m10_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 requests
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 )
```

```python
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]:
```python
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]:
```
# competiton
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
```

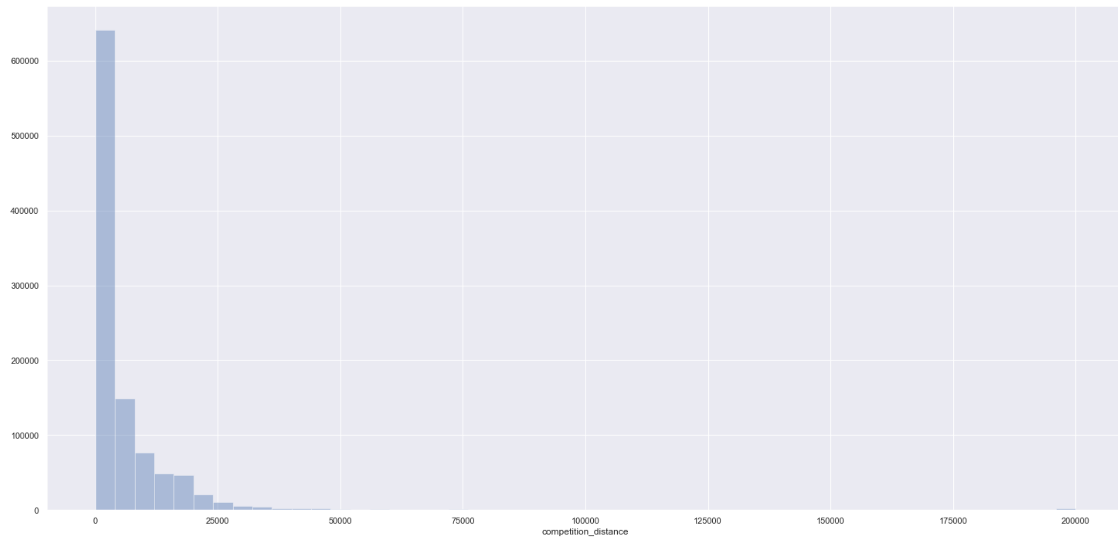
[15]:

```
                      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>



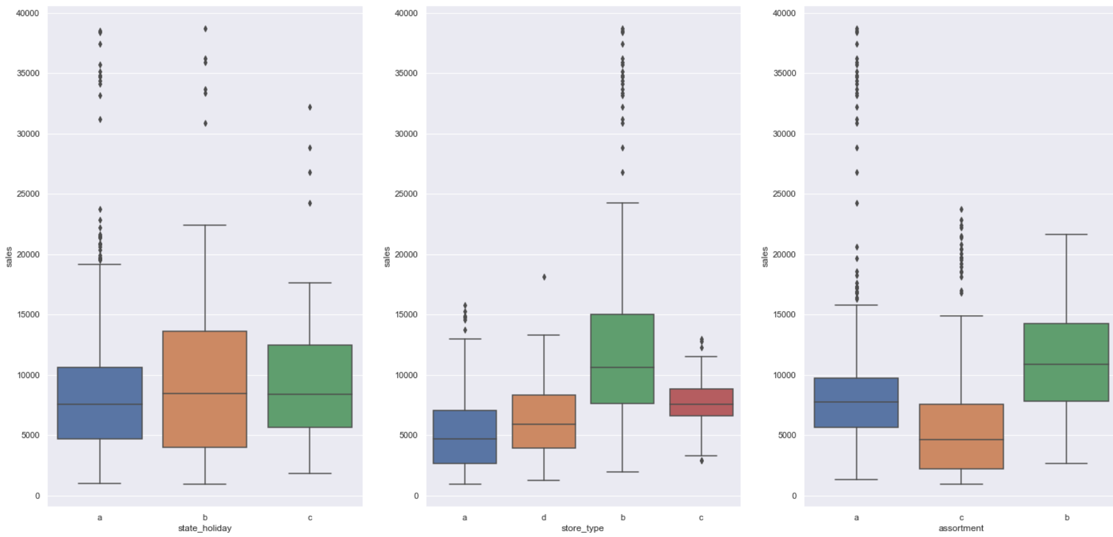
2.7.2 1.7.2. Categorical Atributes

[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.
 ↪strptime( 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

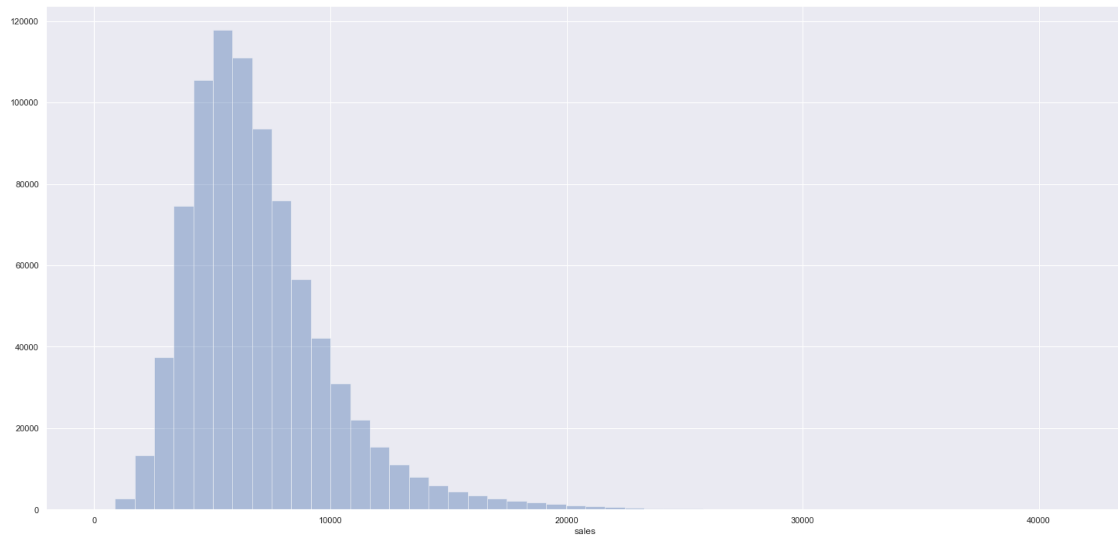
[25]:
```
df4 = df3.copy()
```

5.1 4.1. Analise Univariada

5.1.1 4.1.1. Response Variable

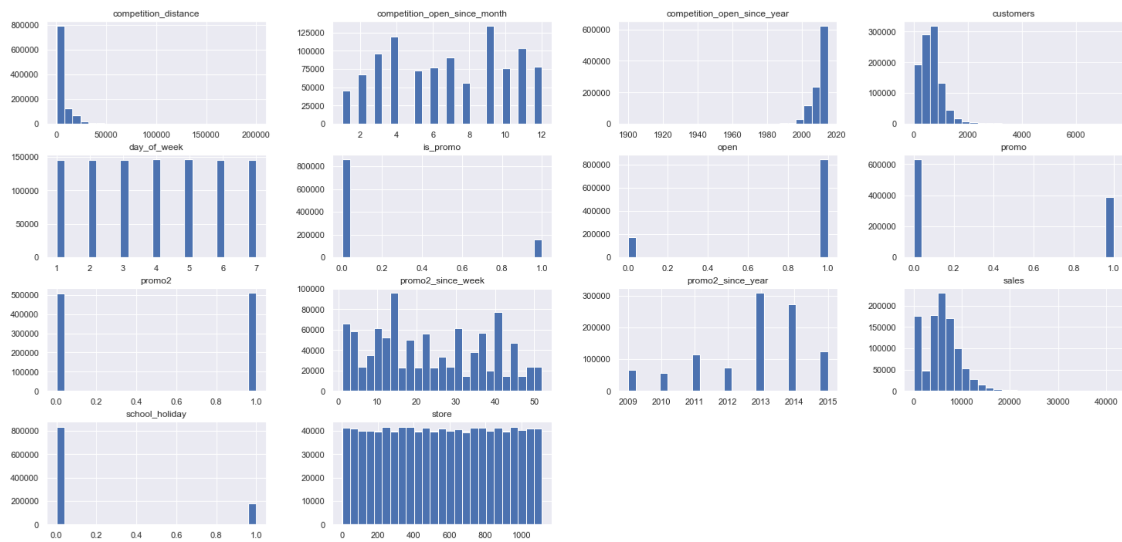
[26]:
```
sns.distplot( df4['sales'], kde=False  )
```

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



5.1.2 4.1.2. Numerical Variable

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

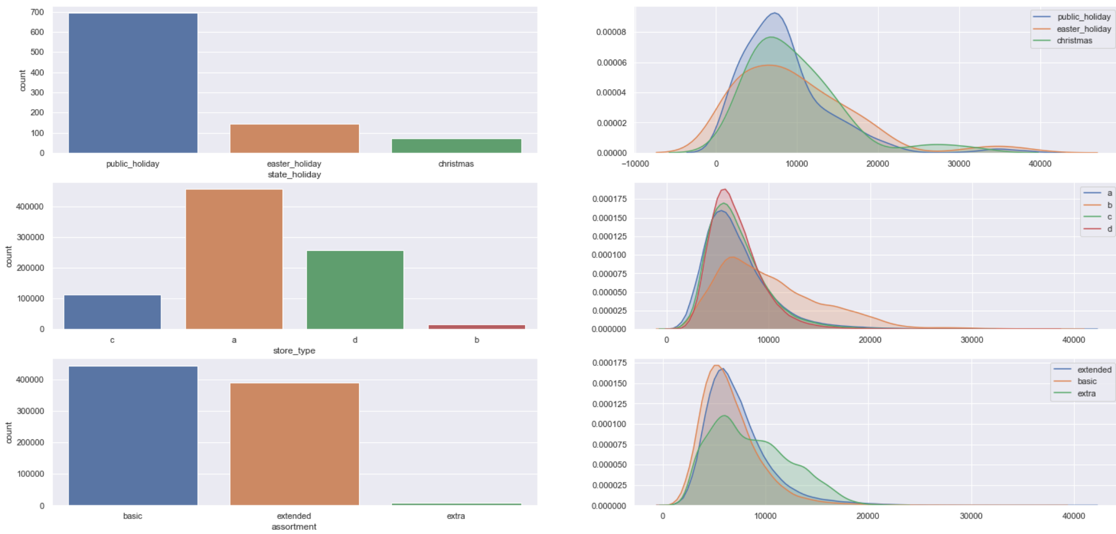


5.1.3 4.1.3. Categorical Variable

[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>



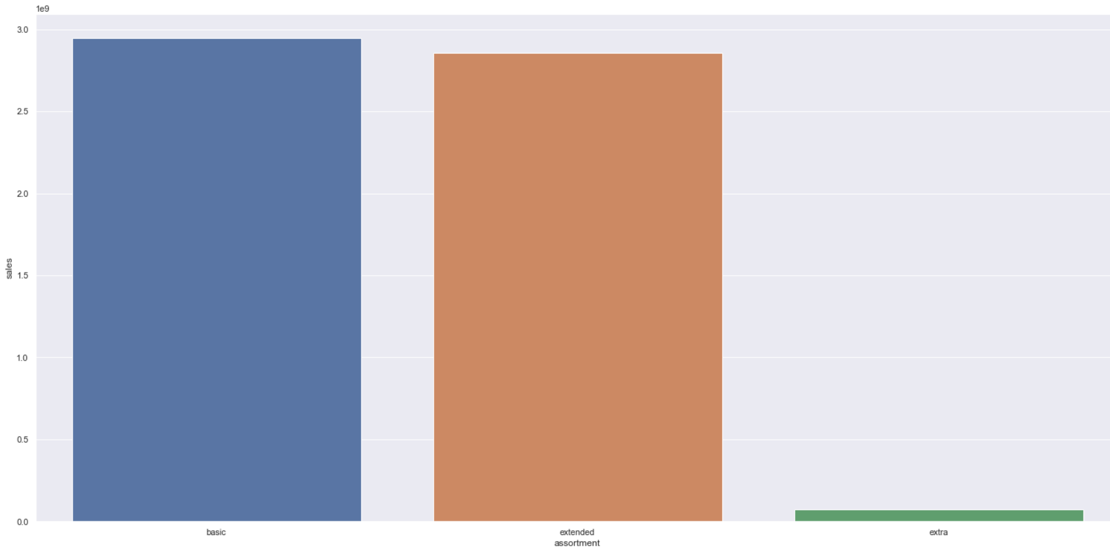
5.2 4.2. Analise Bivariada

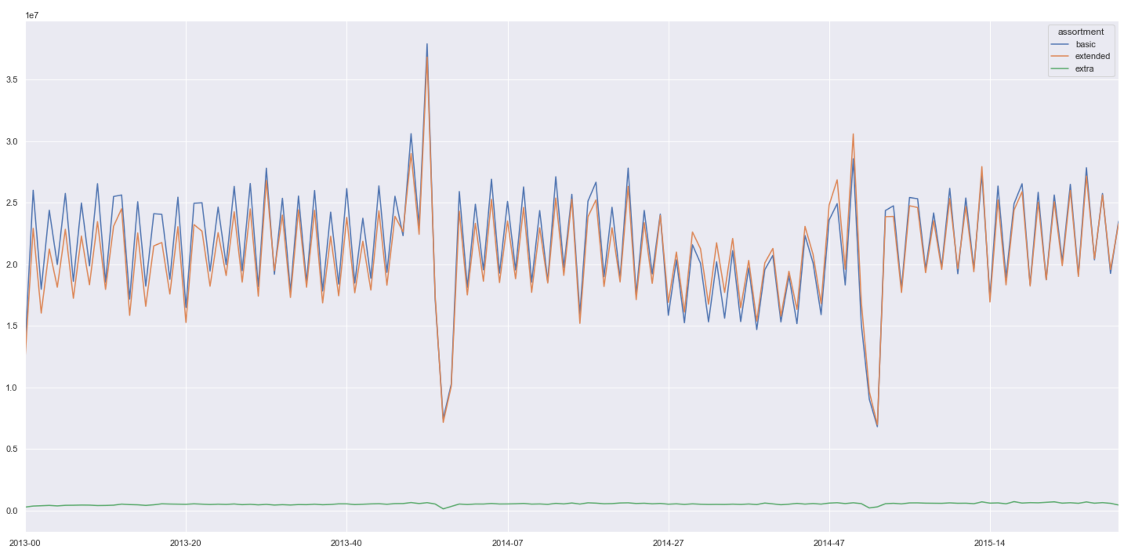
5.2.1 H1. Lojas com maior sortimentos deveriam vender mais.

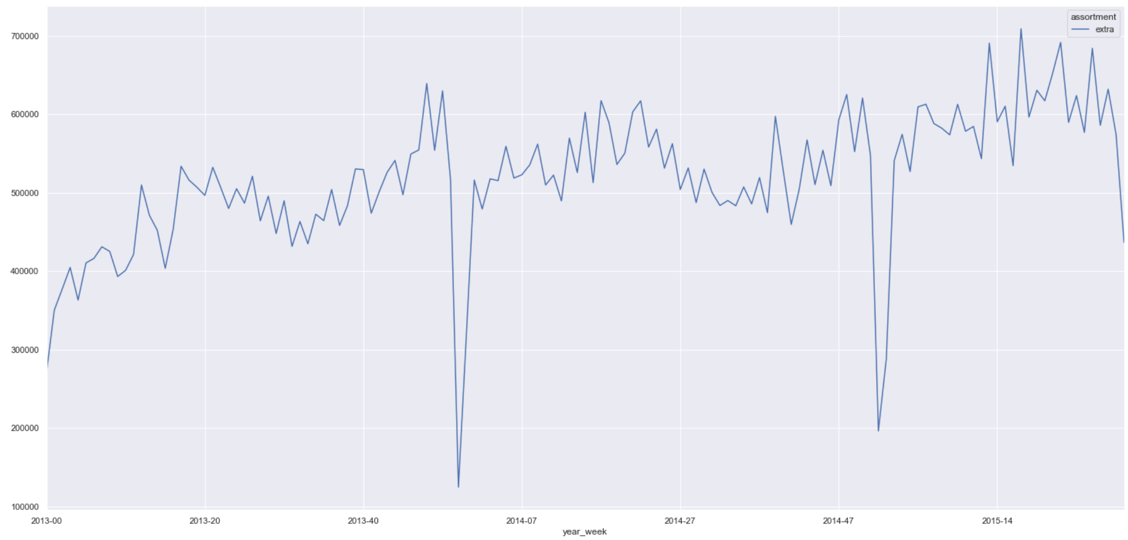
FALSA Lojas com MAIOR SORTIMENTO vendem MENOS.

[29]:
```python
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>
```


1e9
3.0
2.5
2.0
1.5
1.0
0.5
0.0
sales
basic
extended
extra
assortment

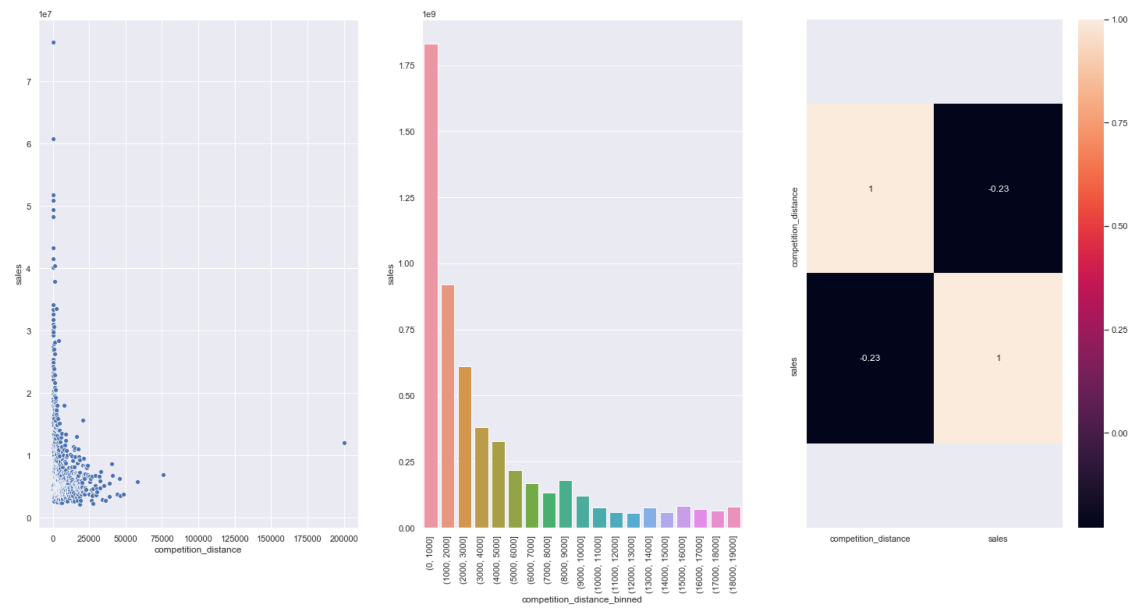

1e7
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
assortment
basic
extended
extra
2013-00
2013-20
2013-40
2014-07
2014-27
2014-47
2015-14
year_week



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

FALSA Lojas com COMPETIDORES MAIS PROXIMOS vendem MAIS.

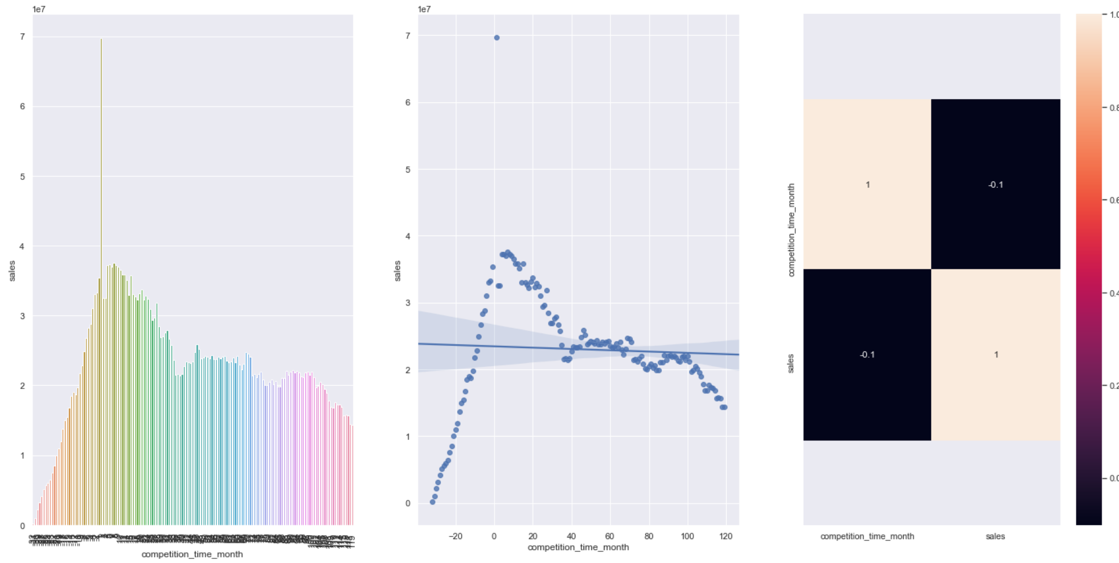
[30]:
```
aux1 = df4[['competition_distance', 'sales']].groupby( 'competition_distance' ).
 ↪sum().reset_index()

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 vendem mais.

FALSE Lojas com COMPETIDORES À MAIS TEMPO vendem MENOS.

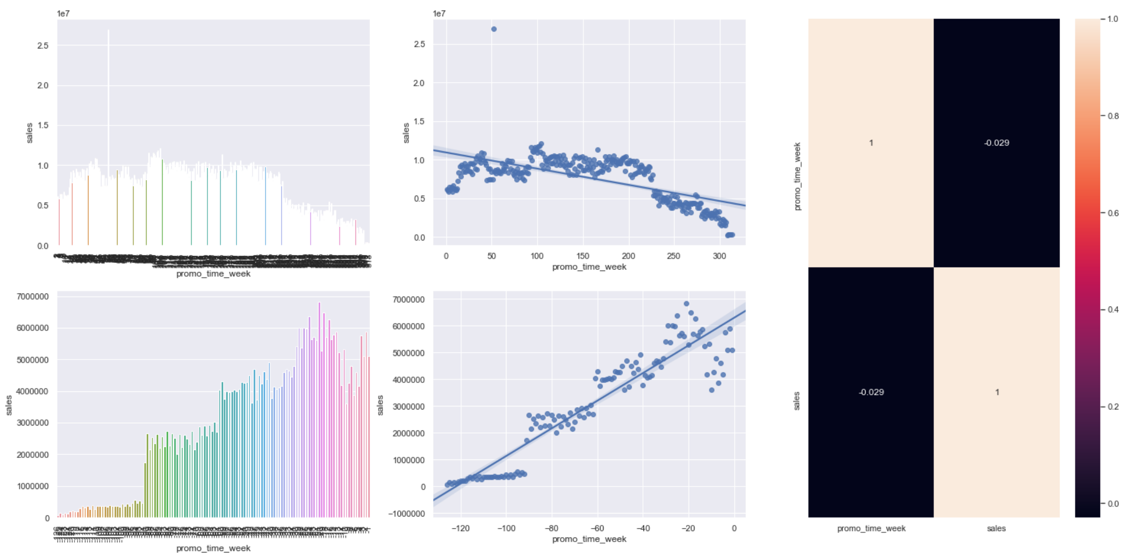
[31]:
```
plt.subplot( 1, 3, 1 )
aux1 = df4[['competition_time_month', 'sales']].groupby( 'competition_time_month' ).sum().reset_index()
aux2 = aux1[( aux1['competition_time_month'] < 120 ) & ( aux1['competition_time_month'] != 0 )]
sns.barplot( x='competition_time_month', y='sales', data=aux2 );
plt.xticks(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

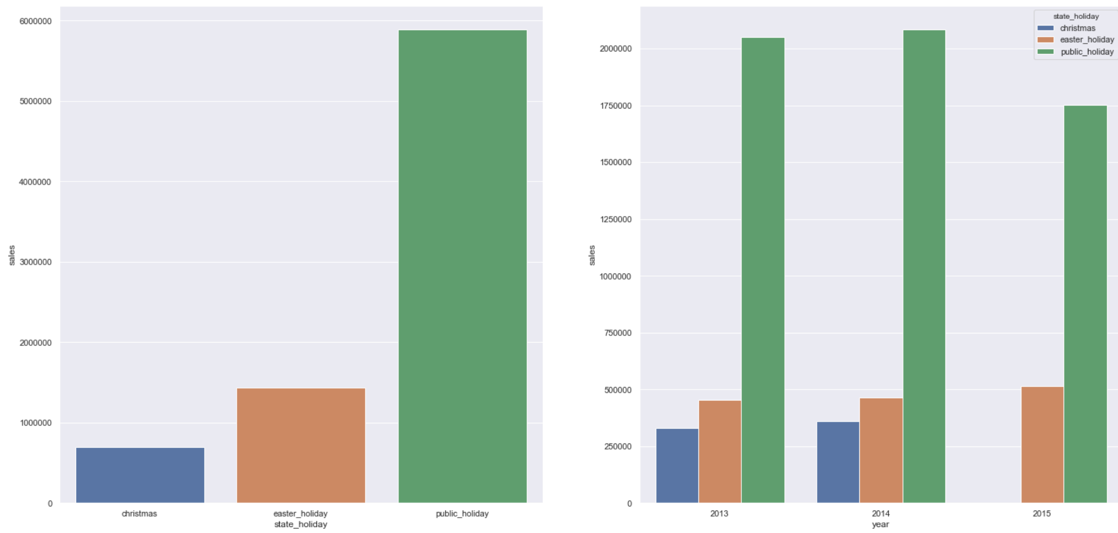
	promo	promo2	sales
0	0	0	1482612096
1	0	1	1289362241
2	1	0	1628930532
3	1	1	1472275754

[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.

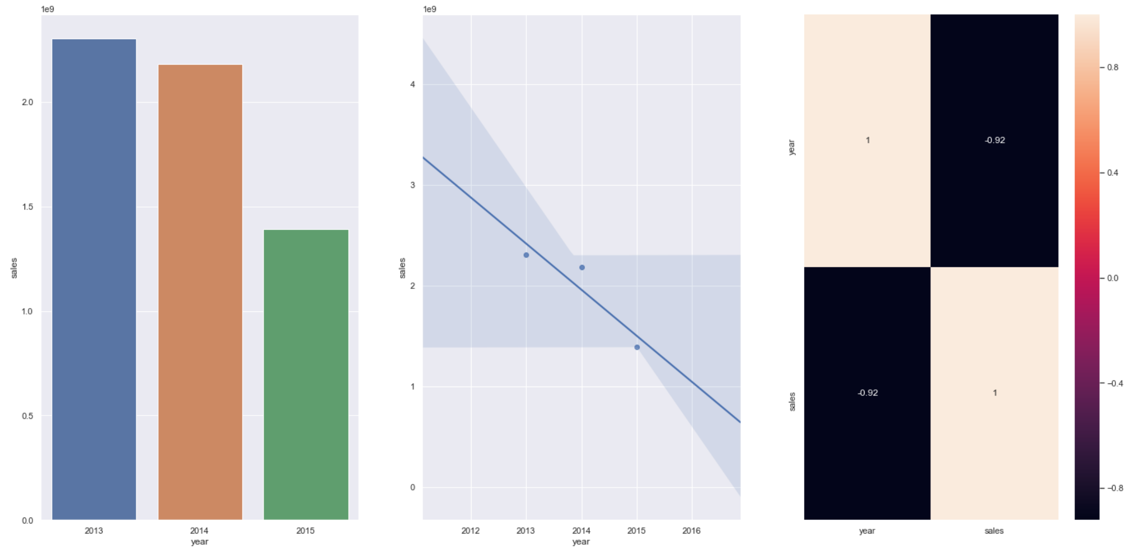
[35]:
```
aux = df4[df4['state_holiday'] != 'regular_day']

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

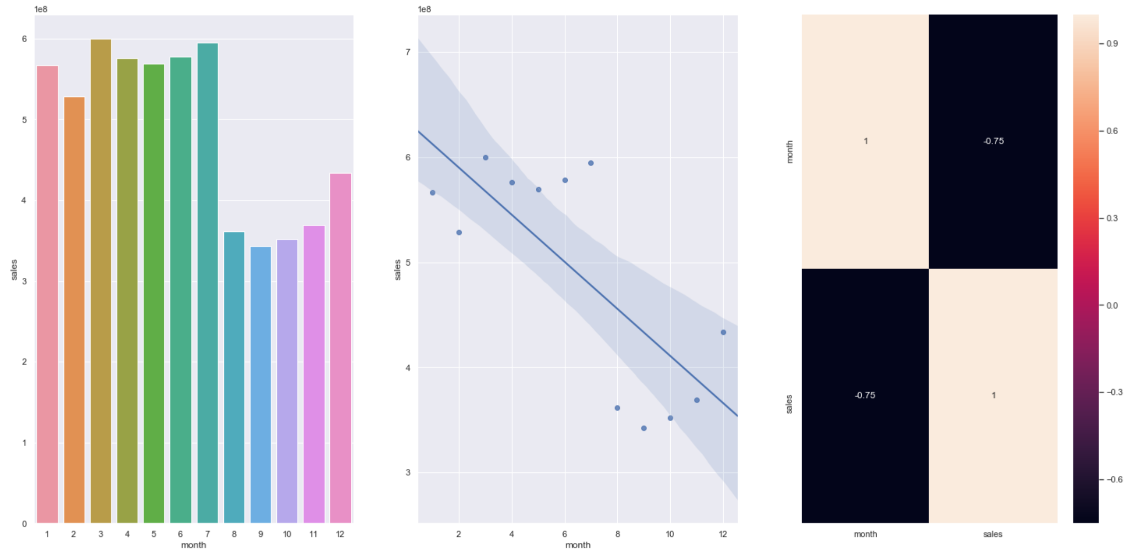
[36]:
```
aux1 = df4[['year', 'sales']].groupby( 'year' ).sum().reset_index()

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

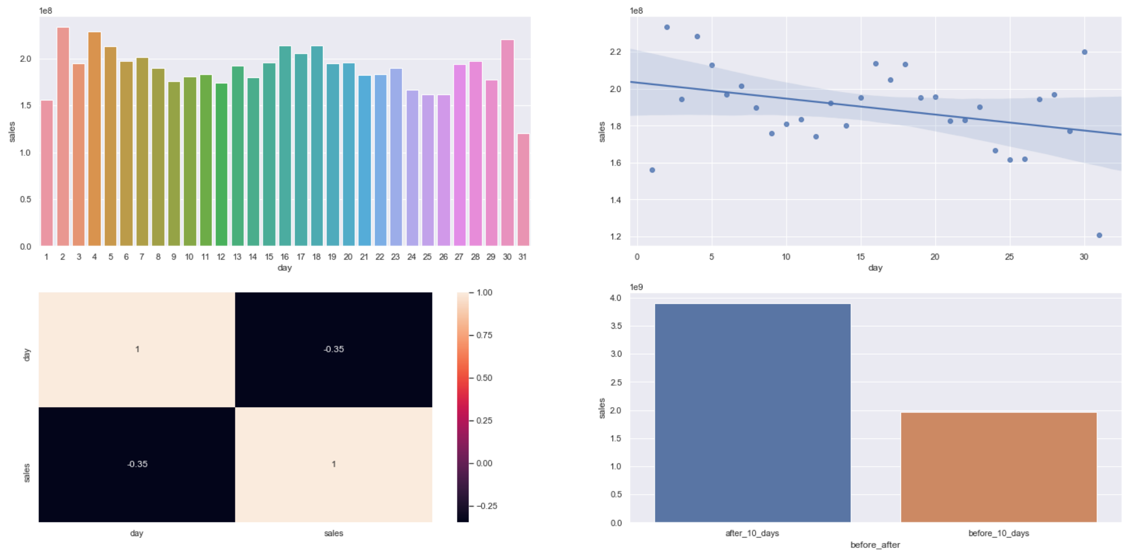
[37]:
```
aux1 = df4[['month', 'sales']].groupby( 'month' ).sum().reset_index()

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.

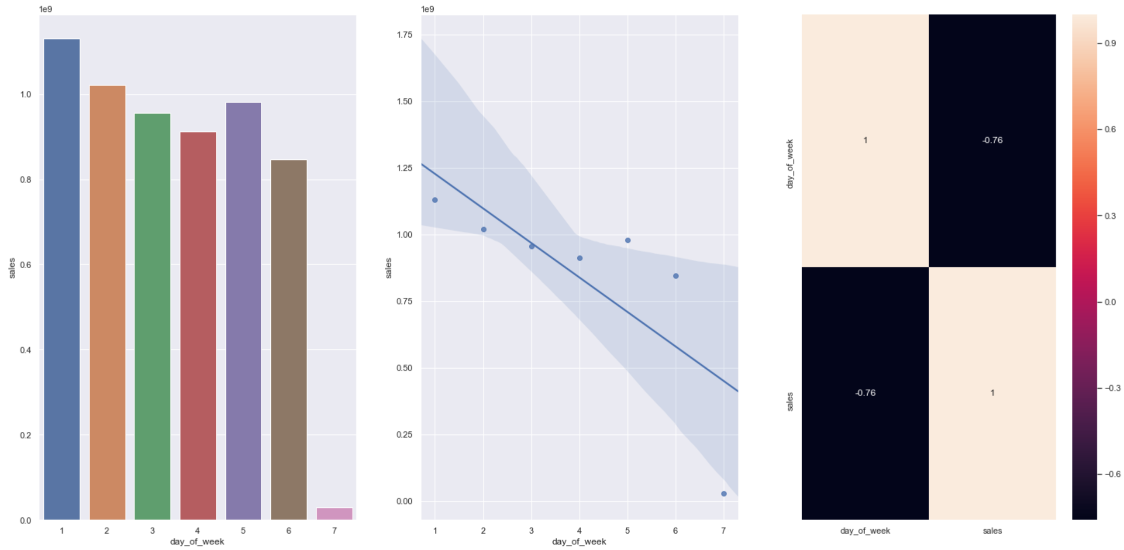
[38]:
```
aux1 = df4[['day', 'sales']].groupby( 'day' ).sum().reset_index()

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

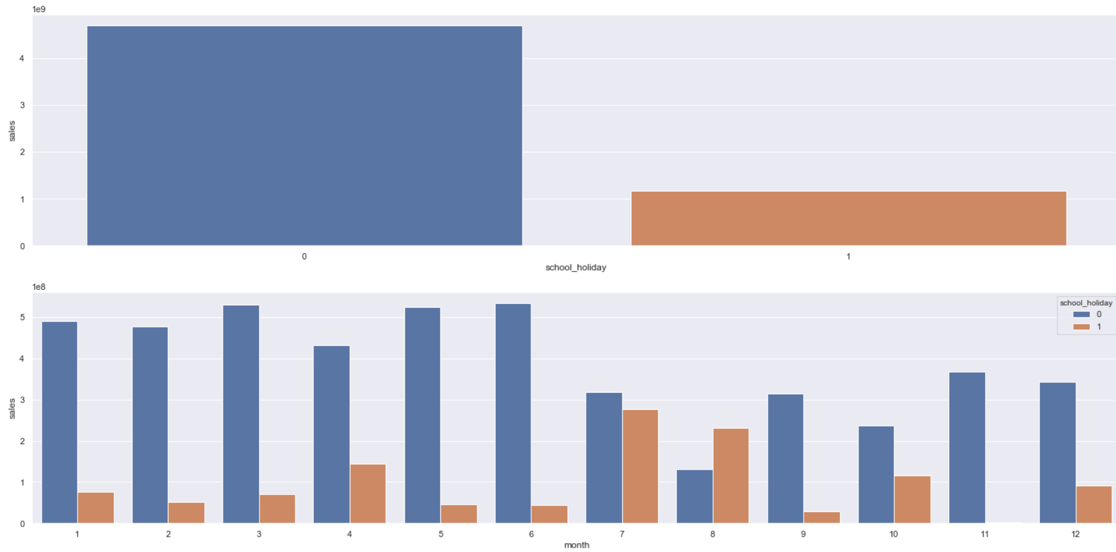
[39]:
```
aux1 = df4[['day_of_week', 'sales']].groupby( 'day_of_week' ).sum().
 ↪reset_index()

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 feriadso 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' ) )
```

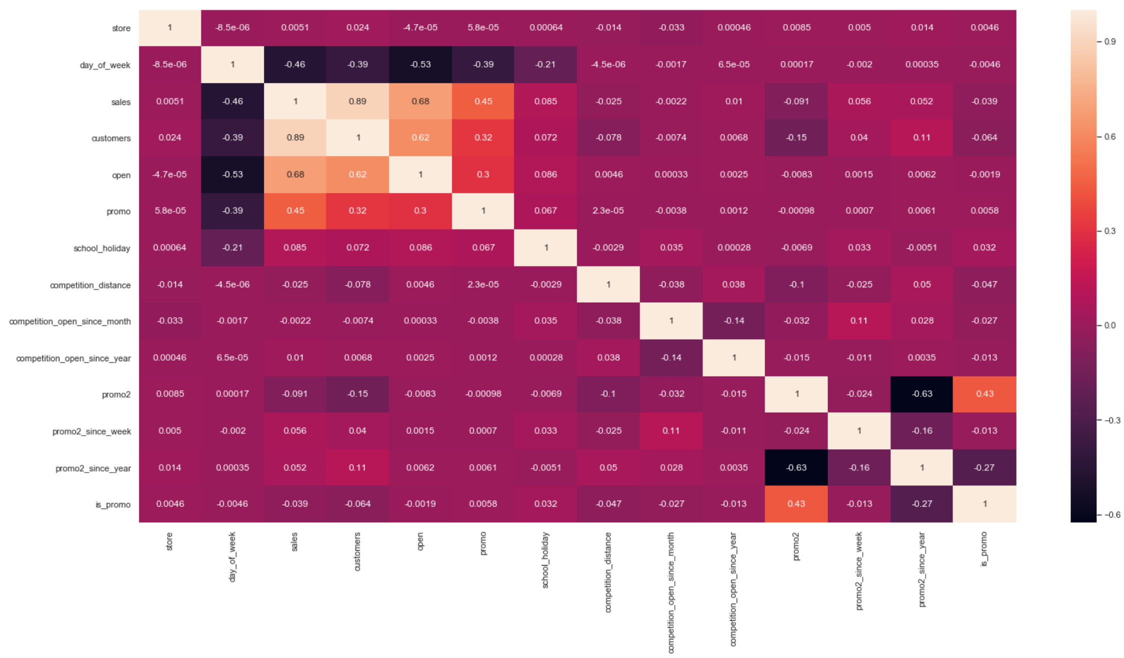
```
Hipoteses    Conclusao    Relevancia
-----------  -----------  ------------
H1           Falsa        Baixa
H2           Falsa        Media
H3           Falsa        Media
H4           Falsa        Baixa
H5           -            -
H7           Falsa        Baixa
H8           Falsa        Media
```

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

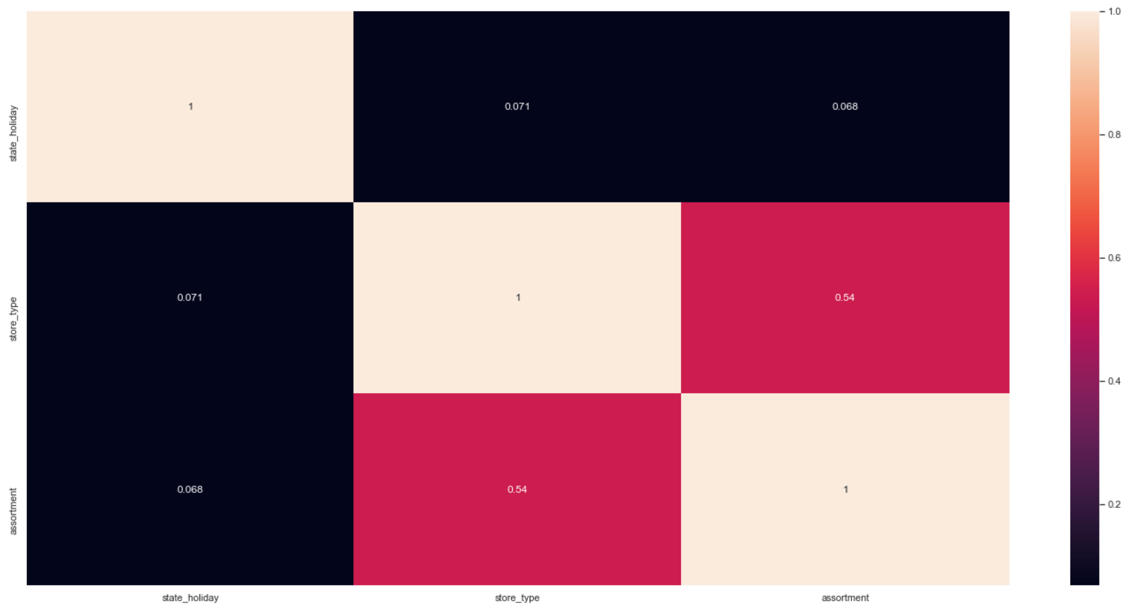


5.3.2 4.3.2. Categorical Attributes

[44]:
```python
# 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() ) )
```

```python
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]:
```python
## 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]:
```python
#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.to_list()
#
## 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]:
```python
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_bytee=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_bytee=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_bytee=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']]
```

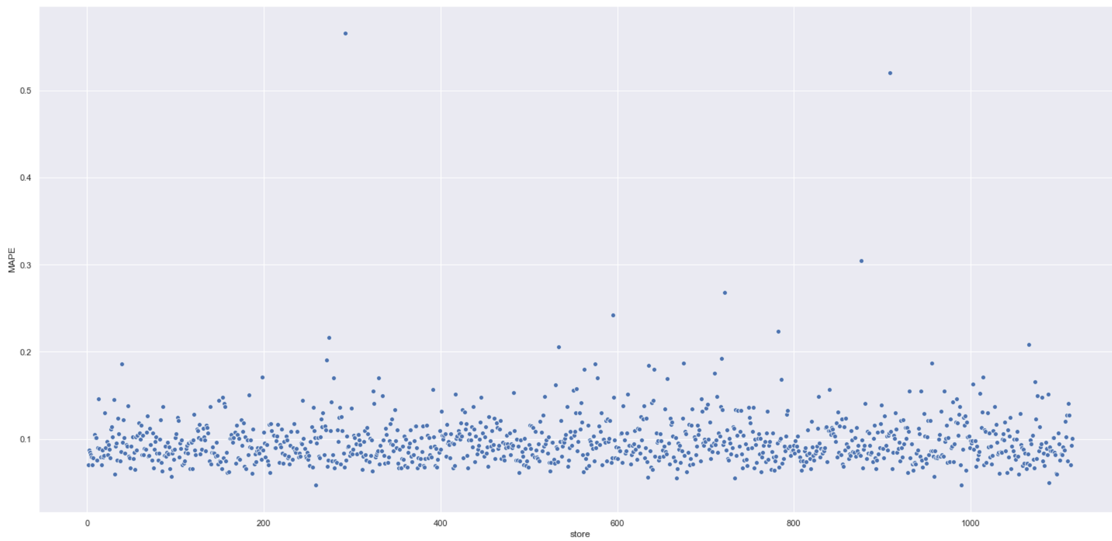
[446]:
```
df92.sort_values( 'MAPE', ascending=False ).head()
```

[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

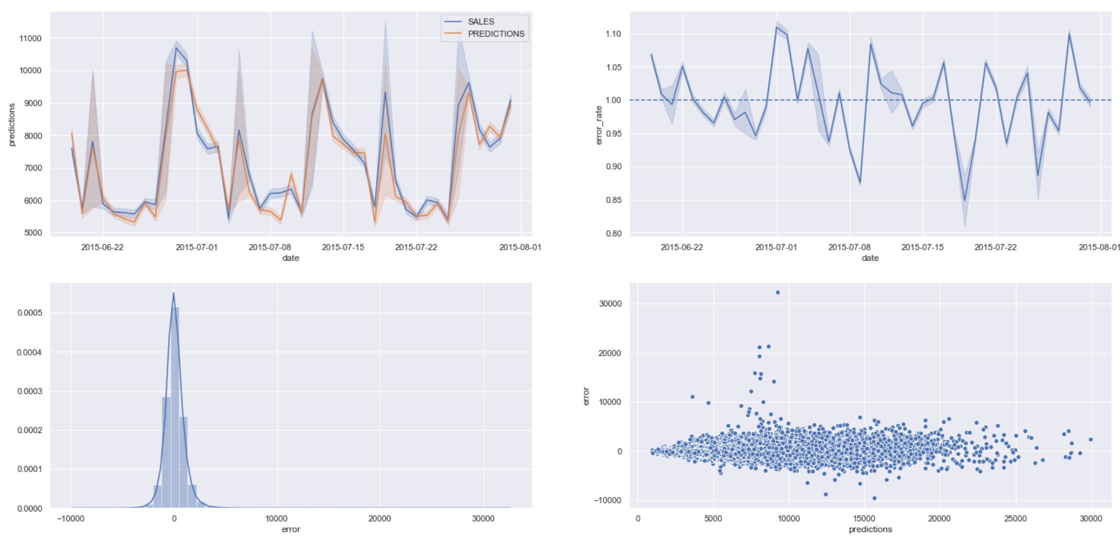
10.3 9.3. Machine Learning Performance

[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>



11 10.0. PASSO 10 - DEPLOY MODEL TO PRODUCTION

[ ]:
```
# Save Trained Model
pickle.dump( model_xgb_tuned, open( '/Users/meigarom/repos/
↪DataScience_Em_Producao/model/model_rossmann.pkl', 'wb' ) )
```

11.1 10.1. Rossmann Class

[ ]:
```
```

[17]:
```
import pickle
import inflection
import pandas as pd
import numpy as np
import math
import datetime
```

```python
class Rossmann( object ):
    def __init__( self ):
        self.home_path='/Users/meigarom/repos/DataScience_Em_Producao/'
        self.competition_distance_scaler   = pickle.load( open( self.home_path␣
↪+ 'parameter/competition_distance_scaler.pkl', 'rb') )
        self.competition_time_month_scaler = pickle.load( open( self.home_path␣
↪+ 'parameter/competition_time_month_scaler.pkl', 'rb') )
        self.promo_time_week_scaler        = pickle.load( open( self.home_path␣
↪+ 'parameter/promo_time_week_scaler.pkl', 'rb') )
        self.year_scaler                   = pickle.load( open( self.home_path␣
↪+ 'parameter/year_scaler.pkl', 'rb') )
        self.store_type_scaler             = pickle.load( open( self.home_path␣
↪+ 'parameter/store_type_scaler.pkl', 'rb') )


    def data_cleaning( self, df1 ):

        ## 1.1. Rename Columns
        cols_old = ['Store', 'DayOfWeek', 'Date', '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

        ## 1.3. Data Types
        df1['date'] = pd.to_datetime( df1['date'] )

        ## 1.5. Fillout NA
        #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 )

        ## 1.6. Change Data Types
        # competiton
        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 )

        return df1


    def feature_engineering( self, df2 ):

        # 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.strptime( 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' )

        # 3.0. PASSO 03 - FILTRAGEM DE VARIÁVEIS
        ## 3.1. Filtragem das Linhas
        df2 = df2[df2['open'] != 0]

        ## 3.2. Selecao das Colunas
        cols_drop = ['open', 'promo_interval', 'month_map']
        df2 = df2.drop( cols_drop, axis=1 )

        return df2


    def data_preparation( self, df5 ):
```

```
        ## 5.2. Rescaling
        # competition distance
        df5['competition_distance'] = self.competition_distance_scaler.
↪fit_transform( df5[['competition_distance']].values )

        # competition time month
        df5['competition_time_month'] = self.competition_time_month_scaler.
↪fit_transform( df5[['competition_time_month']].values )

        # promo time week
        df5['promo_time_week'] = self.promo_time_week_scaler.fit_transform(␣
↪df5[['promo_time_week']].values )

        # year
        df5['year'] = self.year_scaler.fit_transform( df5[['year']].values )

        ### 5.3.1. Encoding
        # state_holiday - One Hot Encoding
        df5 = pd.get_dummies( df5, prefix=['state_holiday'],␣
↪columns=['state_holiday'] )

        # store_type - Label Encoding
        df5['store_type'] = self.store_type_scaler.fit_transform(␣
↪df5['store_type'] )

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


        ### 5.3.3. Nature Transformation
        # 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 ) ) )


        cols_selected = [ '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']

        return df5[ cols_selected ]


    def get_prediction( self, model, original_data, test_data ):
        # prediction
        pred = model.predict( test_data )

        # join pred into the original data
        original_data['prediction'] = np.expm1( pred )

        return original_data.to_json( orient='records', date_format='iso' )
```

11.2 10.2. API Handler

[18]:
```
import pickle
import pandas as pd
from flask             import Flask, request, Response
from rossmann.Rossmann import Rossmann

# loading model
model = pickle.load( open( '/Users/meigarom/repos/DataScience_Em_Producao/model/
↪model_rossmann.pkl', 'rb') )

# initialize API
app = Flask( __name__ )

@app.route( '/rossmann/predict', methods=['POST'] )
```

```
def rossmann_predict():
    test_json = request.get_json()

    if test_json: # there is data
        if isinstance( test_json, dict ): # unique example
            test_raw = pd.DataFrame( test_json, index=[0] )

        else: # multiple example
            test_raw = pd.DataFrame( test_json, columns=test_json[0].keys() )

        # Instantiate Rossmann class
        pipeline = Rossmann()

        # data cleaning
        df1 = pipeline.data_cleaning( test_raw )

        # feature engineering
        df2 = pipeline.feature_engineering( df1 )

        # data preparation
        df3 = pipeline.data_preparation( df2 )

        # prediction
        df_response = pipeline.get_prediction( model, test_raw, df3 )

        return df_response


    else:
        return Reponse( '{}', status=200, mimetype='application/json' )

if __name__ == '__main__':
    app.run( '0.0.0.0' )
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
<ipython-input-18-202fd353a2d0> in <module>
      2 import pandas as pd
      3 from flask             import Flask, request, Response
----> 4 from rossmann.Rossmann import Rossmann
      5
      6 # loading model

ModuleNotFoundError: No module named 'rossmann'
```

11.3 10.3. API Tester

[ ]:
```python
# loading test dataset
df10 = pd.read_csv( '/Users/meigarom/repos/DataScience_Em_Producao/data/test.
↪csv' )
```

[ ]:
```python
# merge test dataset + store
df_test = pd.merge( df10, df_store_raw, how='left', on='Store' )

# choose store for prediction
df_test = df_test[df_test['Store'].isin( [20, 23, 22] )]

# remove closed days
df_test = df_test[df_test['Open'] != 0]
df_test = df_test[~df_test['Open'].isnull()]
df_test = df_test.drop( 'Id', axis=1 )
```

[ ]:
```python
# convert Dataframe to json
data = json.dumps( df_test.to_dict( orient='records' ) )
```

[ ]:
```python
# API Call
#url = 'http://0.0.0.0:5000/rossmann/predict'
url = 'https://rossmann-model-test.herokuapp.com/rossmann/predict'
header = {'Content-type': 'application/json' }
data = data

r = requests.post( url, data=data, headers=header )
print( 'Status Code {}'.format( r.status_code ) )
```

[ ]:
```python
d1 = pd.DataFrame( r.json(), columns=r.json()[0].keys() )
```

[ ]:
```python
d2 = d1[['store', 'prediction']].groupby( 'store' ).sum().reset_index()

for i in range( len( d2 ) ):
    print( 'Store Number {} will sell R${:,.2f} in the next 6 weeks'.format(
            d2.loc[i, 'store'],
            d2.loc[i, 'prediction'] ) )
```