Setup

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
import statsmodels.api as sm

from sklearn.decomposition import PCA
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler


data = pd.read_csv('https://raw.githubusercontent.com/Rwyld/Data-Science-Models/main/Modelos/PCA/HousePriceCSV.csv', sep = ';')

data = data.set_index('Id')
display(data.head(3))
```

	LotFrontage	LotArea	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	TotalBsmt
Id							
1	65.0	8450	196.0	706	0	150	8
2	80.0	9600	0.0	978	0	284	12
3	68.0	11250	162.0	486	0	434	9

Analisis Estadistico

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1460 entries, 1 to 1460
Data columns (total 20 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   LotFrontage    1201 non-null   float64
 1   LotArea        1460 non-null   int64
 2   MasVnrArea     1452 non-null   float64
 3   BsmtFinSF1     1460 non-null   int64
 4   BsmtFinSF2     1460 non-null   int64
 5   BsmtUnfSF      1460 non-null   int64
 6   TotalBsmtSF    1460 non-null   int64
 7   1stFlrSF       1460 non-null   int64
 8   2ndFlrSF       1460 non-null   int64
 9   LowQualFinSF   1460 non-null   int64
 10  GrLivArea      1460 non-null   int64
 11  GarageArea     1460 non-null   int64
 12  WoodDeckSF     1460 non-null   int64
 13  OpenPorchSF    1460 non-null   int64
 14  EnclosedPorch  1460 non-null   int64
 15  3SsnPorch      1460 non-null   int64
 16  ScreenPorch    1460 non-null   int64
 17  PoolArea       1460 non-null   int64
 18  MiscVal        1460 non-null   int64
 19  SalePrice      1460 non-null   int64
dtypes: float64(2), int64(18)
memory usage: 239.5 KB
```

```
data.isna().sum()
```

```
LotFrontage      259
LotArea            0
MasVnrArea         8
BsmtFinSF1         0
BsmtFinSF2         0
```

```
BsmtUnfSF          0
TotalBsmtSF        0
1stFlrSF           0
2ndFlrSF           0
LowQualFinSF       0
GrLivArea          0
GarageArea         0
WoodDeckSF         0
OpenPorchSF        0
EnclosedPorch      0
3SsnPorch          0
ScreenPorch        0
PoolArea           0
MiscVal            0
SalePrice          0
dtype: int64
```

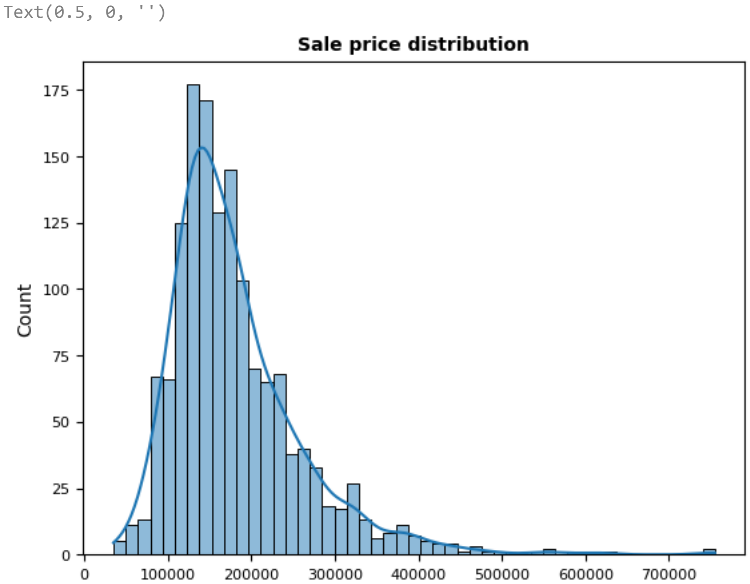
```
# Rellenando datos faltantes
data['LotFrontage'].fillna(data['LotFrontage'].mean(), inplace=True)
data['MasVnrArea'].fillna(data['MasVnrArea'].mean(), inplace=True)
```

```
data.describe()
```

	LotFrontage	LotArea	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfS
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.00000
mean	70.049958	10516.828082	103.685262	443.639726	46.549315	567.24041
std	22.024023	9981.264932	180.569112	456.098091	161.319273	441.86695
min	21.000000	1300.000000	0.000000	0.000000	0.000000	0.00000
25%	60.000000	7553.500000	0.000000	0.000000	0.000000	223.00000
50%	70.049958	9478.500000	0.000000	383.500000	0.000000	477.50000
75%	79.000000	11601.500000	164.250000	712.250000	0.000000	808.00000
max	313.000000	215245.000000	1600.000000	5644.000000	1474.000000	2336.00000

```
ax = sns.histplot(data = data, x = data.SalePrice, stat = 'count', kde = True, alpha = 0.5)
ax.set_title('Sale price distribution', fontsize = 10, fontweight = "bold")
ax.tick_params(labelsize = 8)
ax.set_xlabel("")
```

```
Text(0.5, 0, '')
```

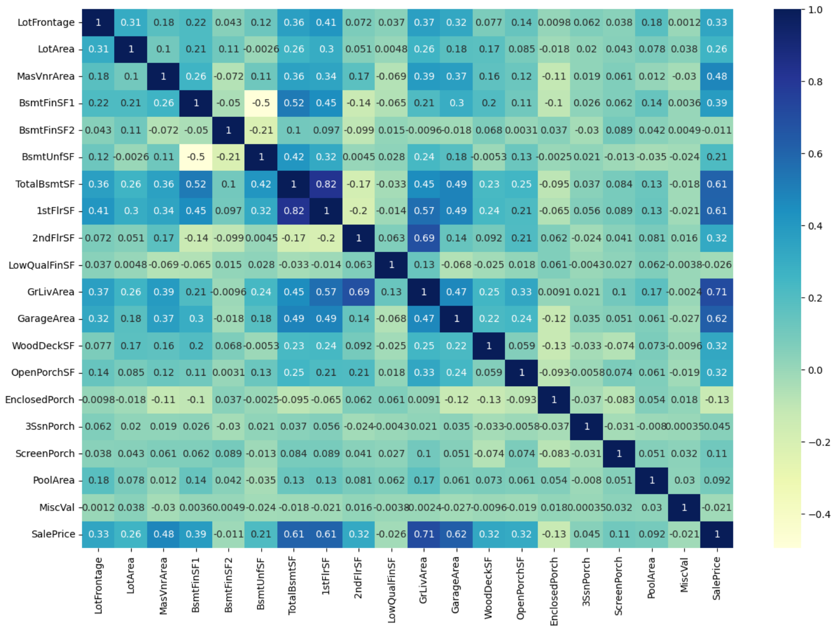


Correlacion

```
corr = data.corr()

fig, ax = plt.subplots(1,1, figsize = (15,10))

ax = sns.heatmap(corr, annot=True, cmap="YlGnBu")
```



Segun el analisis de correlacion, los datos cercanos a 1 (Colores cercanos a azul), son candidatos a estar correlacionadas entre si. Esto es porque tienen similitudes entre si, ya que podria representar una caracteristica en concreto, en este contexto, por ejemplo las variables relacionadas al subterraneo, tienen significados similares.

Modelo Regresion Linear

```
from datetime import datetime
start=datetime.now()

X = data.drop('SalePrice', axis = 1)
y = data['SalePrice']
```

```
modelo = LinearRegression()
modelo.fit(X, y)

print(datetime.now()-start)
```

```
0:00:00.011002
```

Estandarizando

```
# data = pd.DataFrame(StandardScaler().fit_transform(X))
```

```
pca_pipe = make_pipeline(StandardScaler(), PCA())
pca_pipe.fit(data)
```

Pipeline

StandardScaler

PCA

```
modelo_pca = pca_pipe.named_steps['pca']

df = pd.DataFrame(
    data    = modelo_pca.components_,
    columns = data.columns,
    index   = [f"PC{num + 1}" for num in range(data.shape[1])]
)

df.head()
```

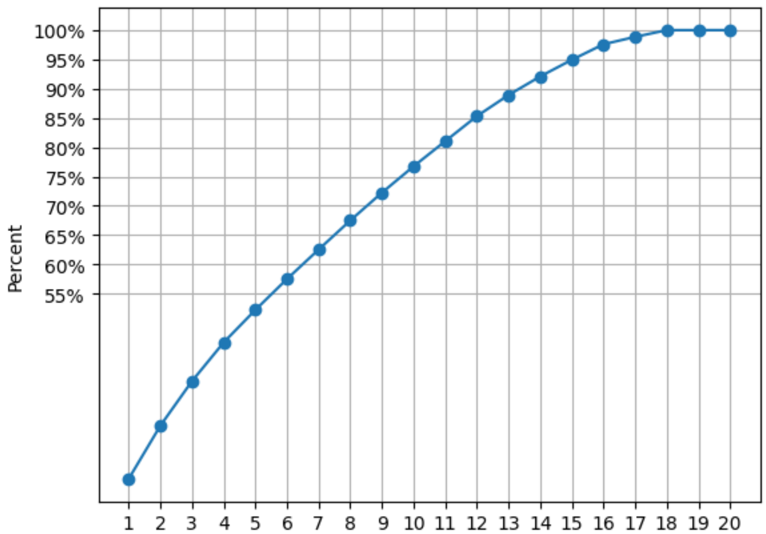
	LotFrontage	LotArea	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	TotalB
PC1	0.245063	0.186298	0.255050	0.232062	0.012145	0.127703	0.3
PC2	-0.033619	-0.108291	0.054309	-0.424484	-0.198500	0.279130	-0.2
PC3	0.012554	0.158542	0.003850	0.348923	0.176845	-0.673187	-0.2
PC4	0.310552	0.252435	-0.304420	-0.169810	0.353251	0.133832	0.0
PC5	-0.148264	-0.098592	-0.013430	-0.099964	0.311122	0.024195	0.0

```
modelo_pca.explained_variance_ratio_
```

```
array([2.33552337e-01, 9.07728573e-02, 7.61633843e-02, 6.60348209e-02,
       5.55115981e-02, 5.28263180e-02, 5.03510776e-02, 4.96412703e-02,
       4.75137423e-02, 4.49883063e-02, 4.29137427e-02, 4.28163245e-02,
       3.60624993e-02, 3.16984500e-02, 2.84566613e-02, 2.65278147e-02,
       1.26313924e-02, 1.15374032e-02, 6.85571648e-33, 1.50832168e-33])
```

```
plt.plot(
    range(1, len(modelo_pca.components_) + 1),
    np.cumsum(modelo_pca.explained_variance_ratio_),
    marker = "o"
)
plt.xticks(
    ticks = np.arange(data.shape[1]) + 1,
)
plt.yticks(
    ticks  = np.linspace(0.55, 1, 10),
    labels = [f"{val:0.0%}" for val in np.linspace(0.55, 1, 10)]
);

plt.ylabel('Percent')
plt.xlabel('PCA')
plt.grid()
```



Se deberian escoger 11 PCA, para explicar un 80% de variabilidad, ya que es la suma acumulativa del porcentaje entre el PCA 1 hasta el PCA 11.

```
newData = pca_pipe.transform(data)

proyecciones = pd.DataFrame(
    newData,
    columns = [f"PC{num + 1}" for num in range(data.shape[1])],
    index   = data.index
)
proyecciones.head(3)
```

Id	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
1	-0.012053	0.794548	1.321619	-1.070734	-0.019385	0.577184	-0.273209	-0.13487
2	0.283746	-1.751354	0.441835	-0.473166	-0.783488	-0.537486	-0.061290	-0.08108

```
modelData = proyecciones.iloc[:, 0:11]
modelData.head(3)
```

Id	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	
1	-0.012053	0.794548	1.321619	-1.070734	-0.019385	0.577184	-0.273209	-0.134874	-0.3
2	0.283746	-1.751354	0.441835	-0.473166	-0.783488	-0.537486	-0.061290	-0.081084	0.8
3	0.282812	1.104295	0.712858	-0.744898	-0.081347	0.359642	-0.032450	-0.015419	-0.3

```
from datetime import datetime
start=datetime.now()

X = modelData

modelo = LinearRegression()
modelo.fit(X, y)

print(datetime.now()-start)
```

```
0:00:00.006324
```

Interpretando

Comparando ambos tiempos de demora obtenidos en los modelos, el que tardo menos tiempo en procesar, fue el que uso como variables predictoras los componentes principales en el modelo de Regresion Linear.

El usar componentes principales, se obtiene un procesamiento mas rapido y como su seleccion es un porcentaje de variabilidad alto, en este caso un 80%, se podria considerarse significativo para el conjunto de datos.