Práctica 6. Regresión Lineal

Dataset: RossmanV1 (Train)

RossmanV1 (Ridge, Lasso, Polynomial, Polynomial cubic case)

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
from sklearn import metrics
from sklearn.linear_model import LinearRegression,Ridge, Lasso
from sklearn.metrics import mean_squared_error,r2_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import PolynomialFeatures
```

In [2]:
```
rossman=pd.read_csv('train.csv')
rossman.head(3)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3146: DtypeWarning: Columns (7) hav
e mixed types.Specify dtype option on import or set low_memory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

Out[2]:

	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

In [3]:
```
rossman.dtypes
```

Out[3]:
```
Store             int64
DayOfWeek         int64
Date             object
Sales             int64
Customers         int64
Open              int64
Promo             int64
StateHoliday     object
SchoolHoliday     int64
dtype: object
```

In [4]:
```
rossman.StateHoliday = rossman.StateHoliday.astype(str)
def count_unique(column):
    return len(column.unique())

rossman.apply(count_unique, axis=0).astype(np.int32)
```

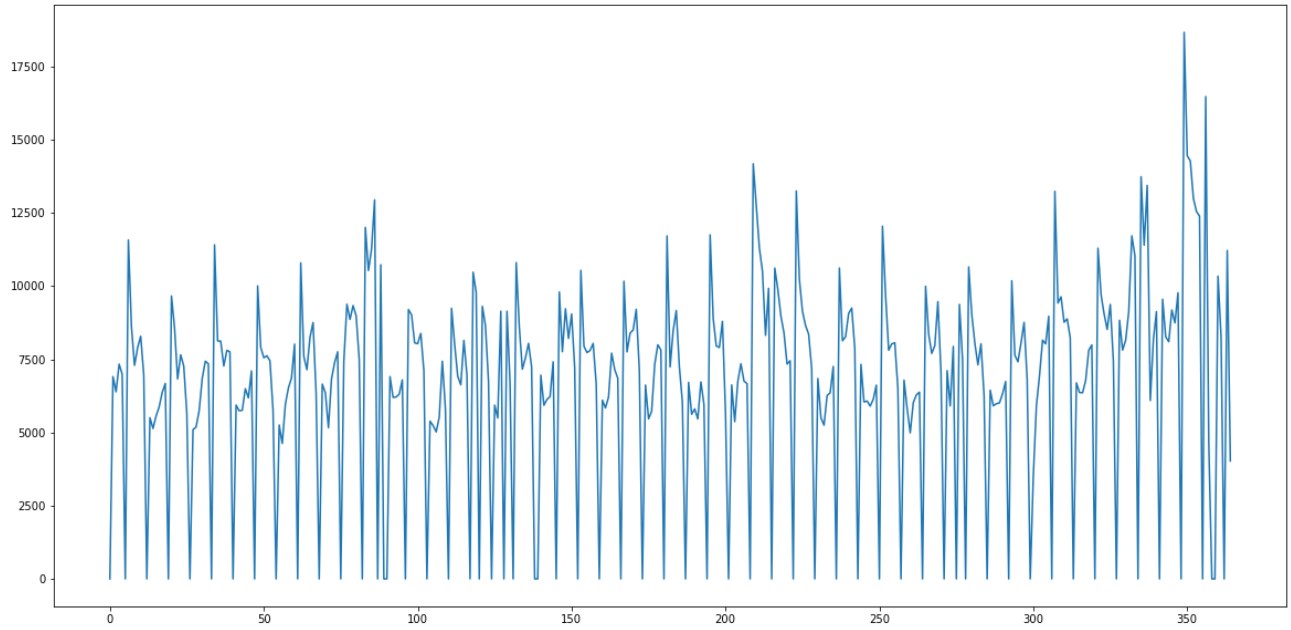
Out[4]:
```
Store            1115
DayOfWeek           7
Date              942
Sales           21734
Customers        4086
Open                2
Promo               2
StateHoliday        4
SchoolHoliday       2
dtype: int32
```

In [5]:
```
rossman.isnull().any()
```

Out[5]:
```
Store           False
DayOfWeek       False
Date            False
Sales           False
Customers       False
Open            False
Promo           False
StateHoliday    False
SchoolHoliday   False
dtype: bool
```

In [6]:
```
store_data = rossman[rossman.Store==150].sort_values('Date')
plt.figure(figsize=(20, 10))
plt.plot(store_data.Sales.values[:365])
```

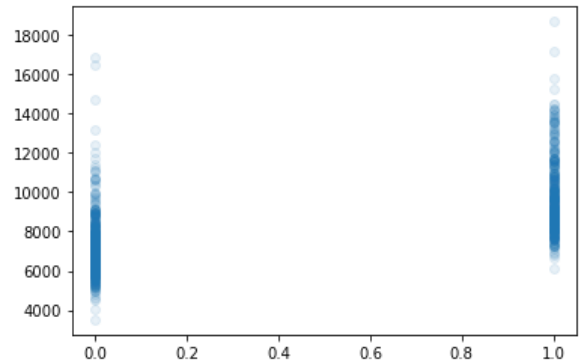
Out[6]:
```
[<matplotlib.lines.Line2D at 0x281cf950730>]
```



In [7]:
```
plt.scatter(x=store_data[rossman.Open==1].Promo, y=store_data[rossman.Open==1].Sales, alpha=0.1)
```

```
<ipython-input-7-1909a9fa42ed>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  plt.scatter(x=store_data[rossman.Open==1].Promo, y=store_data[rossman.Open==1].Sales, alpha=0.1)
<ipython-input-7-1909a9fa42ed>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  plt.scatter(x=store_data[rossman.Open==1].Promo, y=store_data[rossman.Open==1].Sales, alpha=0.1)
```

Out[7]:
```
<matplotlib.collections.PathCollection at 0x281cf9ba8e0>
```

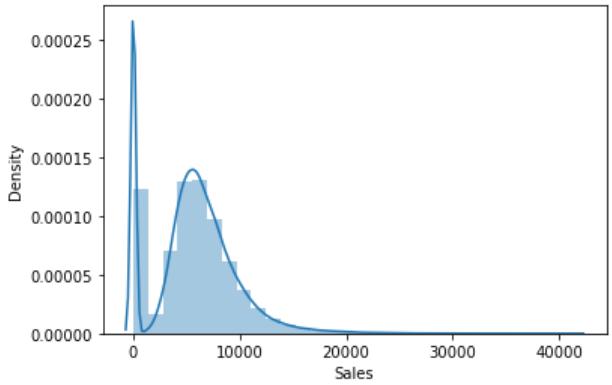


In [8]:
```
rossmanTransformada = rossman.drop(['Store', 'Date', 'Customers'], axis=1)
rossmanTransformada = pd.get_dummies(rossmanTransformada, columns=['DayOfWeek', 'StateHoliday'])
rossmanTransformada = rossmanTransformada[0:500000]
rossmanTransformada.shape
```

Out[8]:
```
(500000, 15)
```

In [9]:
```
sns.distplot(rossman['Sales'], bins=30)
plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprec
ated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



In [10]:
```
X = rossmanTransformada.drop(['Sales'], axis=1)
y = rossmanTransformada.Sales

X_train, X_test, Y_train, Y_test = train_test_split(X, y, test_size = 0.2, random_state=5)
print(X_train.shape, X_test.shape ,Y_train.shape, Y_test.shape)
```

```
(400000, 14) (100000, 14) (400000,) (100000,)
```

Modelo de Regresión Lineal

In [11]:
```
modeloLineal = LinearRegression()
modeloLineal.fit(X_train, Y_train)
print('Interseccion:', modeloLineal.intercept_)
print('Pendiente:', modeloLineal.coef_)
```

```
Interseccion: 406249541046291.7
Pendiente: [ 8.24757169e+03  2.23632348e+03  1.95819011e+02  1.22787243e+14
  1.22787243e+14  1.22787243e+14  1.22787243e+14  1.22787243e+14
  1.22787243e+14  1.22787243e+14 -5.29036784e+14 -5.29036784e+14
 -5.29036784e+14 -5.29036784e+14]
```

In [12]:
```
# Evaluacion del modelo lineal
y_train_predict = modeloLineal.predict(X_train)
rmse = (np.sqrt(mean_squared_error(Y_train, y_train_predict)))
RLinealScoreE = r2_score(Y_train, y_train_predict) # es el r2

y_test_predict = modeloLineal.predict(X_test)
rmse = (np.sqrt(mean_squared_error(Y_test, y_test_predict)))
RLinealScoreT= r2_score(Y_test, y_test_predict)
```

Técnica Ridge

In [13]:
```
ridge = Ridge(alpha=0.1).fit(X_train, Y_train)
RidgeScoreE=ridge.score(X_train, Y_train)
RidgeScoreT=ridge.score(X_test, Y_test)
```

Técnica Lasso

In [14]:
```
lasso = Lasso(alpha=0.1, max_iter=10).fit(X_train, Y_train)
LassoScoreE=lasso.score(X_train, Y_train)
LassoScoreT=lasso.score(X_test, Y_test)
features=np.sum(lasso.coef_ != 0)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:529: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations. Duality gap: 1294909753580.137
7, tolerance: 616169016.0289341
  model = cd_fast.enet_coordinate_descent(
```

Polynomial

In [15]:
```
grado3 = PolynomialFeatures(degree=3)
X_grado3 = grado3.fit_transform(X_train)
lm_grado3 = modeloLineal.fit(X_grado3, Y_train)

y_grado3_fit_train = lm_grado3.predict(grado3.fit_transform(X_train))
grado3_r2E = r2_score(Y_train, y_grado3_fit_train) #lm.predict(X_quad))
#grado2_r2E = r2_score(Y_train, y_grado2_fit)
y_grado3_fit = lm_grado3.predict(grado3.fit_transform(X_test))
grado3_r2T = r2_score(Y_test, y_grado3_fit) #lm.predict(X_quad))
```

Resumen

In [16]:
```
cabeceras= ["Entrenamiento","Test","Features"]
valores= [[RLinealScoreE,RidgeScoreE,LassoScoreE,grado3_r2E ],
          [RLinealScoreT,RidgeScoreT,LassoScoreT,grado3_r2T],
          ["--","--",features,"--"]]
resumen = pd.DataFrame(data=valores, index=cabeceras,columns = ["Modelo Lineal","Ridge","Lasso","Polinomial Cubo"
resumen
```

Out[16]:

	Modelo Lineal	Ridge	Lasso	Polinomial Cubo
Entrenamiento	0.55985	0.55985	0.559616	0.56822
Test	0.565971	0.56597	0.565564	0.575756
Features	--	--	14.000000	--

Interpretación

Interpretación
La regresión lineal simple aplicada a la muestra (500.000 observaciones) ofrece mejor ajuste que las técnicas Ridge, Lasso y polinomial de grado 3