0.0 IMPORTS

In [1]:
```python
import pandas as pd
import inflection
import math
import numpy as np
import seaborn as sns
import datetime
import pickle

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 tabulate import tabulate
```

0.1. Helper Functions

In [2]:
```python
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]:
```python
jupyter_settings()
```

```
Populating the interactive namespace from numpy and matplotlib
```

0.2. Loading data

In [4]:
```python
# 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 [5]:
```python
# teste de leitura simples
df_raw.sample()
```

Out[5]:

	Store	DayOfWeek	Date	Sales	Customers	Open	Promo	StateHoliday	SchoolHoliday	StoreType	Assortment	CompetitionDistance	CompetitionOpenSinceMonth	CompetitionOpenSinceYear	Promo2	Promo2SinceWeek
551911	772	6	2014-02-22	4459	582	1	0	0	0	d	c	1850.0	NaN	NaN	0	NaN

1.0. PASSO 01 - DESCRICAO DOS DADOS

In [6]:
```python
# fazer uma cópia do dataset quando muda de seção, somente para manter os dados , caso seja necessário recomeçar
df1 = df_raw.copy()
```

In [7]:
```python
# visualizando os nomes das colunas do dataset
df1.columns
```

Out[7]:
```
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 [8]:
```python
# 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[8]:
```
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 [9]:
```python
# 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 [10]:
```python
# leitura do tipos de dados de cada coluna
```

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

Out[10]:
```
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 [11]:
```
# Verificando colunas com registros vazios
df1.isna().sum()
```

Out[11]:
```
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 [12]:
```
#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 [13]:
```
# releitura para conferir se ainda temos registros vazios
df1.isna().sum()
```

Out[13]:
```
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 [14]:
```
# 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 [15]:
```
# releitura dos tipos de dados para conferencia
df1.dtypes
```

Out[15]:
```
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 [16]:
```python
# 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 [17]:
```python
# 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
```

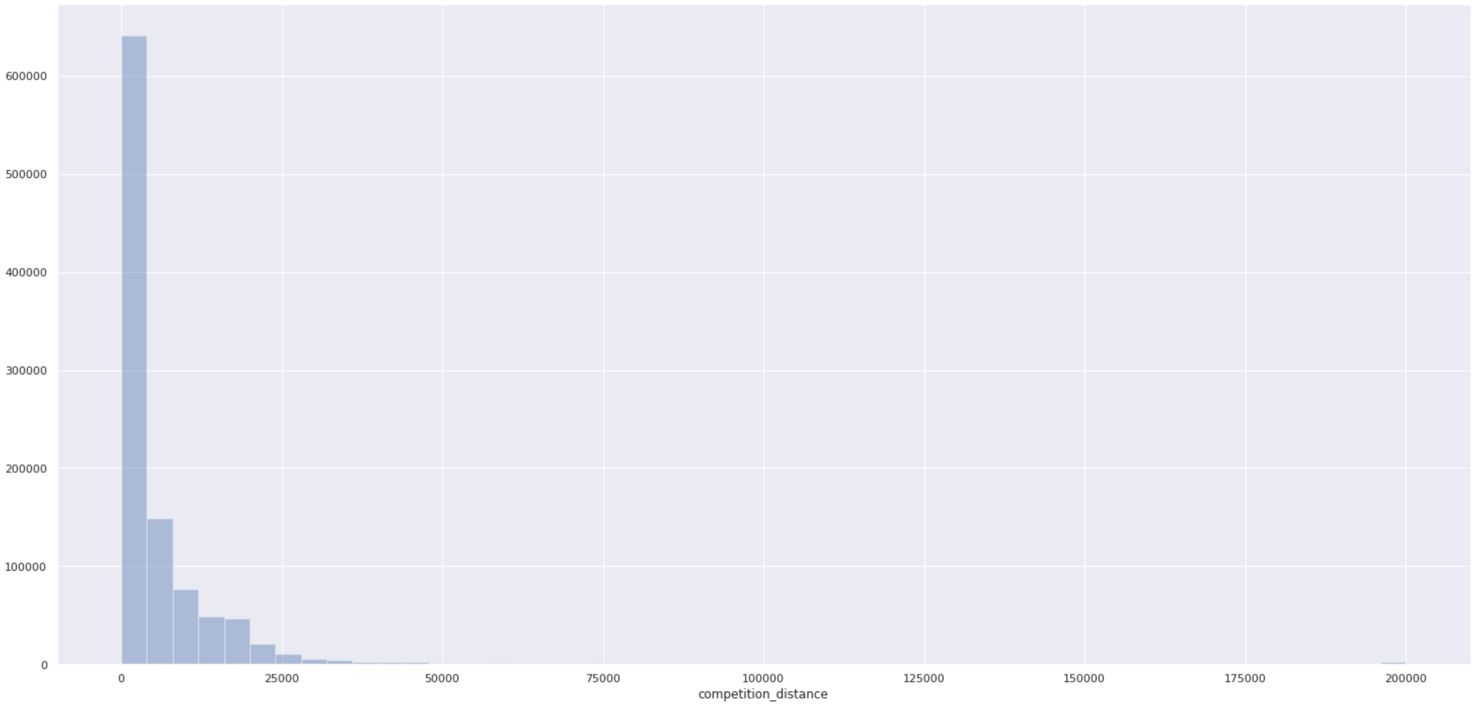
Out[17]:

	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 [18]:
```python
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 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[18]: `<AxesSubplot:xlabel='competition_distance'>`



1.7.2 Caterigal Attributes

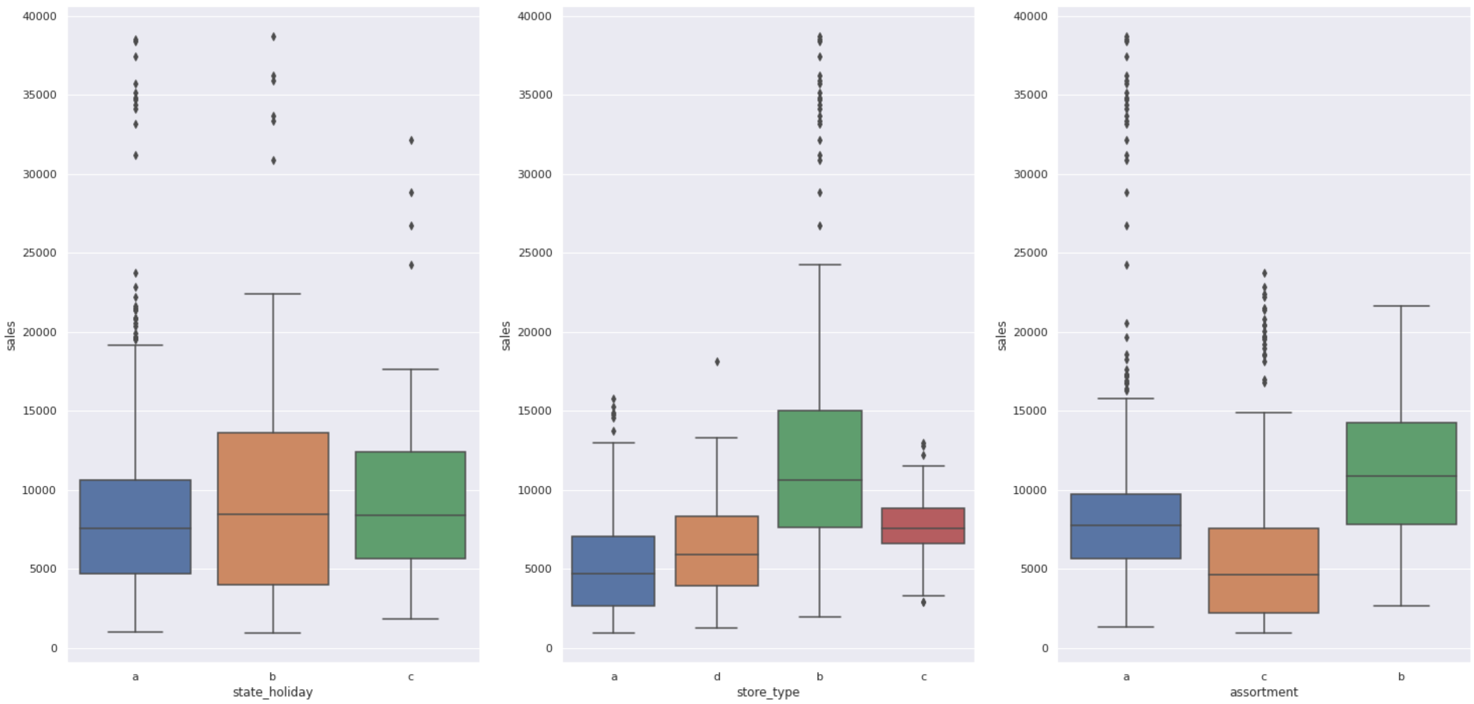
In [19]:
```python
cat_attributes.apply( lambda x: x.unique().shape[0] )
```

Out[19]:
```
state_holiday       4
store_type          4
```

```
assortment         3
promo_interval     4
month_map         12
dtype: int64
```

In [20]:
```python
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[20]: <AxesSubplot:xlabel='assortment', ylabel='sales'>



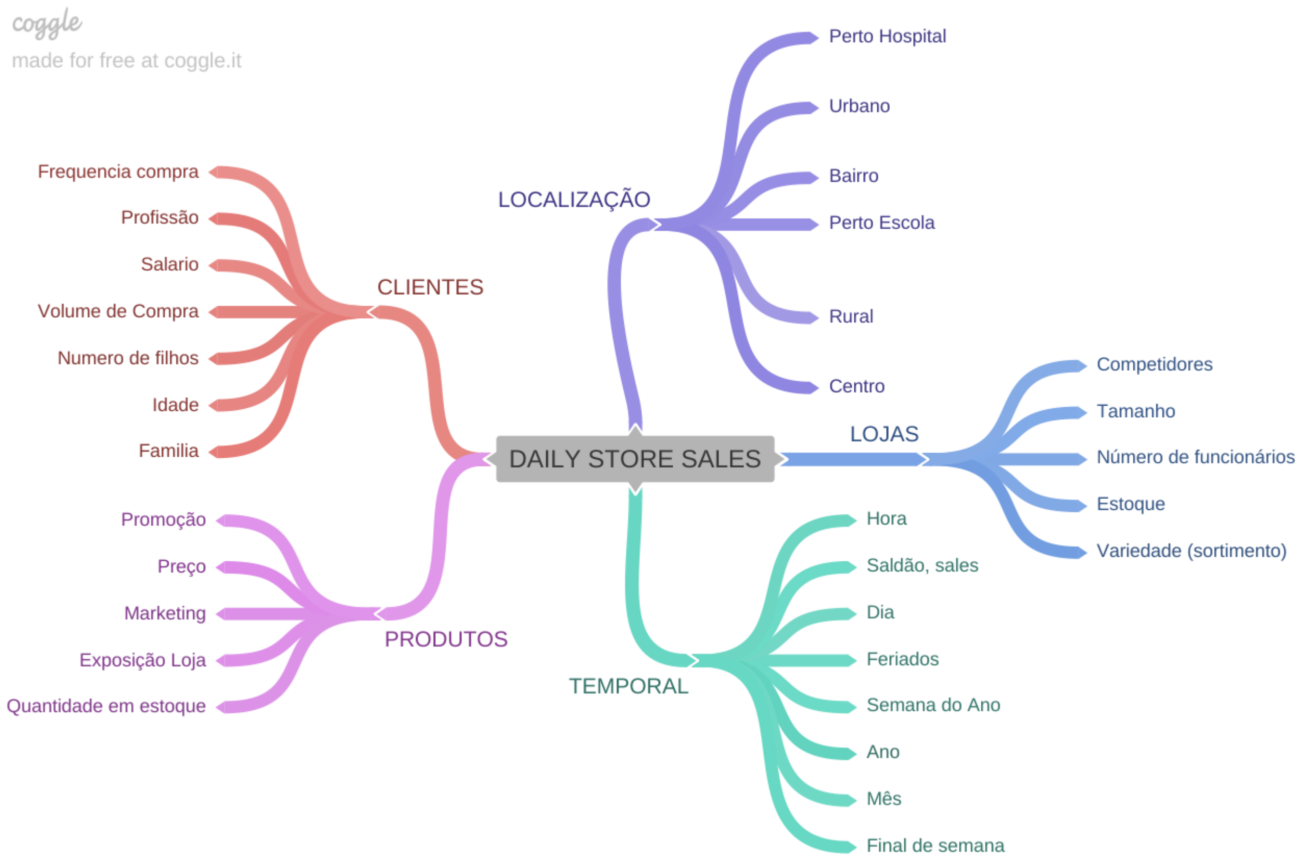
2.0. PASSO 02 - FEATURE ENGINEETING

In [21]:
```python
# 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 [22]:
```python
# Feito Feature Engineering para criar listas de hipóteses e validar dados
Image('../img/DAILY_STORE_SALES.png')
```

Out[22]:



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 [23]:
```
# 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 [24]:
```
#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 [25]:
```
# 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 [26]:
```
# ASSORTMENT
df2['assortment'] = df2['assortment'].apply( lambda x: 'basic' if x == 'a' else 'extra' if x == 'b' else 'extended')
```

In [27]:
```
# 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 [28]:
```
df2.head().T
```

Out[28]:

	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

	0	1	2	3	4
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
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 [29]:
```
df3 = df2.copy()
```

3.1. Filtragem das Linhas

In [30]:
```
# criando novo dataset com lojas abertas e com vendas
df3 = df3[(df3['open'] != 0) & (df3['sales'] > 0)]
```

3.2. Seleção das Colunas

In [31]:
```
# 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 [32]:
```
df3.columns
```

Out[32]:
```
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 [33]:
```
#Etapa para medir impacto das variáveis, quantificar seu impacto, validar hipóteses de negócios e gerar INSIGHTS
df4 = df3.copy()
```

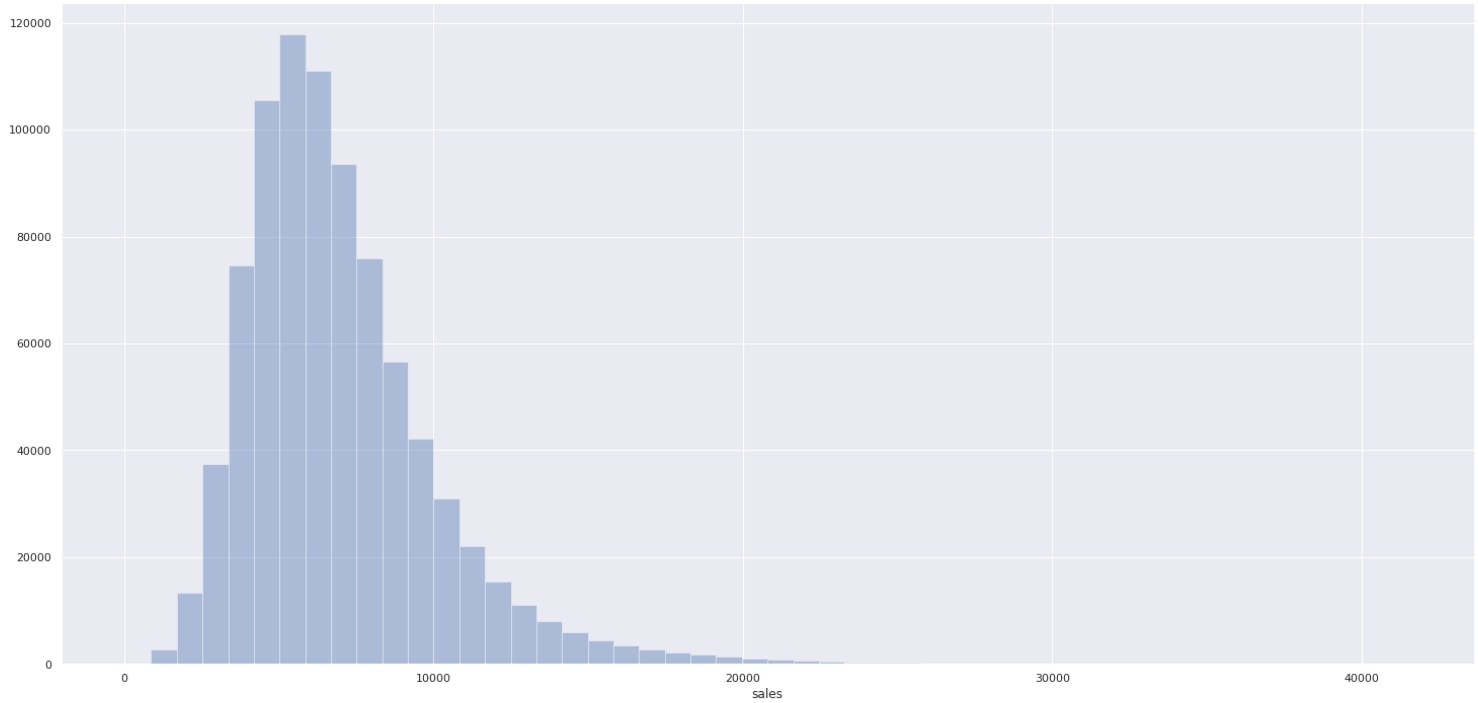
4.1. Analise Univariada

4.1.1. Response Variable

In [34]:
```
#plt.figure( figsize=(220,112))
sns.distplot( df4['sales'], kde=False )
```

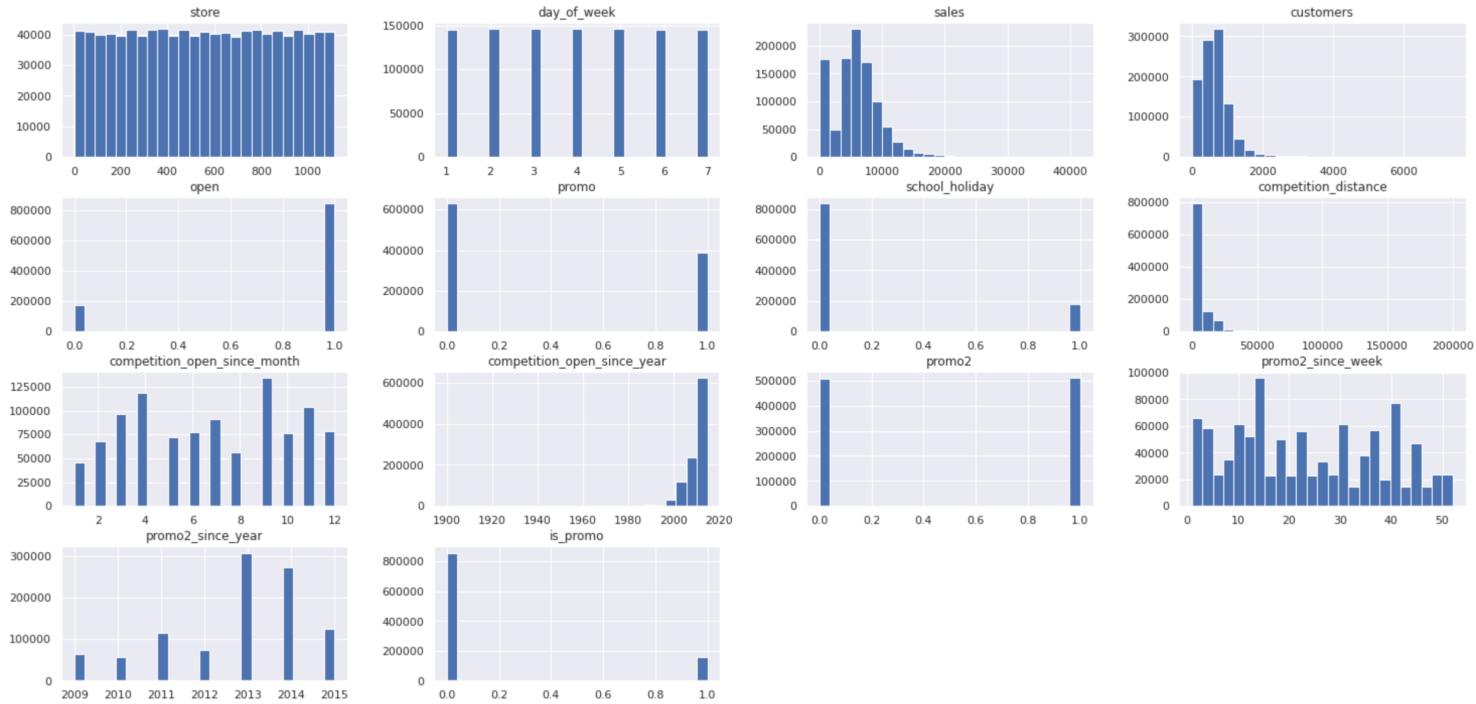
```
/home/leandro/.local/lib/python3.9/site-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please a
dapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level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

Out[34]:
```
<AxesSubplot:xlabel='sales'>
```



4.1.2. Numerical Variable

In [35]:
```
#plt.figure( figsize=(220,112))
num_attributes.hist(bins=25);
```



4.1.3. Categorical Variable

In [36]:
```
df4['state_holiday'].drop_duplicates()
```

Out[36]:
```
0            regular_day
63559     public_holiday
129424    easter_holiday
241126         christmas
Name: state_holiday, dtype: object
```

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

Out[37]:
```
0     c
1     a
12    d
84    b
Name: store_type, dtype: object
```

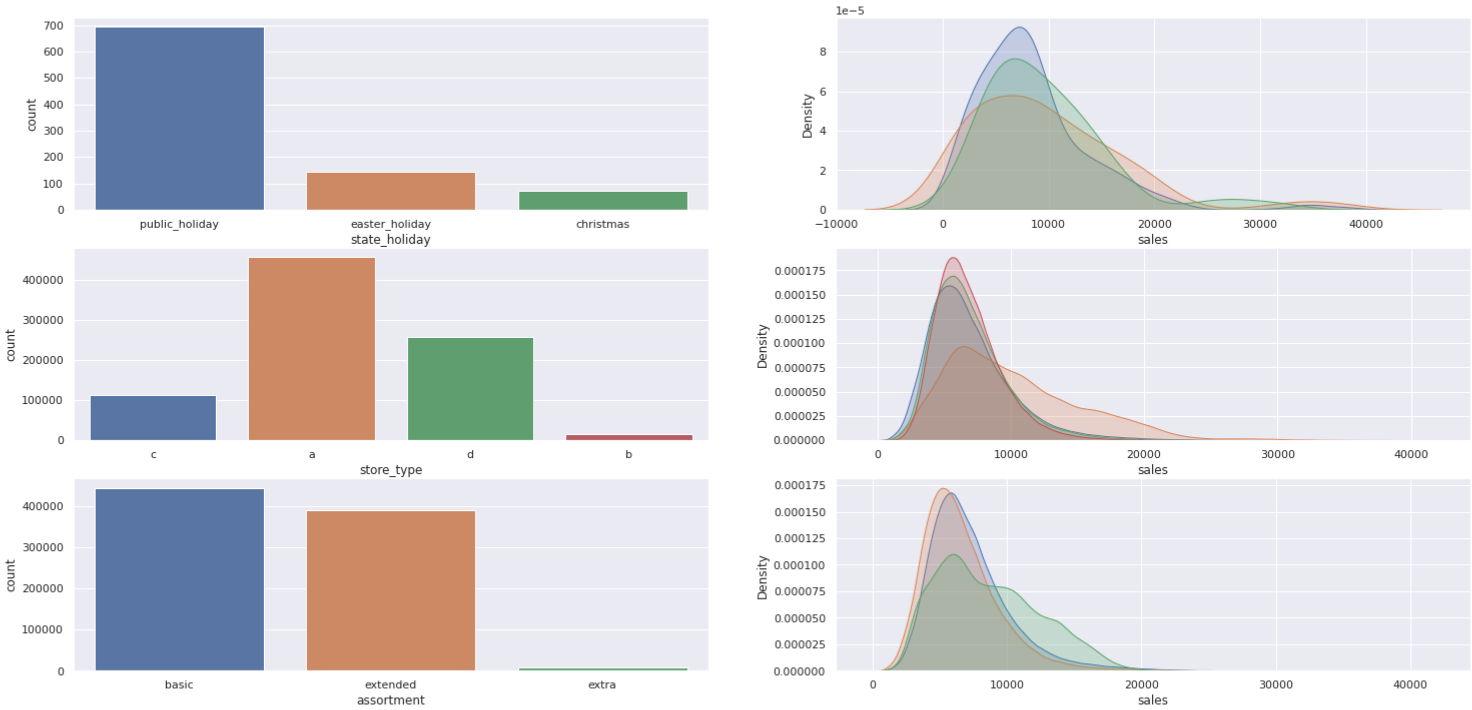
In [38]:
```
df4['assortment'].drop_duplicates()
```

Out[38]:
```
0         basic
3      extended
258       extra
Name: assortment, dtype: object
```

In [39]:
```
# 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[39]:
```
<AxesSubplot:xlabel='sales', ylabel='Density'>
```



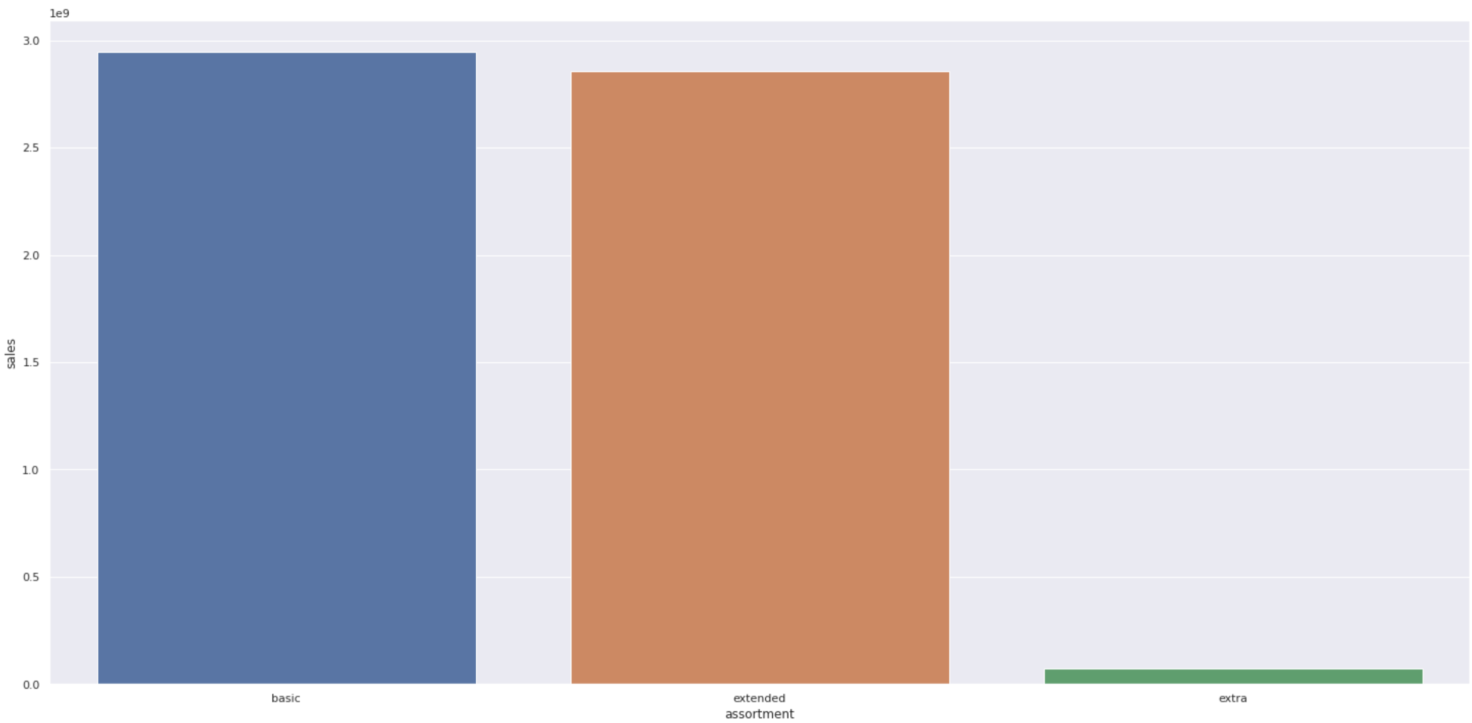
4.2. Analise Bivariada

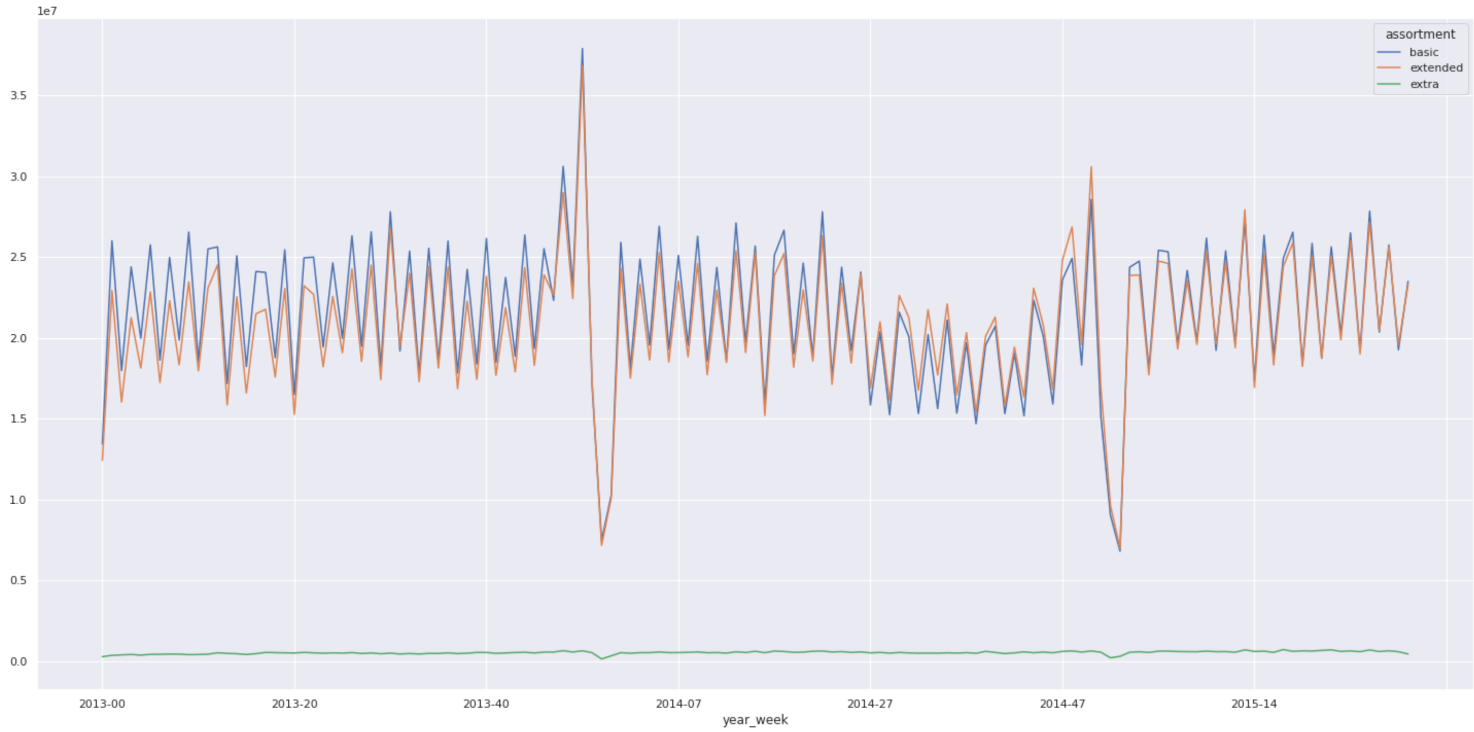
H1. Lojas com maior sortimentos deveriam vender mais.

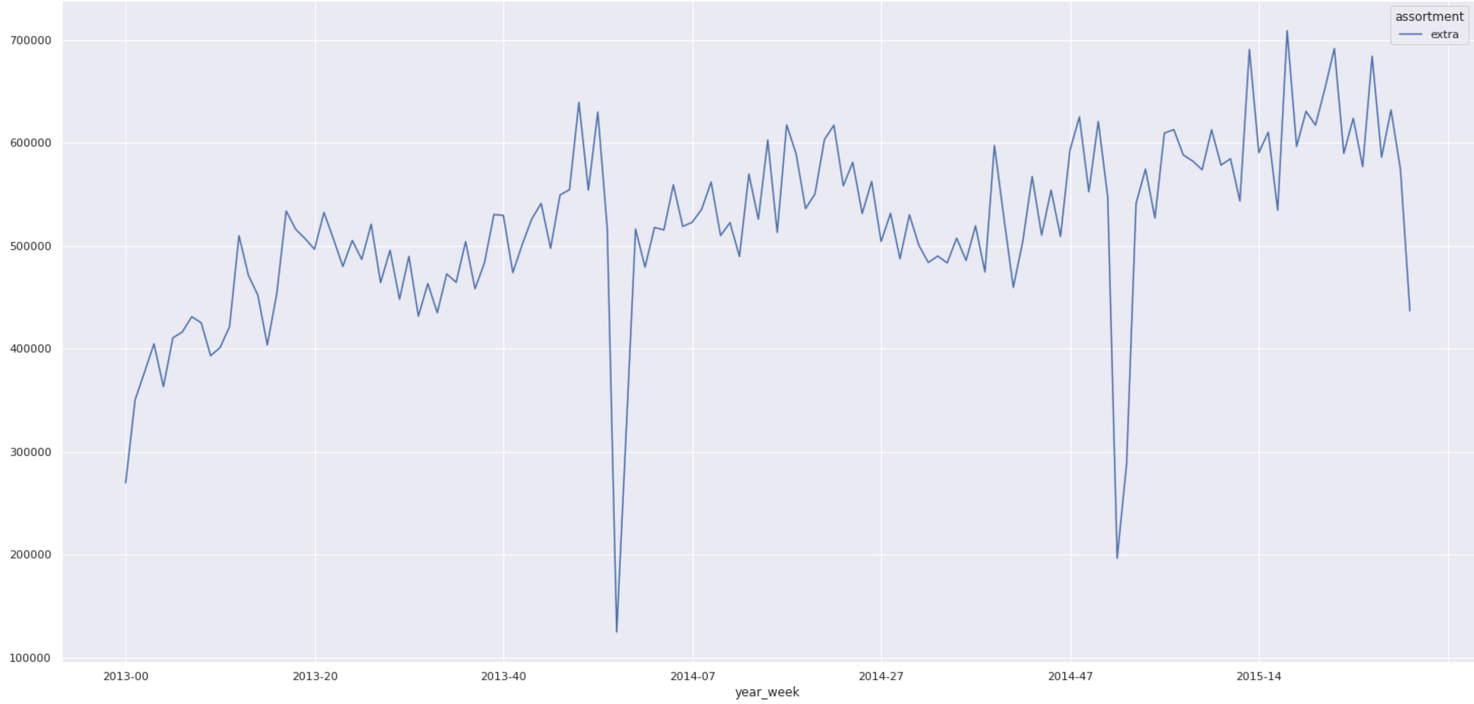
FALSA Lojas cim MAIOR SORTIMENTO vendem MENOS

In [40]:
```python
#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()
```

Out[40]: <AxesSubplot:xlabel='year_week'>



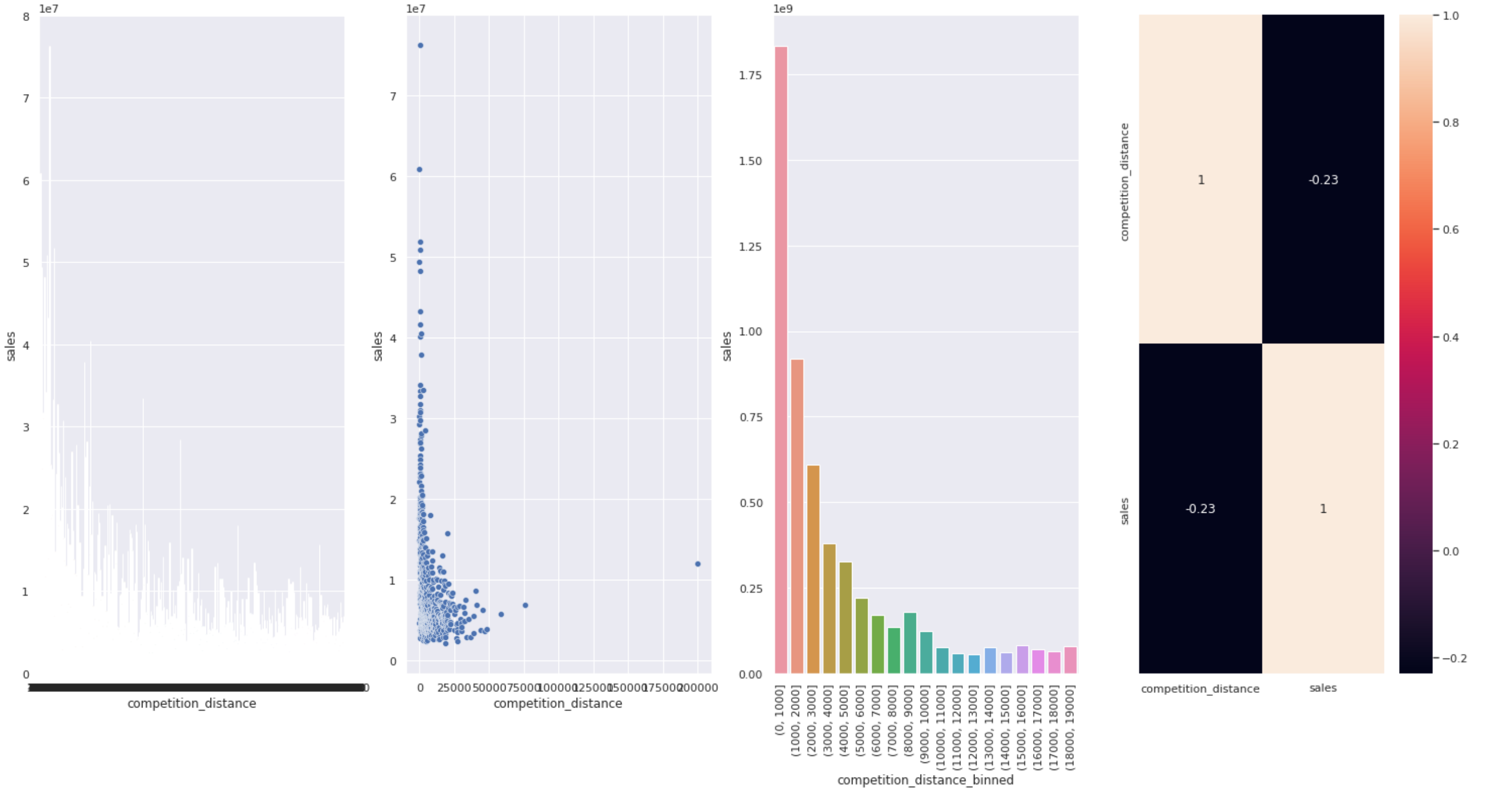




H2. Lojas com competidores mais próximos deveriam vender menos.

Falsa Lojas com COMPETIDORES MAIS PROXIMOS vendem MAIS

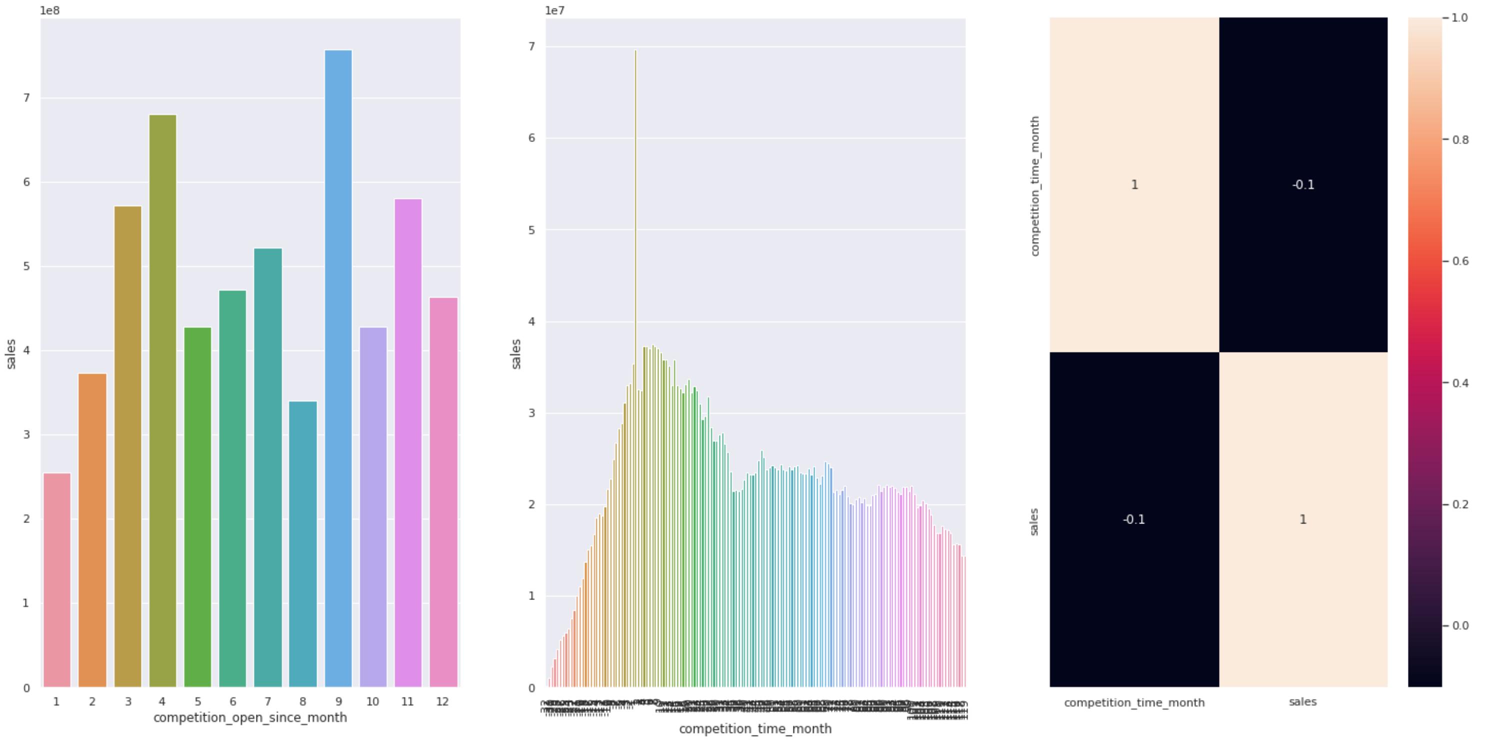
In [41]:
```
#sortimento + vendas --> agrupa por sortimento

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);
```



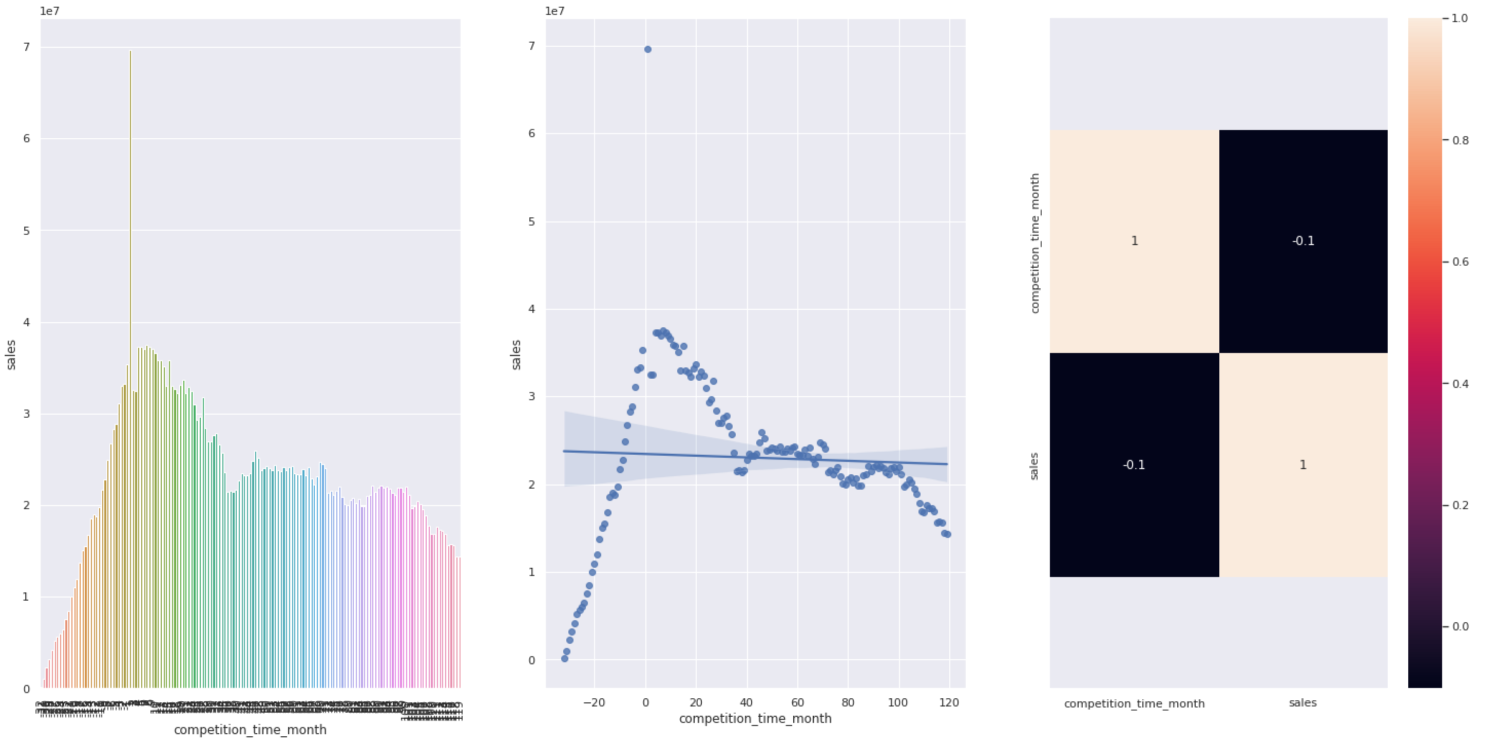
H3. Lojas com competidores a mais tempo deveriam vender mais.

Falsa Lojas com COMPETIDORES A MAIS TEMPO vendem MENOS

In [42]:
```
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);
```



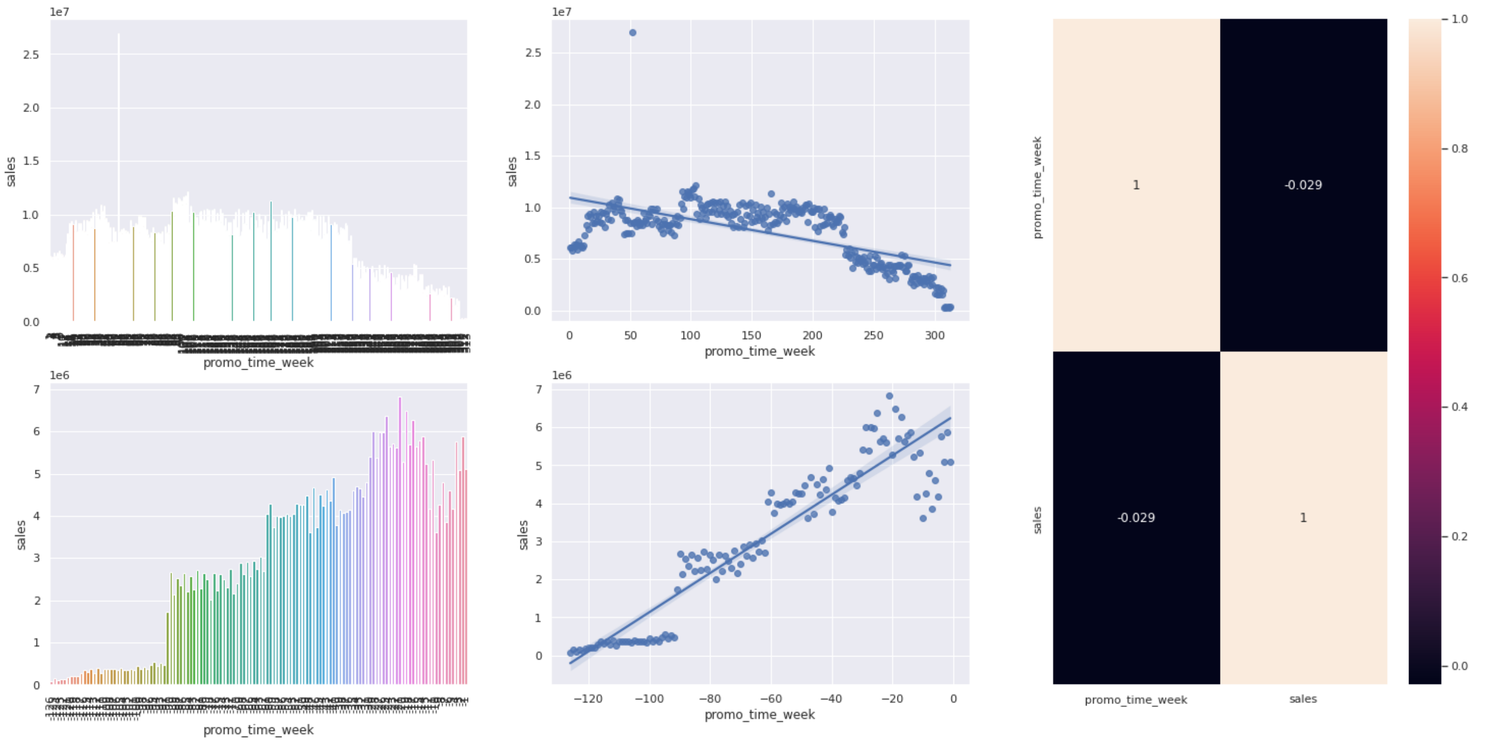
In [43]:
```
plt.subplot( 1, 3, 1 )
aux1 = df4[['competition_time_month', 'sales']].groupby( 'competition_time_month' ).sum().reset_index()
aux2 = aux1[( aux1['competition_time_month'] < 120 ) & ( aux1['competition_time_month'] != 0 )]
sns.barplot( x='competition_time_month', y='sales', data=aux2 );
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 [44]:
```
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

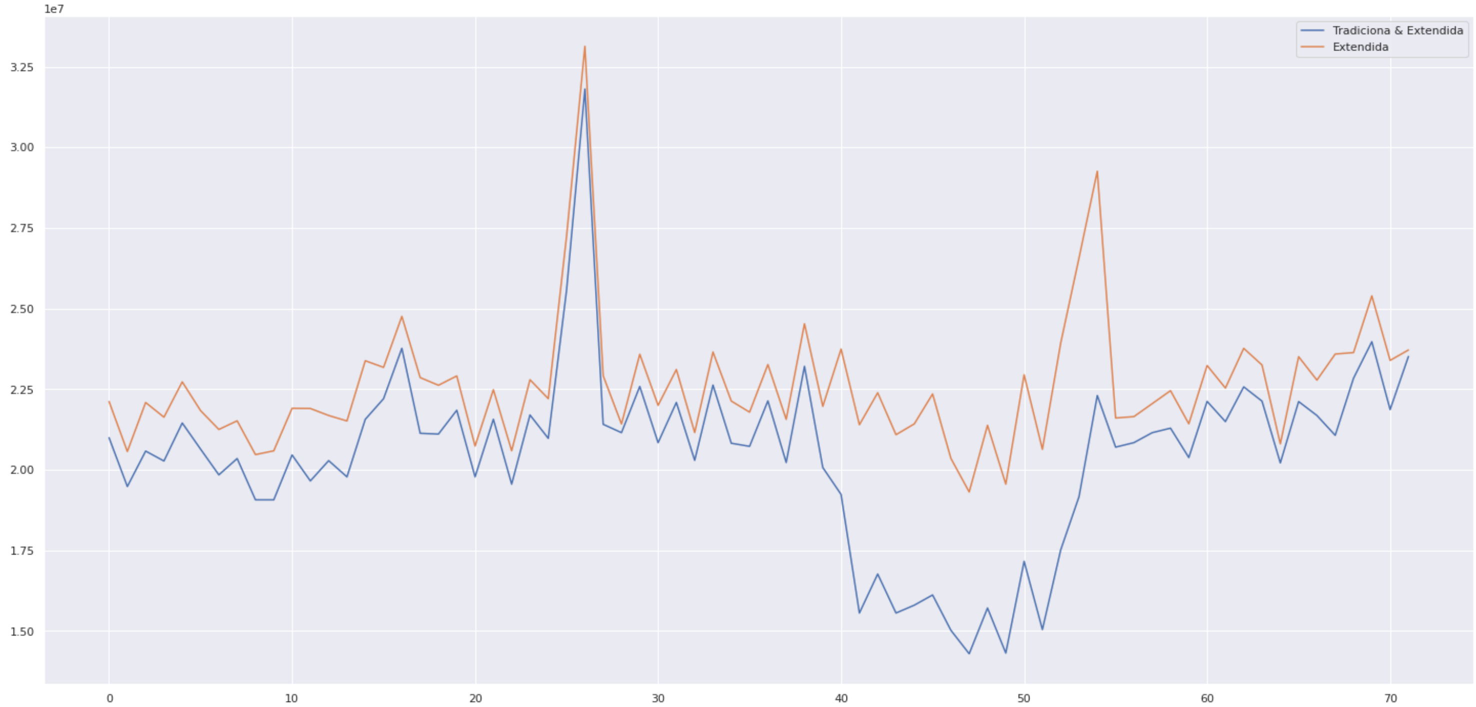
In [45]:
```
df4[['promo', 'promo2', 'sales']].groupby(['promo', 'promo2']).sum().reset_index()
```

Out[45]:

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

In [46]:

```
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']);
```

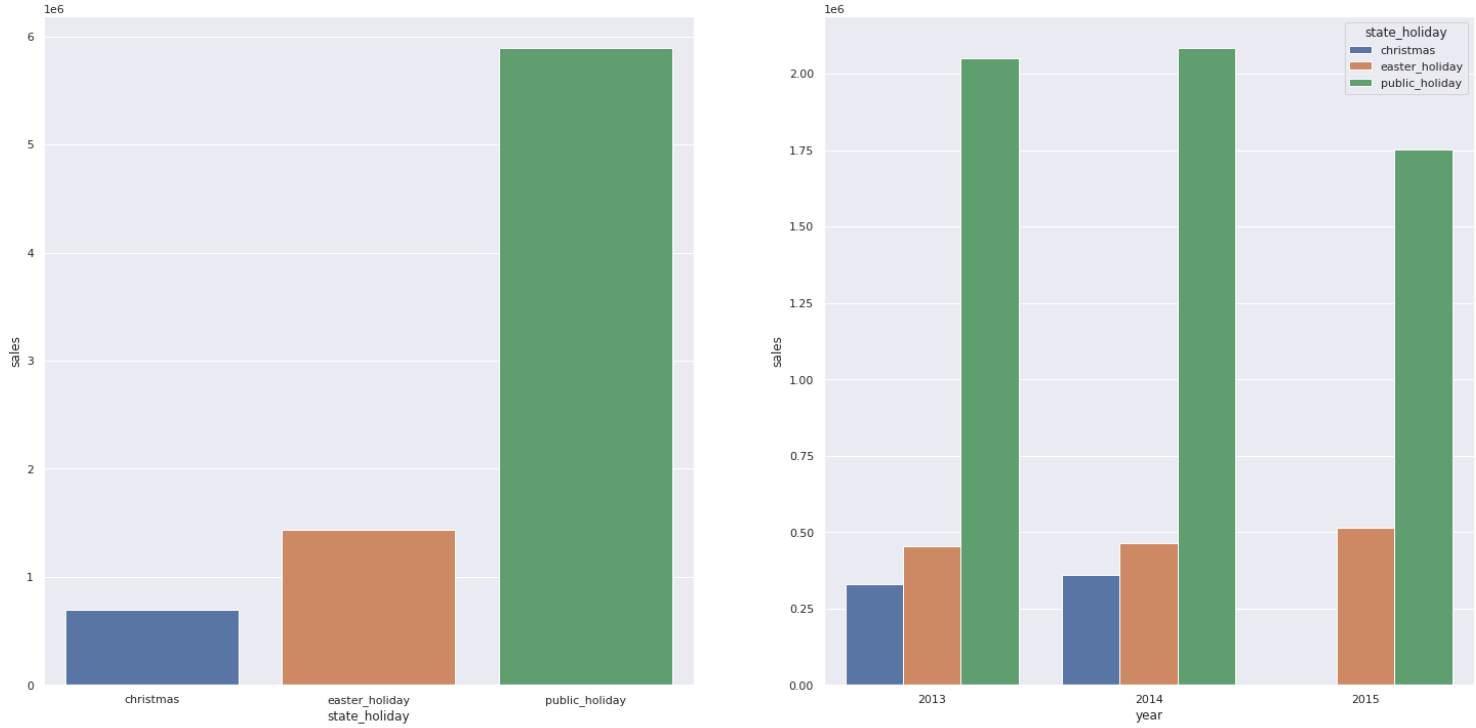


H7. Lojas abertas durante o feriado de Natal deveriam vender mais.

Falsa Lojas abertas durante o feriado do Natal vendem menos

In [47]:

```
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);
```



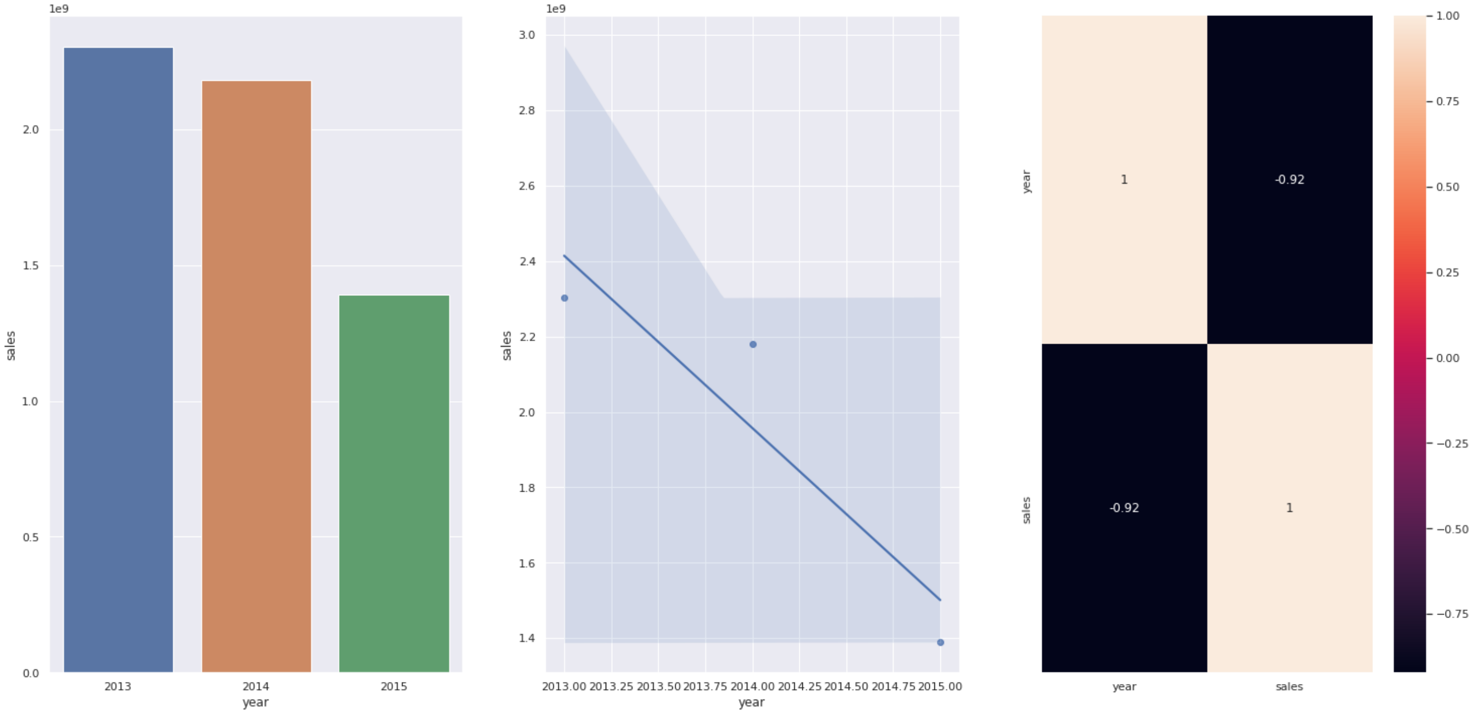
H8. Lojas deveriam vender mais ao lojgo dos anos.

Falsa Lojas vendem menos ao longo dos anos

In [48]:

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

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

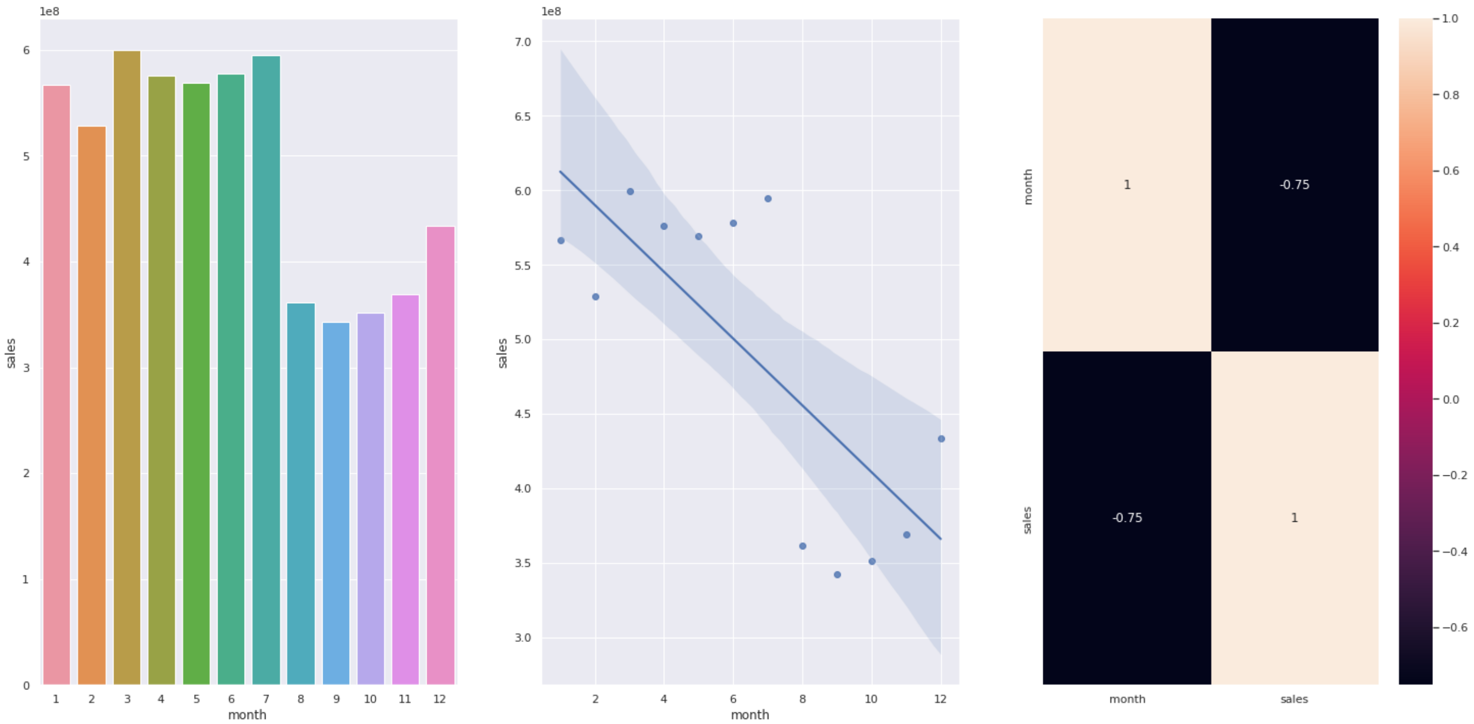
```python
plt.subplot(1,3,2)
sns.regplot(x='year', y='sales', data=aux1);

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 [49]:
```python
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

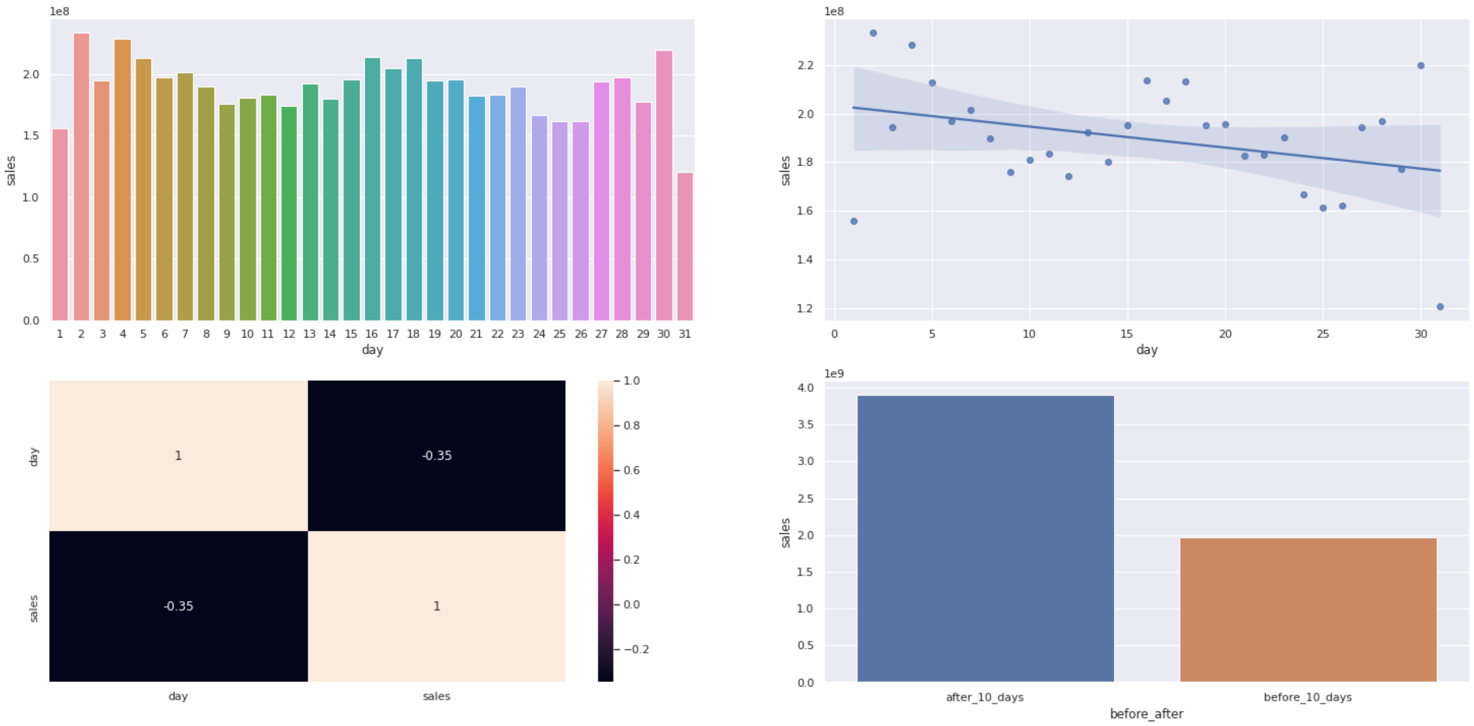
In [50]:
```python
aux1.head(15)
```

Out[50]:

	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

	month	sales
8	9	342570131
9	10	351878728
10	11	369498877
11	12	433831153

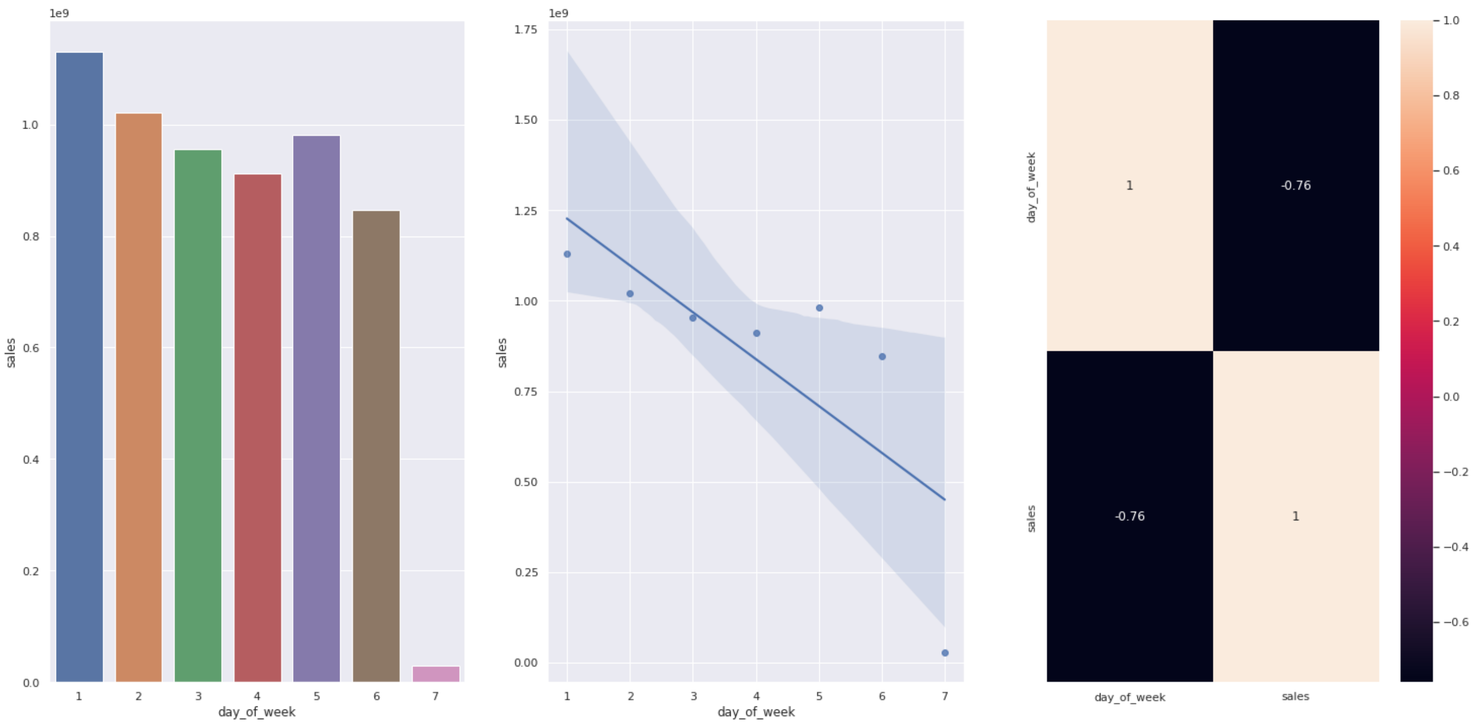
In [51]:
```
aux1 = df4[['day', 'sales']].groupby('day').sum().reset_index()

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

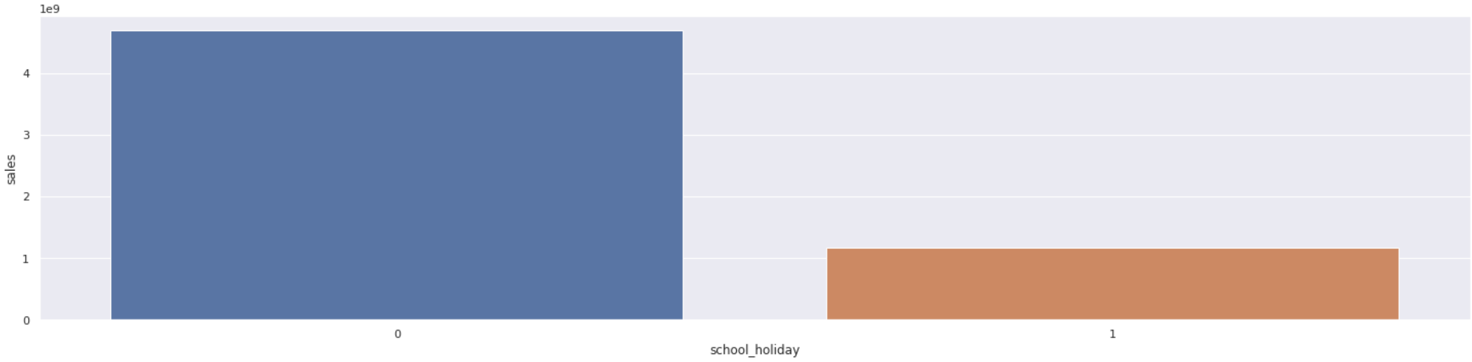
In [52]:
```
aux1 = df4[['day_of_week', 'sales']].groupby('day_of_week').sum().reset_index()

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);
```

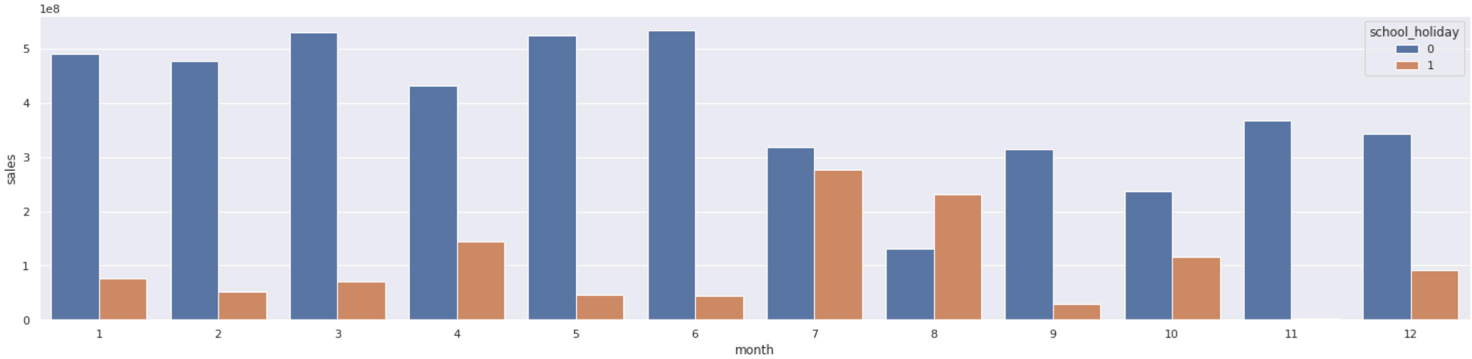


H12. Lojas deveriam vender menos durante os feriados escolares

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

In [53]:
```
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 [54]:
```
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

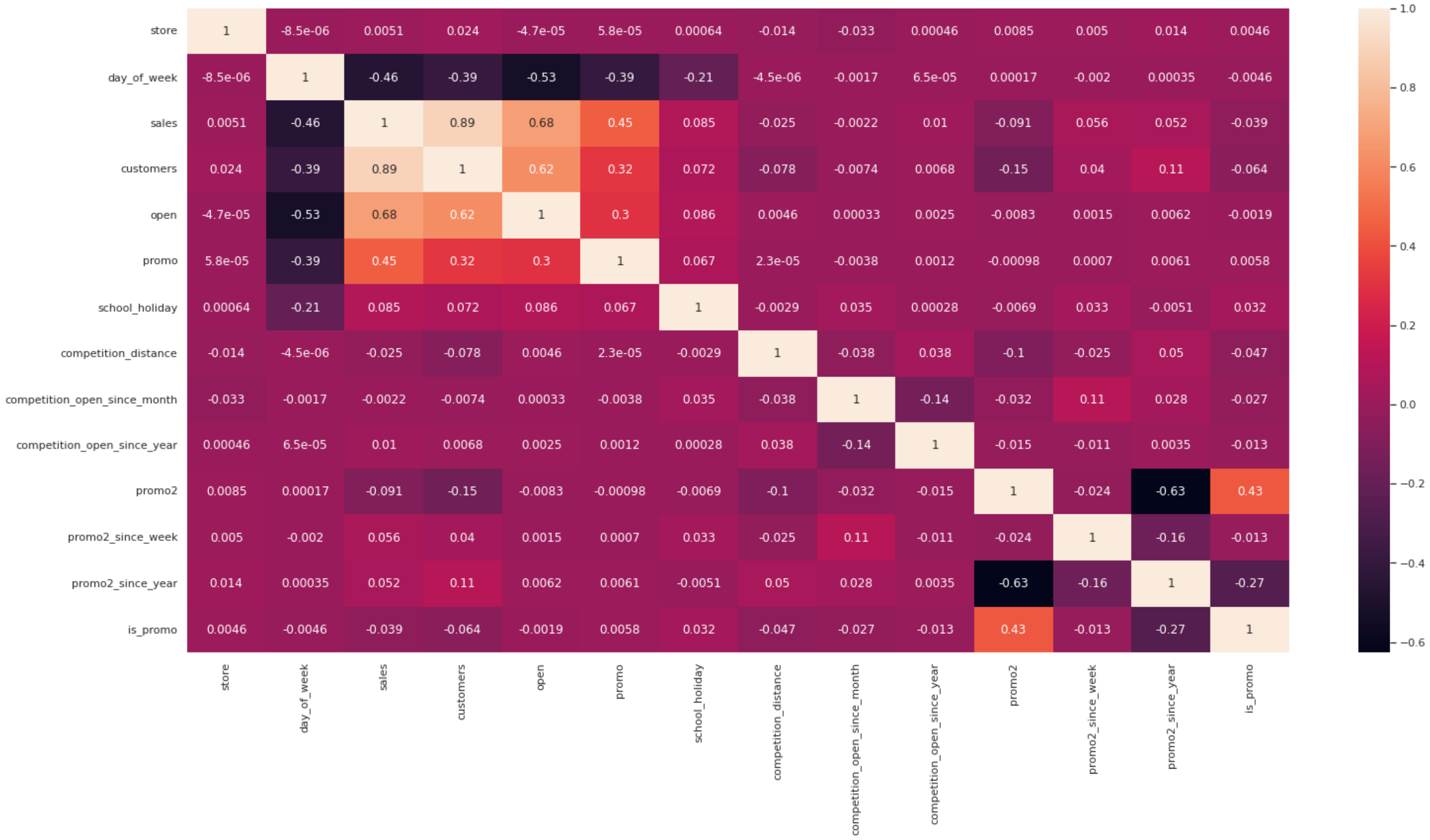
4.3.1. Numerical Attributes

In [55]:
```
num_attributes.head()
```

Out[55]:

	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 [56]:
```
correlation =num_attributes.corr(method='pearson')
sns.heatmap(correlation, annot=True);
```



4.3.2. Categorical Attributes

In [57]:
```
cat_attributes.head()
```

Out[57]:

	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 [58]:
```
a = df4.select_dtypes(include='object')
a.head()
```

Out[58]:

	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

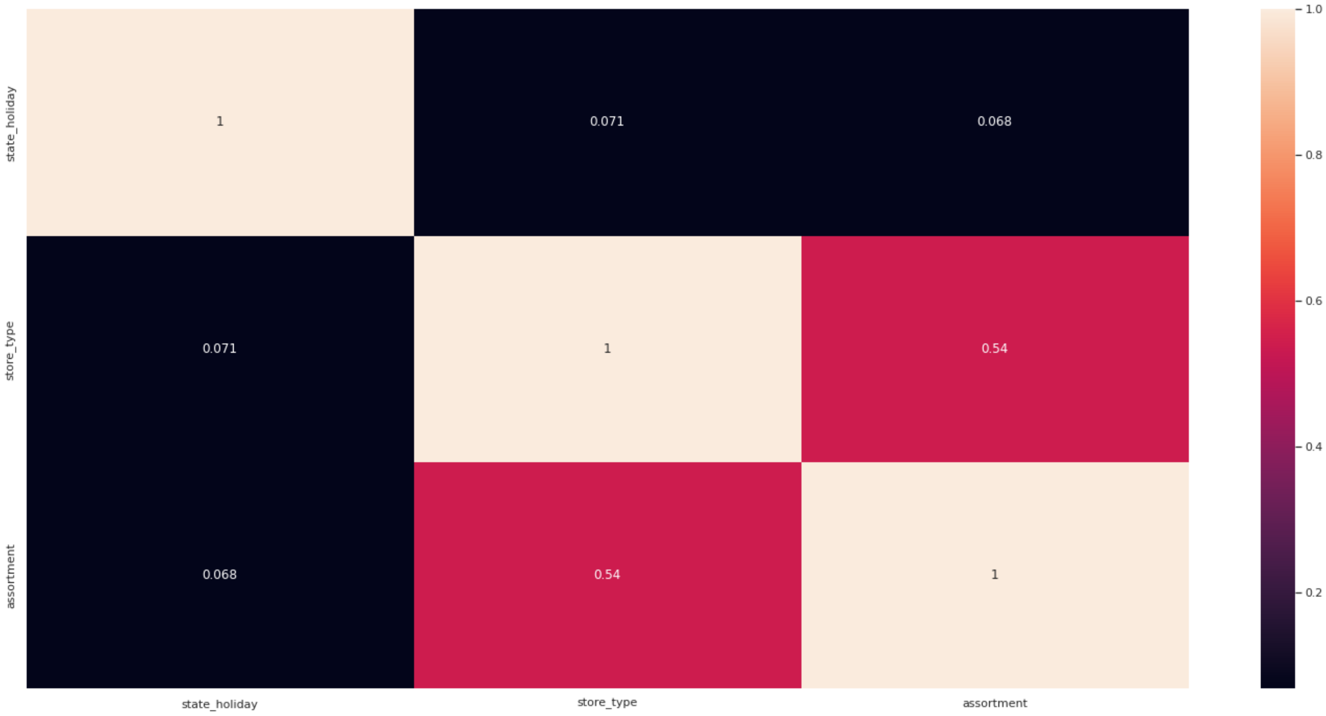
In [59]:
```
#pd.crosstab( a['state_holiday'], a['store_type']).as_matrix()
```

In [60]:
```
# 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 [61]:
```
sns.heatmap(d, annot=True )
```

Out[61]:

<AxesSubplot:>



5.0. PASSO 05 - PREPARAÇÃO DOS DADOS - DATA PREPARATION

In [62]:
```
df5 = df4.copy()
```

5.1. Normalização

In [ ]:
```
```

5.2. Rescaling

In [63]:
```
a =df5.select_dtypes( include=['int64', 'int32', 'float64'])
a.head()
```

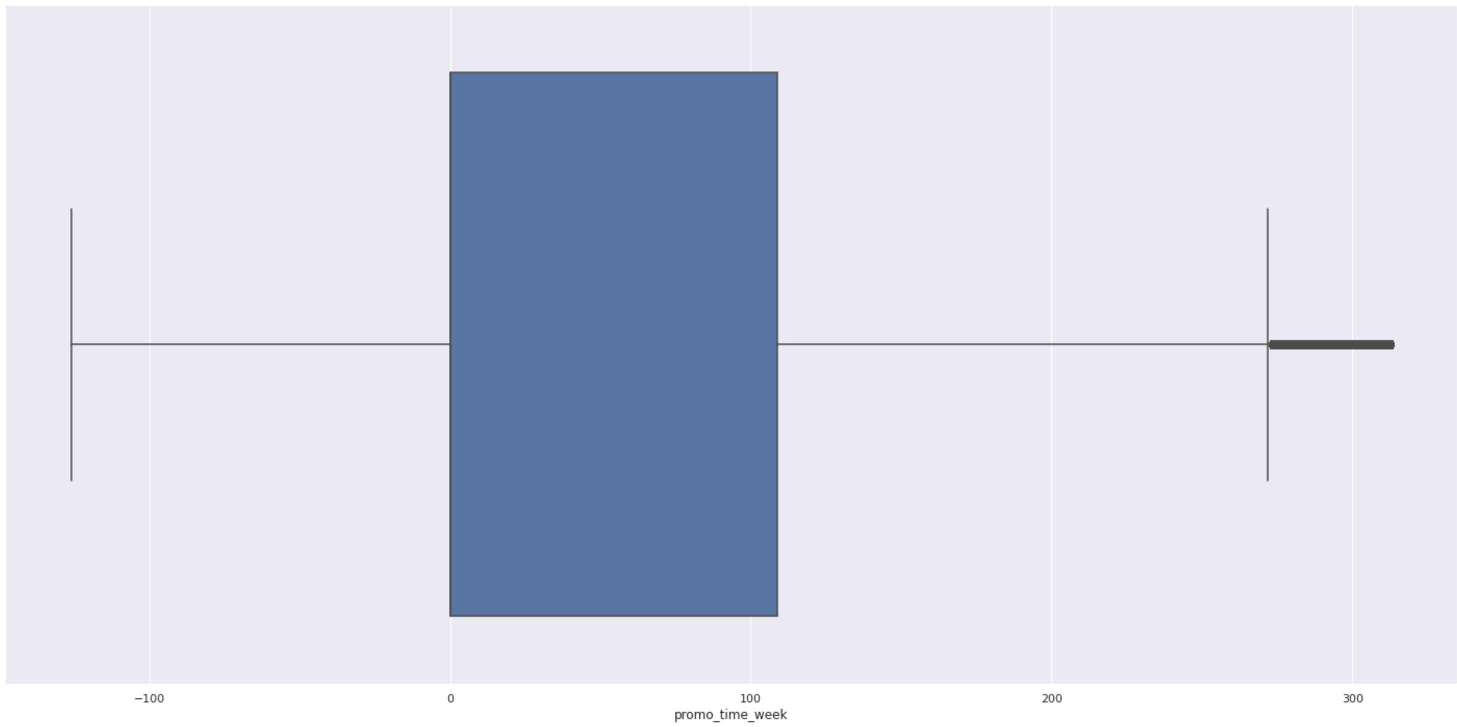
Out[63]:

	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 [64]:
```
# 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[64]:
```
<AxesSubplot:xlabel='promo_time_week'>
```



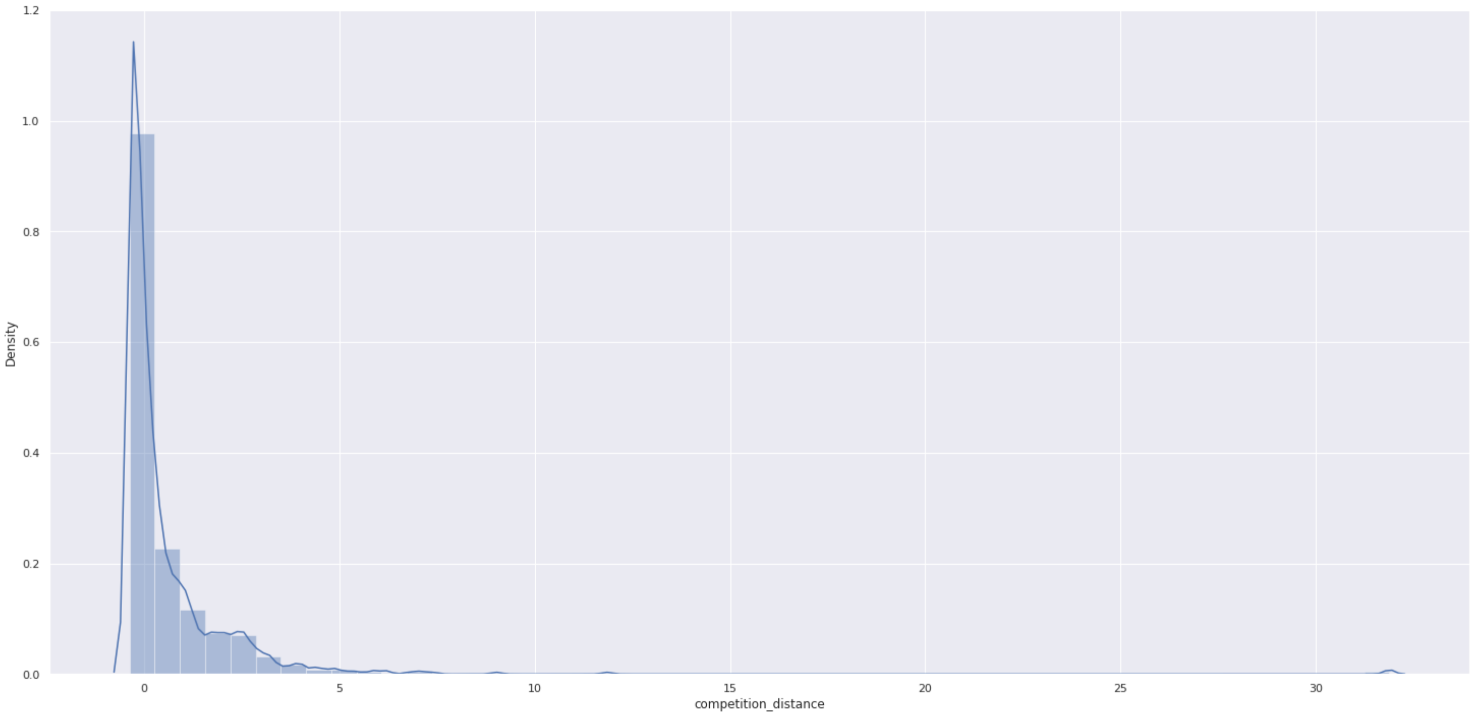
In [65]:
```
rs = RobustScaler()
mms = MinMaxScaler()

# competition distance
```

```python
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 [66]:
```python
# 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[66]:
```
<AxesSubplot:xlabel='competition_distance', ylabel='Density'>
```



5.3. Transformação

5.3.1. Encoding

In [67]:
```python
df5.head()
```

Out[67]:

	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 [68]:
```python
#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[68]:

	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 [69]:
```python
# 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'] )
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	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	
2	3	5	2015-07-31	8314	1	1	0	basic	1.903226	12	2006	1	14	2011	

	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
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 [70]:

```python
# 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	
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]:

```python
#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

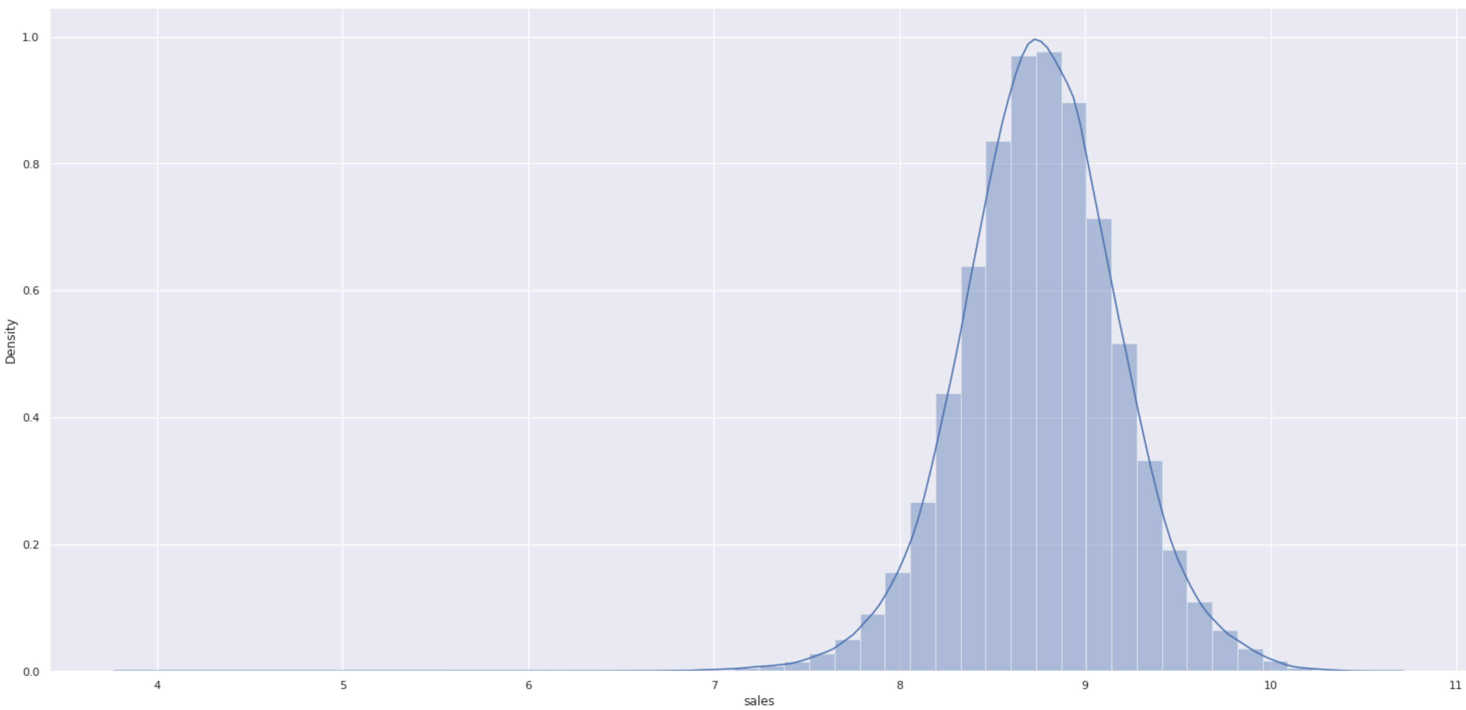
In [72]:

```python
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]:

```python
# 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	

	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
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 [4]:
```
# Descobrindo a menor data de vendas
#df6[['store', 'date']].groupby('store').min().reset_index()['date']
```

In [3]:
```
# Descobrindo a maior data de vendas
#df6[['store', 'date']].groupby('store').max().reset_index()['date']
```

In [78]:
```
# 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[78]:
```
Timestamp('2015-06-19 00:00:00')
```

In [79]:
```
# 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 [80]:
```
# 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
boruta = BorutaPy(rf, n_estimators='auto', verbose=2, random_state=42).fit(x_train_n, y_train_n)
```

```
Iteration: 	1 / 100
Confirmed: 	0
Tentative: 	27
Rejected: 	0
Iteration: 	2 / 100
Confirmed: 	0
Tentative: 	27
Rejected: 	0
Iteration: 	3 / 100
Confirmed: 	0
Tentative: 	27
Rejected: 	0
Iteration: 	4 / 100
Confirmed: 	0
Tentative: 	27
Rejected: 	0
Iteration: 	5 / 100
Confirmed: 	0
Tentative: 	27
Rejected: 	0
Iteration: 	6 / 100
Confirmed: 	0
Tentative: 	27
Rejected: 	0
Iteration: 	7 / 100
Confirmed: 	0
Tentative: 	27
Rejected: 	0
Iteration: 	8 / 100
Confirmed: 	18
Tentative: 	0
Rejected: 	9


BorutaPy finished running.

Iteration: 	9 / 100
Confirmed: 	18
Tentative: 	0
Rejected: 	9
```

In [81]:
```
x_train_n
```

Out[81]:
```
array([[ 1.00000000e+00,  1.00000000e+00,  0.00000000e+00, ...,
        -8.09016994e-01,  1.20536680e-01, -9.92708874e-01],
       [ 2.00000000e+00,  1.00000000e+00,  0.00000000e+00, ...,
        -8.09016994e-01,  1.20536680e-01, -9.92708874e-01],
       [ 3.00000000e+00,  1.00000000e+00,  0.00000000e+00, ...,
        -8.09016994e-01,  1.20536680e-01, -9.92708874e-01],
       ...,
       [ 7.69000000e+02,  0.00000000e+00,  1.00000000e+00, ...,
         9.78147601e-01,  1.20536680e-01,  9.92708874e-01],
       [ 9.48000000e+02,  0.00000000e+00,  1.00000000e+00, ...,
         9.78147601e-01,  1.20536680e-01,  9.92708874e-01],
       [ 1.09700000e+03,  0.00000000e+00,  1.00000000e+00, ...,
         9.78147601e-01,  1.20536680e-01,  9.92708874e-01]])
```

6.2.1. Best Features from Boruta

In [82]:
```python
# 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))
```

6.3. Manual Features Selection

In [2]:
```python
# 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 [1]:
```python
cols_not_selected_boruta = ['school_holiday', 'year']
```

In [ ]:
```python
cols_selected_boruta
```