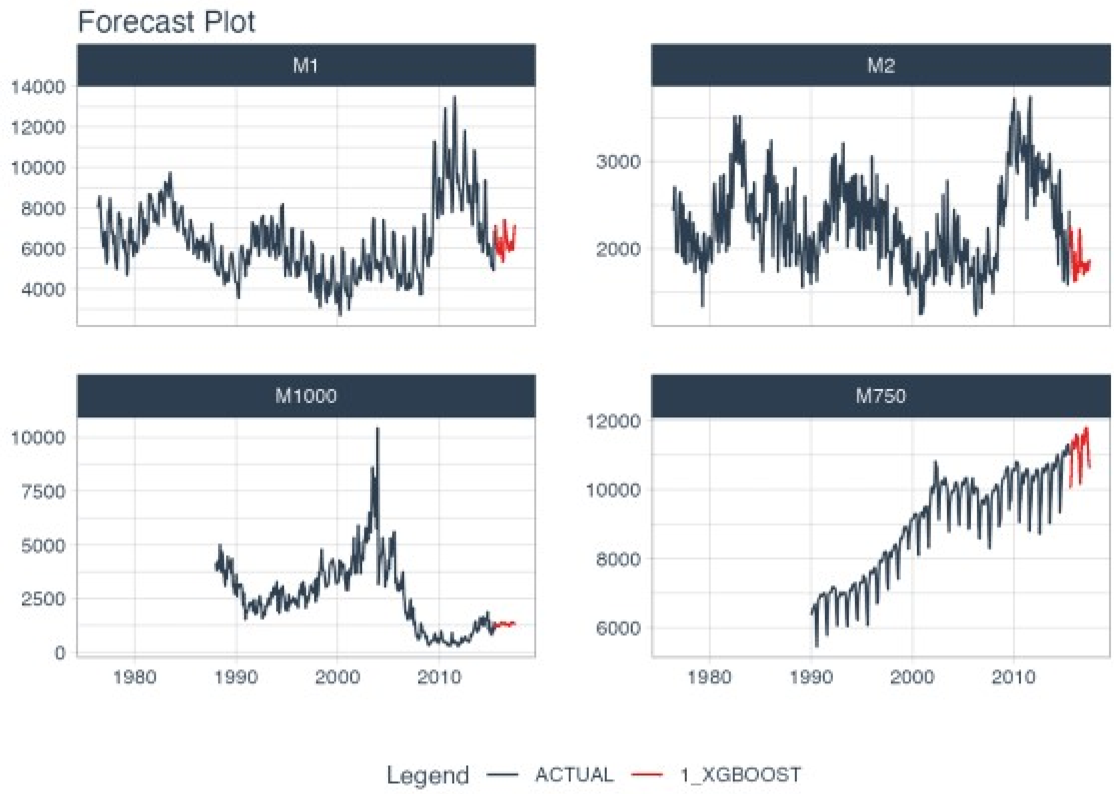
```
remotes::install_github("business-science/modeltime")
```

```
remotes::install_github("business-science/modeltime.
ensemble")
```

Autoregressive Forecast Tutorial
Combine `recursive()` with Modeltime Ensemble

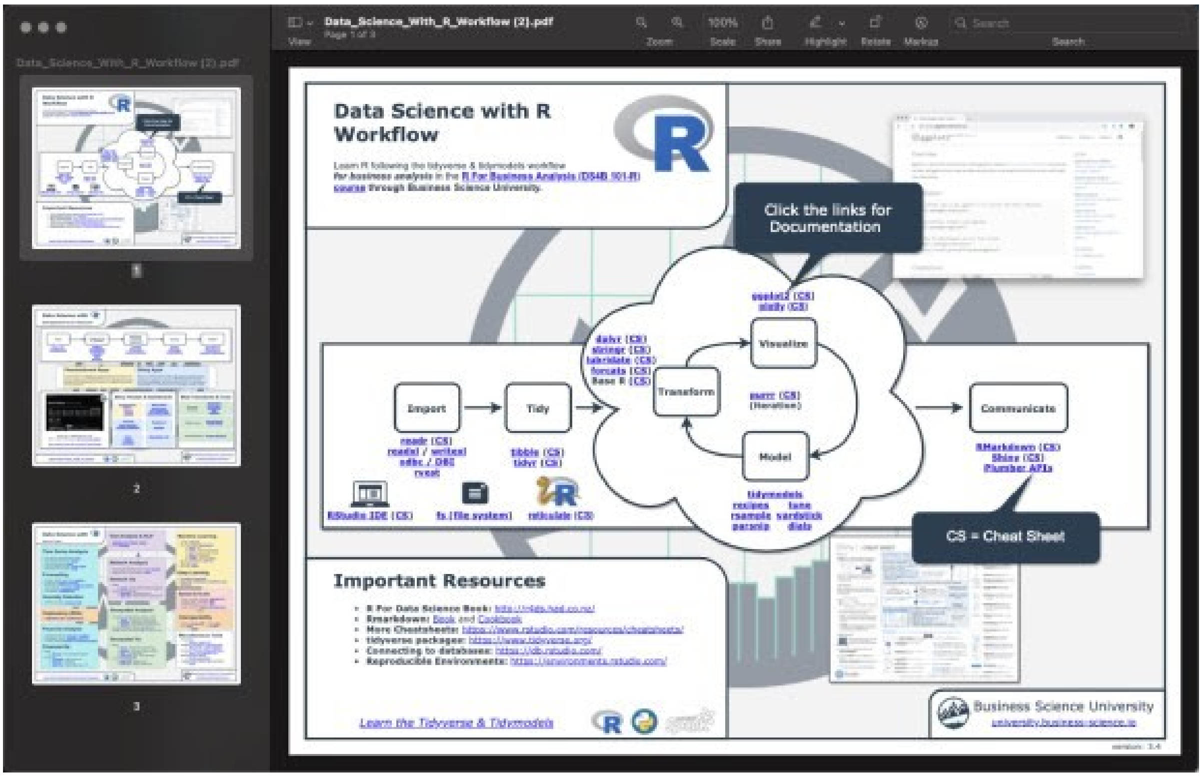
Here's what we're making:

- **A Recursive Ensemble** with `modeltime.ensemble` 0.4.0
- That uses two sub-models: 40% GLMNET and 60% XGBOOST
- With Lags 1-24 as the main features using `modeltime::recursive()` to manage the process
- We will forecast 24 months (2-years) using lags < forecast horizon



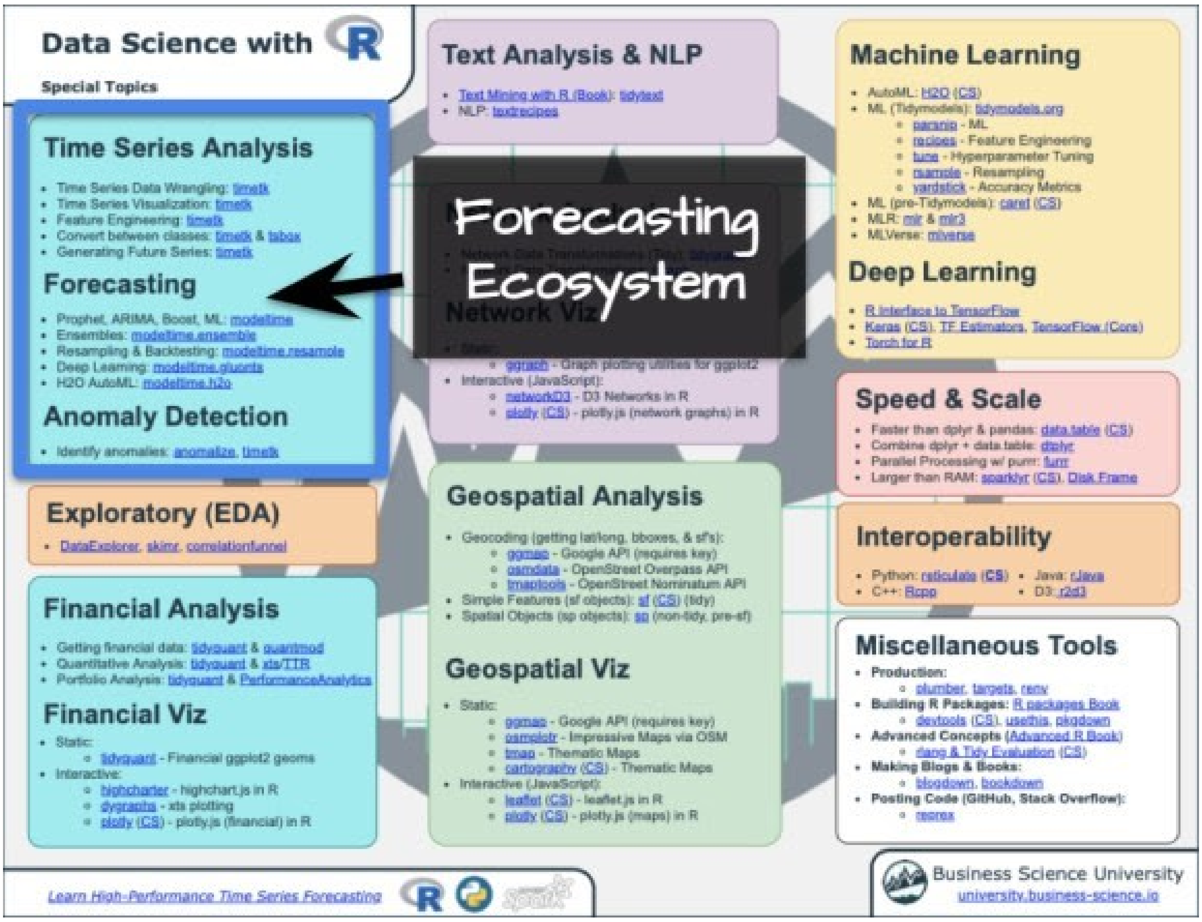
Get the Cheat Sheet

As you go through this tutorial, you will see many references to the Ultimate R Cheat Sheet. The Ultimate R Cheatsheet covers the Modeltime Forecasting Ecosystem with links to key documentation. **You can download the Ultimate R Cheat Sheet for free.**



Download the Ultimate R Cheat Sheet (Free)

We'll be focusing on three key packages: `timetk`, `modeltime` and `modeltime.ensemble`. Links to the documentation are included in the cheat sheet (every package has a hyperlink, and some even have "CS" links to their cheat sheets).



Forecasting Ecosystem Links (Ultimate R Cheat Sheet)

80/20 Recursive Terminology

Things you'll want to be aware of as we go through this tutorial

Autoregressive Forecast

This is an Autoregressive Forecast. We are using **short-term lags (Lags < Forecast Horizon).** These short-term lags are the key features of the model. They are powerful predictors, but they create missing values (`NA`) in the future data. We use `modeltime::recursive()` to manage predictions, updating lags.

Panel Data

We are processing **Multi-Time Series using a single model.** The model processes in batches (panels) that are separated by an ID feature. This is a scalable approach to modeling many time series.

Recursive Forecasting

- The model will predict (forecast) iteratively in batches (1 time stamp x 4 time series = 4 predictions) per loop.
- The iteration continues until all 24 future time stamps have been predicted.

This process is highly scalable. The loop size is determined by the forecast horizon, and not the number of time series. So if you have 1000 time series, but your forecast horizon is only 24 months, the recursive prediction loop is only 24 iterations.

Transformer Function

During this iterative process, a ***transformer function*** is used to create lagged values. We are responsible for defining the transformer function, but we have a lot of tools in `timetk` that help us create the Transformer Function:

- You'll see `tk_augment_lags()`.
- There is also `tk_augment_slidify()` and more.

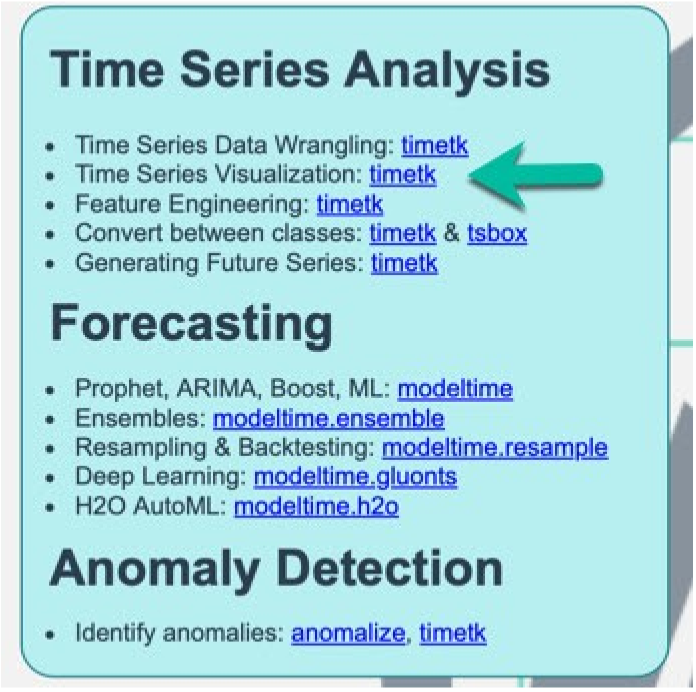
Libraries

First, we need to load the necessary libraries:

```
# Tidymodeling
library(modeltime.ensemble)
library(modeltime)
library(tidymodels)

# Base Models
library(earth)
library(glmnet)
library(xgboost)

# Core Packages
```

```
library(tidyverse)
library(lubridate)
library(timetk)
```

Dataset



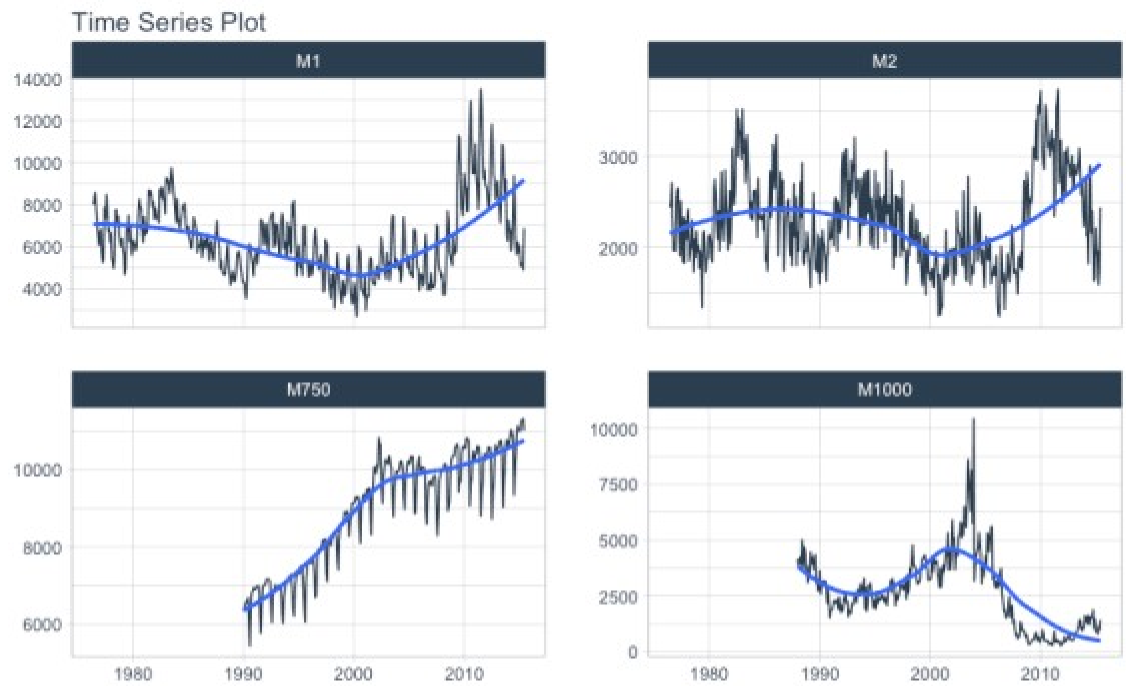
Ultimate R Cheat Sheet

We'll use the `m4_monthly` dataset, which has four monthly time series:

- This is a single data frame
- That contains 4 time series
- Each time series is identified with an "id"
- The date and value columns specify the timestamp data and the target (feature we are predicting)

We can get a visual using `timetk::plot_time_series()`. Refer to the Ultimate R Cheat Sheet for documentation under time series visualization.

```
m4_monthly %>%
    group_by(id) %>%
    plot_time_series(
        date,
        value,
        .facet_ncol = 2,
        .interactive = FALSE
    )
```



We can get a sense of the structure of the data.

- The “id” feature separates the panels.
- The “date” feature contains the timestamp information
- The “value” feature is our target for prediction (forecasting)

```
m4_monthly
```

```
## # A tibble: 1,574 x 3
##    id    date        value
##
##  1 M1    1976-06-01  8000
##  2 M1    1976-07-01  8350
##  3 M1    1976-08-01  8570
##  4 M1    1976-09-01  7700
##  5 M1    1976-10-01  7080
##  6 M1    1976-11-01  6520
##  7 M1    1976-12-01  6070
##  8 M1    1977-01-01  6650
##  9 M1    1977-02-01  6830
## 10 M1    1977-03-01  5710
## # … with 1,564 more rows
```

Extend with `future_frame()`

First, we select a forecast horizon of 24 days and extend the data frame with the function `future_frame()` that comes from the `timetk` package (Refer to the Ultimate R Cheat Sheet).

- We do this to create a future dataset, which we can distinguish because its values will be `NA`.
- The data has been extended by 24 x 4 = 96 rows.

```
FORECAST_HORIZON <- 24
```

```
m4_extended <- m4_monthly %>%
    group_by(id) %>%
    future_frame(
        .length_out = FORECAST_HORIZON,
        .bind_data  = TRUE
    ) %>%
    ungroup()

m4_extended
```

```
## # A tibble: 1,670 x 3
##    id    date       value
##
##  1 M1    1976-06-01  8000
##  2 M1    1976-07-01  8350
##  3 M1    1976-08-01  8570
##  4 M1    1976-09-01  7700
##  5 M1    1976-10-01  7080
##  6 M1    1976-11-01  6520
##  7 M1    1976-12-01  6070
##  8 M1    1977-01-01  6650
##  9 M1    1977-02-01  6830
## 10 M1    1977-03-01  5710
## # … with 1,660 more rows
```

Transformer Function

Then we create a ***Transformer Function*** that will be in charge of generating the lags for each time series up to each forecasting horizon. Note that this time we use **grouped lags** to generate lags by group. This is important when we have multiple time series. Make sure to ungroup after the lagging process.

```
lag_transformer_grouped <- function(data){
    data %>%
        group_by(id) %>%
        tk_augment_lags(value, .lags = 1:FORECAST_HORIZON)
%>%
        ungroup()
}
```

Then, we apply the function and divide the data into training and future set. Note that the tail of the data has `NA` values in the lagged regressors, which makes the problem a ***Recursive Forecasting problem***.

```
m4_lags <- m4_extended %>%
    lag_transformer_grouped()

m4_lags %>% tail(FORECAST_HORIZON)
```

```
## # A tibble: 24 x 27
##    id    date       value value_lag1 value_lag2 value_lag3
value_lag4 value_lag5
```

```
##
##  1 M1000 2015-07-01    NA       1430        970        1140
800        880
##  2 M1000 2015-08-01    NA         NA       1430         970
1140        800
##  3 M1000 2015-09-01    NA         NA         NA        1430
970       1140
##  4 M1000 2015-10-01    NA         NA         NA          NA
1430        970
##  5 M1000 2015-11-01    NA         NA         NA          NA
NA       1430
##  6 M1000 2015-12-01    NA         NA         NA          NA
NA         NA
##  7 M1000 2016-01-01    NA         NA         NA          NA
NA         NA
##  8 M1000 2016-02-01    NA         NA         NA          NA
NA         NA
##  9 M1000 2016-03-01    NA         NA         NA          NA
NA         NA
## 10 M1000 2016-04-01    NA         NA         NA          NA
NA         NA
## # … with 14 more rows, and 19 more variables: value_lag6 ,
## #   value_lag7 , value_lag8 , value_lag9 , value_lag10 ,
## #   value_lag11 , value_lag12 , value_lag13 , value_lag14
,
## #   value_lag15 , value_lag16 , value_lag17 , value_lag18
,
## #   value_lag19 , value_lag20 , value_lag21 , value_lag22
,
## #   value_lag23 , value_lag24
```

Data Split

We split into training data and future data.

- The train data is prepared for training.
- The future data will be used later when we forecast.

```
train_data <- m4_lags %>%
    drop_na()

future_data <- m4_lags %>%
    filter(is.na(value))
```

Training the Submodels

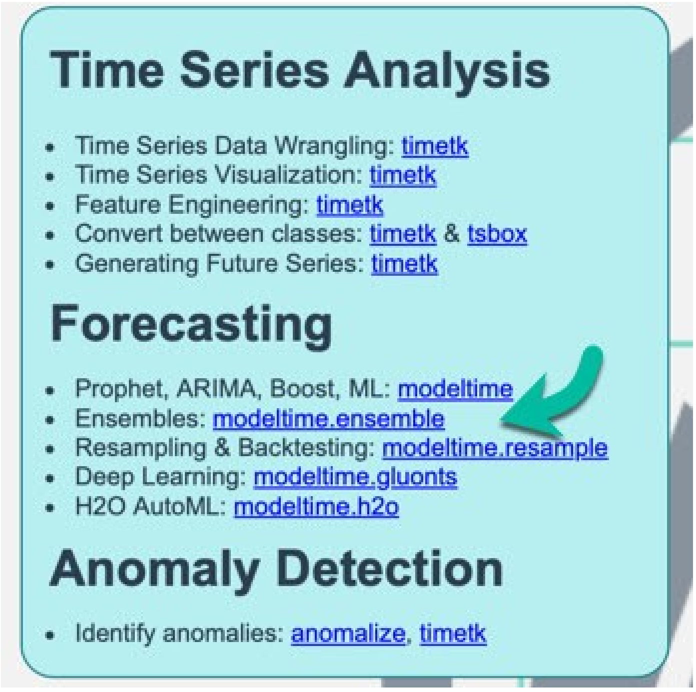
Next, we are going to create two models that we will then join into an ensemble.

1. **The first model is an Elastic Net (GLMNET) model:** An elastic net applies is an improved version of linear regression that applies a penalty to the lagged regressors preventing bad lags from dominating the results. This can show an improvement versus a standard Linear Regression.

2. **The second model is an XGBOOST model:** An xgboost model is a tree-based algorithm that is very different in how it models vs a linear model. It's much better for non-linear data (e.g. seasonality).

```
model_fit_glmnet <- linear_reg(penalty = 1) %>%
    set_engine("glmnet") %>%
    fit(value ~ ., data = train_data)

model_fit_xgboost <- boost_tree("regression", learn_rate =
0.35) %>%
    set_engine("xgboost") %>%
    fit(value ~ ., data = train_data)
```

Create a Recursive Ensemble



Ultimate R Cheat Sheet

The next step is to create an ensemble with `modeltime.ensemble` (Refer to the Ultimate R Cheat Sheet).

We'll use a Weighted Ensemble `ensemble_weighted()` with a 40/60 loading (GLMNET-to-XGBOOST).

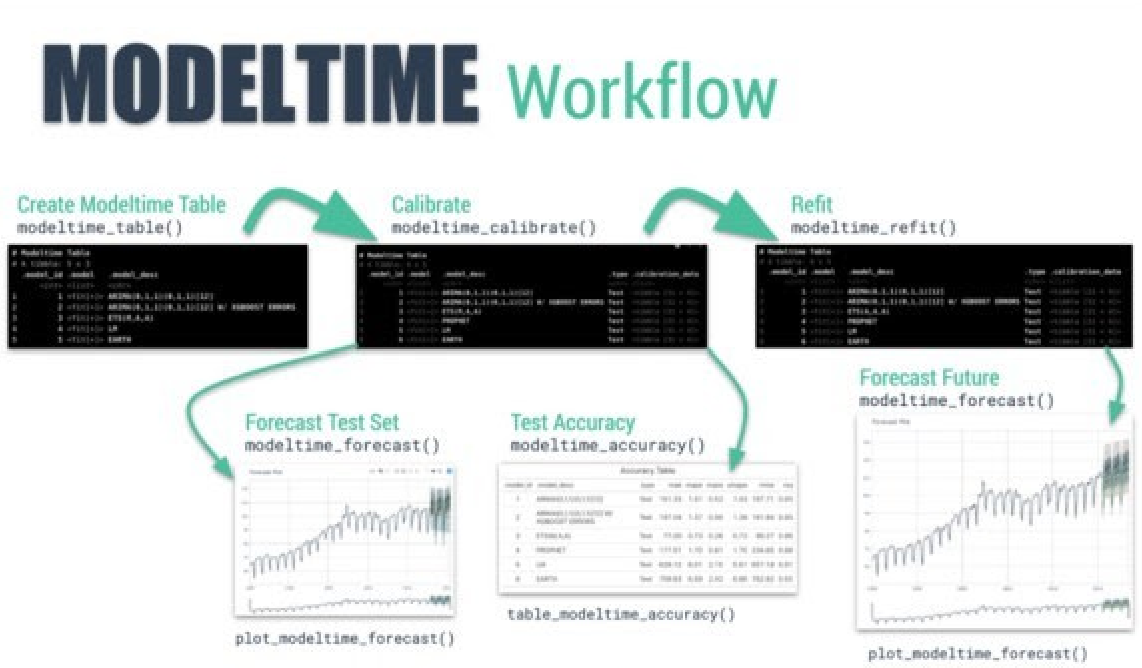
Right after that we use the `recursive()` function to create the recursive model:

- **`transform`**: The transform function gets passed to `recursive`, which tells the predictions how to generate the lagged features
- **`train_tail`**: We have to use the `panel_tail()` function to create the train_tail by group.
- **`id`**: This indicates how the time series panels are grouped within the incoming dataset.

```
recursive_ensemble_panel <- modeltime_table(
    model_fit_glmnet,
    model_fit_xgboost
) %>%
    ensemble_weighted(loadings = c(4, 6)) %>%
    recursive(
        transform  = lag_transformer_grouped,
        train_tail = panel_tail(train_data, id,
FORECAST_HORIZON),
        id         = "id"
    )

recursive_ensemble_panel

## Recursive [modeltime ensemble]
##
## ── Modeltime Ensemble ──────────────────────────────
─────────────
## Ensemble of 2 Models (WEIGHTED)
##
## # Modeltime Table
## # A tibble: 2 x 4
##   .model_id .model   .model_desc .loadings
##
## 1          1  GLMNET             0.4
## 2          2  XGBOOST            0.6
```

Modeltime Table

Next, we add the recursive ensemble to the `modeltime_table()`, which organizes one or more models prior to forecasting. Refer to the Ultimate R Cheat Sheet for the full Modeltime Documentation with Workflow.



A streamlined workflow for forecasting

Ultimate R Cheat Sheet links to Modeltime Workflow

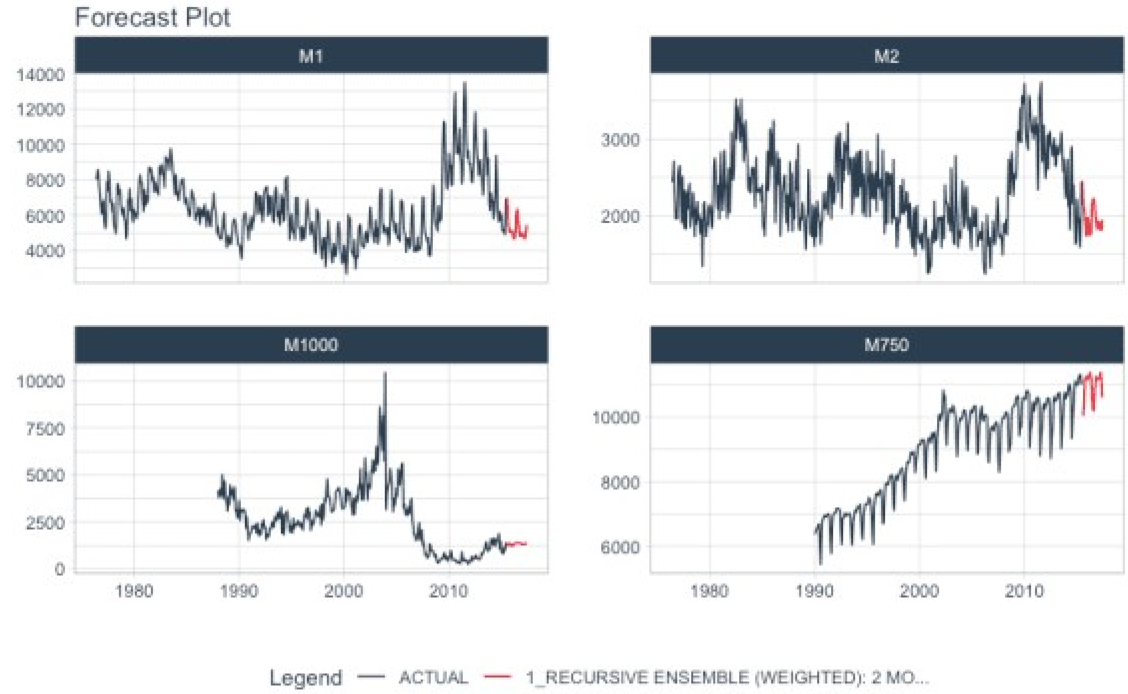
```
model_tbl <- modeltime_table(
    recursive_ensemble_panel
)

model_tbl

## # Modeltime Table
## # A tibble: 1 x 3
##   .model_id .model         .model_desc
##
## 1         1  RECURSIVE ENSEMBLE (WEIGHTED): 2 MODELS
```

Forecast the Ensemble

Finally, we forecast over our dataset and visualize the forecast by following the Modeltime Workflow.

- Use `modeltime_forecast()` to make the forecast
- Use `plot_modeltime_forecast()` to visualize the predictions

```
model_tbl %>%
    modeltime_forecast(
        new_data    = future_data,
        actual_data = m4_lags,
        keep_data   = TRUE
    ) %>%
    group_by(id) %>%
    plot_modeltime_forecast(
        .interactive        = FALSE,
        .conf_interval_show = FALSE,
        .facet_ncol         = 2
    )
```



It gets better
You’ve just scratched the surface,…