Proyecto 1 IA

November 5, 2020

1 Lectura de la base de datos

[1]:
```
import pandas as pd
```

[2]:
```
train = pd.read_csv("train.csv", index_col="Id")
test = pd.read_csv("test.csv", index_col="Id")
ample_submission = pd.read_csv("sample_submission.csv", index_col="Id")
train.fillna(0,inplace=True)
test.fillna(0,inplace=True)
```

[3]:
```
train.head()
```

[3]:
```
    MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
Id
1           60       RL         65.0     8450   Pave     0      Reg
2           20       RL         80.0     9600   Pave     0      Reg
3           60       RL         68.0    11250   Pave     0      IR1
4           70       RL         60.0     9550   Pave     0      IR1
5           60       RL         84.0    14260   Pave     0      IR1

   LandContour Utilities LotConfig  ... PoolArea PoolQC Fence MiscFeature  \
Id                                  ...
1          Lvl    AllPub    Inside  ...        0      0     0           0
2          Lvl    AllPub       FR2  ...        0      0     0           0
3          Lvl    AllPub    Inside  ...        0      0     0           0
4          Lvl    AllPub    Corner  ...        0      0     0           0
5          Lvl    AllPub       FR2  ...        0      0     0           0

   MiscVal MoSold  YrSold  SaleType  SaleCondition  SalePrice
Id
1        0      2    2008        WD         Normal     208500
2        0      5    2007        WD         Normal     181500
3        0      9    2008        WD         Normal     223500
4        0      2    2006        WD        Abnorml     140000
5        0     12    2008        WD         Normal     250000

[5 rows x 80 columns]
```

2 Revisión de la lectura de los datos

Es importante revisar que el tipo de dato de cada variable sea el adecuado y si no, definirlo de forma correcta. También debe verificarse que las celdas no contengan NaN

[4]:
```
print(train.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1460 entries, 1 to 1460
Data columns (total 80 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   MSSubClass     1460 non-null   int64
 1   MSZoning       1460 non-null   object
 2   LotFrontage    1460 non-null   float64
 3   LotArea        1460 non-null   int64
 4   Street         1460 non-null   object
 5   Alley          1460 non-null   object
 6   LotShape       1460 non-null   object
 7   LandContour    1460 non-null   object
 8   Utilities      1460 non-null   object
 9   LotConfig      1460 non-null   object
 10  LandSlope      1460 non-null   object
 11  Neighborhood   1460 non-null   object
 12  Condition1     1460 non-null   object
 13  Condition2     1460 non-null   object
 14  BldgType       1460 non-null   object
 15  HouseStyle     1460 non-null   object
 16  OverallQual    1460 non-null   int64
 17  OverallCond    1460 non-null   int64
 18  YearBuilt      1460 non-null   int64
 19  YearRemodAdd   1460 non-null   int64
 20  RoofStyle      1460 non-null   object
 21  RoofMatl       1460 non-null   object
 22  Exterior1st    1460 non-null   object
 23  Exterior2nd    1460 non-null   object
 24  MasVnrType     1460 non-null   object
 25  MasVnrArea     1460 non-null   float64
 26  ExterQual      1460 non-null   object
 27  ExterCond      1460 non-null   object
 28  Foundation     1460 non-null   object
 29  BsmtQual       1460 non-null   object
 30  BsmtCond       1460 non-null   object
 31  BsmtExposure   1460 non-null   object
 32  BsmtFinType1   1460 non-null   object
 33  BsmtFinSF1     1460 non-null   int64
 34  BsmtFinType2   1460 non-null   object
 35  BsmtFinSF2     1460 non-null   int64
```

```
 36  BsmtUnfSF      1460 non-null   int64
 37  TotalBsmtSF    1460 non-null   int64
 38  Heating        1460 non-null   object
 39  HeatingQC      1460 non-null   object
 40  CentralAir     1460 non-null   object
 41  Electrical     1460 non-null   object
 42  1stFlrSF       1460 non-null   int64
 43  2ndFlrSF       1460 non-null   int64
 44  LowQualFinSF   1460 non-null   int64
 45  GrLivArea      1460 non-null   int64
 46  BsmtFullBath   1460 non-null   int64
 47  BsmtHalfBath   1460 non-null   int64
 48  FullBath       1460 non-null   int64
 49  HalfBath       1460 non-null   int64
 50  BedroomAbvGr   1460 non-null   int64
 51  KitchenAbvGr   1460 non-null   int64
 52  KitchenQual    1460 non-null   object
 53  TotRmsAbvGrd   1460 non-null   int64
 54  Functional     1460 non-null   object
 55  Fireplaces     1460 non-null   int64
 56  FireplaceQu    1460 non-null   object
 57  GarageType     1460 non-null   object
 58  GarageYrBlt    1460 non-null   float64
 59  GarageFinish   1460 non-null   object
 60  GarageCars     1460 non-null   int64
 61  GarageArea     1460 non-null   int64
 62  GarageQual     1460 non-null   object
 63  GarageCond     1460 non-null   object
 64  PavedDrive     1460 non-null   object
 65  WoodDeckSF     1460 non-null   int64
 66  OpenPorchSF    1460 non-null   int64
 67  EnclosedPorch  1460 non-null   int64
 68  3SsnPorch      1460 non-null   int64
 69  ScreenPorch    1460 non-null   int64
 70  PoolArea       1460 non-null   int64
 71  PoolQC         1460 non-null   object
 72  Fence          1460 non-null   object
 73  MiscFeature    1460 non-null   object
 74  MiscVal        1460 non-null   int64
 75  MoSold         1460 non-null   int64
 76  YrSold         1460 non-null   int64
 77  SaleType       1460 non-null   object
 78  SaleCondition  1460 non-null   object
 79  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(34), object(43)
memory usage: 923.9+ KB
None
```

2.1 Var 00 MSSubClass

Por definición de los datos la variable MSSubClass aunque toma valores enteros realmente es una variable categórica, pues indica el tipo de vivienda involucrada en la venta, por lo tanto, debe trabajarse como variable catégorica y no numérica.

[5]:
```
train['MSSubClass'] = train['MSSubClass'].astype('category')
print(train['MSSubClass'].dtype)
print(train['MSSubClass'].isnull().sum())
## este cambio tambien lo hacemos en test
test['MSSubClass'] = test['MSSubClass'].astype('category')
```

```
category
0
```

2.2 Var 01 MSZoning

Por definición esta variable es categórica, así que **está bien definida**.

[6]:
```
print(train['MSZoning'].dtype)
print(train['MSZoning'].isnull().sum())
```

```
object
0
```

2.3 Var 02 LotFrontage

Esta variable representa una medida en pies de la calle conectada a la propiedad, por lo tanto, como flotante **está bien definida**.

[7]:
```
print(train['LotFrontage'].dtype)
print(train['LotFrontage'].isnull().sum())
```

```
float64
0
```

2.4 Var 03 LotArea

Representa la medida del lote en pies cuadrados, si se identificó como entero significa que ningún registro tiene una medida decimal, lo que es raro pero ya ni modo, **el tipo de dato está bien definido**

[8]:
```
print(train['LotArea'].dtype)
print(train['LotArea'].isnull().sum())
```

```
int64
0
```

2.5 Var 04 Street

Igualmente **está bien definida**, representa si calle está pavimentada o es grava.

[9]:
```
print(train['Street'].dtype)
print(train['Street'].isnull().sum())
```

```
object
0
```

2.6 Var 05 Alley

Igualmente **está bien definida**, representa si el acceso a la calle está pavimentada o es grava.

[10]:
```
print(train['Alley'].dtype)
print(train['Alley'].isnull().sum())
```

```
object
0
```

2.7 Var 06 LotShape

Representa la forma del lote, **está bien definida**.

[11]:
```
print(train['LotShape'].dtype)
print(train['LotShape'].isnull().sum())
```

```
object
0
```

2.8 Var 07 LandContour

Representa la inflación de la propiedad, **está bien definida**.

[12]:
```
print(train['LandContour'].dtype)
print(train['LandContour'].isnull().sum())
```

```
object
0
```

2.9 Var 08 Utilities

Variable categórica que indica los serivios que tiene la propiedad (agua, luz, gas, etc). **Está bien definida**.

[13]:
```
print(train['Utilities'].dtype)
print(train['Utilities'].isnull().sum())
```

```
object
0
```

2.10 Var 09 LotConfig

Representa si la propiedad está en una cerrada, sobre la avenida, en esquina o es un predio dentro de otro, etc. **Está bien definida**.

[14]:
```
print(train['LotConfig'].dtype)
print(train['LotConfig'].isnull().sum())
```

```
object
0
```

2.11 Var 10 LandSlope

Indica si la propiedad está sobre terreno plano o si tiene cierta inclinación. **Está bien definido**.

[15]:
```
print(train['LandSlope'].dtype)
print(train['LandSlope'].isnull().sum())
```

```
object
0
```

2.12 Var 11 Neighborhood

Localización física dentro de los límites de Ames City. **Está bien definida**.

[16]:
```
print(train['Neighborhood'].dtype)
print(train['Neighborhood'].isnull().sum())
```

```
object
0
```

2.13 Var 12 Condition1

Proximidad a varias condiciones (cerca a una avenida principal, etc.) **Está bien definida**.

[17]:
```
print(train['Condition1'].dtype)
print(train['Condition1'].isnull().sum())
```

```
object
0
```

2.14 Var 13 Condition2

Igualmente a la anterior es categórica, **está bien definida**.

[18]:
```
print(train['Condition2'].dtype)
print(train['Condition2'].isnull().sum())
```

```
object
0
```

2.15 Var 14 BldgType

Tipo de vivienda (1 familia, originalmente contruida para 1 familia y adaptada para 2, duplex, etc.). **Está bien definida**.

[19]:
```
print(train['BldgType'].dtype)
print(train['BldgType'].isnull().sum())
```

```
object
0
```

2.16 Var 15 HouseStyle

Estilo de vivienda.**Está bien definida**.

[20]:
```
print(train['HouseStyle'].dtype)
print(train['HouseStyle'].isnull().sum())
```

```
object
0
```

2.17 Var 16 OverallQual

Esta variable representa una calificación en la calidad de los materiales y acabados de la clase, aunque es categórica es una variable ordinal, entonces como entero está bien definida pues la calificación, el valor, sí proporcionan información, el 10 es Muy Excelente y el 1 en Muy Pobre. **está bien**.

[21]:
```
print(train['OverallQual'].dtype)
print(train['OverallQual'].isnull().sum())
```

```
int64
0
```

2.18 Var 17 OverallCond

Esta calificación representa una calificación en la condición de la casa, al igual que la anterior, **está bien definida**.

[22]:
```
print(train['OverallCond'].dtype)
print(train['OverallCond'].isnull().sum())
```

```
int64
0
```

2.19 Var 18 YearBuilt

Año de construcción, **está bien definida**.

[23]:
```
print(train['YearBuilt'].dtype)
print(train['YearBuilt'].isnull().sum())
```

```
int64
0
```

2.20 Var 19 YearRemodAdd

Añe de remodelación, mismo año que construcción sino ha sido remodelada, **está bien definida**.

[24]:
```
print(train['YearRemodAdd'].dtype)
print(train['YearRemodAdd'].isnull().sum())
```

```
int64
0
```

2.21 Var 20 RoofStyle

Tipo de techo, variable categ´rotica, **está bien definida**.

[25]:
```
print(train['RoofStyle'].dtype)
print(train['RoofStyle'].isnull().sum())
```

```
object
0
```

2.22 Var 21 RoofMatl

Material del techo, **está bien definida**.

[26]:
```
print(train['RoofMatl'].dtype)
print(train['RoofMatl'].isnull().sum())
```

```
object
0
```

2.23 Var 22 Exterior1st

Cuvierta del exterior de la casa, variable categórica, **está bien definida**.

[27]:
```
print(train['Exterior1st'].dtype)
print(train['Exterior1st'].isnull().sum())
```

```
object
0
```

2.24 Var 23 Exterior2nd

Si es que tiene otro material la fachada de la casa, variable categórica, **está bien definida**.

[28]:
```
print(train['Exterior2nd'].dtype)
print(train['Exterior2nd'].isnull().sum())
```

```
object
0
```

2.25 Var 24 MasVnrType

Tipo de revestimiento de mamposería, **está bien definida**.

[29]:
```
print(train['MasVnrType'].dtype)
print(train['MasVnrType'].isnull().sum())
```

```
object
0
```

2.26 Var 25 MasVnrArea

Área, en pies cuadrados, de recubriminetos de mampostería. **Está bien definida**.

[30]:
```
print(train['MasVnrArea'].dtype)
print(train['MasVnrArea'].isnull().sum())
```

```
float64
0
```

2.27 Var 26 ExterQual

Variable categorica de la calidad del material exterior. **está bien definida**.

[31]:
```
print(train['ExterQual'].dtype)
print(train['ExterQual'].isnull().sum())
```

```
object
0
```

2.28 Var 27 ExterCond

Evalúa la condición de lo materiales del exterior, variable categótica. **Está bien definida**.

[32]:
```
print(train['ExterCond'].dtype)
print(train['ExterCond'].isnull().sum())
```

```
object
0
```

2.29 Var 28 Foundation

Tipo de fundamento, **está bien definida**.

[33]:
```
print(train['Foundation'].dtype)
print(train['Foundation'].isnull().sum())
```

```
object
0
```

2.30 Var 29 BsmtQual

Evalúa el grosor de los fundamentos, variable categórica, **está bien definida**.

[34]:
```
print(train['BsmtQual'].dtype)
print(train['BsmtQual'].isnull().sum())
```

```
object
0
```

2.31 Var 30 BsmtCond

Condición general de los simientos, **está bien definida**.

[35]:
```
print(train['BsmtCond'].dtype)
print(train['BsmtCond'].isnull().sum())
```

```
object
0
```

2.32 Var 31 BsmtExposure

Se refiere a los miros de la entrada o jardín, **está bien definida**.

[36]:
```
print(train['BsmtExposure'].dtype)
print(train['BsmtExposure'].isnull().sum())
```

```
object
0
```

2.33 Var 32 BsmtFinType1

Calificación de los simientos terminados, **está bien definida**.

[37]:
```
print(train['BsmtFinType1'].dtype)
print(train['BsmtFinType1'].isnull().sum())
```

```
object
0
```

2.34 Var 33 BsmtFinSF1

Metros cuadrados terminado, **está bien definida**.

[38]:
```
print(train['BsmtFinSF1'].dtype)
print(train['BsmtFinSF1'].isnull().sum())
```

```
int64
0
```

2.35 Var 34 BsmtFinType2

rango de los simientos del área terminada, **está bien definida**.

[39]:
```
print(train['BsmtFinType2'].dtype)
print(train['BsmtFinType2'].isnull().sum())
```

```
object
0
```

2.36 Var 35 BsmtFinSF2

pies cuadrados terminados, **está bien definida**.

[40]:
```
print(train['BsmtFinSF2'].dtype)
print(train['BsmtFinSF2'].isnull().sum())
```

```
int64
0
```

2.37 Var 36 BsmtUnfSF

pues cuadrados in terminar de área de simientos, **está bien definida**.

[41]:
```
print(train['BsmtUnfSF'].dtype)
print(train['BsmtUnfSF'].isnull().sum())
```

```
int64
0
```

2.38 Var 37 TotalBsmtSF

pies cuadrados totales de área de simientos, **está bien definida**.

[42]:
```
print(train['TotalBsmtSF'].dtype)
print(train['TotalBsmtSF'].isnull().sum())
```

```
int64
0
```

2.39 Var 38 Heating

tipo de califección, **está bien definida**.

[43]:
```
print(train['Heating'].dtype)
print(train['Heating'].isnull().sum())
```

```
object
0
```

2.40 Var 39 HeatingQC

Calidad de la caleffación, **está bien definida**.

[44]:
```
print(train['HeatingQC'].dtype)
print(train['HeatingQC'].isnull().sum())
```

```
object
0
```

2.41 Var 40 CentralAir

si/no tiene aire acondicionado centra, **está bien definida**.

[45]:
```
print(train['CentralAir'].dtype)
print(train['CentralAir'].isnull().sum())
```

```
object
0
```

2.42 Var 41 Electrical

Tipo de sistema eléctrico, **está bien definida**.

[46]:
```
print(train['Electrical'].dtype)
print(train['Electrical'].isnull().sum())
```

```
object
0
```

2.43 Var 42 1stFlrSF

Pies cuadrados del primer piso, **está bien definida**.

[47]:
```
print(train['1stFlrSF'].dtype)
print(train['1stFlrSF'].isnull().sum())
```

```
int64
0
```

2.44 Var 43 2ndFlrSF

Pies cuadrados del segundo piso, **está bien definida**.

[48]:
```
print(train['2ndFlrSF'].dtype)
print(train['2ndFlrSF'].isnull().sum())
```

```
int64
0
```

2.45 Var 44 LowQualFinSF

pies cuadrados de baja calidad, **está bien definida**.

[49]:
```
print(train['LowQualFinSF'].dtype)
print(train['LowQualFinSF'].isnull().sum())
```

```
int64
0
```

2.46 Var 45 GrLivArea

pies cuadrados de superficie habitable, **está bien definida**.

[50]:
```
print(train['GrLivArea'].dtype)
print(train['GrLivArea'].isnull().sum())
```

```
int64
0
```

2.47 Var 46 BsmtFullBath

Baños completos en el sótano, **está bien definida**.

[51]:
```
print(train['BsmtFullBath'].dtype)
print(train['BsmtFullBath'].isnull().sum())
```

```
int64
0
```

2.48 Var 47 BsmtHalfBath

Medios baños en el sótano, **está bien definida**.

[52]:
```
print(train['BsmtHalfBath'].dtype)
print(train['BsmtHalfBath'].isnull().sum())
```

```
int64
0
```

2.49 Var 48 FullBath

Baños completos, **está bien definida**.

[53]:
```
print(train['FullBath'].dtype)
print(train['FullBath'].isnull().sum())
```

```
int64
0
```

2.50 Var 49 HalfBath

Medios baños, **está bien definida**.

[54]:
```
print(train['HalfBath'].dtype)
print(train['HalfBath'].isnull().sum())
```

```
int64
0
```

2.51 Var 50 BedroomAbvGr

Recamaras sin incluir las de sótano, **está bien definida**.

[55]:
```
print(train['BedroomAbvGr'].dtype)
print(train['BedroomAbvGr'].isnull().sum())
```

```
int64
0
```

2.52 Var 51 KitchenAbvGr

Numero de cocinas en la casa, **está bien definida**.

[56]:
```
print(train['KitchenAbvGr'].dtype)
print(train['KitchenAbvGr'].isnull().sum())
```

```
int64
0
```

2.53 Var 52 KitchenQual

Calidad de la cocina, **está bien definida**.

[57]:
```
print(train['KitchenQual'].dtype)
print(train['KitchenQual'].isnull().sum())
```

```
object
0
```

2.54 Var 53 TotRmsAbvGrd

Habitaciones totales sin incluir baños, **está bien definida**.

[58]:
```
print(train['TotRmsAbvGrd'].dtype)
print(train['TotRmsAbvGrd'].isnull().sum())
```

```
int64
0
```

2.55 Var 54 Functional

Funcionalidad de la casa, **está bien definida**.

[59]:
```
print(train['Functional'].dtype)
print(train['Functional'].isnull().sum())
```

```
object
0
```

2.56 Var 55 Fireplaces

Número de chimeneas, **está bien definida**.

[60]:
```
print(train['Fireplaces'].dtype)
print(train['Fireplaces'].isnull().sum())
```

```
int64
0
```

2.57 Var 56 FireplaceQu

Calidad de las chimeneas, **está bien definida**.

[61]:
```
print(train['FireplaceQu'].dtype)
print(train['FireplaceQu'].isnull().sum())
```

```
object
0
```

2.58 Var 57 GarageType

ubicación del gargae, **está bien definida**.

[62]:
```
print(train['GarageType'].dtype)
print(train['GarageType'].isnull().sum())
```

```
object
0
```

2.59 Var 58 GarageYrBlt

año en que el garage se construyó, **está bien definida**.

[63]:
```
print(train['GarageYrBlt'].dtype)
print(train['GarageYrBlt'].isnull().sum())
```

```
float64
0
```

2.60 Var 59 GarageFinish

estatus del garage, **está bien definida**.

[64]:
```
print(train['GarageFinish'].dtype)
print(train['GarageFinish'].isnull().sum())
```

```
object
0
```

2.61 Var 60 GarageCars

Capacidad de carros en el garage, **está bien definida**.

[65]:
```
print(train['GarageCars'].dtype)
print(train['GarageCars'].isnull().sum())
```

```
int64
0
```

2.62 Var 61 GarageArea

pies cuadrados del garage, **está bien definida**.

[66]:
```
print(train['GarageArea'].dtype)
print(train['GarageArea'].isnull().sum())
```

```
int64
0
```

2.63 Var 62 GarageQual

Calidad del garage, **está bien definida**.

[67]:
```
print(train['GarageQual'].dtype)
print(train['GarageQual'].isnull().sum())
```

```
object
0
```

2.64 Var 63 GarageCond

condición del garage, **está bien definida**.

[68]:
```
print(train['GarageCond'].dtype)
print(train['GarageCond'].isnull().sum())
```

```
object
0
```

2.65 Var 64 PavedDrive

Pavimentado, variable categórica, **estábien definida**.

[69]:
```
print(train['PavedDrive'].dtype)
print(train['PavedDrive'].isnull().sum())
```

```
object
0
```

2.66 Var 65 WoodDeckSF

pies cuadrados de área decorada con madera, **está bien definida**.

[70]:
```
print(train['WoodDeckSF'].dtype)
print(train['WoodDeckSF'].isnull().sum())
```

```
int64
0
```

2.67 Var 66 OpenPorchSF

pies cuadrados de porch abierto, **está bien definida**.

[71]:
```
print(train['OpenPorchSF'].dtype)
print(train['OpenPorchSF'].isnull().sum())
```

```
int64
0
```

2.68 Var 67 EnclosedPorch

pies cuadrados de porch cerrado, **está bien definida**.

[72]:
```
print(train['EnclosedPorch'].dtype)
print(train['EnclosedPorch'].isnull().sum())
```

```
int64
0
```

2.69 Var 68 3SsnPorch

pies cuadrados de proch de tres estaciones Q_Q, ,**está bien definida**.

[73]:
```
print(train['3SsnPorch'].dtype)
print(train['3SsnPorch'].isnull().sum())
```

```
int64
0
```

2.70 Var 69 ScreenPorch

pies cuadrados de fachada del proch, **está bien definida**.

[74]:
```
print(train['ScreenPorch'].dtype)
print(train['ScreenPorch'].isnull().sum())
```

```
int64
0
```

2.71 Var 70 PoolArea

pies cuadrados de la superficie de la alberca, **está bien definida**.

[75]:
```
print(train['PoolArea'].dtype)
print(train['PoolArea'].isnull().sum())
```

```
int64
0
```

2.72 Var 71 PoolQC

Calidad de la alberca, **está bien definida**.

[76]:
```
print(train['PoolQC'].dtype)
print(train['PoolQC'].isnull().sum())
```

```
object
0
```

2.73 Var 72 Fence

calidad de la cerca, **está bien definida**.

[77]:
```
print(train['Fence'].dtype)
print(train['Fence'].isnull().sum())
```

```
object
0
```

2.74 Var 73 MiscFeature

articulos miscelaneos, **es´ta bien definida**.

[78]:
```
print(train['MiscFeature'].dtype)
print(train['MiscFeature'].isnull().sum())
```

```
object
0
```

2.75 Var 74 MiscVal

valor de los articulos miscelaneos, **está bien definida**.

[79]:
```
print(train['MiscVal'].dtype)
print(train['MiscVal'].isnull().sum())
```

```
int64
0
```

2.76 Var 75 MoSold

Mes de venta, **está bien definida**.

[80]:
```
print(train['MoSold'].dtype)
print(train['MoSold'].isnull().sum())
```

```
int64
0
```

2.77 Var 76 YrSold

año de venta, **está bien definida**.

[81]:
```
print(train['YrSold'].dtype)
print(train['YrSold'].isnull().sum())
```

```
int64
0
```

2.78 Var 77 SaleType

tipo de venta, **está bien definida**

[82]:
```
print(train['SaleType'].dtype)
print(train['SaleType'].isnull().sum())
```

```
object
0
```

2.79 Var 78 SaleCondition

condiciones en que se dio la venta, **está bien definida**

[83]:
```
print(train['SaleCondition'].dtype)
print(train['SaleCondition'].isnull().sum())
```

```
object
0
```

2.80 Var 79 SalePrice

Precio de venta, **está bien definida**.

[84]:
```
print(train['SalePrice'].dtype)
print(train['SalePrice'].isnull().sum())
```

```
int64
0
```

2.81 Resumen y comentarios

La variable 0 "MSSubClass", originalmente identificada como entero, es en realidad categórica.

Existe inconsistencia en cuanto a la categorización pues hay variables que evalúan calidad como "ExterQual" y "ExterCond" cuyas categórias son:

```
Ex   Excellent
Gd   Good
TA   Average/Typical
Fa   Fair
Po   Poor
```

Sin embargo, "OverallCond" es:

```
10   Very Excellent
9    Excellent
8    Very Good
7    Good
6    Above Average
5    Average
4    Below Average
3    Fair
2    Poor
1    Very Poor
```

Aunque ambas "miden" o "califican" unas decidieron hacerlo catgóricamente y otras numéricamente.

Se decidió dejar "OverallCond" como numérica.

3 Breve análisis descriptivo de los datos

3.1 Variables categóricas

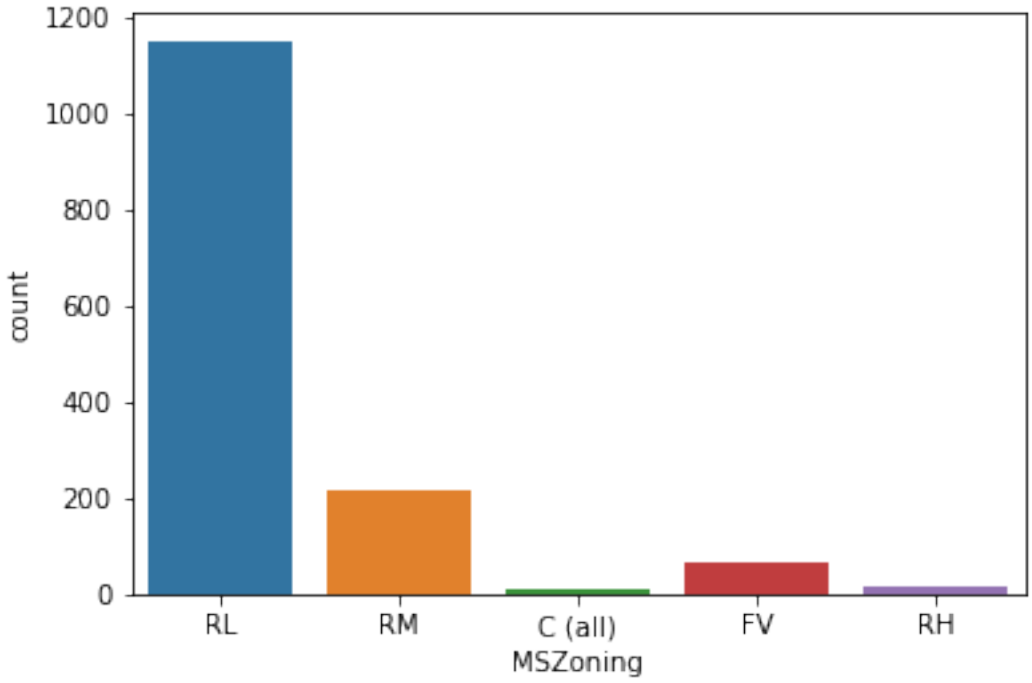
Primeramente, si se realiza un histograma se puede inferir acerca de la distribución de los datos, por ejemplo, a continuación se realiza para aquellas variables que son categóricas, esto porque las variables numéricas sería mejor analizarlo con una matriz de correlación.

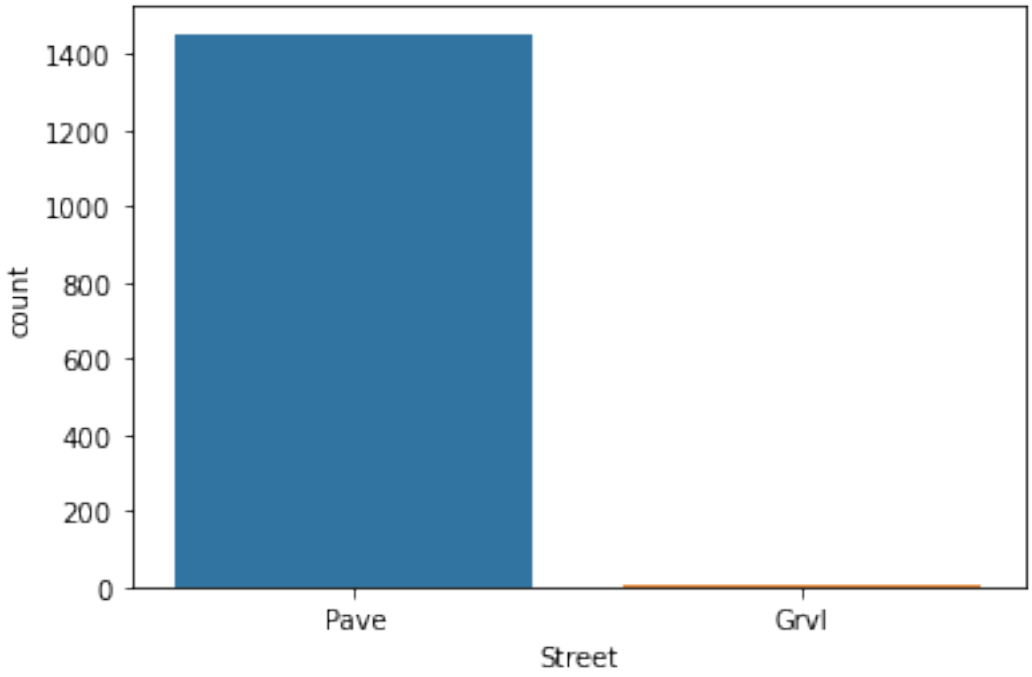
[85]:
```
#Las variables que son object
import numpy as np
import copy
trainObj = train.select_dtypes(include=['object' or 'category']).copy()
#también lo hacemos para test
testObj = test.select_dtypes(include=['object'or 'category']).copy()
trainObj.head()
```

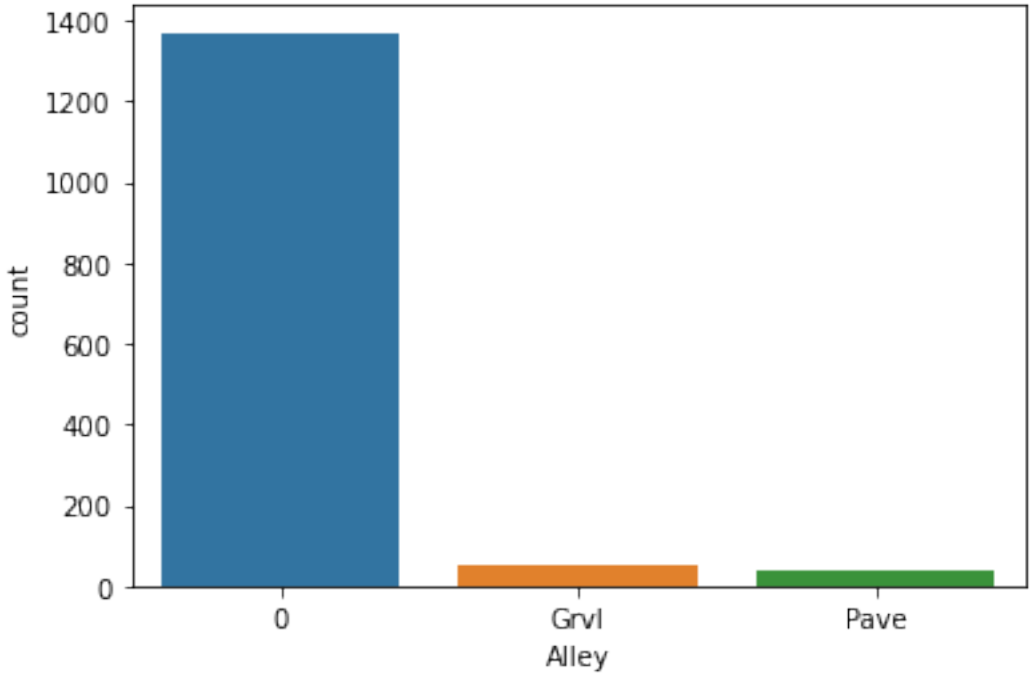
[85]:
```
   MSZoning Street Alley LotShape LandContour Utilities LotConfig LandSlope  \
Id
1        RL   Pave     0      Reg         Lvl    AllPub    Inside       Gtl
2        RL   Pave     0      Reg         Lvl    AllPub       FR2       Gtl
3        RL   Pave     0      IR1         Lvl    AllPub    Inside       Gtl
4        RL   Pave     0      IR1         Lvl    AllPub    Corner       Gtl
5        RL   Pave     0      IR1         Lvl    AllPub       FR2       Gtl

   Neighborhood Condition1  ... GarageType GarageFinish GarageQual GarageCond  \
Id                          ...
1       CollgCr       Norm  ...     Attchd          RFn         TA         TA
2       Veenker      Feedr  ...     Attchd          RFn         TA         TA
3       CollgCr       Norm  ...     Attchd          RFn         TA         TA
4       Crawfor       Norm  ...     Detchd          Unf         TA         TA
5       NoRidge       Norm  ...     Attchd          RFn         TA         TA

   PavedDrive PoolQC Fence MiscFeature SaleType SaleCondition
Id
1           Y      0     0           0       WD        Normal
2           Y      0     0           0       WD        Normal
3           Y      0     0           0       WD        Normal
4           Y      0     0           0       WD       Abnorml
5           Y      0     0           0       WD        Normal

[5 rows x 43 columns]
```

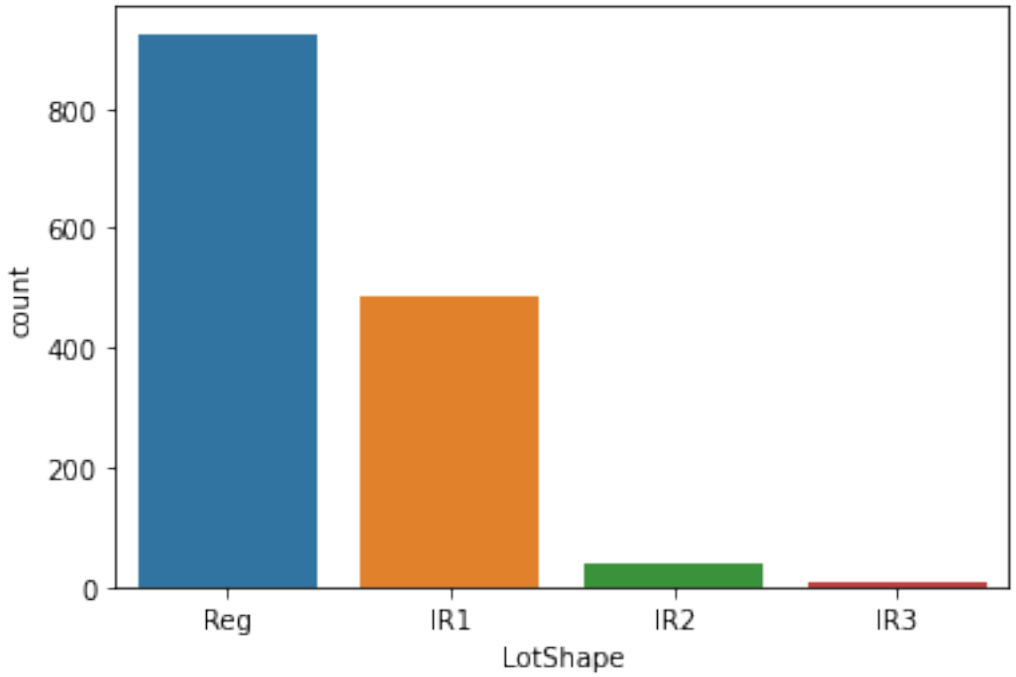
[86]:
```
%matplotlib inline
import seaborn as sns
import matplotlib.pyplot as plt
for i, col in enumerate(trainObj.columns):
    plt.figure(i)
    sns.countplot(x=col, data=trainObj)
```

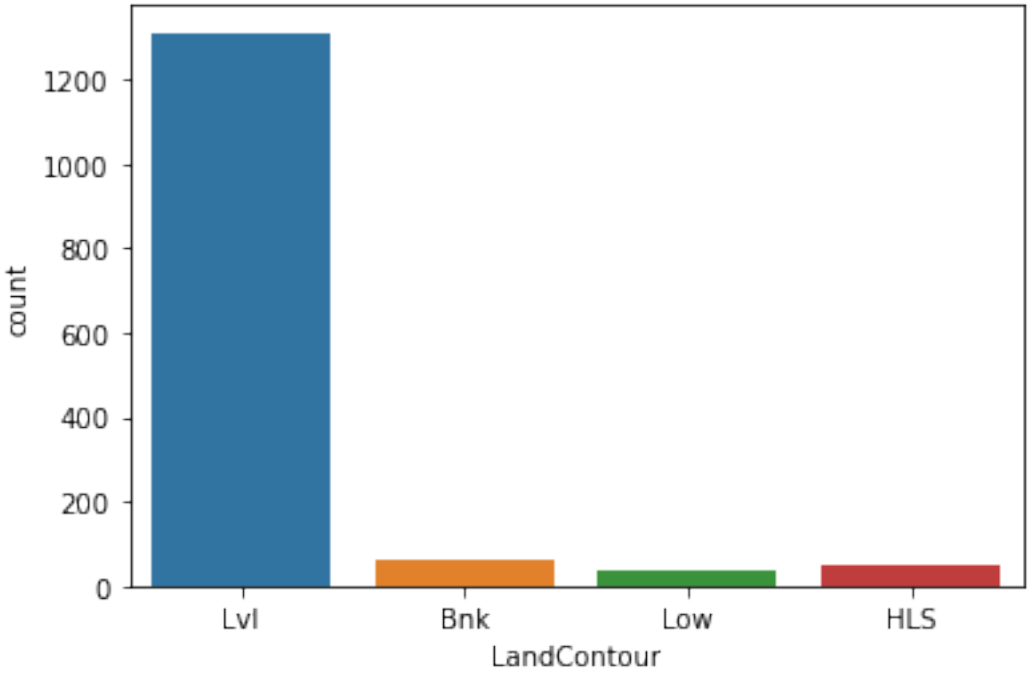
```
<ipython-input-86-d937b5dcecfe>:5: RuntimeWarning: More than 20 figures have
been opened. Figures created through the pyplot interface
(`matplotlib.pyplot.figure`) are retained until explicitly closed and may
consume too much memory. (To control this warning, see the rcParam
`figure.max_open_warning`).
  plt.figure(i)
```

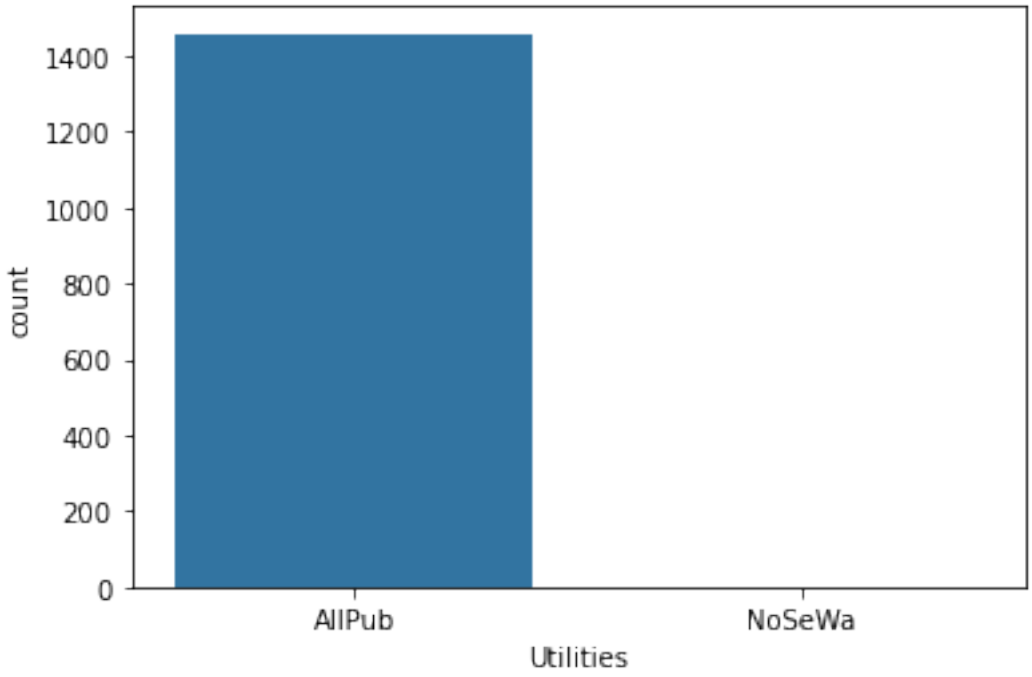


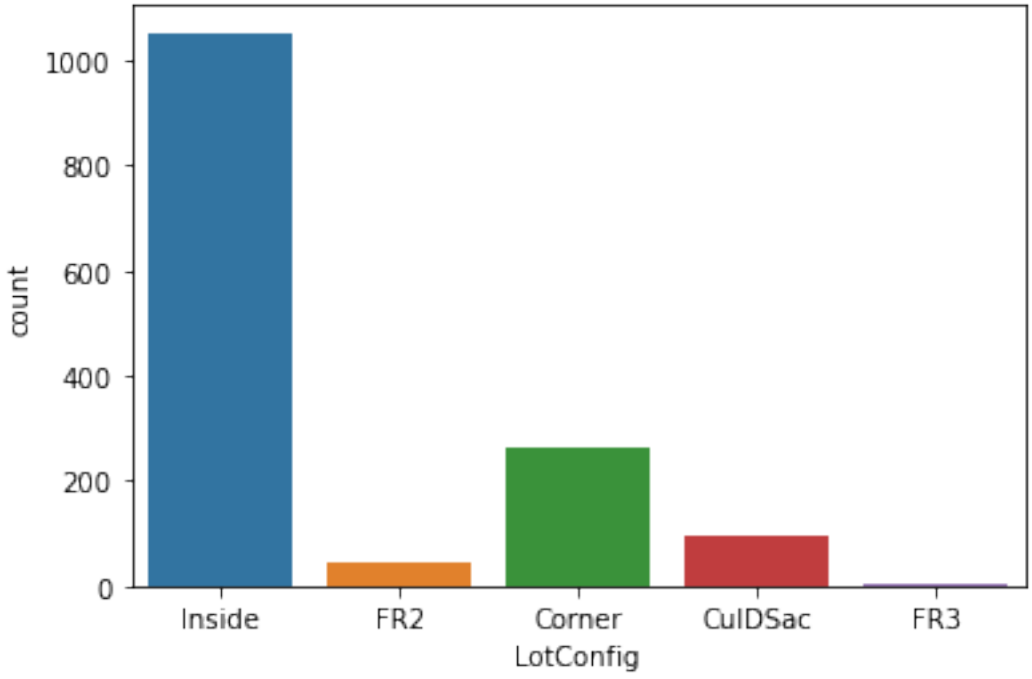

1400
1200
1000
800
600
400
200
0
count
Pave
Grvl
Street

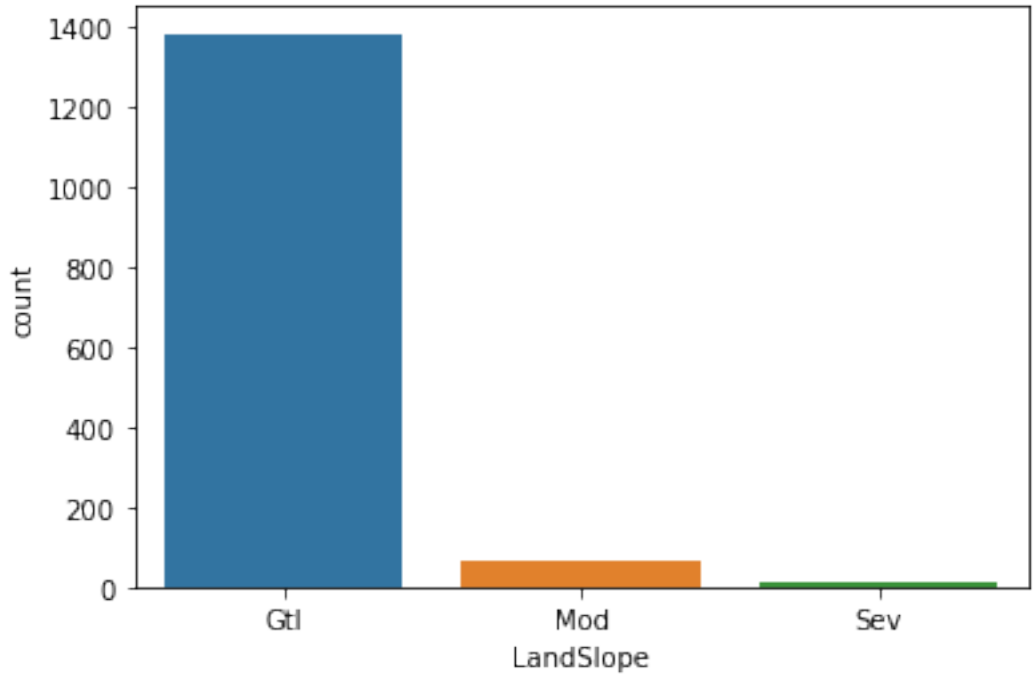

1400
1200
1000
800
600
400
200
0
count
0
Grvl
Pave
Alley


800
600
400
200
0
count
Reg
IR1
IR2
IR3
LotShape


1200
1000
800
600
400
200
0
count
Lvl
Bnk
Low
HLS
LandContour


1400
1200
1000
800
600
400
200
0
count
AllPub
NoSeWa
Utilities


1000
800
600
400
200
0
count
Inside
FR2
Corner
CulDSac
FR3
LotConfig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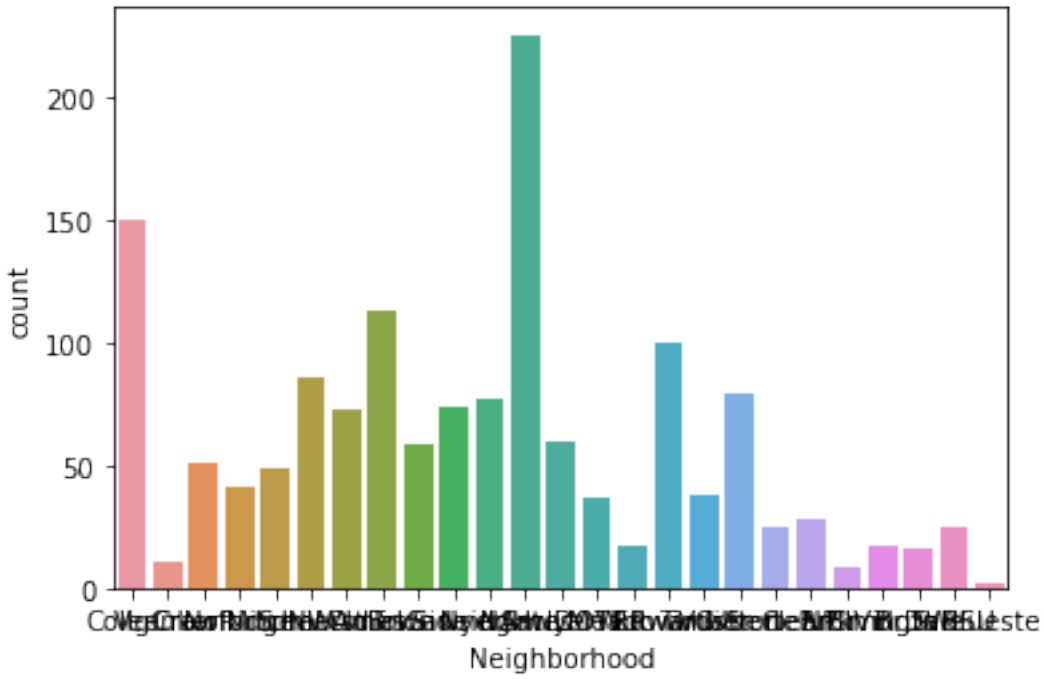
1200
1000
800
600
400
200
0
count
Gtl
Mod
Sev
LandSlope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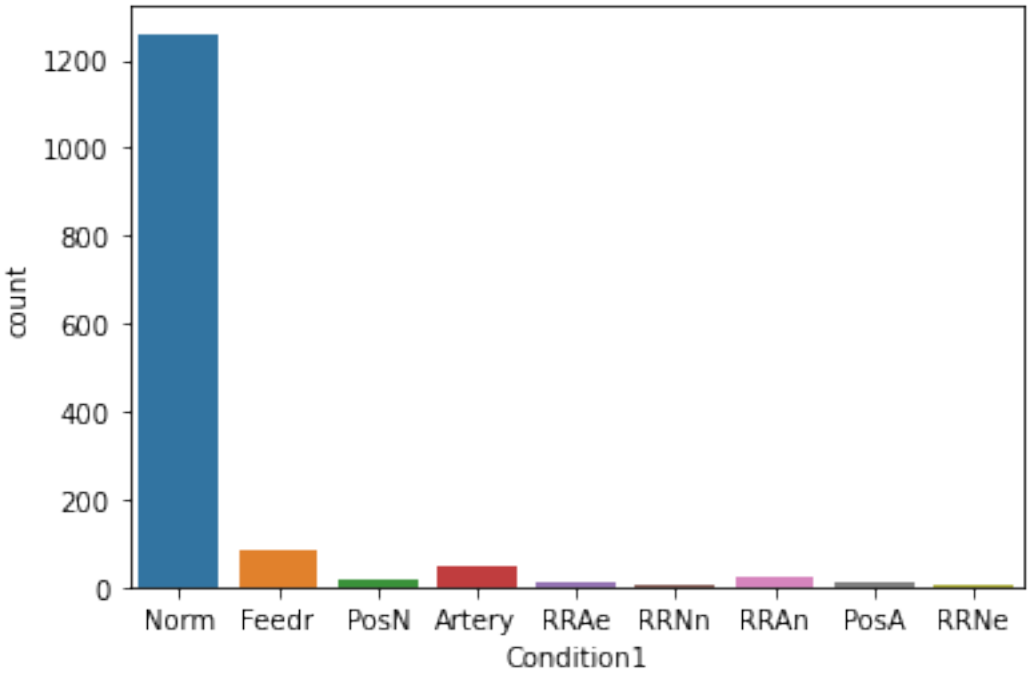
150
100
50
0
count
Neighborhood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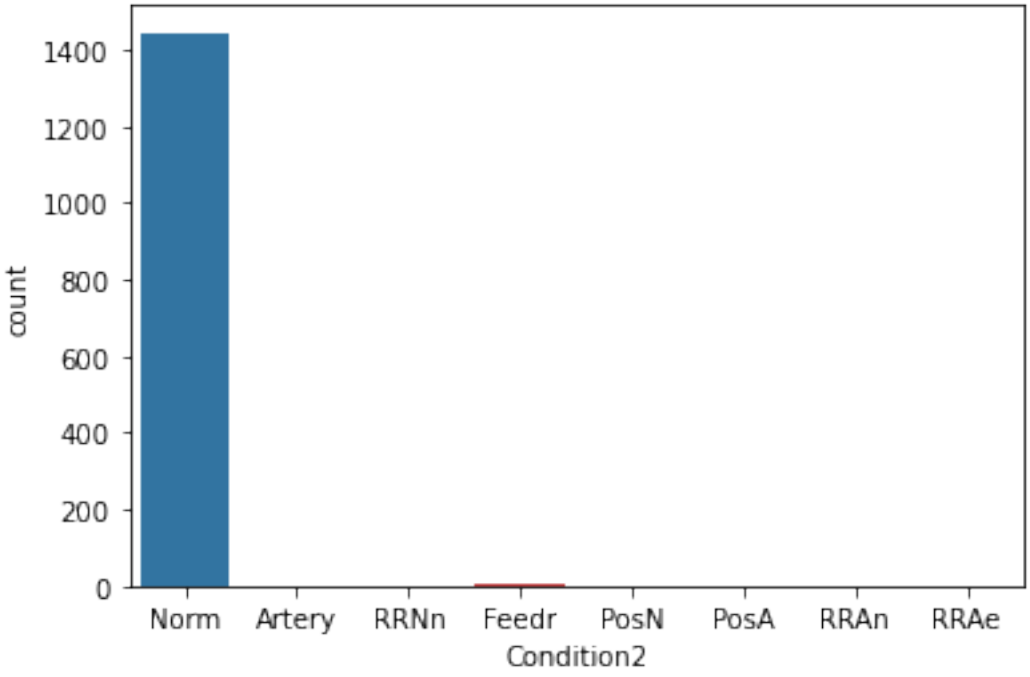
1000
800
600
400
200
0
count
Norm
Feedr
PosN
Artery
RRAe
RRNn
RRAn
PosA
RRNe
Condition1


1400
1200
1000
800
600
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200
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count
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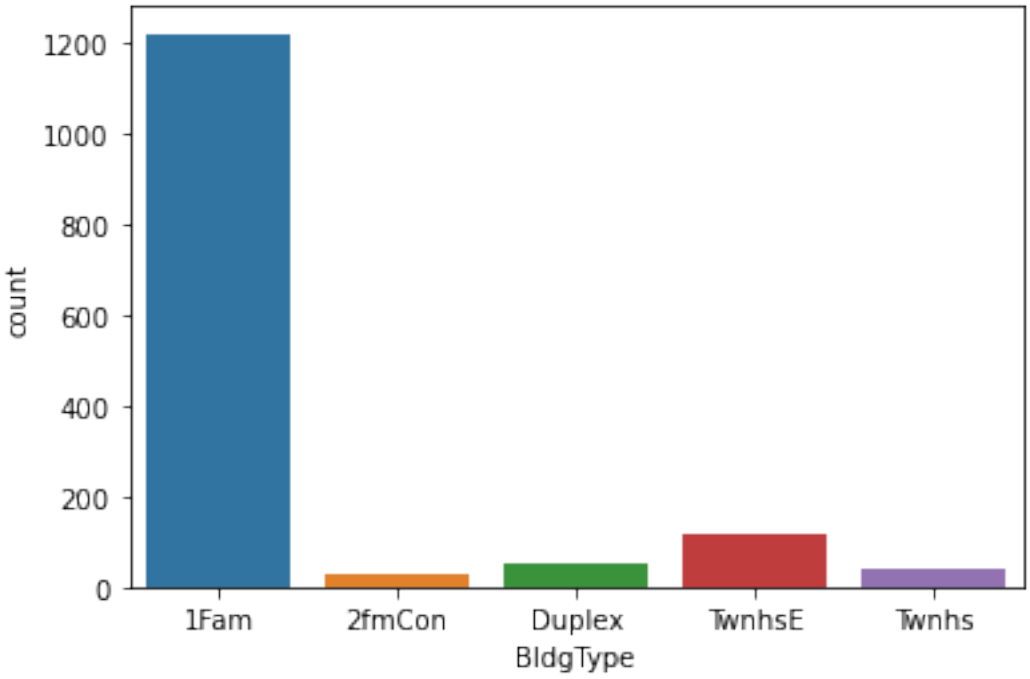
Artery
RRNn
Feedr
PosN
PosA
RRAn
RRAe
Condition2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800
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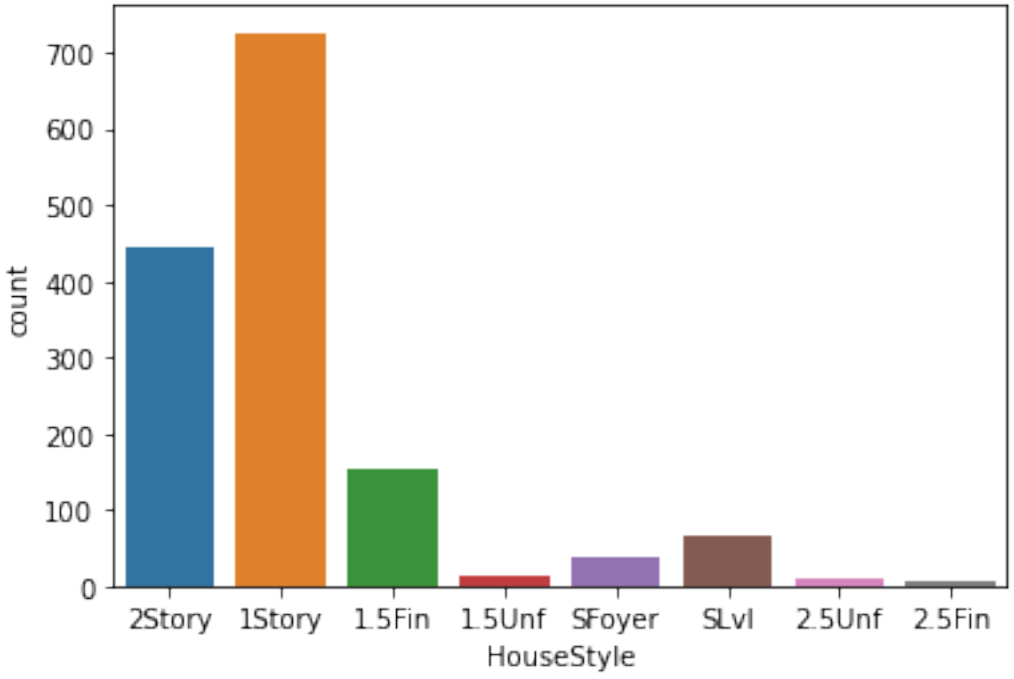
400
200
0
count
1Fam
2fmCon
Duplex
TwnhsE
Twnhs
BldgType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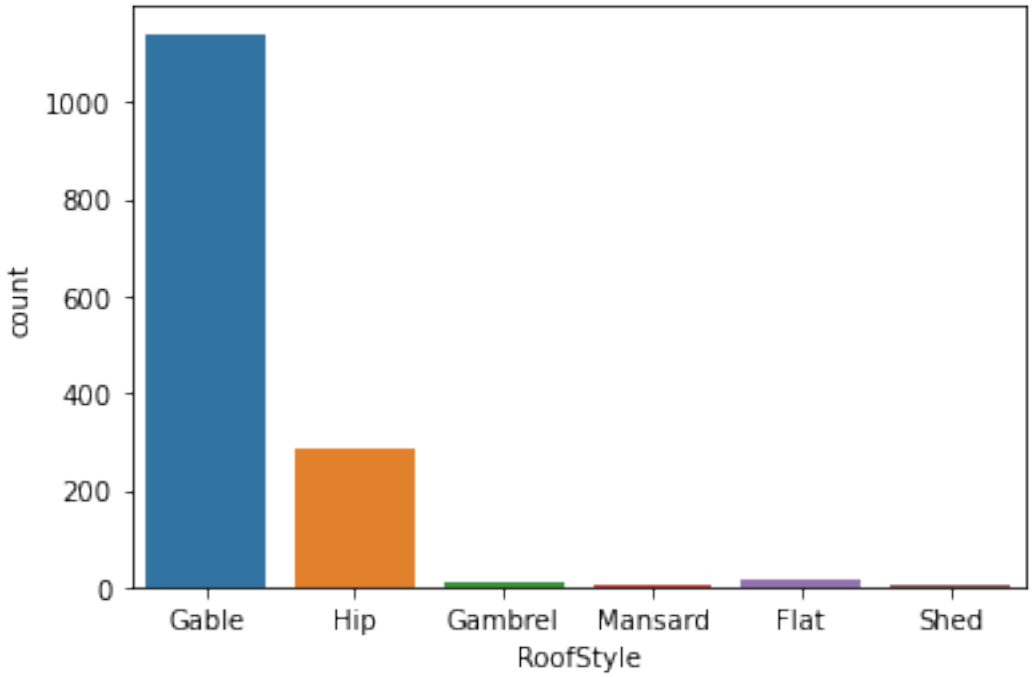
600
500
400
300
200
100
0
count
2Story
1Story
1.5Fin
1.5Unf
SFoyer
SLvl
2.5Unf
2.5Fin
HouseStyle


1000
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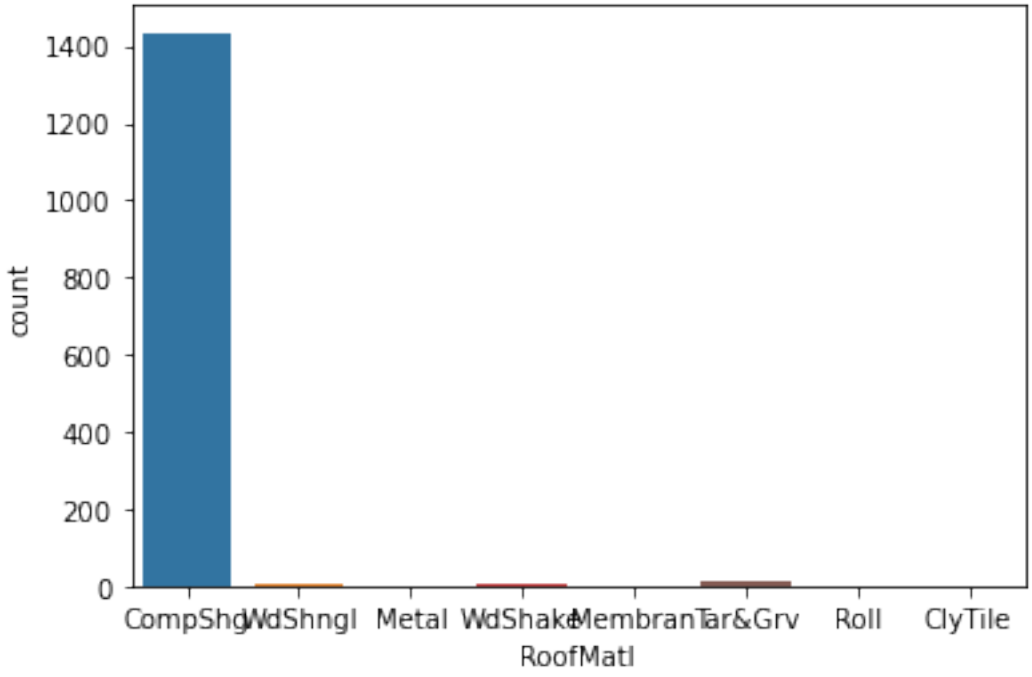
600
400
200
0
count
Gable
Hip
Gambrel
Mansard
Flat
Shed
RoofStyle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800
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200
0
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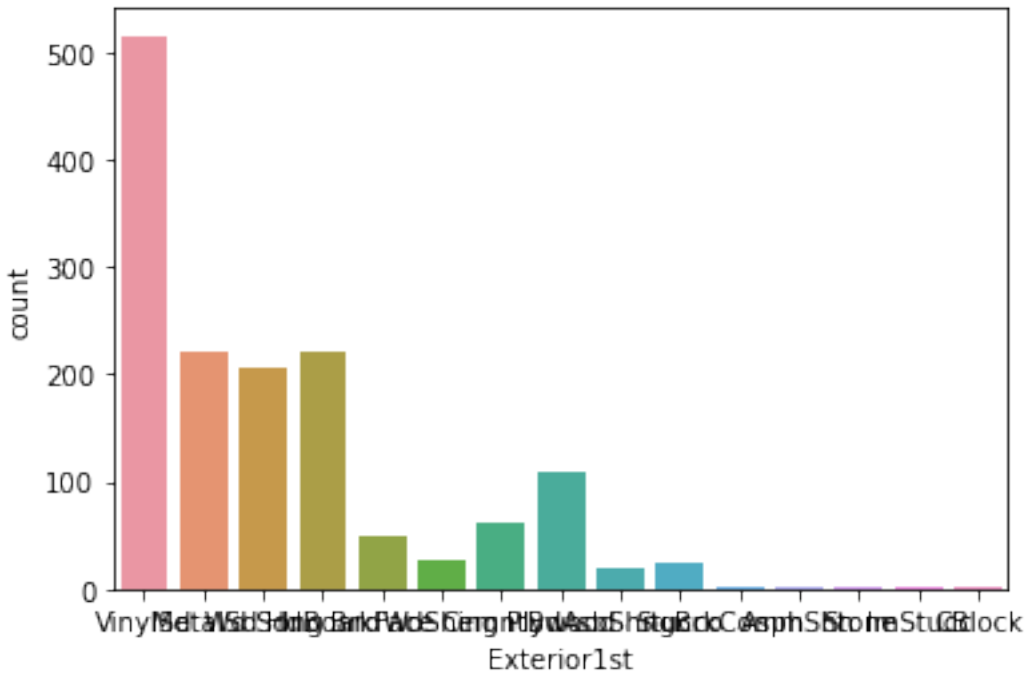
CompShg
WdShngl
Metal
WdShake
Membran
Tar&Grv
Roll
ClyTile
RoofMatl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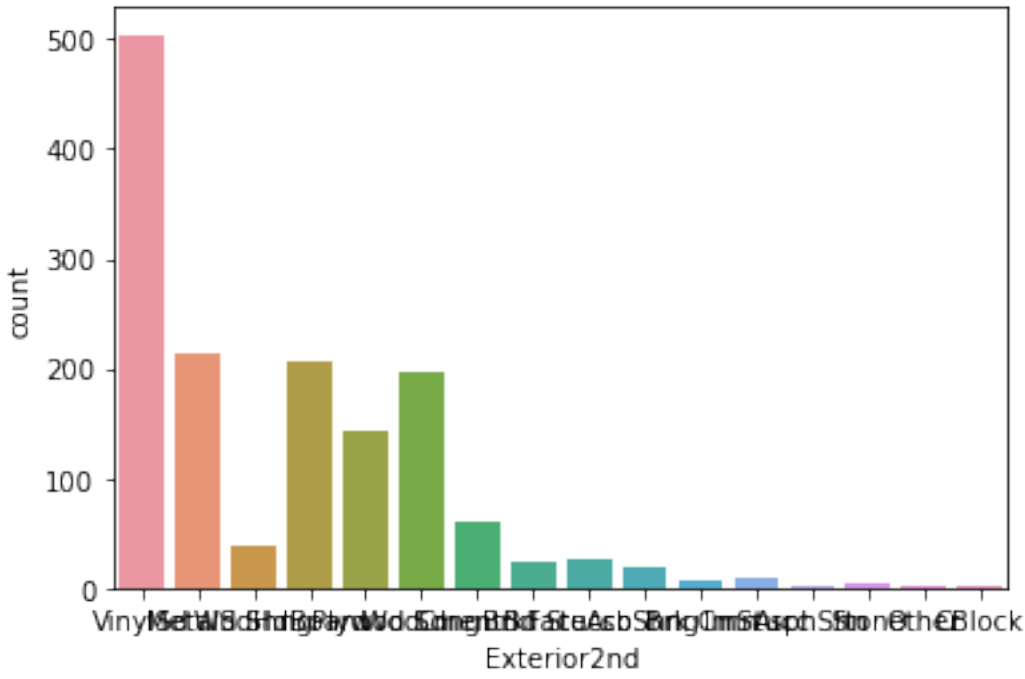
count
Exterior1st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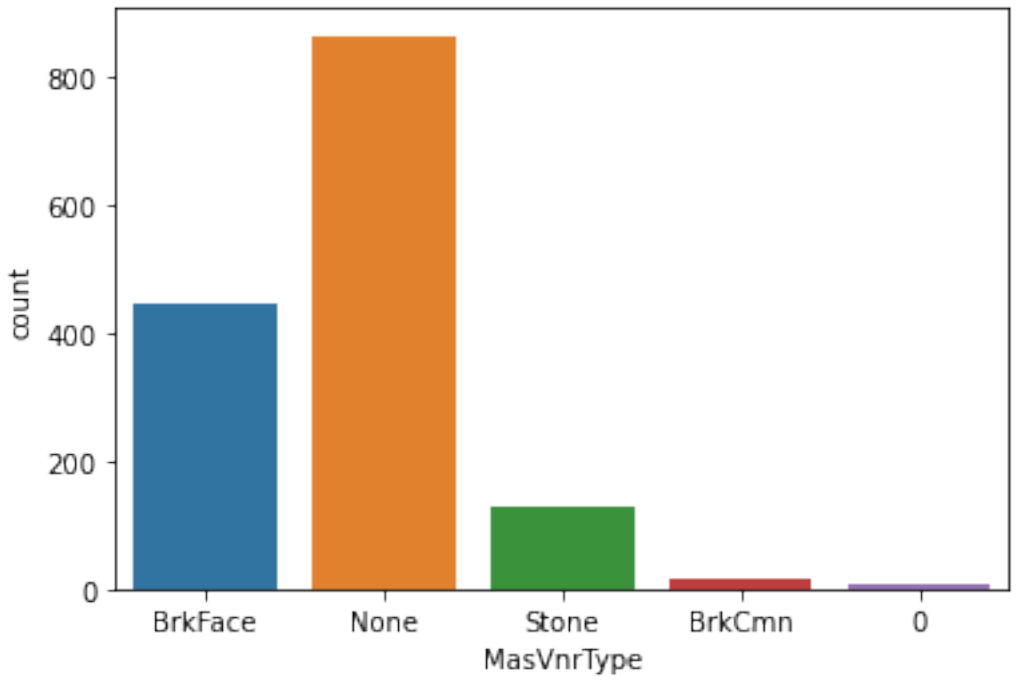
400
300
200
100
0
count
Exterior2nd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400
200
0
count
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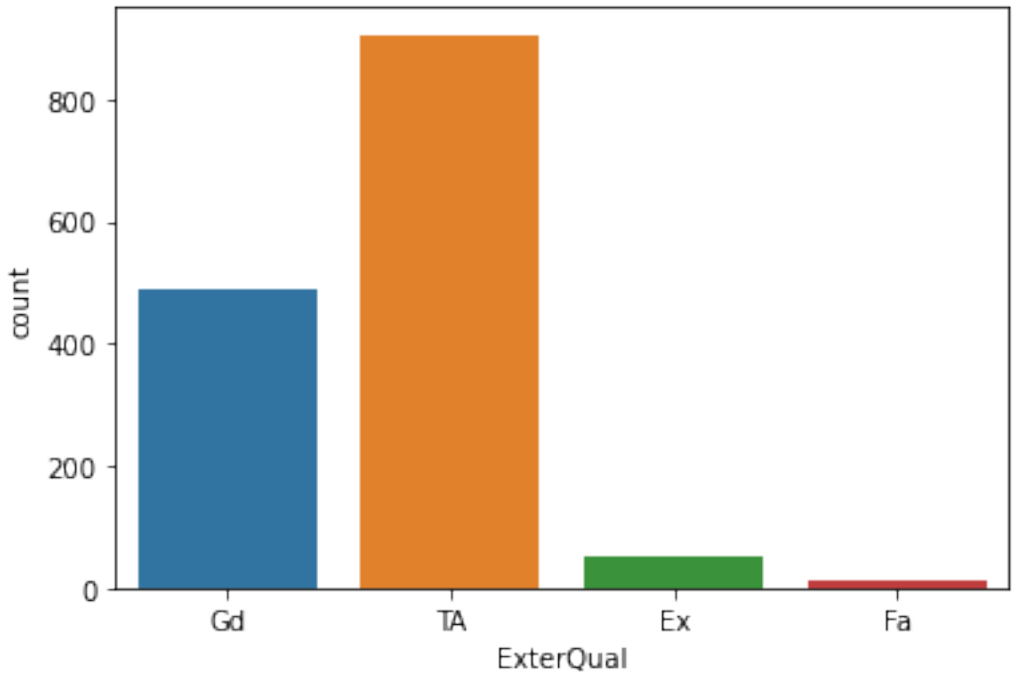
None
Stone
BrkCmn
0
MasVnrType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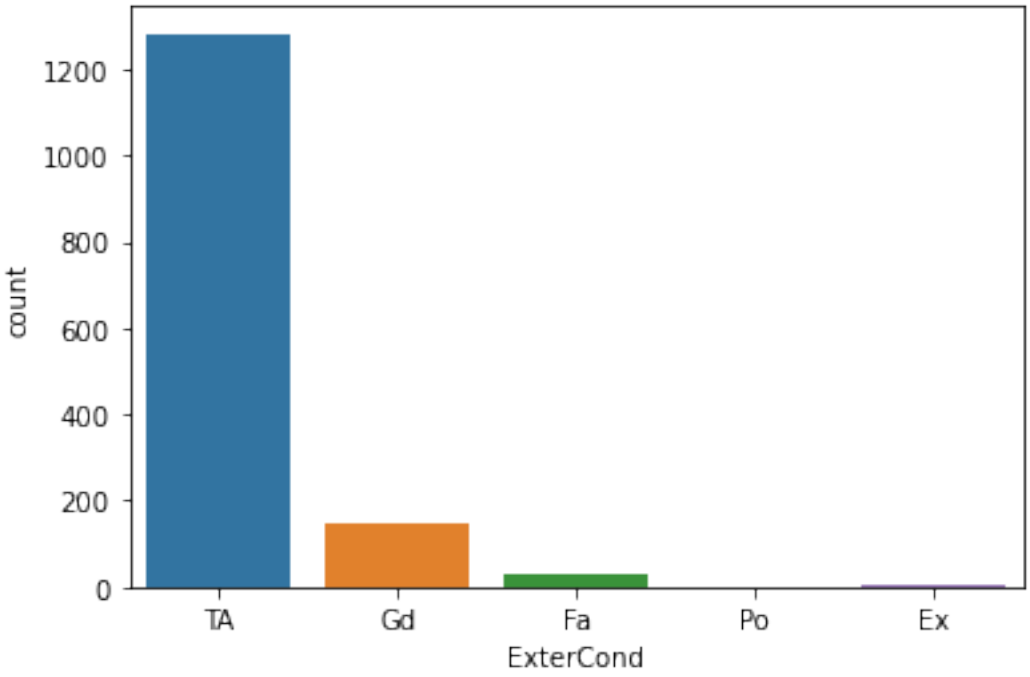
count
Gd
TA
Ex
Fa
ExterQual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400
200
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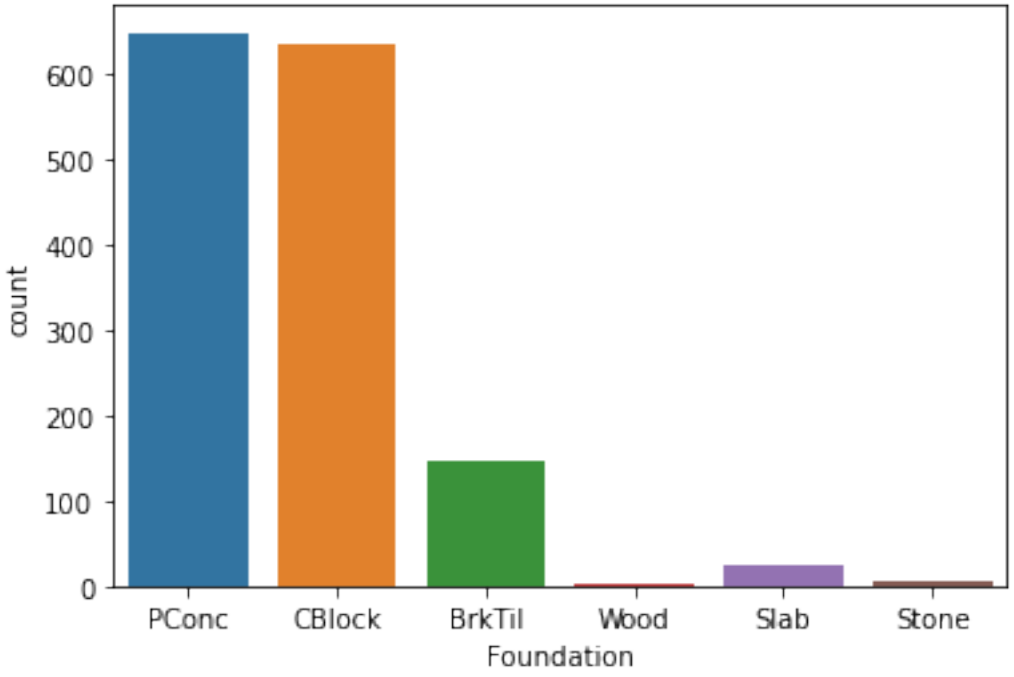
count
TA
Gd
Fa
Po
Ex
ExterCond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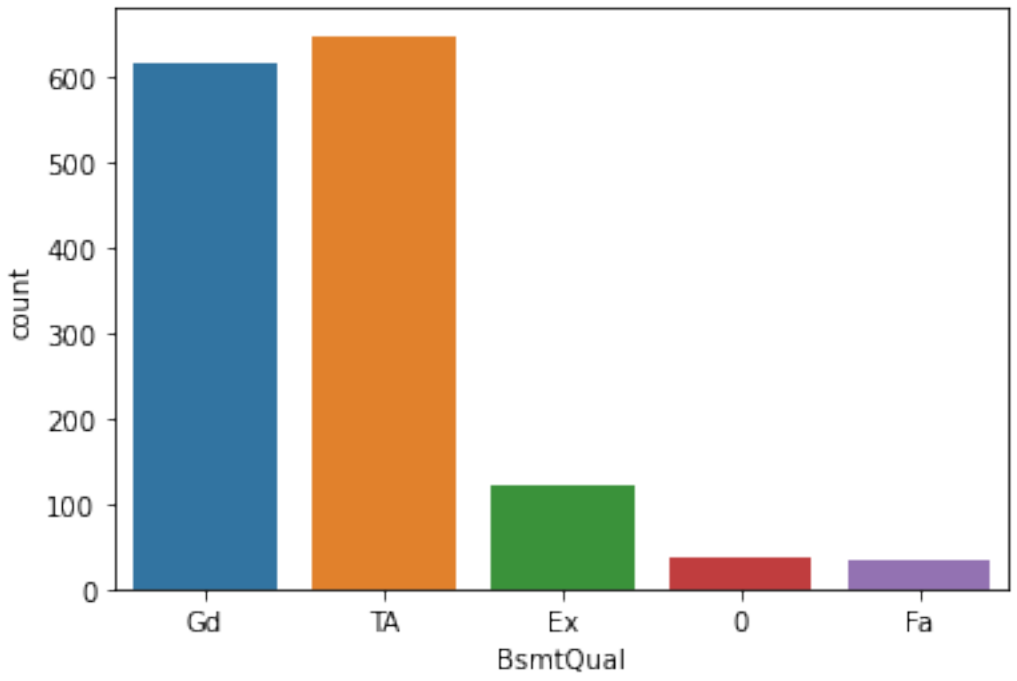
500
400
300
200
100
0
count
PConc
CBlock
BrkTil
Wood
Slab
Stone
Foundation


600
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400
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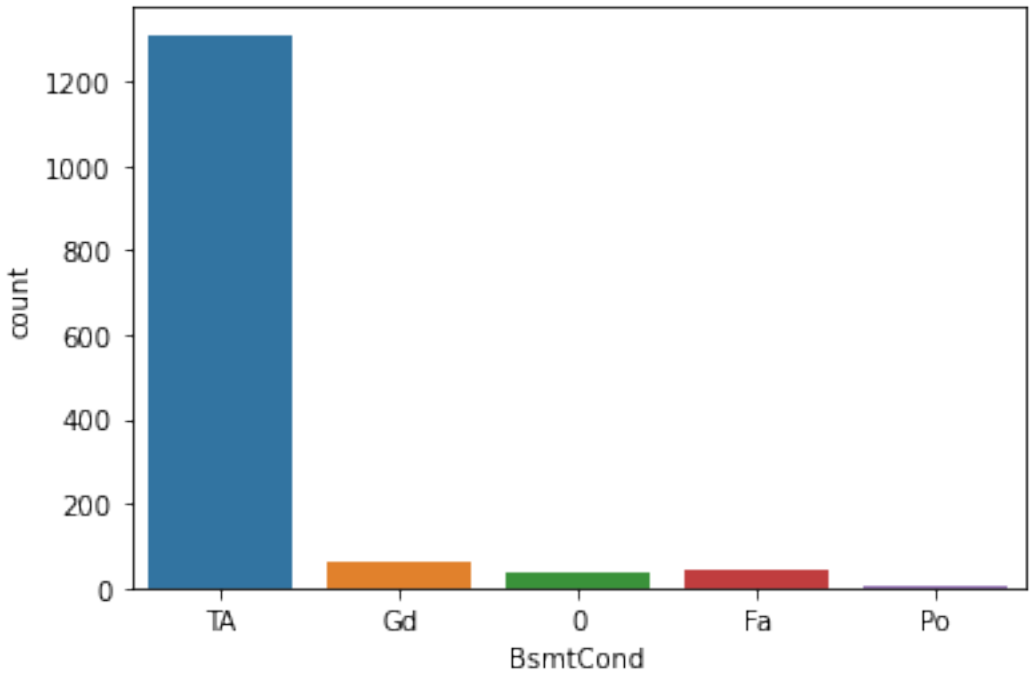
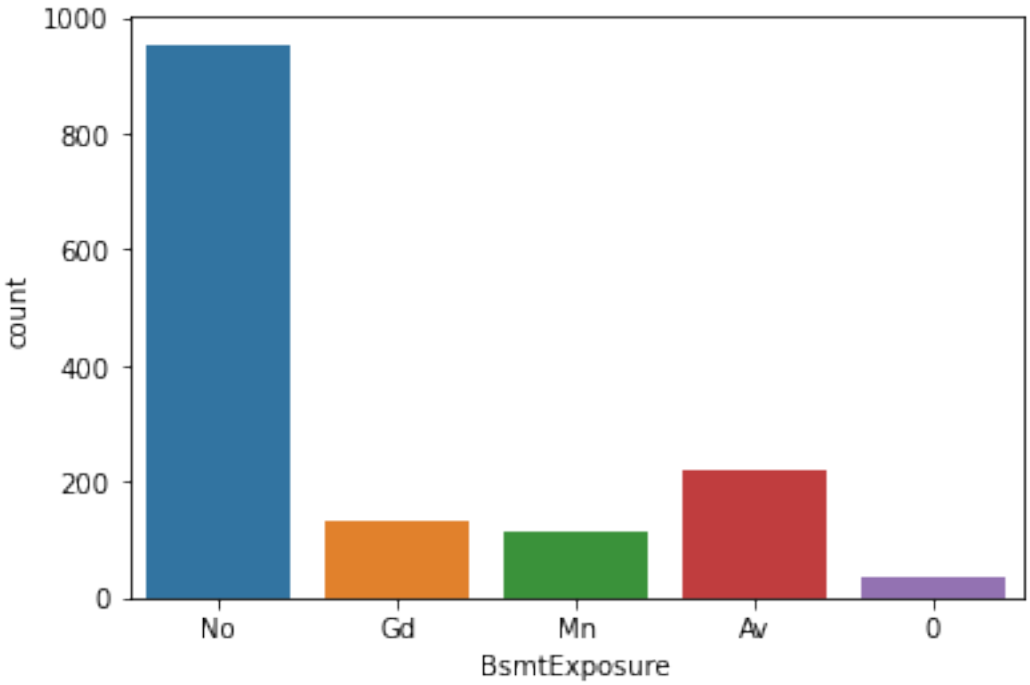
100
0
count
Gd
TA
Ex
0
Fa
BsmtQual


1200
1000
800
600
400
200
0
count
TA
Gd
0
Fa
Po
BsmtCond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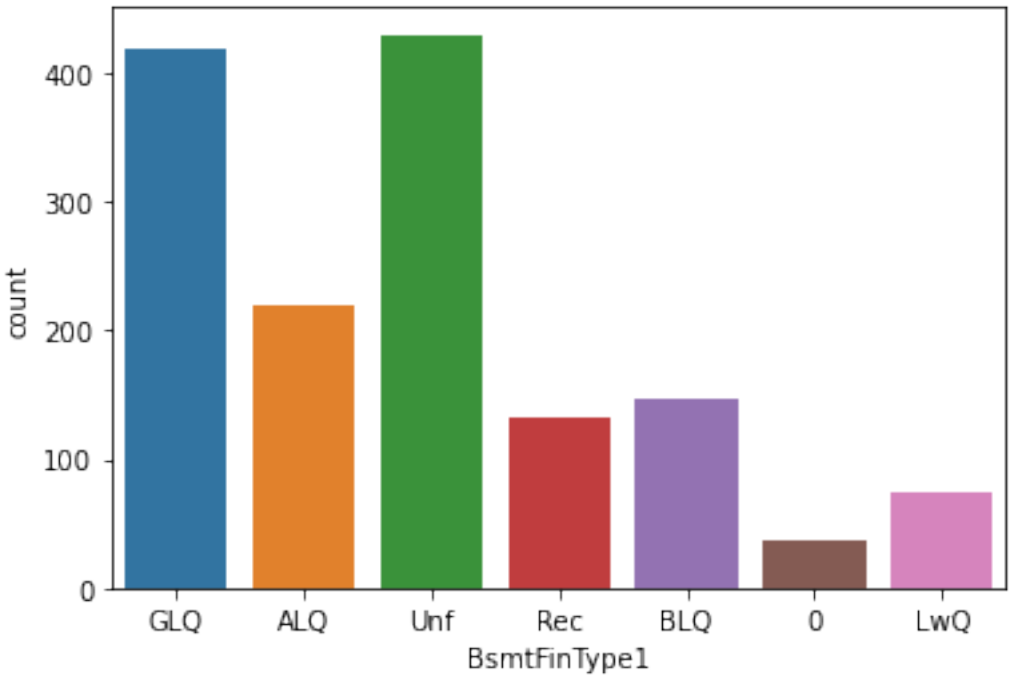
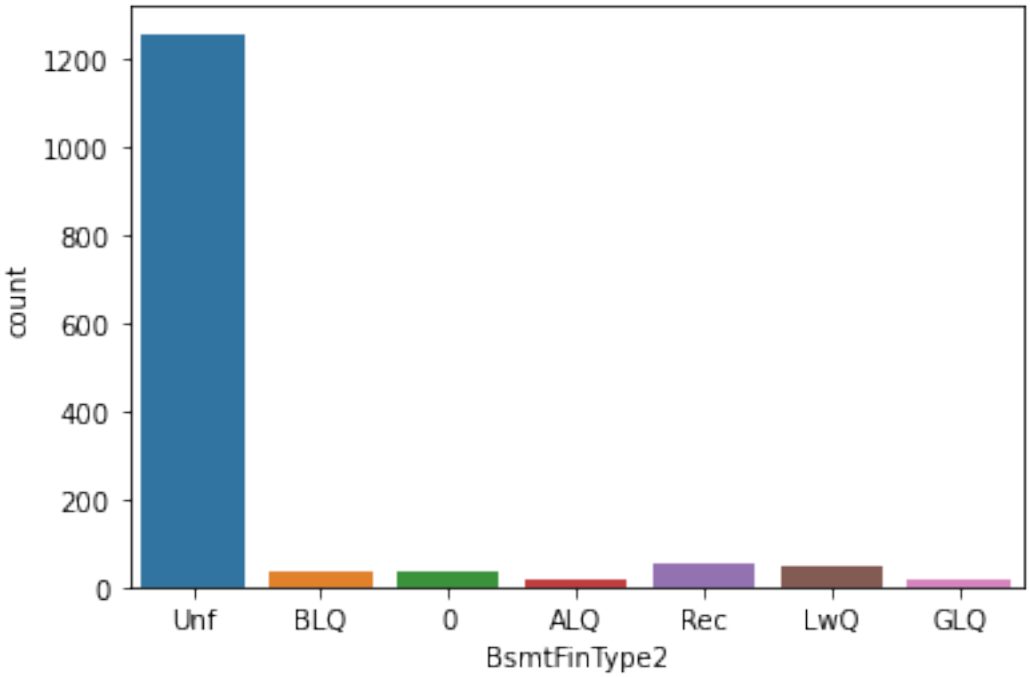
800
600
400
200
0
count
No
Gd
Mn
Av
0
BsmtExposure


400
300
200
100
0
count
GLQ
ALQ
Unf
Rec
BLQ
0
LwQ
BsmtFinType1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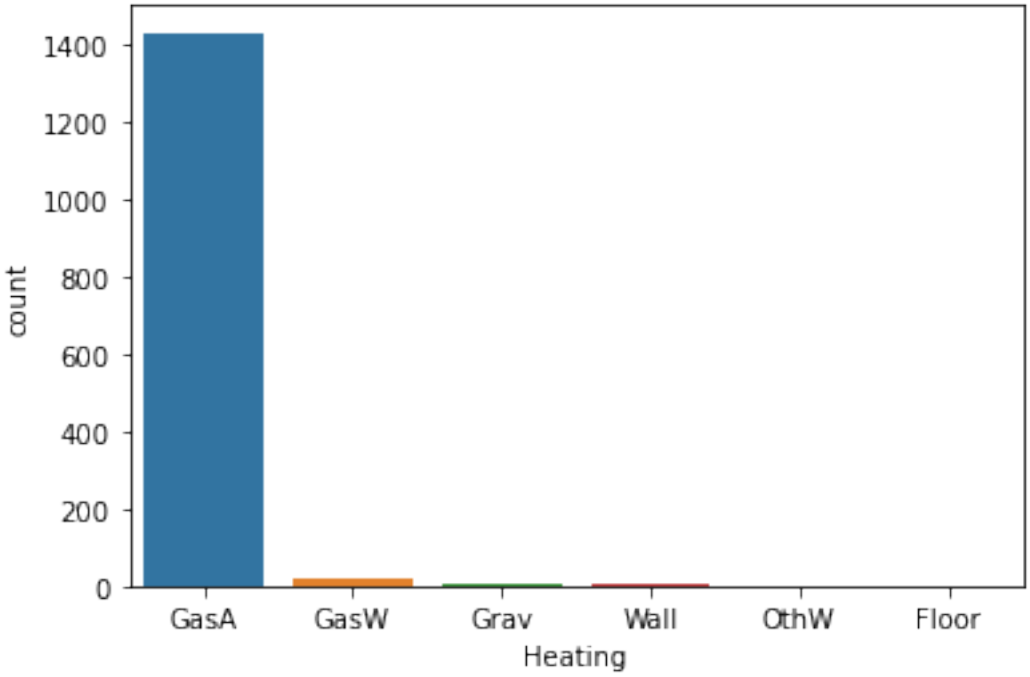
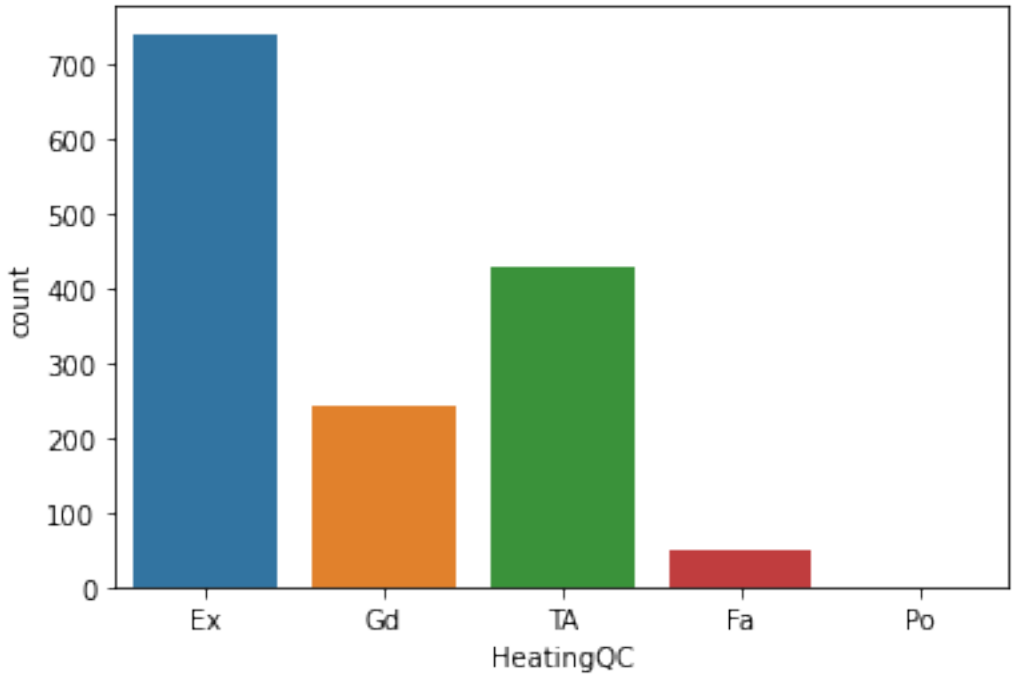
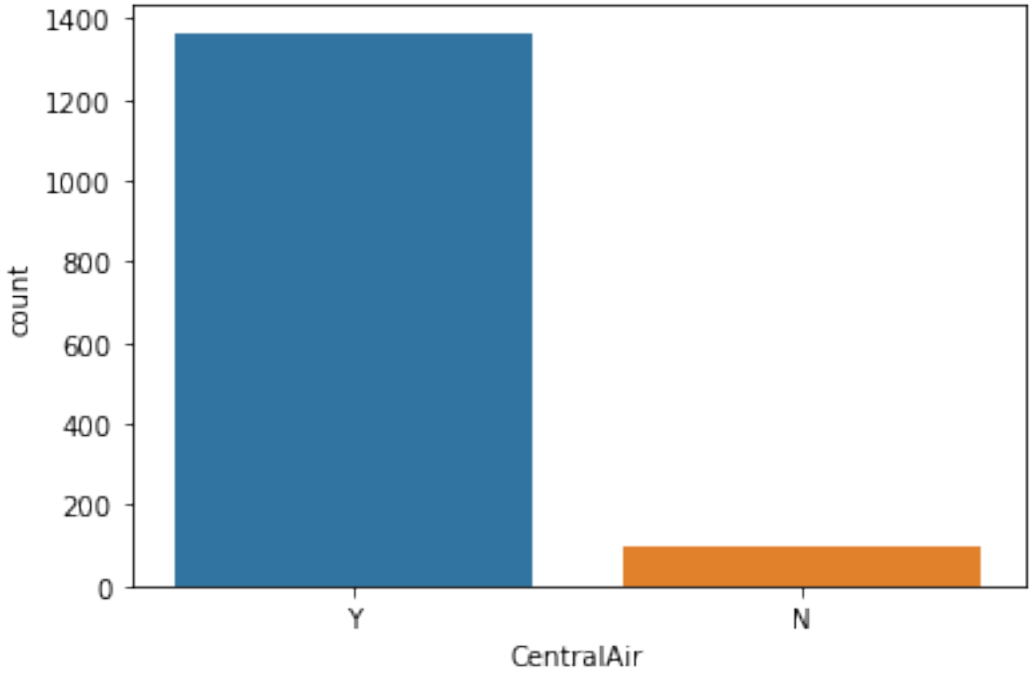
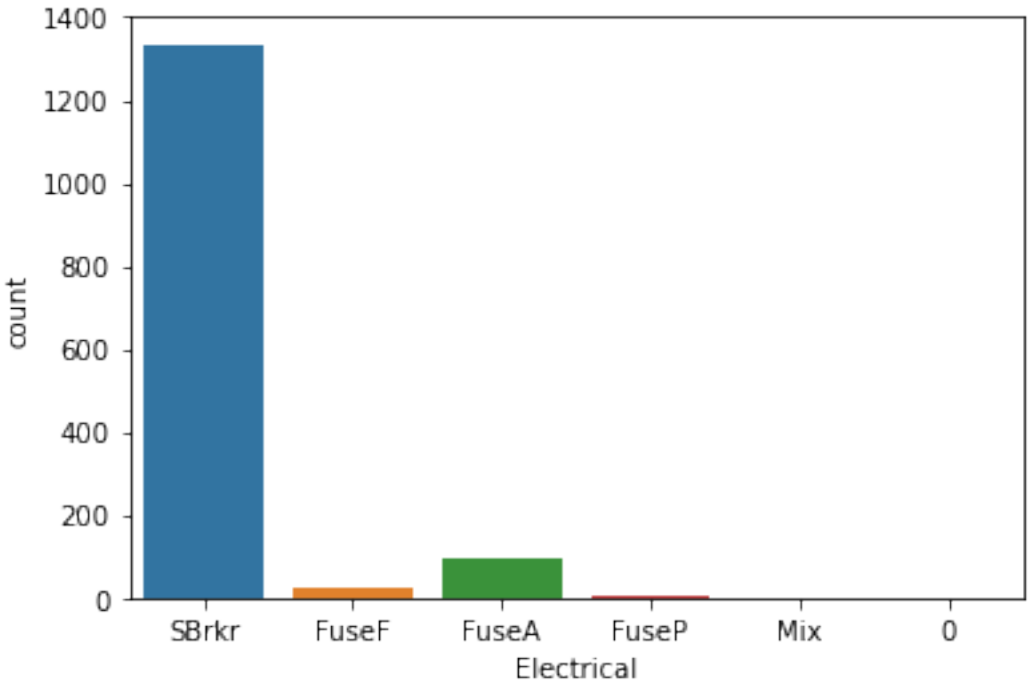
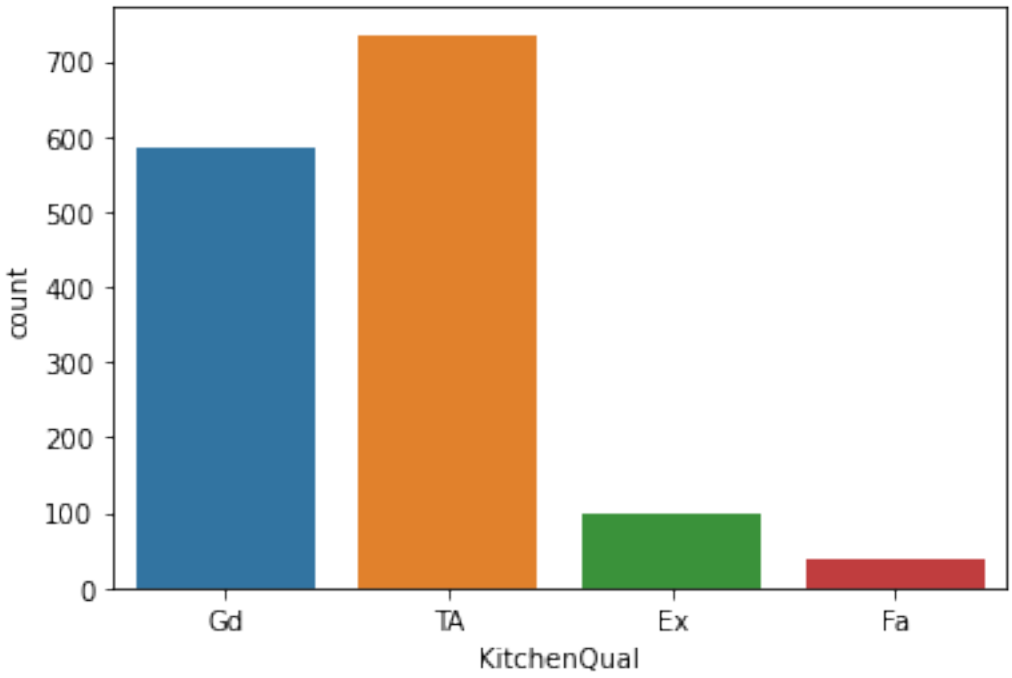
800
600
400
200
0
count
Unf
BLQ
0
ALQ
Rec
LwQ
GLQ
BsmtFinType2

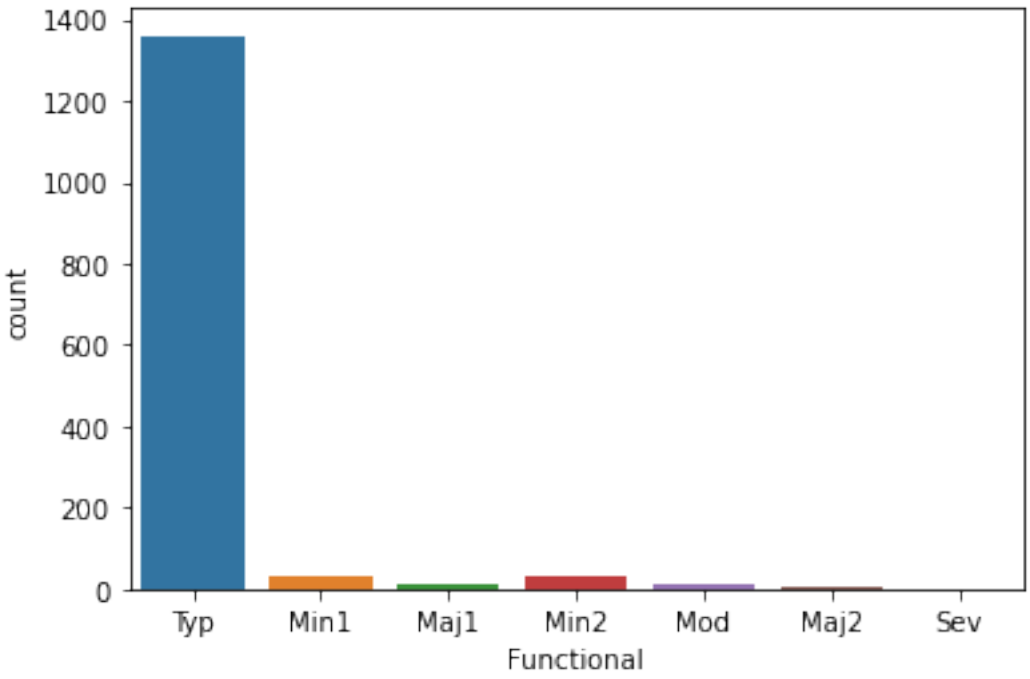

1400
1200
1000
800
600
400
200
0
count
GasA
GasW
Grav
Wall
OthW
Floor
Heating

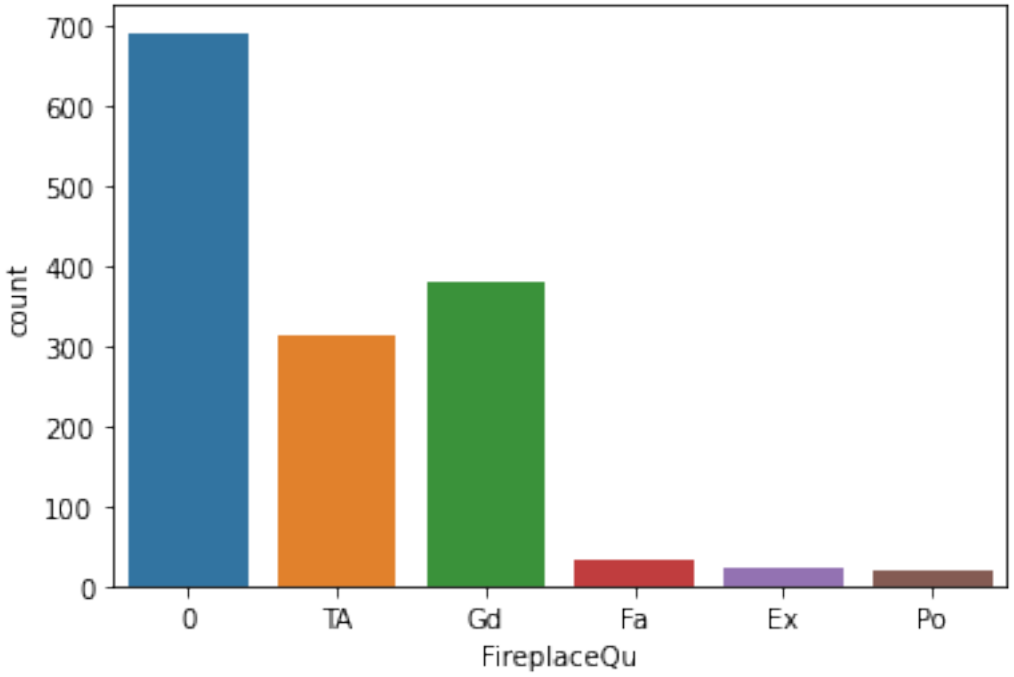

700
600
500
400
300
200
100
0
count
Ex
Gd
TA
Fa
Po
HeatingQC

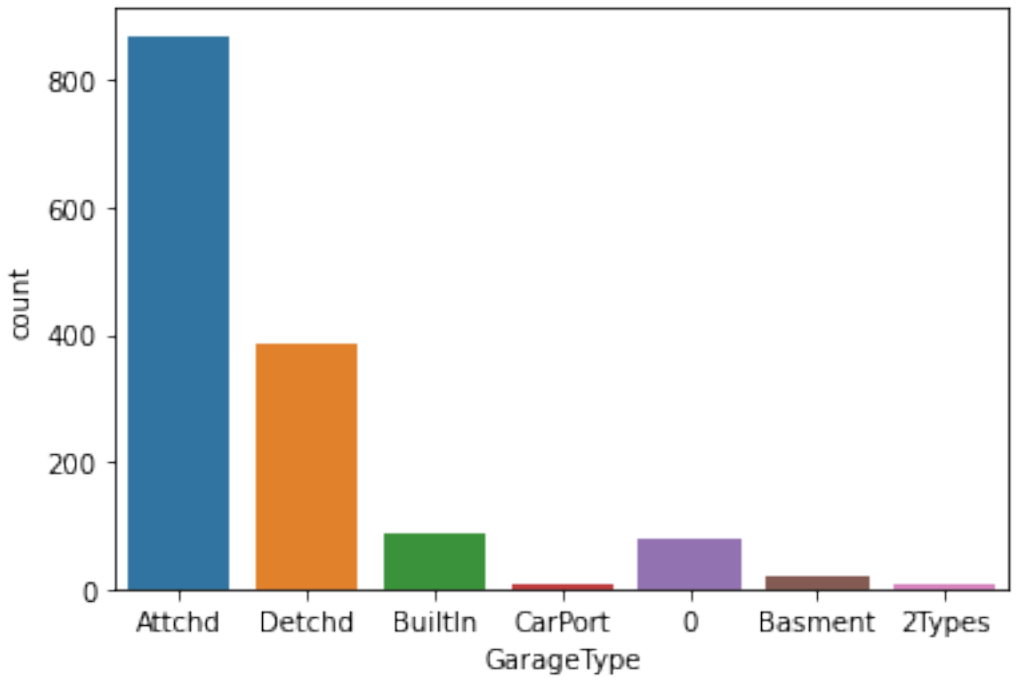

1400
1200
1000
800
600
400
200
0
count
Y
N
CentralAir

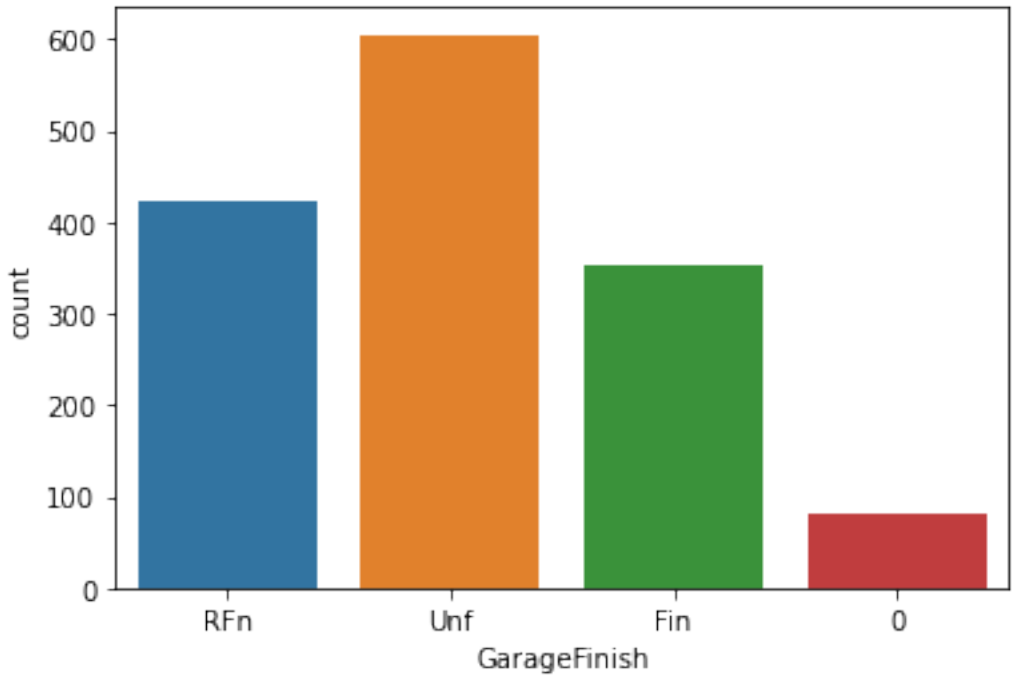

1400
1200
1000
800
600
400
200
0
count
SBrkr
FuseF
FuseA
FuseP
Mix
0
Electrical

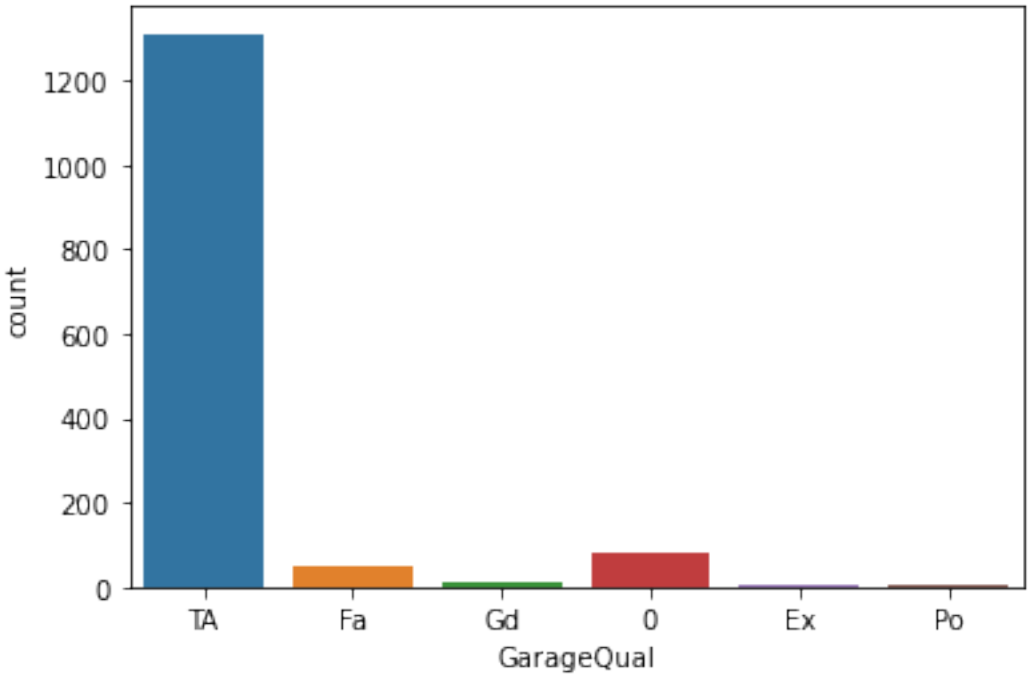

700
600
500
400
300
200
100
0
count
Gd
TA
Ex
Fa
KitchenQual

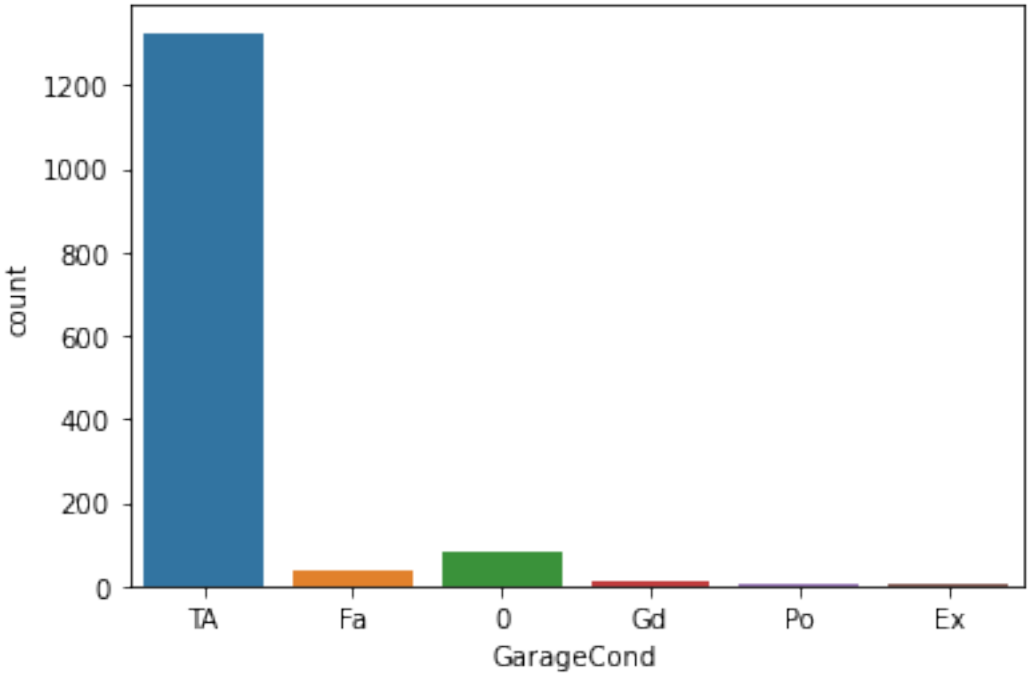

1400
1200
1000
800
600
400
200
0
count
Typ
Min1
Maj1
Min2
Mod
Maj2
Sev
Functional

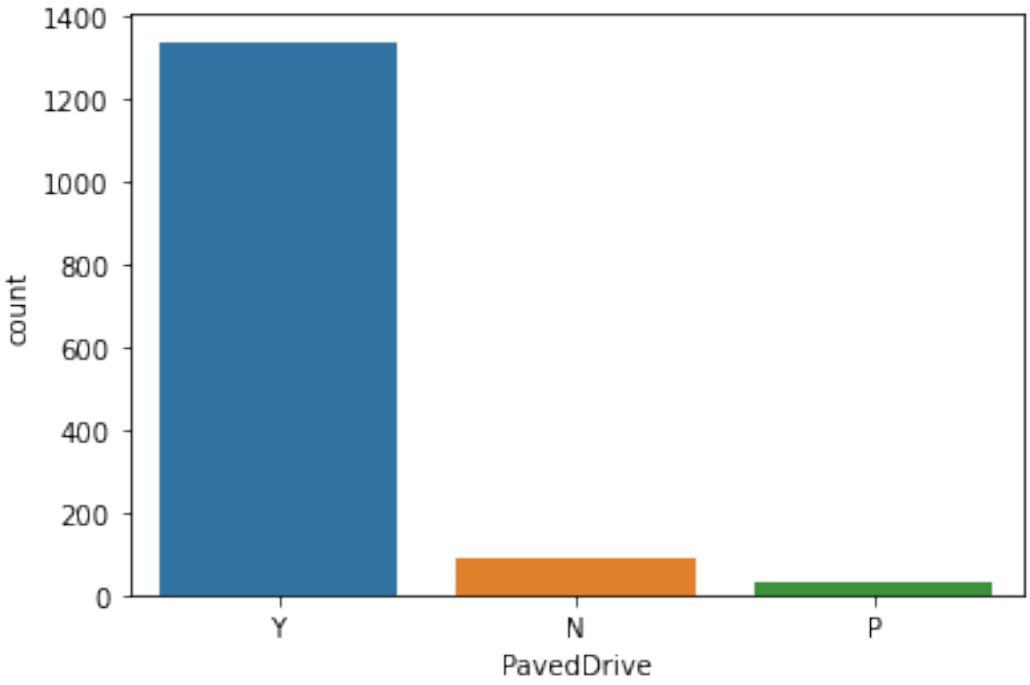

700
600
500
400
300
200
100
0
count
0
TA
Gd
Fa
Ex
Po
FireplaceQu

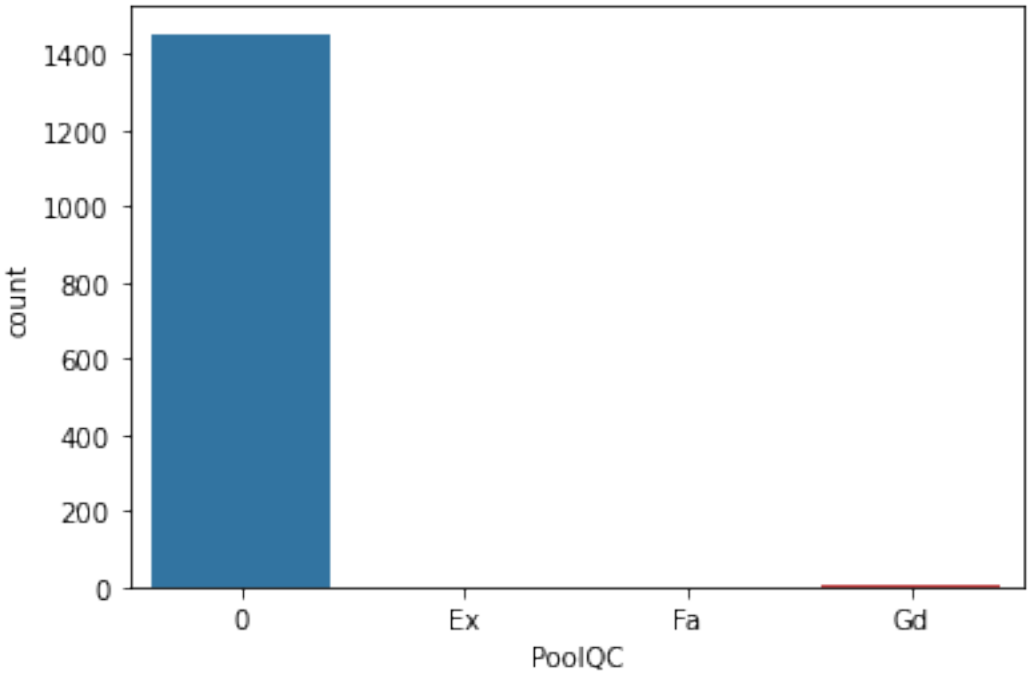

800
600
400
200
0
count
Attchd
Detchd
BuiltIn
CarPort
0
Basment
2Types
GarageType

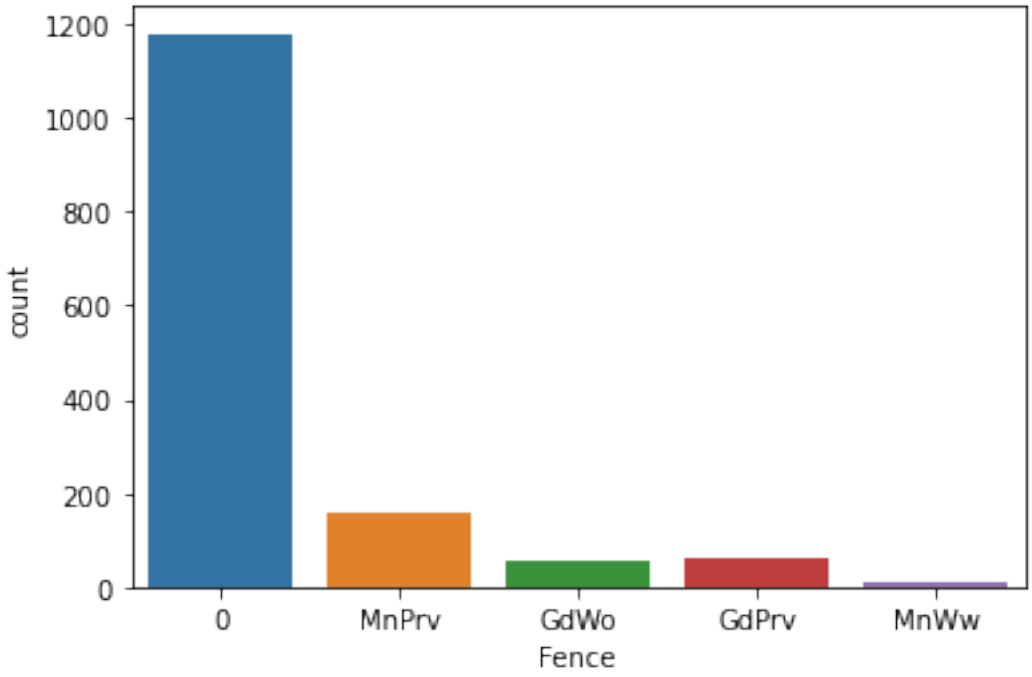

600
500
400
300
200
100
0
count
RFn
Unf
Fin
0
GarageFinish

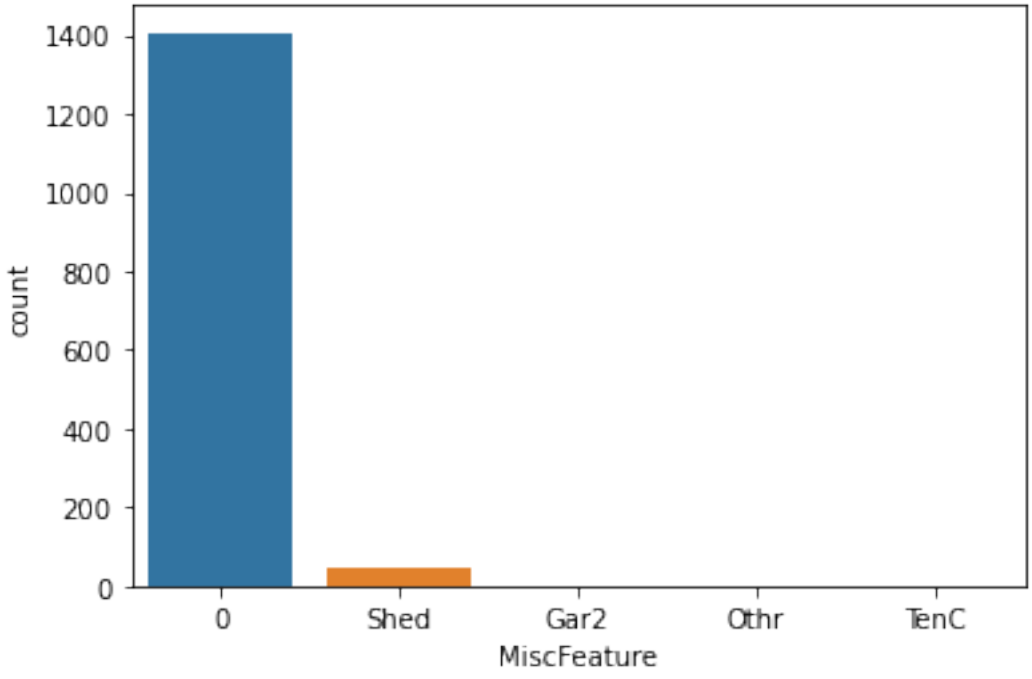

1200
1000
800
600
400
200
0
count
TA
Fa
Gd
0
Ex
Po
GarageQual

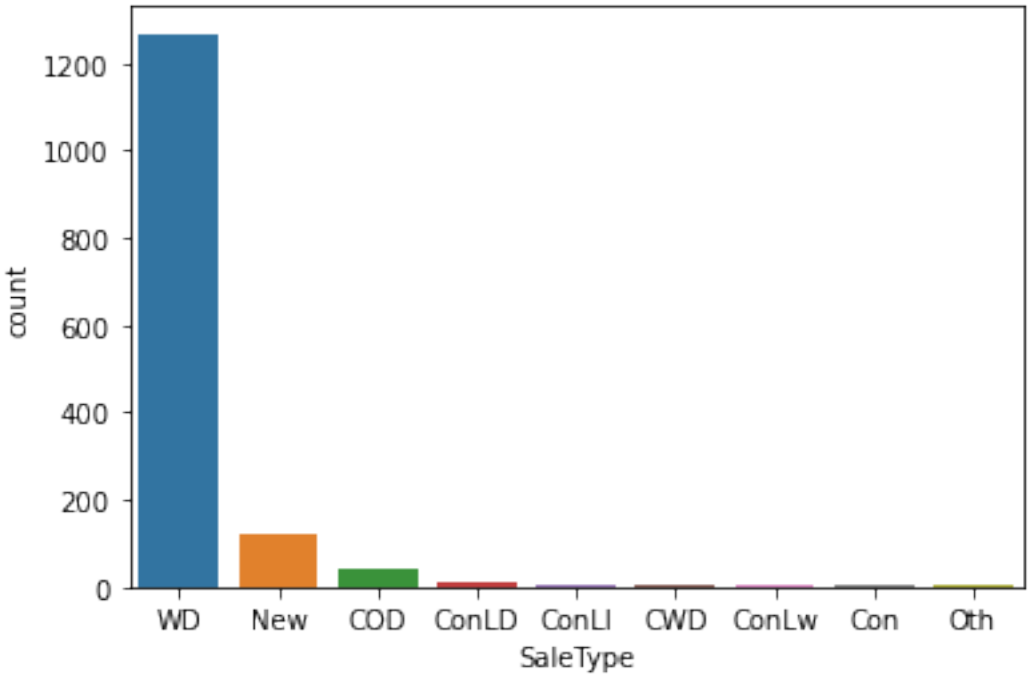

1200
1000
800
600
400
200
0
count
TA
Fa
0
Gd
Po
Ex
GarageCond

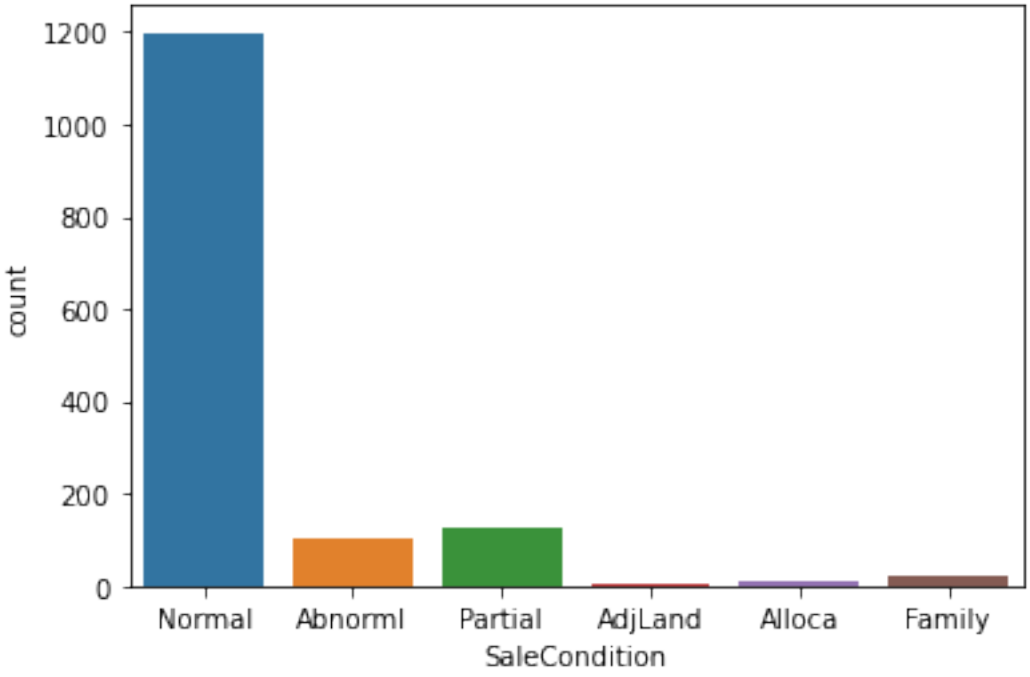

1400
1200
1000
800
600
400
200
0
count
Y
N
P
PavedDrive


1400
1200
1000
800
600
400
200
0
count
0
Ex
Fa
Gd
PoolQC


1200
1000
800
600
400
200
0
count
0
MnPrv
GdWo
GdPrv
MnWw
Fence


1400
1200
1000
800
600
400
200
0
count
0
Shed
Gar2
Othr
TenC
MiscFeature


1200
1000
800
600
400
200
0
count
WD
New
COD
ConLD
ConLI
CWD
ConLw
Con
Oth
SaleType


1200
1000
800
600
400
200
0
count
Normal
Abnorml
Partial
AdjLand
Alloca
Family
SaleCondition

3.1.1 Conclusión

Existen varias variables que no tienen mucho sentido, por ejemplo "street"en la que casi el total de las casas pertencen a la categoría "Pave", o la variable "Utilities" sucede lo mismo, todas las casas son "AllPub", y también con "Condition2", "RoofMatl", "BsmtFinType2", "Heating", "Functional" y "PoolQC". Seguramente el método LASSO hará que estas variables tengan coeficiente cero, pues realmente no describen/modelan el precio de venta.

[87]:
```
#Variables explicativas categóricas
XtrainCat = trainObj.copy()
#también lo hacemos para test
XtestCat = test[XtrainCat.columns]
XtrainCat
```

[87]:

Id	MSZoning	Street	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	...
1	RL	Pave	0	Reg	Lvl	AllPub	Inside	Gtl	...
2	RL	Pave	0	Reg	Lvl	AllPub	FR2	Gtl	...
3	RL	Pave	0	IR1	Lvl	AllPub	Inside	Gtl	...
4	RL	Pave	0	IR1	Lvl	AllPub	Corner	Gtl	...
5	RL	Pave	0	IR1	Lvl	AllPub	FR2	Gtl	...
...	...	...	...	...	...	...	...	...	...
1456	RL	Pave	0	Reg	Lvl	AllPub	Inside	Gtl	...
1457	RL	Pave	0	Reg	Lvl	AllPub	Inside	Gtl	...
1458	RL	Pave	0	Reg	Lvl	AllPub	Inside	Gtl	...
1459	RL	Pave	0	Reg	Lvl	AllPub	Inside	Gtl	...
1460	RL	Pave	0	Reg	Lvl	AllPub	Inside	Gtl	...

Id	Neighborhood	Condition1	...	GarageType	GarageFinish	GarageQual	...
1	CollgCr	Norm	...	Attchd	RFn	TA	...
2	Veenker	Feedr	...	Attchd	RFn	TA	...
3	CollgCr	Norm	...	Attchd	RFn	TA	...
4	Crawfor	Norm	...	Detchd	Unf	TA	...
5	NoRidge	Norm	...	Attchd	RFn	TA	...
...	...	...	...	...	...	...	...
1456	Gilbert	Norm	...	Attchd	RFn	TA	...
1457	NWAmes	Norm	...	Attchd	Unf	TA	...
1458	Crawfor	Norm	...	Attchd	RFn	TA	...
1459	NAmes	Norm	...	Attchd	Unf	TA	...
1460	Edwards	Norm	...	Attchd	Fin	TA	...

Id	GarageCond	PavedDrive	PoolQC	Fence	MiscFeature	SaleType	SaleCondition
1	TA	Y	0	0	0	WD	Normal
2	TA	Y	0	0	0	WD	Normal
3	TA	Y	0	0	0	WD	Normal
4	TA	Y	0	0	0	WD	Abnorml

```
5            TA          Y      0      0           0       WD        Normal
...         ...        ...    ...    ...         ...      ...           ...
1456         TA          Y      0      0           0       WD        Normal
1457         TA          Y      0  MnPrv           0       WD        Normal
1458         TA          Y      0  GdPrv        Shed       WD        Normal
1459         TA          Y      0      0           0       WD        Normal
1460         TA          Y      0      0           0       WD        Normal

[1460 rows x 43 columns]
```

3.2 Variables numéricas

Para ver la matríz de correlaciones primero seleccionamos las variables numéricas de la base de datos Train

[88]:
```
trainNum = train.select_dtypes(include=['int64' or 'float64']).copy()
trainNum
```

[88]:
```
      LotArea  OverallQual  OverallCond  YearBuilt  YearRemodAdd  BsmtFinSF1  \
Id
1        8450            7            5       2003          2003         706
2        9600            6            8       1976          1976         978
3       11250            7            5       2001          2002         486
4        9550            7            5       1915          1970         216
5       14260            8            5       2000          2000         655
...       ...          ...          ...        ...           ...         ...
1456     7917            6            5       1999          2000           0
1457    13175            6            6       1978          1988         790
1458     9042            7            9       1941          2006         275
1459     9717            5            6       1950          1996          49
1460     9937            5            6       1965          1965         830

      BsmtFinSF2  BsmtUnfSF  TotalBsmtSF  1stFlrSF  ...  WoodDeckSF  \
Id                                                  ...
1              0        150          856       856  ...           0
2              0        284         1262      1262  ...         298
3              0        434          920       920  ...           0
4              0        540          756       961  ...           0
5              0        490         1145      1145  ...         192
...          ...        ...          ...       ...  ...         ...
1456           0        953          953       953  ...           0
1457         163        589         1542      2073  ...         349
1458           0        877         1152      1188  ...           0
1459        1029          0         1078      1078  ...         366
1460         290        136         1256      1256  ...         736

      OpenPorchSF  EnclosedPorch  3SsnPorch  ScreenPorch  PoolArea  MiscVal  \
```

```
Id
1              61              0          0            0          0        0
2               0              0          0            0          0        0
3              42              0          0            0          0        0
4              35            272          0            0          0        0
5              84              0          0            0          0        0
...           ...            ...        ...          ...        ...      ...
1456           40              0          0            0          0        0
1457            0              0          0            0          0        0
1458           60              0          0            0          0     2500
1459            0            112          0            0          0        0
1460           68              0          0            0          0        0

      MoSold  YrSold  SalePrice
Id
1          2    2008     208500
2          5    2007     181500
3          9    2008     223500
4          2    2006     140000
5         12    2008     250000
...      ...     ...        ...
1456       8    2007     175000
1457       2    2010     210000
1458       5    2010     266500
1459       4    2010     142125
1460       6    2008     147500

[1460 rows x 33 columns]
```

Ahora busquemos variables que no estén correlacionadas con la variable respuesta.

[89]:
```
MC=trainNum.corr()
SaleCorr=abs(MC.loc[:,"SalePrice"])
aux=SaleCorr.sort_values(ascending=False)
to_drop=aux.index[aux<0.1]
to_drop
```

[89]:
```
Index(['PoolArea', 'OverallCond', 'MoSold', '3SsnPorch', 'YrSold',
       'LowQualFinSF', 'MiscVal', 'BsmtHalfBath', 'BsmtFinSF2'],
      dtype='object')
```

Las variables anteriores tienen una correlación menor a 0.1, no tiene caso que estén en el modelo, por lo tanto las quitamos de la matriz.

[90]:
```
#Generamos la matriz de X de variables numéricas quitando la var resp
XtrainNum = trainNum.iloc[:,0:32].copy()
XtrainNum=XtrainNum.drop(XtrainNum[to_drop], axis=1).copy()
XtrainNum
```

[90]:

Id	LotArea	OverallQual	YearBuilt	YearRemodAdd	BsmtFinSF1	BsmtUnfSF	\
1	8450	7	2003	2003	706	150	
2	9600	6	1976	1976	978	284	
3	11250	7	2001	2002	486	434	
4	9550	7	1915	1970	216	540	
5	14260	8	2000	2000	655	490	
...	...	...	...	...	...	...	
1456	7917	6	1999	2000	0	953	
1457	13175	6	1978	1988	790	589	
1458	9042	7	1941	2006	275	877	
1459	9717	5	1950	1996	49	0	
1460	9937	5	1965	1965	830	136	

Id	TotalBsmtSF	1stFlrSF	2ndFlrSF	GrLivArea	...	BedroomAbvGr	\
1	856	856	854	1710	...	3	
2	1262	1262	0	1262	...	3	
3	920	920	866	1786	...	3	
4	756	961	756	1717	...	3	
5	1145	1145	1053	2198	...	4	
...	...	...	...	...	...	...	
1456	953	953	694	1647	...	3	
1457	1542	2073	0	2073	...	3	
1458	1152	1188	1152	2340	...	4	
1459	1078	1078	0	1078	...	2	
1460	1256	1256	0	1256	...	3	

Id	KitchenAbvGr	TotRmsAbvGrd	Fireplaces	GarageCars	GarageArea	\
1	1	8	0	2	548	
2	1	6	1	2	460	
3	1	6	1	2	608	
4	1	7	1	3	642	
5	1	9	1	3	836	
...	...	...	...	...	...	
1456	1	7	1	2	460	
1457	1	7	2	2	500	
1458	1	9	2	1	252	
1459	1	5	0	1	240	
1460	1	6	0	1	276	

Id	WoodDeckSF	OpenPorchSF	EnclosedPorch	ScreenPorch
1	0	61	0	0
2	298	0	0	0
3	0	42	0	0

```
4              0           35            272            0
5            192           84              0            0
...          ...          ...            ...          ...
1456           0           40              0            0
1457         349            0              0            0
1458           0           60              0            0
1459         366            0            112            0
1460         736           68              0            0

[1460 rows x 23 columns]
```

[91]:
```
print(XtrainNum.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1460 entries, 1 to 1460
Data columns (total 23 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   LotArea         1460 non-null   int64
 1   OverallQual     1460 non-null   int64
 2   YearBuilt       1460 non-null   int64
 3   YearRemodAdd    1460 non-null   int64
 4   BsmtFinSF1      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   GrLivArea       1460 non-null   int64
 10  BsmtFullBath    1460 non-null   int64
 11  FullBath        1460 non-null   int64
 12  HalfBath        1460 non-null   int64
 13  BedroomAbvGr    1460 non-null   int64
 14  KitchenAbvGr    1460 non-null   int64
 15  TotRmsAbvGrd    1460 non-null   int64
 16  Fireplaces      1460 non-null   int64
 17  GarageCars      1460 non-null   int64
 18  GarageArea      1460 non-null   int64
 19  WoodDeckSF      1460 non-null   int64
 20  OpenPorchSF     1460 non-null   int64
 21  EnclosedPorch   1460 non-null   int64
 22  ScreenPorch     1460 non-null   int64
dtypes: int64(23)
memory usage: 273.8 KB
None
```

A continuación, vamos a explorar la correlación entre las variables explicativas y filtramos aquellas que tienen una correlación (en valor absoluto) mayor que 0.6

[92]:
```
import numpy as np
corr_matrix = XtrainNum.corr().abs()
#La mitad de arriba de la matriz de correlaciones en valores absolutos
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(np.
 ↪bool))
#Lista de variables con correlación mayor a 0.6
to_drop2 = [column for column in upper.columns if any(upper[column] > 0.6)]
to_drop2
#
```

[92]:
```
['1stFlrSF',
 'GrLivArea',
 'BsmtFullBath',
 'FullBath',
 'HalfBath',
 'TotRmsAbvGrd',
 'GarageCars',
 'GarageArea']
```

Estas variables tienen una correlación mayor a 0.6 con alguna otra de las variables explicativas, por ejemplo, '1stFlrSF' tiene una correlación de 0.819530 con 'TotalBsmtSF', basta con dejar solo una de estas dos variables y el algoritmo anterior seleccionó a '1stFlrSF', 'GrLivArea' tiene una correlación de 0.687501 con '2ndFlrSF', basta con dejar solo una de estas dos variables y así sucesivamente.

[93]:
```
corr_matrix.iloc[:,[7,9]]
```

[93]:

	1stFlrSF	GrLivArea
LotArea	0.299475	0.263116
OverallQual	0.476224	0.593007
YearBuilt	0.281986	0.199010
YearRemodAdd	0.240379	0.287389
BsmtFinSF1	0.445863	0.208171
BsmtUnfSF	0.317987	0.240257
TotalBsmtSF	0.819530	0.454868
1stFlrSF	1.000000	0.566024
2ndFlrSF	0.202646	0.687501
GrLivArea	0.566024	1.000000
BsmtFullBath	0.244671	0.034836
FullBath	0.380637	0.630012
HalfBath	0.119916	0.415772
BedroomAbvGr	0.127401	0.521270
KitchenAbvGr	0.068101	0.100063
TotRmsAbvGrd	0.409516	0.825489
Fireplaces	0.410531	0.461679
GarageCars	0.439317	0.467247
GarageArea	0.489782	0.468997
WoodDeckSF	0.235459	0.247433

```
OpenPorchSF    0.211671   0.330224
EnclosedPorch  0.065292   0.009113
ScreenPorch    0.088758   0.101510
```

[94]:
```
XtrainNum=XtrainNum.drop(XtrainNum[to_drop2], axis=1).copy()
XtrainNum
```

[94]:

Id	LotArea	OverallQual	YearBuilt	YearRemodAdd	BsmtFinSF1	BsmtUnfSF
1	8450	7	2003	2003	706	150
2	9600	6	1976	1976	978	284
3	11250	7	2001	2002	486	434
4	9550	7	1915	1970	216	540
5	14260	8	2000	2000	655	490
...	...	...	...	...	...	...
1456	7917	6	1999	2000	0	953
1457	13175	6	1978	1988	790	589
1458	9042	7	1941	2006	275	877
1459	9717	5	1950	1996	49	0
1460	9937	5	1965	1965	830	136

Id	TotalBsmtSF	2ndFlrSF	BedroomAbvGr	KitchenAbvGr	Fireplaces
1	856	854	3	1	0
2	1262	0	3	1	1
3	920	866	3	1	1
4	756	756	3	1	1
5	1145	1053	4	1	1
...	...	...	...	...	...
1456	953	694	3	1	1
1457	1542	0	3	1	2
1458	1152	1152	4	1	2
1459	1078	0	2	1	0
1460	1256	0	3	1	0

Id	WoodDeckSF	OpenPorchSF	EnclosedPorch	ScreenPorch
1	0	61	0	0
2	298	0	0	0
3	0	42	0	0
4	0	35	272	0
5	192	84	0	0
...	...	...	...	...
1456	0	40	0	0
1457	349	0	0	0
1458	0	60	0	0
1459	366	0	112	0

```
1460         736           68              0            0

[1460 rows x 15 columns]
```

Y únicamente nos quedamos con 15 variables numéricas para inlcuir en el modelo.

[95]:
```
#Preparamos la base de Test
XtestNum = test[XtrainNum.columns]
```

3.3 Conclusión

La matriz de variables explicativas queda de la siguietne forma con 58 variables:

[96]:
```
Xtrain = pd.merge(XtrainNum, XtrainCat, on='Id')
#lo mismo para test
Xtest = pd.merge(XtestNum, XtestCat, on='Id')
Xtrain.head()
```

[96]:

Id	LotArea	OverallQual	YearBuilt	YearRemodAdd	BsmtFinSF1	BsmtUnfSF	TotalBsmtSF	2ndFlrSF	BedroomAbvGr	KitchenAbvGr	...	GarageType	GarageFinish	GarageQual	GarageCond	PavedDrive	PoolQC	Fence	MiscFeature	SaleType	SaleCondition
1	8450	7	2003	2003	706	150	856	854	3	1	...	Attchd	RFn	TA	TA	Y	0	0	0	WD	Normal
2	9600	6	1976	1976	978	284	1262	0	3	1	...	Attchd	RFn	TA	TA	Y	0	0	0	WD	Normal
3	11250	7	2001	2002	486	434	920	866	3	1	...	Attchd	RFn	TA	TA	Y	0	0	0	WD	Normal
4	9550	7	1915	1970	216	540	756	756	3	1	...	Detchd	Unf	TA	TA	Y	0	0	0	WD	Normal
5	14260	8	2000	2000	655	490	1145	1053	4	1	...	Attchd	RFn	TA	TA	Y	0	0	0	WD	Normal

```
4         WD        Abnorml
5         WD         Normal

[5 rows x 58 columns]
```

4 Modelo LASSO

[97]:
```
dummies = []
for i in Xtrain.columns:
    if (train[i].dtype=='object'):
        dummies.append(i)
dummies
```

[97]:
```
['MSZoning',
 'Street',
 'Alley',
 'LotShape',
 'LandContour',
 'Utilities',
 'LotConfig',
 'LandSlope',
 'Neighborhood',
 'Condition1',
 'Condition2',
 'BldgType',
 'HouseStyle',
 'RoofStyle',
 'RoofMatl',
 'Exterior1st',
 'Exterior2nd',
 'MasVnrType',
 'ExterQual',
 'ExterCond',
 'Foundation',
 'BsmtQual',
 'BsmtCond',
 'BsmtExposure',
 'BsmtFinType1',
 'BsmtFinType2',
 'Heating',
 'HeatingQC',
 'CentralAir',
 'Electrical',
 'KitchenQual',
 'Functional',
 'FireplaceQu',
```

```
 'GarageType',
 'GarageFinish',
 'GarageQual',
 'GarageCond',
 'PavedDrive',
 'PoolQC',
 'Fence',
 'MiscFeature',
 'SaleType',
 'SaleCondition']
```

[98]:
```
status =  pd.get_dummies(Xtrain[dummies],drop_first=True) ## one hot encoding on
 ↪all variables
Xtrain = pd.concat([train,status],axis=1)
Xtrain.drop(dummies,axis=1,inplace=True)
Xtrain.head()
```

[98]:

Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	\
1	60	65.0	8450	7	5	2003	
2	20	80.0	9600	6	8	1976	
3	60	68.0	11250	7	5	2001	
4	70	60.0	9550	7	5	1915	
5	60	84.0	14260	8	5	2000	

Id	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	...	SaleType_ConLI	\
					...		
1	2003	196.0	706	0	...	0	
2	1976	0.0	978	0	...	0	
3	2002	162.0	486	0	...	0	
4	1970	0.0	216	0	...	0	
5	2000	350.0	655	0	...	0	

Id	SaleType_ConLw	SaleType_New	SaleType_Oth	SaleType_WD	\
1	0	0	0	1	
2	0	0	0	1	
3	0	0	0	1	
4	0	0	0	1	
5	0	0	0	1	

Id	SaleCondition_AdjLand	SaleCondition_Alloca	SaleCondition_Family	\
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

```
5                       0                       0                       0

    SaleCondition_Normal  SaleCondition_Partial
Id
1                       1                       0
2                       1                       0
3                       1                       0
4                       0                       0
5                       1                       0

[5 rows x 262 columns]
```

[99]:
```
ytrain=train.iloc[:,79]
ytrain.head()
```

[99]:
```
Id
1    208500
2    181500
3    223500
4    140000
5    250000
Name: SalePrice, dtype: int64
```

[100]:
```
from sklearn.linear_model import Lasso
alpha = 0.0002

lasso = Lasso(alpha=alpha)

lasso.fit(Xtrain, ytrain)
#lasso.coef_
```

[100]:
```
Lasso(alpha=0.0002)
```

[101]:
```
lasso_df=pd.DataFrame()
lasso_df['Features'] = Xtrain.columns
lasso_df['Coefficients']=lasso.coef_
lasso_df['ABS Coefficients'] = abs(lasso.coef_)
lasso_df.sort_values(by=['ABS Coefficients'],ascending=False,inplace = True)
lasso_df
```

[101]:
```
           Features  Coefficients  ABS Coefficients
226  GarageQual_Ex -22126.186003      22126.186003
228  GarageQual_Gd -21807.597215      21807.597215
230  GarageQual_TA -21591.166645      21591.166645
227  GarageQual_Fa -21180.530486      21180.530486
229  GarageQual_Po -20926.678894      20926.678894
..             ...           ...               ...
```

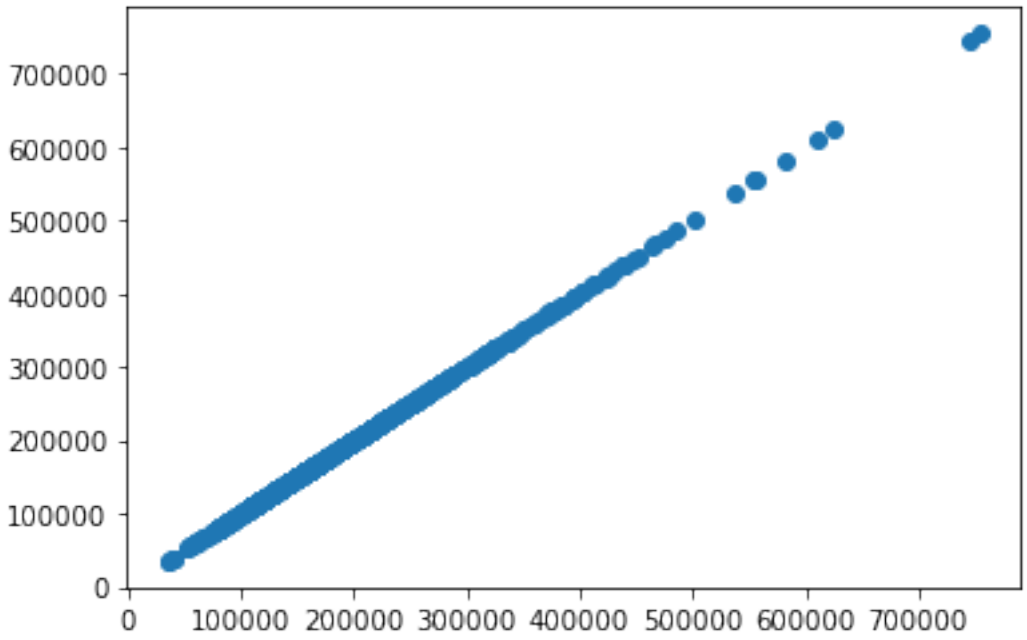
```
31      ScreenPorch      0.026423          0.026423
7        MasVnrArea      0.026289          0.026289
15         GrLivArea      0.014352          0.014352
12          1stFlrSF      0.013917          0.013917
2            LotArea      0.003269          0.003269

[262 rows x 3 columns]
```

[102]:
```
ygorro = lasso.predict(Xtrain)
ygorro
```

[102]:
```
array([208571.87785598, 181577.80032264, 223610.81721633, ...,
       266096.49623843, 141812.07731144, 147447.94724785])
```

[103]:
```
plt.scatter(ytrain,ygorro)
```

[103]:
```
<matplotlib.collections.PathCollection at 0x201f9c071f0>
```



5 Probando con la base test

[104]:
```
dummiestest = []
for i in Xtest.columns:
    if (test[i].dtype=='object'):
        dummiestest.append(i)
dummiestest
```

[104]:
```
['MSZoning',
 'Street',
 'Alley',
 'LotShape',
 'LandContour',
 'Utilities',
 'LotConfig',
 'LandSlope',
 'Neighborhood',
 'Condition1',
 'Condition2',
 'BldgType',
 'HouseStyle',
 'RoofStyle',
 'RoofMatl',
 'Exterior1st',
 'Exterior2nd',
 'MasVnrType',
 'ExterQual',
 'ExterCond',
 'Foundation',
 'BsmtQual',
 'BsmtCond',
 'BsmtExposure',
 'BsmtFinType1',
 'BsmtFinType2',
 'Heating',
 'HeatingQC',
 'CentralAir',
 'Electrical',
 'KitchenQual',
 'Functional',
 'FireplaceQu',
 'GarageType',
 'GarageFinish',
 'GarageQual',
 'GarageCond',
 'PavedDrive',
 'PoolQC',
 'Fence',
 'MiscFeature',
 'SaleType',
 'SaleCondition']
```

[105]:
```
status =  pd.get_dummies(Xtest[dummiestest],drop_first=True) ## one hot encoding␣
 ↪on all variables
Xtest = pd.concat([test,status],axis=1)
```

```
Xtest.drop(dummiestest,axis=1,inplace=True)
Xtest.head()
```

[105]:

Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	\
1461	20	80.0	11622	5	6	1961	
1462	20	81.0	14267	6	6	1958	
1463	60	74.0	13830	5	5	1997	
1464	60	78.0	9978	6	6	1998	
1465	120	43.0	5005	8	5	1992	

Id	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	...	SaleType_ConLI	\
					...		
1461	1961	0.0	468.0	144.0	...	0	
1462	1958	108.0	923.0	0.0	...	0	
1463	1998	0.0	791.0	0.0	...	0	
1464	1998	20.0	602.0	0.0	...	0	
1465	1992	0.0	263.0	0.0	...	0	

Id	SaleType_ConLw	SaleType_New	SaleType_Oth	SaleType_WD	\
1461	0	0	0	1	
1462	0	0	0	1	
1463	0	0	0	1	
1464	0	0	0	1	
1465	0	0	0	1	

Id	SaleCondition_AdjLand	SaleCondition_Alloca	SaleCondition_Family	\
1461	0	0	0	
1462	0	0	0	
1463	0	0	0	
1464	0	0	0	
1465	0	0	0	

Id	SaleCondition_Normal	SaleCondition_Partial
1461	1	0
1462	1	0
1463	1	0
1464	1	0
1465	1	0

[5 rows x 249 columns]

5.1 Conclusión

No se puede obtener la estimación del precio de venta con la codificación de las variables categóricas porque la dimensión de la matriz no coincide. Debe trabajarse más a detalle la codificación.

[ ]:

[ ]:

[ ]: