Challenge Answers

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Data loading

```
# Imports dataset made in EDA script
cwd <- getwd()
daily.revenue.listings <- read_csv(paste0(cwd, "/../data/output/daily_revenue_listings.csv"))
```

```
## Rows: 289021 Columns: 26
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr   (6): listing, Localização, Categoria, Hotel, Status, Tipo
## dbl  (17): last_offered_price, occupancy, revenue, blocked, reservation_adva...
## date  (3): date, creation_date, Data.Inicial.do.contrato
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Question 1

What is the expected price and revenue for a listing tagged as JUR MASTER 2Q in march?

The expected value for a random variable is better estimated by its average over observed values:

```
(daily.revenue.listings %>%
  select(date, Localização, Categoria, Quartos, last_offered_price, comission) %>%
  mutate(month=month(date, label=TRUE)) %>%
  filter(month=="mar",
         Localização=="JUR",
         Categoria=="MASTER",
         Quartos==2))
```

```
## # A tibble: 0 x 7
## # ... with 7 variables: date <date>, Localização <chr>, Categoria <chr>,
## #   Quartos <dbl>, last_offered_price <dbl>, comission <dbl>, month <ord>
```

However the query above returns 0 results. Therefore, it is necessary to model the data to predict price and revenue (comission earned by Seazone) from the 4 features: month, location, category and number of bedrooms. Two predictive models, also considered in the EDA script, are tested and applied below:

```
comission.earned.data <- daily.revenue.listings %>%
  filter(occupancy==1, blocked==0) %>%
  select(date, Localização, Categoria, Quartos,
         last_offered_price, revenue, Comissão) %>%
  mutate(month=month(date, label=TRUE)) %>%
  # Limits earnings data to only consolidated observations
```

```r
  mutate(across(c(Localização, Categoria), ~as.factor(.))) %>%
  filter(date <= "2022-03-15")


# Temporal subsetting
train <- comission.earned.data %>%
  filter(date <= "2022-01-31")

test <- comission.earned.data %>%
  filter(date > "2022-01-31")


# Linear model fitting
linear.model.price <- lm(last_offered_price ~ month + Localização + Categoria + Quartos, train)
linear.model.revenue <- lm(revenue ~ month + Localização + Categoria + Quartos, train)

# XGBoost model fitting
make.matrix.from <- function(data){
  as.matrix(data %>%
    select(-c(last_offered_price, revenue, Comissão, date)) %>%
    mutate(month=factor(month, levels=levels(month), ordered=FALSE)) %>%
    dummy_cols(remove_selected_columns = TRUE)
  )
}

train.matrix <- make.matrix.from(train)
test.matrix <- make.matrix.from(test%>%
                                  filter(Localização != "ILC",
                                         Localização != "JBV"))

xgboost.model.price <- xgboost(data=train.matrix,
                               label=train$last_offered_price,
                               nrounds=20,
                               max.depth=6,
                               verbose=0)
xgboost.model.revenue <- xgboost(data=train.matrix,
                                 label=train$revenue,
                                 nrounds=20,
                                 max.depth=6,
                                 verbose=0)


# Assessing model accuracy
RMSE <- function(predictions, response, filter_new_factors=FALSE){
  test.set <-
    if(filter_new_factors){
    test %>%
      filter(Localização != "ILC",
             Localização != "JBV")
    } else{
    test
    }
  n <- dim(test.set)[1]
```

```
  sqrt(sum((predictions - test.set[,response])^2)/n)
}

## Price
mean.predictions <- rep(mean(train$last_offered_price),  #Baseline
                        length(test$last_offered_price))
linear.predictions <- predict(linear.model.price,
                                test %>%
                                  filter(Localização != "ILC",
                                         Localização != "JBV"))
xgboost.predictions <- predict(xgboost.model.price, test.matrix)

RMSE(mean.predictions, "last_offered_price")    # 352.3382
RMSE(linear.predictions, "last_offered_price",  # 260.2715
     filter_new_factors = TRUE)
RMSE(xgboost.predictions, "last_offered_price", # 239.7306
     filter_new_factors = TRUE)

## Revenue
mean.predictions <- rep(mean(train$revenue),  #Baseline
                        length(test$revenue))
linear.predictions <- predict(linear.model.revenue,
                                test %>%
                                  filter(Localização != "ILC",
                                         Localização != "JBV"))
xgboost.predictions <- predict(xgboost.model.revenue, test.matrix)

RMSE(mean.predictions, "revenue")    # 351.9307
RMSE(linear.predictions, "revenue",  # 260.7388
     filter_new_factors = TRUE)
RMSE(xgboost.predictions, "revenue", # 239.9097
     filter_new_factors = TRUE)
```

Above, new locations are filtered in the test set since these models aim to estimate price and revenue under known conditions.

Finally, predicting for the required case:

```
case <- train %>%
  add_row(date=ymd("2022-03-01"), Localização="JUR", Categoria="MASTER",
          Quartos=2, last_offered_price=NA, revenue=NA, Comissão=0.2,
          month="mar") %>%
  mutate(month=ordered(month, levels=levels(train$month)))

case.matrix <- make.matrix.from(case)
case.index <- dim(case.matrix)[1]
case.row <- case %>% dplyr::slice(n())

predict(linear.model.price, case.row)                   # 586.2073
predict(xgboost.model.price, case.matrix)[case.index]   # 312.2011
predict(linear.model.revenue, case.row)                 # 586.2073
predict(xgboost.model.revenue, case.matrix)[case.index] # 312.2011
```

Comparing predictions to actual data, we might see that a good estimate should be in between R$ 383,00 and R$ 531,64.

```r
(comparison <- comission.earned.data %>%
  filter(Localização=="JUR", month=="mar", Categoria=="MASTER") %>%
  group_by(month, Localização, Categoria, Quartos) %>%
  summarise(avg_revenue=mean(revenue)))
```

```
## # A tibble: 3 x 5
## # Groups:   month, Localização, Categoria [1]
##   month Localização Categoria Quartos avg_revenue
##   <ord> <fct>       <fct>       <dbl>       <dbl>
## 1 mar   JUR         MASTER          1        383.
## 2 mar   JUR         MASTER          3        532.
## 3 mar   JUR         MASTER          4       2244.
```

To get inside this interval, an average between XGBoost and Linear model is taken. Only one value is predicted since the models setted the same value for both revenue and price.

```r
average.prediction <- mean(c(312.2011, 586.2073))
average.prediction
```

```
## [1] 449.2042
```

This process suggests an ensemble model:

```r
RMSE(0.1*linear.predictions + 0.9*xgboost.predictions,
     "revenue",
     filter_new_factors = TRUE)
```

```
## [1] 238.2749
```

```r
RMSE(0.2*linear.predictions + 0.8*xgboost.predictions,
     "revenue",
     filter_new_factors = TRUE)
```

```
## [1] 237.484
```

```r
RMSE(0.3*linear.predictions + 0.7*xgboost.predictions,
     "revenue",
     filter_new_factors = TRUE)
```

```
## [1] 237.5454
```

```r
RMSE(0.4*linear.predictions + 0.6*xgboost.predictions,
     "revenue",
     filter_new_factors = TRUE)
```

```
## [1] 238.4585
```

```r
RMSE(0.5*linear.predictions + 0.5*xgboost.predictions,
     "revenue",
     filter_new_factors = TRUE)
```

```
## [1] 240.2135
```

```r
RMSE(0.6*linear.predictions + 0.4*xgboost.predictions,
     "revenue",
     filter_new_factors = TRUE)
```

```
## [1] 242.7922
```

```r
RMSE(0.7*linear.predictions + 0.3*xgboost.predictions,
     "revenue",
     filter_new_factors = TRUE)
```

```
## [1] 246.1687
```

```r
RMSE(0.8*linear.predictions + 0.2*xgboost.predictions,
     "revenue",
     filter_new_factors = TRUE)
```

```
## [1] 250.3108
```

```r
RMSE(0.9*linear.predictions + 0.1*xgboost.predictions,
     "revenue",
     filter_new_factors = TRUE)
```

```
## [1] 255.1811
```

Answer

Using the ensemble as final predictor:

```r
final.prediction.price <- 0.2*586.2073 + 0.8*312.2011
# R$ 367,00

final.prediction.comission <- 0.2*final.prediction.price
# R$ 73,40
```

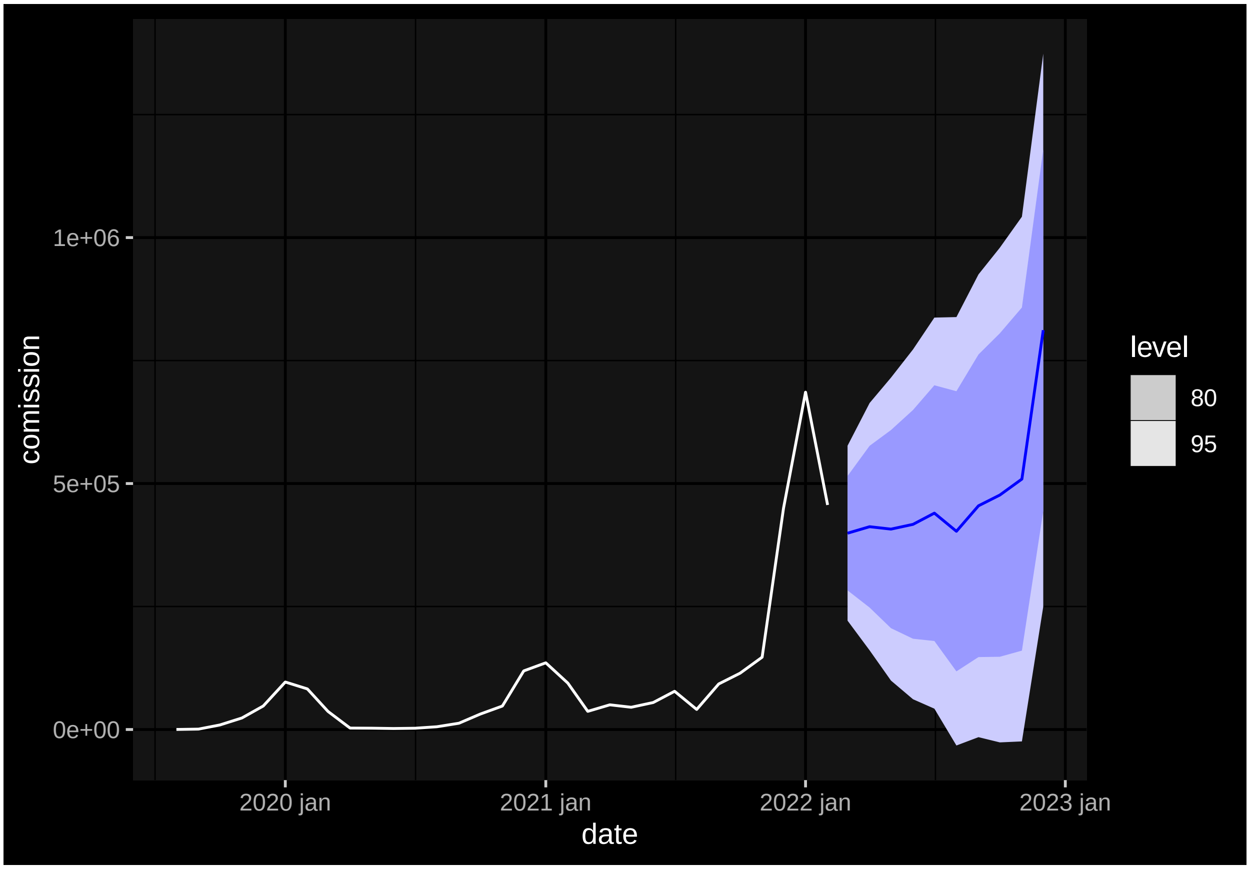
Even though it is not contained in the proposed interval, it is informed by all the data points rather than those few in the comparison table and should be a more robust prediction therefore.

Question 2

What is Seazone expected revenue for 2022? Why?

As developed in the Modeling script, a SARIMA(1, 0, 0)(0, 1, 0)[12] model, the best performer in cross-validation tests, forecasts the below results in terms of revenue for Seazone (comissions earned total):

```r
monthly.comissions <- daily.revenue.listings %>%
  select(date, comission) %>%
  mutate(date=yearmonth(date)) %>%
  group_by(date) %>%
  summarise(comission=sum(comission)) %>%
  as_tsibble(index=date) %>%
  filter_index(~"2022-02")

monthly.comissions.forecast <- monthly.comissions %>%
  model(ARIMA(comission)) %>%
  forecast(h=10)

monthly.comissions.forecast %>%
  autoplot(monthly.comissions)
```

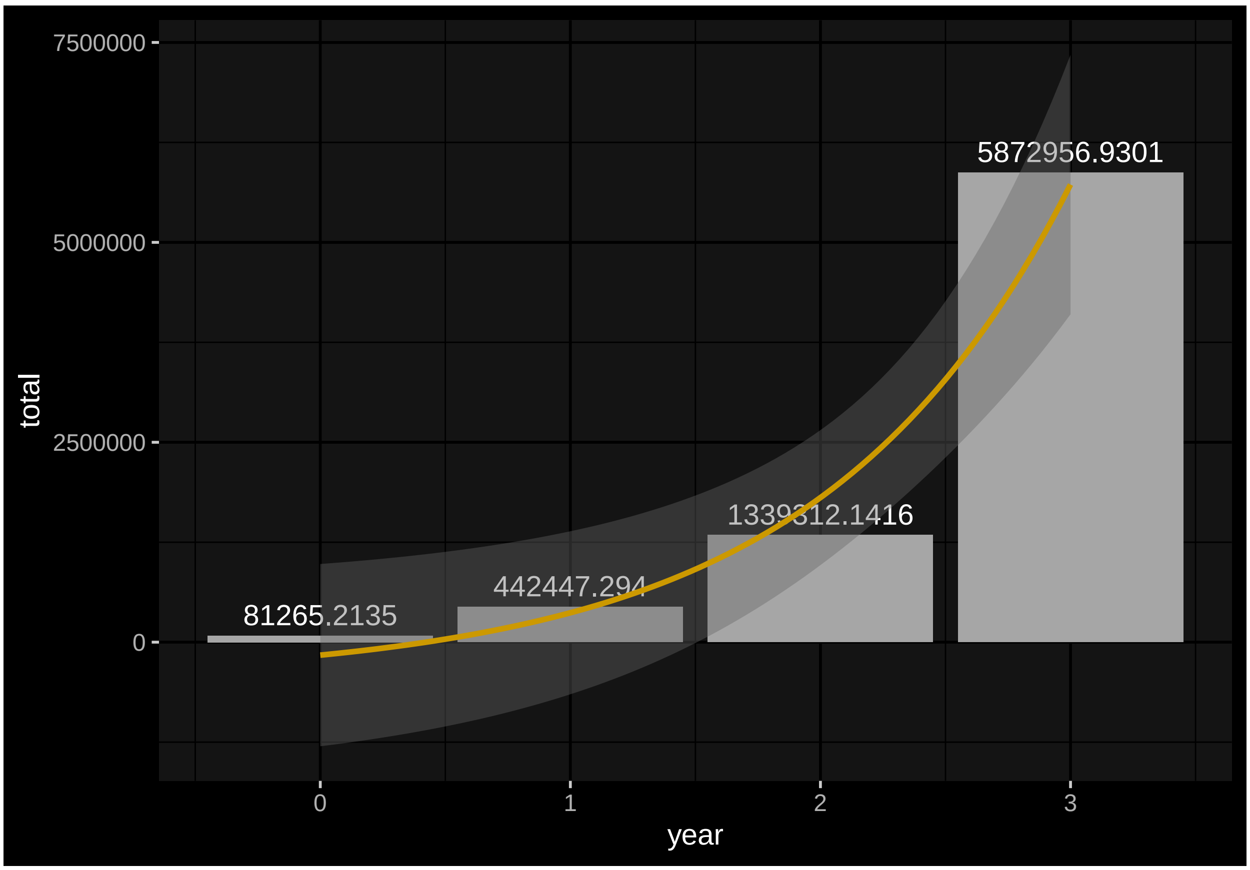



```
monthly.comissions.forecasted <- monthly.comissions.forecast %>%
  hilo() %>%
  unpack_hilo(c("80%", "95%")) %>%
  select(-c(.model, comission)) %>%
  rename(forecast=.mean)

monthly.comissions.actual.and.forecasted <- monthly.comissions %>%
  full_join(monthly.comissions.forecasted, by=c("date"="date"))

revenue_by_year <- monthly.comissions.actual.and.forecasted %>%
  as_tibble() %>%
  select(date, comission, forecast, "80%_lower", "80%_upper") %>%
  rename(upper80="80%_upper", lower80="80%_lower") %>%
  mutate(year=year(date)) %>%
  group_by(year) %>%
  summarise(realized=sum(comission, na.rm=TRUE),
            forecasted_mean=sum(forecast, na.rm=TRUE),
            upper80=sum(upper80, na.rm=TRUE),
            lower80=sum(lower80, na.rm=TRUE)) %>%
  mutate(total_lower=realized+lower80,
         total=realized+forecasted_mean,
         total_upper=realized+upper80)

revenue_by_year
```

```
## # A tibble: 4 x 8
```

```
##     year realized forecasted_mean  upper80 lower80 total_lower   total total_upper
##    <dbl>    <dbl>           <dbl>    <dbl>   <dbl>       <dbl>   <dbl>       <dbl>
## 1  2019   81265.               0        0  0            81265. 8.13e4      81265.
## 2  2020  442447.               0        0  0           442447. 4.42e5     442447.
## 3  2021 1339312.               0        0  0          1339312. 1.34e6    1339312.
## 4  2022 1142237.         4730720. 7342358.  2.12e6    3261319. 5.87e6    8484595.
```

```
revenue_by_year %>%
  mutate(year=year-2019) %>%
  ggplot(aes(x=year, y=total, label=total)) +
  geom_col() +
  geom_text(vjust=-0.5) +
  geom_smooth(method = "lm", formula = y ~ exp(x))
```



Answer

The predicted total revenue is in an 80% confidence interval ranging from R$ 3.261.318,82 to R$ 8.484.595,04 with expected value R$ 5.872.956,93