In this tutorial, we’ll show how we used clean\_anomalies() from the anomalize package to ***reduce forecast error by 9%.***

**R Packages Covered**:

* anomalize – Time series anomaly detection

**Cleaning Anomalies to Reduce Forecast Error by 9%**

We can often improve forecast performance by cleaning anomalous data prior to forecasting. This is the perfect use case for integrating the clean\_anomalies() function from anomalize into your ***forecast workflow***.

**Forecast Workflow**

We’ll use the following workflow to remove time series anomalies prior to forecasting.

1. **Identify the anomalies** – Decompose the time series with time\_decompose() and anomalize() the remainder (residuals)
2. **Clean the anomalies** – Use the new clean\_anomalies() function to reconstruct the time series, replacing anomalies with the trend and seasonal components
3. **Forecast** – Use a forecasting algorithm to predict new observations from a training set, then compare to test set with and without anomalies cleaned

**Step 1 – Load Libraries**

First, load the following libraries to follow along.

library(tidyverse) # Core data manipulation and visualization libraries

library(tidyquant) # Used for business-ready ggplot themes

library(anomalize) # Identify and clean time series anomalies

library(timetk) # Time Series Machine Learning Features

library(knitr) # For kable() function

**Step 2 – Get the Data**

This tutorial uses the tidyverse\_cran\_downloads dataset that comes with anomalize. These are the historical downloads of several “tidy” R packages from 2017-01-01 to 2018-03-01.

Let’s take one package with some extreme events. We’ll hone in on lubridate (but you could pick any).

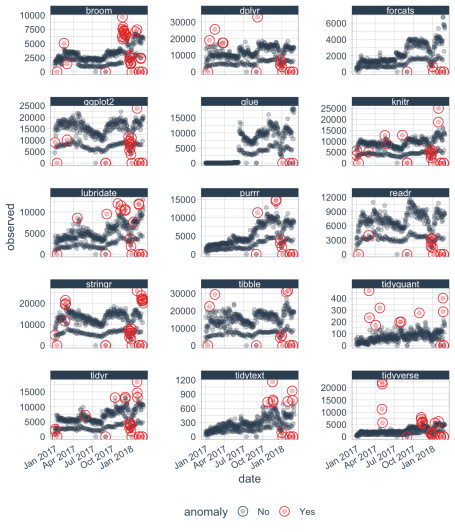
tidyverse\_cran\_downloads %>%

time\_decompose(count) %>%

anomalize(remainder) %>%

time\_recompose() %>%

plot\_anomalies(ncol = 3, alpha\_dots = 0.3)



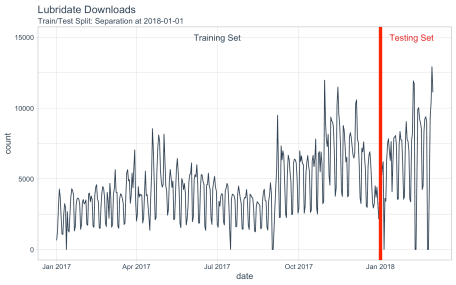
We’ll filter() downloads of the lubridate R package.

lubridate\_tbl <- tidyverse\_cran\_downloads %>%

ungroup() %>%

filter(package == "lubridate")

Here’s a visual representation of the forecast experiment setup. Training data will be any data before “2018-01-01”.



**Step 3 – Workflow for Cleaning Anomalies**

The workflow to clean anomalies:

1. We decompose the “counts” column using time\_decompose() – This returns a Seasonal-Trend-Loess (STL) Decomposition in the form of “observed”, “season”, “trend” and “remainder”.
2. We fix any negative values – If present, they can throw off forecasting transformations (e.g. log and power transformations)
3. We identifying anomalies (anomalize()) on the “remainder” column – Returns “remainder\_l1” (lower limit), “remainder\_l2” (upper limit), and “anomaly” (Yes/No).
4. We use the function, **clean\_anomalies()**, to add new column called “observed\_cleaned” that ***repairs the anomalous data*** by replacing all anomalies with the trend + seasonal components from the decompose operation.

lubridate\_anomalized\_tbl <- lubridate\_tbl %>%

# 1. Decompose download counts and anomalize the STL decomposition remainder

time\_decompose(count) %>%

# 2. Fix negative values if any in observed

mutate(observed = ifelse(observed < 0, 0, observed)) %>%

# 3. Identify anomalies

anomalize(remainder) %>%

# 4. Clean & repair anomalous data

clean\_anomalies()

# Show change in observed vs observed\_cleaned

lubridate\_anomalized\_tbl %>%

filter(anomaly == "Yes") %>%

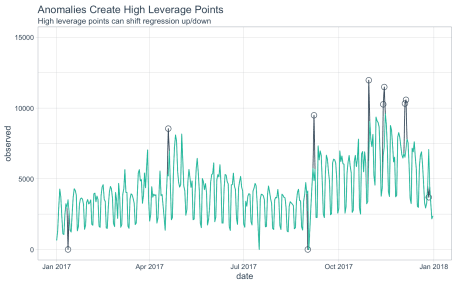
select(date, anomaly, observed, observed\_cleaned) %>%

head() %>%

kable()

| **date** | **anomaly** | **observed** | **observed\_cleaned** |
| --- | --- | --- | --- |
| 2017-01-12 | Yes | 0 | 3522.194 |
| 2017-04-19 | Yes | 8549 | 5201.716 |
| 2017-09-01 | Yes | 0 | 4136.721 |
| 2017-09-07 | Yes | 9491 | 4871.176 |
| 2017-10-30 | Yes | 11970 | 6412.571 |
| 2017-11-13 | Yes | 10267 | 6640.871 |

Here’s a visual of the “observed” (uncleaned) vs the “observed\_cleaned” (cleaned) training sets. We’ll see what influence these anomalies have on a forecast regression (next).



**Step 4 – Forecasting Downloads of the Lubridate Package**

First, we’ll make a function, forecast\_downloads(), that can take the input of both cleaned and uncleaned anomalies and return the forecasted downloads versus actual downloads. The modeling function is described in the [Appendix – Forecast Downloads Function](https://www.business-science.io/code-tools/2019/09/30/anomalize-improve-forecast.html#appendix).

**Step 4.1 – Before Cleaning with anomalize**

We’ll first perform a forecast without cleaning anomalies (high leverage points).

* The forecast\_downloads() function trains on the “observed” (uncleaned) data and returns predictions versus actual.
* Internally, a power transformation (square-root) is applied to improve the forecast due to the multiplicative properties.
* The model uses a linear regression of the form sqrt(observed) ~ numeric index + year + quarter + month + day of week.

lubridate\_forecast\_with\_anomalies\_tbl <- lubridate\_anomalized\_tbl %>%

# See Apendix - Forecast Downloads Function

forecast\_downloads(

col\_train = observed, # First train with anomalies included

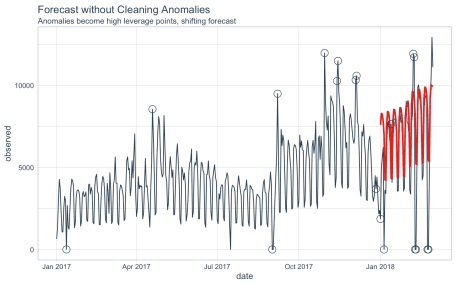
sep = "2018-01-01", # Separate at 1st of year

trans = "sqrt" # Perform sqrt() transformation

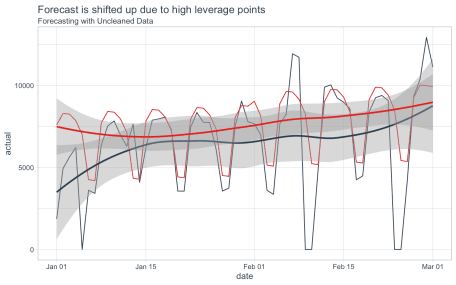
)

**Forecast vs Actual Values**

The forecast is overplotted against the actual values.



We can see that the forecast is shifted vertically, an effect of the high leverage points.



**Forecast Error Calculation**

***The mean absolute error (MAE) is 1570***, meaning on average the forecast is off by 1570 downloads each day.

lubridate\_forecast\_with\_anomalies\_tbl %>%

summarise(mae = mean(abs(prediction - actual)))

## # A tibble: 1 x 1

## mae

##

## 1 1570.

**Step 4.2 – After Cleaning with anomalize**

We’ll next perform a forecast this time using the repaired data from clean\_anomalies().

* The forecast\_downloads() function trains on the “observed\_cleaned” (cleaned) data and returns predictions versus actual.
* Internally, a power transformation (square-root) is applied to improve the forecast due to the multiplicative properties.
* The model uses a linear regression of the form sqrt(observed\_cleaned) ~ numeric index + year + quarter + month + day of week

lubridate\_forecast\_without\_anomalies\_tbl <- lubridate\_anomalized\_tbl %>%

# See Appendix - Forecast Downloads Function

forecast\_downloads(

col\_train = observed\_cleaned, # Forecast with cleaned anomalies

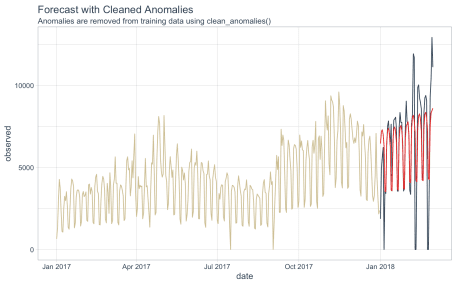
sep = "2018-01-01", # Separate at 1st of year

trans = "sqrt" # Perform sqrt() transformation

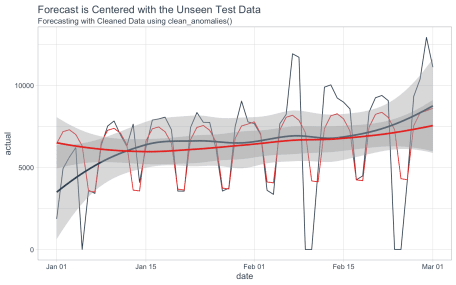
)

**Forecast vs Actual Values**

The forecast is overplotted against the actual values. The cleaned data is shown in Yellow.



Zooming in on the forecast region, we can see that the forecast does a better job following the trend in the test data.



**Forecast Error Calculation**

***The mean absolute error (MAE) is 1435***, meaning on average the forecast is off by 1435 downloads each day.

lubridate\_forecast\_without\_anomalies\_tbl %>%

summarise(mae = mean(abs(prediction - actual)))

## # A tibble: 1 x 1

## mae

##

## 1 1435.

**8.6% Reduction in Forecast Error**

Using the new anomalize function, clean\_anomalies(), prior to forecasting results in an **8.6% reduction in forecast error** as measure by Mean Absolute Error (MAE).

((1435 - 1570) / 1570)

## [1] -0.08598726

**Conclusion**

Forecasting with clean anomalies is a good practice that can provide **substantial improvement to forecasting accuracy by removing high leverage points**. The new clean\_anomalies() function in the anomalize package provides an easy workflow for removing anomalies prior to forecasting. Learn more in the [anomalize documentation](https://business-science.github.io/anomalize/).

**Data Science Training**

**Interested in Learning Anomaly Detection?**

Business Science offers two 1-hour labs on Anomaly Detection:

* [Learning Lab 18](https://university.business-science.io/p/learning-labs-pro) – Time Series Anomaly Detection with anomalize
* [Learning Lab 17](https://university.business-science.io/p/learning-labs-pro) – Anomaly Detection with H2O Machine Learning

**Interested in Improving Your Forecasting?**

Business Science offers a 1-hour lab on increasing Forecasting Accuracy:

* [Learning Lab 5](https://university.business-science.io/p/learning-labs-pro) – 5 Strategies to Improve Forecasting Performance by 50% (or more) using arima and glmnet

**Interested in Becoming an Expert in Data Science for Business?**

Business Science offers a [3-Course Data Science for Business R-Track](https://university.business-science.io/p/machine-learning-web-apps-level-1-bundle-r-track-courses-101-102-201) designed to take students from no experience to an expert data scientists (advanced machine learning and web application development) in under 6-months.

**Appendix – Forecast Downloads Function**

The forecast\_downloads() function uses the following procedure:

* Split the data into training and testing data using a date specified using the sep argument.
* Apply a statistical transformation: none, log-1-plus (log1p()), or power (sqrt())
* Model the daily time series of the training data set from observed (demonstrates no cleaning) or observed and cleaned (demonstrates improvement from cleaning). Specified by the col\_train argument.
* Compares the predictions to the observed values.

forecast\_downloads <- function(data, col\_train,

sep = "2018-01-01",

trans = c("none", "log1p", "sqrt")) {

predict\_expr <- enquo(col\_train)

trans <- trans[1]

# Spit into training/testing sets

train\_tbl <- data %>% filter(date < ymd(sep))

test\_tbl <- data %>% filter(date >= ymd(sep))

# Apply Transformation

pred\_form <- quo\_name(predict\_expr)

if (trans != "none") pred\_form <- str\_glue("{trans}({pred\_form})")

# Make the model formula

model\_formula <- str\_glue("{pred\_form} ~ index.num + half

+ quarter + month.lbl + wday.lbl") %>%

as.formula()

# Apply model formula to data that is augmented with time-based features

model\_glm <- train\_tbl %>%

tk\_augment\_timeseries\_signature() %>%

glm(model\_formula, data = .)

# Make Prediction

suppressWarnings({

# Suppress rank-deficit warning

prediction <- predict(model\_glm, newdata = test\_tbl %>%

tk\_augment\_timeseries\_signature())

actual <- test\_tbl %>% pull(!! actual\_expr)

})

if (trans == "log1p") prediction <- expm1(prediction)

if (trans == "sqrt") prediction <- ifelse(prediction < 0, 0, prediction)^2

# Return predictions and actual

tibble(

date = tk\_index(test\_tbl),

prediction = prediction,

actual = observed

)

}