0.0. Imports

In [209…

```
import numpy as np
import pandas as pd
import inflection
import math
import matplotlib.pyplot as plt
import seaborn as sns
from IPython.core.display import HTML
from IPython.display import Image
import datetime
from scipy import stats  as ss
import random
import warnings
warnings.filterwarnings('ignore')
import pickle
import requests

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
from sklearn.ensemble import RandomForestRegressor
import xgboost as xgb
```

0.1 Helper Functions

In [113…

```
def cross_validation(x_training, kfold, model_name, model, verbose=False):
    mae_list = []
    mape_list = []
    rmse_list = []

    for k in reversed(range(1, kfold)):
        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

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

        # training and validation dataset
        xtraining = training.drop(['date','sales'],axis=1)
        ytraining = training['sales']
        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('Linear Regression', np.expm1(yvalidation),np.expm1(yhat))
```

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

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

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 ).values
    n = cm.sum()
    r, k = cm.shape

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

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

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

def jupyter_settings():
    %matplotlib inline
    %pylab inline
    plt.style.use( 'bmh' )
    plt.rcParams['figure.figsize'] = [25, 12]
    plt.rcParams['font.size'] = 24
    display( HTML( '<style>.container { width:100% !important; }</style>') )
    pd.options.display.max_columns = None
    pd.options.display.max_rows = None
    pd.set_option( 'display.expand_frame_repr', False )
    sns.set()

jupyter_settings()
```

```
%pylab is deprecated, use %matplotlib inline and import the required libraries.
Populating the interactive namespace from numpy and matplotlib
```

0.2 Loading data

In [115…

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

In [116…

```
# dataset with sales informations
df_sales_raw.head()
```

Out[116]:

	Store	DayOfWeek	Date	Sales	Customers	Open	Promo	StateHoliday	SchoolHoliday
0	1	5	2015-07-31	5263	555	1	1	0	1
1	2	5	2015-07-31	6064	625	1	1	0	1
2	3	5	2015-07-31	8314	821	1	1	0	1
3	4	5	2015-07-31	13995	1498	1	1	0	1
4	5	5	2015-07-31	4822	559	1	1	0	1

In [117…

```
# dataset with store attributes
df_store_raw.head()
```

Out[117]:

	Store	StoreType	Assortment	CompetitionDistance	CompetitionOpenSinceMonth	CompetitionOpenSinceYear
0	1	c	a	1270.0	9.0	2008.0
1	2	a	a	570.0	11.0	2007.0
2	3	a	a	14130.0	12.0	2006.0
3	4	c	c	620.0	9.0	2009.0
4	5	a	a	29910.0	4.0	2015.0

In [118…

```
# dataset with all data
df_raw.head()
```

Out[118]:

	Store	DayOfWeek	Date	Sales	Customers	Open	Promo	StateHoliday	SchoolHoliday	StoreType	Assortm
0	1	5	2015-07-31	5263	555	1	1	0	1	c	
1	2	5	2015-07-31	6064	625	1	1	0	1	a	
2	3	5	2015-07-31	8314	821	1	1	0	1	a	
3	4	5	2015-07-31	13995	1498	1	1	0	1	c	
4	5	5	2015-07-31	4822	559	1	1	0	1	a	

1.0. Data Description

In [119…

```
df1 = df_raw.copy()
```

In [120…

```
list(df_raw.columns)
```

Out[120]:

```
['Store',
 'DayOfWeek',
 'Date',
 'Sales',
 'Customers',
 'Open',
 'Promo',
```

```
 'StateHoliday',
 'SchoolHoliday',
 'StoreType',
 'Assortment',
 'CompetitionDistance',
 'CompetitionOpenSinceMonth',
 'CompetitionOpenSinceYear',
 'Promo2',
 'Promo2SinceWeek',
 'Promo2SinceYear',
 'PromoInterval']
```

Id - an Id that represents a (Store, Date) duple within the test set

Store - a unique Id for each store

Sales - the turnover for any given day (this is what you are predicting)

Customers - the number of customers on a given day

Open - an indicator for whether the store was open: 0 = closed, 1 = open

StateHoliday - indicates a state holiday. Normally all stores, with few exceptions, are closed on state holidays. Note that all schools are closed on public holidays and weekends. a = public holiday, b = Easter holiday, c = Christmas, 0 = None

SchoolHoliday - indicates if the (Store, Date) was affected by the closure of public schools

StoreType - differentiates between 4 different store models: a, b, c, d

Assortment - describes an assortment level: a = basic, b = extra, c = extended

CompetitionDistance - distance in meters to the nearest competitor store

CompetitionOpenSince[Month/Year] - gives the approximate year and month of the time the nearest competitor was opened

Promo - indicates whether a store is running a promo on that day

Promo2 - Promo2 is a continuing and consecutive promotion for some stores: 0 = store is not participating, 1 = store is participating

Promo2Since[Year/Week] - describes the year and calendar week when the store started participating in Promo2

PromoInterval - describes the consecutive intervals Promo2 is started, naming the months the promotion is started anew. E.g. "Feb,May,Aug,Nov" means each round starts in February, May, August, November of any given year for that store

1.1 Rename Columns

In [121…

```
cols_old = ['Store', 'DayOfWeek', 'Date', 'Sales', 'Customers', 'Open', 'Promo', 'StateH
            'SchoolHoliday', 'StoreType', 'Assortment','CompetitionDistance', 'Competiti
            'CompetitionOpenSinceYear', 'Promo2', 'Promo2SinceWeek','Promo2SinceYear', '

# lowercase
snakecase = lambda x: inflection.underscore(x)
```

```python
cols_new = list(map(snakecase, cols_old))

# rename
df1.columns = cols_new
```

1.2 - Data Dimensions

In [122…
```python
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 [123…
```python
df1.dtypes
```

Out[123]:
```
store                             int64
day_of_week                       int64
date                             object
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
```

In [124…
```python
# date to datetime
df1['date'] = pd.to_datetime(df1['date'])
```

In [125…
```python
df1.dtypes
```

Out[125]:
```
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 Check NA

In [126…
```
df1.isna().sum()
```

Out[126]:
```
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 [127…
```
df1.sample(1)
```

Out[127]:

	store	day_of_week	date	sales	customers	open	promo	state_holiday	school_holiday	store_type	as
370286	247	7	2014-08-10	0	0	0	0	0	1	d	

In [128…
```
# competition_distance
# Se vazio, não há competidor mais próximo (a distancia até o competidor é mto grande)
df1['competition_distance'] = df1['competition_distance'].apply(lambda x: 2*10**5 if mat

# competition_open_since_month
# Se vazio, considerar a data da primeira compra
df1['competition_open_since_month'] = df1[['competition_open_since_month','date']].apply

# competition_open_since_year
df1['competition_open_since_year'] = df1[['competition_open_since_year','date']].apply(l

# promo2_since_week
df1['promo2_since_week'] = df1[['promo2_since_week','date']].apply(lambda x: x['date'].w

# promo2_since_year
df1['promo2_since_year'] = df1[['promo2_since_year','date']].apply(lambda x: x['date'].y

# promo_interval
# Se promo_interval for igual a zero, a loja não participou da promoção estendida em nen
# se o promo_interval in month_map, a loja estava em promoção estendida no momento da ve
month_map = {1:'Jan',2:'Feb',3:'Mar',4:'Apr',5:'May',6:'Jun',7:'Jul',8:'Aug',9:'Sept',10

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

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

df1['is_promo'] = df1[['promo_interval', 'month_map']].apply( lambda x: 0 if x['promo_in
```

```
df1.sample(5).T
```

In [129…

Out[129]:

	682565	412845	11407	797734	405608
store	971	1081	258	180	1108
day_of_week	1	5	2	2	5
date	2013-10-28 00:00:00	2014-06-27 00:00:00	2015-07-21 00:00:00	2013-07-16 00:00:00	2014-07-04 00:00:00
sales	5874	5772	4796	7772	5758
customers	833	1043	451	854	618
open	1	1	1	1	1
promo	0	0	0	1	1
state_holiday	0	0	0	0	0
school_holiday	1	0	0	1	0
store_type	c	b	a	d	a
assortment	a	a	a	a	a
competition_distance	1140.0	400.0	27190.0	5800.0	540.0
competition_open_since_month	5.0	3.0	7.0	9.0	4.0
competition_open_since_year	2011.0	2006.0	2010.0	2010.0	2004.0
promo2	1	0	1	0	0
promo2_since_week	14.0	26.0	37.0	29.0	27.0
promo2_since_year	2012.0	2014.0	2009.0	2013.0	2014.0
promo_interval	Mar,Jun,Sept,Dec	0	Jan,Apr,Jul,Oct	0	0
month_map	Out	Jun	Jul	Jul	Jul
is_promo	0	0	1	0	0

1.6 Change Types

In [130…

```
df1.dtypes
```

Out[130]:

```
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
month_map                               object
```

```
is_promo                          int64
dtype: object
```

In [131…

```
df1['competition_open_since_month'] = df1['competition_open_since_month'].astype(int64)
df1['competition_open_since_year'] = df1['competition_open_since_year'].astype(int64)

df1['promo2_since_week'] = df1['promo2_since_week'].astype(int64)
df1['promo2_since_year'] = df1['promo2_since_year'].astype(int64)
```

1.7 Descriptive Statistical

In [132…

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

1.7.1 Numerical Attributes

In [133…

```
# 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

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

In [134…

```
m
```

Out[134]:

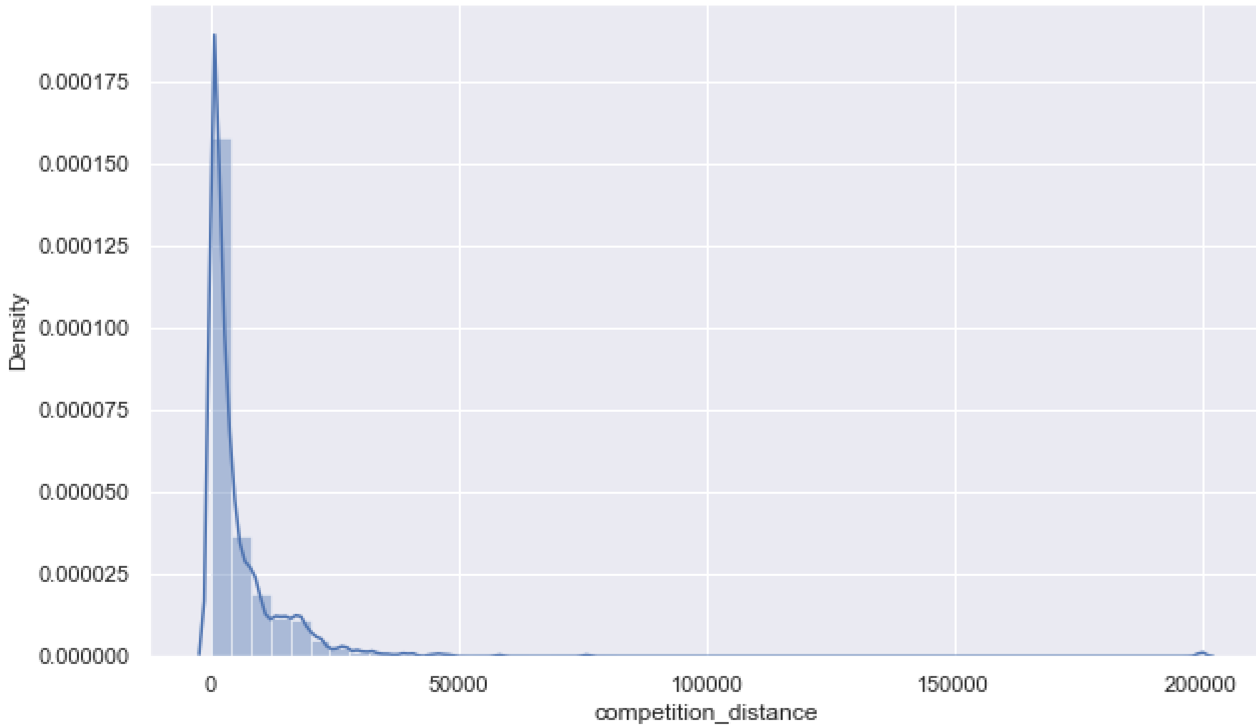
	attributes	min	max	range	mean	median	std	skew	ku
0	store	1.0	1115.0	1114.0	558.429727	558.0	321.908493	-0.000955	-1.2
1	day_of_week	1.0	7.0	6.0	3.998341	4.0	1.997390	0.001593	-1.2
2	sales	0.0	41551.0	41551.0	5773.818972	5744.0	3849.924283	0.641460	1.7
3	customers	0.0	7388.0	7388.0	633.145946	609.0	464.411506	1.598650	7.0
4	open	0.0	1.0	1.0	0.830107	1.0	0.375539	-1.758045	1.0
5	promo	0.0	1.0	1.0	0.381515	0.0	0.485758	0.487838	-1.7
6	school_holiday	0.0	1.0	1.0	0.178647	0.0	0.383056	1.677842	0.8
7	competition_distance	20.0	200000.0	199980.0	5935.442677	2330.0	12547.646829	10.242344	147.7
8	competition_open_since_month	1.0	12.0	11.0	6.786849	7.0	3.311085	-0.042076	-1.2
9	competition_open_since_year	1900.0	2015.0	115.0	2010.324840	2012.0	5.515591	-7.235657	124.0
10	promo2	0.0	1.0	1.0	0.500564	1.0	0.500000	-0.002255	-1.9
11	promo2_since_week	1.0	52.0	51.0	23.619033	22.0	14.310057	0.178723	-1.1
12	promo2_since_year	2009.0	2015.0	6.0	2012.793297	2013.0	1.662657	-0.784436	-0.2
13	is_promo	0.0	1.0	1.0	0.155134	0.0	0.362033	1.905166	1.6

In [135…

```
fig = plt.figure(figsize=(10,6))
```

```
sns.distplot(df1['competition_distance'])
```

Out[135]: <AxesSubplot:xlabel='competition_distance', ylabel='Density'>



1.7.2 Categorical Attributes

In [136…

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

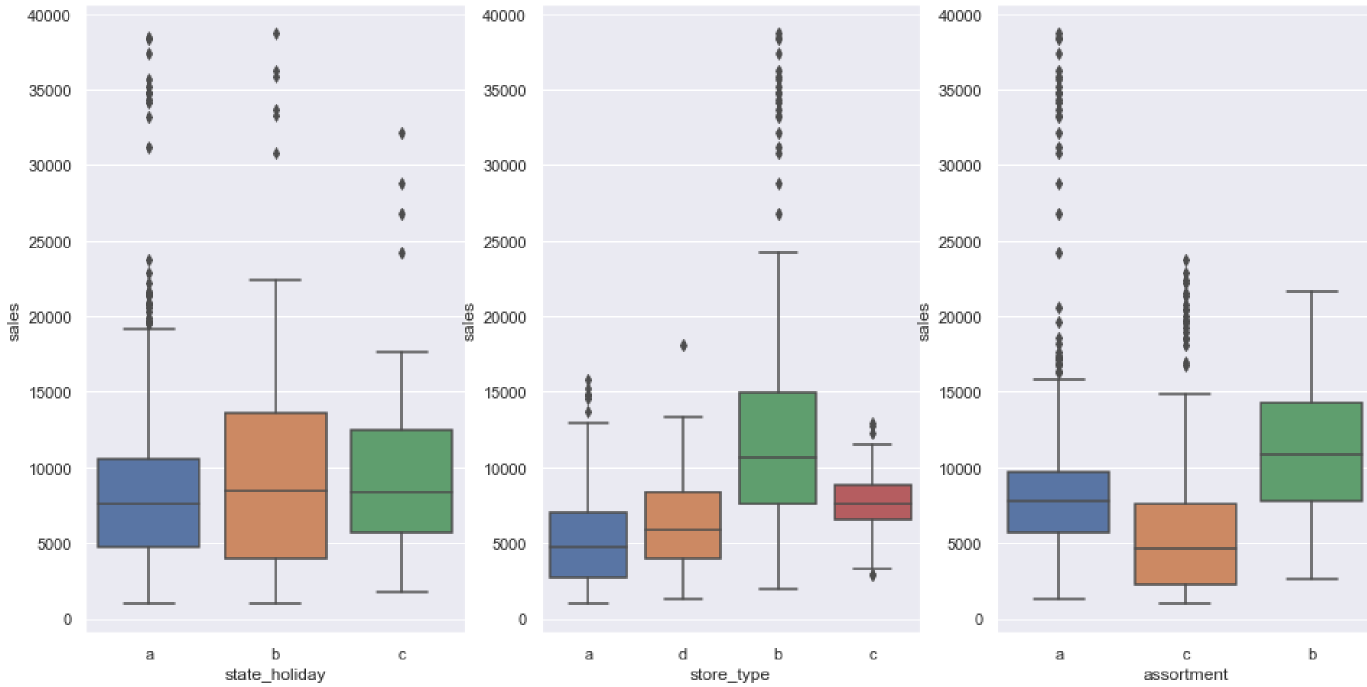
Out[136]:

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

In [137…

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

plt.figure(figsize=(16,8))

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[137]: <AxesSubplot:xlabel='assortment', ylabel='sales'>



2.0. Feature Engeneering

In [138…

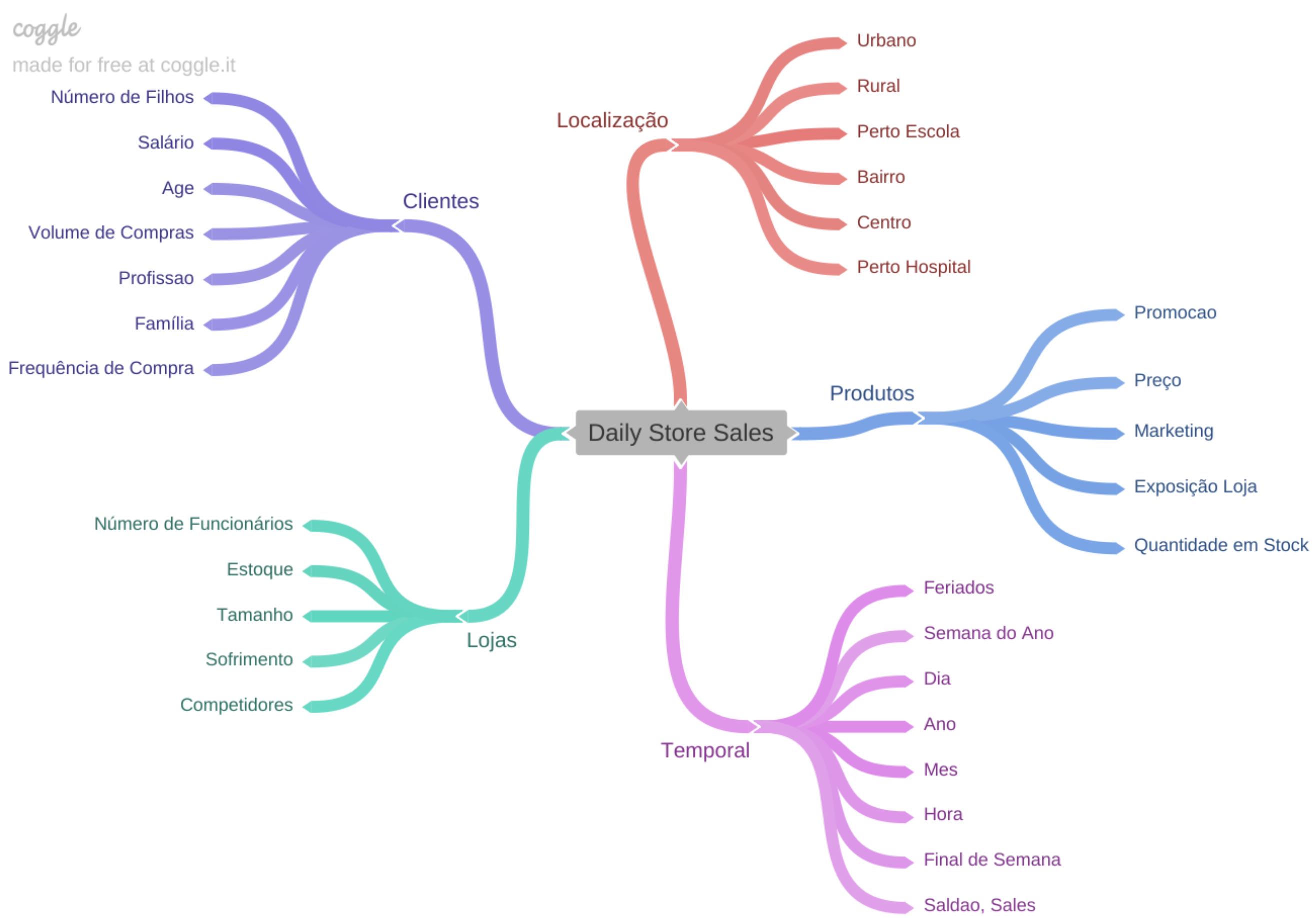
```
df2 = df1.copy()
```

2.1 - Hypothesis Mind Map

In [139…

```
Image('img/Daily_Store_Sales.png')
```

Out[139]:



2.1.1. Store Hypothesys

1. Lojas com número maior de funcionários deveriam vender mais.

2. Lojas com maior capacidade de estoque deveriam vender mais.

3. Lojas com maior porte deveriam vender mais.

4. Lojas com maior sortimentos deveriam vender mais.

5. Lojas com competidores mais próximos deveriam vender menos.

6. Lojas com competidores à mais tempo deveriam vendem mais.

2.1.2. Product Hypothesis

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

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

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

5. Lojas com promoções mais agressivas (descontos maiores), deveriam vender mais.

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

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

8. Lojas com mais promoções consecutivas deveriam vender mais.

2.1.3. Temporal Hypothesys

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

2. Lojas deveriam vender mais ao longo dos anos.

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

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

5. Lojas deveriam vender menos aos finais de semana.

6. Lojas deveriam vender menos durante os feriados escolares.

2.2. Final Hypothesis List

1. Lojas com maior sortimentos deveriam vender mais.

2. Lojas com competidores mais próximos deveriam vender menos.

3. Lojas com competidores à mais tempo deveriam vendem mais.

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

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

7. Lojas com mais promoções consecutivas deveriam vender mais.

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

9. Lojas deveriam vender mais ao longo dos anos.

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

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

12. Lojas deveriam vender menos aos finais de semana.

13. Lojas deveriam vender menos durante os feriados escolares.

2.3. Feature Engineering

In [140…

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

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

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

# week of day
df2['week_of_year'] = df2['date'].dt.isocalendar().week

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

# competition_since
df2['competition_since'] = df2.apply( lambda x: datetime.datetime(year=x['competition_op
df2['competition_time_month'] = ((df2['date'] - df2['competition_since'])/30).apply(lamb

# promo since
df2['promo_since'] = df2['promo2_since_year'].astype(str) + '-' + df2['promo2_since_week
df2['promo_since'] = df2['promo_since'].apply(lambda x: datetime.datetime.strptime(x, '%
df2['promo_time_week'] = ((df2['date'] - df2['promo_since'])/7).apply(lambda x: x.days)

# assortment
df2['assortment'] = df2['assortment'].apply(lambda x: 'basic' if x == 'a' else 'extra' i

# state holiday
df2['state_holiday'] = df2['state_holiday'].apply(lambda x: 'public_holiday' if x == 'a'
```

In [141…

```
df2.head().T
```

Out[141]:

	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
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

In [142…
```
df2.dtypes
```

Out[142]:
```
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
year                                       int64
month                                      int64
day                                        int64
week_of_year                              UInt32
year_week                                 object
competition_since                 datetime64[ns]
competition_time_month                     int64
promo_since                       datetime64[ns]
promo_time_week                            int64
dtype: object
```

3.0. Variable Filtering

In [143…

```
df3 = df2.copy()
```

In [144…

```
df3.head()
```

Out[144]:

	store	day_of_week	date	sales	customers	open	promo	state_holiday	school_holiday	store_type	assortn
0	1	5	2015-07-31	5263	555	1	1	regular_day	1	c	b
1	2	5	2015-07-31	6064	625	1	1	regular_day	1	a	b
2	3	5	2015-07-31	8314	821	1	1	regular_day	1	a	b
3	4	5	2015-07-31	13995	1498	1	1	regular_day	1	c	exter
4	5	5	2015-07-31	4822	559	1	1	regular_day	1	a	b

3.1 Row Filtering

In [145…

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

3.2 Columns Selection

In [146…

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

In [147…

```
df3.columns
```

Out[147]:

```
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. Exploratory Data Analysis

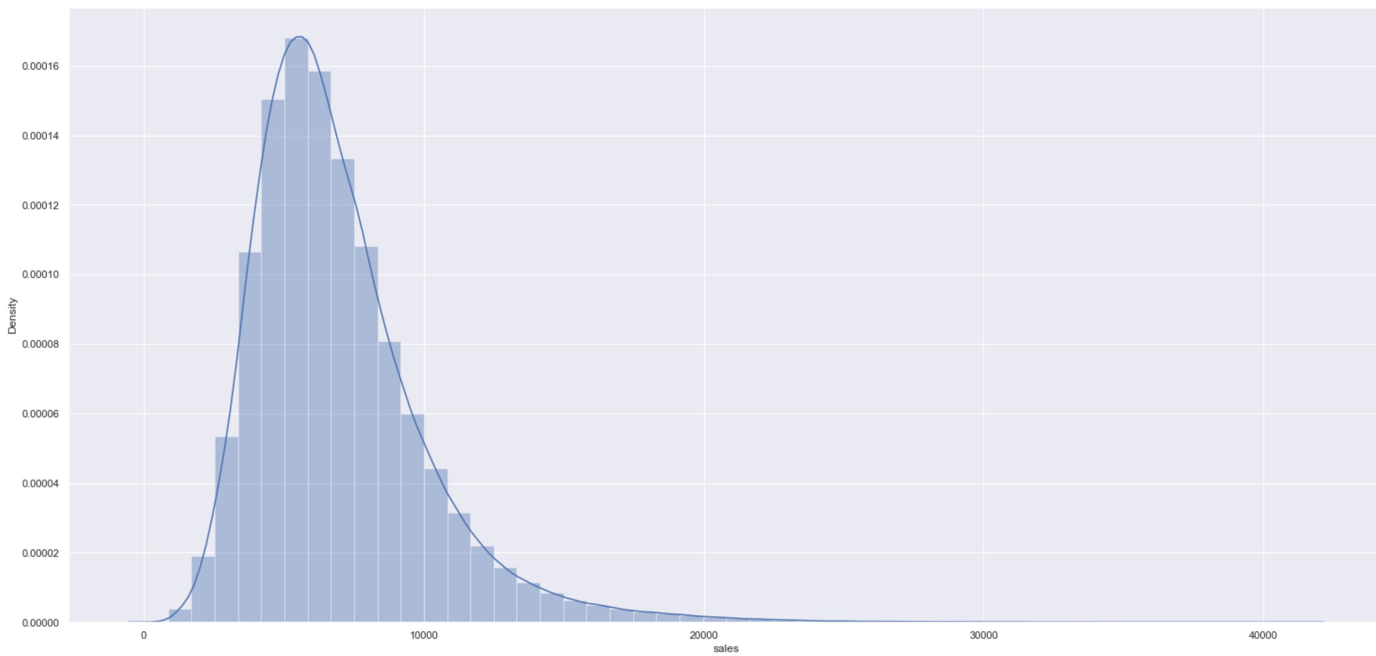
In [148…
```
df4 = df3.copy()
```

4.1. Univariate Analysis

4.1.1. Response Variable

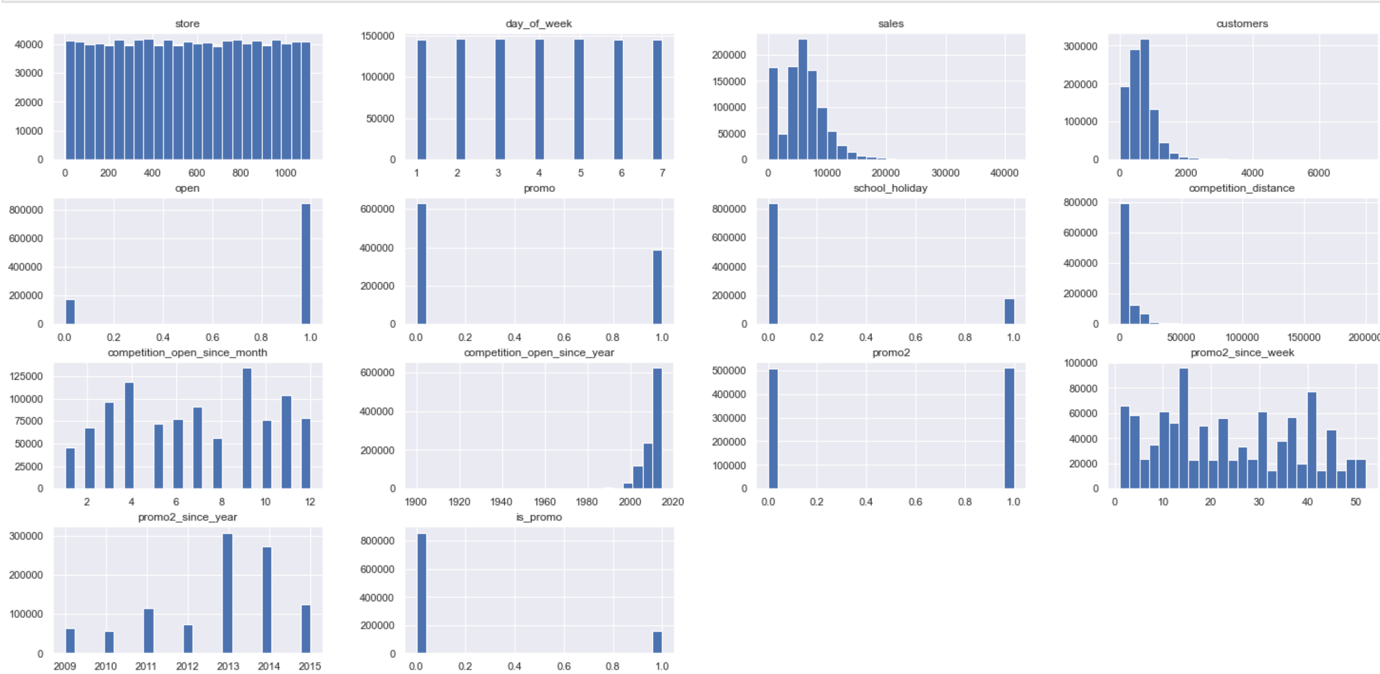
In [149…
```
sns.distplot(df4['sales'])
```

Out[149]:
```
<AxesSubplot:xlabel='sales', ylabel='Density'>
```



4.1.2. Numerical Variable

In [150…
```
num_attributes.hist(bins=25);
```

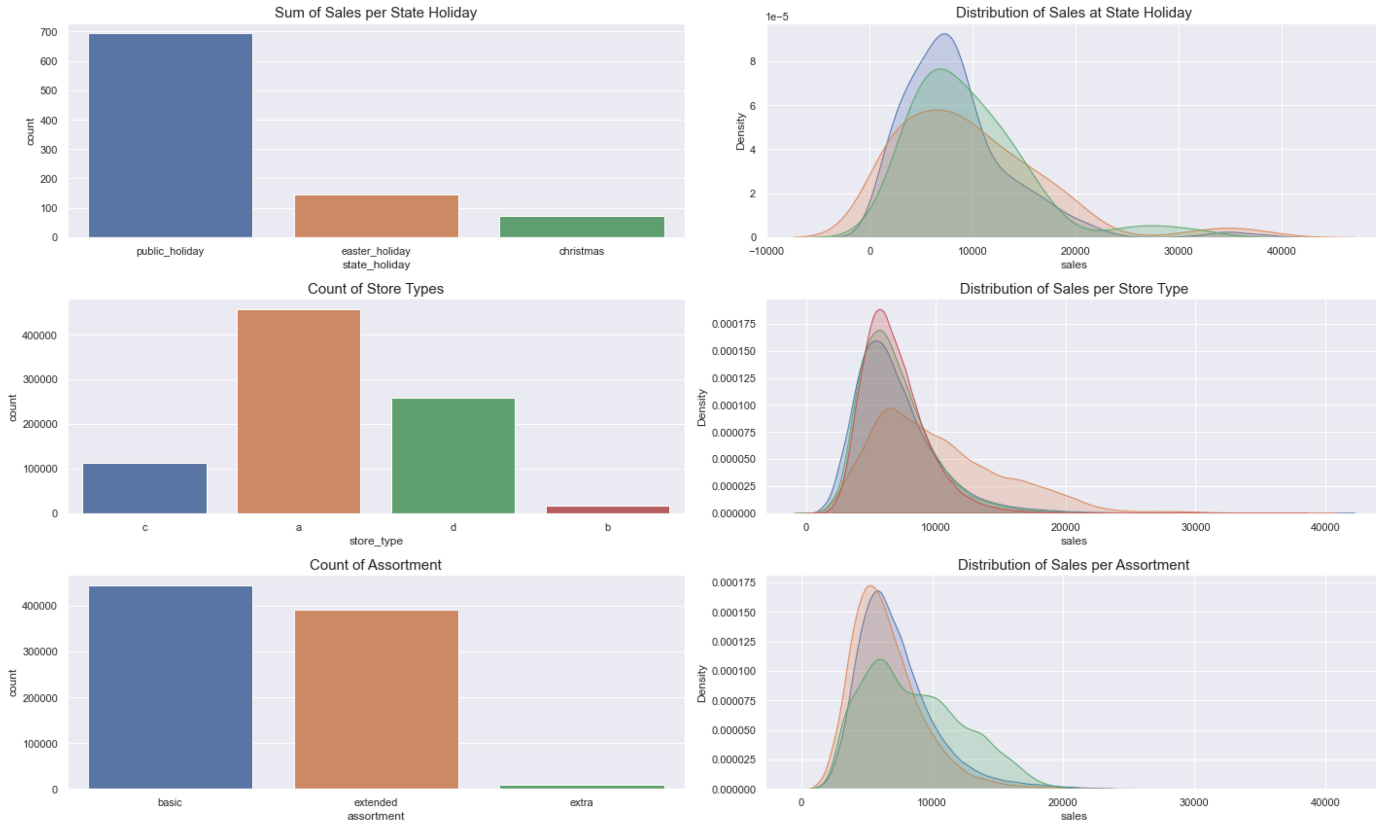


4.1.3. Categorical Variable

In [151…
```
df4['state_holiday'].value_counts(normalize=True)
```

Out[151]:
```
regular_day       0.998922
public_holiday    0.000822
easter_holiday    0.000172
christmas         0.000084
Name: state_holiday, dtype: float64
```

In [152…
```
plt.figure(figsize=(20,12))

plt.subplot(3,2,1)
plt.title('Sum of Sales per State Holiday',fontsize=15)
a = df4[df4['state_holiday'] != 'regular_day']
sns.countplot(a['state_holiday'])

plt.subplot(3,2,2)
plt.title('Distribution of Sales at State Holiday',fontsize=15)
sns.kdeplot(df4[df4['state_holiday'] == 'public_holiday']['sales'],label='public_holiday
sns.kdeplot(df4[df4['state_holiday'] == 'easter_holiday']['sales'],label='easter_holiday
sns.kdeplot(df4[df4['state_holiday'] == 'christmas']['sales'],label='christmas',shade=Tr

plt.subplot(3,2,3)
plt.title('Count of Store Types',fontsize=15)
sns.countplot(df4['store_type'])

plt.subplot(3,2,4)
plt.title('Distribution of Sales per Store Type',fontsize=15)
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)

plt.subplot(3,2,5)
plt.title('Count of Assortment',fontsize=15)
sns.countplot(df4['assortment'])

plt.subplot(3,2,6)
plt.title('Distribution of Sales per Assortment',fontsize=15)
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')

plt.tight_layout()
```



4.2. Bivariate Analysis

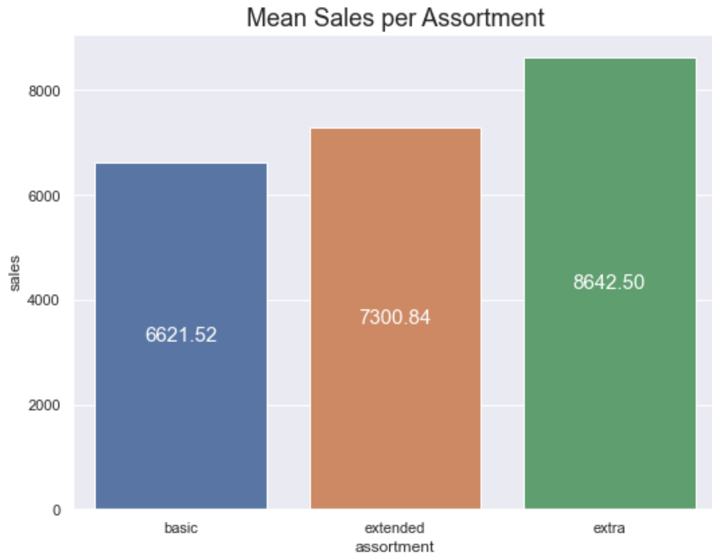
H1. Lojas com maior variedade de produtos, em média, deveriam vender mais.

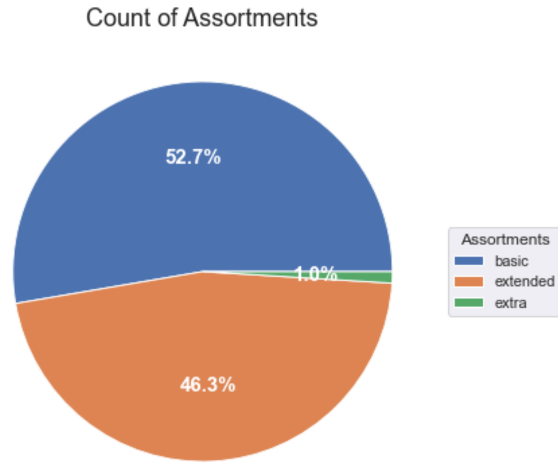
In [153…

```
grid = GridSpec(1,2)

plt.figure(figsize=(15,6))

# bar plot
plt.subplot(grid[0,0])
plt.title('Mean Sales per Assortment',fontsize=18)
aux1 = df4[['assortment','sales']].groupby('assortment').mean().reset_index()
aux1['AoA'] = aux1['sales'].rolling(window=2).apply( lambda x: round((x.iloc[1] / x.iloc
g = sns.barplot(x='assortment',y='sales',data=aux1)

# incluindo labels nas barras
for i in g.containers:
    g.bar_label(i, color='white', label_type= 'center',fontsize=15,fmt='%.2f')

# pie plot
ax = plt.subplot(grid[0,1])
aux2 = pd.DataFrame(df4['assortment'].value_counts()).reset_index()
wedges, texts, autotexts = ax.pie( data = aux2,
                                   x = 'assortment',
                                   autopct = lambda x: str(round(float(x),1)) + "%",
                                   textprops = dict(color="w"))
ax.legend( wedges, list(aux2['index']),
          title = "Assortments",
          loc="center left",
          bbox_to_anchor = (1, 0, 0.5, 1))
plt.setp(autotexts, size=15, weight="bold")
ax.set_title("Count of Assortments",fontsize = 18);

plt.savefig("img//H1.png",dpi=600)
```

```
plt.tight_layout()

print(f'Verdadeiro. Lojas com maior diversidade de produtos vendem 18% mais em média que
```

```
Verdadeiro. Lojas com maior diversidade de produtos vendem 18% mais em média que as loja
s com diversidade estendida
```

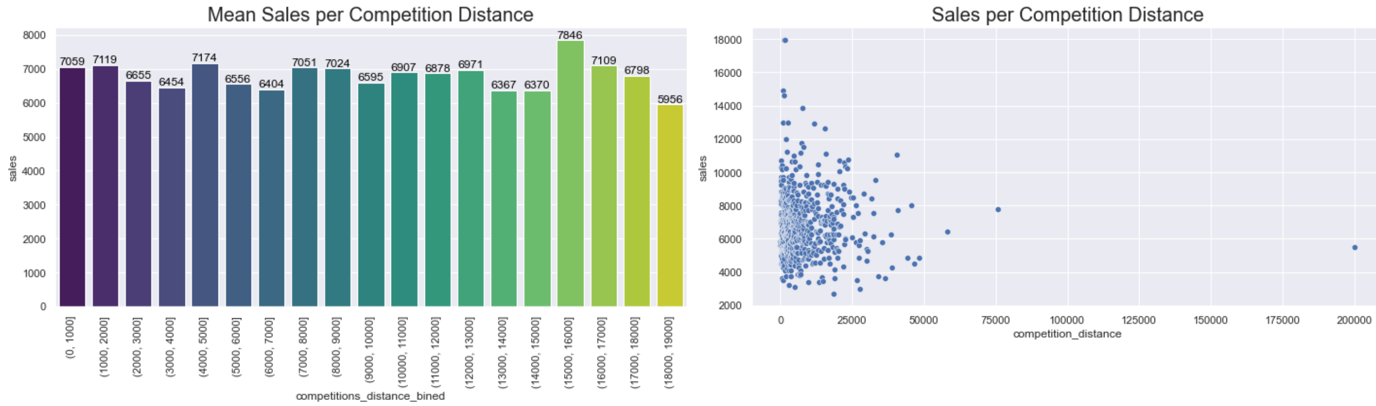




H2. Lojas com competidores mais próximos deveriam vender menos.

In [154…

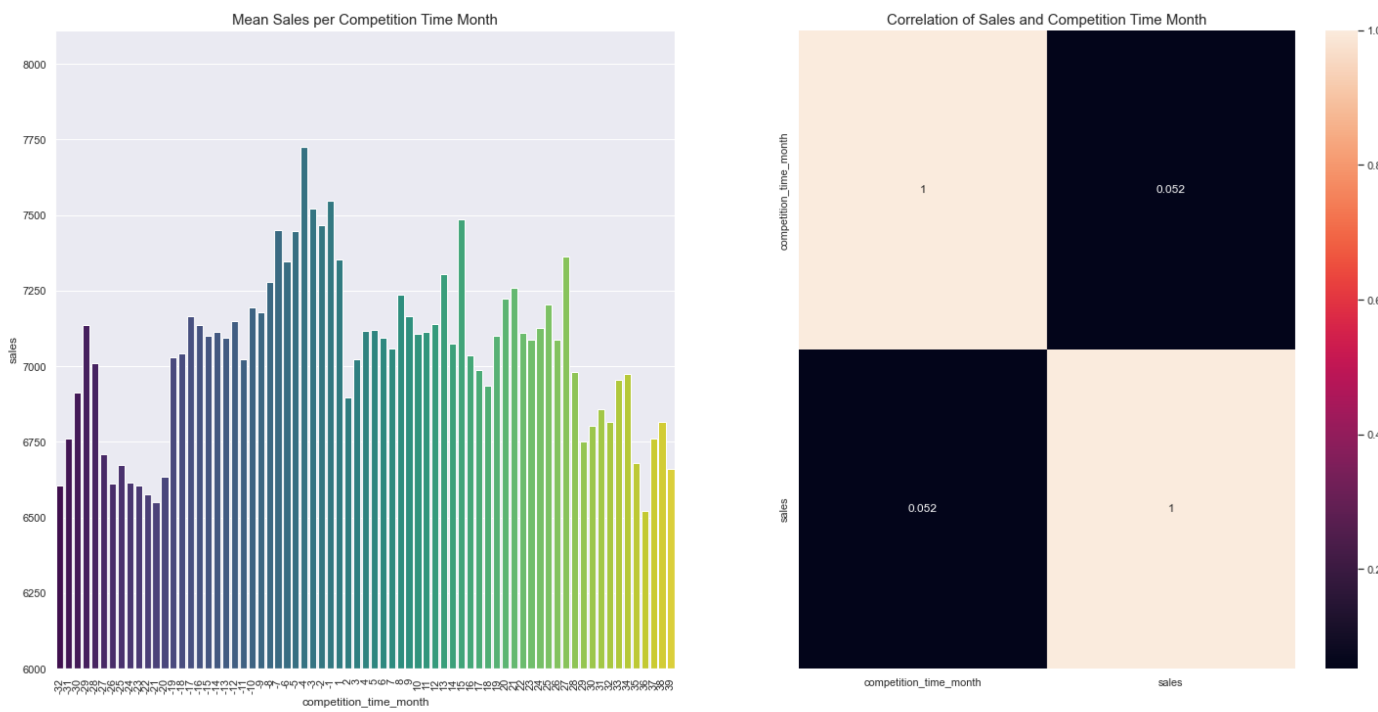
```
grid = GridSpec(1,2)

plt.figure(figsize=(20,6))

plt.subplot(grid[0,0])

aux1 = df4[['competition_distance','sales']].groupby('competition_distance').mean().rese
bins = list(np.arange(0,20000,1000))
aux1['competitions_distance_bined'] = pd.cut(aux1['competition_distance'],bins=bins)
aux2 = aux1[['competitions_distance_bined','sales']].groupby('competitions_distance_bine

# bar plot
g = sns.barplot(x='competitions_distance_bined',y='sales',data=aux2,palette='viridis')
plt.title('Mean Sales per Competition Distance',size=20)
plt.xticks(rotation=90)
# incluindo labels nas barras
for i in g.containers:
    g.bar_label(i, color='black', label_type= 'edge',fontsize=12,fmt='%.0f',rotation=0)

# scatter plot
plt.subplot(grid[0,1])
sns.scatterplot(x='competition_distance', y='sales',data=aux1);
plt.title('Sales per Competition Distance',size=20)
plt.tight_layout()
plt.savefig("img//H2.png",dpi=300)
```



H3. Lojas com competidores à mais tempo deveriam vendem mais.

In [155…

```
grid = GridSpec(1,2)

plt.subplot( grid[0,0] )
plt.title( 'Mean Sales per Competition Time Month', fontsize = 15 )
aux1 = df4[['competition_time_month','sales']].groupby('competition_time_month').mean().
aux2 = aux1[( aux1['competition_time_month'] < 40 ) & ( aux1['competition_time_month'] !
sns.barplot( x = 'competition_time_month', y = 'sales', data = aux2, palette = 'viridis'
plt.xticks( rotation = 90 )
plt.ylim( bottom = 6000 )

plt.subplot(grid[0,1])
plt.title('Correlation of Sales and Competition Time Month', fontsize = 15)
sns.heatmap( aux2.corr(method='pearson'), annot = True);

plt.savefig("img//H3.png",dpi=300)

# plt.subplot(grid[1,:])
# plt.title('Tendence of Sales per Competition Time Month', fontsize=15)
# sns.regplot(x='competition_time_month', y='sales',data=aux2);
# plt.tight_layout()
```



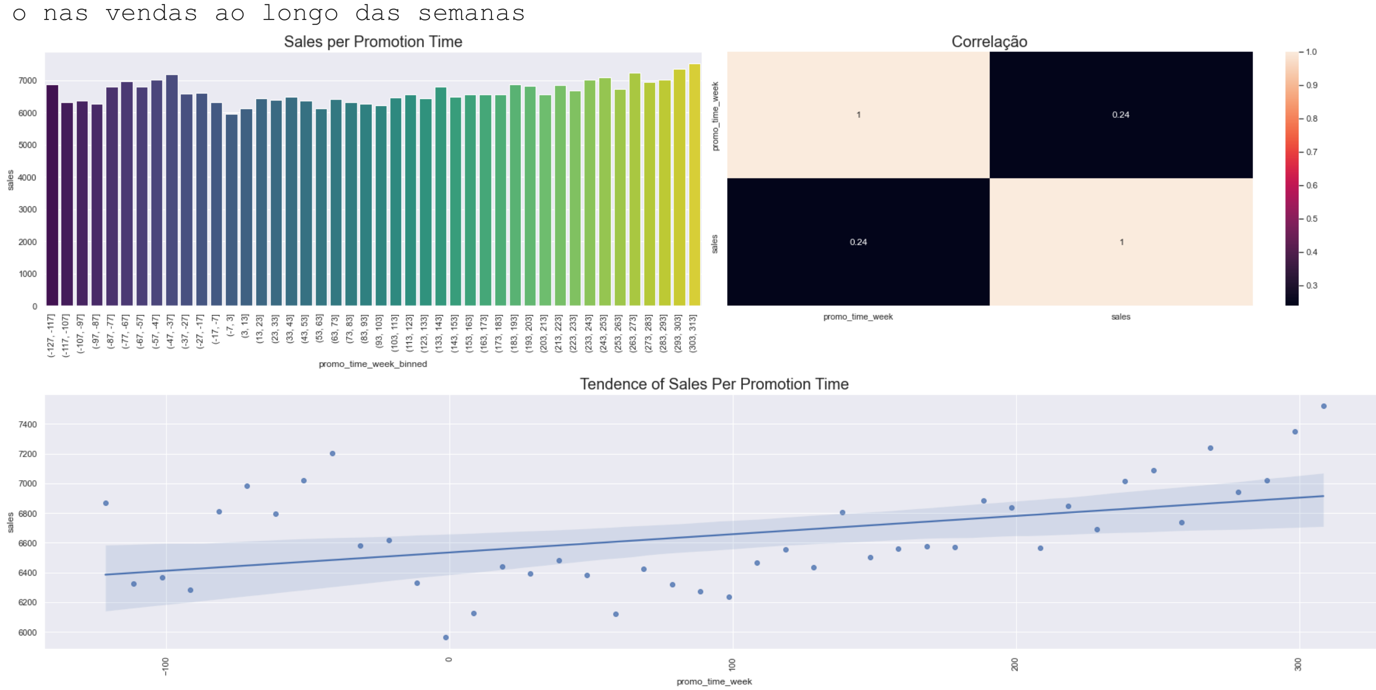
H4. Lojas com promoções ativas por mais tempo deveriam vender mais.

In [156…

```
aux1 = df4[['promo_time_week','sales']].groupby('promo_time_week').mean().reset_index()
```

```
bins = list(np.arange(aux1['promo_time_week'].min()-1,aux1['promo_time_week'].max()+1,10
aux1['promo_time_week_binned'] = pd.cut(aux1['promo_time_week'],bins=bins)

aux2 = aux1.groupby('promo_time_week_binned').mean().reset_index()

grid = GridSpec(2,2)

plt.subplot(grid[0,0])
sns.barplot(x='promo_time_week_binned', y='sales', data=aux2, palette='viridis');
plt.title('Sales per Promotion Time',fontsize=20)
plt.xticks(rotation=90);
plt.tight_layout()

plt.subplot(grid[1,:])
sns.regplot(x='promo_time_week', y='sales',data=aux2);
plt.xticks(rotation=90);
plt.title('Tendence of Sales Per Promotion Time',fontsize=20)
plt.tight_layout()

plt.subplot(grid[0,1])
sns.heatmap(aux1.corr(method='pearson'),annot=True);
plt.title('Correlação',fontsize=20)
plt.tight_layout()
plt.savefig("img//H4.png",dpi=300)

print(f'Verdadeiro. Lojas com promoções ativas por mais tempo possuem um tendencia de cr
```

```
Verdadeiro. Lojas com promoções ativas por mais tempo possuem um tendencia de cresciment
o nas vendas ao longo das semanas
```



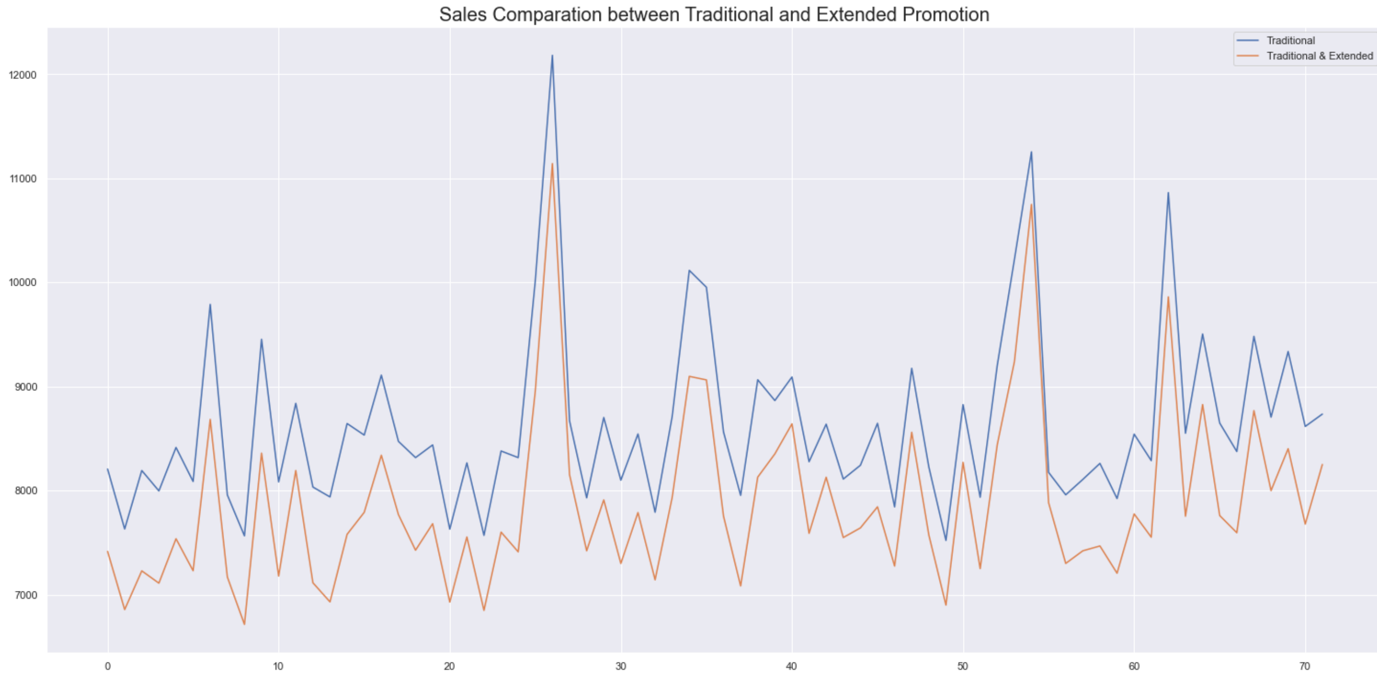
H5. Lojas com mais dias de promoção deveriam vender mais.

H7. Lojas com mais promoções consecutivas deveriam vender mais.

In [157…

```
aux1 = df4[(df4['promo'] == 1) & (df4['promo2'] == 0)][['year_week','sales']].groupby('y
aux2 = df4[(df4['promo'] == 1) & (df4['promo2'] == 1)][['year_week','sales']].groupby('y

ax = aux1.plot()
aux2.plot(ax=ax)

plt.title('Sales Comparation between Traditional and Extended Promotion',fontsize=20)
```

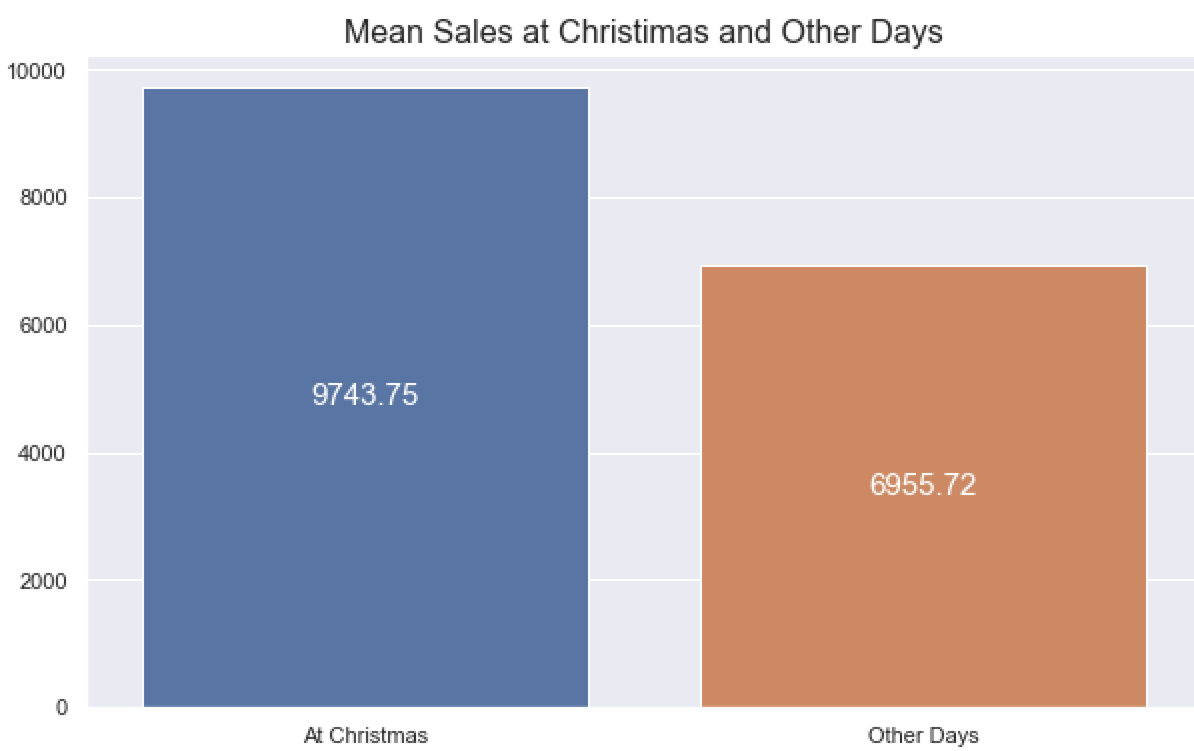
```
ax.legend(labels=['Traditional','Traditional & Extended'])
plt.savefig("img//H7.png",dpi=300)
```



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

In [158…

```
sales_on_christmas = df4[df4['state_holiday'] == 'christmas']['sales'].mean()
sales_others_days = df4[df4['state_holiday'] != 'christmas']['sales'].mean()

fig = plt.figure(figsize=(10,6))
g = sns.barplot(x=['At Christmas','Other Days'],y=[sales_on_christmas,sales_others_days]
plt.title('Mean Sales at Christimas and Other Days',fontsize=16)

for i in g.containers:
    g.bar_label(i,color='white', label_type= 'center',fontsize=15,fmt='%.2f')

plt.savefig("img//H8.png",dpi=300)
```

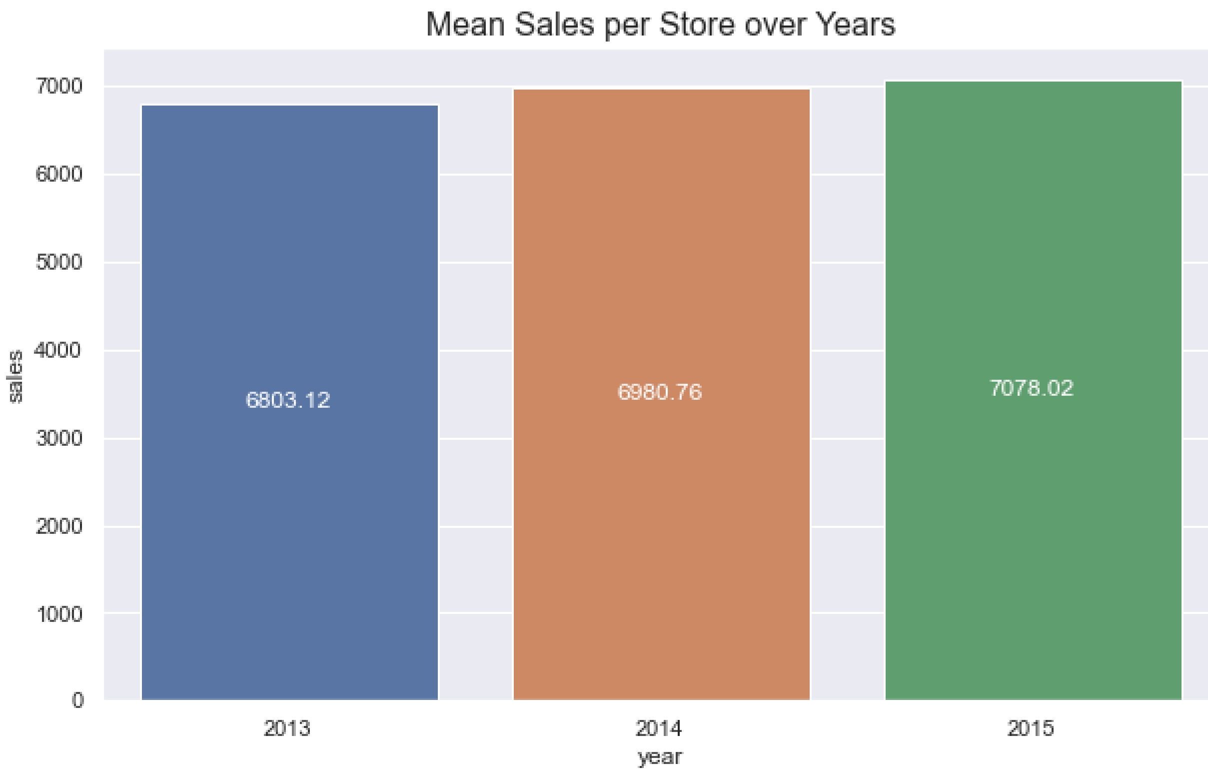


H9. Lojas deveriam vender mais ao longo dos anos.

In [159…

```
aux1 = df4[['year','store','sales']].groupby(['year','store']).mean().reset_index()
sales_per_year = aux1[['year','sales']].groupby('year').mean().reset_index()
sales_per_year['YoY'] = sales_per_year['sales'].rolling(window=2).apply( lambda x: round

fig = plt.figure(figsize=(10,6))
plt.title('Mean Sales per Store over Years',fontsize=16)
g = sns.barplot(x='year',y='sales',data=sales_per_year)

for i in g.containers:
    g.bar_label(i,color='white',label_type='center')

plt.savefig("img//H9.png",dpi=300)

YoY_mean = sales_per_year['YoY'].mean()

print(f'VERDADEIRO. Ao longo dos anos o crescimento médio das vendas é de {YoY_mean}%')
```

```
VERDADEIRO. Ao longo dos anos o crescimento médio das vendas é de 2.0%
```

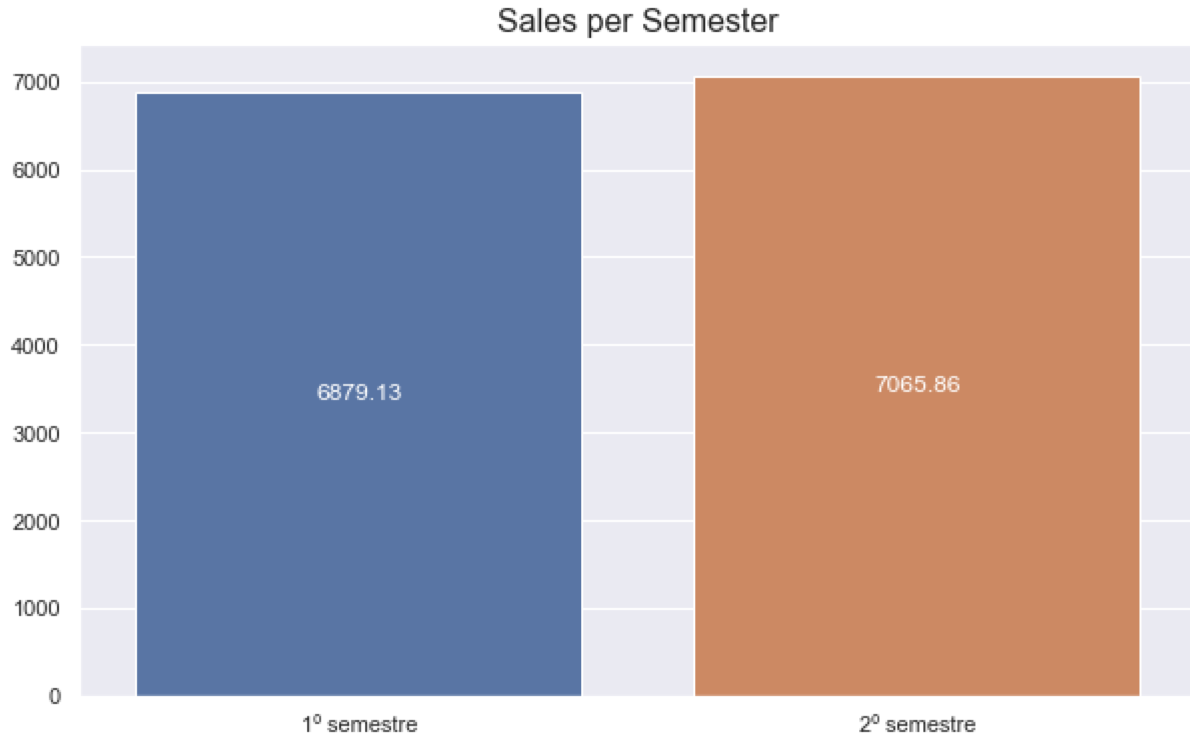


H10. Lojas deveriam vender mais no segundo semestre do ano.

In [160…

```
S1 = df4[df4['month'] <= 6]['sales'].mean()
S2 = df4[df4['month'] > 6]['sales'].mean()

diff = (S2 - S1)

fig = plt.figure(figsize=(10,6))
plt.title('Sales per Semester',fontsize=16)
g = sns.barplot(x=['1° semestre','2° semestre'],y=[S1,S2])

for i in g.containers:
    g.bar_label(i, color='white',label_type='center')

print(f'VERDADEIRO. No 2° semestre as vendas são {round(diff*100/(S1),2)}% maior que no

plt.savefig("img//H10.png",dpi=300)
```

VERDADEIRO. No 2° semestre as vendas são 2.71% maior que no 1° semestre

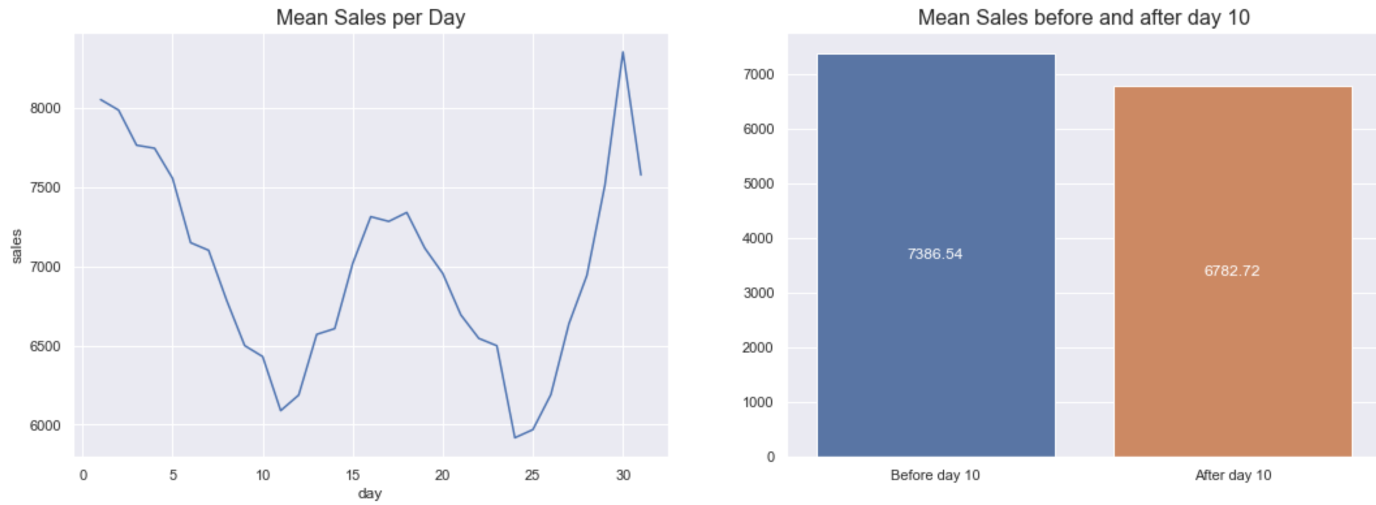


H11. Lojas deveriam vender mais depois do dia 10 de cada mês.

In [161…

```
grid = GridSpec(1,2)

plt.figure(figsize=(18,6))
plt.subplot(grid[0,0])

aux1 = df4[['day','sales']].groupby('day').mean().reset_index()
sns.lineplot(x='day',y='sales',data=aux1)
plt.title('Mean Sales per Day',fontsize=16)

plt.subplot(grid[0,1])

sales_before_10d = df4[df4['day'] < 10]['sales'].mean()
sales_after_10d = df4[df4['day'] >= 10]['sales'].mean()
diff = sales_before_10d - sales_after_10d

print(f'Após o dia 10, as vendas são em média {round(diff*100/sales_before_10d)}% menore

plt.title('Mean Sales before and after day 10',fontsize=16)
g = sns.barplot(x=['Before day 10', 'After day 10'],y=[sales_before_10d,sales_after_10d]
for i in g.containers:
    g.bar_label(i, color='white',label_type='center')

plt.savefig("img//H11.png",dpi=300)
```

Após o dia 10, as vendas são em média 8% menores

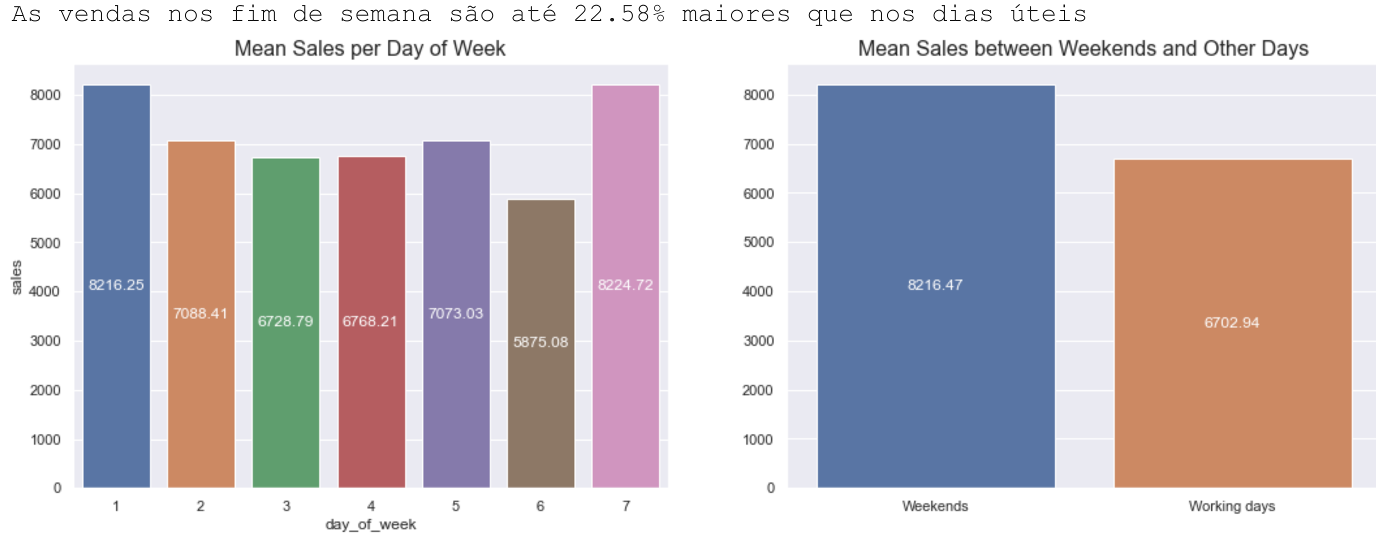


H12. Lojas deveriam vender menos aos finais de semana.

In [162…

```
grid = GridSpec(1,2)
plt.figure(figsize=(18,6))

plt.subplot(grid[0,0])
aux1 = df4[['day_of_week','sales']].groupby('day_of_week').mean().reset_index()
g = sns.barplot(x='day_of_week',y='sales',data=aux1)
plt.title('Mean Sales per Day of Week', fontsize=16)
for i in g.containers:
    g.bar_label(i,color='white',label_type='center')

plt.subplot(grid[0,1])

sales_on_weekend = df4[(df4['day_of_week'] == 1) | (df4['day_of_week'] == 7)]['sales'].m
sales_on_weekday = df4[(df4['day_of_week'] != 1) & (df4['day_of_week'] != 7)]['sales'].m
diff = sales_on_weekend - sales_on_weekday

g = sns.barplot(x=['Weekends','Working days'],y=[sales_on_weekend,sales_on_weekday])
plt.title('Mean Sales between Weekends and Other Days',fontsize=16)
for i in g.containers:
    g.bar_label(i,color='white',label_type='center')

print(f'As vendas nos fim de semana são até {round(diff*100/sales_on_weekday,2)}% maiore

plt.savefig("img//H12.png",dpi=300)
```

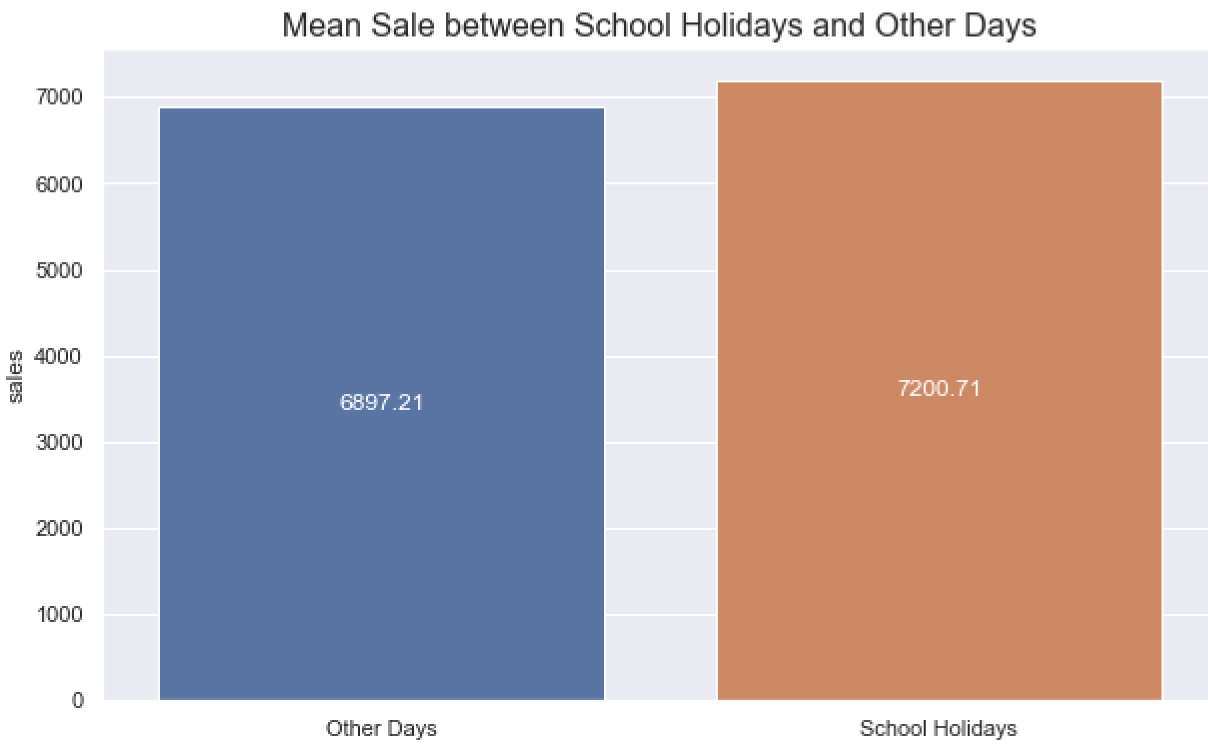
```
As vendas nos fim de semana são até 22.58% maiores que nos dias úteis
```



H13. Lojas deveriam vender menos durante os feriados escolares.

In [163…

```
aux1 = df4[['school_holiday','sales']].groupby('school_holiday').mean().reset_index()

fig = plt.figure(figsize=(10,6))
plt.title('Mean Sale between School Holidays and Other Days',fontsize=16)
g = sns.barplot(x=['Other Days','School Holidays'],y='sales',data=aux1)
for i in g.containers:
    g.bar_label(i,color='white',label_type='center')

plt.savefig("img//H13.png",dpi=300)
```

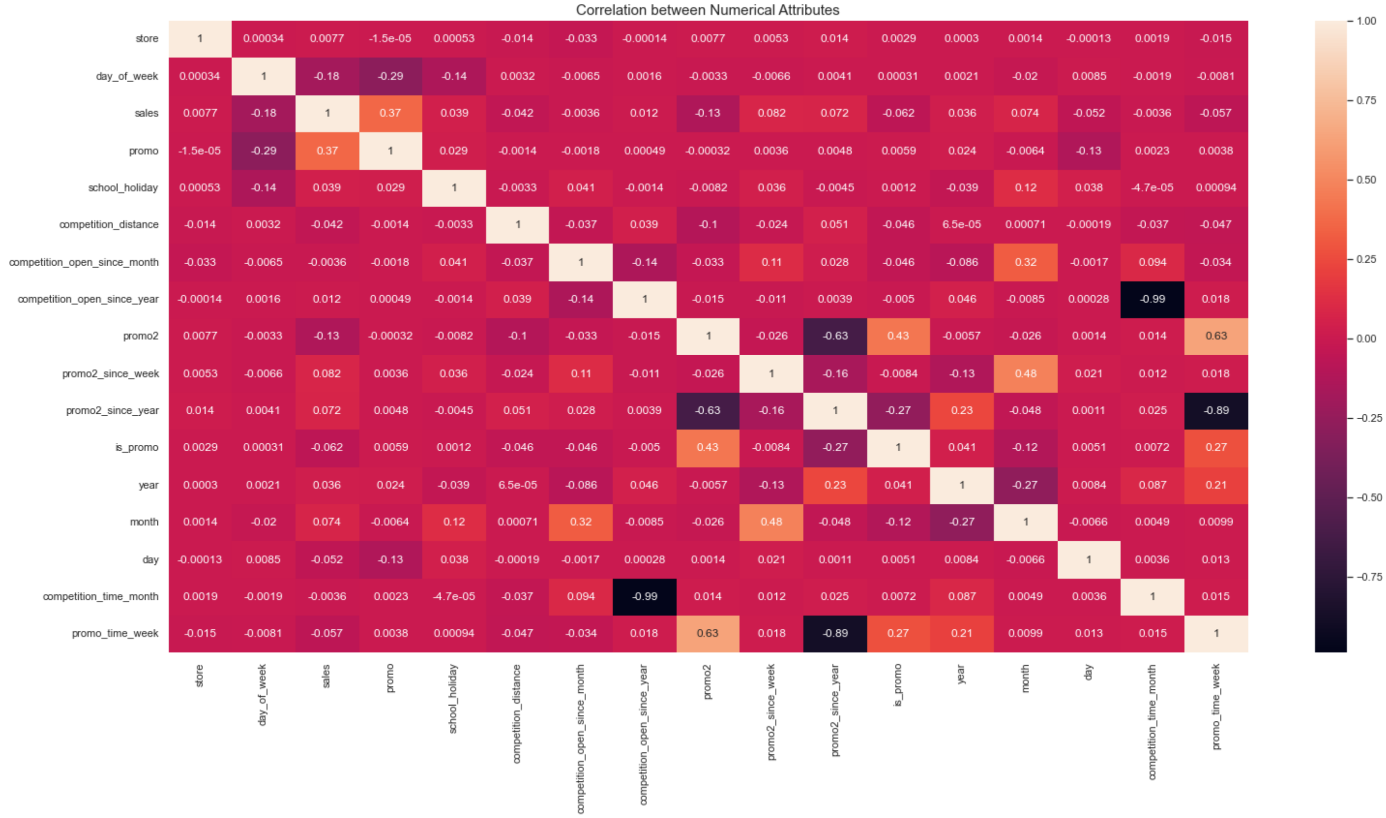


4.3. Multivariate Analysis

4.3.1 Numerical Attributes

In [164…

```
num_attributes = df4.select_dtypes(include=['int64','float64'])
correlations = num_attributes.corr(method='pearson')
plt.title('Correlation between Numerical Attributes',fontsize=15)
sns.heatmap(correlations,annot=True);
```



4.3.2 Categorical Attributes

In [165…

```
a = df4.select_dtypes(include='object')
```

In [166…

```
a.head()
```

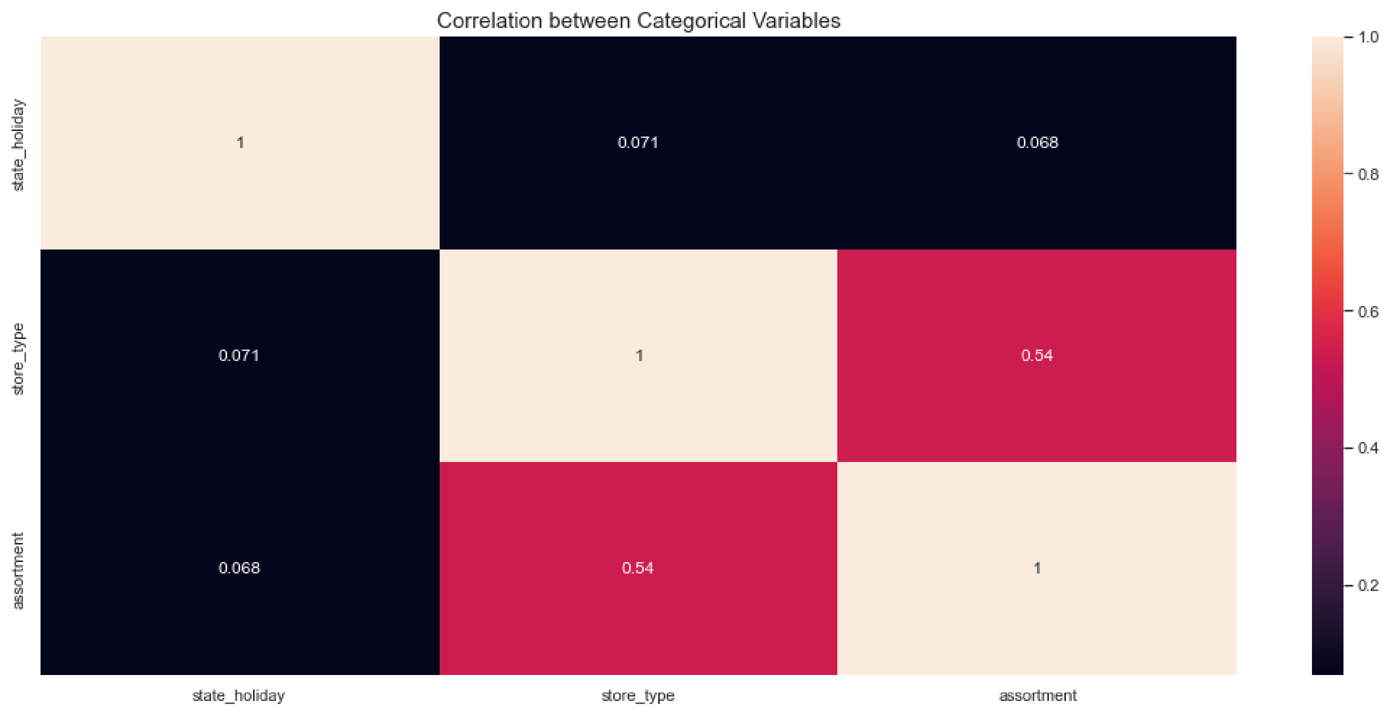
Out[166]:

	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 [167…

```
# only categorical data
a = df4.select_dtypes( include='object' )

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

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

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

# Final dataset
d = pd.DataFrame( {'state_holiday': [a1, a2, a3],
                   'store_type': [a4, a5, a6],
```

```python
                 'assortment': [a7, a8, a9]  })
d = d.set_index( d.columns )

plt.figure(figsize=(15,7))
plt.title('Correlation between Categorical Variables',fontsize=15)
sns.heatmap( d, annot=True )
plt.tight_layout()
```



5.0. Data Preparation

In [168…

```python
df5 = df4.copy()
```

5.1. Normalization

In [169…

```python
# As the data has not a normal distribution, don't make sense to apply normalization in
```

5.2. Rescaling

In [170…

```python
a = df5.select_dtypes(include=['int64','float64'])
a.head().T
```

Out[170]:

	0	1	2	3	4
store	1.0	2.0	3.0	4.0	5.0
day_of_week	5.0	5.0	5.0	5.0	5.0
sales	5263.0	6064.0	8314.0	13995.0	4822.0
promo	1.0	1.0	1.0	1.0	1.0
school_holiday	1.0	1.0	1.0	1.0	1.0
competition_distance	1270.0	570.0	14130.0	620.0	29910.0
competition_open_since_month	9.0	11.0	12.0	9.0	4.0
competition_open_since_year	2008.0	2007.0	2006.0	2009.0	2015.0

promo2	0.0	1.0	1.0	0.0	0.0
promo2_since_week	31.0	13.0	14.0	31.0	31.0
promo2_since_year	2015.0	2010.0	2011.0	2015.0	2015.0
is_promo	0.0	1.0	1.0	0.0	0.0
year	2015.0	2015.0	2015.0	2015.0	2015.0
month	7.0	7.0	7.0	7.0	7.0
day	31.0	31.0	31.0	31.0	31.0
competition_time_month	84.0	94.0	105.0	71.0	4.0
promo_time_week	0.0	279.0	226.0	0.0	0.0

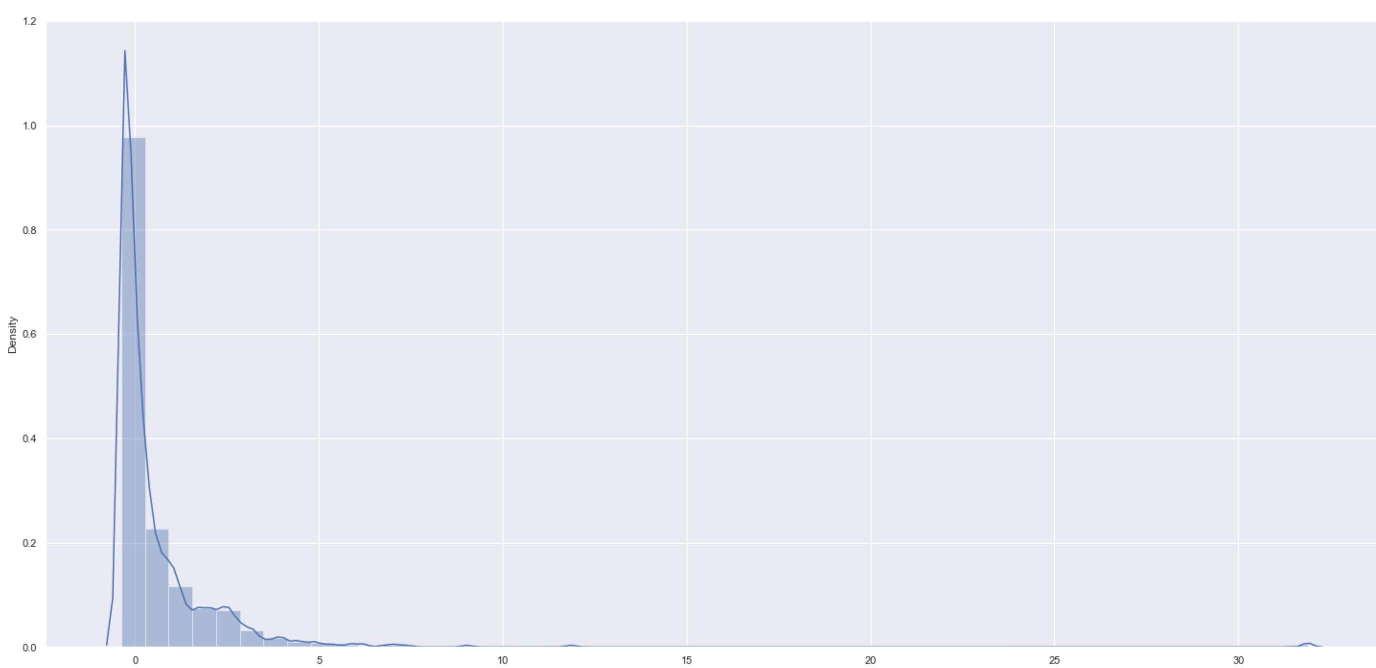
In [171…

```
from sklearn.preprocessing import RobustScaler, MinMaxScaler
import pickle
rs = RobustScaler()
mms = MinMaxScaler()

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

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

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

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

In [172…

```
sns.distplot(df5['competition_distance'])
```

Out[172]: <AxesSubplot:xlabel='competition_distance', ylabel='Density'>



5.3. Transformation

5.3.1. Enconding

In [173...

```
# state holiday
df5 = pd.get_dummies(df5, prefix=['state_holiday'], columns=['state_holiday'])

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

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

5.3.2. Response variable transformation

In [174...

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

In [175...

```
df5.head()
```

Out[175]:

	store	day_of_week	date	sales	promo	school_holiday	store_type	assortment	competition_distance	co
0	1	5	2015-07-31	8.568646	1	1	2	1	-0.170968	
1	2	5	2015-07-31	8.710290	1	1	0	1	-0.283871	
2	3	5	2015-07-31	9.025816	1	1	0	1	1.903226	
3	4	5	2015-07-31	9.546527	1	1	2	3	-0.275806	
4	5	5	2015-07-31	8.481151	1	1	0	1	4.448387	

5.3.3. Nature transformation

In [176...

```
# 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)))

# 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)))
```

In [177...

```
df5.head()
```

Out[177]:

store	day_of_week	date	sales	promo	school_holiday	store_type	assortment	competition_distance	co

0	1	5	2015-07-31	8.568646	1	1	2	1	-0.170968
1	2	5	2015-07-31	8.710290	1	1	0	1	-0.283871
2	3	5	2015-07-31	9.025816	1	1	0	1	1.903226
3	4	5	2015-07-31	9.546527	1	1	2	3	-0.275806
4	5	5	2015-07-31	8.481151	1	1	0	1	4.448387

6.0. Feature Selection

In [178…

```
df6 = df5.copy()
```

6.1. Split dataframe into training and test dataset

In [179…

```
cols_drop = ['day', 'month', 'day_of_week', "week_of_year", 'promo_since', 'competition_
df6 = df6.drop(cols_drop, axis=1)
```

In [180…

```
df6[['store','date']].groupby('store').max().reset_index()['date'][0] - datetime.timedel
```

Out[180]:

```
Timestamp('2015-06-19 00:00:00')
```

In [181…

```
X_train = df6[df6['date'] < '2015-06-19']
y_train = X_train['sales']

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('Teste 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
Teste Max Date: 2015-07-31 00:00:00
```

6.2. Boruta as Feature Selector

In [182…

```
# Comment this code to save time. Boruta takes to long

# # training and test dataset for boruta
# X_train_n = X_train.drop(['date','sales'],axis=1).values
# y_train_n = y_train.values.ravel()

# # define RandomForestRegressor
# rf = RandomForestRegressor(n_jobs =-1)

# boruta = BorutaPy(rf, n_estimators = 'auto', verbose=2, random_state=42).fit(X_train_n
```

6.2.1 Best features from boruta

In [183…

```
# Comment this code to save time. Boruta takes to long

# cols_select = boruta.support_.tolist()

# # best features
# X_train_fs = X_train.drop(['date','sales'],axis=1)
# cols_select_boruta = X_train_fs.iloc[:, cols_select].columns.tolist()

# not select boruta
# cols_not_select_boruta = np.setdiff1d(X_train_fs.columns, cols_select_boruta)
```

In [184…

```
cols_select_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_cos',
                      'month_sin',
                      'day_sin',
                      'day_cos',
                      'week_of_year_cos',
                      'week_of_year_sin']
```

In [185…

```
cols_not_select_boruta = ['is_promo',
                          'school_holiday',
                          'state_holiday_christmas',
                          'state_holiday_easter_holiday',
                          'state_holiday_public_holiday',
                          'state_holiday_regular_day',
                          'year']
```

In [186…

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

# final features
cols_select_boruta_full = cols_select_boruta.copy()
cols_select_boruta_full.extend(feat_to_add)
```

In [187…

```
cols_select_boruta_full
```

Out[187]:

```
['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_cos',
 'month_sin',
 'day_sin',
 'day_cos',
 'week_of_year_cos',
 'week_of_year_sin',
 'date',
 'sales']
```

7.0. Machine Learning Modeling

In [188…

```
df7 = df6.copy()
```

In [189…

```
x_train = X_train[cols_select_boruta]
x_test = X_test[cols_select_boruta]

# Time Series Data Preparation
x_training = X_train[cols_select_boruta_full]
```

7.1. Average Model

In [191…

```
aux1 = X_test.copy()
aux1['sales'] = y_test.copy()

# prediction
aux2 = aux1[['store','sales']].groupby('store').mean().reset_index().rename(columns={'sa
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[191]:

	Model Name	MAE	MAPE	RMSE
0	Average Model	1354.800353	0.455051	1835.135542

7.2. Linear Regression Model

In [80]:

```
## 7.2. Linear Regression Model# 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[80]:

	Model Name	MAE	MAPE	RMSE
0	Linear Regression	1867.089774	0.292694	2671.049215

7.2.1 Linear Regression Model - Cross Validation

In [81]:
```
lr_result_cv = cross_validation(x_training,5,'Linear Regression', lr)
lr_result_cv
```

Out[81]:

	Model Name	MAE CV	MAPE CV	RMSE CV
0	Linear Regression	1940.46 +/- 97.24	0.3 +/- 0.02	2735.18 +/- 194.98

7.3. Lasso Model

In [82]:
```
# model
lrr = Lasso(alpha=0.01).fit(x_train,y_train)

# prediction
yhat_lrr = lrr.predict(x_test)

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

lrr_result
```

Out[82]:

	Model Name	MAE	MAPE	RMSE
0	Linear Regression - Lasso	1891.704881	0.289106	2744.451737

7.3.1 Lasso - Cross Validation

In [83]:
```
lrr_result_cv = cross_validation(x_training,5,'Lasso', lrr)
lrr_result_cv
```

Out[83]:

	Model Name	MAE CV	MAPE CV	RMSE CV
0	Lasso	1957.62 +/- 140.52	0.29 +/- 0.0	2828.15 +/- 232.95

7.4. Random Forest Regressor

In [85]:
```
# model
rf = RandomForestRegressor(n_estimators=100,n_jobs=-1,random_state=42).fit(x_train,y_tra

# 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[85]:

	Model Name	MAE	MAPE	RMSE
0	Random Forest Regressor	677.455795	0.099667	1007.9169

7.4.1 Random Forest Regressor - Cross Validation

In [88]:
```
rf_result_cv = cross_validation(x_training,5,'Random Forest', rf, verbose=True)
```

```
rf_result_cv
```

```
KFold Number: 4

KFold Number: 3

KFold Number: 2

KFold Number: 1
```

Out[88]:

	Model Name	MAE CV	MAPE CV	RMSE CV
0	Random Forest	747.02 +/- 133.64	0.11 +/- 0.02	1126.63 +/- 203.71

7.5. XGBoost Regressor

In [94]:

```
# model
model_xgb = xgb.XGBRegressor( objective='reg:squarederror',
                              n_estimators=2500,
                              eta=0.01,
                              max_depth=9,
                              subsample=0.5,
                              colsample_bytree=0.3 ).fit( x_train, y_train )

# prediction
yhat_xgb = model_xgb.predict( x_test )

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

Out[94]:

	Model Name	MAE	MAPE	RMSE
0	XGBoost Regressor	797.142725	0.118088	1146.255415

7.5.1 XGBoost Regressor - Cross Validation

In [95]:

```
xgb_result_cv = cross_validation(x_training,5,'XGBooster', model_xgb, verbose=True)
xgb_result_cv
```

```
KFold Number: 4

KFold Number: 3

KFold Number: 2

KFold Number: 1
```

Out[95]:

	Model Name	MAE CV	MAPE CV	RMSE CV
0	XGBooster	901.14 +/- 90.25	0.13 +/- 0.01	1308.94 +/- 142.96

7.6. Compare Model's Performance

7.6.1 Single Performance

In [96]:

```
pd.concat([baseline_result,lr_result,lrr_result,rf_result,xgb_result])
```

Out[96]:

	Model Name	MAE	MAPE	RMSE

0	Average Model	1354.800353	0.455051	1835.135542
0	Linear Regression	1867.089774	0.292694	2671.049215
0	Linear Regression - Lasso	1891.704881	0.289106	2744.451737
0	Random Forest Regressor	677.455795	0.099667	1007.916900
0	XGBoost Regressor	797.142725	0.118088	1146.255415

7.6.2 Real Performance - Cross Validation

In [97]:
```
pd.concat([lr_result_cv,lrr_result_cv,rf_result_cv,xgb_result_cv])
```

Out[97]:

	Model Name	MAE CV	MAPE CV	RMSE CV
0	Linear Regression	1940.46 +/- 97.24	0.3 +/- 0.02	2735.18 +/- 194.98
0	Lasso	1957.62 +/- 140.52	0.29 +/- 0.0	2828.15 +/- 232.95
0	Random Forest	747.02 +/- 133.64	0.11 +/- 0.02	1126.63 +/- 203.71
0	XGBooster	901.14 +/- 90.25	0.13 +/- 0.01	1308.94 +/- 142.96

8.0. Hyperparameter Fine Tuning

In [192...
```
df8 = df7.copy()
```

8.1. Random Search

In [114...
```
import random
import warnings
warnings.filterwarnings('ignore')
```

In [115...
```
param = {
            'n_estimators':[1500, 1700, 2500, 3000, 3500],
            'eta':[0.01, 0.03],
            'max_depth':[3,5,9],
            'subsample':[0.1, 0.5, 0.7],
            'colsample_bytree': [0.3, 0.7, 0.9],
            'min_child_weigth': [3,8,15]
}

MAX_EVAL = 10
```

In [116...
```
final_result = pd.DataFrame()

for i in range(MAX_EVAL):

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

    # model
    model_xgb = xgb.XGBRegressor( objective='reg:squarederror',
                                  n_estimators=hp['n_estimators'],
                                  eta=hp['eta'],
                                  max_depth=hp['max_depth'],
```

```
                                   subsample=hp['subsample'],
                                   colsample_bytree=hp['colsample_bytree'],
                                   min_child_weigth = hp['min_child_weigth'])

    # performance
    result = cross_validation( x_training, 2, 'XGBoost Regressor', model_xgb, verbose=Fa

    final_result = pd.concat([final_result, result])

final_result
```

```
{'n_estimators': 1700, 'eta': 0.01, 'max_depth': 9, 'subsample': 0.1, 'colsample_bytre
e': 0.3, 'min_child_weigth': 8}
[17:41:16] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.6.0/src/lea
rner.cc:627:
Parameters: { "min_child_weigth" } might not be used.

  This could be a false alarm, with some parameters getting used by language bindings bu
t
  then being mistakenly passed down to XGBoost core, or some parameter actually being us
ed
  but getting flagged wrongly here. Please open an issue if you find any such cases.


{'n_estimators': 3500, 'eta': 0.01, 'max_depth': 5, 'subsample': 0.5, 'colsample_bytre
e': 0.3, 'min_child_weigth': 8}
[17:52:41] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.6.0/src/lea
rner.cc:627:
Parameters: { "min_child_weigth" } might not be used.

  This could be a false alarm, with some parameters getting used by language bindings bu
t
  then being mistakenly passed down to XGBoost core, or some parameter actually being us
ed
  but getting flagged wrongly here. Please open an issue if you find any such cases.


{'n_estimators': 2500, 'eta': 0.03, 'max_depth': 9, 'subsample': 0.1, 'colsample_bytre
e': 0.3, 'min_child_weigth': 3}
[18:11:26] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.6.0/src/lea
rner.cc:627:
Parameters: { "min_child_weigth" } might not be used.

  This could be a false alarm, with some parameters getting used by language bindings bu
t
  then being mistakenly passed down to XGBoost core, or some parameter actually being us
ed
  but getting flagged wrongly here. Please open an issue if you find any such cases.


{'n_estimators': 1700, 'eta': 0.01, 'max_depth': 3, 'subsample': 0.1, 'colsample_bytre
e': 0.9, 'min_child_weigth': 15}
[18:28:23] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.6.0/src/lea
rner.cc:627:
Parameters: { "min_child_weigth" } might not be used.

  This could be a false alarm, with some parameters getting used by language bindings bu
t
  then being mistakenly passed down to XGBoost core, or some parameter actually being us
ed
  but getting flagged wrongly here. Please open an issue if you find any such cases.


{'n_estimators': 1700, 'eta': 0.03, 'max_depth': 5, 'subsample': 0.5, 'colsample_bytre
e': 0.9, 'min_child_weigth': 8}
[18:35:20] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.6.0/src/lea
```

```
rner.cc:627:
Parameters: { "min_child_weigth" } might not be used.

  This could be a false alarm, with some parameters getting used by language bindings bu
t
  then being mistakenly passed down to XGBoost core, or some parameter actually being us
ed
  but getting flagged wrongly here. Please open an issue if you find any such cases.


{'n_estimators': 3000, 'eta': 0.03, 'max_depth': 5, 'subsample': 0.1, 'colsample_bytre
e': 0.3, 'min_child_weigth': 3}
[18:49:29] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.6.0/src/lea
rner.cc:627:
Parameters: { "min_child_weigth" } might not be used.

  This could be a false alarm, with some parameters getting used by language bindings bu
t
  then being mistakenly passed down to XGBoost core, or some parameter actually being us
ed
  but getting flagged wrongly here. Please open an issue if you find any such cases.


{'n_estimators': 1700, 'eta': 0.03, 'max_depth': 3, 'subsample': 0.5, 'colsample_bytre
e': 0.9, 'min_child_weigth': 15}
[19:02:33] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.6.0/src/lea
rner.cc:627:
Parameters: { "min_child_weigth" } might not be used.

  This could be a false alarm, with some parameters getting used by language bindings bu
t
  then being mistakenly passed down to XGBoost core, or some parameter actually being us
ed
  but getting flagged wrongly here. Please open an issue if you find any such cases.


{'n_estimators': 3000, 'eta': 0.03, 'max_depth': 5, 'subsample': 0.5, 'colsample_bytre
e': 0.3, 'min_child_weigth': 8}
[19:12:02] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.6.0/src/lea
rner.cc:627:
Parameters: { "min_child_weigth" } might not be used.

  This could be a false alarm, with some parameters getting used by language bindings bu
t
  then being mistakenly passed down to XGBoost core, or some parameter actually being us
ed
  but getting flagged wrongly here. Please open an issue if you find any such cases.


{'n_estimators': 2500, 'eta': 0.01, 'max_depth': 3, 'subsample': 0.5, 'colsample_bytre
e': 0.9, 'min_child_weigth': 15}
[19:27:07] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.6.0/src/lea
rner.cc:627:
Parameters: { "min_child_weigth" } might not be used.

  This could be a false alarm, with some parameters getting used by language bindings bu
t
  then being mistakenly passed down to XGBoost core, or some parameter actually being us
ed
  but getting flagged wrongly here. Please open an issue if you find any such cases.


{'n_estimators': 1700, 'eta': 0.01, 'max_depth': 3, 'subsample': 0.7, 'colsample_bytre
e': 0.9, 'min_child_weigth': 3}
[19:39:49] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.6.0/src/lea
rner.cc:627:
```

```
Parameters: { "min_child_weigth" } might not be used.

  This could be a false alarm, with some parameters getting used by language bindings bu
t
  then being mistakenly passed down to XGBoost core, or some parameter actually being us
ed
  but getting flagged wrongly here. Please open an issue if you find any such cases.
```

Out[116]:

	Model Name	MAE CV	MAPE CV	RMSE CV
0	XGBoost Regressor	1018.34 +/- 0.0	0.14 +/- 0.0	1455.35 +/- 0.0
0	XGBoost Regressor	1254.78 +/- 0.0	0.17 +/- 0.0	1813.47 +/- 0.0
0	XGBoost Regressor	779.72 +/- 0.0	0.11 +/- 0.0	1084.11 +/- 0.0
0	XGBoost Regressor	1711.75 +/- 0.0	0.24 +/- 0.0	2469.05 +/- 0.0
0	XGBoost Regressor	961.12 +/- 0.0	0.13 +/- 0.0	1377.35 +/- 0.0
0	XGBoost Regressor	954.95 +/- 0.0	0.13 +/- 0.0	1346.82 +/- 0.0
0	XGBoost Regressor	1422.65 +/- 0.0	0.2 +/- 0.0	2068.97 +/- 0.0
0	XGBoost Regressor	943.73 +/- 0.0	0.13 +/- 0.0	1330.98 +/- 0.0
0	XGBoost Regressor	1634.17 +/- 0.0	0.23 +/- 0.0	2365.05 +/- 0.0
0	XGBoost Regressor	1732.57 +/- 0.0	0.24 +/- 0.0	2496.37 +/- 0.0

In [83]:

```
param_tuned = {'n_estimators': 2500, 'eta': 0.03, 'max_depth': 9, 'subsample': 0.1, 'col
```

In [84]:

```
# 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_weigth = param_tuned['min_child_weigth']).fit(x_

yhat_xgb_tuned = model_xgb_tuned.predict(x_test)

# xgb_result_tuned = ml_error('XGBooster', np.expm1(y_test),np.expm1(yhat_xgb_tuned))

# xgb_result_tuned
```

```
[14:47:52] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.6.0/src/lea
rner.cc:627:
Parameters: { "min_child_weigth" } might not be used.

  This could be a false alarm, with some parameters getting used by language bindings bu
t
  then being mistakenly passed down to XGBoost core, or some parameter actually being us
ed
  but getting flagged wrongly here. Please open an issue if you find any such cases.
```

Out[84]:

	Model Name	MAE	MAPE	RMSE
0	XGBooster	701.119281	0.102318	1009.038292

In [87]:

```
# save model
pickle.dump(model_xgb_tuned,open('C:\\Users\\Notebook\\repos\\DS-Producao\\model_rossman
```

9.0. PASSO 9 - Tradução e Interpretação do Erro

In [193…

```
# load model
with open('model_rossmann.pkl','rb') as model:
    model_xgb_tuned = pickle.load(model)

yhat_xgb_tuned = model_xgb_tuned.predict(x_test)

xgb_result_tuned = ml_error('XGBooster', np.expm1(y_test),np.expm1(yhat_xgb_tuned))
xgb_result_tuned
```

Out[193]:

	Model Name	MAE	MAPE	RMSE
0	XGBooster	701.119281	0.102318	1009.038292

In [195…

```
df9 = X_test[cols_select_boruta_full]

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

9.1. Bussines Performance

9.1.1. Baseline Model

In [196…

```
# sum of mean sales - baseline aproach
df9_baseline = X_train[cols_select_boruta_full]

# rescaling
df9_baseline['sales'] = np.expm1(df9_baseline['sales'])

# group mean sales by store
df9_baseline = df9_baseline[['store','sales']].groupby('store').mean().reset_index()

# project the mean over 6 weeks
df9_baseline['mean_sales'] = df9_baseline['sales']*42

df9_baseline = df9_baseline.drop('sales', axis=1)
```

9.1.2. Machine Learning Scenarios

In [197…

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

# MAE e MAPE
df9_aux1 = df9[['store','sales','predictions']].groupby('store').apply(lambda x: mean_ab
df9_aux2 = df9[['store','sales','predictions']].groupby('store').apply(lambda x: mean_ab

# merge
df9_aux3 = pd.merge(df9_aux1,df9_aux2,how='inner',on='store')
df92 = pd.merge(df91, df9_aux3, how='inner', on='store')
df92 = pd.merge(df9_baseline, df92, how='inner', on='store')

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

```
# order columns
df92 = df92[['store','mean_sales','sales','predictions','worst_scenario','best_scenario'
```

9.1.3. Comparation between Scenarios

In [198…

```
df92.sample(4)
```

Out[198]:

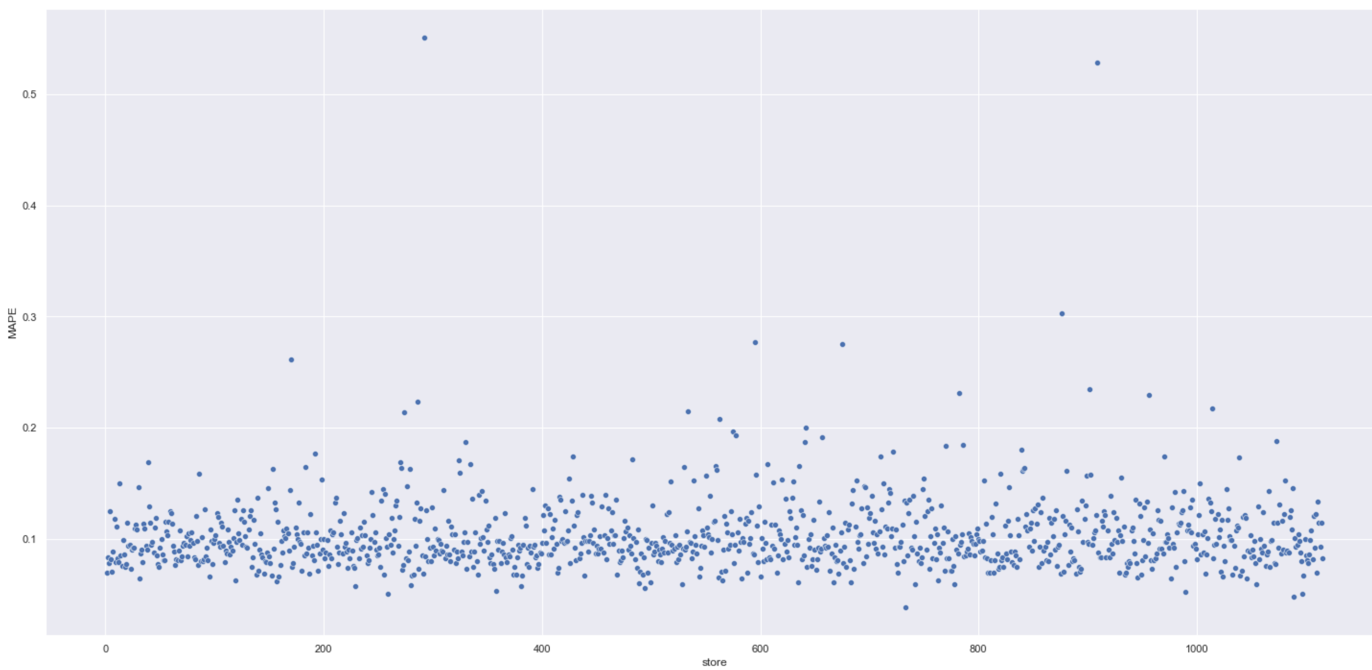
	store	mean_sales	sales	predictions	worst_scenario	best_scenario	MAE	MAPE
240	241	276692.660377	240097.0	241176.609375	240640.043167	241713.175583	536.566208	0.081060
328	329	290761.245283	248224.0	261684.906250	260996.400364	262373.412136	688.505886	0.105376
123	124	185780.150943	164294.0	169031.234375	168504.939513	169557.529237	526.294862	0.117676
727	728	219857.002703	202244.0	197765.359375	197262.290963	198268.427787	503.068412	0.092472

In [199…

```
sns.scatterplot(x='store',y='MAPE',data=df92)
```

Out[199]:

```
<AxesSubplot:xlabel='store', ylabel='MAPE'>
```



9.2. Total Performance

In [200…

```
df93 = df92[['sales','mean_sales','predictions','worst_scenario','best_scenario']].apply
df93['Values'] = df93['Values'].map('R${:,.2f}'.format)
df93
```

Out[200]:

	Scenario	Values
0	sales	R$289,571,750.00
1	mean_sales	R$324,608,344.45
2	predictions	R$282,756,416.00
3	worst_scenario	R$281,970,740.56
4	best_scenario	R$283,542,087.76

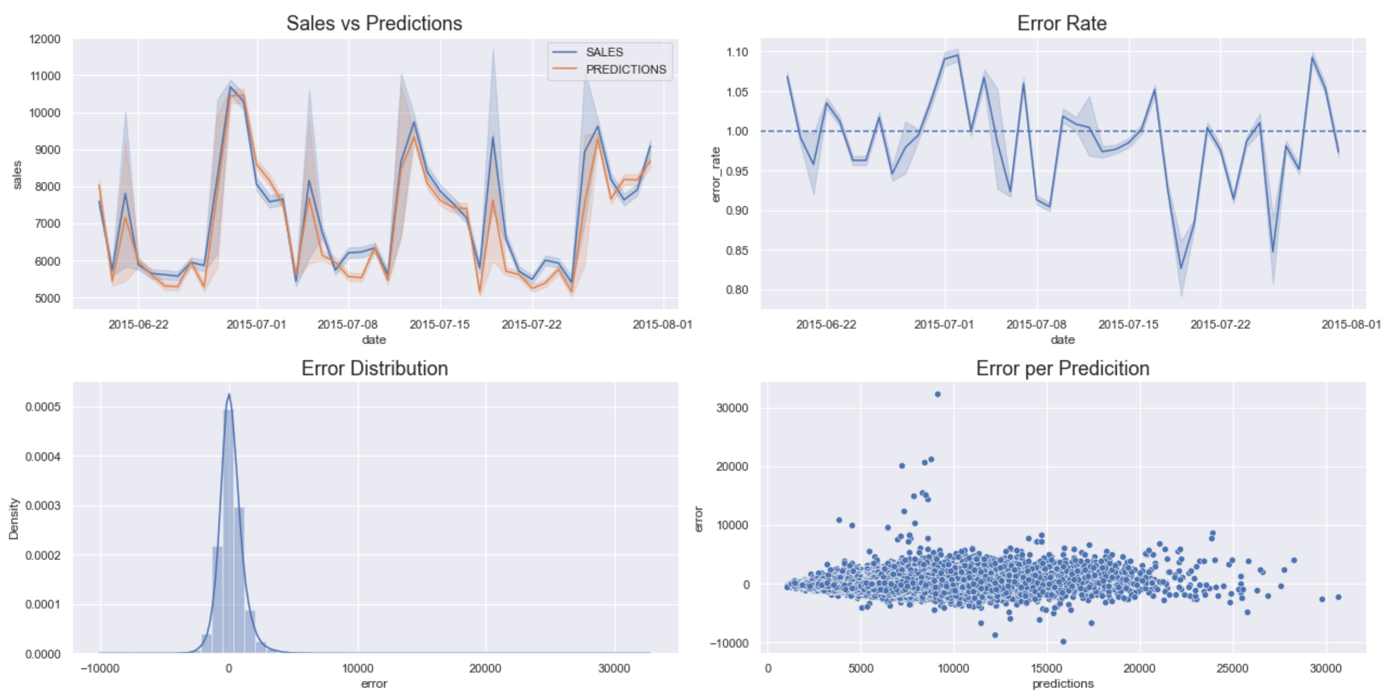
9.3. Machine Learning Performance

In [201…

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

In [202…

```
plt.figure(figsize=(18,9))

plt.subplot(2,2,1)
plt.title('Sales vs Predictions',fontsize=18)
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)
plt.title('Error Rate',fontsize=18)
sns.lineplot(x='date',y='error_rate',data=df9)
plt.axhline(1,linestyle='--')

plt.subplot(2,2,3)
plt.title('Error Distribution',fontsize=18)
sns.distplot(df9['error'])

plt.subplot(2,2,4)
plt.title('Error per Predicition',fontsize=18)
sns.scatterplot(df9['predictions'],df9['error'])

plt.tight_layout()

plt.savefig("img//ML_error.png",dpi=600)
```



10. PASSO 10 - DEPLOY MODEL TO PRODUCTION

10.1. Rossmann Class

In [104…

```
import pickle
import inflection
import pandas as pd
import numpy as np
import math
```

```python
import datetime

class Rossmann(object):
    def __init__(self):
        state = 1
        self.home.path = 'C:\\Users\\Notebook\\repos\\DS-Producao\\'
        self.competition_distance_scaler = pickle.load(open(self.home.path + 'parameter\
        self.competition_time_month_scaler = pickle.load(open(self.home.path + 'paramete
        self.competition_promo_time_week_scaler = pickle.load(open(self.home.path + 'par
        self.year_scaler = pickle.load(open(self.home.path + 'parameter\\competition_dis
        self.store_type_scaler = pickle.load(open(self.home.path + 'parameter\\store_typ


    def data_cleaning(self,df1):

        ## 1.1 Rename Columns

        cols_old = ['Store', 'DayOfWeek', 'Date', 'Open', 'Promo', 'StateHoliday',
                    'SchoolHoliday', 'StoreType', 'Assortment','CompetitionDistance', 'C
                    'CompetitionOpenSinceYear', 'Promo2', 'Promo2SinceWeek','Promo2Since

        snakecase = lambda x: inflection.underscore(x)

        cols_new = list(map(snakecase, cols_old))

        # rename
        df1.columns = cols_new

        ## 1.3 - Data Types

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

        ## 1.5 Fillout NA

        # competition_distance
        # Se vazio, não há competidor mais próximo (a distancia até o competidor é mto g
        df1['competition_distance'] = df1['competition_distance'].apply(lambda x: 2*10**

        # competition_open_since_month
        df1['competition_open_since_month'] = df1[['competition_open_since_month','date'

        # competition_open_since_year
        df1['competition_open_since_year'] = df1[['competition_open_since_year','date']]

        # promo2_since_week
        df1['promo2_since_week'] = df1[['promo2_since_week','date']].apply(lambda x: x['

        # promo2_since_year
        df1['promo2_since_year'] = df1[['promo2_since_year','date']].apply(lambda x: x['

        # promo_interval
        month_map = {1:'Jan',2:'Feb',3:'Mar',4:'Apr',5:'May',6:'Jun',7:'Jul',8:'Aug',9:'

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

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

        df1['is_promo'] = df1[['promo_interval', 'month_map']].apply( lambda x: 0 if x['

        ## 1.6 Change Types

        df1.dtypes

        df1['competition_open_since_month'] = df1['competition_open_since_month'].astype
        df1['competition_open_since_year'] = df1['competition_open_since_year'].astype(i
```

```
        df1['promo2_since_week'] = df1['promo2_since_week'].astype(int64)
        df1['promo2_since_year'] = df1['promo2_since_year'].astype(int64)

        return df1

    def feature_engineering( self, df2):
        # year
        df2['year'] = df2['date'].dt.year

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

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

        # week of day
        df2['week_of_year'] = df2['date'].dt.isocalendar().week

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

        # competition_sice
        df2['competition_since'] = df2.apply( lambda x: datetime.datetime(year=x['compet
        df2['competition_time_month'] = ((df2['date'] - df2['competition_since'])/30).ap

        # promo sice
        df2['promo_since'] = df2['promo2_since_year'].astype(str) + '-' + df2['promo2_si
        df2['promo_since'] = df2['promo_since'].apply(lambda x: datetime.datetime.strpti
        df2['promo_time_week'] = ((df2['date'] - df2['promo_since'])/7).apply(lambda x:

        # assortment
        df2['assortment'] = df2['assortment'].apply(lambda x: 'basic' if x == 'a' else '

        # state holiday
        df2['state_holiday'] = df2['state_holiday'].apply(lambda x: 'public_holiday' if

        # 3.0 PASSO 3 - FILTRAGEM DE VARIÁVEIS

        ## 3.1 Filtragem das Linhas

        df2 = df2[(df2['open'] != 0)]

        ## 3.2 Selecao das Colunas

        cols_drop = ['open','promo_interval','month_map']
        df2 = df2.drop(cols_drop, axis=1)

        return df2

    def data_preparation(self, df5):

        ## 5.2. Rescaling

        # competition distance
        df5['competition_distance'] = self.competition_distance_scaler.transform( df5[['

        # competition time month
        df5['competition_time_month'] = self.competition_time_month_scaler.transform( df

        # promo time week
        df5['promo_time_week'] = self.competition_promo_time_week_scaler.transform( df5[

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

        # store type
```

```
        df5['store_type'] = self.store_type_scaler.transform(df5['store_type'])
        pickle.dump(le, open('parameter/store_type_scaler.pkl','wb'))

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

        ### 5.3.3. Nature transformation

        # 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/
        df5['week_of_year_cos'] = df5['week_of_year'].apply(lambda x: np.cos(x*(2*np.pi/

        # 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)

        cols_select = ['store', 'promo', 'store_type', 'assortment', 'competition_distan
                       'promo2_since_year','competition_time_month', 'promo_time_week','d
                       'week_of_year_sin']
        df5[cols_select]

        return df5

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

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

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

10.2. API Handler

In [105…

```
import pandas as pd
from flask import Flask, request, Response
# from rossmann.Rossmann import Rossmann

model = pickle.load(open('C:\\Users\\Notebook\\repos\\DS-Producao\\model_rossmann.pkl','

app = Flask(__name__)

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

# initialize API
def rossmann_predict():
    test_json = request.get_json()

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

        else: # multiple example
```

```python
            test_raw = pd.DataFrame(test_json, columns=test_json[0].keys())

        # Instantiate Rossamann class
        pipeline = Rossmann()

        # data cleaning
        df1 = pipeline.data_cleaning(test_raw)

        # feature engineering
        df2 = pipeline.feature_engineering(df1)

        # data preparation
        df3 = pipeline.data_preparation(df2)

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

        return df_response

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

if __name__ == '__main__':
    app.run('192.168.18.4')
```

```
 * Serving Flask app '__main__' (lazy loading)
 * Environment: production
   WARNING: This is a development server. Do not use it in a production deployment.
   Use a production WSGI server instead.
 * Debug mode: off
 * Running on http://192.168.18.4:5000 (Press CTRL+C to quit)
```

10.3. API Tester

In [204…

```python
df10 = pd.read_csv('C:\\Users\\Notebook\\repos\\DS-Producao\\data\\test.csv')
```

In [206…

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

# choose store for prediction
df_test = df_test[df_test['Store'].isin([24])]

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

Out[206]:

	Store	DayOfWeek	Date	Open	Promo	StateHoliday	SchoolHoliday	StoreType	Assortment	Competitio
17	24	4	2015-09-17	1.0	1	0	0	a	c	
873	24	3	2015-09-16	1.0	1	0	0	a	c	
1729	24	2	2015-09-15	1.0	1	0	0	a	c	
2585	24	1	2015-09-14	1.0	1	0	0	a	c	
4297	24	6	2015-09-12	1.0	0	0	0	a	c	

In [207…

```python
data = json.dumps(df_test.to_dict(orient='records'))
```

In [210…

```python
# call request

# local test
# url = 'http://192.168.18.4:5000/rossmann/predict'

# cloud test
url = 'https://rossmann-predict-models.herokuapp.com/rossmann/predict'

header = {'Content-type': 'application/json'}
data = json.dumps(df_test.to_dict(orient='records'))

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

```
Status Code 200
```

In [211…

```python
# transform dataframe in json
# prediction on the last column

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

Out[211]:

	store	day_of_week	date	open	promo	state_holiday	school_holiday	store_type	assortment	cor
0	24	4	2015-09-17T00:00:00.000Z	1.0	1	regular_day	0	a	extended	
1	24	3	2015-09-16T00:00:00.000Z	1.0	1	regular_day	0	a	extended	
2	24	2	2015-09-15T00:00:00.000Z	1.0	1	regular_day	0	a	extended	
3	24	1	2015-09-14T00:00:00.000Z	1.0	1	regular_day	0	a	extended	
4	24	6	2015-09-12T00:00:00.000Z	1.0	0	regular_day	0	a	extended	

In [212…

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

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

```
Store Number 24 will sell R$ 284,016.13 in the next 6 weeks
```