Let's Get Started

```
library(tidyverse)
library(timetk)

# Setup for the plotly charts (# FALSE returns ggplots)
interactive <- TRUE
```

Correlation Plots

`plot_acf_diagnostics()` returns the ACF and PACF of a target and optionally CCF's of one or more lagged predictors in interactive plotly plots. We also scale to multiple time series using `group_by()`.

- ACF = Autocorrelation between a target variable and lagged versions of itself.
- PACF = Partial Autocorrelation removes the dependence of lags on other lags highlighting key seasonalities.
- CCF = Shows how lagged predictors can be used for prediction of a target variable.

Lag Specification

Lags (`.lags`) can either be specified as:

- A time-based phrase indicating a duraction (e.g. 2 months)
- A maximum lag (e.g. .lags = 28)
- A sequence of lags (e.g. .lags = 7:28)

Scales to Multiple Time Series with Groups

The `plot_acf_diagnostics()` works with grouped_df's, meaning you can group your time series by one or more categorical columns with `dplyr::group_by()` and then apply `plot_acf_diagnostics()` to return group-wise lag diagnostics.

Special Note on Groups

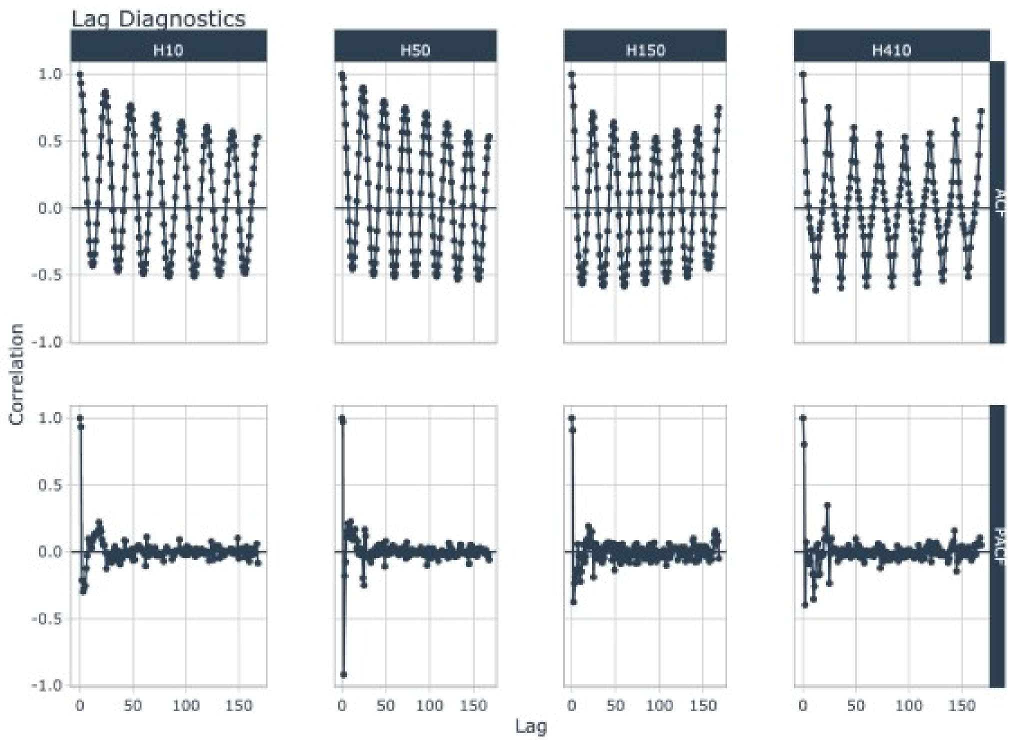
Unlike other plotting utilities, the .facet_vars arguments is NOT included. Use `dplyr::group_by()` for processing multiple time series groups.

Calculating the White Noise Significance Bars

The formula for the significance bars is +2/sqrt(T) and -2/sqrt(T) where T is the length of the time series. For a white noise time series, 95% of the data points should fall within this range. Those that don't may be significant autocorrelations.

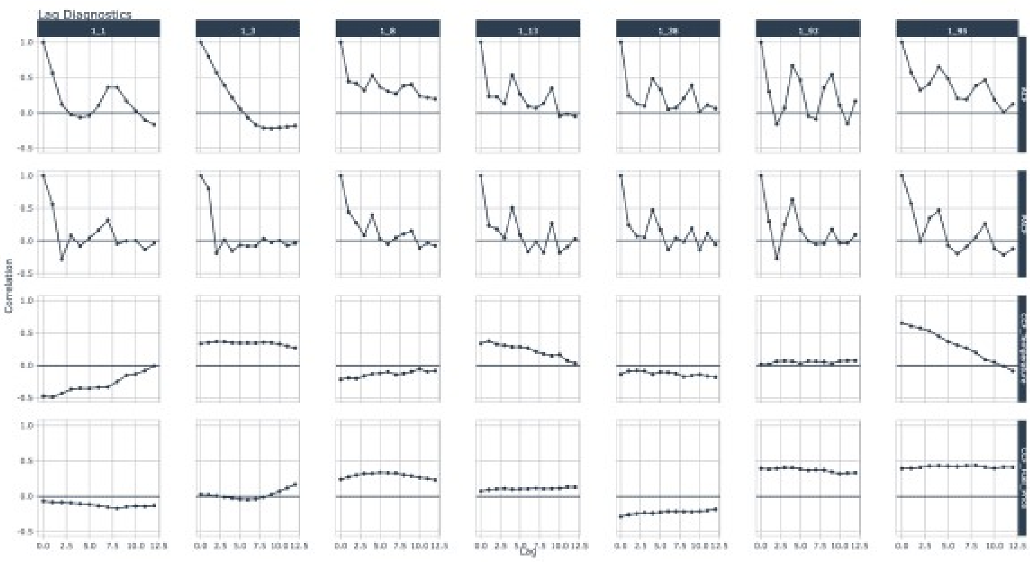
Grouped ACF Diagnostics

```
m4_hourly %>%
    group_by(id) %>%
    plot_acf_diagnostics(
        date, value,               # ACF & PACF
        .lags = "7 days",          # 7-Days of hourly lags
        .interactive = interactive
    )
```



Grouped CCF Plots

```
walmart_sales_weekly %>%
    select(id, Date, Weekly_Sales, Temperature, Fuel_Price) %>%
    group_by(id) %>%
    plot_acf_diagnostics(
        Date, Weekly_Sales,        # ACF & PACF
        .ccf_vars    = c(Temperature, Fuel_Price),   # CCFs
        .lags        = "3 months",    # 3 months of weekly lags
        .interactive = interactive
    )
```



Seasonality

`plot_seasonal_diagnostics()` is an interactive and scalable function for visualizing time series seasonality.

Automatic Feature Selection

Internal calculations are performed to detect a sub-range of features to include using the following logic:

- The *minimum* feature is selected based on the median difference between consecutive timestamps
- The *maximum* feature is selected based on having 2 full periods.

Example: Hourly timestamp data that lasts more than 2 weeks will have the following features: “hour”, “wday.lbl”, and “week”.

Scalable with Grouped Data Frames

This function respects grouped data.frame and tibbles that were made with `dplyr::group_by()`.

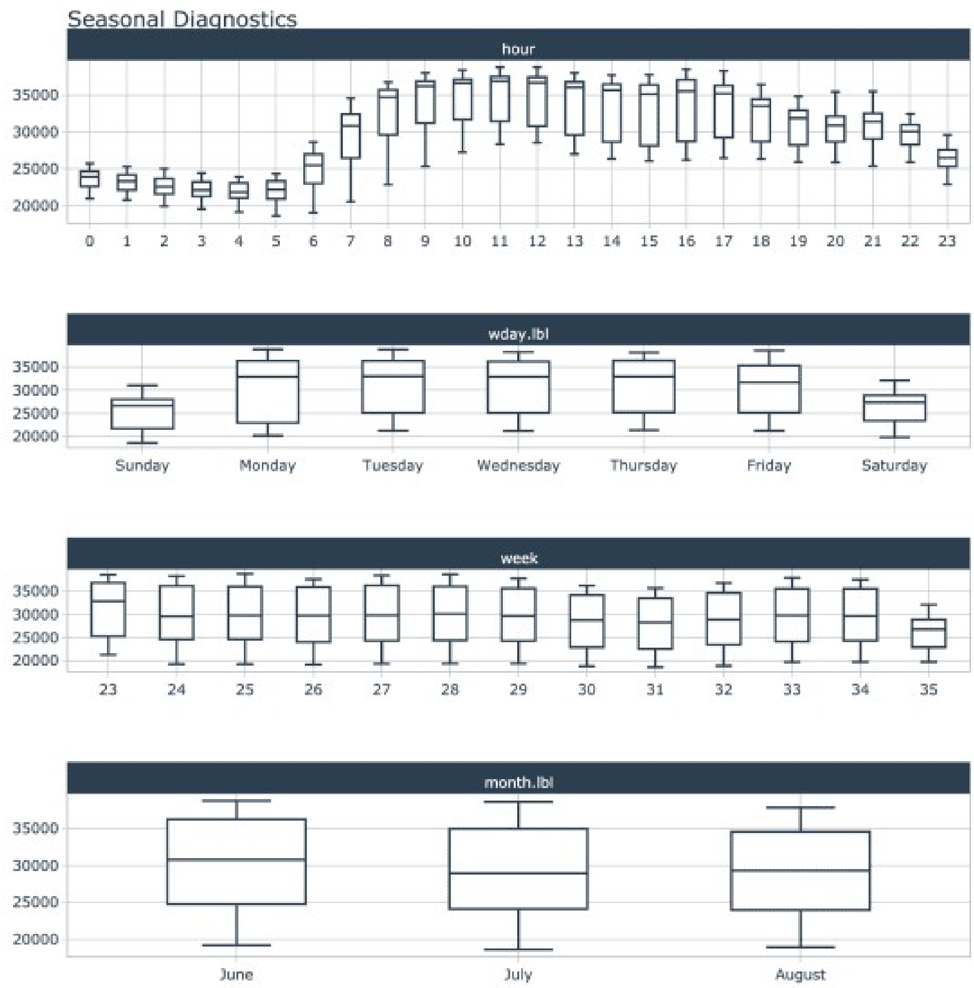
For grouped data, the automatic feature selection returned is a collection of all features within the sub-groups. This means extra features are returned even though they may be meaningless for some of the groups.

Transformations

The `.value` parameter respects transformations (e.g. .value = log(sales))

Seasonal Visualizations

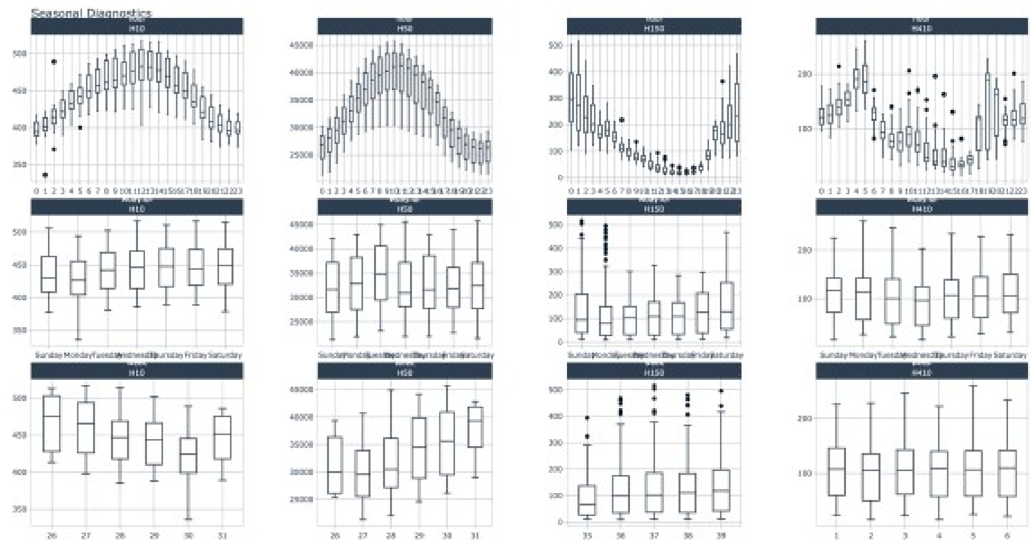
```
taylor_30_min %>%
    plot_seasonal_diagnostics(date, value, .interactive = interactive)
```



Grouped Seasonal Visualizations

```
m4_hourly %>%
```

```
    group_by(id) %>%
    plot_seasonal_diagnostics(date, value, .interactive = interactive)
```



STL Diagnostics

The `plot_stl_diagnostics()` function generates a Seasonal-Trend-Loess decomposition. The function is “tidy” in the sense that it works on data frames and is designed to work with dplyr groups.

STL method

The STL method implements time series decomposition using the underlying `stats::stl()`. The decomposition separates the “season” and “trend” components from the “observed” values leaving the “remainder”.

Frequency & Trend Selection

The user can control two parameters: `.frequency` and `.trend`.

- The `.frequency` parameter adjusts the “season” component that is removed from the “observed” values.
- The `.trend` parameter adjusts the trend window (`t.window` parameter from `stl()`) that is used.

The user may supply both `.frequency` and `.trend` as time-based durations (e.g. “6 weeks”) or numeric values (e.g. 180) or “auto”, which automatically selects the frequency and/or trend based on the scale of the time series.

```
m4_hourly %>%
    group_by(id) %>%
    plot_stl_diagnostics(
        date, value,
        .frequency = "auto", .trend = "auto",
        .feature_set = c("observed", "season", "trend", "remainder"),
        .interactive = interactive)
```

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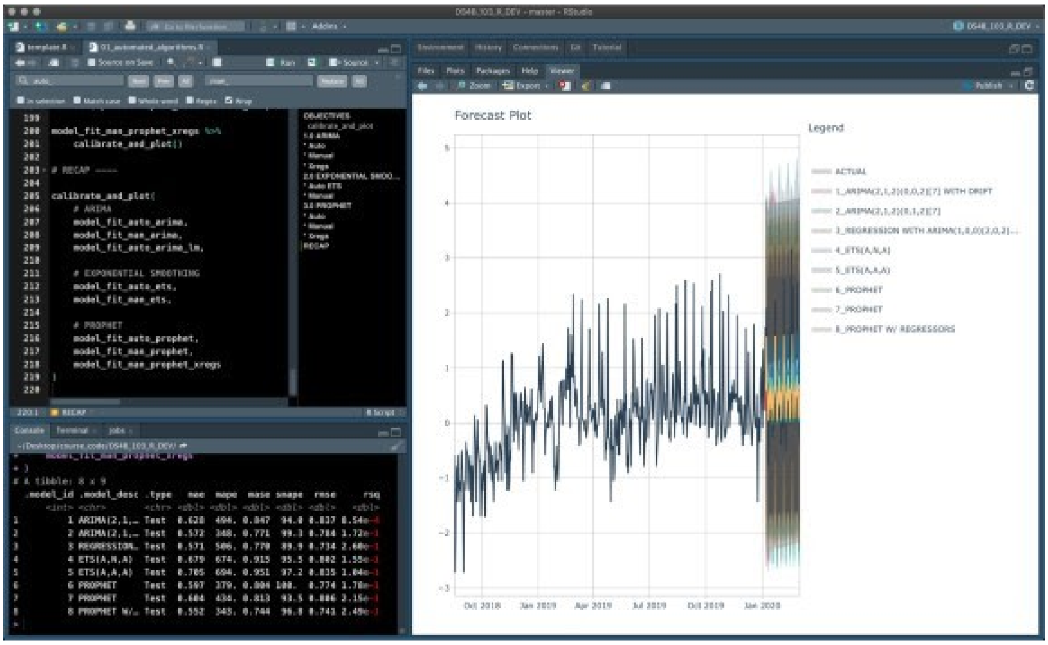

You will learn:

- Time Series Preprocessing, Noise Reduction, & Anomaly Detection
- Feature engineering using lagged variables & external regressors
- Hyperparameter tuning
- Time series cross-validation
- Ensembling Multiple Machine Learning & Univariate Modeling Techniques (Competition Winner)
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