Práctica 10: Datos Multivariados

- Martínez Ostoa Néstor Iván
- Visualización de la Información
- LCD, IIMAS, UNAM

1. Exploración de Datos

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.graph_objects as go
import plotly.express as px
from plotly.subplots import make_subplots
# ------------------------------------------
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
```

In [2]:

```
train_df = pd.read_csv('train.csv')
train_df.head()
```

Out[2]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	U
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	

5 rows × 81 columns

In [3]:

```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1459 entries, 0 to 1458
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1459 non-null   int64
 1   MSSubClass     1459 non-null   int64
 2   MSZoning       1459 non-null   object
 3   LotFrontage    1200 non-null   float64
 4   LotArea        1459 non-null   int64
```

```
 5   Street         1459 non-null   object
 6   Alley          91 non-null     object
 7   LotShape       1459 non-null   object
 8   LandContour    1459 non-null   object
 9   Utilities      1459 non-null   object
 10  LotConfig      1459 non-null   object
 11  LandSlope      1459 non-null   object
 12  Neighborhood   1459 non-null   object
 13  Condition1     1459 non-null   object
 14  Condition2     1459 non-null   object
 15  BldgType       1459 non-null   object
 16  HouseStyle     1459 non-null   object
 17  OverallQual    1459 non-null   int64
 18  OverallCond    1459 non-null   int64
 19  YearBuilt      1459 non-null   int64
 20  YearRemodAdd   1459 non-null   int64
 21  RoofStyle      1459 non-null   object
 22  RoofMatl       1459 non-null   object
 23  Exterior1st    1459 non-null   object
 24  Exterior2nd    1459 non-null   object
 25  MasVnrType     1451 non-null   object
 26  MasVnrArea     1451 non-null   float64
 27  ExterQual      1459 non-null   object
 28  ExterCond      1459 non-null   object
 29  Foundation     1459 non-null   object
 30  BsmtQual       1422 non-null   object
 31  BsmtCond       1422 non-null   object
 32  BsmtExposure   1421 non-null   object
 33  BsmtFinType1   1422 non-null   object
 34  BsmtFinSF1     1459 non-null   int64
 35  BsmtFinType2   1421 non-null   object
 36  BsmtFinSF2     1459 non-null   int64
 37  BsmtUnfSF      1459 non-null   int64
 38  TotalBsmtSF    1459 non-null   int64
 39  Heating        1459 non-null   object
 40  HeatingQC      1459 non-null   object
 41  CentralAir     1459 non-null   object
 42  Electrical     1458 non-null   object
 43  1stFlrSF       1459 non-null   int64
 44  2ndFlrSF       1459 non-null   int64
 45  LowQualFinSF   1459 non-null   int64
 46  GrLivArea      1459 non-null   int64
 47  BsmtFullBath   1459 non-null   int64
 48  BsmtHalfBath   1459 non-null   int64
 49  FullBath       1459 non-null   int64
 50  HalfBath       1459 non-null   int64
 51  BedroomAbvGr   1459 non-null   int64
 52  KitchenAbvGr   1459 non-null   int64
 53  KitchenQual    1459 non-null   object
 54  TotRmsAbvGrd   1459 non-null   int64
 55  Functional     1459 non-null   object
 56  Fireplaces     1459 non-null   int64
 57  FireplaceQu    770 non-null    object
 58  GarageType     1378 non-null   object
 59  GarageYrBlt    1378 non-null   float64
 60  GarageFinish   1378 non-null   object
 61  GarageCars     1459 non-null   int64
 62  GarageArea     1459 non-null   int64
 63  GarageQual     1378 non-null   object
 64  GarageCond     1378 non-null   object
```

```
 65  PavedDrive     1459 non-null   object
 66  WoodDeckSF     1459 non-null   int64
 67  OpenPorchSF    1459 non-null   int64
 68  EnclosedPorch  1459 non-null   int64
 69  3SsnPorch      1459 non-null   int64
 70  ScreenPorch    1459 non-null   int64
 71  PoolArea       1459 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          281 non-null    object
 74  MiscFeature    54 non-null     object
 75  MiscVal        1459 non-null   int64
 76  MoSold         1459 non-null   int64
 77  YrSold         1459 non-null   int64
 78  SaleType       1459 non-null   object
 79  SaleCondition  1459 non-null   object
 80  SalePrice      1459 non-null   int64
dtypes: float64(3), int64(35), object(43)
```

In [4]:

```
null_count = [train_df[c].isna().sum() for c in train_df.columns]
temp_df = pd.DataFrame(data={'Column name':train_df.columns, 'Number of null
temp_df = temp_df.sort_values(by='Number of null values')
temp_df = temp_df[temp_df['Number of null values'] > 0]
```

In [5]:

```
temp_df.head()
```

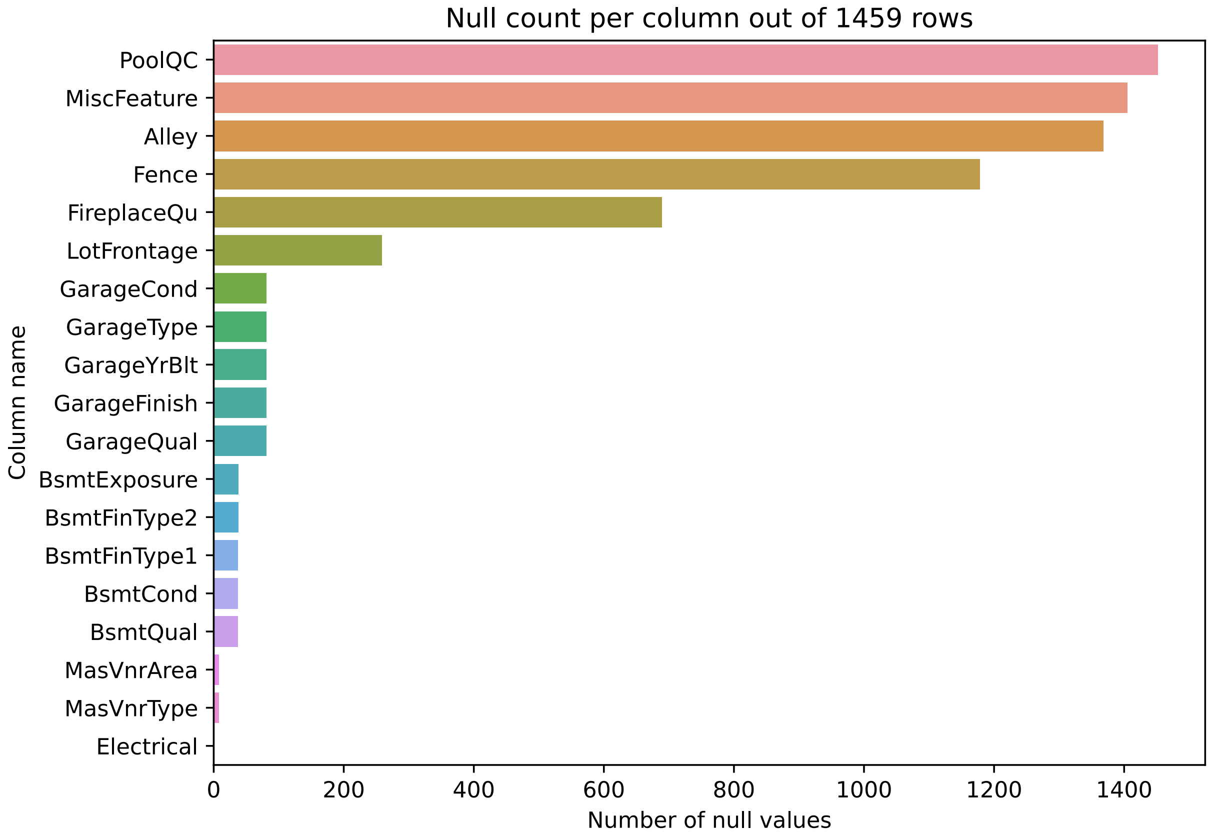
Out[5]:

	Column name	Number of null values
42	Electrical	1
25	MasVnrType	8
26	MasVnrArea	8
30	BsmtQual	37
31	BsmtCond	37

1.1 Valores faltantes?

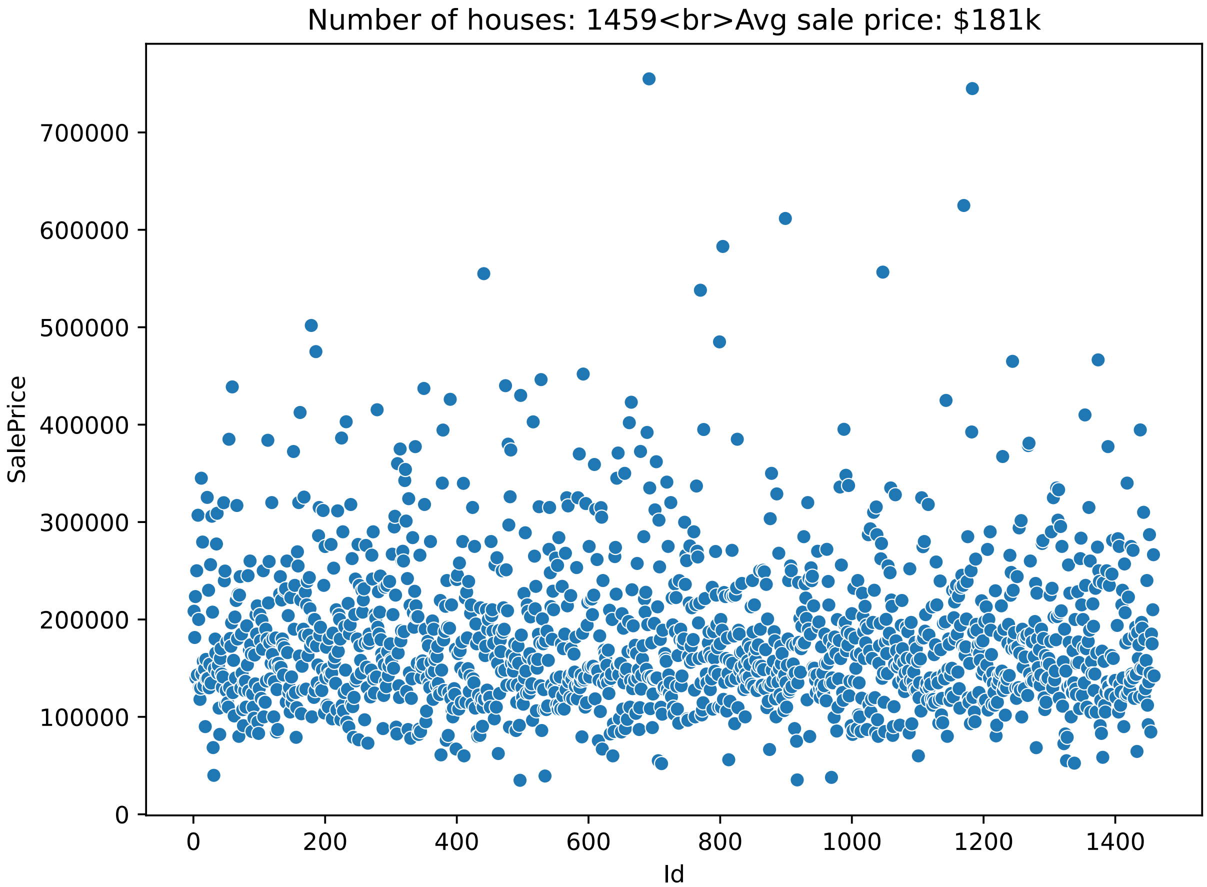
In [6]:

```
f, ax = plt.subplots(figsize=(8, 6))
sns.barplot(
    x="Number of null values", y="Column name",
    data=temp_df[::-1]
).set(
    title=f'Null count per column out of {train_df.shape[0]} rows'
)
plt.show()
```



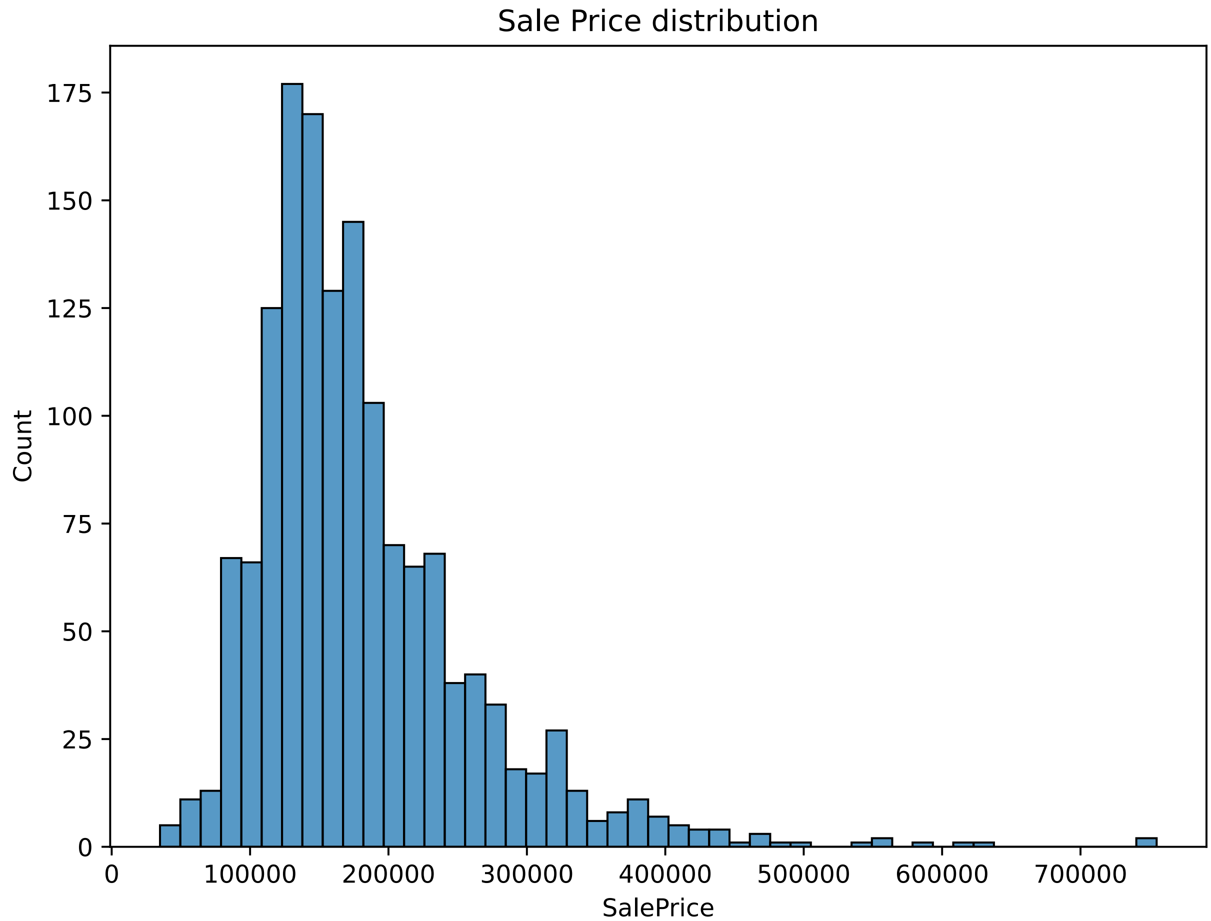
In [7]:

```
f, ax = plt.subplots(figsize=(8, 6))
sns.scatterplot(
    data=train_df, x="Id", y="SalePrice"
).set(
    title=f"Number of houses: {train_df.shape[0]}<br>Avg sale price: ${round(
)
plt.show()
```



In [8]:

```
f, ax = plt.subplots(figsize=(8, 6))
sns.histplot(data=train_df, x='SalePrice').set(
    title="Sale Price distribution"
)
plt.show()
```



2. Limpieza de datos

2.1 Reemplazo de `nan`

In [9]:

```
nan_replacements = dict.fromkeys(temp_df['Column name'])
nan_replacements["PoolQC"] = "No Pool"
nan_replacements["MiscFeature"] = "None"
nan_replacements["Alley"] = "No Alley"
nan_replacements["Fence"] = "No Fence"
nan_replacements["FireplaceQu"] = "No Fireplace"
nan_replacements["LotFrontage"] = 0
nan_replacements["GarageCond"] = "No Garage"
nan_replacements["GarageType"] = "No Garage"
#--------
#nan_replacements["GarageYrBlt"] <- year 0 would be incorrect, thus, this rem
nan_replacements.pop("GarageYrBlt")
#--------
nan_replacements["GarageFinish"] = "No Garage"
nan_replacements["GarageQual"] = "No Garage"
nan_replacements["BsmtExposure"] = "No Basement"
nan_replacements["BsmtFinType2"] = "No Basement"
nan_replacements["BsmtFinType1"] = "No Basement"
nan_replacements["BsmtCond"] = "No Basement"
nan_replacements["BsmtQual"] = "No Basement"
nan_replacements["MasVnrArea"] = 0
nan_replacements["MasVnrType"] = "None"
nan_replacements["Electrical"] = train_df["Electrical"].mode().values[0] #mos
#--------
train_df = train_df.fillna(value=nan_replacements)
```

2.2 Reemplazo de nombres

In [10]:

```
train_df.replace(
    {
        'MSZoning': {'C (all)': 'C'},
        'Exterior2nd': {'Brk Cmn': 'BrkComm'}
    },
    inplace=True
)
print(train_df["MSZoning"].unique())
print(train_df["Exterior2nd"].unique())
```

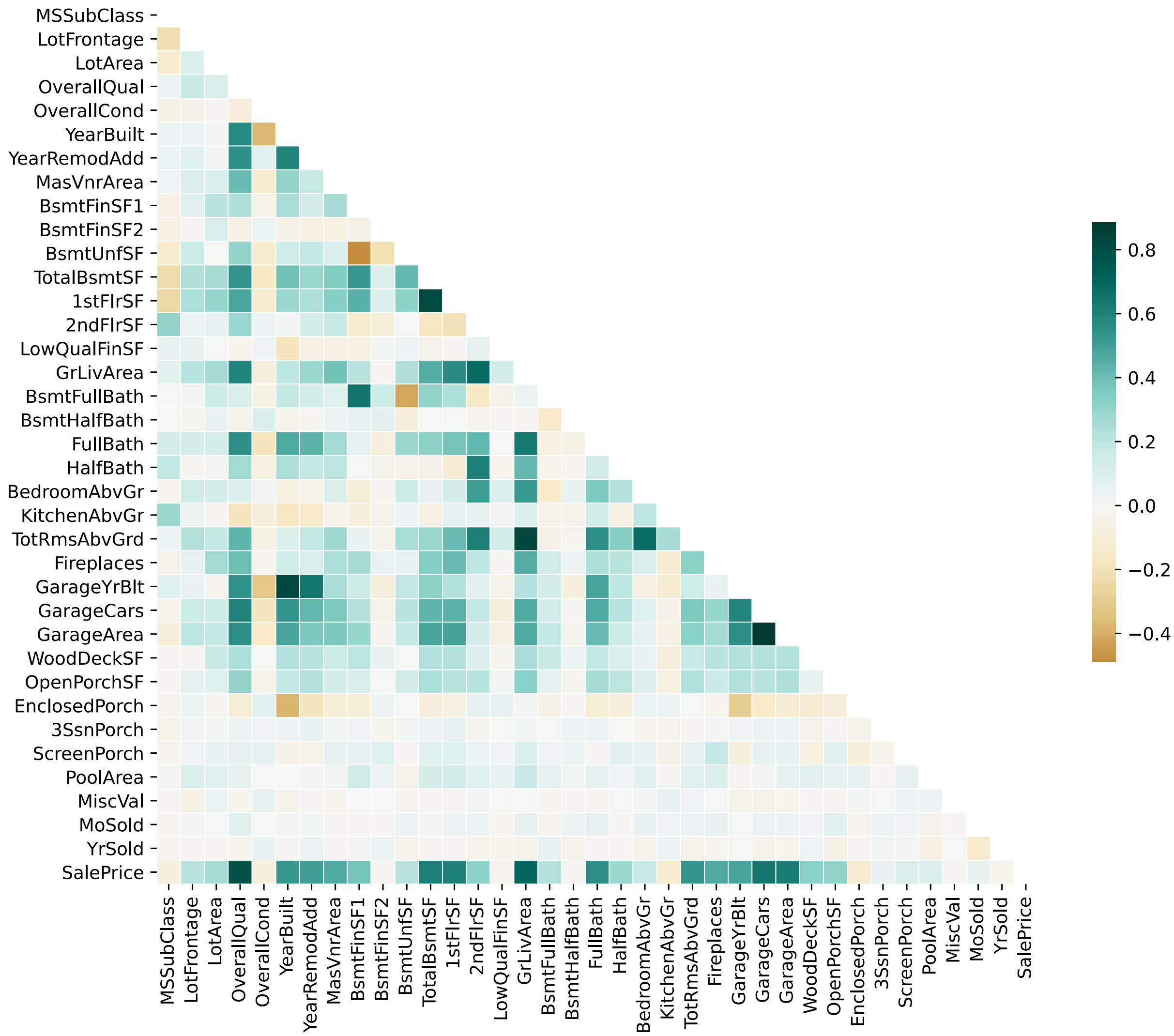
```
['RL' 'RM' 'C' 'FV' 'RH']
['VinylSd' 'MetalSd' 'Wd Shng' 'HdBoard' 'Plywood' 'Wd Sdng' 'CmentBd'
 'BrkFace' 'Stucco' 'AsbShng' 'BrkComm' 'ImStucc' 'AsphShn' 'Stone'
 'Other' 'CBlock']
```

3. Selección de características relevantes por medio de análisis de correlación

3.1 Matriz de correlación

In [11]:

```
corr = train_df.iloc[:, 1:].corr(method='pearson') #Removing ID
mask = np.triu(np.ones_like(corr, dtype=bool))
f, ax = plt.subplots(figsize=(11, 9))
sns.heatmap(corr, mask=mask, cmap="BrBG", center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
plt.show()
```



3.2 Filtrando por coeficiente de correlación de Pearson

Obtenemos aquellas variables que tengan un coeficiente de correlación de Pearson mayor a 0.3 con respecto a la variable `SalePrice`

In [12]:

```
top_correlated = corr[corr["SalePrice"] > 0.2].loc[:, "SalePrice"].to_frame()
top_correlated_columns = top_correlated.index.values
print(f"Number of variables: {top_correlated.shape[0]}\n")
print(top_correlated_columns)
top_correlated
```

```
Number of variables: 23

['LotFrontage' 'LotArea' 'OverallQual' 'YearBuilt' 'YearRemodAdd'
```

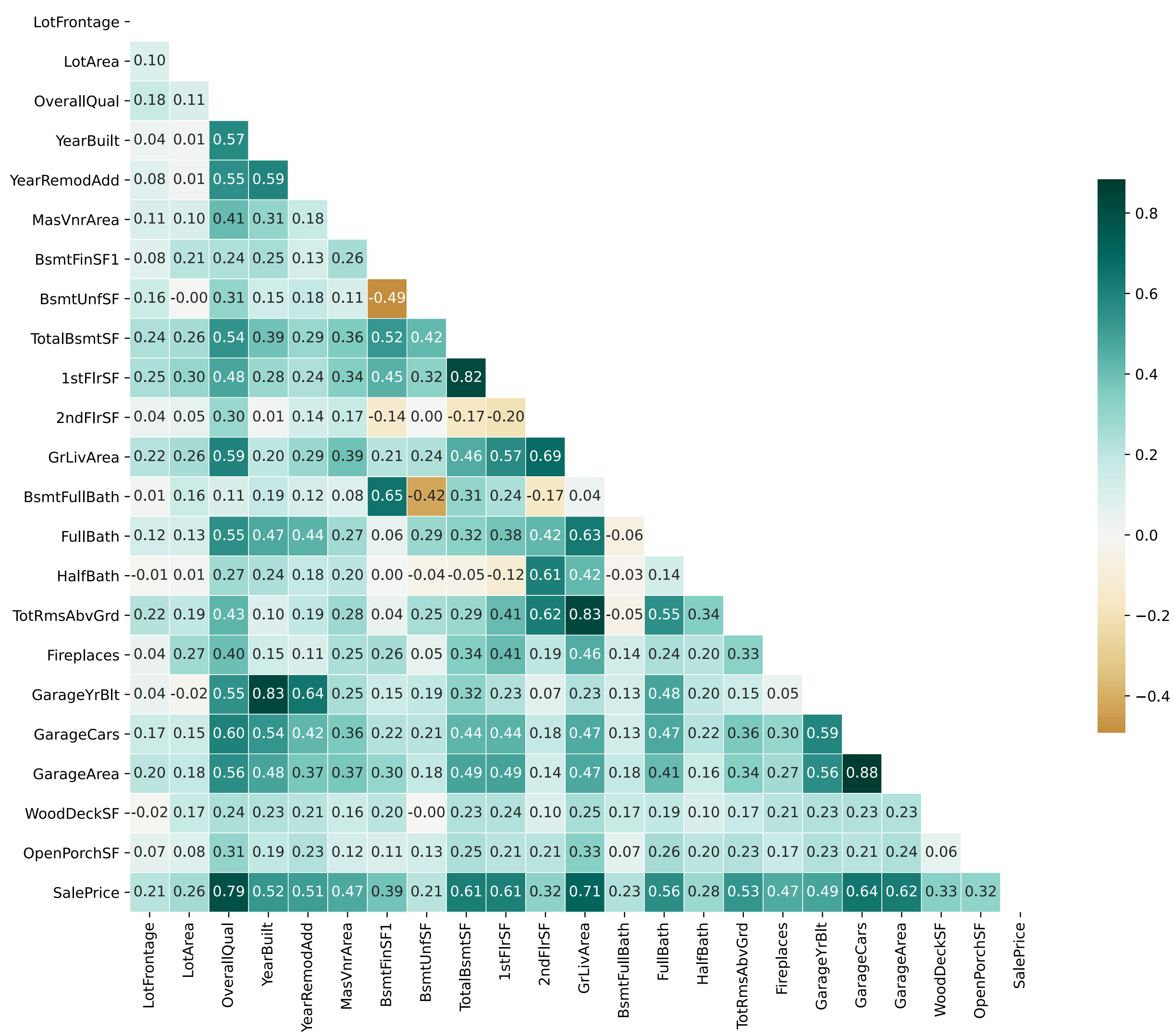
```
'MasVnrArea' 'BsmtFinSF1' 'BsmtUnfSF' 'TotalBsmtSF' '1stFlrSF' '2ndFlrSF'
'GrLivArea' 'BsmtFullBath' 'FullBath' 'HalfBath' 'TotRmsAbvGrd'
'Fireplaces' 'GarageYrBlt' 'GarageCars' 'GarageArea' 'WoodDeckSF'
'OpenPorchSF' 'SalePrice']
```

Out[12]:

	SalePrice
LotFrontage	0.209799
LotArea	0.263843
OverallQual	0.790972
YearBuilt	0.522877
YearRemodAdd	0.507015
MasVnrArea	0.472531
BsmtFinSF1	0.386783
BsmtUnfSF	0.214281
TotalBsmtSF	0.613792
1stFlrSF	0.605971
2ndFlrSF	0.319193
GrLivArea	0.708584
BsmtFullBath	0.227551
FullBath	0.560604
HalfBath	0.284626
TotRmsAbvGrd	0.533682
Fireplaces	0.466828
GarageYrBlt	0.486264
GarageCars	0.640383
GarageArea	0.623385
WoodDeckSF	0.328881
OpenPorchSF	0.315980
SalePrice	1.000000

In [13]:

```
corr = train_df[top_correlated_columns].iloc[:, :].corr(method='pearson')
mask = np.triu(np.ones_like(corr, dtype=bool))
f, ax = plt.subplots(figsize=(14, 14))
sns.heatmap(corr, mask=mask, cmap="BrBG", center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5},
            annot=True, fmt='.2f')
plt.show()
```



Columnas a borrar debido a una alta correlación con otra columna:

- `1stFlrSF`
- `TotRmsAbvGrd`
- `GarageYrBlt`
- `GarageCars`

In [14]:
```
cols_to_delete = ["1stFlrSF", "TotRmsAbvGrd", "GarageYrBlt", "GarageCars"]
top_correlated_columns = np.array([c for c in top_correlated_columns if c not
top_correlated_columns
```

Out[14]:
```
array(['LotFrontage', 'LotArea', 'OverallQual', 'YearBuilt',
       'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1', 'BsmtUnfSF',
       'TotalBsmtSF', '2ndFlrSF', 'GrLivArea', 'BsmtFullBath', 'FullBath',
       'HalfBath', 'Fireplaces', 'GarageArea', 'WoodDeckSF',
       'OpenPorchSF', 'SalePrice'], dtype='<U12')
```

3.3 Gráficos con las características seleccionadas

In [15]:
```
fig = make_subplots(rows=5, cols=4, subplot_titles=top_correlated_columns[:-1
row, col = 1,1
for c in top_correlated_columns[:-1]:
    fig.add_trace(
        go.Scatter(
            y=train_df[top_correlated_columns]['SalePrice'], x=train_df[top_c
            showlegend=False, mode='markers'
        ),
        row = row, col = col
    )
    if col < 4:
        col += 1
    else:
        row += 1
        col = 1
fig.update_layout(height=900, width=1000, title_text="Top Correlated Colums v
fig.show()
```

In [16]:
```
train_df[top_correlated_columns].describe()
```

Out[16]:

	LotFrontage	LotArea	OverallQual	YearBuilt	YearRemodAdd	MasVnrArea
count	1459.000000	1459.000000	1459.000000	1459.000000	1459.000000	1459.000000
mean	57.611378	10517.225497	6.100069	1971.272104	1984.879369	103.187800
std	34.673201	9984.675721	1.383171	30.212814	20.645927	180.773158
min	0.000000	1300.000000	1.000000	1872.000000	1950.000000	0.000000
25%	42.000000	7549.000000	5.000000	1954.000000	1967.000000	0.000000
50%	63.000000	9477.000000	6.000000	1973.000000	1994.000000	0.000000
75%	79.000000	11603.000000	7.000000	2000.000000	2004.000000	164.500000
max	313.000000	215245.000000	10.000000	2010.000000	2010.000000	1600.000000

3.4 Distribución de las variables

In [17]:
```
train_df = train_df[top_correlated_columns]
```

In [18]:
```
fig = make_subplots(rows=5, cols=4, subplot_titles=top_correlated_columns)
row, col = 1,1
for c in top_correlated_columns:
    fig.add_trace(
        go.Histogram(
            x = train_df[c], showlegend=False
        ),
        row = row, col = col
    )
    if col < 4:
        col += 1
    else:
        row += 1
        col = 1
fig.update_layout(height=900, width=1000, title_text="Distribution for top co
fig.show()
```

4. Estimación del precio de las casas

In [19]:
```
test_df = pd.read_csv('test.csv')
house_ids = test_df['Id']
test_df = test_df[top_correlated_columns[:-1]]
print(test_df.shape)
test_df.head()
```

```
(1459, 18)
```

Out[19]:

	LotFrontage	LotArea	OverallQual	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	Bsm
0	80.0	11622	5	1961	1961	0.0	468.0	
1	81.0	14267	6	1958	1958	108.0	923.0	
2	74.0	13830	5	1997	1998	0.0	791.0	
3	78.0	9978	6	1998	1998	20.0	602.0	
4	43.0	5005	8	1992	1992	0.0	263.0	

In [20]:
```
train_target_label = train_df["SalePrice"]
training_sample_df = train_df[top_correlated_columns[:-1]]
test_sample_df = test_df[top_correlated_columns[:-1]]
```

In [21]:
```
training_sample_df.head()
```

Out[21]:

	LotFrontage	LotArea	OverallQual	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	Bsm
0	65.0	8450	7	2003	2003	196.0	706	
1	80.0	9600	6	1976	1976	0.0	978	
2	68.0	11250	7	2001	2002	162.0	486	
3	60.0	9550	7	1915	1970	0.0	216	

LotFrontage	LotArea	OverallQual	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	Bsm

In [22]:
```
test_sample_df.head()
```

Out[22]:

	LotFrontage	LotArea	OverallQual	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	Bsm
0	80.0	11622	5	1961	1961	0.0	468.0	
1	81.0	14267	6	1958	1958	108.0	923.0	
2	74.0	13830	5	1997	1998	0.0	791.0	
3	78.0	9978	6	1998	1998	20.0	602.0	
4	43.0	5005	8	1992	1992	0.0	263.0	

In [23]:
```
print(training_sample_df.shape)
print(test_sample_df.shape)
```

```
(1459, 18)
(1459, 18)
```

4.1 Imputación por la mediana

In [24]:
```
imputer = SimpleImputer(strategy='median')
training_sample_df = imputer.fit_transform(training_sample_df)
test_sample_df = imputer.fit_transform(test_sample_df)
```

4.2 Estandarización

In [25]:
```
scaler = StandardScaler()
training_sample_df = scaler.fit_transform(training_sample_df)
test_sample_df = scaler.fit_transform(test_sample_df)
```

4.3 Regresión Lineal

In [26]:
```
X_train_split, X_test_split, y_train, y_test = train_test_split(
    training_sample_df, train_target_label, random_state=42,
    train_size=0.8
)
print(X_train_split.shape, X_test_split.shape, training_sample_df.shape, test
```

```
(1167, 18) (292, 18) (1459, 18) (1459, 18)
```

In [27]:
```
model = LinearRegression()
model.fit(X_train_split, y_train)
model.fit(training_sample_df, train_target_label)
LinearRegression(copy_X = True, fit_intercept=True, n_jobs=None, normalize=Fa
```

Out[27]:
```
LinearRegression()
```

4.4 Evaluación del modelo

In [28]:
```
print(f"Intercept: {model.intercept_}\n")
print(f"Slope (coefficient of x): \n{model.coef_}")
```

```
Intercept: 180944.10281014396

Slope (coefficient of x):
[ 1.41994338e+03  4.66797585e+03  2.72831589e+04  5.98969793e+03
  7.21555479e+03  5.66596916e+03  3.98459229e+03 -1.00520111e+03
  5.27527054e+03 -2.62166395e+03  2.49189398e+04  3.19590884e+03
  1.63465402e+02  7.36171748e+00  4.75238559e+03  7.74015453e+03
  3.46252974e+03  2.71022716e+02]
```

In [29]:
```
print(f"Regression score: \n{model.score(training_sample_df, train_target_lab
print(f"Train_target_label: \n{train_target_label}")
```

```
Regression score:
0.7937088330392428

Train_target_label:
0       208500
1       181500
2       223500
3       140000
4       250000
         ...
1454    185000
1455    175000
1456    210000
1457    266500
1458    142125
Name: SalePrice, Length: 1459, dtype: int64
```

4.5 Predicciones

In [30]:
```
y_pred = model.predict(X_test_split)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print(f"Root Mean Squared Error: \n{rmse}")
```

```
Root Mean Squared Error:
26793.771698019907
```

In [31]:
```
pred_on_test = model.predict(test_sample_df)
print(f"Regression score: \n{abs(model.score(test_sample_df, train_target_lab
```

```
Regression score:
0.8067995477908481
```

In [32]:
```
house_predictions_df = pd.DataFrame()
house_predictions_df['House Id'] = house_ids
house_predictions_df['Predicted Sale Price'] = pred_on_test
house_predictions_df
```

Out[32]:

	House Id	Predicted Sale Price
0	1461	123875.600898
1	1462	170602.799580
2	1463	183109.126906
3	1464	199931.669615
4	1465	198543.357673
...	...	...
1454	2915	64615.312872
1455	2916	77662.953307
1456	2917	194140.012993
1457	2918	112977.469295
1458	2919	240893.679225

1459 rows × 2 columns

In [ ]: