

# m09\_v01\_store\_sales\_prediction

September 12, 2021

## 1 0.0. IMPORTS

```
[1]: import math
import numpy as np
import pandas as pd
import random
import pickle
import warnings
import inflection
import seaborn as sns
import xgboost as xgb

from scipy import stats as ss
from boruta import BorutaPy
from matplotlib import pyplot as plt
from IPython.display import Image
from IPython.core.display import HTML

from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression, Lasso
from sklearn.preprocessing import RobustScaler, MinMaxScaler, LabelEncoder

warnings.filterwarnings( 'ignore' )
```

### 1.1 0.1. Helper Functions

```
[2]: def cross_validation( x_training, kfold, model_name, model, verbose=False ):
    mae_list = []
    mape_list = []
    rmse_list = []
    for k in reversed( range( 1, kfold+1 ) ):
        if verbose:
            print( '\nKFold Number: {}'.format( k ) )
            # start and end date for validation
```

```

        validation_start_date = x_training['date'].max() - datetime.timedelta(
↪days=k*6*7)
        validation_end_date = x_training['date'].max() - datetime.timedelta(
↪days=(k-1)*6*7)

        # filtering dataset
        training = x_training[x_training['date'] < validation_start_date]
        validation = x_training[(x_training['date'] >= validation_start_date) &
↪(x_training['date'] <= validation_end_date)]

        # training and validation dataset
        # training
        xtraining = training.drop( ['date', 'sales'], axis=1 )
        ytraining = training['sales']

        # validation
        xvalidation = validation.drop( ['date', 'sales'], axis=1 )
        yvalidation = validation['sales']

        # model
        m = model.fit( xtraining, ytraining )

        # prediction
        yhat = m.predict( xvalidation )

        # performance
        m_result = ml_error( model_name, np.expm1( yvalidation ), np.expm1(
↪yhat ) )

        # store performance of each kfold iteration
        mae_list.append( m_result['MAE'] )
        mape_list.append( m_result['MAPE'] )
        rmse_list.append( m_result['RMSE'] )

        return pd.DataFrame( {'Model Name': model_name,
                               'MAE CV': np.round( np.mean( mae_list ), 2 ).astype(
↪str ) + ' +/- ' + np.round( np.std( mae_list ), 2 ).astype( str ),
                               'MAPE CV': np.round( np.mean( mape_list ), 2 ).
↪astype( str ) + ' +/- ' + np.round( np.std( mape_list ), 2 ).astype( str ),
                               'RMSE CV': np.round( np.mean( rmse_list ), 2 ).
↪astype( str ) + ' +/- ' + np.round( np.std( rmse_list ), 2 ).astype( str )
↪}, index=[0] )

def mean_percentage_error( y, yhat ):
    return np.mean( ( y - yhat ) / y )

```

```

def mean_absolute_percentage_error( y, yhat ):
    return np.mean( np.abs( ( y - yhat ) / y ) )

def ml_error( model_name, y, yhat ):
    mae = mean_absolute_error( y, yhat )
    mape = mean_absolute_percentage_error( y, yhat )
    rmse = np.sqrt( mean_squared_error( y, yhat ) )

    return pd.DataFrame( { 'Model Name': model_name,
                          'MAE': mae,
                          'MAPE': mape,
                          'RMSE': rmse }, index=[0] )

def cramer_v( x, y ):
    cm = pd.crosstab( x, y ).as_matrix()
    n = cm.sum()
    r, k = cm.shape

    chi2 = ss.chi2_contingency( cm )[0]
    chi2corr = max( 0, chi2 - (k-1)*(r-1)/(n-1) )

    kcorr = k - (k-1)**2/(n-1)
    rcorr = r - (r-1)**2/(n-1)

    return np.sqrt( (chi2corr/n) / ( min( kcorr-1, rcorr-1 ) ) )

def jupyter_settings():
    %matplotlib inline
    %pylab inline

    plt.style.use( 'bmh' )
    plt.rcParams['figure.figsize'] = [25, 12]
    plt.rcParams['font.size'] = 24

    display( HTML( '<style>.container { width:100% !important; }</style>' ) )
    pd.options.display.max_columns = None
    pd.options.display.max_rows = None
    pd.set_option( 'display.expand_frame_repr', False )

    sns.set()

```

```
[3]: jupyter_settings()
```

Populating the interactive namespace from numpy and matplotlib

<IPython.core.display.HTML object>

## 1.2 0.2. Loading data

```
[4]: df_sales_raw = pd.read_csv( '../data/train.csv', low_memory=False )
df_store_raw = pd.read_csv( '../data/store.csv', low_memory=False )

# merge
df_raw = pd.merge( df_sales_raw, df_store_raw, how='left', on='Store' )
```

## 2 1.0. PASSO 01 - DESCRICAO DOS DADOS

```
[5]: df1 = df_raw.copy()
```

### 2.1 1.1. Rename Columns

```
[6]: cols_old = ['Store', 'DayOfWeek', 'Date', 'Sales', 'Customers', 'Open',
    ↳ 'Promo', 'StateHoliday', 'SchoolHoliday',
    ↳ 'StoreType', 'Assortment', 'CompetitionDistance',
    ↳ 'CompetitionOpenSinceMonth',
    ↳ 'CompetitionOpenSinceYear', 'Promo2', 'Promo2SinceWeek',
    ↳ 'Promo2SinceYear', 'PromoInterval']

snakecase = lambda x: inflection.underscore( x )

cols_new = list( map( snakecase, cols_old ) )

# rename
df1.columns = cols_new
```

### 2.2 1.2. Data Dimensions

```
[7]: print( 'Number of Rows: {}'.format( df1.shape[0] ) )
print( 'Number of Cols: {}'.format( df1.shape[1] ) )
```

Number of Rows: 1017209

Number of Cols: 18

### 2.3 1.3. Data Types

```
[8]: df1['date'] = pd.to_datetime( df1['date'] )
df1.dtypes
```

```
[8]: store                                int64
day_of_week                             int64
date                                    datetime64[ns]
```

```

sales                int64
customers            int64
open                int64
promo               int64
state_holiday       object
school_holiday      int64
store_type          object
assortment          object
competition_distance float64
competition_open_since_month float64
competition_open_since_year float64
promo2              int64
promo2_since_week   float64
promo2_since_year   float64
promo_interval      object
dtype: object

```

## 2.4 1.4. Check NA

```
[9]: df1.isna().sum()
```

```

[9]: store                0
    day_of_week           0
    date                 0
    sales                0
    customers            0
    open                0
    promo               0
    state_holiday       0
    school_holiday      0
    store_type          0
    assortment          0
    competition_distance 2642
    competition_open_since_month 323348
    competition_open_since_year 323348
    promo2              0
    promo2_since_week   508031
    promo2_since_year   508031
    promo_interval      508031
    dtype: int64

```

## 2.5 1.5. Fillout NA

```
[10]: df1.sample()
```

```

[10]:      store  day_of_week      date  sales  customers  open  promo
      state_holiday  school_holiday  store_type  assortment  competition_distance

```

competition_open_since_month	competition_open_since_year	promo2
promo2_since_week	promo2_since_year	promo_interval
1010793	274	7 2013-01-06 3802 932 1 0
0	1	b b 3640.0
NaN	NaN	1 10.0 2013.0
Jan, Apr, Jul, Oct		

```
[11]: #competition_distance
df1['competition_distance'] = df1['competition_distance'].apply( lambda x:
    ↪200000.0 if math.isnan( x ) else x )

#competition_open_since_month
df1['competition_open_since_month'] = df1.apply( lambda x: x['date'].month if
    ↪math.isnan( x['competition_open_since_month'] ) else
    ↪x['competition_open_since_month'], axis=1 )

#competition_open_since_year
df1['competition_open_since_year'] = df1.apply( lambda x: x['date'].year if
    ↪math.isnan( x['competition_open_since_year'] ) else
    ↪x['competition_open_since_year'], axis=1 )

#promo2_since_week
df1['promo2_since_week'] = df1.apply( lambda x: x['date'].week if math.isnan(
    ↪x['promo2_since_week'] ) else x['promo2_since_week'], axis=1 )

#promo2_since_year
df1['promo2_since_year'] = df1.apply( lambda x: x['date'].year if math.isnan(
    ↪x['promo2_since_year'] ) else x['promo2_since_year'], axis=1 )

#promo_interval
month_map = {1: 'Jan', 2: 'Fev', 3: 'Mar', 4: 'Apr', 5: 'May', 6: 'Jun',
    ↪7: 'Jul', 8: 'Aug', 9: 'Sep', 10: 'Oct', 11: 'Nov', 12: 'Dec'}

df1['promo_interval'].fillna(0, inplace=True )

df1['month_map'] = df1['date'].dt.month.map( month_map )

df1['is_promo'] = df1[['promo_interval', 'month_map']].apply( lambda x: 0 if
    ↪x['promo_interval'] == 0 else 1 if x['month_map'] in x['promo_interval'].
    ↪split( ',' ) else 0, axis=1 )
```

```
[12]: df1.isna().sum()
```

```
[12]: store          0
      day_of_week    0
      date           0
      sales          0
```

```

customers          0
open               0
promo              0
state_holiday      0
school_holiday     0
store_type         0
assortment         0
competition_distance 0
competition_open_since_month 0
competition_open_since_year 0
promo2             0
promo2_since_week  0
promo2_since_year  0
promo_interval     0
month_map          0
is_promo           0
dtype: int64

```

## 2.6 1.6. Change Data Types

```

[13]: # competition
df1['competition_open_since_month'] = df1['competition_open_since_month'].
      ↪astype( int )
df1['competition_open_since_year'] = df1['competition_open_since_year'].astype(
      ↪int )

# promo2
df1['promo2_since_week'] = df1['promo2_since_week'].astype( int )
df1['promo2_since_year'] = df1['promo2_since_year'].astype( int )

```

## 2.7 1.7. Descriptive Statistics

```

[14]: num_attributes = df1.select_dtypes( include=['int64', 'float64'] )
cat_attributes = df1.select_dtypes( exclude=['int64', 'float64',
      ↪'datetime64[ns]' ] )

```

### 2.7.1 1.7.1. Numerical Atributes

```

[15]: # Central Tendency - mean, meadina
ct1 = pd.DataFrame( num_attributes.apply( np.mean ) ).T
ct2 = pd.DataFrame( num_attributes.apply( np.median ) ).T

# dispersion - std, min, max, range, skew, kurtosis
d1 = pd.DataFrame( num_attributes.apply( np.std ) ).T
d2 = pd.DataFrame( num_attributes.apply( min ) ).T
d3 = pd.DataFrame( num_attributes.apply( max ) ).T
d4 = pd.DataFrame( num_attributes.apply( lambda x: x.max() - x.min() ) ).T

```

```

d5 = pd.DataFrame( num_attributes.apply( lambda x: x.skew() ) ).T
d6 = pd.DataFrame( num_attributes.apply( lambda x: x.kurtosis() ) ).T

# concatenar
m = pd.concat( [d2, d3, d4, ct1, ct2, d1, d5, d6] ).T.reset_index()
m.columns = ['attributes', 'min', 'max', 'range', 'mean', 'median', 'std', 'skew', 'kurtosis']
m

```

```

[15]:

```

		attributes	min	max	range	mean
median	std	skew	kurtosis			
0		store	1.0	1115.0	1114.0	558.429727
558.0	321.908493	-0.000955	-1.200524			
1		day_of_week	1.0	7.0	6.0	3.998341
4.0	1.997390	0.001593	-1.246873			
2		sales	0.0	41551.0	41551.0	5773.818972
5744.0	3849.924283	0.641460	1.778375			
3		customers	0.0	7388.0	7388.0	633.145946
609.0	464.411506	1.598650	7.091773			
4		open	0.0	1.0	1.0	0.830107
1.0	0.375539	-1.758045	1.090723			
5		promo	0.0	1.0	1.0	0.381515
0.0	0.485758	0.487838	-1.762018			
6		school_holiday	0.0	1.0	1.0	0.178647
0.0	0.383056	1.677842	0.815154			
7		competition_distance	20.0	200000.0	199980.0	5935.442677
2330.0	12547.646829	10.242344	147.789712			
8		competition_open_since_month	1.0	12.0	11.0	6.786849
7.0	3.311085	-0.042076	-1.232607			
9		competition_open_since_year	1900.0	2015.0	115.0	2010.324840
2012.0	5.515591	-7.235657	124.071304			
10		promo2	0.0	1.0	1.0	0.500564
1.0	0.500000	-0.002255	-1.999999			
11		promo2_since_week	1.0	52.0	51.0	23.619033
22.0	14.310057	0.178723	-1.184046			
12		promo2_since_year	2009.0	2015.0	6.0	2012.793297
2013.0	1.662657	-0.784436	-0.210075			
13		is_promo	0.0	1.0	1.0	0.155231
0.0	0.362124	1.904152	1.625796			

```

[16]: sns.distplot( df1['competition_distance'], kde=False )

```

```

[16]: <matplotlib.axes._subplots.AxesSubplot at 0x1098a77f0>

```





## 2.7.2 1.7.2. Categorical Atributes

```
[17]: cat_attributes.apply( lambda x: x.unique().shape[0] )
```

```
[17]: state_holiday      4
      store_type        4
      assortment        3
      promo_interval    4
      month_map         12
      dtype: int64
```

```
[18]: aux = df1[(df1['state_holiday'] != '0') & (df1['sales'] > 0)]

plt.subplot( 1, 3, 1 )
sns.boxplot( x='state_holiday', y='sales', data=aux )

plt.subplot( 1, 3, 2 )
sns.boxplot( x='store_type', y='sales', data=aux )

plt.subplot( 1, 3, 3 )
sns.boxplot( x='assortment', y='sales', data=aux )
```

```
[18]: <matplotlib.axes._subplots.AxesSubplot at 0x109917760>
```



## 3 2.0. PASSO 02 - FEATURE ENGINEERING

```
[19]: df2 = df1.copy()
```

### 3.1 2.1. Mapa Mental de Hipoteses

```
[20]: Image( 'img/MindMapHypothesis.png' )
```

[20]:



### **3.2 2.2. Criacao das Hipoteses**

#### **3.2.1 2.2.1. Hipoteses Loja**

1. Lojas com número maior de funcionários deveriam vender mais.
2. Lojas com maior capacidade de estoque deveriam vender mais.
3. Lojas com maior porte deveriam vender mais.
4. Lojas com maior sortimentos deveriam vender mais.
5. Lojas com competidores mais próximos deveriam vender menos.
6. Lojas com competidores à mais tempo deveriam vendem mais.

#### **3.2.2 2.2.2. Hipoteses Produto**

1. Lojas que investem mais em Marketing deveriam vender mais.
2. Lojas com maior exposição de produto deveriam vender mais.
3. Lojas com produtos com preço menor deveriam vender mais.
5. Lojas com promoções mais agressivas ( descontos maiores ), deveriam vender mais.
6. Lojas com promoções ativas por mais tempo deveriam vender mais.
7. Lojas com mais dias de promoção deveriam vender mais.
8. Lojas com mais promoções consecutivas deveriam vender mais.

#### **3.2.3 2.2.3. Hipoteses Tempo**

1. Lojas abertas durante o feriado de Natal deveriam vender mais.
2. Lojas deveriam vender mais ao longo dos anos.
3. Lojas deveriam vender mais no segundo semestre do ano.
4. Lojas deveriam vender mais depois do dia 10 de cada mês.
5. Lojas deveriam vender menos aos finais de semana.
6. Lojas deveriam vender menos durante os feriados escolares.

### **3.3 2.3. Lista Final de Hipóteses**

1. Lojas com maior sortimentos deveriam vender mais.
2. Lojas com competidores mais próximos deveriam vender menos.
3. Lojas com competidores à mais tempo deveriam vendem mais.
4. Lojas com promoções ativas por mais tempo deveriam vender mais.

5. Lojas com mais dias de promoção deveriam vender mais.
7. Lojas com mais promoções consecutivas deveriam vender mais.
8. Lojas abertas durante o feriado de Natal deveriam vender mais.
9. Lojas deveriam vender mais ao longo dos anos.
10. Lojas deveriam vender mais no segundo semestre do ano.
11. Lojas deveriam vender mais depois do dia 10 de cada mês.
12. Lojas deveriam vender menos aos finais de semana.
13. Lojas deveriam vender menos durante os feriados escolares.

### 3.4 2.4. Feature Engineering

```
[21]: # year
df2['year'] = df2['date'].dt.year

# month
df2['month'] = df2['date'].dt.month

# day
df2['day'] = df2['date'].dt.day

# week of year
df2['week_of_year'] = df2['date'].dt.weekofyear

# year week
df2['year_week'] = df2['date'].dt.strftime( '%Y-%W' )

# competition since
df2['competition_since'] = df2.apply( lambda x: datetime.datetime(
    ↳year=x['competition_open_since_year'],
    ↳month=x['competition_open_since_month'],day=1 ), axis=1 )
df2['competition_time_month'] = ( ( df2['date'] - df2['competition_since'] )/30
    ↳).apply( lambda x: x.days ).astype( int )

# promo since
df2['promo_since'] = df2['promo2_since_year'].astype( str ) + '-' +
    ↳df2['promo2_since_week'].astype( str )
df2['promo_since'] = df2['promo_since'].apply( lambda x: datetime.datetime.
    ↳strftime( x + '-1', '%Y-%W-%w' ) - datetime.timedelta( days=7 ) )
df2['promo_time_week'] = ( ( df2['date'] - df2['promo_since'] )/7 ).apply(
    ↳lambda x: x.days ).astype( int )

# assortment
```

```
df2['assortment'] = df2['assortment'].apply( lambda x: 'basic' if x == 'a' else
↳ 'extra' if x == 'b' else 'extended' )

# state holiday
df2['state_holiday'] = df2['state_holiday'].apply( lambda x: 'public_holiday'
↳ if x == 'a' else 'easter_holiday' if x == 'b' else 'christmas' if x == 'c'
↳ else 'regular_day' )
```

## 4 3.0. PASSO 03 - FILTRAGEM DE VARIÁVEIS

```
[22]: df3 = df2.copy()
```

### 4.1 3.1. Filtragem das Linhas

```
[23]: df3 = df3[(df3['open'] != 0) & (df3['sales'] > 0)]
```

### 4.2 3.2. Selecao das Colunas

```
[24]: cols_drop = ['customers', 'open', 'promo_interval', 'month_map']
df3 = df3.drop( cols_drop, axis=1 )
```

## 5 4.0. PASSO 04 - ANALISE EXPLORATORIA DOS DADOS

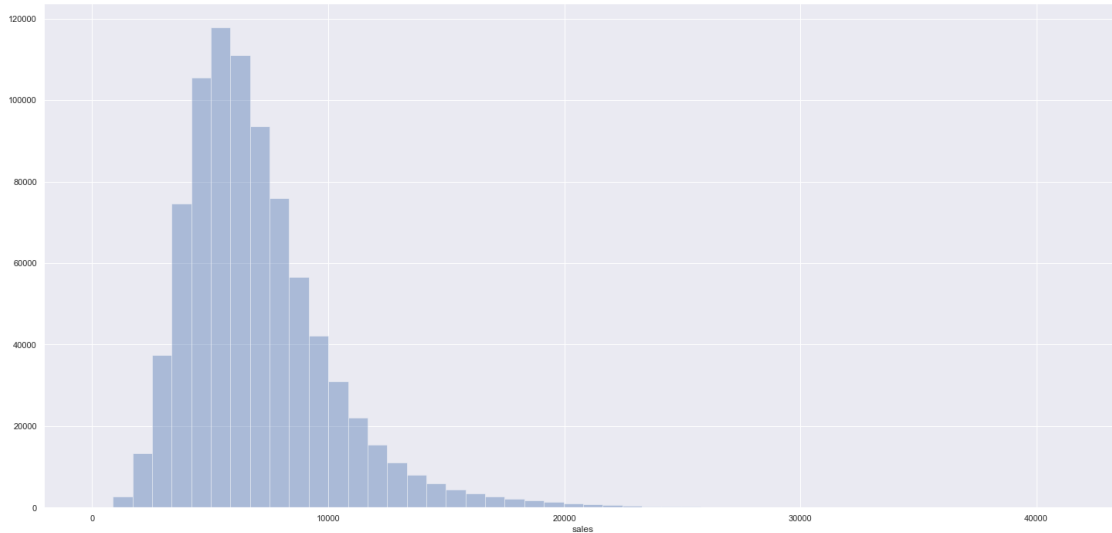
```
[25]: df4 = df3.copy()
```

### 5.1 4.1. Analise Univariada

#### 5.1.1 4.1.1. Response Variable

```
[26]: sns.distplot( df4['sales'], kde=False )
```

```
[26]: <matplotlib.axes._subplots.AxesSubplot at 0x11f7a3910>
```



### 5.1.2 4.1.2. Numerical Variable

```
[27]: num_attributes.hist( bins=25 );
```



### 5.1.3 4.1.3. Categorical Variable

```
[28]: # state_holiday
plt.subplot( 3, 2, 1 )
a = df4[df4['state_holiday'] != 'regular_day']
sns.countplot( a['state_holiday'] )
```

```

plt.subplot( 3, 2, 2 )
sns.kdeplot( df4[df4['state_holiday'] == 'public_holiday']['sales'],
    ↳label='public_holiday', shade=True )
sns.kdeplot( df4[df4['state_holiday'] == 'easter_holiday']['sales'],
    ↳label='easter_holiday', shade=True )
sns.kdeplot( df4[df4['state_holiday'] == 'christmas']['sales'],
    ↳label='christmas', shade=True )

# store_type
plt.subplot( 3, 2, 3 )
sns.countplot( df4['store_type'] )

plt.subplot( 3, 2, 4 )
sns.kdeplot( df4[df4['store_type'] == 'a']['sales'], label='a', shade=True )
sns.kdeplot( df4[df4['store_type'] == 'b']['sales'], label='b', shade=True )
sns.kdeplot( df4[df4['store_type'] == 'c']['sales'], label='c', shade=True )
sns.kdeplot( df4[df4['store_type'] == 'd']['sales'], label='d', shade=True )

# assortment
plt.subplot( 3, 2, 5 )
sns.countplot( df4['assortment'] )

plt.subplot( 3, 2, 6 )
sns.kdeplot( df4[df4['assortment'] == 'extended']['sales'], label='extended',
    ↳shade=True )
sns.kdeplot( df4[df4['assortment'] == 'basic']['sales'], label='basic',
    ↳shade=True )
sns.kdeplot( df4[df4['assortment'] == 'extra']['sales'], label='extra',
    ↳shade=True )

```

[28]: <matplotlib.axes.\_subplots.AxesSubplot at 0x15bf1af40>



## 5.2 4.2. Análise Bivariada

### 5.2.1 H1. Lojas com maior sortimentos deveriam vender mais.

**FALSA** Lojas com MAIOR SORTIMENTO vendem MENOS.

```
[29]: aux1 = df4[['assortment', 'sales']].groupby( 'assortment' ).sum().reset_index()
      sns.barplot( x='assortment', y='sales', data=aux1 );

      aux2 = df4[['year_week', 'assortment', 'sales']].groupby(
        ↳[['year_week', 'assortment']] ).sum().reset_index()
      aux2.pivot( index='year_week', columns='assortment', values='sales' ).plot()

      aux3 = aux2[aux2['assortment'] == 'extra']
      aux3.pivot( index='year_week', columns='assortment', values='sales' ).plot()
```

```
[29]: <matplotlib.axes._subplots.AxesSubplot at 0x171f91a30>
```







## 5.2.2 H2. Lojas com competidores mais próximos deveriam vender menos.

**FALSA** Lojas com COMPETIDORES MAIS PROXIMOS vendem MAIS.

```
[30]: aux1 = df4[['competition_distance', 'sales']].groupby( 'competition_distance' ).
      ↪sum().reset_index()

plt.subplot( 1, 3, 1 )
sns.scatterplot( x ='competition_distance', y='sales', data=aux1 );

plt.subplot( 1, 3, 2 )
bins = list( np.arange( 0, 20000, 1000) )
aux1['competition_distance_binned'] = pd.cut( aux1['competition_distance'],
      ↪bins=bins )
aux2 = aux1[['competition_distance_binned', 'sales']].groupby(
      ↪'competition_distance_binned' ).sum().reset_index()
sns.barplot( x='competition_distance_binned', y='sales', data=aux2 );
plt.xticks( rotation=90 );

plt.subplot( 1, 3, 3 )
x = sns.heatmap( aux1.corr( method='pearson' ), annot=True );
bottom, top = x.get_ylim()
x.set_ylim( bottom+0.5, top-0.5 );
```



### 5.2.3 H3. Lojas com competidores à mais tempo deveriam vender mais.

**FALSE** Lojas com COMPETIDORES À MAIS TEMPO vendem MENOS.

```
[31]: plt.subplot( 1, 3, 1 )
aux1 = df4[['competition_time_month', 'sales']].groupby(
    ↳'competition_time_month' ).sum().reset_index()
aux2 = aux1[( aux1['competition_time_month'] < 120 ) & (
    ↳aux1['competition_time_month'] != 0 )]
sns.barplot( x='competition_time_month', y='sales', data=aux2 );
plt.xticks( rotation=90 );

plt.subplot( 1, 3, 2 )
sns.regplot( x='competition_time_month', y='sales', data=aux2 );

plt.subplot( 1, 3, 3 )
x = sns.heatmap( aux1.corr( method='pearson'), annot=True );
bottom, top = x.get_ylim()
x.set_ylim( bottom+0.5, top-0.5);
```



#### 5.2.4 H4. Lojas com promoções ativas por mais tempo deveriam vender mais.

**FALSA** Lojas com promocoões ativas por mais tempo vendem menos, depois de um certo periodo de promocao

```
[32]: aux1 = df4[['promo_time_week', 'sales']].groupby( 'promo_time_week').sum().
      ↪reset_index()

grid = GridSpec( 2, 3 )

plt.subplot( grid[0,0] )
aux2 = aux1[aux1['promo_time_week'] > 0] # promo extendido
sns.barplot( x='promo_time_week', y='sales', data=aux2 );
plt.xticks( rotation=90 );

plt.subplot( grid[0,1] )
sns.regplot( x='promo_time_week', y='sales', data=aux2 );

plt.subplot( grid[1,0] )
aux3 = aux1[aux1['promo_time_week'] < 0] # promo regular
sns.barplot( x='promo_time_week', y='sales', data=aux3 );
plt.xticks( rotation=90 );

plt.subplot( grid[1,1] )
sns.regplot( x='promo_time_week', y='sales', data=aux3 );

plt.subplot( grid[:,2] )
sns.heatmap( aux1.corr( method='pearson' ), annot=True );
```



**5.2.5 H5. Lojas com mais dias de promoção deveriam vender mais.**

**5.2.6 H7. Lojas com mais promoções consecutivas deveriam vender mais.**

**FALSA** Lojas com mais promocoes consecutivas vendem menos

```
[33]: df4[['promo', 'promo2', 'sales']].groupby( ['promo', 'promo2'] ).sum().
      ↪reset_index()
```

```
[33]:   promo  promo2      sales
0      0         0  1482612096
1      0         1  1289362241
2      1         0  1628930532
3      1         1  1472275754
```

```
[34]: aux1 = df4[( df4['promo'] == 1 ) & ( df4['promo2'] == 1 )][['year_week',
      ↪ 'sales']].groupby( 'year_week' ).sum().reset_index()
ax = aux1.plot()

aux2 = df4[( df4['promo'] == 1 ) & ( df4['promo2'] == 0 )][['year_week',
      ↪ 'sales']].groupby( 'year_week' ).sum().reset_index()
aux2.plot( ax=ax )

ax.legend( labels=['Tradicional & Extendida', 'Extendida']);
```



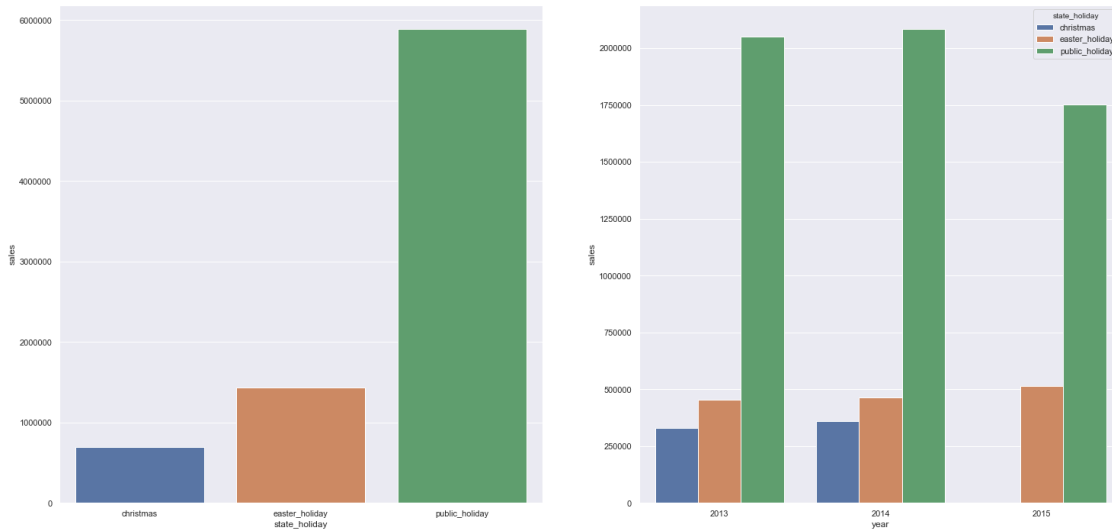
### 5.2.7 H8. Lojas abertas durante o feriado de Natal deveriam vender mais.

**FALSA** Lojas abertas durante o feriado do Natal vendem menos.

```
[35]: aux = df4[df4['state_holiday'] != 'regular_day']

plt.subplot( 1, 2, 1 )
aux1 = aux[['state_holiday', 'sales']].groupby( 'state_holiday' ).sum().
    ↪reset_index()
sns.barplot( x='state_holiday', y='sales', data=aux1 );

plt.subplot( 1, 2, 2 )
aux2 = aux[['year', 'state_holiday', 'sales']].groupby( ['year', 'state_holiday'] ).sum().reset_index()
sns.barplot( x='year', y='sales', hue='state_holiday', data=aux2 );
```



### 5.2.8 H9. Lojas deveriam vender mais ao longo dos anos.

**FALSA** Lojas vendem menos ao longo dos anos

```
[36]: aux1 = df4[['year', 'sales']].groupby( 'year' ).sum().reset_index()

plt.subplot( 1, 3, 1 )
sns.barplot( x='year', y='sales', data=aux1 );

plt.subplot( 1, 3, 2 )
sns.regplot( x='year', y='sales', data=aux1 );

plt.subplot( 1, 3, 3 )
sns.heatmap( aux1.corr( method='pearson' ), annot=True );
```



### 5.2.9 H10. Lojas deveriam vender mais no segundo semestre do ano.

**FALSA** Lojas vendem menos no segundo semestre do ano

```
[37]: aux1 = df4[['month', 'sales']].groupby( 'month' ).sum().reset_index()

plt.subplot( 1, 3, 1 )
sns.barplot( x='month', y='sales', data=aux1 );

plt.subplot( 1, 3, 2 )
sns.regplot( x='month', y='sales', data=aux1 );

plt.subplot( 1, 3, 3 )
sns.heatmap( aux1.corr( method='pearson' ), annot=True );
```





### 5.2.10 H11. Lojas deveriam vender mais depois do dia 10 de cada mês.

**VERDADEIRA** Lojas vendem mais depois do dia 10 de cada mes.

```
[38]: aux1 = df4[['day', 'sales']].groupby( 'day' ).sum().reset_index()

plt.subplot( 2, 2, 1 )
sns.barplot( x='day', y='sales', data=aux1 );

plt.subplot( 2, 2, 2 )
sns.regplot( x='day', y='sales', data=aux1 );

plt.subplot( 2, 2, 3 )
sns.heatmap( aux1.corr( method='pearson' ), annot=True );

aux1['before_after'] = aux1['day'].apply( lambda x: 'before_10_days' if x <= 10
↳ else 'after_10_days' )
aux2 =aux1[['before_after', 'sales']].groupby( 'before_after' ).sum().
↳ reset_index()

plt.subplot( 2, 2, 4 )
sns.barplot( x='before_after', y='sales', data=aux2 );
```



### 5.2.11 H12. Lojas deveriam vender menos aos finais de semana.

VERDADEIRA Lojas vendem menos nos final de semana

```
[39]: aux1 = df4[['day_of_week', 'sales']].groupby( 'day_of_week' ).sum().
      ↪reset_index()

plt.subplot( 1, 3, 1 )
sns.barplot( x='day_of_week', y='sales', data=aux1 );

plt.subplot( 1, 3, 2 )
sns.regplot( x='day_of_week', y='sales', data=aux1 );

plt.subplot( 1, 3, 3 )
sns.heatmap( aux1.corr( method='pearson' ), annot=True );
```

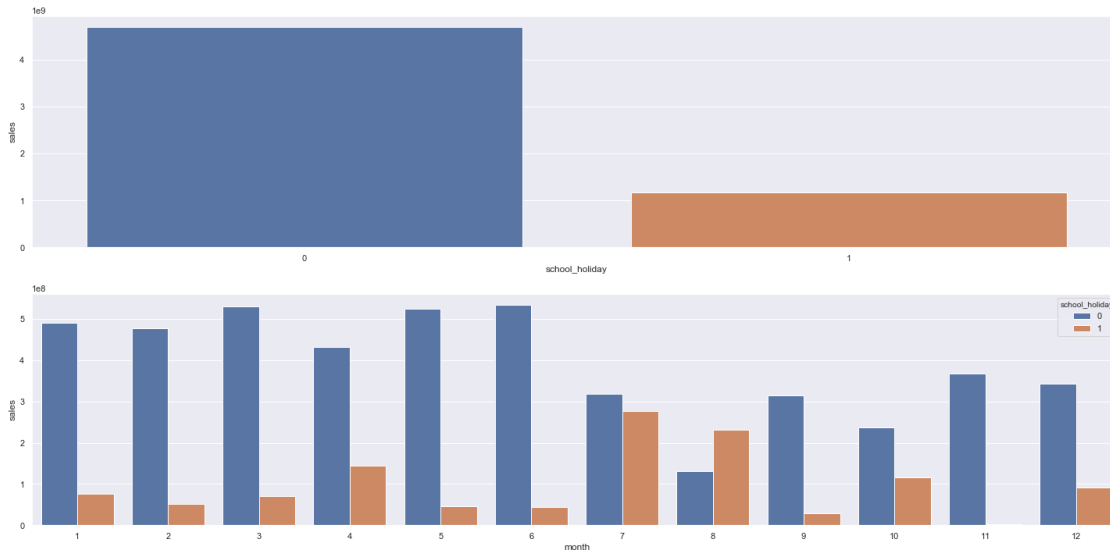


### 5.2.12 H13. Lojas deveriam vender menos durante os feriados escolares.

**VERDADEIRA** Lojas vendem menos durante os feriados escolares, except os meses de Julho e Agosto.

```
[40]: aux1 = df4[['school_holiday', 'sales']].groupby( 'school_holiday' ).sum().
      ↪reset_index()
plt.subplot( 2, 1, 1 )
sns.barplot( x='school_holiday', y='sales', data=aux1 );

aux2 = df4[['month', 'school_holiday', 'sales']].groupby(
      ↪['month', 'school_holiday'] ).sum().reset_index()
plt.subplot( 2, 1, 2 )
sns.barplot( x='month', y='sales', hue='school_holiday', data=aux2 );
```



### 5.2.13 4.2.1. Resumo das Hipoteses

```
[41]: from tabulate import tabulate
```

```
[42]: tab = [['Hipoteses', 'Conclusao', 'Relevancia'],
             ['H1', 'Falsa', 'Baixa'],
             ['H2', 'Falsa', 'Media'],
             ['H3', 'Falsa', 'Media'],
             ['H4', 'Falsa', 'Baixa'],
             ['H5', '-', '-'],
             ['H7', 'Falsa', 'Baixa'],
             ['H8', 'Falsa', 'Media'],
             ['H9', 'Falsa', 'Alta'],
             ['H10', 'Falsa', 'Alta'],
             ['H11', 'Verdadeira', 'Alta'],
             ['H12', 'Verdadeira', 'Alta'],
             ['H13', 'Verdadeira', 'Baixa'],
             ]
print( tabulate( tab, headers='firstrow' ) )
```

Hipoteses	Conclusao	Relevancia
H1	Falsa	Baixa
H2	Falsa	Media
H3	Falsa	Media
H4	Falsa	Baixa
H5	-	-
H7	Falsa	Baixa
H8	Falsa	Media

H9	Falsa	Alta
H10	Falsa	Alta
H11	Verdadeira	Alta
H12	Verdadeira	Alta
H13	Verdadeira	Baixa

### 5.3 4.3. Analise Multivariada

#### 5.3.1 4.3.1. Numerical Attributes

```
[43]: correlation = num_attributes.corr( method='pearson' )
sns.heatmap( correlation, annot=True );
```



#### 5.3.2 4.3.2. Categorical Attributes

```
[44]: # only categorical data
a = df4.select_dtypes( include='object' )

# Calculate cramer V
a1 = cramer_v( a['state_holiday'], a['state_holiday'] )
a2 = cramer_v( a['state_holiday'], a['store_type'] )
a3 = cramer_v( a['state_holiday'], a['assortment'] )

a4 = cramer_v( a['store_type'], a['state_holiday'] )
a5 = cramer_v( a['store_type'], a['store_type'] )
a6 = cramer_v( a['store_type'], a['assortment'] )
```

```

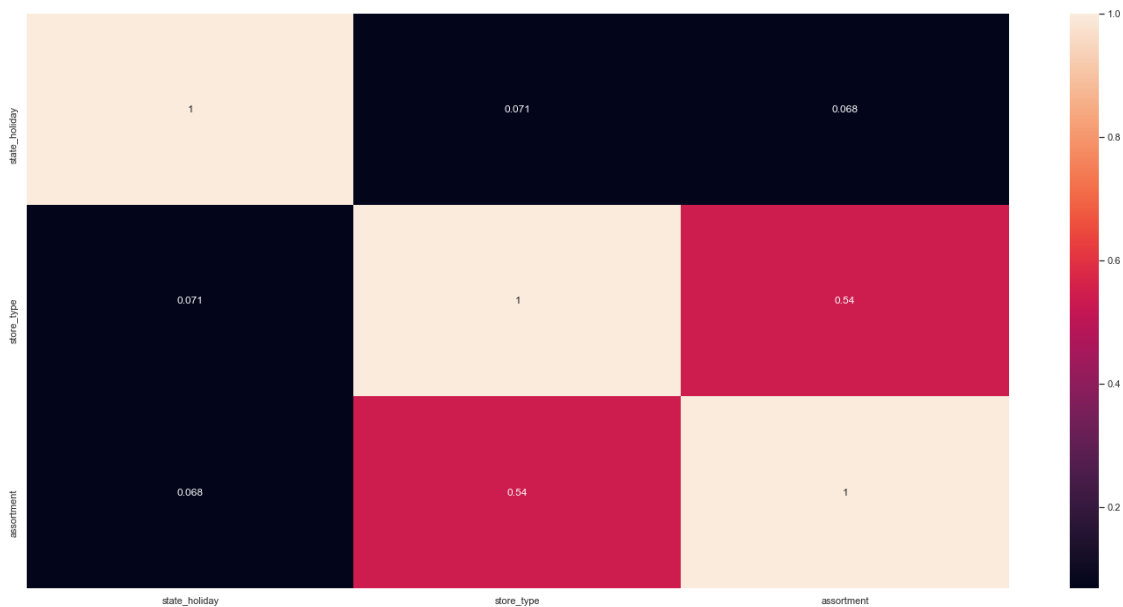
a7 = cramer_v( a['assortment'], a['state_holiday'] )
a8 = cramer_v( a['assortment'], a['store_type'] )
a9 = cramer_v( a['assortment'], a['assortment'] )

# Final dataset
d = pd.DataFrame( {'state_holiday': [a1, a2, a3],
                  'store_type': [a4, a5, a6],
                  'assortment': [a7, a8, a9]  })
d = d.set_index( d.columns )

sns.heatmap( d, annot=True )

```

[44]: <matplotlib.axes.\_subplots.AxesSubplot at 0x122d1ad30>



[ ]:

## 6 5.0. PASSO 05 - DATA PREPARATION

[476]: df5 = df4.copy()

### 6.1 5.1. Normalizacao

[ ]:

## 6.2 5.2. Rescaling

```
[477]: rs = RobustScaler()
mms = MinMaxScaler()

# competition distance
df5['competition_distance'] = rs.fit_transform( df5[['competition_distance']].
    ↪values )
pickle.dump( rs, open( 'parameter/competition_distance_scaler.pkl', 'wb') )

# competition time month
df5['competition_time_month'] = rs.fit_transform(
    ↪df5[['competition_time_month']].values )
pickle.dump( rs, open( 'parameter/competition_time_month_scaler.pkl', 'wb') )

# promo time week
df5['promo_time_week'] = mms.fit_transform( df5[['promo_time_week']].values )
pickle.dump( rs, open( 'parameter/promo_time_week_scaler.pkl', 'wb') )

# year
df5['year'] = mms.fit_transform( df5[['year']].values )
pickle.dump( mms, open( 'parameter/year_scaler.pkl', 'wb') )
```

## 6.3 5.3. Transformacao

### 6.3.1 5.3.1. Encoding

```
[475]: # state_holiday - One Hot Encoding
df5 = pd.get_dummies( df5, prefix=['state_holiday'], columns=['state_holiday'] )

# store_type - Label Encoding
le = LabelEncoder()
df5['store_type'] = le.fit_transform( df5['store_type'] )
pickle.dump( le, open( 'parameter/store_type_scaler.pkl', 'wb') )

# assortment - Ordinal Encoding
assortment_dict = {'basic': 1, 'extra': 2, 'extended': 3}
df5['assortment'] = df5['assortment'].map( assortment_dict )
```

### 6.3.2 5.3.2. Response Variable Transformation

```
[48]: df5['sales'] = np.log1p( df5['sales'] )
```

### 6.3.3 5.3.3. Nature Transformation

```
[49]: # day of week
df5['day_of_week_sin'] = df5['day_of_week'].apply( lambda x: np.sin( x * ( 2. *
↳ np.pi/7 ) ) )
df5['day_of_week_cos'] = df5['day_of_week'].apply( lambda x: np.cos( x * ( 2. *
↳ np.pi/7 ) ) )

# month
df5['month_sin'] = df5['month'].apply( lambda x: np.sin( x * ( 2. * np.pi/12 )
↳ ) )
df5['month_cos'] = df5['month'].apply( lambda x: np.cos( x * ( 2. * np.pi/12 )
↳ ) )

# day
df5['day_sin'] = df5['day'].apply( lambda x: np.sin( x * ( 2. * np.pi/30 ) ) )
df5['day_cos'] = df5['day'].apply( lambda x: np.cos( x * ( 2. * np.pi/30 ) ) )

# week of year
df5['week_of_year_sin'] = df5['week_of_year'].apply( lambda x: np.sin( x * ( 2.
↳ * np.pi/52 ) ) )
df5['week_of_year_cos'] = df5['week_of_year'].apply( lambda x: np.cos( x * ( 2.
↳ * np.pi/52 ) ) )
```

## 7 6.0. PASSO 06 - FEATURE SELECTION

```
[50]: df6 = df5.copy()
```

### 7.1 6.1. Split dataframe into training and test dataset

```
[51]: cols_drop = ['week_of_year', 'day', 'month', 'day_of_week', 'promo_since',
↳ 'competition_since', 'year_week' ]
df6 = df6.drop( cols_drop, axis=1 )
```

```
[52]: # training dataset
X_train = df6[df6['date'] < '2015-06-19']
y_train = X_train['sales']

# test dataset
X_test = df6[df6['date'] >= '2015-06-19']
y_test = X_test['sales']

print( 'Training Min Date: {}'.format( X_train['date'].min() ) )
print( 'Training Max Date: {}'.format( X_train['date'].max() ) )

print( '\nTest Min Date: {}'.format( X_test['date'].min() ) )
```



```
print( 'Test Max Date: {}'.format( X_test['date'].max() ) )
```

Training Min Date: 2013-01-01 00:00:00

Training Max Date: 2015-06-18 00:00:00

Test Min Date: 2015-06-19 00:00:00

Test Max Date: 2015-07-31 00:00:00

## 7.2 6.2. Boruta as Feature Selector

```
[53]: ## training and test dataset for Boruta
#X_train_n = X_train.drop( ['date', 'sales'], axis=1 ).values
#y_train_n = y_train.values.ravel()
#
## define RandomForestRegressor
#rf = RandomForestRegressor( n_jobs=-1 )
#
## define Boruta
#boruta = BorutaPy( rf, n_estimators='auto', verbose=2, random_state=42 ).fit(
    ↪X_train_n, y_train_n )
```

### 7.2.1 6.2.1. Best Features from Boruta

```
[54]: #cols_selected = boruta.support_.tolist()
#
## best features
#X_train_fs = X_train.drop( ['date', 'sales'], axis=1 )
#cols_selected_boruta = X_train_fs.iloc[:, cols_selected].columns.tolist()
#
## not selected boruta
#cols_not_selected_boruta = list( np.setdiff1d( X_train_fs.columns,
    ↪cols_selected_boruta ) )
```

## 7.3 6.3. Manual Feature Selection

```
[55]: cols_selected_boruta = [
    'store',
    'promo',
    'store_type',
    'assortment',
    'competition_distance',
    'competition_open_since_month',
    'competition_open_since_year',
    'promo2',
    'promo2_since_week',
    'promo2_since_year',
    'competition_time_month',
    'promo_time_week',
```

```

        'day_of_week_sin',
        'day_of_week_cos',
        'month_sin',
        'month_cos',
        'day_sin',
        'day_cos',
        'week_of_year_sin',
        'week_of_year_cos']

# columns to add
feat_to_add = ['date', 'sales']

cols_selected_boruta_full = cols_selected_boruta.copy()
cols_selected_boruta_full.extend( feat_to_add )

```

## 8 7.0. PASSO 07 - MACHINE LEARNING MODELLING

```

[56]: x_train = X_train[ cols_selected_boruta ]
      x_test = X_test[ cols_selected_boruta ]

# Time Series Data Preparation
x_training = X_train[ cols_selected_boruta_full ]

```

### 8.1 7.1. Average Model

```

[57]: aux1 = x_test.copy()
      aux1['sales'] = y_test.copy()

# prediction
aux2 = aux1[['store', 'sales']].groupby( 'store' ).mean().reset_index().rename(
    ↪columns={'sales': 'predictions'} )
aux1 = pd.merge( aux1, aux2, how='left', on='store' )
yhat_baseline = aux1['predictions']

# performance
baseline_result = ml_error( 'Average Model', np.expm1( y_test ), np.expm1(
    ↪yhat_baseline ) )
baseline_result

```

```

[57]:      Model Name      MAE      MAPE      RMSE
0  Average Model  1354.800353  0.455051  1835.135542

```

## 8.2 7.2. Linear Regression Model

```
[58]: # model
lr = LinearRegression().fit( x_train, y_train )

# prediction
yhat_lr = lr.predict( x_test )

# performance
lr_result = ml_error( 'Linear Regression', np.expm1( y_test ), np.expm1(
    ↪yhat_lr ) )
lr_result
```

```
[58]:          Model Name          MAE          MAPE          RMSE
0  Linear Regression  1867.089774  0.292694  2671.049215
```

### 8.2.1 7.2.1. Linear Regression Model - Cross Validation

```
[59]: lr_result_cv = cross_validation( x_training, 5, 'Linear Regression', lr,
    ↪verbose=False )
lr_result_cv
```

```
[59]:          Model Name          MAE CV          MAPE CV          RMSE CV
0  Linear Regression  2081.73 +/- 295.63  0.3 +/- 0.02  2952.52 +/- 468.37
```

## 8.3 7.3. Linear Regression Regularized Model - Lasso

```
[60]: # model
lrr = Lasso( alpha=0.01 ).fit( x_train, y_train )

# prediction
yhat_lrr = lrr.predict( x_test )

# performance
lrr_result = ml_error( 'Linear Regression - Lasso', np.expm1( y_test ), np.
    ↪expm1( yhat_lrr ) )
lrr_result
```

```
[60]:          Model Name          MAE          MAPE          RMSE
0  Linear Regression - Lasso  1891.704881  0.289106  2744.451737
```

### 8.3.1 7.3.1. Lasso - Cross Validation

```
[61]: lrr_result_cv = cross_validation( x_training, 5, 'Lasso', lrr, verbose=False )
lrr_result_cv
```

```
[61]:          Model Name          MAE CV          MAPE CV          RMSE CV
0      Lasso  2116.38 +/- 341.5  0.29 +/- 0.01  3057.75 +/- 504.26
```

## 8.4 7.4. Random Forest Regressor

```
[62]: # model
rf = RandomForestRegressor( n_estimators=100, n_jobs=-1, random_state=42 ).fit(
    ↪x_train, y_train )

# prediction
yhat_rf = rf.predict( x_test )

# performance
rf_result = ml_error( 'Random Forest Regressor', np.expm1( y_test ), np.expm1(
    ↪yhat_rf ) )
rf_result
```

```
[62]:
```

	Model Name	MAE	MAPE	RMSE
0	Random Forest Regressor	679.622763	0.09996	1011.191561

### 8.4.1 7.4.1. Random Forest Regressor - Cross Validation

```
[63]: rf_result_cv = cross_validation( x_training, 5, 'Random Forest Regressor', rf,
    ↪verbose=True )
rf_result_cv
```

KFold Number: 5

KFold Number: 4

KFold Number: 3

KFold Number: 2

KFold Number: 1

```
[63]:
```

	Model Name	MAE CV	MAPE CV	RMSE CV
0	Random Forest Regressor	837.68 +/- 219.1	0.12 +/- 0.02	1256.08 +/- 320.36

## 8.5 7.5. XGBoost Regressor

```
[64]: # model
model_xgb = xgb.XGBRegressor( objective='reg:squarederror',
                               n_estimators=100,
                               eta=0.01,
                               max_depth=10,
                               subsample=0.7,
                               colsample_bytree=0.9 ).fit( x_train, y_train )

# prediction
```

```

yhat_xgb = model_xgb.predict( x_test )

# performance
xgb_result = ml_error( 'XGBoost Regressor', np.expm1( y_test ), np.expm1(
    ↪yhat_xgb ) )
xgb_result

```

```

[64]:
      Model Name      MAE      MAPE      RMSE
0  XGBoost Regressor  843.112292  0.122609  1250.952634

```

### 8.5.1 7.5.1. XGBoost Regressor - Cross Validation

```

[65]: xgb_result_cv = cross_validation( x_training, 5, 'XGBoost Regressor',
    ↪model_xgb, verbose=True )
xgb_result_cv

```

KFold Number: 5

KFold Number: 4

KFold Number: 3

KFold Number: 2

KFold Number: 1

```

[65]:
      Model Name      MAE CV      MAPE CV      RMSE CV
0  XGBoost Regressor  1030.28 +/- 167.19  0.14 +/- 0.02  1478.26 +/- 229.79

```

## 8.6 7.6. Compare Model's Performance

### 8.6.1 7.6.1. Single Performance

```

[66]: modelling_result = pd.concat( [baseline_result, lr_result, lrr_result,
    ↪rf_result, xgb_result] )
modelling_result.sort_values( 'RMSE' )

```

```

[66]:
      Model Name      MAE      MAPE      RMSE
0  Random Forest Regressor  679.622763  0.099960  1011.191561
0      XGBoost Regressor  843.112292  0.122609  1250.952634
0      Average Model  1354.800353  0.455051  1835.135542
0      Linear Regression  1867.089774  0.292694  2671.049215
0  Linear Regression - Lasso  1891.704881  0.289106  2744.451737

```

## 8.6.2 7.6.2. Real Performance - Cross Validation

```
[67]: modelling_result_cv = pd.concat( [lr_result_cv, lrr_result_cv, rf_result_cv,
    ↪ xgb_result_cv] )
modelling_result_cv
```

```
[67]:
```

	Model Name	MAE CV	MAPE CV	RMSE
CV				
0	Linear Regression	2081.73 +/- 295.63	0.3 +/- 0.02	2952.52 +/-
468.37				
0	Lasso	2116.38 +/- 341.5	0.29 +/- 0.01	3057.75 +/-
504.26				
0	Random Forest Regressor	837.68 +/- 219.1	0.12 +/- 0.02	1256.08 +/-
320.36				
0	XGBoost Regressor	1030.28 +/- 167.19	0.14 +/- 0.02	1478.26 +/-
229.79				

## 9 8.0. PASSO 08 - HYPERPARAMETER FINE TUNING

### 9.1 8.1. Random Search

```
[68]: #param = {
#     'n_estimators': [1500, 1700, 2500, 3000, 3500],
#     'eta': [0.01, 0.03],
#     'max_depth': [3, 5, 9],
#     'subsample': [0.1, 0.5, 0.7],
#     'colsample_bytree': [0.3, 0.7, 0.9],
#     'min_child_weight': [3, 8, 15]
# }
#
# MAX_EVAL = 5
```

```
[69]: #final_result = pd.DataFrame()
#
# for i in range( MAX_EVAL ):
#     # choose values for parameters randomly
#     hp = { k: random.sample( v, 1 )[0] for k, v in param.items() }
#     print( hp )
#
#     # model
#     model_xgb = xgb.XGBRegressor( objective='reg:squarederror',
#                                   n_estimators=hp['n_estimators'],
#                                   eta=hp['eta'],
#                                   max_depth=hp['max_depth'],
#                                   subsample=hp['subsample'],
#                                   colsample_bytree=hp['colsample_bytree'],
#                                   min_child_weight=hp['min_child_weight'] )
```

```
#
# # performance
# result = cross_validation( x_training, 5, 'XGBoost Regressor', model_xgb,
↳ verbose=True )
# final_result = pd.concat( [final_result, result] )
#
#final_result
```

```
[70]: #final_result
```

## 9.2 8.2. Final Model

```
[71]: param_tuned = {
    'n_estimators': 3000,
    'eta': 0.03,
    'max_depth': 5,
    'subsample': 0.7,
    'colsample_bytree': 0.7,
    'min_child_weight': 3
}
```

```
[72]: # model
model_xgb_tuned = xgb.XGBRegressor( objective='reg:squarederror',
                                   n_estimators=param_tuned['n_estimators'],
                                   eta=param_tuned['eta'],
                                   max_depth=param_tuned['max_depth'],
                                   subsample=param_tuned['subsample'],
                                   ↳
↳ colsample_bytree=param_tuned['colsample_bytree'],
                                   ↳
↳ min_child_weight=param_tuned['min_child_weight'] ).fit( x_train, y_train )

# prediction
yhat_xgb_tuned = model_xgb_tuned.predict( x_test )

# performance
xgb_result_tuned = ml_error( 'XGBoost Regressor', np.expm1( y_test ), np.expm1(
↳ yhat_xgb_tuned ) )
xgb_result_tuned
```

```
[72]:
```

	Model Name	MAE	MAPE	RMSE
0	XGBoost Regressor	664.974996	0.097529	957.774225

```
[73]: mpe = mean_percentage_error( np.expm1( y_test ), np.expm1( yhat_xgb_tuned ) )
mpe
```

```
[73]: -0.0035453341443739675
```

## 10 9.0. PASSO 09 - TRADUCAO E INTERPRETACAO DO ERRO

```
[435]: df9 = X_test[ cols_selected_boruta_full ]

# rescale
df9['sales'] = np.expm1( df9['sales'] )
df9['predictions'] = np.expm1( yhat_xgb_tuned )
```

### 10.1 9.1. Business Performance

```
[443]: # sum of predictions
df91 = df9[['store', 'predictions']].groupby( 'store' ).sum().reset_index()

# MAE and MAPE
df9_aux1 = df9[['store', 'sales', 'predictions']].groupby( 'store' ).apply(
    ↪lambda x: mean_absolute_error( x['sales'], x['predictions'] ) ).
    ↪reset_index().rename( columns={0:'MAE'})
df9_aux2 = df9[['store', 'sales', 'predictions']].groupby( 'store' ).apply(
    ↪lambda x: mean_absolute_percentage_error( x['sales'], x['predictions'] ) ).
    ↪reset_index().rename( columns={0:'MAPE'})

# Merge
df9_aux3 = pd.merge( df9_aux1, df9_aux2, how='inner', on='store' )
df92 = pd.merge( df91, df9_aux3, how='inner', on='store' )

# Scenarios
df92['worst_scenario'] = df92['predictions'] - df92['MAE']
df92['best_scenario'] = df92['predictions'] + df92['MAE']

# order columns
df92 = df92[['store', 'predictions', 'worst_scenario', 'best_scenario', 'MAE',
    ↪'MAPE']]
```

```
[446]: df92.sort_values( 'MAPE', ascending=False ).head()
```

```
[446]:
```

	store	predictions	worst_scenario	best_scenario	MAE \
291	292	104033.078125	100714.973723	107351.182527	3318.104402
908	909	238233.875000	230573.337190	245894.412810	7660.537810
875	876	203030.156250	199110.952435	206949.360065	3919.203815
721	722	353005.781250	351013.625224	354997.937276	1992.156026
594	595	400883.625000	397415.263170	404351.986830	3468.361830

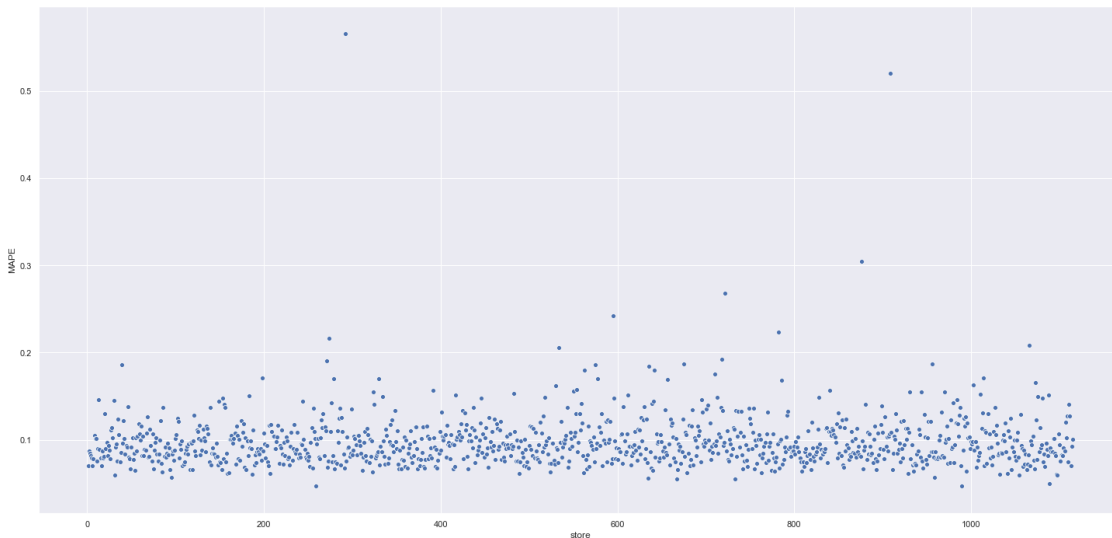
	MAPE
291	0.565828
908	0.520433
875	0.305099



```
721 0.268338
594 0.242192
```

```
[448]: sns.scatterplot( x='store', y='MAPE', data=df92 )
```

```
[448]: <matplotlib.axes._subplots.AxesSubplot at 0x16a890280>
```



## 10.2 9.2. Total Performance

```
[455]: df93 = df92[['predictions', 'worst_scenario', 'best_scenario']].apply( lambda x:
    ↳ np.sum( x ), axis=0 ).reset_index().rename( columns={'index': 'Scenario', 0:
    ↳ 'Values'} )
df93['Values'] = df93['Values'].map( 'R${:,.2f}'.format )
df93
```

```
[455]:
```

	Scenario	Values
0	predictions	R\$285,860,497.77
1	worst_scenario	R\$285,115,015.71
2	best_scenario	R\$286,605,979.84

## 10.3 9.3. Machine Learning Performance

```
[457]: df9['error'] = df9['sales'] - df9['predictions']
df9['error_rate'] = df9['predictions'] / df9['sales']
```

```
[459]: plt.subplot( 2, 2, 1 )
sns.lineplot( x='date', y='sales', data=df9, label='SALES' )
sns.lineplot( x='date', y='predictions', data=df9, label='PREDICTIONS' )
```

```
plt.subplot( 2, 2, 2 )
sns.lineplot( x='date', y='error_rate', data=df9 )
plt.axhline( 1, linestyle='--')

plt.subplot( 2, 2, 3 )
sns.distplot( df9['error'] )

plt.subplot( 2, 2, 4 )
sns.scatterplot( df9['predictions'], df9['error'] )
```

[459]: <matplotlib.axes.\_subplots.AxesSubplot at 0x1689cf700>

