0.0 IMPORTS

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

from tabulate              import tabulate
from matplotlib            import pyplot as plt
from IPython.core.display  import HTML
from IPython.display       import Image
from matplotlib.gridspec   import GridSpec
from scipy                 import stats
from sklearn.preprocessing import RobustScaler, MinMaxScaler, LabelEncoder
from boruta                import BorutaPy
from sklearn.ensemble      import RandomForestRegressor
from sklearn.metrics       import mean_absolute_error, mean_squared_error
from sklearn.linear_model  import LinearRegression, Lasso
```

0.1. Helper Functions

In [2]:
```
def cramer_v( x, y ):
    #cm = pd.crosstab( x, y ).as_matrix()
    cm = pd.crosstab( x, y ).to_numpy()
    n = cm.sum()
    r, k = cm.shape

    chi2 = stats.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 )))

# Função para ampliar area de edição do jupyter notebook
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()
```

In [3]:
```
####   CROSS VALIDATION

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 iteraction
        mae_list.append( m_result['MAE'] )
        mape_list.append( m_result['MAPE'] )
        rmse_list.append( m_result['RMSE'] )

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


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

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

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

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

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

    chi2 = stats.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 )))

# Função para ampliar area de edição do jupyter notebook
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()
```

In [4]:
```
jupyter_settings()
```

```
Populating the interactive namespace from numpy and matplotlib
/home/leandro/.local/lib/python3.9/site-packages/IPython/core/magics/pylab.py:159: UserWarning: pylab import has clobbered these variables: ['random']
`%matplotlib` prevents importing * from pylab and numpy
  warn("pylab import has clobbered these variables: %s"  % clobbered +
```

0.2. Loading data

In [5]:
```
# leitura dos dados fornecidos
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 de datasets
df_raw = pd.merge(df_sales_raw, df_store_raw, how='left', on='Store')
```

In [6]:
```
# teste de leitura simples
df_raw.sample()
```

Out[6]:

	Store	DayOfWeek	Date	Sales	Customers	Open	Promo	StateHoliday	SchoolHoliday	StoreType	Assortment	CompetitionDistance	CompetitionOpenSinceMonth	CompetitionOpenSinceYear	Promo2	Promo2SinceWeek
493315	156	2	2014-04-15	11636	1054	1	1	0	0	a	a	2020.0	2.0	2011.0	1	14.0

1.0. PASSO 01 - DESCRICAO DOS DADOS

In [7]:
```
# fazer uma cópia do dataset quando muda de seção, somente para manter os dados , caso seja necessário recomeçar
df1 = df_raw.copy()
```

In [8]:
```
# visualizando os nomes das colunas do dataset
df1.columns
```

Out[8]:
```
Index(['Store', 'DayOfWeek', 'Date', 'Sales', 'Customers', 'Open', 'Promo',
       'StateHoliday', 'SchoolHoliday', 'StoreType', 'Assortment',
       'CompetitionDistance', 'CompetitionOpenSinceMonth',
       'CompetitionOpenSinceYear', 'Promo2', 'Promo2SinceWeek',
       'Promo2SinceYear', 'PromoInterval'],
      dtype='object')
```

1.1. Rename Columns

In [9]:
```
# renomenado as colunas para facilitar analise dos dados
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
#visualizando as colunas renomeadas
df1.columns
```

Out[9]:
```
Index(['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'],
      dtype='object')
```

1.2. Data Dimensions

In [10]:
```
# leitura de colunas/linhas do dataset para dimensionar os dados
print('Number of Rows: {}'.format(df1.shape[0]))
print('Number of Cols: {}'.format(df1.shape[1]))
```

```
Number of Rows: 1017209
Number of Cols: 18
```

1.3. Data Types

In [11]:
```
# leitura do tipos de dados de cada coluna
df1['date'] = pd.to_datetime(df1['date'])
df1.dtypes
```

Out[11]:
```
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
```

1.4. Ckeck NA

In [12]:
```
# Verificando colunas com registros vazios
df1.isna().sum()
```

Out[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            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
```

1.5. Fillout NA

In [13]:
```
#competition_distance --> 2642 registros vazios
# Verificando qual a maior distancia de um concorrente  -> 75860.0
# SOLUÇÃO para popular registros vazios-> Vou aplicar uma distancia maxima = 200000.0 para os registros NAN desta coluna
df1['competition_distance'] = df1['competition_distance'].apply( lambda x: 200000.0 if math.isnan(x) else x )

#=========================================================================================================================
#competition_open_since_month --> 323348 registros vazios
# mes que o concorrente mais proximo foi aberto. Pq este campo esta vazio? a loja ja estava aberta quando instalou a nossa loja ou ninguem resgistrou esta informação
# SOLUÇÃO para popular registros vazios-> APLICAR A DATA (mes) DE VENDA NESTE CAMPO, PARA DEPOIS TESTAR USANDO CRISP E AVALIAR O ALGORITMO
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 --> 323348 registros vazios
# IDEM solução do item anterior
# SOLUÇÃO para popular registros vazios-> APLICAR A DATA (ano) DE VENDA NESTE CAMPO, PARA DEPOIS TESTAR USANDO CRISP E AVALIAR O ALGORITMO
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 --> 508031 registros vazios
# SOLUÇÃO para popular registros vazios-> APLICAR A DATA (semana) DE VENDA NESTE CAMPO, PARA DEPOIS TESTAR USANDO CRISP E AVALIAR O ALGORITMO
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 --> 508031 registros vazios
# SOLUÇÃO para popular registros vazios-> APLICAR A DATA (ano) DE VENDA NESTE CAMPO, PARA DEPOIS TESTAR USANDO CRISP E AVALIAR O ALGORITMO
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 --> 508031 registros vazios
#criando um mapa de mês
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'}

# Colocando 0 nos registros que possui a coluna promo_interval = 0
df1['promo_interval'].fillna( 0, inplace=True )

# Criei uma coluna month_map onde será gravado o mes da coluna 'date' do registro, já convertido de acordo com a biblioteca criada
df1['month_map'] = df1['date'].dt.month.map( month_map )

# Criei uma nova coluna que vai registrar 1 para quem tem promoção no mes de venda e 0 data de venda fora da promoçao
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 )
```

In [14]:
```
# releitura para conferir se ainda temos registros vazios
df1.isna().sum()
```

Out[14]:
```
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
```

1.6. Change types

In [15]:
```
# 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)
```

In [16]:
```
# releitura dos tipos de dados para conferencia
df1.dtypes
```

Out[16]:
```
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           int64
competition_open_since_year            int64
promo2                                 int64
promo2_since_week                      int64
promo2_since_year                      int64
promo_interval                        object
month_map                             object
is_promo                               int64
dtype: object
```

1.7. Descriptive Statistical

In [17]:
```
# Criando dataframes de acordo com o typo da coluna
num_attributes = df1.select_dtypes( include=['int64', 'int32', 'float64'])
cat_attributes = df1.select_dtypes( exclude=['int64', 'int32', 'float64', 'datetime64[ns]'])
```

1.7.1 Numerical Attributes

In [18]:
```
# Dividindo o datafame em dados numéricos e categóricos
# Realizar calculos basicos para cada coluna, para ter uma noção dos dados
```

```
# Central Tendency - mean, median
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

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

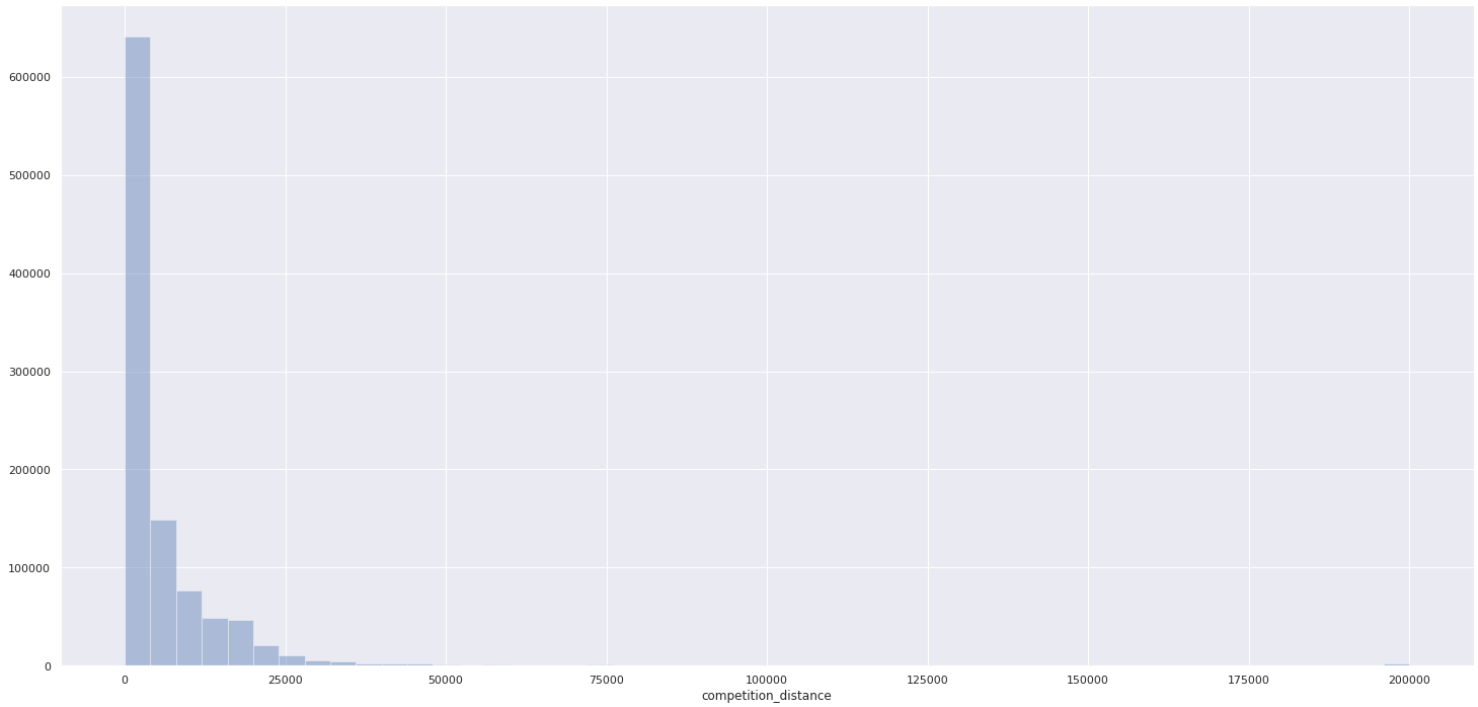
Out[18]:

	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

In [19]:
```
sns.distplot( df1['competition_distance'], kde=False )
```

```
/home/leandro/.local/lib/python3.9/site-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[19]:
```
<AxesSubplot:xlabel='competition_distance'>
```



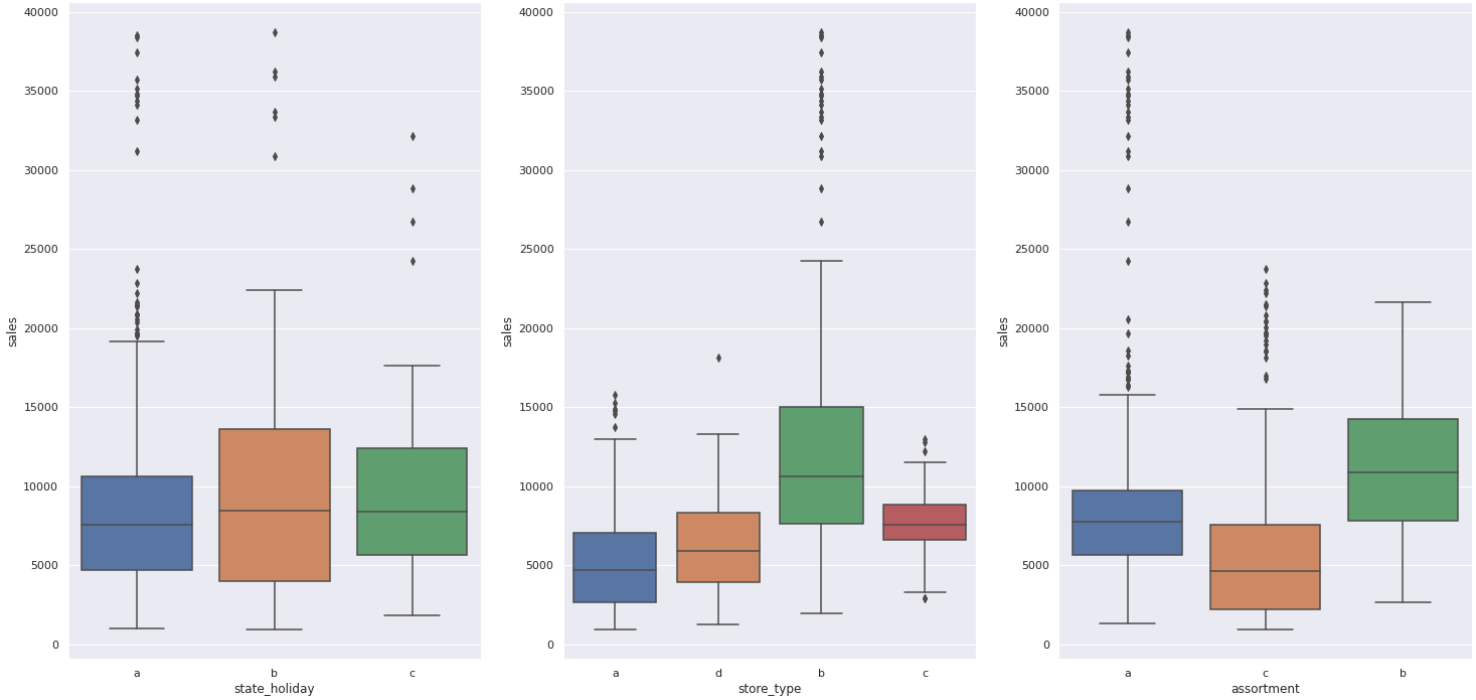
1.7.2 Caterigal Attributes

In [20]:
```
cat_attributes.apply( lambda x: x.unique().shape[0] )
```

Out[20]:
```
state_holiday      4
store_type         4
assortment         3
promo_interval     4
month_map         12
dtype: int64
```

In [21]:
```
aux1 = df1[(df1['state_holiday'] != '0' ) & (df1['sales'] > 0)]

plt.subplot( 1, 3, 1)
sns.boxplot( x='state_holiday', y='sales', data=aux1 )

plt.subplot( 1, 3, 2)
sns.boxplot( x='store_type', y='sales', data=aux1 )

plt.subplot( 1, 3, 3)
sns.boxplot( x='assortment', y='sales', data=aux1 )
```

Out[21]:
```
<AxesSubplot:xlabel='assortment', ylabel='sales'>
```



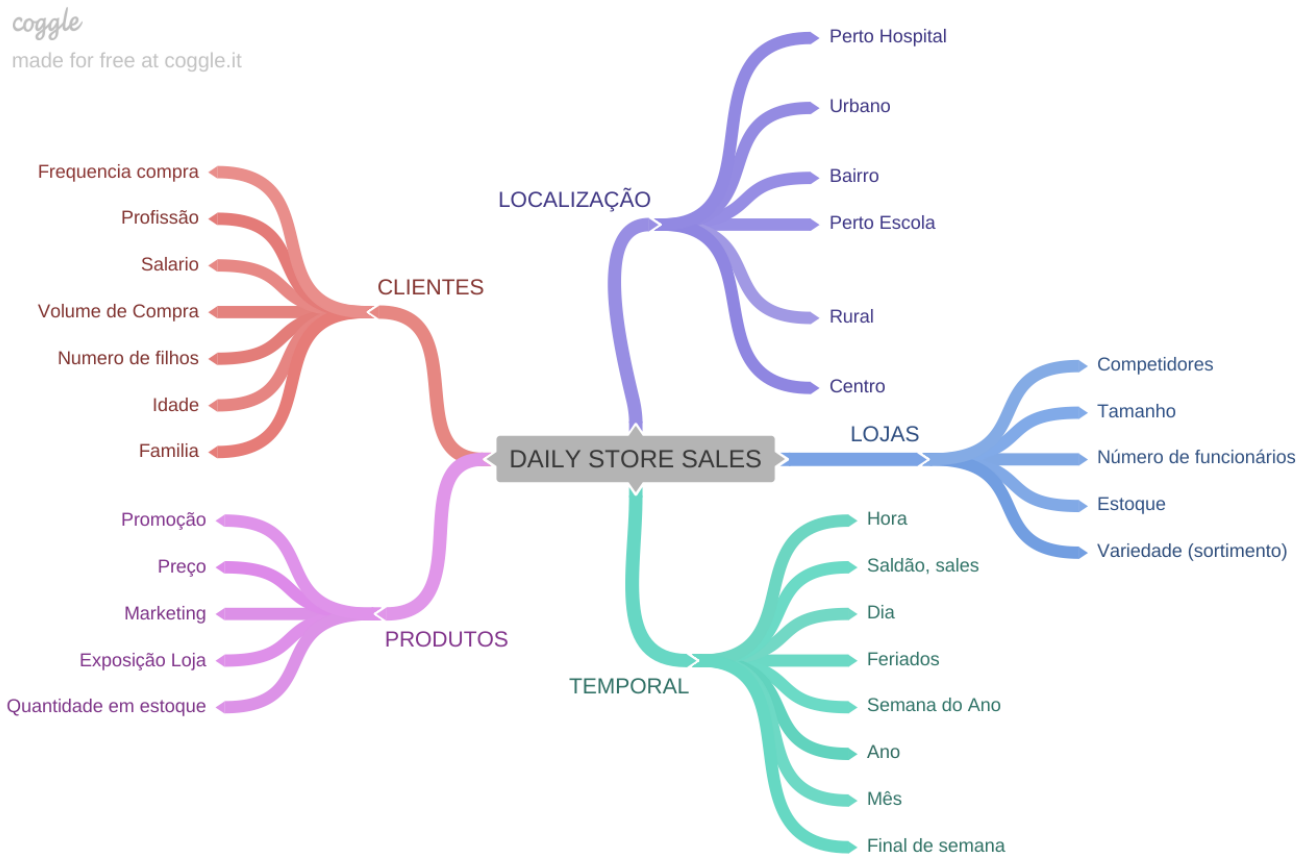
2.0. PASSO 02 - FEATURE ENGINEETING

In [22]:
```
# fazer uma cópia do dataset ao ir para um próximo passo ou seção, somente para manter os dados , caso seja necessário recomeçar
df2 = df1.copy()
```

2.1. Mapa Mental de Hipóteses

In [23]:
```
# Feito Feature Engineering para criar listas de hipóteses e validar dados
Image('../img/DAILY_STORE_SALES.png')
```

Out[23]:



2.1. Criação das Hipóteses

2.1.1. Hipóteses 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 a mais tempo deveriam vender mais.

2.1.2. Hipóteses Produto

1. Lojas que investem mais em Marketing deveriam vender mais.

2. Lojas com maior exposição de produtos deveriam vender mais.

3. Lojas com produtos com preço menor deveriam vender mais.

4. Lojas com promoções mais agressivas (desconto maiores), deveriam vender mais.

5. Lojas com promoções ativas por mais tempo deveriam vender mais.

6. Lojas com mais dias de promoção deveriam vender mais.

7. Lojas com mais promoções consecutivas deveriam vender mais.

2.1.3. Hipóteses Tempo

1. Lojas abertas durante o feriado de Natal deveriam vender mais.

2. Lojas deveriam vender mais ao lojgo 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

2.2. 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 a mais tempo deveriam vender mais.

4. Lojas com promoções ativas por mais tempo deveriam vender mais.

5. Lojas com mais dias de promoção deveriam vender mais.

6. Lojas com mais promoções consecutivas deveriam vender mais.

7. Lojas abertas durante o feriado de Natal deveriam vender mais.

8. Lojas deveriam vender mais ao lojgo dos anos.

9. Lojas deveriam vender mais no segundo semestre do ano.

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

11. Lojas deveriam vender menos aos finais de semana.

12. Lojas deveriam vender menos durante os feriados escolares

2.2. Feature Engineering

In [24]:
```
# Criando novas features utilizando os dados do dataset
# 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
df2['week_of_year'] = df2['date'].dt.isocalendar().week

# Year Week
df2['year_week'] = df2['date'].dt.strftime('%Y-%W')
```

In [25]:
```
#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)
```

In [26]:
```
# 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)
```

In [27]:
```
# ASSORTMENT
df2['assortment'] = df2['assortment'].apply( lambda x: 'basic' if x == 'a' else 'extra' if x == 'b' else 'extended')
```

In [28]:
```
# 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' )
```

In [29]:
```
df2.head().T
```

Out[29]:

	0	1	2	3	4
store	1	2	3	4	5
day_of_week	5	5	5	5	5
date	2015-07-31 00:00:00	2015-07-31 00:00:00	2015-07-31 00:00:00	2015-07-31 00:00:00	2015-07-31 00:00:00
sales	5263	6064	8314	13995	4822
customers	555	625	821	1498	559
open	1	1	1	1	1
promo	1	1	1	1	1
state_holiday	regular_day	regular_day	regular_day	regular_day	regular_day
school_holiday	1	1	1	1	1
store_type	c	a	a	c	a
assortment	basic	basic	basic	extended	basic
competition_distance	1270.0	570.0	14130.0	620.0	29910.0
competition_open_since_month	9	11	12	9	4
competition_open_since_year	2008	2007	2006	2009	2015
promo2	0	1	1	0	0
promo2_since_week	31	13	14	31	31
promo2_since_year	2015	2010	2011	2015	2015
promo_interval	0	Jan,Apr,Jul,Oct	Jan,Apr,Jul,Oct	0	0
month_map	Jul	Jul	Jul	Jul	Jul
is_promo	0	1	1	0	0

	0	1	2	3	4
year	2015	2015	2015	2015	2015
month	7	7	7	7	7
day	31	31	31	31	31
week_of_year	31	31	31	31	31
year_week	2015-30	2015-30	2015-30	2015-30	2015-30
competition_since	2008-09-01 00:00:00	2007-11-01 00:00:00	2006-12-01 00:00:00	2009-09-01 00:00:00	2015-04-01 00:00:00
competition_time_month	84	94	105	71	4
promo_since	2015-07-27 00:00:00	2010-03-22 00:00:00	2011-03-28 00:00:00	2015-07-27 00:00:00	2015-07-27 00:00:00
promo_time_week	0	279	226	0	0

3.0. PASSO 03 - FILTRAGEM DE VARIÁVEIS

In [30]:
```
df3 = df2.copy()
```

3.1. Filtragem das Linhas

In [31]:
```
# criando novo dataset com lojas abertas e com vendas
df3 = df3[(df3['open'] != 0) & (df3['sales'] > 0)]
```

3.2. Seleção das Colunas

In [32]:
```
# removendo colunas desnecessárias para analise de dados e deixar o processamento mais rapido
cols_drop = ['customers', 'open', 'promo_interval', 'month_map']
df3 = df3.drop(cols_drop, axis=1)
```

In [33]:
```
df3.columns
```

Out[33]:
```
Index(['store', 'day_of_week', 'date', 'sales', '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', 'is_promo', 'year', 'month',
       'day', 'week_of_year', 'year_week', 'competition_since',
       'competition_time_month', 'promo_since', 'promo_time_week'],
      dtype='object')
```

4.0. PASSO 04 - ANALISE EXPLORATORIA DOS DADOS (EDA)

In [34]:
```
#Etapa para medir impacto das variáveis, quantificar seu impacto, validar hipóteses de negócios e gerar INSIGHTS
df4 = df3.copy()
```

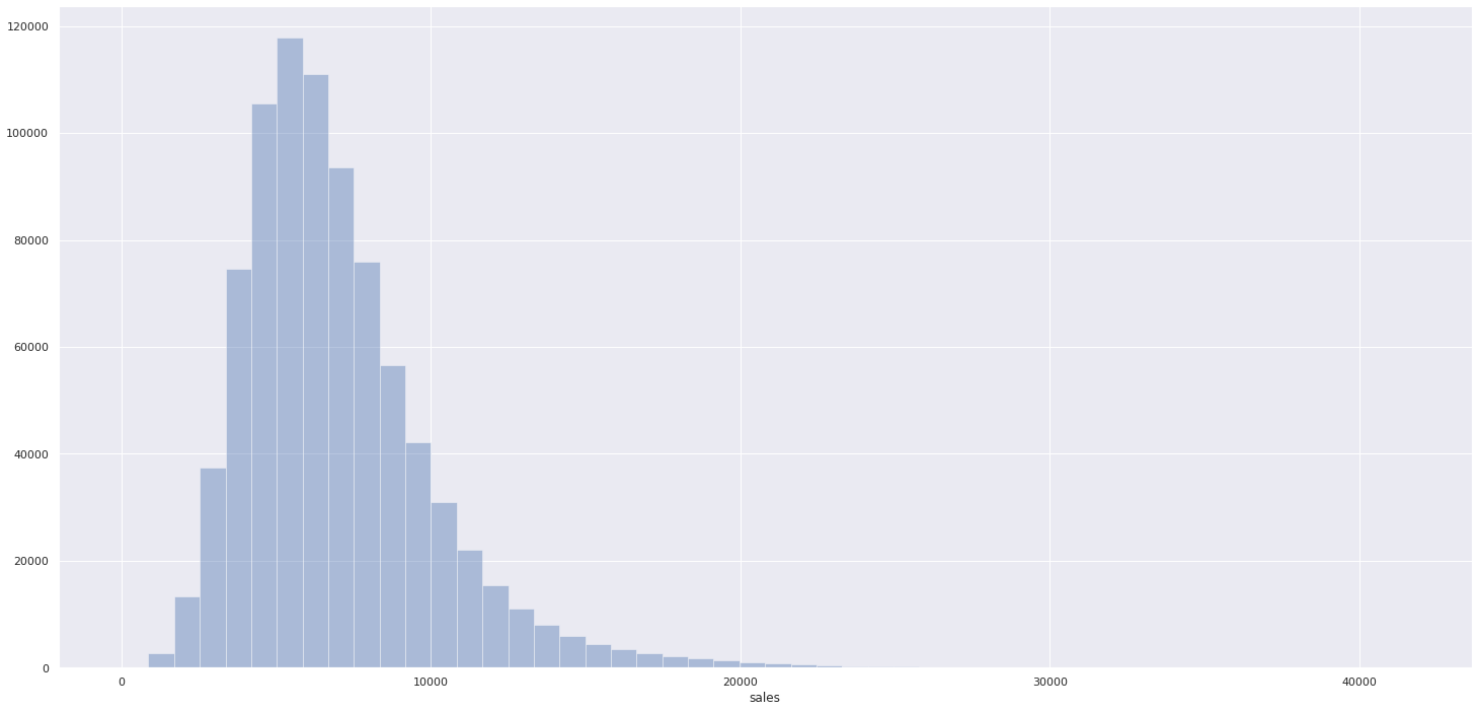
4.1. Analise Univariada

4.1.1. Response Variable

In [35]:
```
#plt.figure( figsize=(220,112))
sns.distplot( df4['sales'], kde=False )
```

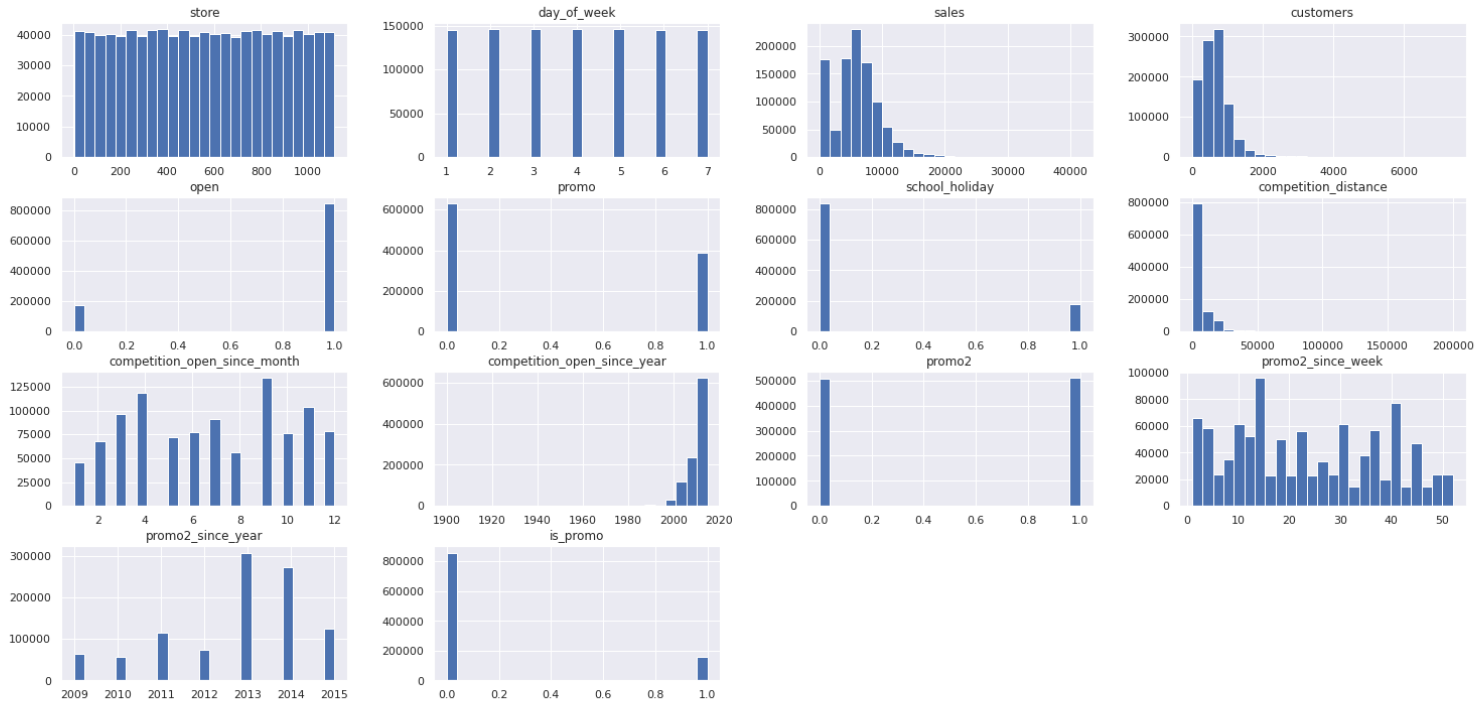
```
/home/leandro/.local/lib/python3.9/site-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please a
dapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[35]:
```
<AxesSubplot:xlabel='sales'>
```



4.1.2. Numerical Variable

In [36]:
```
#plt.figure( figsize=(220,112))
num_attributes.hist(bins=25);
```



4.1.3. Categorical Variable

In [37]:
```
df4['state_holiday'].drop_duplicates()
```

Out[37]:
```
0             regular_day
63559     public_holiday
129424    easter_holiday
241126         christmas
Name: state_holiday, dtype: object
```

In [38]:
```
df4['store_type'].drop_duplicates()
```

Out[38]:
```
0     c
1     a
12    d
84    b
Name: store_type, dtype: object
```

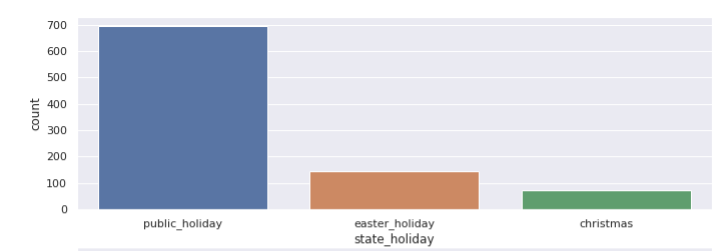
In [39]:
```
df4['assortment'].drop_duplicates()
```

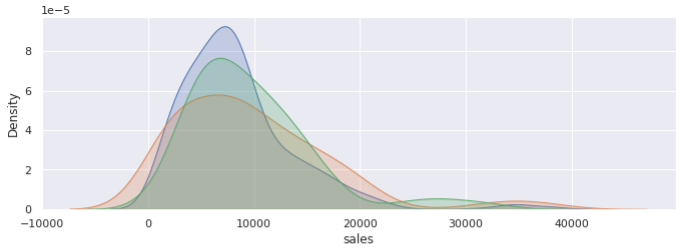
Out[39]:
```
0         basic
3      extended
258       extra
Name: assortment, dtype: object
```

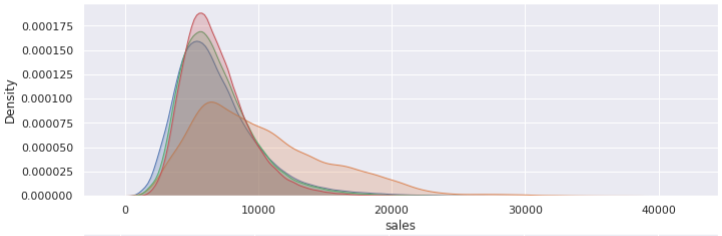
In [40]:
```
# state_holiday
#criando um grafico com todos os feriados

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

#Criando um grafico com as colunas sobrepostas -> shade=True
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 )
```

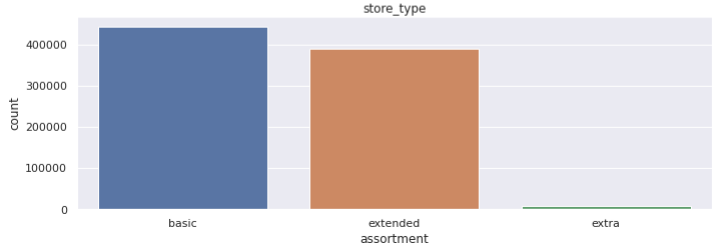
```
/home/leandro/.local/lib/python3.9/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
/home/leandro/.local/lib/python3.9/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
/home/leandro/.local/lib/python3.9/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

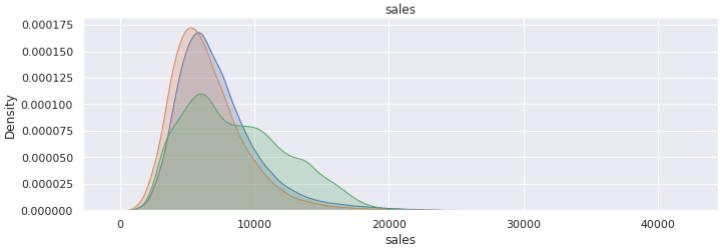
Out[40]:
```
<AxesSubplot:xlabel='sales', ylabel='Density'>
```









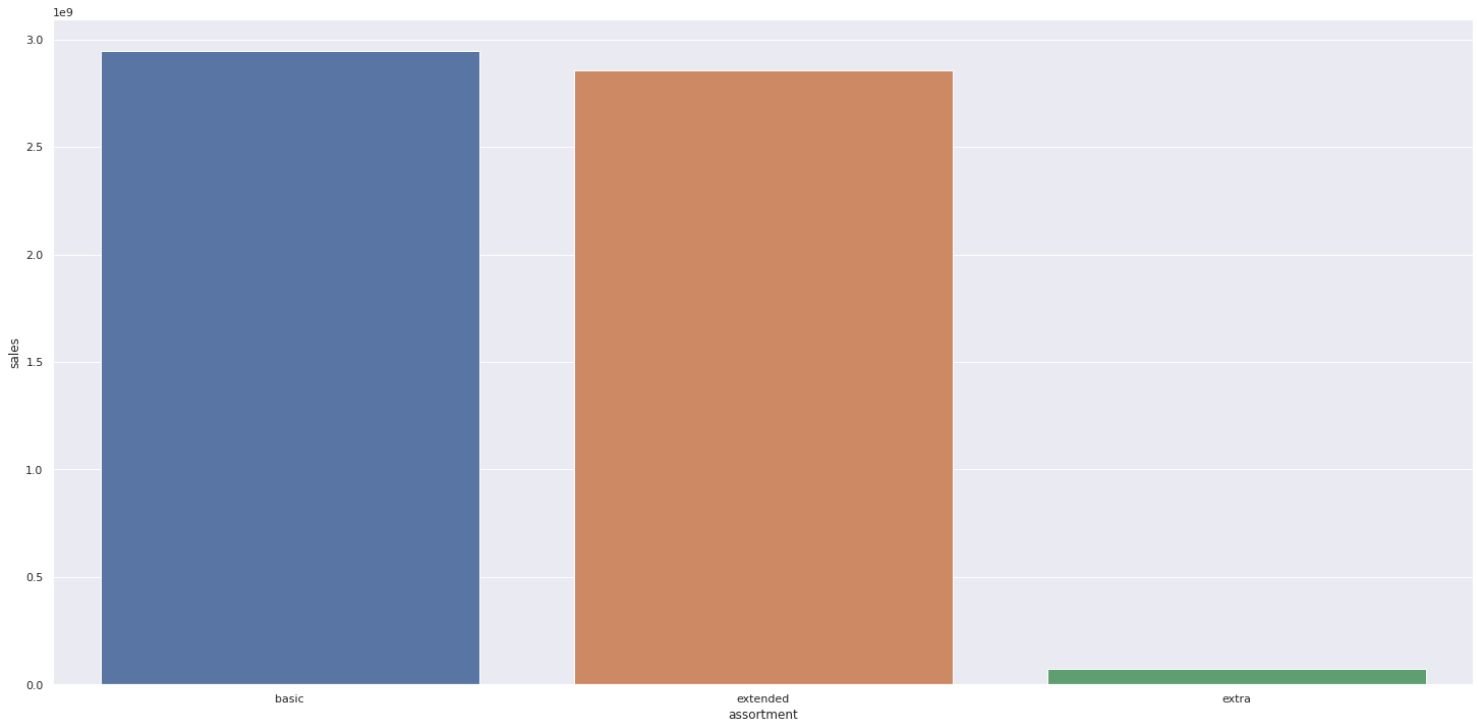


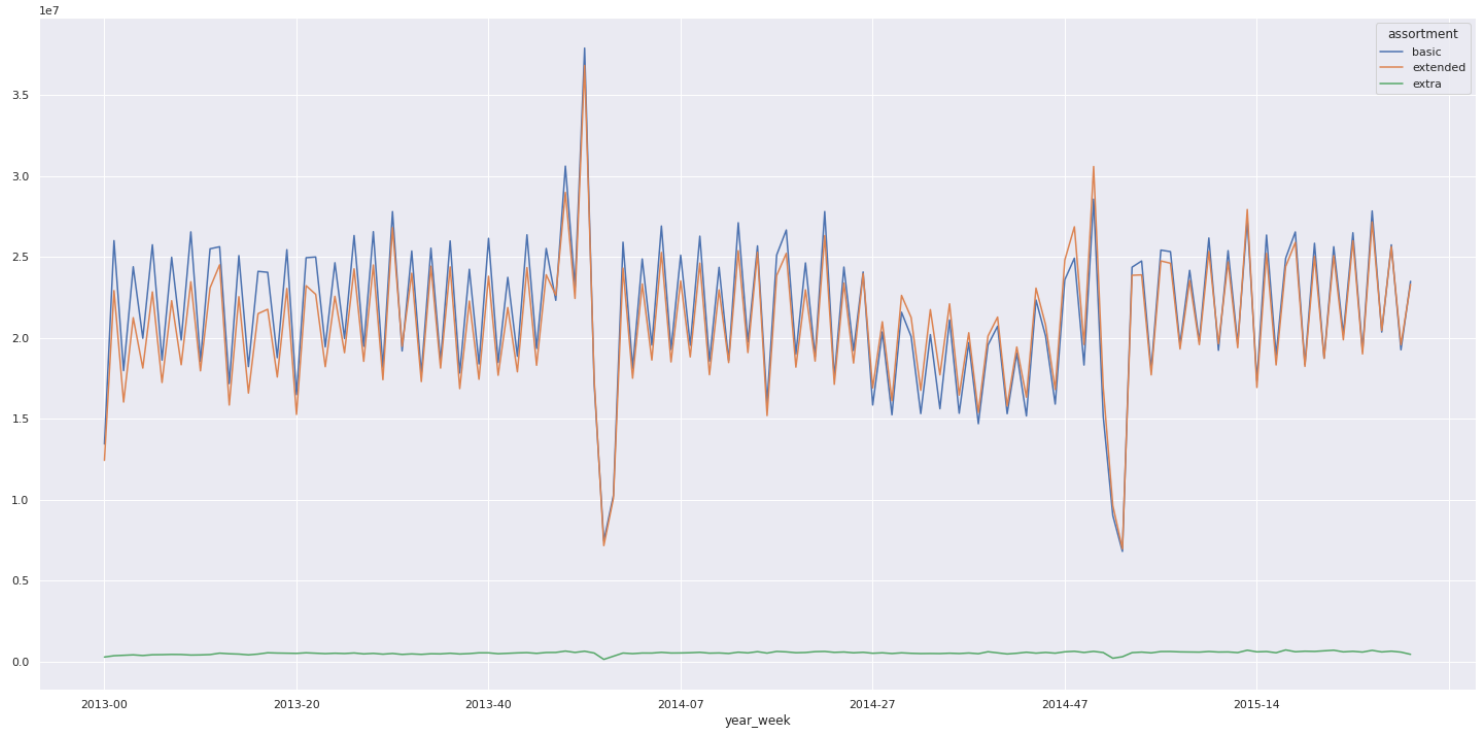
4.2. Analise Bivariada

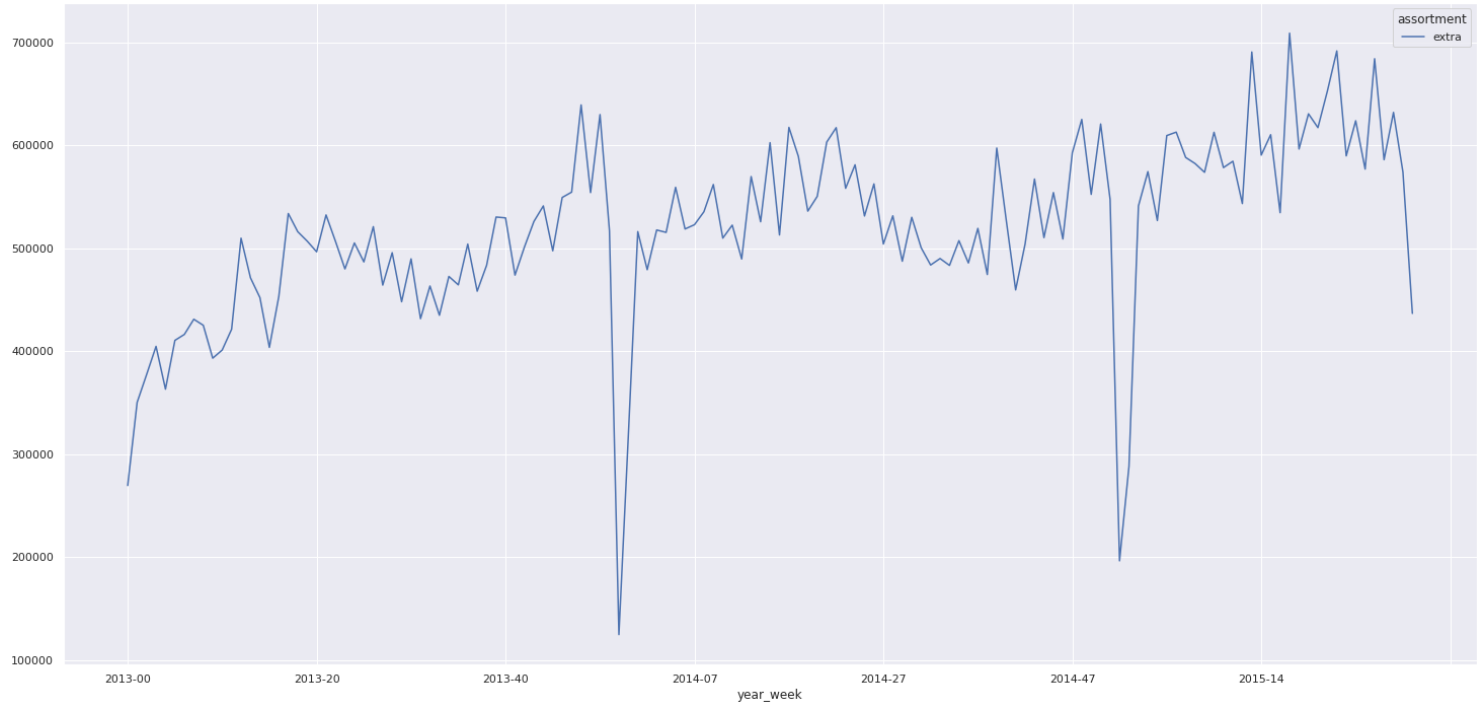
H1. Lojas com maior sortimentos deveriam vender mais.

FALSA Lojas cim MAIOR SORTIMENTO vendem MENOS

In [41]:
```
#sortimento + vendas --> agrupa por sortimento
aux1 = df4[['assortment', 'sales']].groupby('assortment').sum().reset_index()
sns.barplot(x='assortment', y='sales', data=aux1);

#semana do ano + sortimento + vendas  --> agrupa por semana di ano + sortimento
aux2 = df4[['year_week', 'assortment', 'sales']].groupby(['year_week', 'assortment']).sum().reset_index()
aux2.pivot( index='year_week', columns='assortment', values='sales').plot()

# verificando somente o sortimento extra
aux3 = aux2[aux2['assortment'] == 'extra']
aux3.pivot( index='year_week', columns='assortment', values='sales').plot();
```





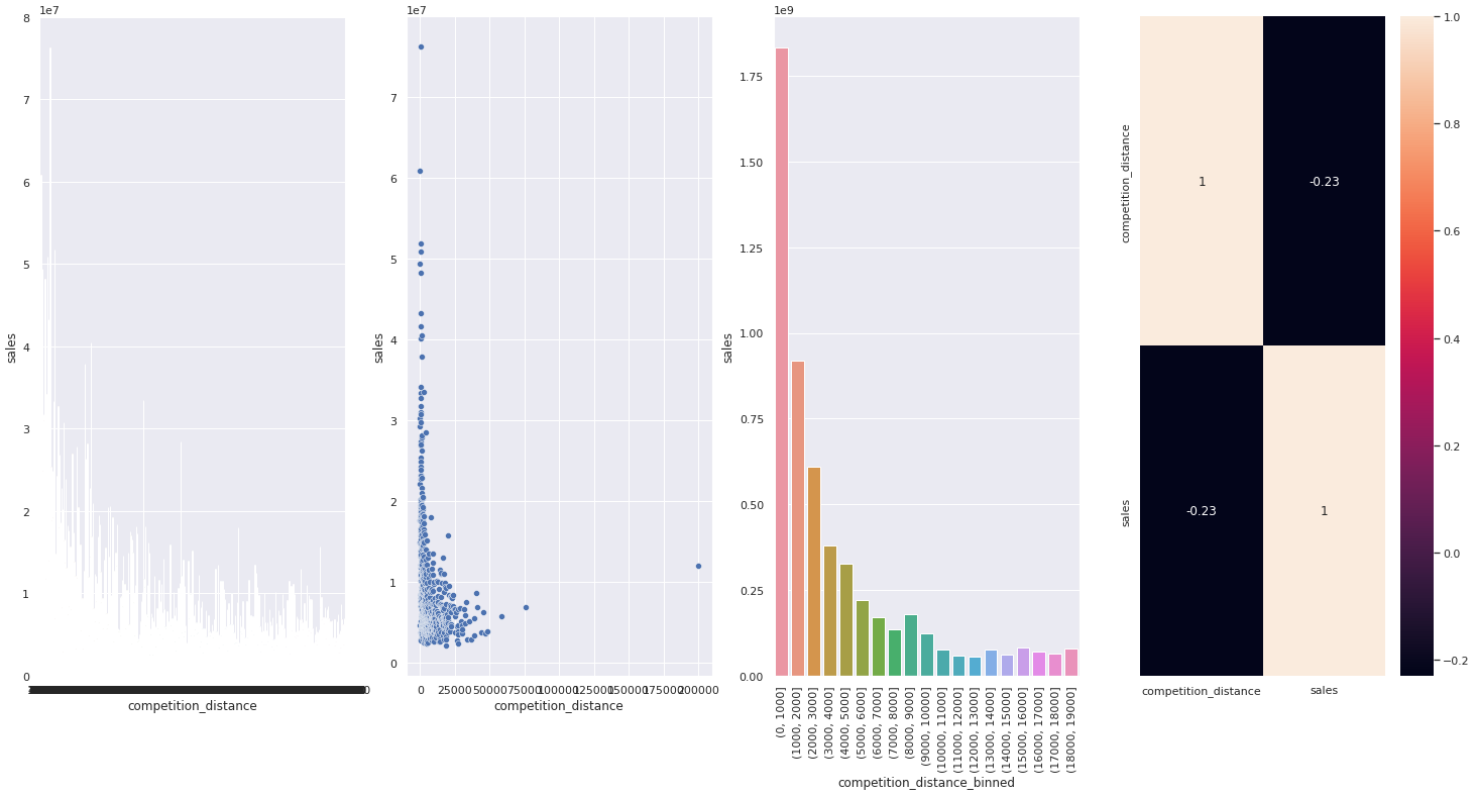


H2. Lojas com competidores mais próximos deveriam vender menos.

Falsa Lojas com COMPETIDORES MAIS PROXIMOS vendem MAIS

In [42]:

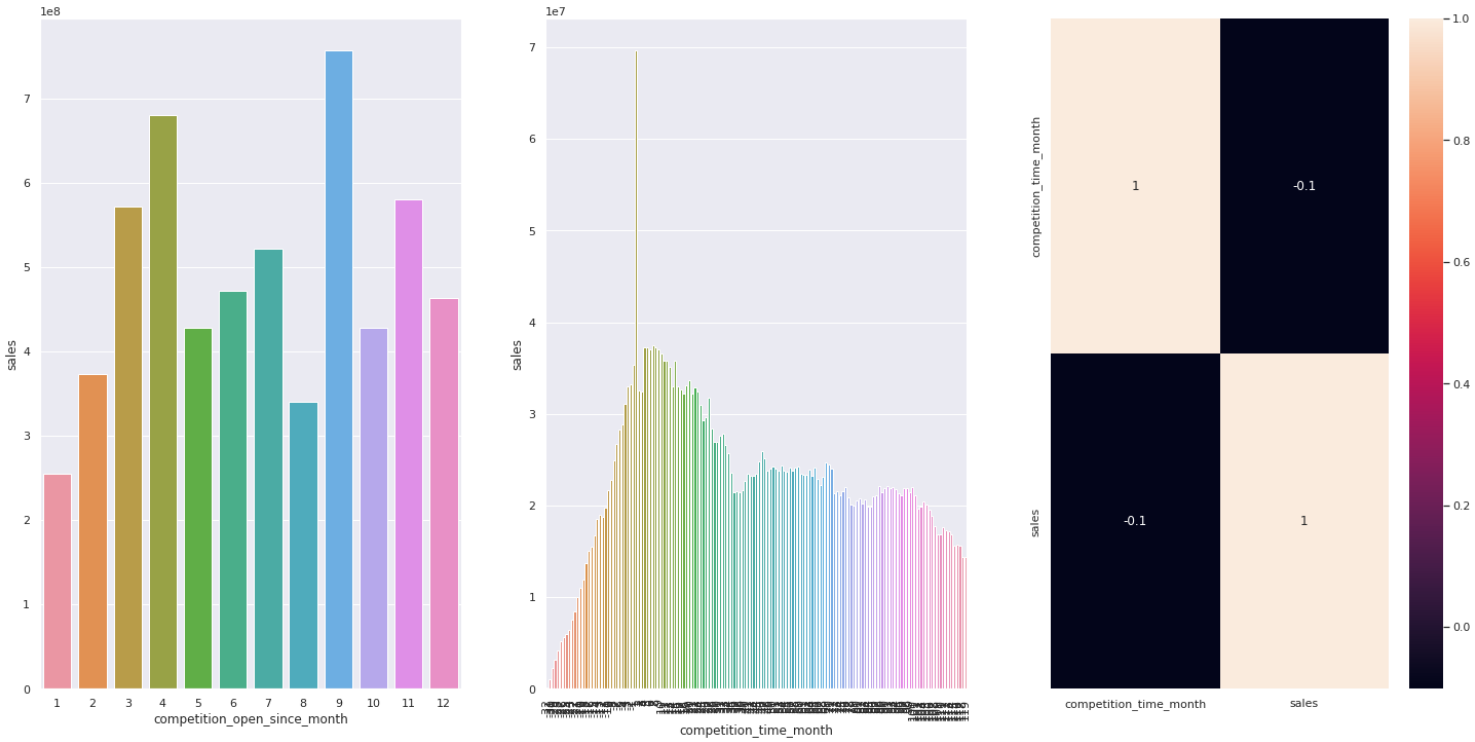
```
#sortimento + vendas --> agrupa por sortimento

aux1 = df4[['competition_distance', 'sales']].groupby('competition_distance').sum().reset_index()
plt.subplot(1,4,1)
sns.barplot(x='competition_distance', y='sales', data=aux1);


aux1 = df4[['competition_distance', 'sales']].groupby('competition_distance').sum().reset_index()
plt.subplot(1,4,2)
sns.scatterplot(x='competition_distance', y='sales', data=aux1);


plt.subplot(1,4,3)
#criando uma lista para agrupar as distancias
# vai de 0 a 20000 e com 1000(grupos) agrupamentos
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(1,4,4)
sns.heatmap(aux1.corr(method='pearson'), annot=True);
```



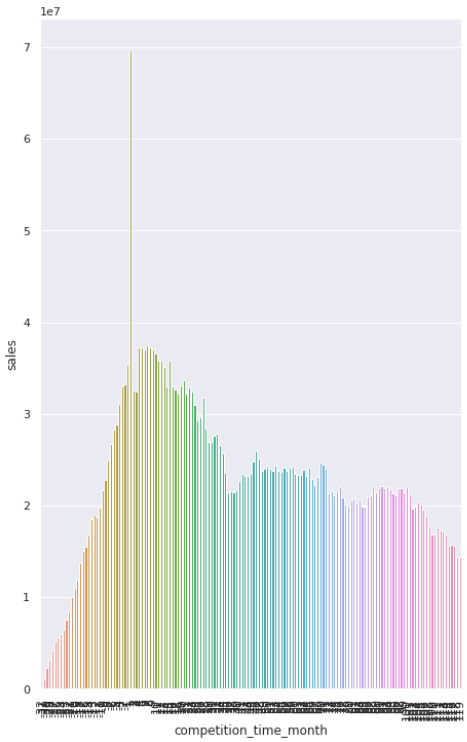
H3. Lojas com competidores a mais tempo deveriam vender mais.

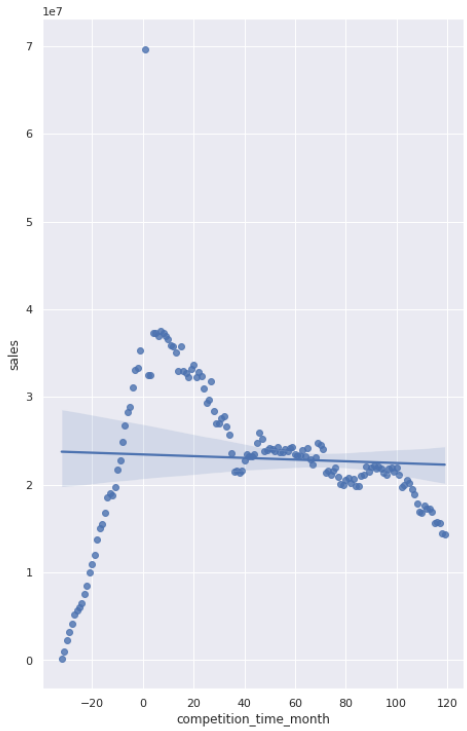
Falsa Lojas com COMPETIDORES A MAIS TEMPO vendem MENOS

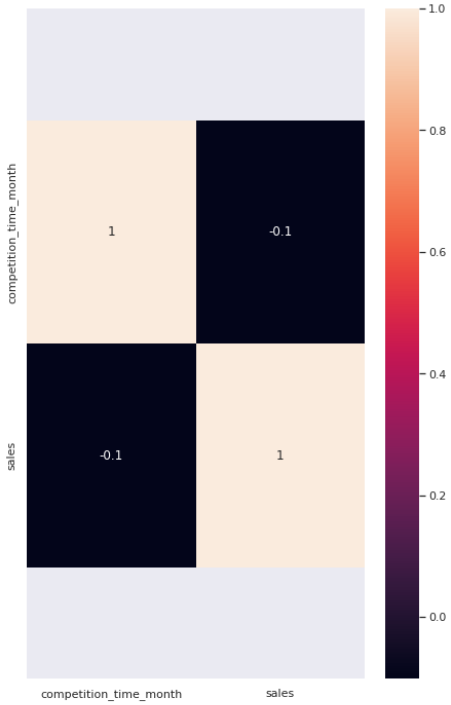
In [43]:
```
plt.subplot(1, 3, 1)
aux1 = df4[['competition_open_since_month', 'sales']].groupby('competition_open_since_month').sum().reset_index()
sns.barplot( x='competition_open_since_month', y='sales', data=aux1);

plt.subplot(1, 3, 2)
aux2 = df4[['competition_time_month', 'sales']].groupby('competition_time_month').sum().reset_index()
aux3 = aux2[( aux2['competition_time_month'] < 120) & (aux2['competition_time_month'] != 0)]
sns.barplot( x='competition_time_month', y='sales', data=aux3);
plt.xticks( rotation=90);

plt.subplot(1, 3, 3)
sns.heatmap( aux2.corr(method='pearson'), annot=True);
```



In [44]:
```
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);
```



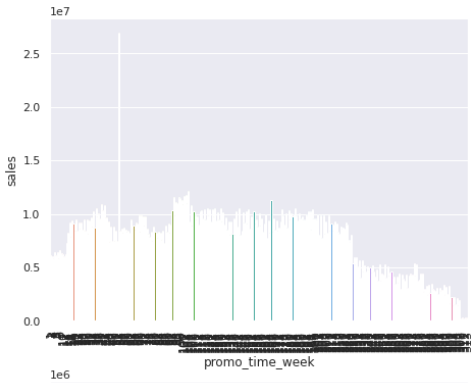


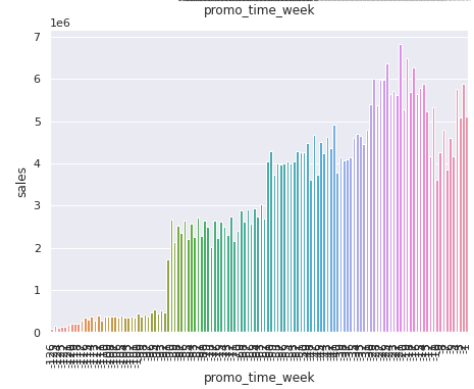


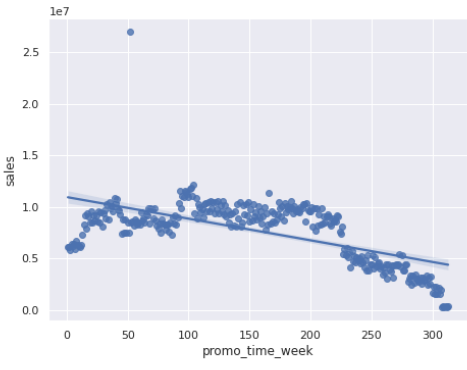
H4. Lojas com promoções ativas por mais tempo deveriam vender mais.

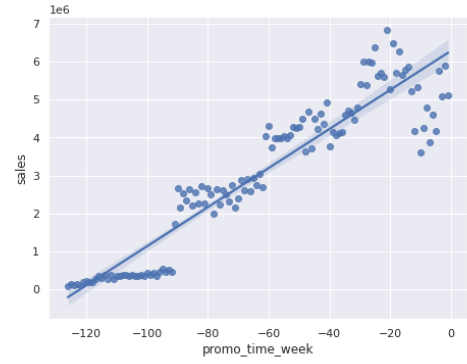
Falsa Lojas com promoções ativas por mais tempo vendem menos, depois de um certo periodo de promoção

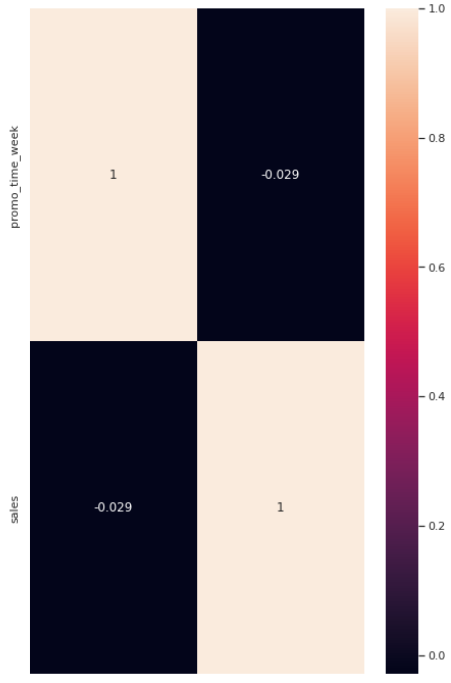
In [45]:
```
aux1 = df4[['promo_time_week', 'sales']].groupby('promo_time_week').sum().reset_index()

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);
```











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

Validar no proximo ciclo crisp

H6. Lojas com mais promoções consecutivas deveriam vender mais.

Falsa Lojas com ais promoções consecutivas vendem menos

In [46]:
```
df4[['promo', 'promo2', 'sales']].groupby(['promo', 'promo2']).sum().reset_index()
```

Out[46]:

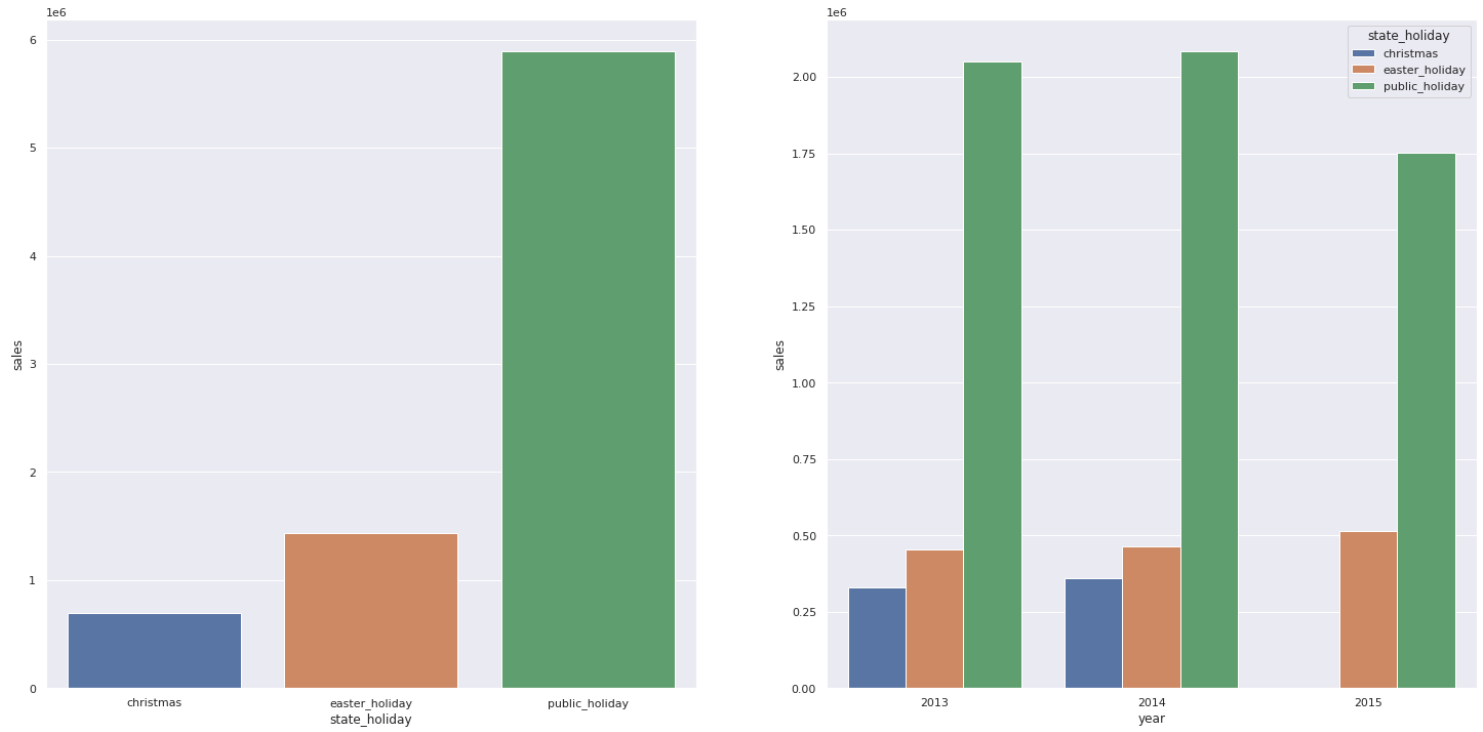
	promo	promo2	sales
0	0	0	1482612096
1	0	1	1289362241
2	1	0	1628930532
3	1	1	1472275754

In [47]:
```
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=['Tradiciona & Extendida', 'Extendida']);
```

H7. Lojas abertas durante o feriado de Natal deveriam vender mais.

Falsa Lojas abertas durante o feriado do Natal vendem menos

In [48]:
```
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);
```

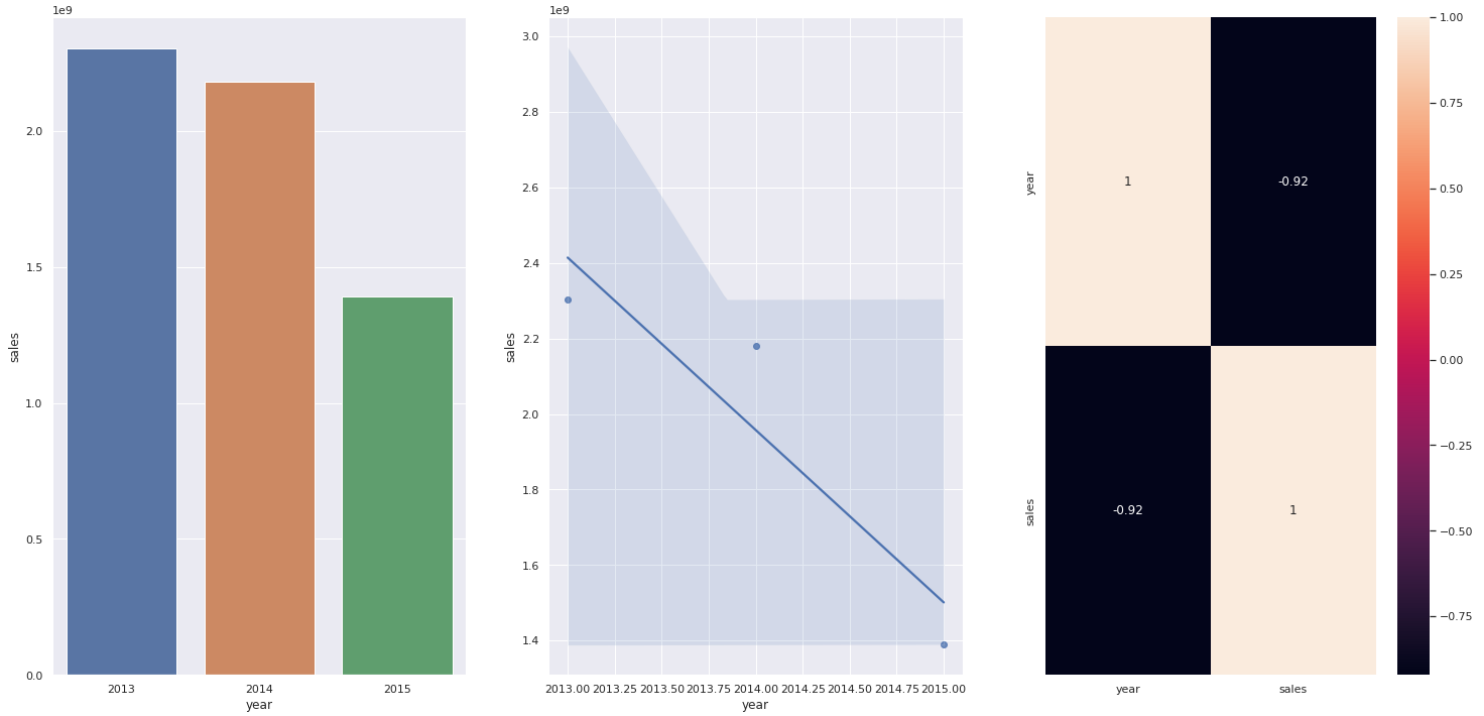


H8. Lojas deveriam vender mais ao lojgo dos anos.

Falsa Lojas vendem menos ao longo dos anos

In [49]:
```
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);
```

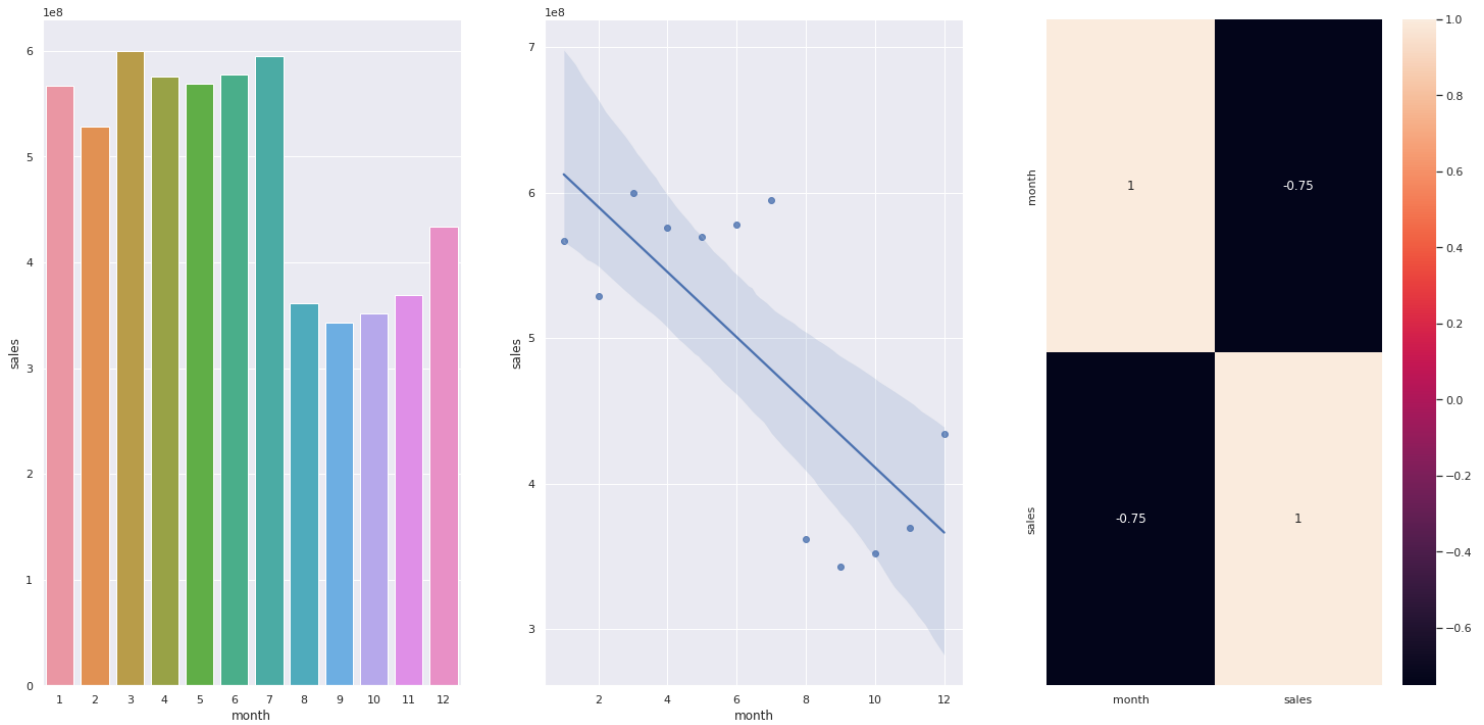
```
plt.subplot(1,3,3)
sns.heatmap(aux1.corr(method='pearson'), annot=True);
```



H9. Lojas deveriam vender mais no segundo semestre do ano.

Falsa Lojasvendem menos no segundo semestre do ano

In [50]:
```
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);
```



H10. Lojas deveriam vender mais depois do dia 10 de cada mês.

Verdadeira Lojas vendem mais depois do dia 10 de cada mes

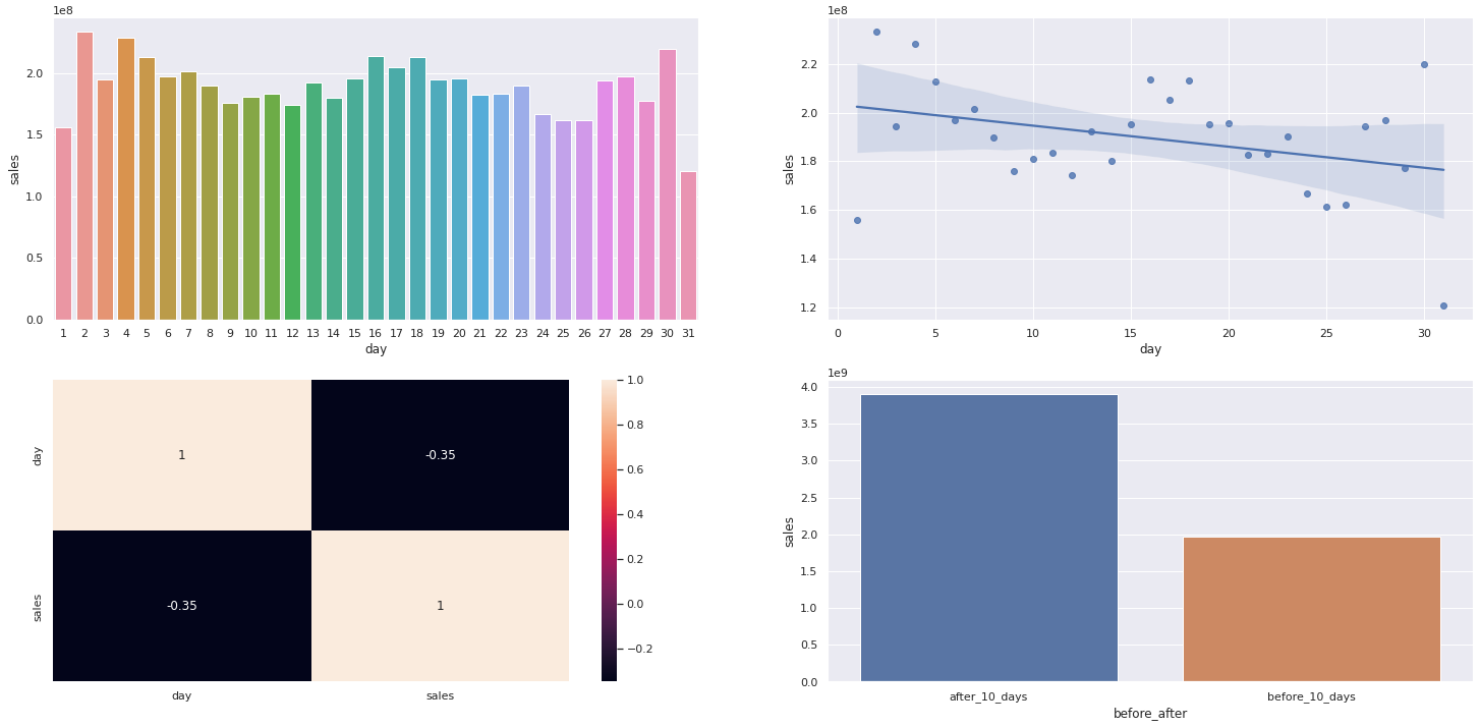
In [51]:
```
aux1.head(15)
```

Out[51]:

	month	sales
0	1	566728724
1	2	528734410
2	3	599831906
3	4	575895295
4	5	569248217
5	6	578112775
6	7	595059205
7	8	361791202
8	9	342570131
9	10	351878728

	month	sales
10	11	369498877
11	12	433831153

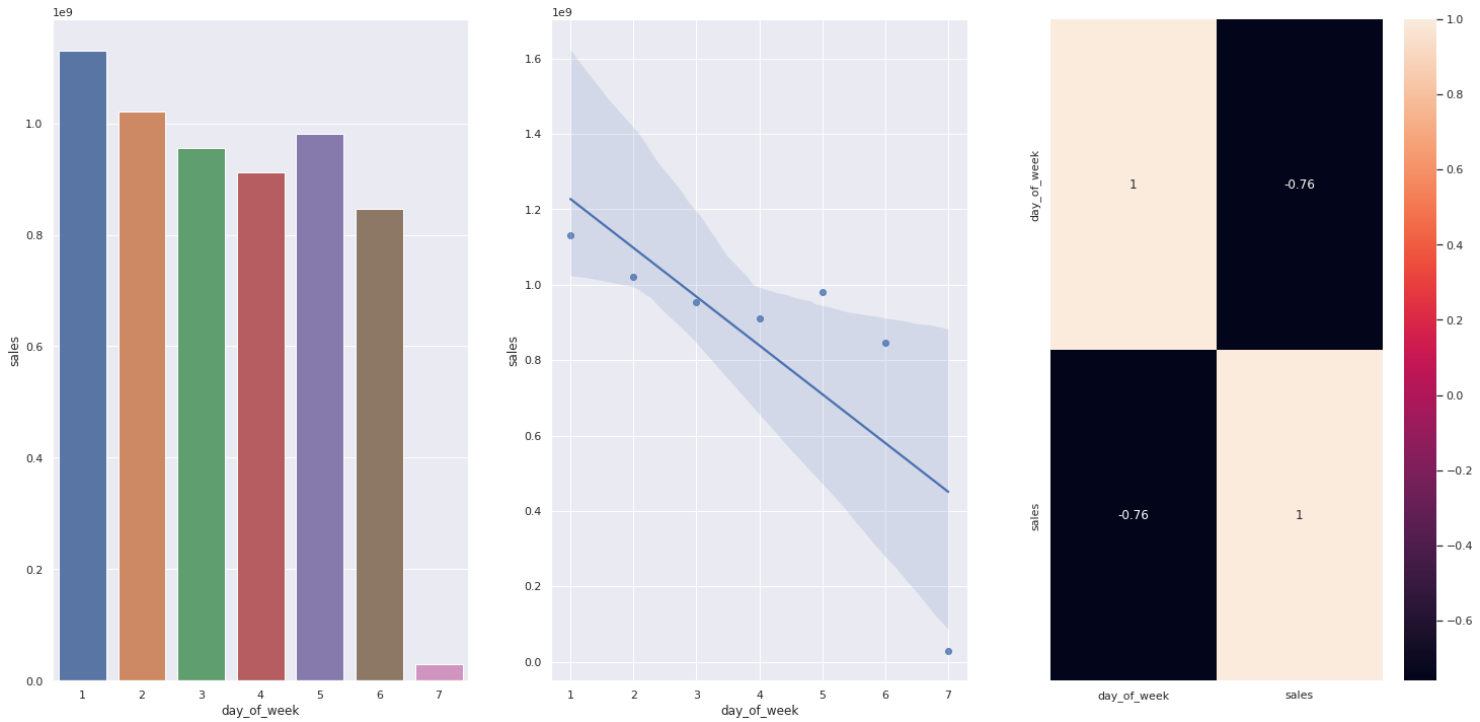
In [52]:
```
aux1 = df4[['day', 'sales']].groupby('day').sum().reset_index()

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);
```



H11. Lojas deveriam vender menos aos finais de semana.

Verdadeira Lojas vendem menos no final de semana

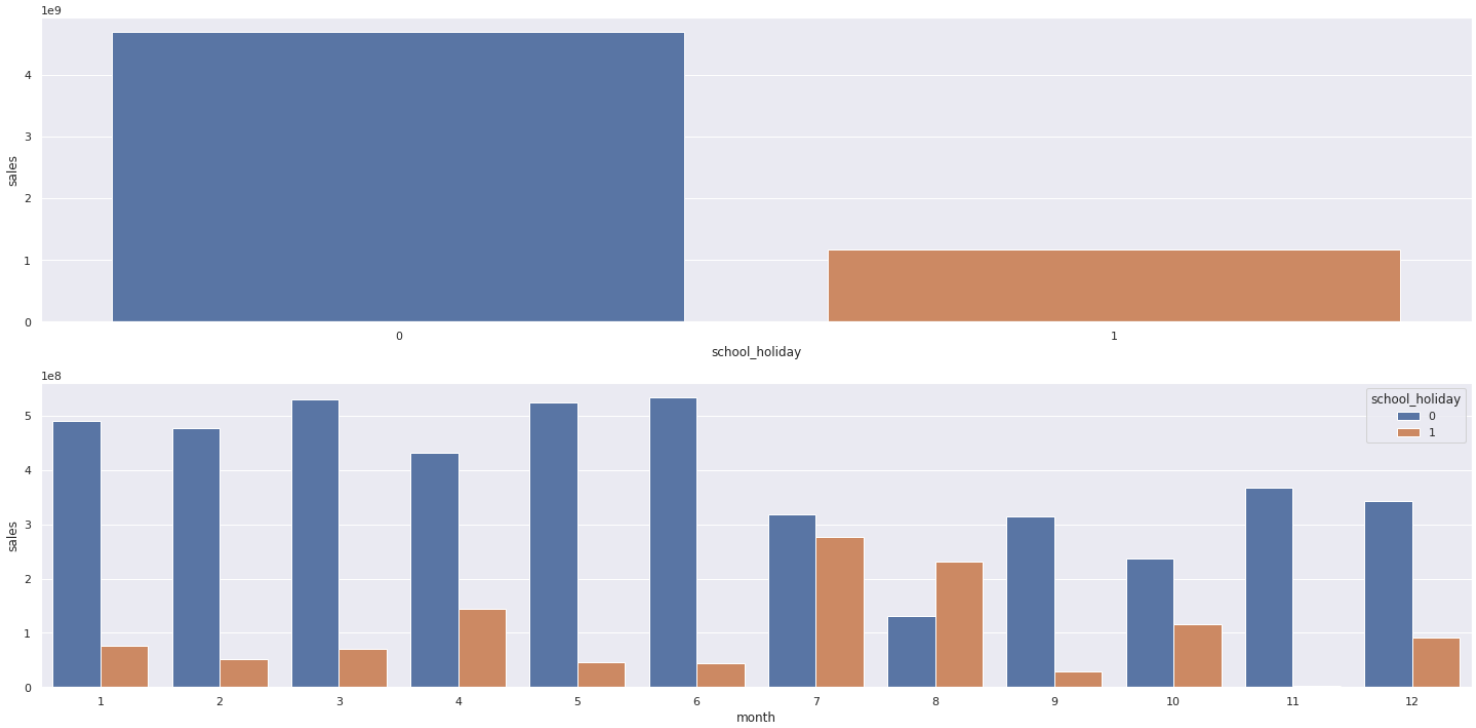
In [53]:
```
aux1 = df4[['day_of_week', 'sales']].groupby('day_of_week').sum().reset_index()

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);
```



H12. Lojas deveriam vender menos durante os feriados escolares

Verddeiro Lojas vendem menos durante os feriados escolares, exceto os meses de Julho e agosto

In [54]:
```
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);
```



4.2.1. Resumo das Hipoteses

In [55]:
```
tab =[ ['Hipoteses', 'Conclusao', 'Relevancia'],
       ['H1', 'Falsa', 'Baixa'],
       ['H2', 'Falsa', 'Media'],
       ['H3', 'Falsa', 'Media'],
       ['H4', 'Falsa', 'Media'],
       ['H5', '-', '-'],
       ['H6', 'Falsa', 'Baixa'],
       ['H7', 'Falsa', 'Media'],
       ['H8', 'Falsa', 'Alta'],
       ['H9', 'Falsa', 'Alta'],
       ['H10', 'Verdadeira', 'Alta'],
       ['H11', 'Verdadeira', 'Alta'],
       ['H12', 'Verdadeira', 'Baixa'],
     ]
print( tabulate(tab, headers='firstrow'))
```

```
Hipoteses    Conclusao    Relevancia
-----------  -----------  ------------
H1           Falsa        Baixa
H2           Falsa        Media
H3           Falsa        Media
H4           Falsa        Media
H5           -            -
H6           Falsa        Baixa
H7           Falsa        Media
H8           Falsa        Alta
H9           Falsa        Alta
H10          Verdadeira   Alta
H11          Verdadeira   Alta
H12          Verdadeira   Baixa
```

4.3. Analise Multivariada

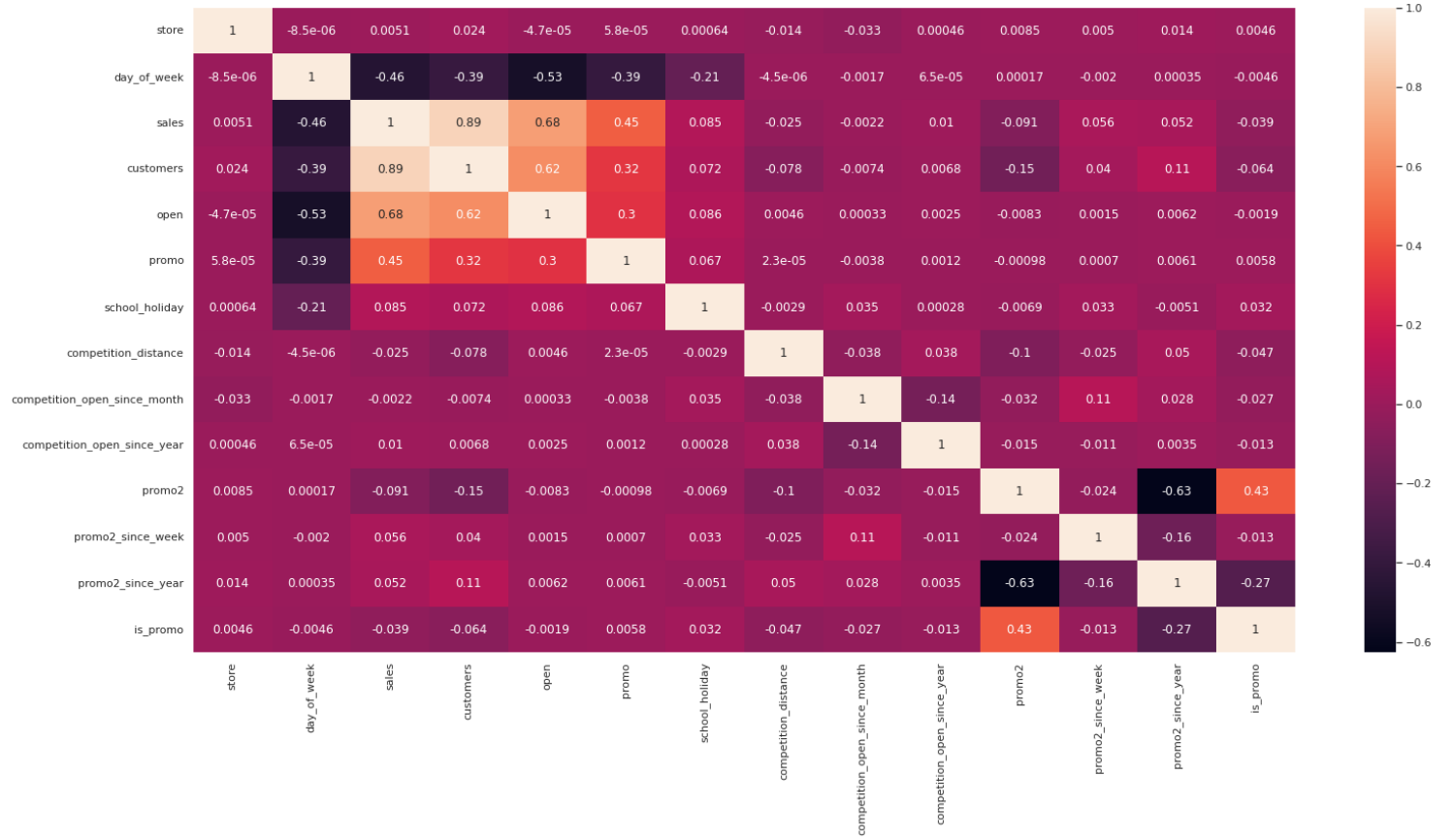
4.3.1. Numerical Attributes

In [56]:
```
num_attributes.head()
```

Out[56]:

	store	day_of_week	sales	customers	open	promo	school_holiday	competition_distance	competition_open_since_month	competition_open_since_year	promo2	promo2_since_week	promo2_since_year	is_promo
0	1	5	5263	555	1	1	1	1270.0	9	2008	0	31	2015	0
1	2	5	6064	625	1	1	1	570.0	11	2007	1	13	2010	1
2	3	5	8314	821	1	1	1	14130.0	12	2006	1	14	2011	1
3	4	5	13995	1498	1	1	1	620.0	9	2009	0	31	2015	0
4	5	5	4822	559	1	1	1	29910.0	4	2015	0	31	2015	0

In [57]:
```
correlation =num_attributes.corr(method='pearson')
sns.heatmap(correlation, annot=True);
```



4.3.2. Categorical Attributes

In [58]:
```
cat_attributes.head()
```

Out[58]:

	state_holiday	store_type	assortment	promo_interval	month_map
0	0	c	a	0	Jul
1	0	a	a	Jan,Apr,Jul,Oct	Jul
2	0	a	a	Jan,Apr,Jul,Oct	Jul
3	0	c	c	0	Jul
4	0	a	a	0	Jul

In [59]:
```
a = df4.select_dtypes(include='object')
a.head()
```

Out[59]:

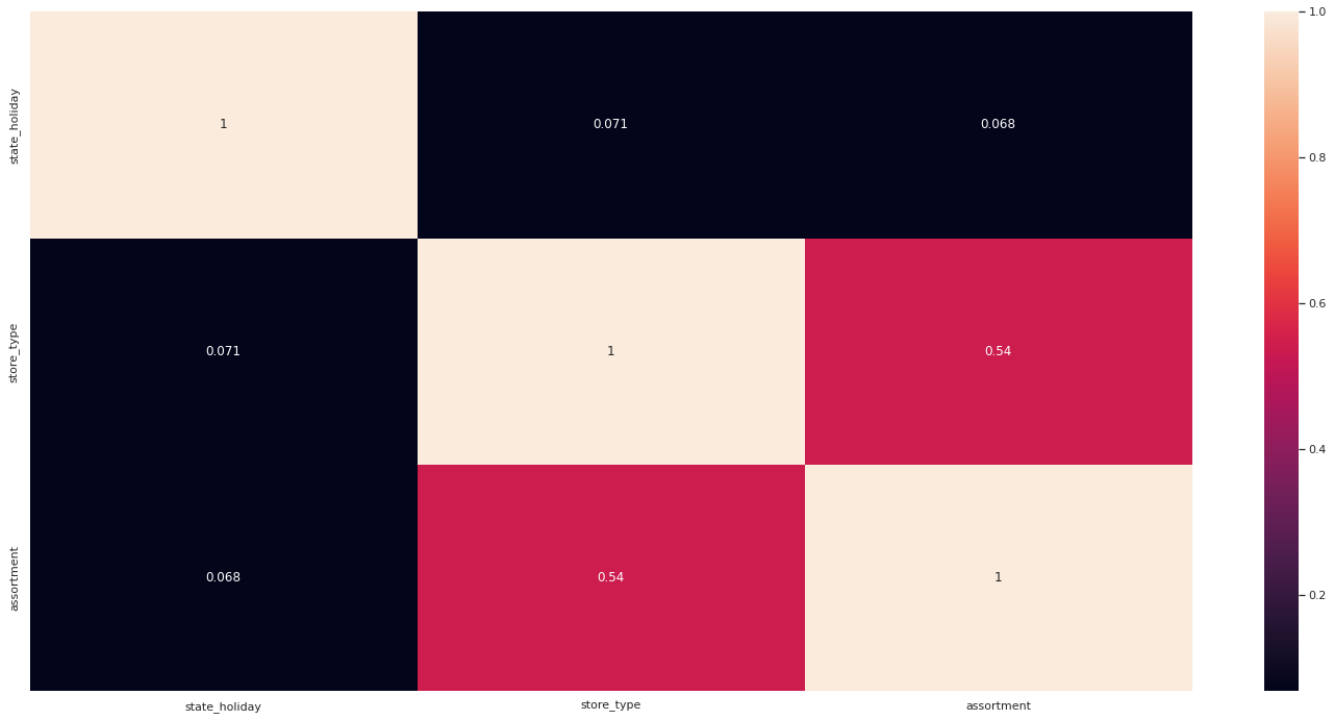
	state_holiday	store_type	assortment	year_week
0	regular_day	c	basic	2015-30
1	regular_day	a	basic	2015-30
2	regular_day	a	basic	2015-30
3	regular_day	c	extended	2015-30
4	regular_day	a	basic	2015-30

In [60]:
```
#pd.crosstab( a['state_holiday'], a['store_type']).as_matrix()
```

In [61]:
```
# only categorical data
a = df4.select_dtypes( include='object')
#cramer_v( a['state_holiday'], a['state_holiday'] )

# 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 )
```

In [62]:
```
sns.heatmap(d, annot=True )
```

Out[62]:
```
<AxesSubplot:>
```



5.0. PASSO 05 - PREPARAÇÃO DOS DADOS - DATA PREPARATION

In [63]:
```
df5 = df4.copy()
```

5.1. Normalização

In [ ]:
```
```

5.2. Rescaling

In [64]:
```
a =df5.select_dtypes( include=['int64', 'int32', 'float64'])
a.head()
```

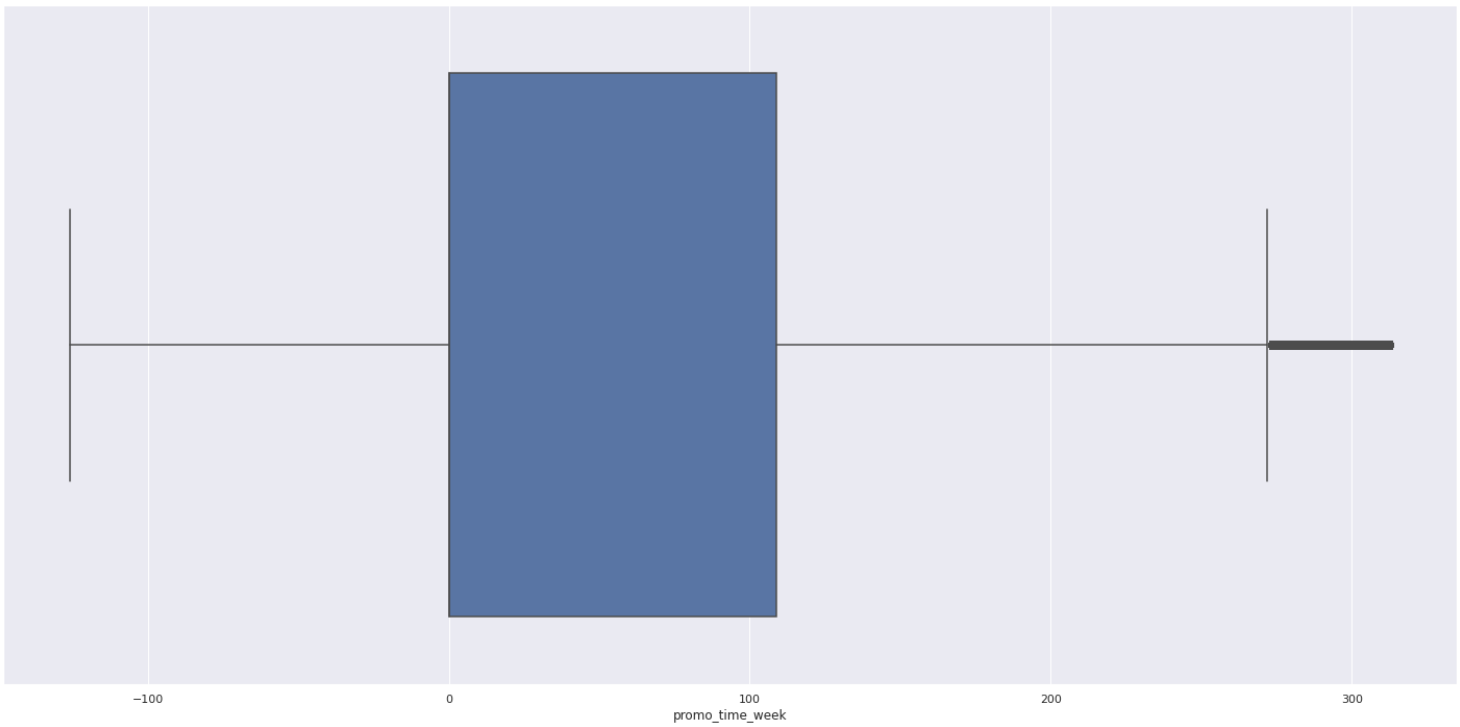
Out[64]:

	store	day_of_week	sales	promo	school_holiday	competition_distance	competition_open_since_month	competition_open_since_year	promo2	promo2_since_week	promo2_since_year	is_promo	year	month	day	competiti
0	1	5	5263	1	1	1270.0	9	2008	0	31	2015	0	2015	7	31	
1	2	5	6064	1	1	570.0	11	2007	1	13	2010	1	2015	7	31	
2	3	5	8314	1	1	14130.0	12	2006	1	14	2011	1	2015	7	31	
3	4	5	13995	1	1	620.0	9	2009	0	31	2015	0	2015	7	31	
4	5	5	4822	1	1	29910.0	4	2015	0	31	2015	0	2015	7	31	

In [65]:
```
# verificando colunas com outliers
#sns.boxplot( df5['competition_distance'])
#sns.boxplot( df5['competition_time_month'])
sns.boxplot( df5['promo_time_week'])
#sns.boxplot( df5['year'])
```

```
/home/leandro/.local/lib/python3.9/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positi
onal argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[65]:
```
<AxesSubplot:xlabel='promo_time_week'>
```



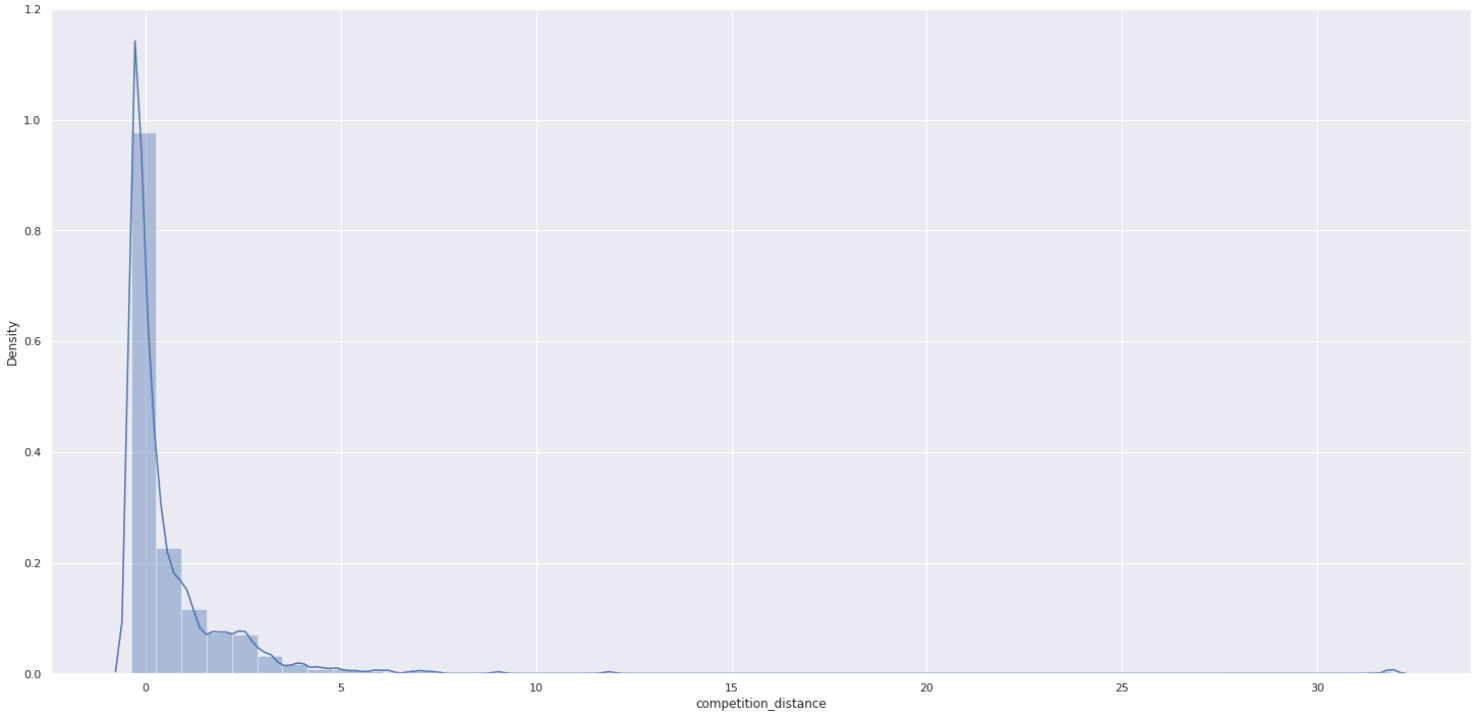
In [66]:
```
rs = RobustScaler()
mms = MinMaxScaler()

# competition distance
```

```
df5['competition_distance'] = rs.fit_transform( df5[['competition_distance']].values)
#salvando
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)
#salvando
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)
#salvando
pickle.dump( rs, open('../parameter/promo_time_week_scaler.pkl', 'wb'))

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

In [67]:
```
# verificando colunas depois de fazer o rescaling
sns.distplot( df5['competition_distance'])
#sns.distplot( df5['competition_time_month'])
#sns.distplot( df5['promo_time_week'])
#sns.distplot( df5['year'])
```

```
/home/leandro/.local/lib/python3.9/site-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please a
dapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[67]:
```
<AxesSubplot:xlabel='competition_distance', ylabel='Density'>
```



5.3. Transformação

5.3.1. Encoding

In [68]:
```
df5.head()
```

Out[68]:

	store	day_of_week	date	sales	promo	state_holiday	school_holiday	store_type	assortment	competition_distance	competition_open_since_month	competition_open_since_year	promo2	promo2_since_week	promo2_since
0	1	5	2015-07-31	5263	1	regular_day	1	c	basic	-0.170968	9	2008	0	31	
1	2	5	2015-07-31	6064	1	regular_day	1	a	basic	-0.283871	11	2007	1	13	
2	3	5	2015-07-31	8314	1	regular_day	1	a	basic	1.903226	12	2006	1	14	
3	4	5	2015-07-31	13995	1	regular_day	1	c	extended	-0.275806	9	2009	0	31	
4	5	5	2015-07-31	4822	1	regular_day	1	a	basic	4.448387	4	2015	0	31	

In [69]:
```
#state_holiday - One Hot Encoding  - cria uma coluna para cada tipo de feriado colocando 0 ou 1
df5 = pd.get_dummies(df5, prefix=['state_holiday'], columns=['state_holiday'])
df5.head()
```

Out[69]:

	store	day_of_week	date	sales	promo	school_holiday	store_type	assortment	competition_distance	competition_open_since_month	competition_open_since_year	promo2	promo2_since_week	promo2_since_year	is_prom
0	1	5	2015-07-31	5263	1	1	c	basic	-0.170968	9	2008	0	31	2015	
1	2	5	2015-07-31	6064	1	1	a	basic	-0.283871	11	2007	1	13	2010	
2	3	5	2015-07-31	8314	1	1	a	basic	1.903226	12	2006	1	14	2011	
3	4	5	2015-07-31	13995	1	1	c	extended	-0.275806	9	2009	0	31	2015	
4	5	5	2015-07-31	4822	1	1	a	basic	4.448387	4	2015	0	31	2015	

In [70]:
```
# store_type - Label Encoding - coloca um numero sequencial para cada valor dentro da coluna
le = LabelEncoder()
df5['store_type'] = le.fit_transform( df5['store_type'] )
#salvando
pickle.dump( le, open('../parameter/store_type_scaler.pkl', 'wb'))

df5.head()
```

Out[70]:

	store	day_of_week	date	sales	promo	school_holiday	store_type	assortment	competition_distance	competition_open_since_month	competition_open_since_year	promo2	promo2_since_week	promo2_since_year	is_prom
0	1	5	2015-07-31	5263	1	1	2	basic	-0.170968	9	2008	0	31	2015	
1	2	5	2015-07-31	6064	1	1	0	basic	-0.283871	11	2007	1	13	2010	

	store	day_of_week	date	sales	promo	school_holiday	store_type	assortment	competition_distance	competition_open_since_month	competition_open_since_year	promo2	promo2_since_week	promo2_since_year	is_prom
2	3	5	2015-07-31	8314	1	1	0	basic	1.903226	12	2006	1	14	2011	
3	4	5	2015-07-31	13995	1	1	2	extended	-0.275806	9	2009	0	31	2015	
4	5	5	2015-07-31	4822	1	1	0	basic	4.448387	4	2015	0	31	2015	

In [71]:
```
#assortment - Ordinal Encoding - eu defino o numero para cada valor dentro da coluna
assortment_dict = {'basic': 1, 'extra': 2, 'extended': 3}
df5['assortment'] = df5['assortment'].map(assortment_dict)
df5.head()
```

Out[71]:

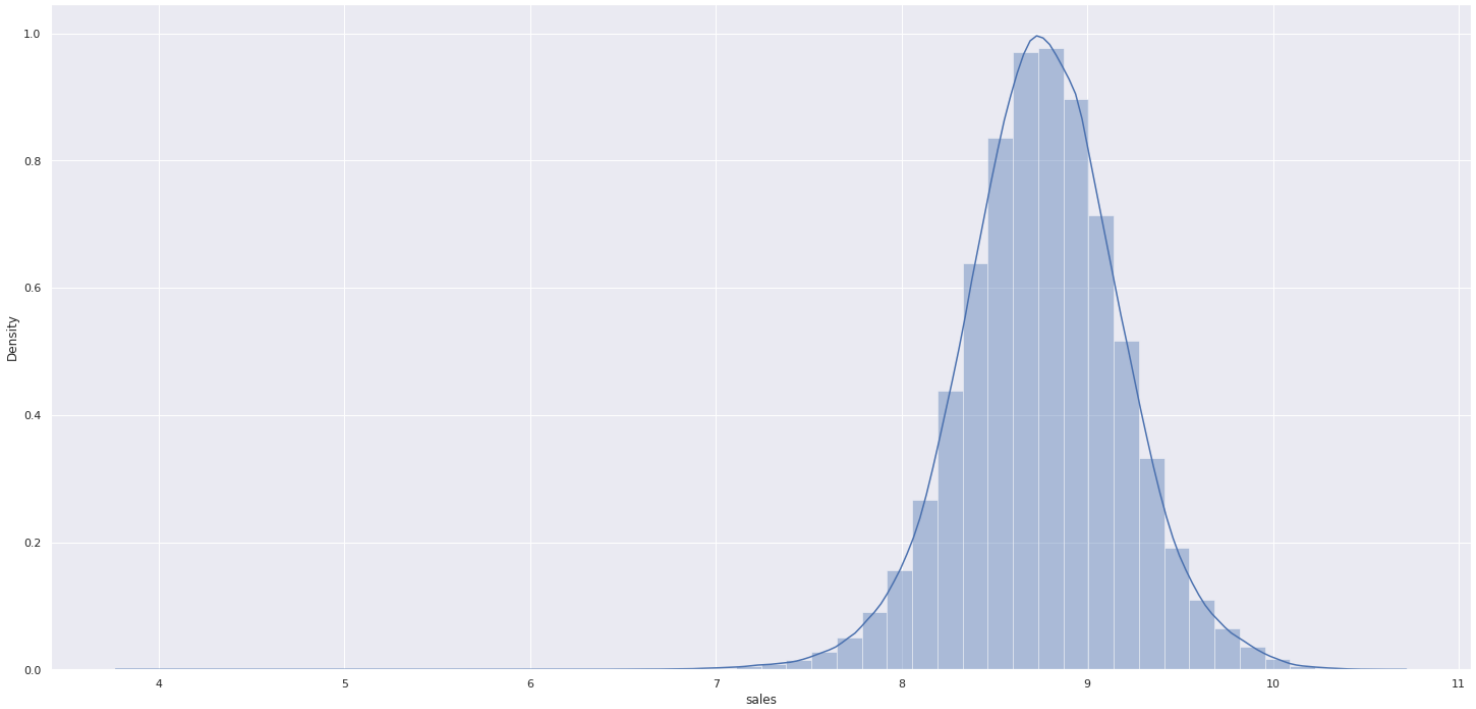
	store	day_of_week	date	sales	promo	school_holiday	store_type	assortment	competition_distance	competition_open_since_month	competition_open_since_year	promo2	promo2_since_week	promo2_since_year	is_prom
0	1	5	2015-07-31	5263	1	1	2	1	-0.170968	9	2008	0	31	2015	
1	2	5	2015-07-31	6064	1	1	0	1	-0.283871	11	2007	1	13	2010	
2	3	5	2015-07-31	8314	1	1	0	1	1.903226	12	2006	1	14	2011	
3	4	5	2015-07-31	13995	1	1	2	3	-0.275806	9	2009	0	31	2015	
4	5	5	2015-07-31	4822	1	1	0	1	4.448387	4	2015	0	31	2015	

5.3.2. Response Variable Transformation

In [72]:
```
df5['sales'] = np.log1p( df5['sales'] )
sns.distplot( df5['sales'])
```

```
/home/leandro/.local/lib/python3.9/site-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please a
dapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[72]:
```
<AxesSubplot:xlabel='sales', ylabel='Density'>
```



5.3.3. Nature Transformation

In [73]:
```
# 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) ) )

df5.head()
```

Out[73]:

	store	day_of_week	date	sales	promo	school_holiday	store_type	assortment	competition_distance	competition_open_since_month	competition_open_since_year	promo2	promo2_since_week	promo2_since_year	is_pr
0	1	5	2015-07-31	8.568646	1	1	2	1	-0.170968	9	2008	0	31	2015	
1	2	5	2015-07-31	8.710290	1	1	0	1	-0.283871	11	2007	1	13	2010	
2	3	5	2015-07-31	9.025816	1	1	0	1	1.903226	12	2006	1	14	2011	
3	4	5	2015-07-31	9.546527	1	1	2	3	-0.275806	9	2009	0	31	2015	
4	5	5	2015-07-31	8.481151	1	1	0	1	4.448387	4	2015	0	31	2015	

6.0. PASSO 06 - FEATURE SELECTION

In [74]:
```
df6 = df5.copy()
```

6.1. SPLIT DATAFRAME INTO TRAINING AND TEST DATASET

In [75]:
```
# REMOVER AS COLUNAS COM DADOS DUPLICADOS OU DADOS QUE GERARAM OUTRAS COLUNAS
cols_drop = ['week_of_year', 'day', 'month', 'day_of_week', 'promo_since', 'competition_since', 'year_week']
df6 = df6.drop( cols_drop, axis=1)
```

In [76]:
```
# Descobrindo a menor data de vendas
#print( df6[['store', 'date']].groupby('store').min().reset_index()['date'] )

# Descobrindo a maior data de vendas
#print( df6[['store', 'date']].groupby('store').max().reset_index()['date'] )
```

In [77]:
```
# Descobrindo a maior data de vendas - Removendo 6 semanas
df6[['store', 'date']].groupby('store').max().reset_index()['date'][0] - datetime.timedelta( days= 6*7)
```

Out[77]:
```
Timestamp('2015-06-19 00:00:00')
```

In [78]:
```
# training dataset
X_train = df6[df6['date'] < '2015-06-19']
y_train = X_train['sales']

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

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

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

```
Training Min Date: 2013-01-01 00:00:00
Training Max Date: 2015-06-18 00:00:00

Test Min Date: 2015-06-19 00:00:00
Test Max Date: 2015-07-31 00:00:00
```

6.2. BORUTA AS FEATURE SELECTOR

In [79]:
```
# training and test dataset for Boruta
# deletando as colunas date, sales e copiando só os valores, sem copiar o dataframe
#X_train_n = X_train.drop( ['date', 'sales'], axis=1).values

# copiando só os valores, sem copiar o dataframe,  ravel --> coloca dentro de um vetor
#y_train_n = y_train.values.ravel()

# define RandomForestRegressor
# ( n_jobs=-1 )  -->  usar todos os cores da maquina e fazer o processamento em paralelo
#rf = RandomForestRegressor( n_jobs=-1 )

# define Boruta
# comentei paa não rodar o boruta e preciso gravar  o resultado, que são as features mais importantes
#boruta = BorutaPy(rf, n_estimators='auto', verbose=2, random_state=42).fit(X_train_n, y_train_n)
```

In [80]:
```
#X_train_n
```

6.2.1. Best Features from Boruta

In [81]:
```
# support_ --> ranking de classificação das variaveis (colunas)
#cols_selected = boruta.support_.tolist()

# x_train é um vetor e preciso colocar este resultado em um DF
# Crio uma variavel x_train_fs --> coloco os dados do DF xtrain e dropo as colunas q tirei
# coloco o resultado do boruta neste DF
#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
# comparo as colunas selecionadas , menos todas as colunas,para identificar as colunas não selecionadas --> setdiff1d
#cols_not_selected_boruta = list( np.setdiff1d(X_train_fs.columns, cols_selected_boruta))
```

In [82]:
```
#cols_selected_boruta
#cols_not_selected_boruta
```

6.3. Manual Features Selection

In [83]:
```
# depois de rodar o boruta para classificação das features, fiz a copia das features para uso manual posterior, não sendo necessário rodar o boruta novamente
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']

# final features
cols_selected_boruta_full = cols_selected_boruta.copy()
cols_selected_boruta_full.extend(feat_to_add)
```

In [84]:
```
#cols_not_selected_boruta = ['school_holiday', 'year']
```

In [85]:
```
#cols_selected_boruta
```

7.0. PASSO 07 - MACHINE LEARNING MODELLING

In [86]:
```
df7 = df6.copy()
```

In [87]:
```
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 ]
x_training.head()
```

Out[87]:

	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_
47945	1	1	2	1	-0.170968	9	2008	0	25	2015	0.891892	0.287016	
47946	2	1	0	1	-0.283871	11	2007	1	13	2010	1.027027	0.908884	

	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_
47947	3	1	0	1	1.903226	12	2006	1	14	2011	1.189189	0.788155	
47948	4	1	2	3	-0.275806	9	2009	0	25	2015	0.729730	0.287016	
47949	5	1	0	1	4.448387	4	2015	0	25	2015	-0.189189	0.287016	

7.1. Average Model

In [88]:
```
#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] )
```

In [89]:
```
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
```

Out[89]:

	Model Name	MAE	MAPE	RMSE
0	Average Model	1354.800353	0.455051	1835.135542

7.2. Linear Regression Model

In [90]:
```
# 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
```

Out[90]:

	Model Name	MAE	MAPE	RMSE
0	Linear Regression	1867.089774	0.292694	2671.049215

7.2.1. Linear Regression Model - Cross Validation

In [91]:
```
lr_result_cv = cross_validation( x_training, 5, 'Linear Regression', lr, verbose=True )
```

```
KFold Number: 5

KFold Number: 4

KFold Number: 3

KFold Number: 2

KFold Number: 1
```

In [92]:
```
lr_result_cv
```

Out[92]:

	Model Name	MAE CV	MAPE CV	RMSE CV
0	Linear Regression	2081.73 +/- 295.63	0.3 +/- 0.02	2952.52 +/- 468.37

7.3. Linear Regression Regularized Model - Lasso

In [93]:
```
# Model
lrr = Lasso(alpha=0.000001).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
```

```
/home/leandro/.local/lib/python3.9/site-packages/sklearn/linear_model/_coordinate_descent.py:645: ConvergenceWarning: Objective did not converge. You might want to increase the num
ber of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 5.401e+04, tolerance: 1.455e+01
  model = cd_fast.enet_coordinate_descent(
```

Out[93]:

	Model Name	MAE	MAPE	RMSE
0	Linear Regression - Lasso	1867.266034	0.292721	2671.419124

7.3.1. Lasso - Linear Regression Regularized Model - Cross Validation

In [94]:
```
lrr_result_cv = cross_validation( x_training, 5, 'Lasso', lrr, verbose=True )
```

```
KFold Number: 5
/home/leandro/.local/lib/python3.9/site-packages/sklearn/linear_model/_coordinate_descent.py:645: ConvergenceWarning: Objective did not converge. You might want to increase the num
ber of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 4.140e+04, tolerance: 1.117e+01
  model = cd_fast.enet_coordinate_descent(
KFold Number: 4
/home/leandro/.local/lib/python3.9/site-packages/sklearn/linear_model/_coordinate_descent.py:645: ConvergenceWarning: Objective did not converge. You might want to increase the num
ber of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 4.436e+04, tolerance: 1.194e+01
  model = cd_fast.enet_coordinate_descent(
KFold Number: 3
/home/leandro/.local/lib/python3.9/site-packages/sklearn/linear_model/_coordinate_descent.py:645: ConvergenceWarning: Objective did not converge. You might want to increase the num
ber of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 4.630e+04, tolerance: 1.257e+01
  model = cd_fast.enet_coordinate_descent(
KFold Number: 2
/home/leandro/.local/lib/python3.9/site-packages/sklearn/linear_model/_coordinate_descent.py:645: ConvergenceWarning: Objective did not converge. You might want to increase the num
ber of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 4.935e+04, tolerance: 1.321e+01
  model = cd_fast.enet_coordinate_descent(
KFold Number: 1
/home/leandro/.local/lib/python3.9/site-packages/sklearn/linear_model/_coordinate_descent.py:645: ConvergenceWarning: Objective did not converge. You might want to increase the num
ber of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 5.141e+04, tolerance: 1.392e+01
  model = cd_fast.enet_coordinate_descent(
```

In [95]:
```
lrr_result_cv
```

Out[95]:

	Model Name	MAE CV	MAPE CV	RMSE CV
0	Lasso	2081.76 +/- 295.68	0.3 +/- 0.02	2952.6 +/- 468.35

7.4. Random Forest Regressor

In [96]:
```
# 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
```

Out[96]:

	Model Name	MAE	MAPE	RMSE
0	Random Forest Regressor	679.080548	0.099879	1010.101738

7.4.1 Random Forest Regressor - Cross Validation

In [97]:
```
rf_result_cv = cross_validation( x_training, 5, 'Random Forest Regressor', rf, verbose=True )
```

```
KFold Number: 5

KFold Number: 4

KFold Number: 3

KFold Number: 2

KFold Number: 1
```

In [98]:
```
rf_result_cv
```

Out[98]:

	Model Name	MAE CV	MAPE CV	RMSE CV
0	Random Forest Regressor	837.7 +/- 219.24	0.12 +/- 0.02	1256.59 +/- 320.28

7.5. XGBoost Regressor

In [99]:
```
# Model
model_xgb = xgb.XGBRegressor(objective= 'reg:squarederror',
                             n_estimators=100,
                             eta=0.01,
                             max_depth=10,
                             subsample=0.7,
                             colsample_bytree=0.9).fit( x_train, y_train )
                            # colsample_bytee

# 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
```

Out[99]:

	Model Name	MAE	MAPE	RMSE
0	XGBoost Regressor	6683.6739	0.949475	7330.979785

7.5.1. XGBoost Regressor - Cross Validation

In [100…
```
xgb_result_cv = cross_validation( x_training, 5, 'XGBoost Regressor', model_xgb, verbose=True )
```

```
KFold Number: 5

KFold Number: 4

KFold Number: 3

KFold Number: 2

KFold Number: 1
```

In [101…
```
xgb_result_cv
```

Out[101…

	Model Name	MAE CV	MAPE CV	RMSE CV
0	XGBoost Regressor	7049.16 +/- 588.44	0.95 +/- 0.0	7715.2 +/- 689.21

7.6. Compare Model´s Performance

7.6.1 Single Performance

In [102…
```
modelling_result = pd.concat([baseline_result, lr_result, lrr_result, rf_result, xgb_result])
modelling_result.sort_values('RMSE')
```

Out[102…

	Model Name	MAE	MAPE	RMSE
0	Random Forest Regressor	679.080548	0.099879	1010.101738
0	Average Model	1354.800353	0.455051	1835.135542
0	Linear Regression	1867.089774	0.292694	2671.049215
0	Linear Regression - Lasso	1867.266034	0.292721	2671.419124
0	XGBoost Regressor	6683.673900	0.949475	7330.979785

7.6.2 Real Performance - Cross Validation

In [103…
```
modelling_result_cv = pd.concat([lr_result_cv, lrr_result_cv, rf_result_cv, xgb_result_cv])
modelling_result_cv
```

Out[103…

	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	2081.76 +/- 295.68	0.3 +/- 0.02	2952.6 +/- 468.35
0	Random Forest Regressor	837.7 +/- 219.24	0.12 +/- 0.02	1256.59 +/- 320.28
0	XGBoost Regressor	7049.16 +/- 588.44	0.95 +/- 0.0	7715.2 +/- 689.21

Testando Cross Validation

In [104…
```
model = LinearRegression()
a = cross_validation( x_training, 5, 'Linear Regression', model, verbose=True )
```

```
KFold Number: 5

KFold Number: 4

KFold Number: 3
```

```
KFold Number: 2

KFold Number: 1
```

In [105…
```
a
```

Out[105…

	Model Name	MAE CV	MAPE CV	RMSE CV
0	Linear Regression	2081.73 +/- 295.63	0.3 +/- 0.02	2952.52 +/- 468.37

In [106…
```
model = Lasso()
b = cross_validation( x_training, 5, 'Lasso', model,  verbose=True  )
```

```
KFold Number: 5

KFold Number: 4

KFold Number: 3

KFold Number: 2

KFold Number: 1
```

In [107…
```
b
```

Out[107…

	Model Name	MAE CV	MAPE CV	RMSE CV
0	Lasso	2388.68 +/- 398.48	0.34 +/- 0.01	3369.37 +/- 567.55

8.0 PASSO 08 - HYPERPARAMETER FINE TUNING

8.1 Random Search

In [108…
```
warnings.filterwarnings( 'ignore' )
```

In [109…
```
# Comentar para não executar mais
#param = {
#    'n_estimators': [1500, 1700, 2500, 3000, 3500],
#     #'n_estimators': [15, 17, 25, 30, 35],
#    '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 = 10
#MAX_EVAL = 2
```

In [110…
```
# Comentar para não executar mais

#final_result = pd.DataFrame()

#for i in range ( MAX_EVAL):
    # choose values for parameters dandomly
#    hp = { k: random.sample( v, 1 )[0] for k, v in param.items() }
#    print( hp )

    #model
#    model_xgb = xgb.XGBRegressor(objective= 'reg:squarederror',
#                                 n_estimators=hp['n_estimators'],
#                                 eta=hp['eta'],
#                                 max_depth=hp['max_depth'],
#                                 subsample=hp['subsample'],
#                                 colsample_bytree=hp['colsample_bytree'],
#                                 min_child_weight=hp['min_child_weight'] )
    # Performance
#    result = cross_validation(x_training, 2, 'XGBoost Regressor', model_xgb, verbose=False)
#    final_result = pd.concat( [final_result, result] )

#final_result
```

8.2 Final Model

In [111…
```
# depois de XBost para identificar os melhores parametros para o modelo, fiz a cópia dos dados para rodar manualmente em uso posterioir
param_tuned = {
    'n_estimators': 3500,
    'eta': 0.01,
    'max_depth': 9,
    'subsample': 0.7,
    'colsample_bytree': 0.9,
    'min_child_weight': 8
        }

#MAX_EVAL = 2
```

In [112…
```
# Model
model_xgb_tuned = xgb.XGBRegressor(objective= 'reg:squarederror',
                                   n_estimators=param_tuned['n_estimators'],
                                   eta=param_tuned['eta'],
                                   max_depth=param_tuned['max_depth'],
                                   subsample=param_tuned['subsample'],
                                   colsample_bytree=param_tuned['colsample_bytree'],
                                   min_child_weight=param_tuned['min_child_weight'] ).fit( x_train, y_train )
                               # colsample_bytee

# 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) )
xgb_result_tuned
```

Out[112…

	Model Name	MAE	MAPE	RMSE
0	XGBoost Regressor	6683.6739	0.949475	7330.979785

In [113…
```
np.expm1( y_test ).min()
```

Out[113…
```
569.0000000000002
```

In [114…
```
np.expm1( y_test ).max()
```

Out[114…
```
41550.99999999998
```

In [115…
```
np.expm1( y_test ).max() - np.expm1( y_test ).min()
```

Out[115…
```
40981.99999999998
```

In [116…
```
np.expm1( y_test ).mean()
```

Out[116…
```
6995.162576094309
```

In [117…
```
mpe = mean_percentage_error( np.expm1( y_test ), np.expm1( yhat_xgb_tuned ))
```

```
mpe
```

Out[117…
```
0.0021387351624184182
```

In [118…
```
# Salvando o resultado (modelo treinado)
pickle.dump(model_xgb_tuned, open('/home/leandro/repos/rossmann_store_sales_prediction/model/model_rossmann.pkl', 'wb'))
```

9.0 PASSO 09 - Tradução e Interpretação do ERRO

In [119…
```
df9 = X_test[cols_selected_boruta_full]

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

9.1 Business Performance

In [120…
```
# 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=

# 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']]
```

In [121…
```
df9_aux1.head()
```

Out[121…

	store	MAE
0	1	274.239951
1	2	354.195247
2	3	557.133453
3	4	860.489614
4	5	430.349217

In [122…
```
df9_aux2.head()
```

Out[122…

	store	MAPE
0	1	0.062431
1	2	0.071873
2	3	0.077539
3	4	0.081605
4	5	0.098023

In [123…
```
df9_aux3.head()
```

Out[123…

	store	MAE	MAPE
0	1	274.239951	0.062431
1	2	354.195247	0.071873
2	3	557.133453	0.077539
3	4	860.489614	0.081605
4	5	430.349217	0.098023

In [124…
```
df92.head()
```

Out[124…

	store	predictions	worst_scenario	best_scenario	MAE	MAPE
0	1	162758.59375	162484.353799	163032.833701	274.239951	0.062431
1	2	178902.25000	178548.054753	179256.445247	354.195247	0.071873
2	3	257953.56250	257396.429047	258510.695953	557.133453	0.077539
3	4	341295.62500	340435.135386	342156.114614	860.489614	0.081605
4	5	175411.46875	174981.119533	175841.817967	430.349217	0.098023

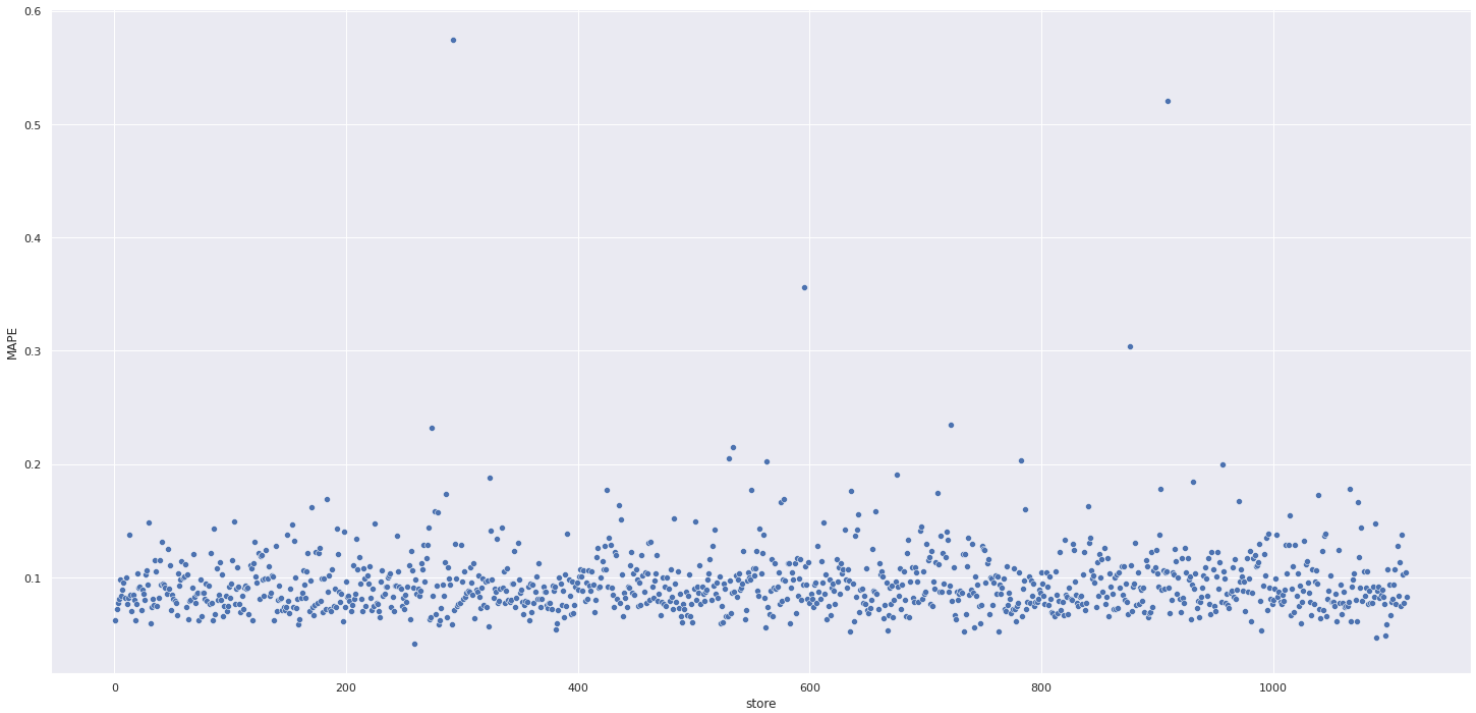
In [125…
```
df92.sort_values( 'MAPE', ascending=False).head()
```

Out[125…

	store	predictions	worst_scenario	best_scenario	MAE	MAPE
291	292	105250.898438	101877.263492	108624.533383	3373.634946	0.574750
908	909	230364.593750	222634.300930	238094.886570	7730.292820	0.520151
594	595	338123.437500	332958.854400	343288.020600	5164.583100	0.356162
875	876	202521.640625	198535.253110	206508.028140	3986.387515	0.304386
721	722	343582.468750	341844.996556	345319.940944	1737.472194	0.234821

In [126…
```
sns.scatterplot( x='store', y='MAPE', data=df92 )
```

Out[126…
```
<AxesSubplot:xlabel='store', ylabel='MAPE'>
```



9.2 Total Performance

In [127…
```
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
```

Out[127…

	Scenario	Values
0	predictions	R$283,098,176.00
1	worst_scenario	R$282,362,558.52
2	best_scenario	R$283,833,768.53

9.3 Machine Learning Performance

In [128…
```
df9['error'] = df9['sales'] -df9['predictions']
df9['error_rate'] = df9['predictions'] / df9['sales']
```

In [129…
```
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'])
```

Out[129…
```
<AxesSubplot:xlabel='predictions', ylabel='error'>
```

In [ ]: