Modeling Demand

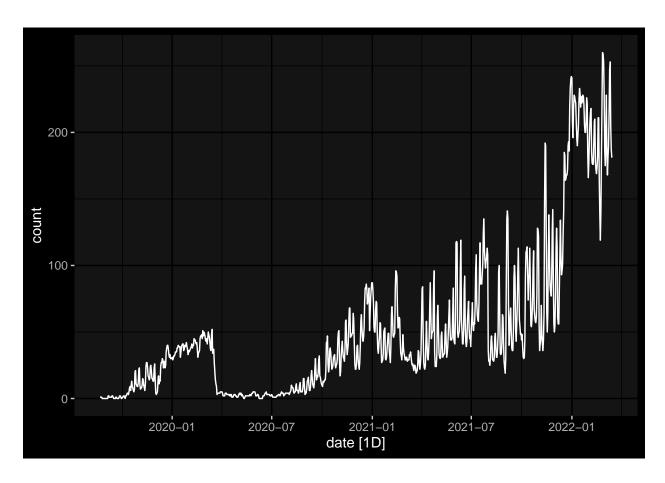
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2022-03-28

Data loading

Reservations across time

Plot variable not specified, automatically selected `.vars = count`



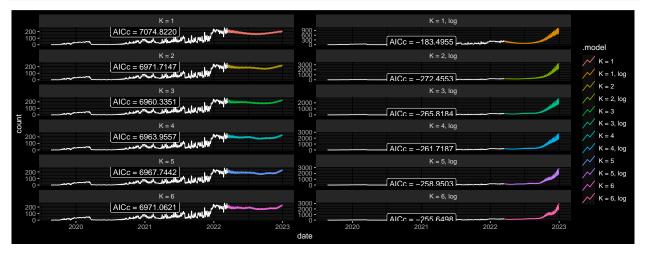
Forecasting

Dynamic Harmonic Regression

To forecast with this dataset, we need a model that captures multiple seasonalities and is robust to sudden changes (like the pandemic). Also, as the seasonality effects seems to scale with the response variable magnitude, it is reasonable to test applying a log transform prior to modeling. For these reasons, a dynamic harmonic regression model is fitted using Fourier terms to account for seasonality and an ARMA model to account for short-term dynamics.

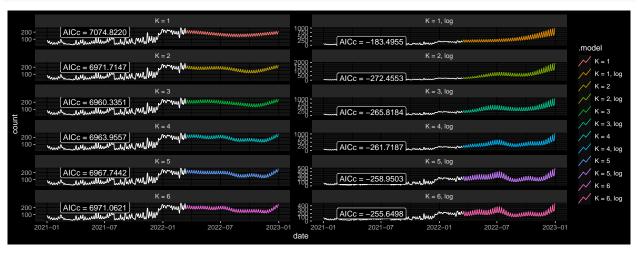
```
dynamic_harmonic_regression <- function(K, log_transform=FALSE){</pre>
  K_{weekly} \leftarrow if (K > 3) \{3\} else \{K\}
  if(log_transform){
    ARIMA(log(count) ~ PDQ(0, 0, 0)
                        + fourier(K=K_weekly, period=7)
                        + fourier(K=K, period=365.25)
                        + is.workday)
  } else{
    ARIMA(count ~ PDQ(0, 0, 0)
                   + fourier(K=K_weekly, period=7)
                   + fourier(K=K, period=365.25)
                   + is.workday)
  }
}
fit <- reservations.daily %>%
  mutate(count=count + 1) %>%
```

```
model("K = 1"
                     = dynamic_harmonic_regression(K=1),
        "K = 2"
                     = dynamic_harmonic_regression(K=2),
        "K = 3"
                     = dynamic_harmonic_regression(K=3),
        "K = 4"
                     = dynamic_harmonic_regression(K=4),
        "K = 5"
                     = dynamic_harmonic_regression(K=5),
        "K = 6"
                     = dynamic_harmonic_regression(K=6),
        "K = 1, log" = dynamic_harmonic_regression(K=1, log_transform = TRUE),
        "K = 2, log" = dynamic harmonic regression(K=2, log transform = TRUE),
        "K = 3, log" = dynamic_harmonic_regression(K=3, log_transform = TRUE),
        "K = 4, log" = dynamic_harmonic_regression(K=4, log_transform = TRUE),
        "K = 5, log" = dynamic_harmonic_regression(K=5, log_transform = TRUE),
        "K = 6, log" = dynamic_harmonic_regression(K=6, log_transform = TRUE))
reservations.daily.new.data <- reservations.daily %>%
  new_data(291L) %>%
  mutate(is.workday = !(timeDate::isWeekend(date)
                        | (date %in% holidaysANBIMA)))
fit %>%
  forecast(new_data=reservations.daily.new.data) %>%
  autoplot(reservations.daily, level=NULL) +
  facet_wrap(vars(.model), ncol=2, scale="free_y") +
  geom_label(
    aes(x = ymd("2021-01-01"), y = 200,
        label = paste0("AICc = ", format(AICc))),
    data = glance(fit))
```



DHR excluding COVID lockdowns in 2022 and prior data

```
= dynamic_harmonic_regression(K=5),
        "K = 6"
                     = dynamic_harmonic_regression(K=6),
        "K = 1, log" = dynamic_harmonic_regression(K=1, log_transform = TRUE),
        "K = 2, log" = dynamic_harmonic_regression(K=2, log_transform = TRUE),
        "K = 3, log" = dynamic_harmonic_regression(K=3, log_transform = TRUE),
        "K = 4, log" = dynamic_harmonic_regression(K=4, log_transform = TRUE),
        "K = 5, log" = dynamic_harmonic_regression(K=5, log_transform = TRUE),
        "K = 6, log" = dynamic harmonic regression(K=6, log transform = TRUE))
reservations.daily.COVID.excluded.new.data <- reservations.daily.COVID.excluded %>%
  new data(291L) %>%
  mutate(is.workday = !(timeDate::isWeekend(date))
                        | (date %in% holidaysANBIMA)))
fit.COVID.excluded %>%
  forecast(new_data=reservations.daily.COVID.excluded.new.data) %>%
  autoplot(reservations.daily.COVID.excluded,
           level=NULL) +
  facet_wrap(vars(.model), ncol=2, scale="free_y") +
  geom_label(
    aes(x = ymd("2021-06-01"), y = 200,
        label = paste0("AICc = ", format(AICc))),
    data = glance(fit))
```



K hyperparameter tuning

```
data = glance(fit))
models <- reservations.daily.COVID.excluded %>%
  filter_index(~ "2022-03-04") %>%
  stretch_tsibble(.init = 369, .step=10) %>%
    "K = 1" = dynamic_harmonic_regression(K=1, log_transform=TRUE),
    "K = 2" = dynamic_harmonic_regression(K=2, log_transform=TRUE),
    "K = 5" = dynamic_harmonic_regression(K=5, log_transform=TRUE)#, Cached
    # "K = 10" = dynamic_harmonic_regression(K=10, log_transform=TRUE),
    # "K = 20" = dynamic_harmonic_regression(K=20, log_transform=TRUE),
    # "K = 30" = dynamic_harmonic_regression(K=30, log_transform=TRUE),
    # "K = 50" = dynamic_harmonic_regression(K=50, log_transform=TRUE)
CV.data <- reservations.daily.COVID.excluded %>%
  filter_index(~ "2022-03-04") %>%
  stretch_tsibble(.init = 369, .step=10) %>%
  new_data(10L) %>%
  mutate(is.workday = !(timeDate::isWeekend(date)
                        | (date %in% holidaysANBIMA)))
results <- models %>%
  forecast(new data=CV.data) %>%
  accuracy(reservations.daily.COVID.excluded) %>%
  select(.model, RMSE:MAPE)
results %>% arrange(RMSE)
## # A tibble: 3 x 5
##
     .model RMSE MAE
                        MPE MAPE
     <chr> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 K = 1 48.5 38.6 -8.35 19.0
## 2 K = 2 53.8 40.2 -5.59 19.3
## 3 K = 5
           55.7 42.6 11.0 20.5
cross.validate.for <- function(K){</pre>
  model_for_K <- reservations.daily.COVID.excluded %>%
    filter_index(~ "2022-03-04") %>%
    stretch_tsibble(.init = 369, .step=10) %>%
    model(dynamic_harmonic_regression(K=K, log_transform=TRUE))
  CV.data <- reservations.daily.COVID.excluded %>%
  filter_index(~ "2022-03-04") %>%
  stretch_tsibble(.init = 369, .step=10) %>%
  new_data(10L) %>%
  mutate(is.workday = !(timeDate::isWeekend(date)
                        | (date %in% holidaysANBIMA)))
  model_for_K %>%
  forecast(new_data=CV.data) %>%
  accuracy(reservations.daily.COVID.excluded) %>%
  select(.model, RMSE:MAPE)
}
```

```
parameter_metrics <- results %>%
  mutate(K=sapply(results$.model,
                 function(x){
                   parse_integer(substring(x, first=5))
                 })) %>%
  add_row(.model="K = 10", RMSE=82.92, MAE=64.47,
         MPE=9.77, MAPE=31.11, K=10L) %>%
  add row(.model="K = 20", RMSE=91.61, MAE=74.54,
         MPE=14.24, MAPE=35.70, K=20L) %>%
  add_row(.model="K = 30", RMSE=96.51, MAE=77.95,
         MPE=13.52, MAPE=37.41, K=30L) %>%
  add_row(.model="K = 50", RMSE=81.98, MAE=65.69,
          MPE=4.72, MAPE=31.93, K=50L) %>%
  add_row(.model="K = 100", RMSE=98.63, MAE=77.58,
         MPE=6.63, MAPE=38.10, K=100L) %>%
  add_row(.model="K = 60", RMSE=67.92, MAE=56.39,
         MPE=6.19, MAPE=27.67, K=60L) %>%
  add_row(.model="K = 40", RMSE=79.48, MAE=63.04,
         MPE=5.30, MAPE=30.54, K=40L) %>%
  add_row(.model="K = 70", RMSE=63.83, MAE=54.16,
          MPE=3.14, MAPE=26.76, K=70L) %>%
  add_row(.model="K = 80", RMSE=92.31, MAE=73.40,
         MPE=12.94, MAPE=35.53, K=80L) %>%
  add_row(.model="K = 65", RMSE=66.08, MAE=56.02,
         MPE=3.40, MAPE=27.61, K=65L) %>%
  add_row(.model="K = 75", RMSE=61.54, MAE=51.18,
         MPE=2.17, MAPE=25.34, K=75L) %>%
  add_row(.model="K = 77", RMSE=65.98, MAE=55.84,
         MPE=0.93, MAPE=27.39, K=77L) %>%
  add_row(.model="K = 73", RMSE=64.54, MAE=53.98,
         MPE=1.01, MAPE=26.69, K=73L) %>%
  arrange(K)
parameter_metrics
## # A tibble: 16 x 6
##
      .model
              RMSE
                     MAE
                           MPE MAPE
                                         K
##
             <dbl> <dbl> <dbl> <int>
      <chr>
## 1 K = 1
              48.5 38.6 -8.35
                                19.0
                                         1
## 2 K = 2
              53.8 40.2 -5.59
                                19.3
                                         2
##
   3 K = 5
              55.7 42.6 11.0
                                20.5
                                         5
## 4 K = 10
              82.9 64.5 9.77
                                31.1
                                         10
## 5 K = 20
              91.6 74.5 14.2
                                35.7
                                         20
## 6 K = 30
              96.5
                    78.0 13.5
                                37.4
                                         30
## 7 K = 40
              79.5 63.0 5.3
                                30.5
                                         40
## 8 K = 50
              82.0 65.7 4.72
                                31.9
                                         50
## 9 K = 60
              67.9
                    56.4 6.19
                                27.7
                                         60
## 10 K = 65
              66.1
                    56.0 3.4
                                 27.6
                                         65
## 11 K = 70
              63.8 54.2 3.14
                                26.8
                                        70
## 12 K = 73
              64.5 54.0 1.01
                                        73
                                26.7
## 13 K = 75
              61.5 51.2 2.17
                                25.3
                                        75
## 14 K = 77
              66.0
                    55.8 0.93
                                27.4
                                        77
```

80

100

35.5

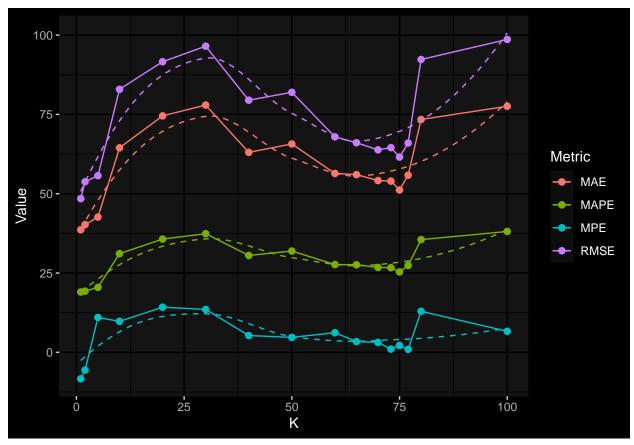
15 K = 80

92.3 73.4 12.9

16 K = 100 98.6 77.6 6.63 38.1

```
parameter_metrics %>%
  pivot_longer(RMSE:MAPE, names_to = "Metric", values_to = "Value") %>%
  ggplot(aes(x=K, y=Value, color=Metric)) +
  geom_point(size=2) +
  geom_line() +
  geom_smooth(se=FALSE, linetype="dashed", size=0.5)
```

`geom_smooth()` using method = 'loess' and formula 'y ~ x'



Final model selection The MPE may be seen as a bias metric while the other accuracy assessors act more like variance metrics. For this reason, since the model is expected to forecast to a distant horizon (291 days into the future), a low bias is prioritized and balanced with lesser possible variance.

