m05_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 )
```

```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
```

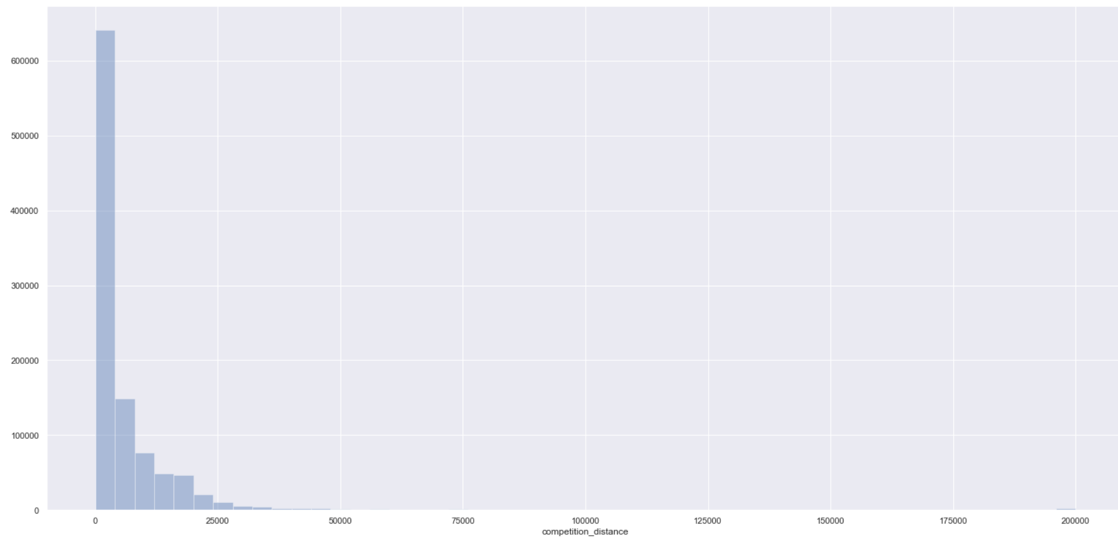
[15]:

```
                      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
```

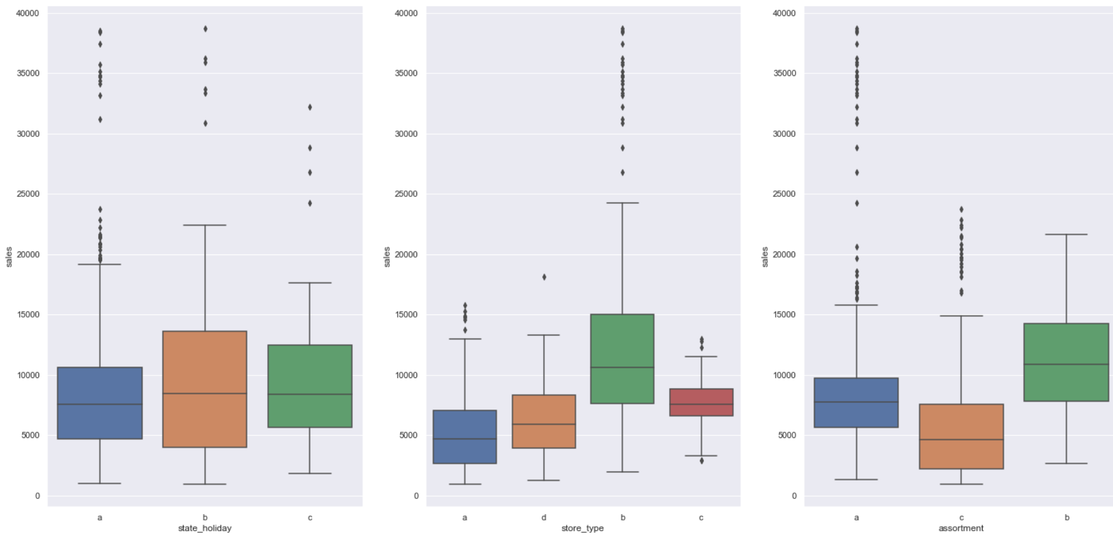
[18]:
```
aux = df1[(df1['state_holiday'] != '0') & (df1['sales'] > 0)]

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]:

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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

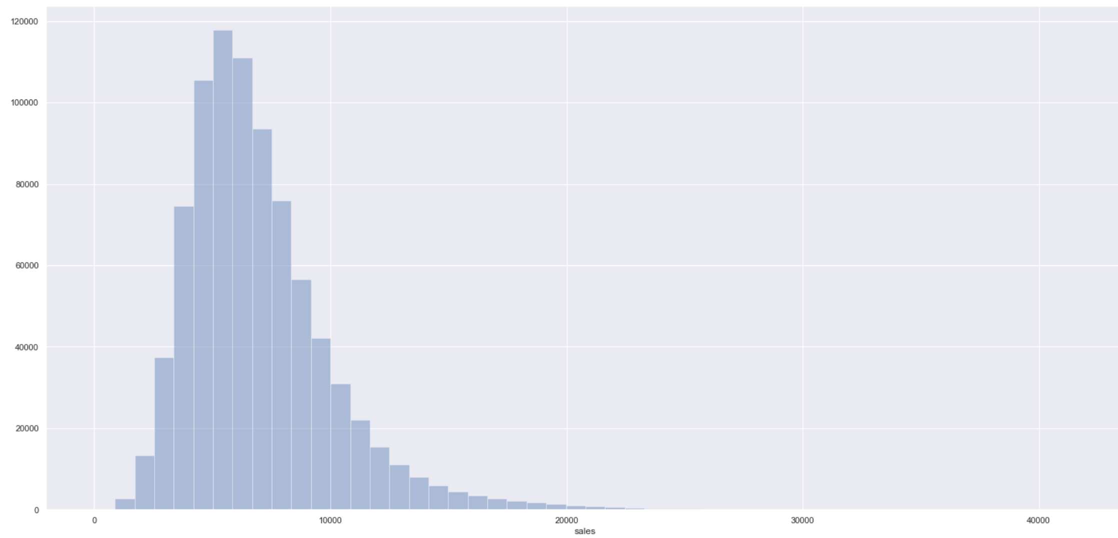
[25]:
```
df4 = df3.copy()
```

5.1 4.1. Analise Univariada

5.1.1 4.1.1. Response Variable

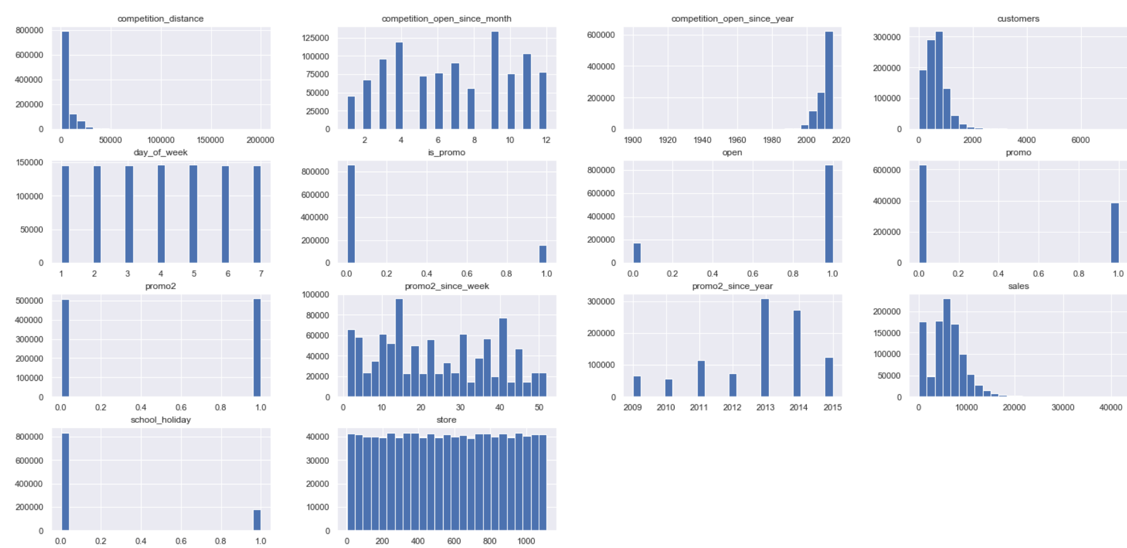
[26]:
```
sns.distplot( df4['sales'], kde=False  )
```

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



5.1.2 4.1.2. Numerical Variable

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

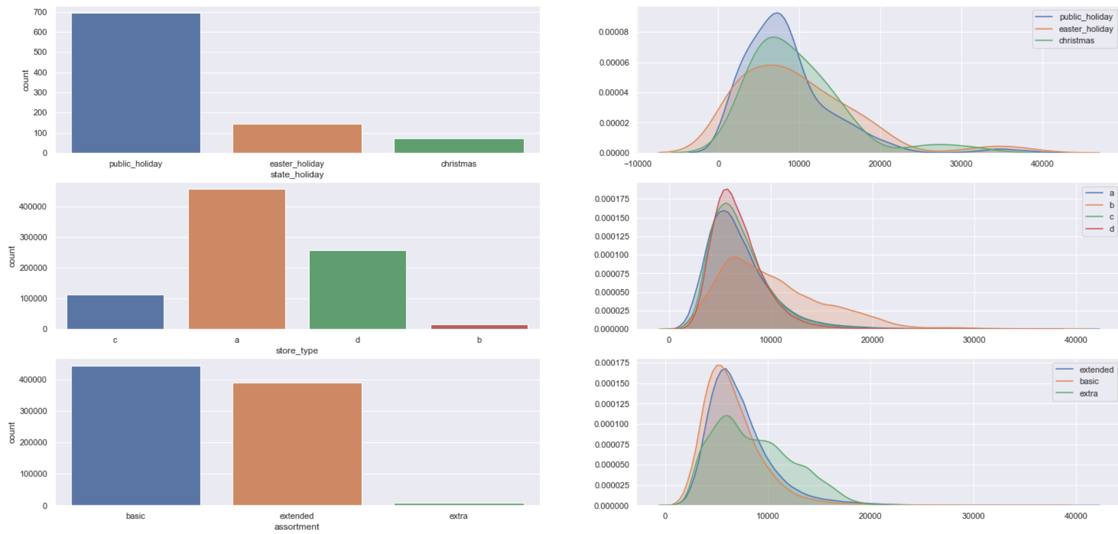


5.1.3 4.1.3. Categorical Variable

[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>



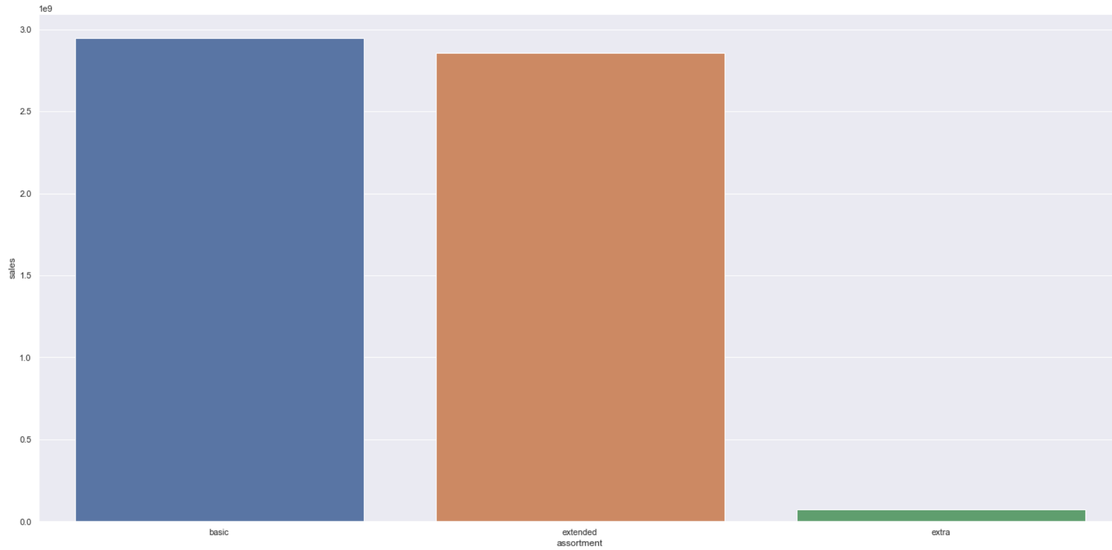
5.2 4.2. Analise Bivariada

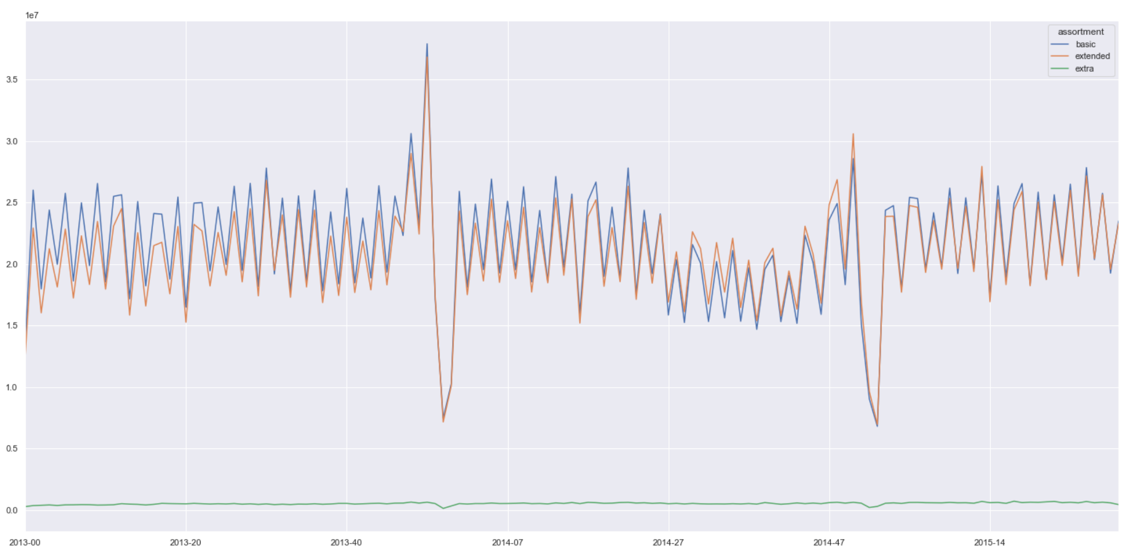
5.2.1 H1. Lojas com maior sortimentos deveriam vender mais.

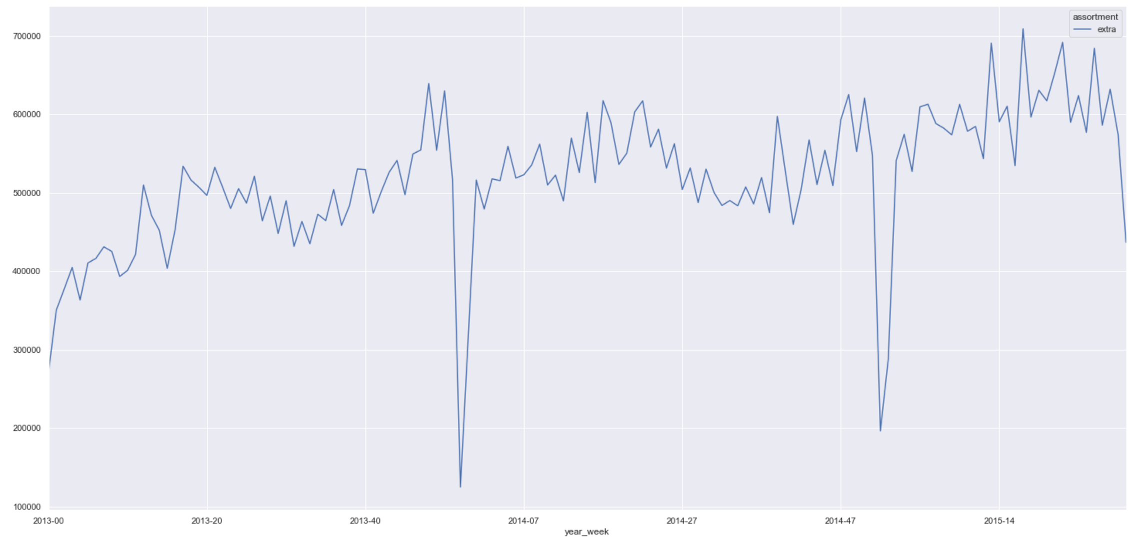
FALSA Lojas com MAIOR SORTIMENTO vendem MENOS.

[29]:
```
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

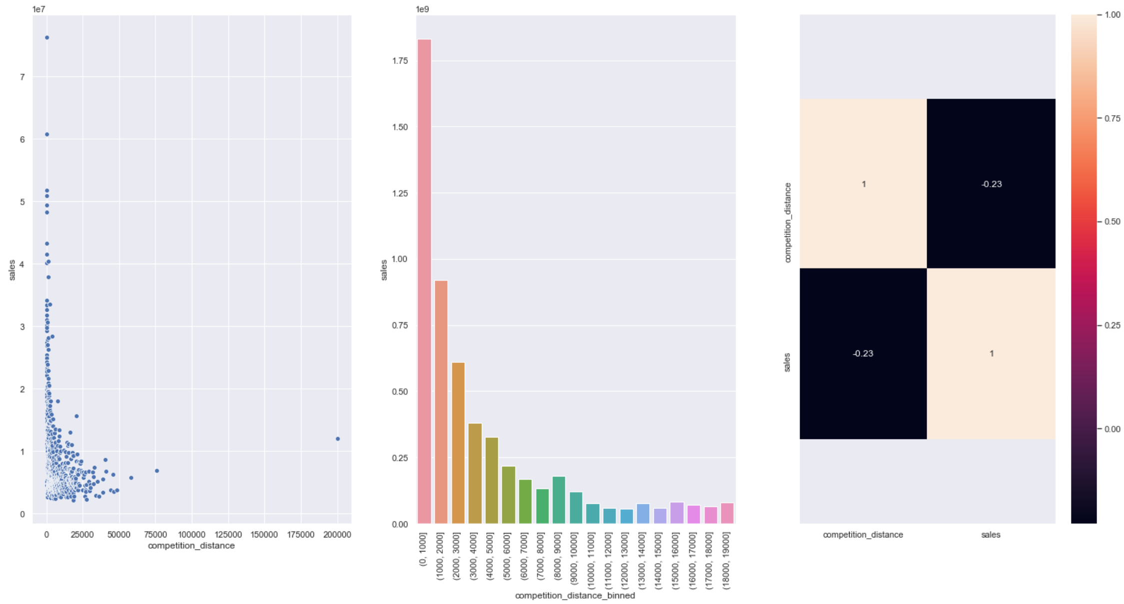

1e7
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
assortment
basic
extended
extra
2013-00
2013-20
2013-40
2014-07
2014-27
2014-47
2015-14
year_week



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

FALSA Lojas com COMPETIDORES MAIS PROXIMOS vendem MAIS.

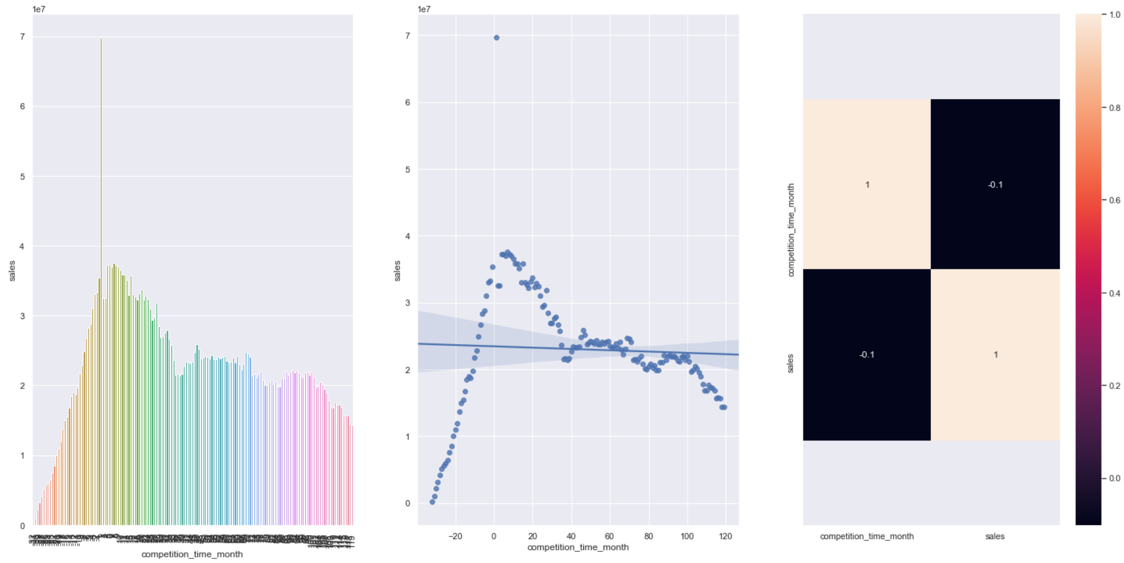
[30]:
```
aux1 = df4[['competition_distance', 'sales']].groupby( 'competition_distance' ).
 ↪sum().reset_index()

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.

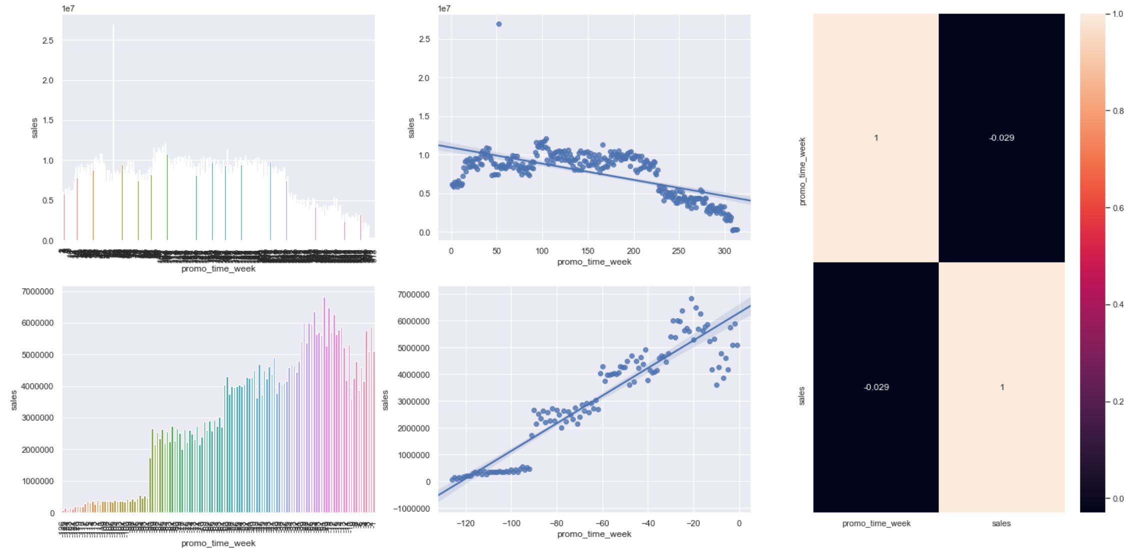
[31]:
```python
plt.subplot( 1, 3, 1 )
aux1 = df4[['competition_time_month', 'sales']].groupby( 'competition_time_month' ).sum().reset_index()
aux2 = aux1[( aux1['competition_time_month'] < 120 ) & ( aux1['competition_time_month'] != 0 )]
sns.barplot( x='competition_time_month', y='sales', data=aux2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

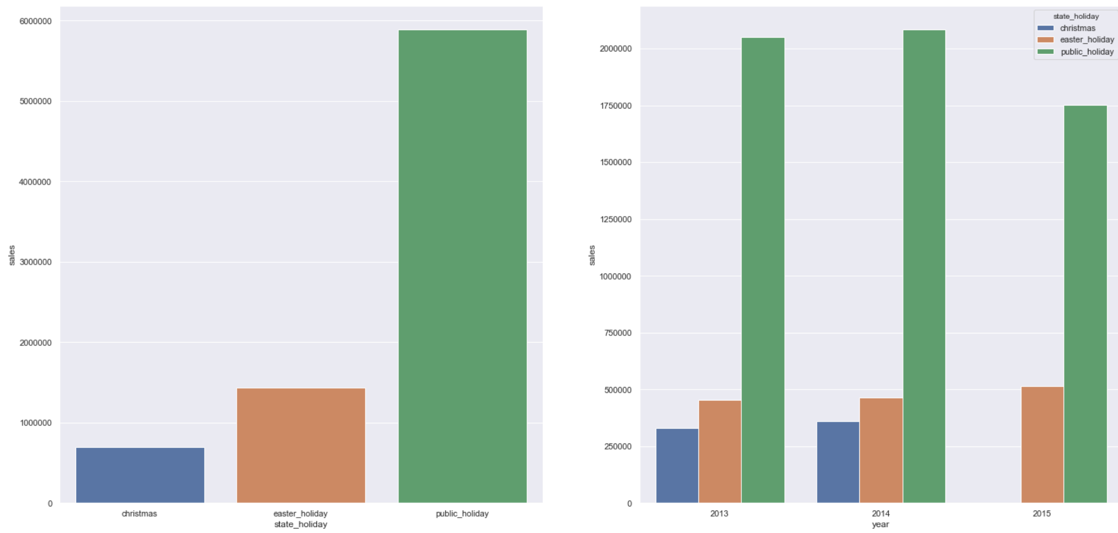
	promo	promo2	sales
0	0	0	1482612096
1	0	1	1289362241
2	1	0	1628930532
3	1	1	1472275754

[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.

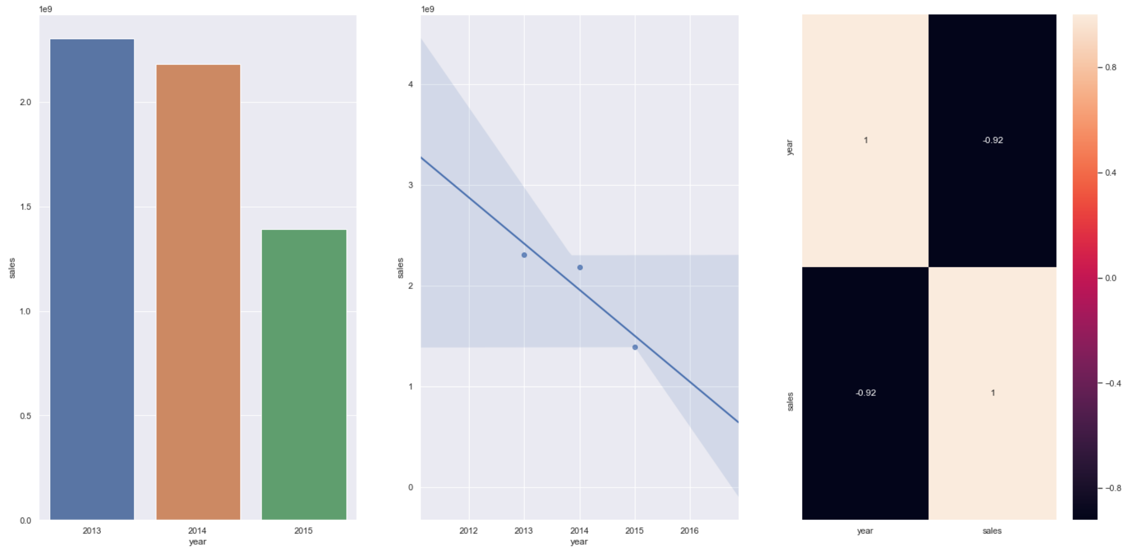
[35]:
```
aux = df4[df4['state_holiday'] != 'regular_day']

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

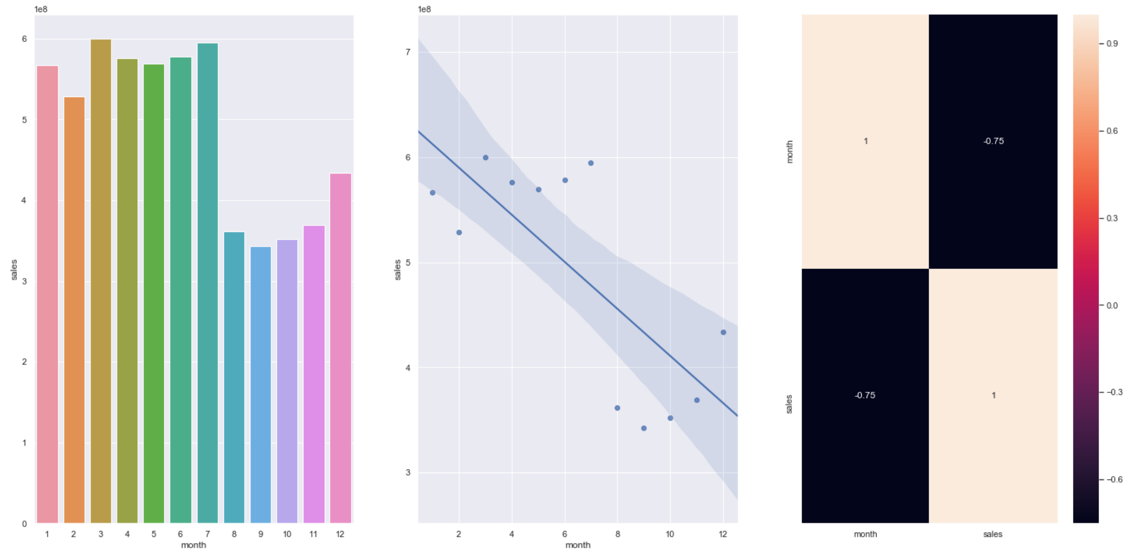
[36]:
```
aux1 = df4[['year', 'sales']].groupby( 'year' ).sum().reset_index()

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

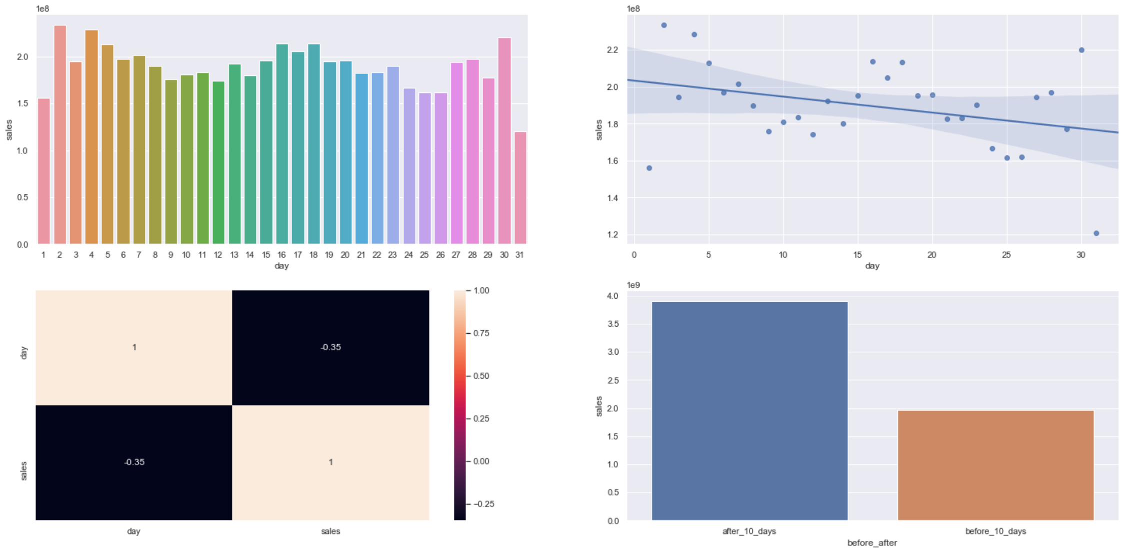
[37]:
```
aux1 = df4[['month', 'sales']].groupby( 'month' ).sum().reset_index()

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.

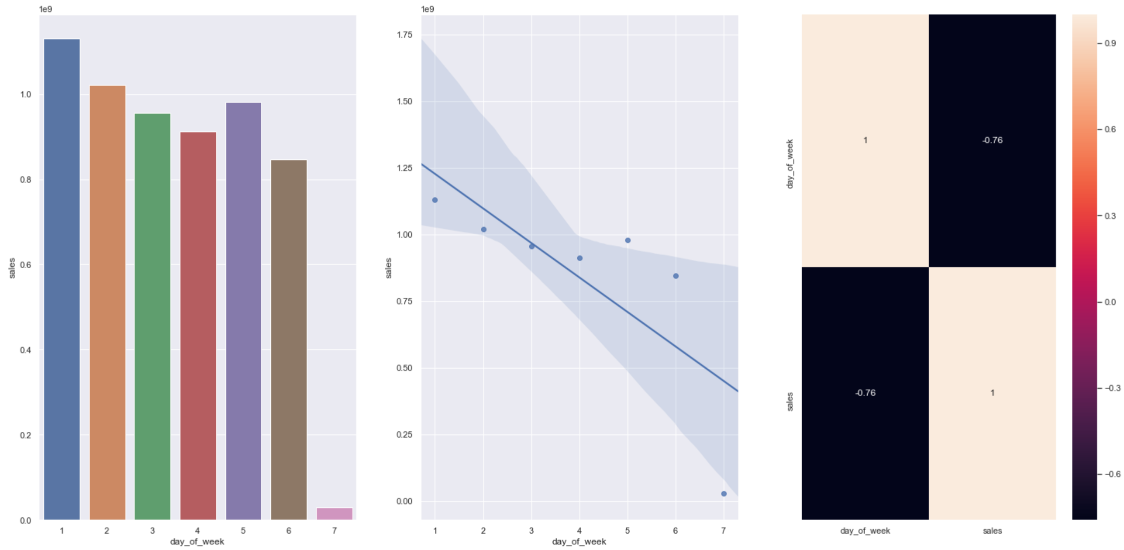
[38]:
```
aux1 = df4[['day', 'sales']].groupby( 'day' ).sum().reset_index()

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

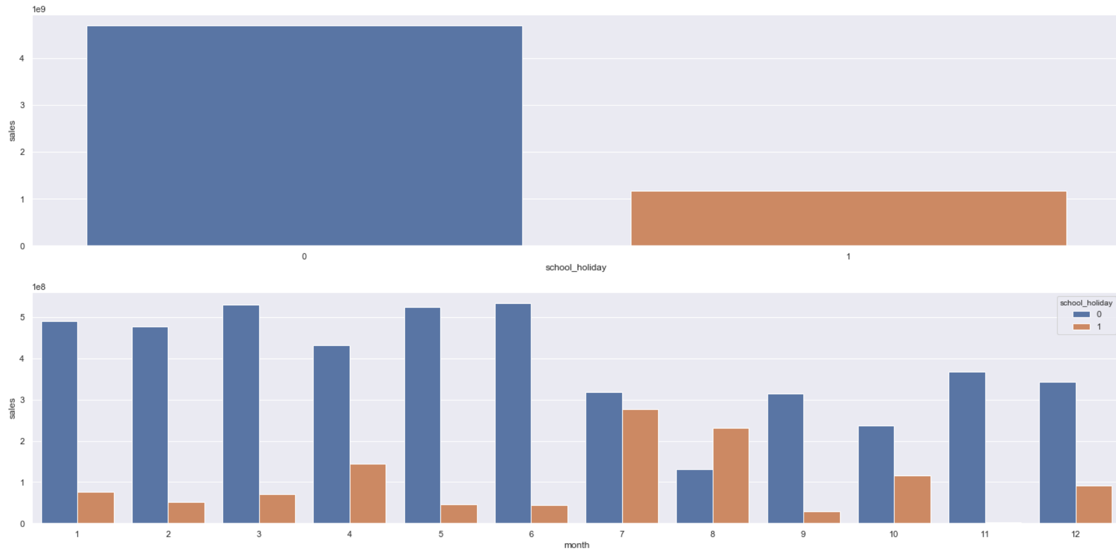
[39]:
```
aux1 = df4[['day_of_week', 'sales']].groupby( 'day_of_week' ).sum().
 ↪reset_index()

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]:
```python
from tabulate import tabulate
```

[42]:
```python
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' ) )
```

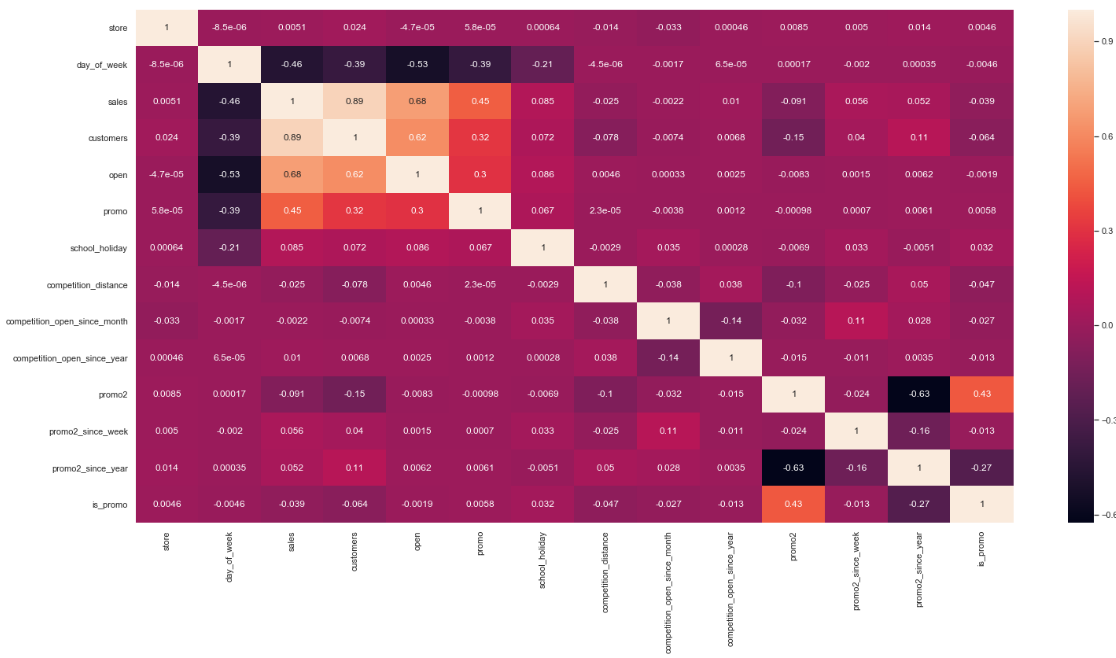
```
Hipoteses    Conclusao    Relevancia
-----------  -----------  ------------
H1           Falsa        Baixa
H2           Falsa        Media
H3           Falsa        Media
H4           Falsa        Baixa
H5           -            -
H7           Falsa        Baixa
H8           Falsa        Media
```

```
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 );
```

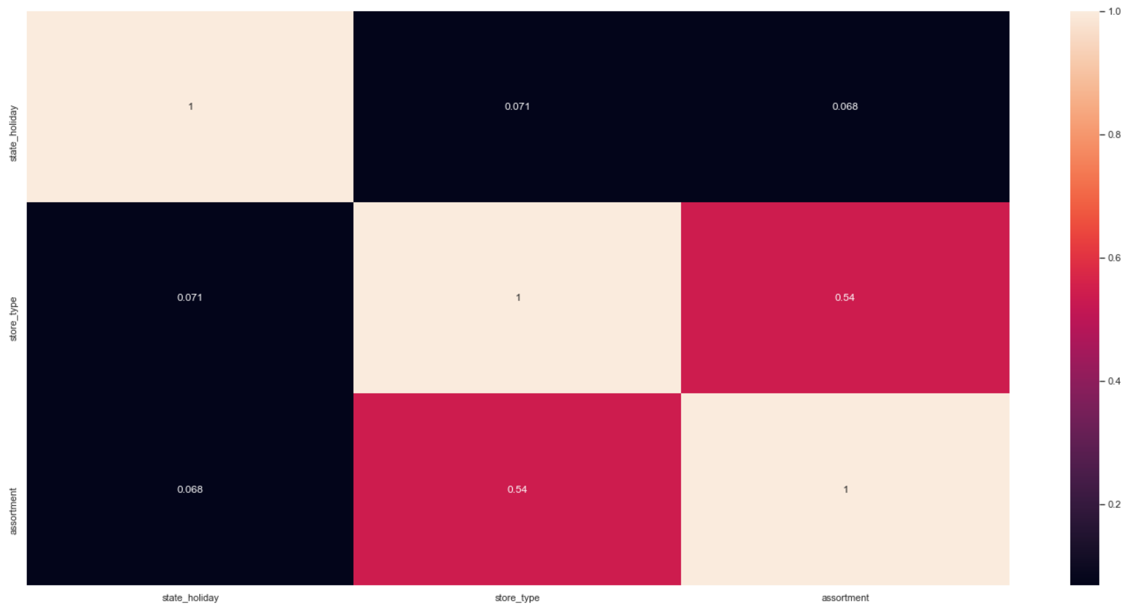


5.3.2 4.3.2. Categorical Attributes

[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'] )
```

```python
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]:
```python
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 ) ) )
```