Logistic Regression & Data Preprocessing

Week of November 21st, 2020

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In this session, we will learn the following points :

```
1 - Data pre-processing: Statiscal significance using P-values
2 - Plotting : Matplotlib library
3 - Categorical Variables
4 - Practical Example on Logistic Regression
```

1 - Multi Linear Regression : P-values

In [211]:
```
import pandas as pd
df = pd.read_csv("house_price_data.csv")
```

In [212]:
```
dataset = df.copy()
dataset.head()
```

Out[212]:

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

5 rows × 81 columns

In [213]:
```
dataset = dataset[["LotFrontage","LotArea","GarageCars","GarageArea","SalePrice"]
```

In [214]:
```
dataset.isnull().sum()
```

Out[214]:
```
LotFrontage    259
LotArea          0
GarageCars       0
GarageArea       0
SalePrice        0
dtype: int64
```

In [215]:
```
dataset.fillna(value=dataset["LotFrontage"].mean(), inplace = True)
```

In [216]:
```
dataset.isnull().sum()
```

Out[216]:
```
LotFrontage    0
LotArea        0
GarageCars     0
GarageArea     0
SalePrice      0
dtype: int64
```

In [217]:
```
dataset.head(5)
```

Out[217]:

	LotFrontage	LotArea	GarageCars	GarageArea	SalePrice
0	65.0	8450	2	548	208500
1	80.0	9600	2	460	181500
2	68.0	11250	2	608	223500
3	60.0	9550	3	642	140000
4	84.0	14260	3	836	250000

In [218]:
```
X = dataset[['LotFrontage', 'LotArea', 'GarageCars', 'GarageArea']]
y = dataset["SalePrice"]
```

In [219]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, randon
```

In [220]:
```
from sklearn.linear_model import LinearRegression

#Create the model :
regressor = LinearRegression()

#Train the model :
regressor.fit(X_train, y_train)
```

Out[220]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [221]:
```
L = regressor.coef_
print("Price = {:.2f} + {:.2f}*LotFrontage + {:.2f}*LotArea + {:.2f}*GarageCars +
      format(regressor.intercept_,L[0], L[1], L[2] ,L[3]))
```

```
Price = 22887.31 + 429.69*LotFrontage + 0.93*LotArea + 42758.97*GarageCars + 8
9.41*GarageArea
```

In [222]:
```
y_pred = regressor.predict(X_test)
```

In [223]:
```
from sklearn.metrics import r2_score
#R_squared :
R_squared = r2_score(y_test, y_pred)
print("R^2 Value in %:            {:.2f} % ".format((R_squared*100)))
```

```
R^2 Value in %:            36.32 %
```

Select the features based on P-values : Backward Elimination

In [224]:
```
import statsmodels.api as sm
```

In [230]:
```
dataset.columns
```

Out[230]:
```
Index(['LotFrontage', 'LotArea', 'GarageCars', 'GarageArea', 'SalePrice'], dtyp
e='object')
```

In [231]:
```
dataset = df.copy()
X = dataset[['LotFrontage', 'LotArea', 'GarageCars', 'GarageArea','PoolArea', 'Yr
```

In [233]:
```
#Fill in the missing values for the following columns
X['LotFrontage'] = X.fillna(X['LotFrontage'].mean(), axis = 1)
X['GarageYrBlt'] = X.fillna(X['GarageYrBlt'].mode()[0], axis = 1)
```

```
C:\Users\pc\anaconda3\lib\site-packages\ipykernel_launcher.py:2: SettingWithCop
yWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)

C:\Users\pc\anaconda3\lib\site-packages\ipykernel_launcher.py:3: SettingWithCop
yWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  This is separate from the ipykernel package so we can avoid doing imports unt
il
```

In [234]:
```
X.isnull().sum()
```

Out[234]:
```
LotFrontage    0
LotArea        0
GarageCars     0
GarageArea     0
PoolArea       0
YrSold         0
OverallCond    0
OverallQual    0
GarageYrBlt    0
dtype: int64
```

In [235]:
```
y = dataset["SalePrice"]
X = X.values
y = y.values
X
```

Out[235]:
```
array([[6.500e+01, 8.450e+03, 2.000e+00, ..., 5.000e+00, 7.000e+00,
        6.500e+01],
       [8.000e+01, 9.600e+03, 2.000e+00, ..., 8.000e+00, 6.000e+00,
        8.000e+01],
       [6.800e+01, 1.125e+04, 2.000e+00, ..., 5.000e+00, 7.000e+00,
        6.800e+01],
       ...,
       [6.600e+01, 9.042e+03, 1.000e+00, ..., 9.000e+00, 7.000e+00,
        6.600e+01],
       [6.800e+01, 9.717e+03, 1.000e+00, ..., 6.000e+00, 5.000e+00,
        6.800e+01],
       [7.500e+01, 9.937e+03, 1.000e+00, ..., 6.000e+00, 5.000e+00,
        7.500e+01]])
```

In [236]:
```
# Multiple Linear Regression equation :
```

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \ldots$$

In [237]:
```
import numpy as np
arr_ones = np.ones((X.shape[0],1))
X_new = np.append( values= X , arr = arr_ones , axis = 1)
X_new
```

Out[237]:
```
array([[1.000e+00, 6.500e+01, 8.450e+03, ..., 5.000e+00, 7.000e+00,
        6.500e+01],
       [1.000e+00, 8.000e+01, 9.600e+03, ..., 8.000e+00, 6.000e+00,
        8.000e+01],
       [1.000e+00, 6.800e+01, 1.125e+04, ..., 5.000e+00, 7.000e+00,
        6.800e+01],
       ...,
       [1.000e+00, 6.600e+01, 9.042e+03, ..., 9.000e+00, 7.000e+00,
        6.600e+01],
       [1.000e+00, 6.800e+01, 9.717e+03, ..., 6.000e+00, 5.000e+00,
        6.800e+01],
       [1.000e+00, 7.500e+01, 9.937e+03, ..., 6.000e+00, 5.000e+00,
        7.500e+01]])
```

In [238]:
```
# columns names and the corresponding indexes :
d = {'ones' : 0, 'LotFrontage': 1 , 'LotArea': 2, 'GarageCars': 3, 'GarageArea':
     'PoolArea':5, 'YrSold':6, 'OverallCond':7,'OverallQual':8 ,'GarageYrBlt':9}
```

In [239]:
```
X_select = X_new[:, [0, 1, 2, 3, 4, 5, 6, 7, 8, 9] ]

d = {'ones' : 0, 'LotFrontage': 1 , 'LotArea': 2, 'GarageCars': 3, 'GarageArea':
     'PoolArea':5, 'YrSold':6, 'OverallCond':7,'OverallQual':8 ,'GarageYrBlt':9}
```

In [240]:
```
# Ordinary least squares (OLS) regression is a statistical method of analysis tha
# between one or more independent variables and a dependent variable

OLS_regressor = sm.OLS(y,X_select)

OLS_regressor.fit().summary()
```

Out[240]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.704
Model:	OLS	**Adj. R-squared:**	0.702
Method:	Least Squares	**F-statistic:**	431.1
Date:	Thu, 19 Nov 2020	**Prob (F-statistic):**	0.00
Time:	19:54:09	**Log-Likelihood:**	-17656.
No. Observations:	1460	**AIC:**	3.533e+04
Df Residuals:	1451	**BIC:**	3.538e+04
Df Model:	8		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	1.647e+05	1.72e+06	0.096	0.924	-3.21e+06	3.54e+06
x1	135.1278	28.717	4.705	0.000	78.796	191.459
x2	1.0597	0.120	8.827	0.000	0.824	1.295
x3	1.411e+04	3390.737	4.163	0.000	7462.793	2.08e+04
x4	42.4327	11.553	3.673	0.000	19.770	65.096
x5	36.5694	28.880	1.266	0.206	-20.081	93.220
x6	-142.0257	857.852	-0.166	0.869	-1824.788	1540.737
x7	1830.1669	1039.694	1.760	0.079	-209.297	3869.631
x8	3.541e+04	1034.924	34.218	0.000	3.34e+04	3.74e+04
x9	135.1278	28.717	4.705	0.000	78.796	191.459

Omnibus:	618.619	**Durbin-Watson:**	1.970
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	11796.420
Skew:	1.489	**Prob(JB):**	0.00
Kurtosis:	16.603	**Cond. No.**	1.76e+19

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1e-27. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [241]:
```
X_select = X_new[:, [0, 1, 2, 3, 4, 5, 7, 8, 9] ]

d = {'ones' : 0, 'LotFrontage': 1 , 'LotArea': 2, 'GarageCars': 3, 'GarageArea':
     'PoolArea':5, 'OverallCond':7,'OverallQual':8 ,'GarageYrBlt':9}

OLS_regressor = sm.OLS(y,X_select)
OLS_regressor.fit().summary()
```

Out[241]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.704
Model:	OLS	**Adj. R-squared:**	0.702
Method:	Least Squares	**F-statistic:**	493.0
Date:	Thu, 19 Nov 2020	**Prob (F-statistic):**	0.00
Time:	19:54:09	**Log-Likelihood:**	-17656.
No. Observations:	1460	**AIC:**	3.533e+04
Df Residuals:	1452	**BIC:**	3.537e+04
Df Model:	7		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-1.204e+05	8530.004	-14.119	0.000	-1.37e+05	-1.04e+05
x1	134.9881	28.695	4.704	0.000	78.700	191.276
x2	1.0599	0.120	8.833	0.000	0.825	1.295
x3	1.413e+04	3388.247	4.170	0.000	7483.554	2.08e+04
x4	42.4028	11.548	3.672	0.000	19.750	65.055
x5	36.8730	28.812	1.280	0.201	-19.644	93.390
x6	1823.6797	1038.607	1.756	0.079	-213.652	3861.011
x7	3.541e+04	1034.562	34.231	0.000	3.34e+04	3.74e+04
x8	134.9881	28.695	4.704	0.000	78.700	191.276

Omnibus:	618.366	**Durbin-Watson:**	1.970
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	11795.830
Skew:	1.488	**Prob(JB):**	0.00
Kurtosis:	16.603	**Cond. No.**	1.75e+19

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1e-27. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [242]:
```
X_select = X_new[:, [0, 1, 2, 3, 4, 5, 8, 9] ]

d = {'ones' : 0, 'LotFrontage': 1 , 'LotArea': 2, 'GarageCars': 3, 'GarageArea':
     'PoolArea':5, 'OverallQual':8 ,'GarageYrBlt':9}

OLS_regressor = sm.OLS(y,X_select)
OLS_regressor.fit().summary()
```

Out[242]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.703
Model:	OLS	**Adj. R-squared:**	0.702
Method:	Least Squares	**F-statistic:**	573.8
Date:	Thu, 19 Nov 2020	**Prob (F-statistic):**	0.00
Time:	19:54:09	**Log-Likelihood:**	-17657.
No. Observations:	1460	**AIC:**	3.533e+04
Df Residuals:	1453	**BIC:**	3.537e+04
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-1.095e+05	5842.465	-18.745	0.000	-1.21e+05	-9.81e+04
x1	134.1878	28.712	4.674	0.000	77.866	190.509
x2	1.0652	0.120	8.873	0.000	0.830	1.301
x3	1.345e+04	3368.509	3.993	0.000	6843.113	2.01e+04
x4	42.9116	11.553	3.714	0.000	20.250	65.573
x5	36.8325	28.832	1.277	0.202	-19.725	93.390
x6	3.546e+04	1035.008	34.258	0.000	3.34e+04	3.75e+04
x7	134.1878	28.712	4.674	0.000	77.866	190.509

Omnibus:	614.482	**Durbin-Watson:**	1.970
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	11745.399
Skew:	1.475	**Prob(JB):**	0.00
Kurtosis:	16.579	**Cond. No.**	1.75e+19

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.01e-27. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [243]:
```
X_select = X_new[:, [0, 1, 2, 3, 4, 8, 9] ]

d = {'ones' : 0, 'LotFrontage': 1 , 'LotArea': 2, 'GarageCars': 3, 'GarageArea':

OLS_regressor = sm.OLS(y,X_select)
OLS_regressor.fit().summary()
```

Out[243]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.703
Model:	OLS	**Adj. R-squared:**	0.702
Method:	Least Squares	**F-statistic:**	688.0
Date:	Thu, 19 Nov 2020	**Prob (F-statistic):**	0.00
Time:	19:54:10	**Log-Likelihood:**	-17658.
No. Observations:	1460	**AIC:**	3.533e+04
Df Residuals:	1454	**BIC:**	3.536e+04
Df Model:	5		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-1.104e+05	5801.179	-19.033	0.000	-1.22e+05	-9.9e+04
x1	139.7900	28.381	4.925	0.000	84.117	195.463
x2	1.0689	0.120	8.905	0.000	0.833	1.304
x3	1.313e+04	3359.692	3.907	0.000	6536.667	1.97e+04
x4	43.7053	11.538	3.788	0.000	21.072	66.339
x5	3.552e+04	1034.122	34.347	0.000	3.35e+04	3.75e+04
x6	139.7900	28.381	4.925	0.000	84.117	195.463

Omnibus:	639.877	**Durbin-Watson:**	1.966
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	12085.236
Skew:	1.564	**Prob(JB):**	0.00
Kurtosis:	16.743	**Cond. No.**	1.74e+19

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.01e-27. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [244]:
```
Optimal_features = X_new[:, [0, 1, 2, 3, 4, 8, 9] ]

d
```

Out[244]:
```
{'ones': 0,
 'LotFrontage': 1,
 'LotArea': 2,
 'GarageCars': 3,
 'GarageArea': 4,
 'OverallQual': 8,
 'GarageYrBlt': 9}
```

In [ ]:

In [ ]:

2 - Plotting : Matplotlib library

In [245]:
```
import matplotlib.pyplot as plt
```

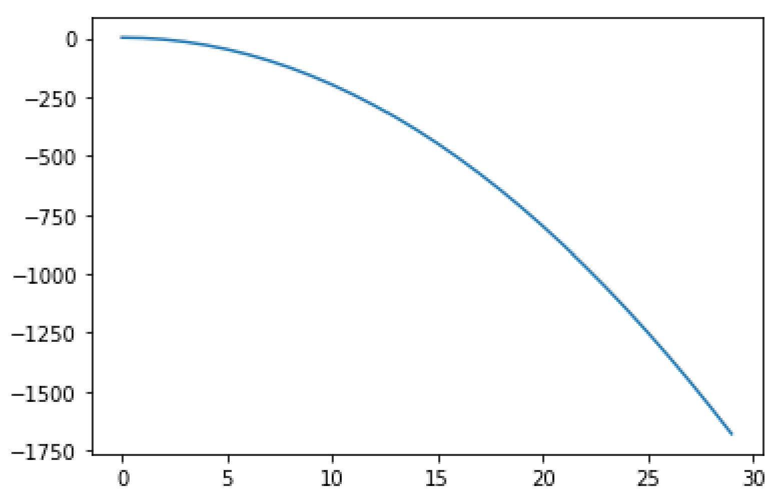
In [246]:
```
# allows to see the plots on jupyter notebook, if you are using another editor, y
%matplotlib inline
```

In [247]:
```
plt.show()  # you don't need to use it on jupyter notebook.
```

In [34]:
```
import numpy as np

x = np.arange(30)
y = -2*x**2 + 3
```

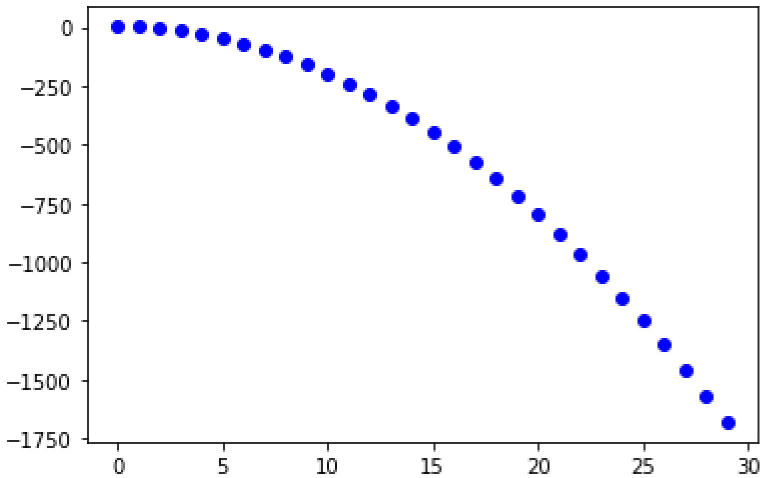
In [38]:
```
plt.plot(x, y)
#plt.show()   # it's printing the plot instead of just showing it
```

Out[38]:
```
[<matplotlib.lines.Line2D at 0x889c0c8>]
```



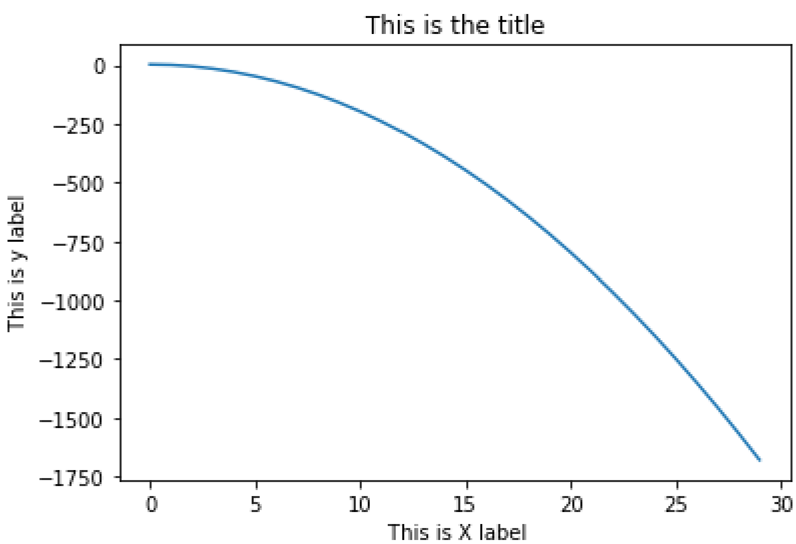
In [39]:
```
plt.plot(x, y , "bo" )
```

Out[39]:
```
[<matplotlib.lines.Line2D at 0x89242c8>]
```



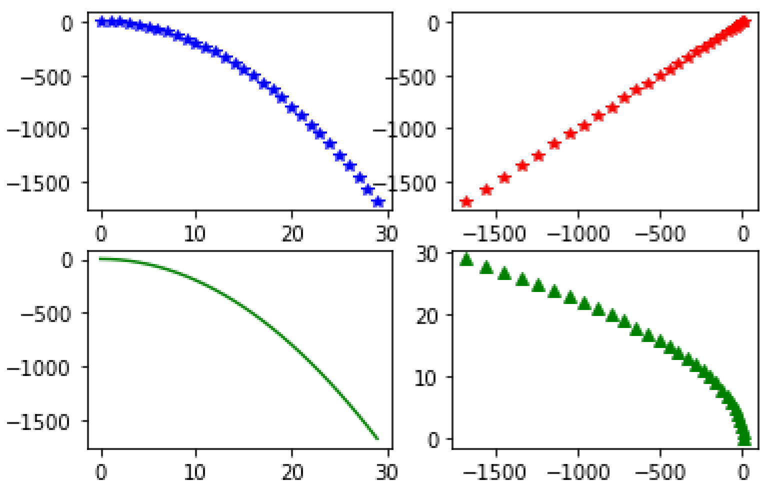
In [118]:
```
# These are the basics to plot a simple graph
plt.plot(x, y)
plt.xlabel(" This is X label")
plt.ylabel(" This is y label")
plt.title(" This is the title ")
```

Out[118]:
```
Text(0.5, 1.0, ' This is the title ')
```



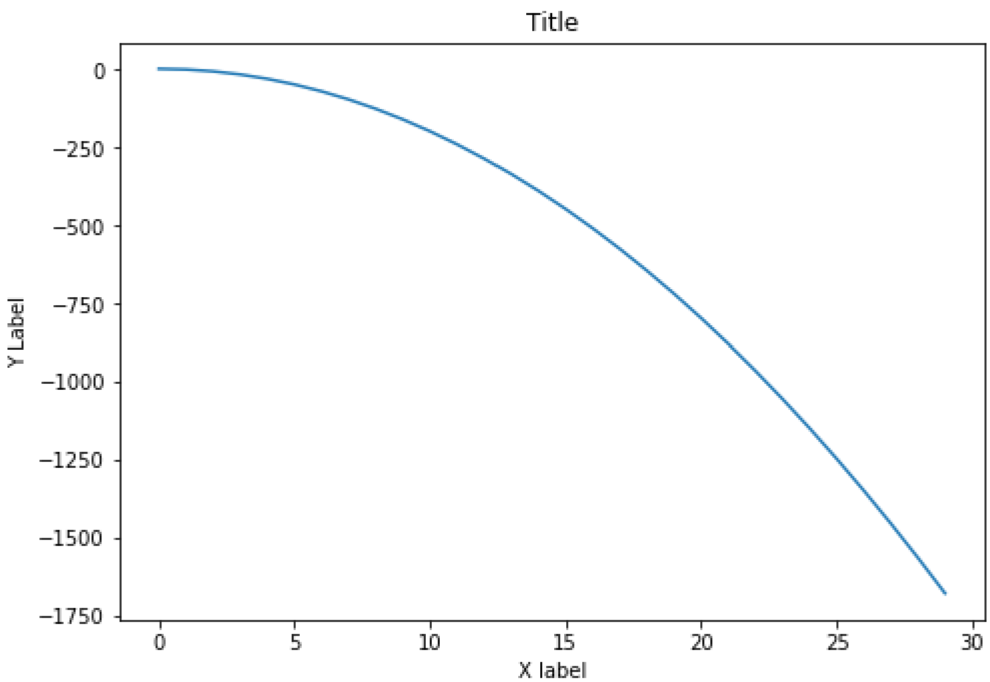
In [49]:
```
## plt.subplot(nrows, ncols, plot_number) , to create multiple plots on the same

plt.subplot(2,2,1)
plt.plot(x,y , "b*")

plt.subplot(2,2,2)
plt.plot(y,y , "r*")

plt.subplot(2,2,3)
plt.plot(x,y , "g-")

plt.subplot(2,2,4)
plt.plot(y,x , "g^")
```

Out[49]:
```
[<matplotlib.lines.Line2D at 0xa036d88>]
```



In [63]:
```
# Object oriented method

# Create empty canvas
fig  =  plt.figure()

# Add set of axes to figure
ax = fig.add_axes([1,1,1,1]) # left, bottom, width, height (range 0 to 1)

# Plot on that set of axes
ax.plot(x, y)
ax.set_xlabel("X label")
ax.set_ylabel("Y Label")
ax.set_title("Title")
```

Out[63]: [<matplotlib.lines.Line2D at 0xb321988>]

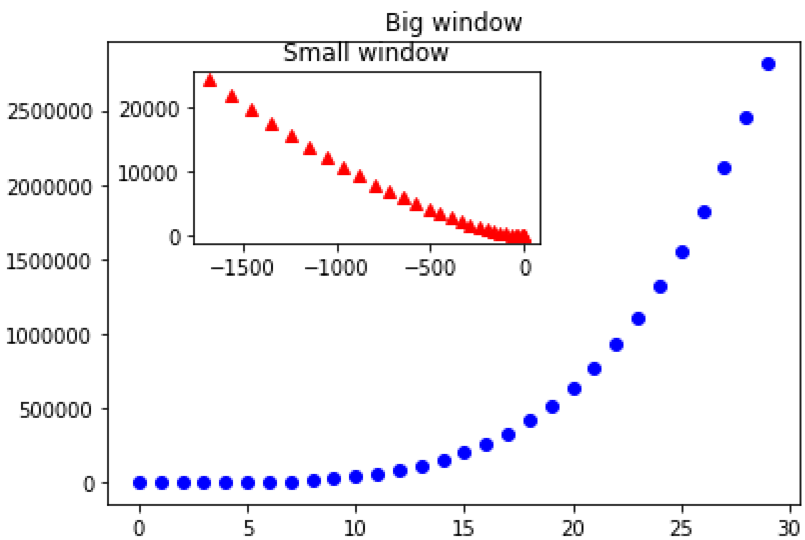


In [74]:

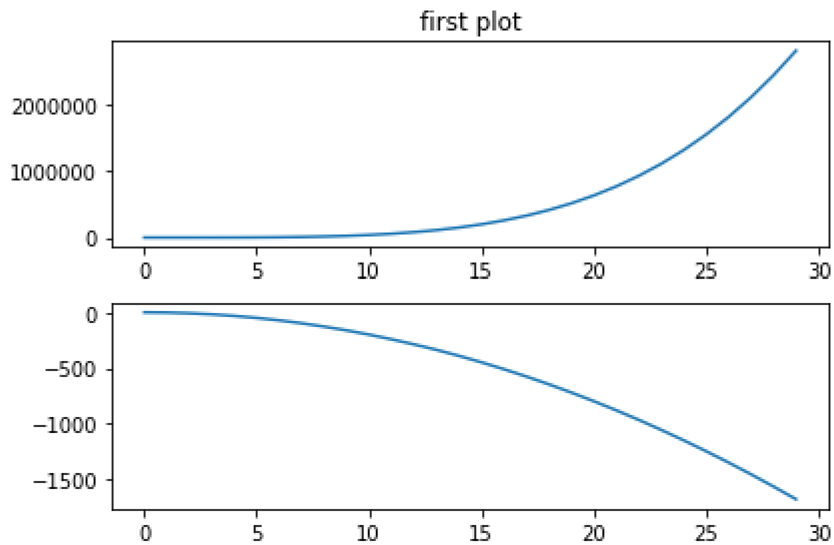
```
# Create empty canvas
fig  =  plt.figure()

# adding axes into fig
ax1 = fig.add_axes([0.1,0.1,0.8,0.8]) #Main axes
ax2 = fig.add_axes([0.2,0.55,0.4,0.3]) #inserted axes

ax1.plot(x, y**2, "bo")
ax1.set_title("Big window")

ax2.plot(y,x**3, "r^")
ax2.set_title("Small window")
```

Out[74]:

```
Text(0.5, 1.0, 'Small window')
```



In [82]:
```
#Creating Subplots

fig, ax = plt.subplots(nrows = 2, ncols = 1)

ax[0].plot(x, y**2)
ax[0].set_title("first plot")
ax[1].plot(x,y)
```

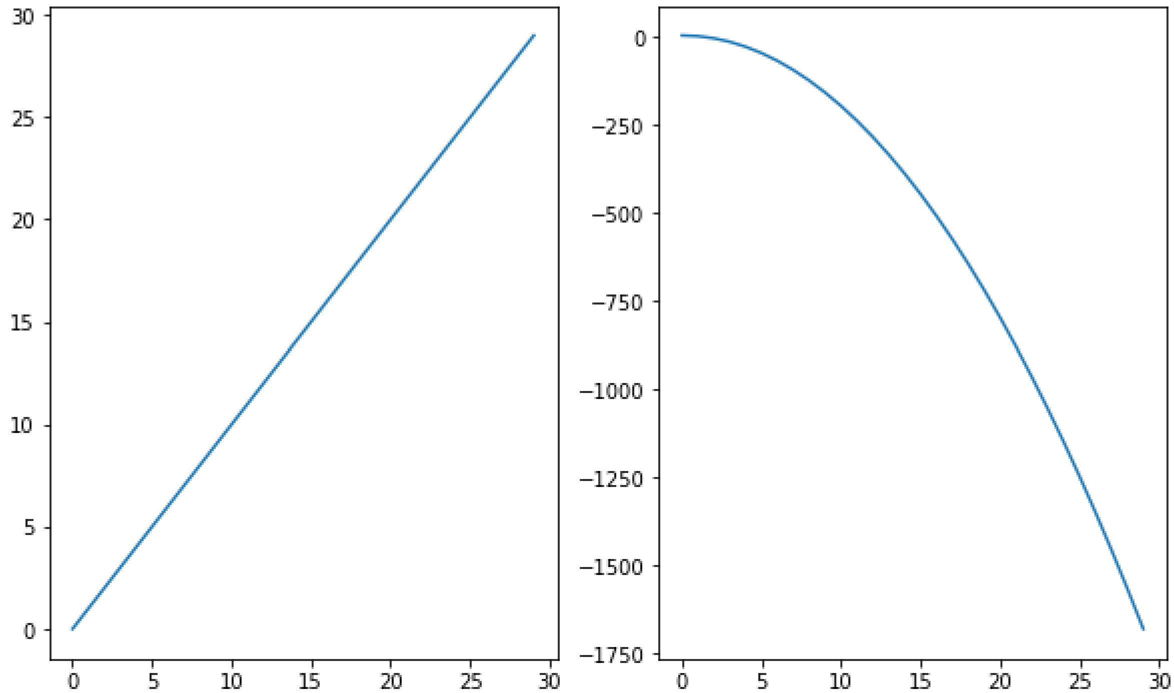


In [78]:
```
ax  # is an array of matplotlib axes, we can index it
```

Out[78]:
```
array([<matplotlib.axes._subplots.AxesSubplot object at 0x0000000004F94C88>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B5FAA08>],
      dtype=object)
```

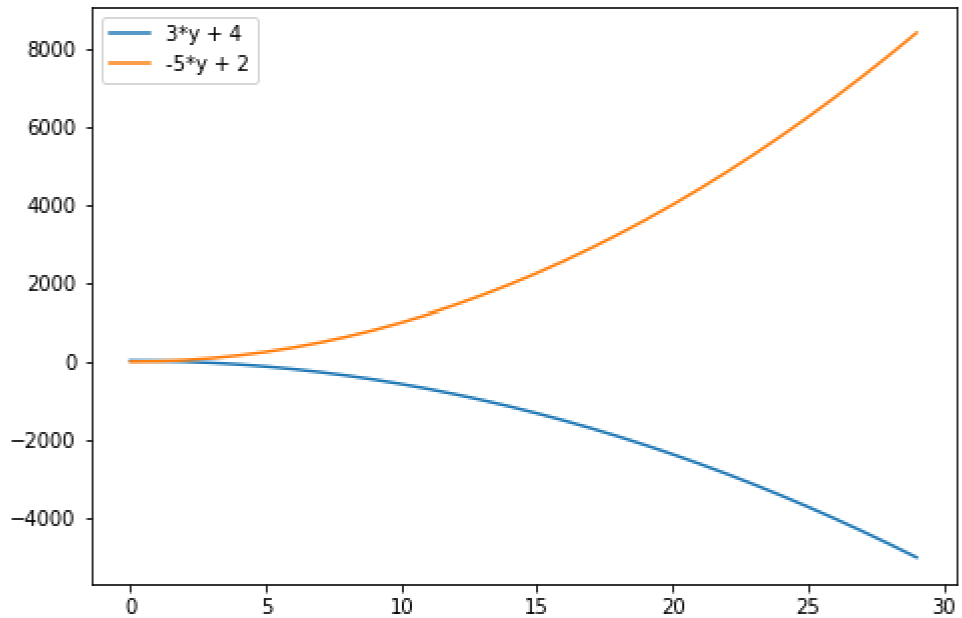
In [120]:
```
fig, ax = plt.subplots(nrows = 1, ncols = 2, figsize=(10,6))

ax[0].plot(x,x)
ax[1].plot(x,y)
```

Out[120]:
```
[<matplotlib.lines.Line2D at 0xeacde08>]
```



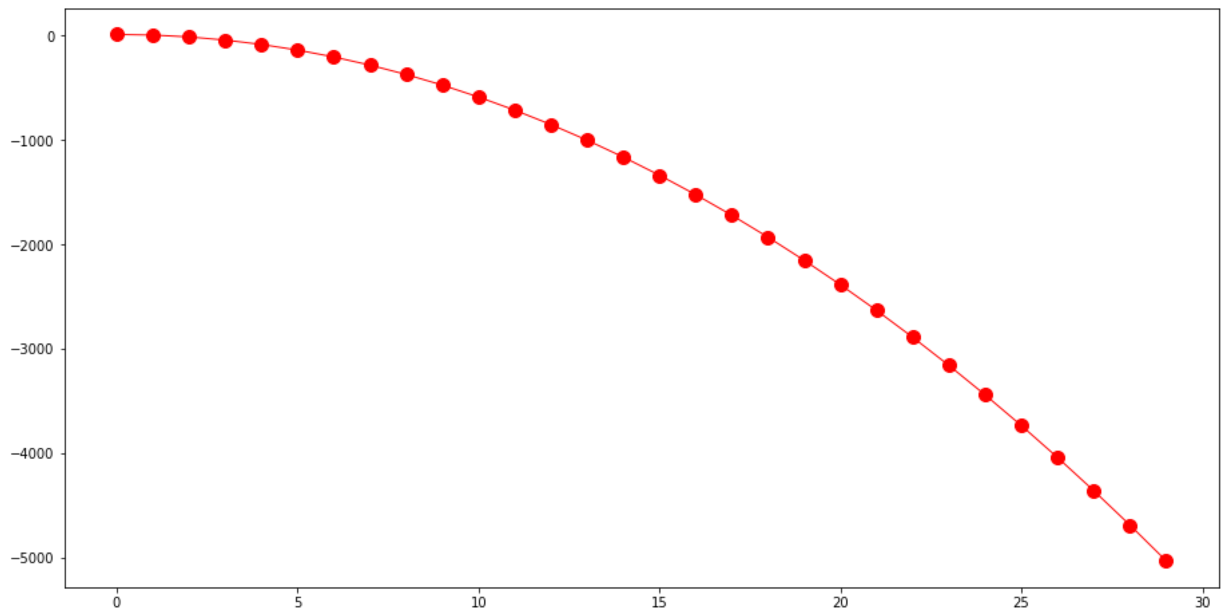
In [121]:
```
#legend

#Creating empty figure
fig = plt.figure()

#adding axes
ax = fig.add_axes([0,0,1,1])

#ploting some graphs into axes
ax.plot(x, 3*y + 4 , label = "3*y + 4")
ax.plot(x, -5*y + 2, label = "-5*y + 2")

#Plot legen
plt.legend(loc = 0)  # loc = 0 : to look for the best localtion

#plt.legend(loc = (.3,.5))
```

Out[121]: `<matplotlib.legend.Legend at 0xed73cc8>`



In [117]:
```
# Create an empty canvas with a specified size
fig = plt.figure(figsize=(12,6))

#adding axes
ax = fig.add_axes([0,0,1,1])

#Ploting and adjusting some parameters
ax.plot(x, 3*y + 4 , color = "red", linewidth = 1, linestyle = "-" , marker = "o'
```

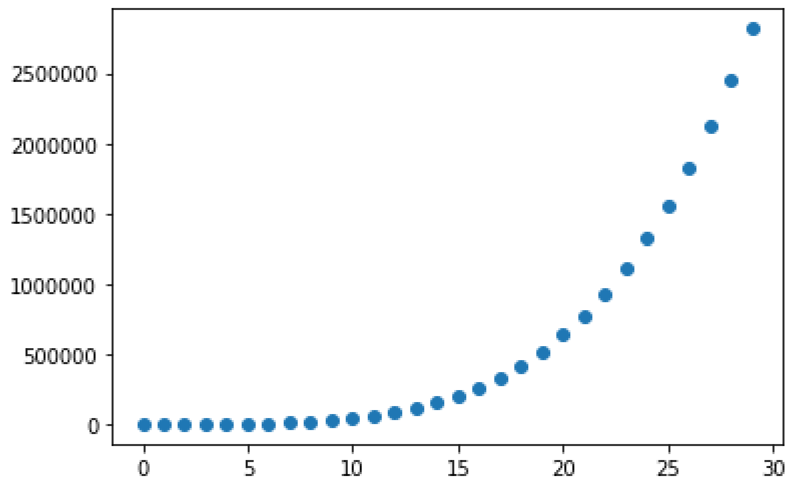
Out[117]:
```
[<matplotlib.lines.Line2D at 0xe92c5c8>]
```



In [ ]:
```
# Some other plots
```

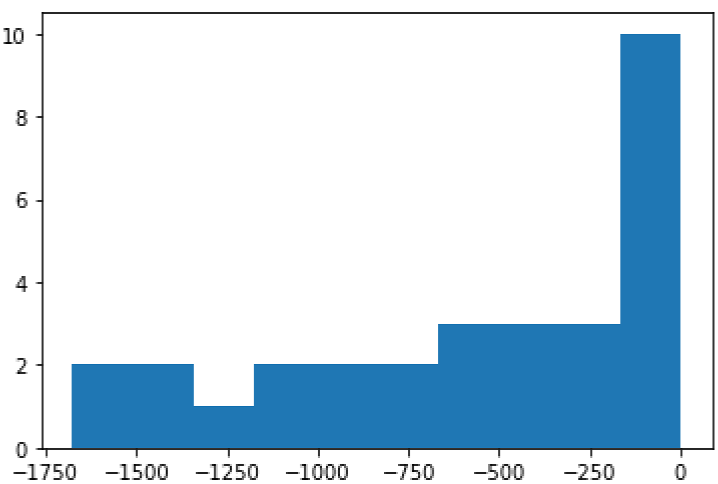
In [124]:
```
plt.scatter(x,y**2)
```

Out[124]: <matplotlib.collections.PathCollection at 0xef34688>



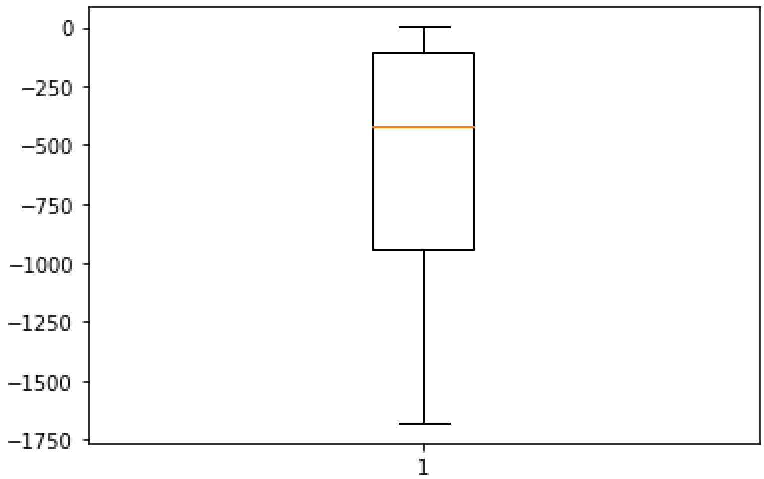
In [126]:
```
plt.hist(y)
```

Out[126]:
```
(array([ 2.,  2.,  1.,  2.,  2.,  2.,  3.,  3.,  3., 10.]),
 array([-1679. , -1510.8, -1342.6, -1174.4, -1006.2,  -838. ,  -669.8,
         -501.6,  -333.4,  -165.2,     3. ]),
 <a list of 10 Patch objects>)
```



In [131]:
```
plt.boxplot(y)
```

Out[131]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x1023e788>,
  <matplotlib.lines.Line2D at 0x1023ed08>],
 'caps': [<matplotlib.lines.Line2D at 0x1023ee08>,
  <matplotlib.lines.Line2D at 0x1023ee88>],
 'boxes': [<matplotlib.lines.Line2D at 0x10236fc8>],
 'medians': [<matplotlib.lines.Line2D at 0x10243d88>],
 'fliers': [<matplotlib.lines.Line2D at 0x10243e88>],
 'means': []}
```



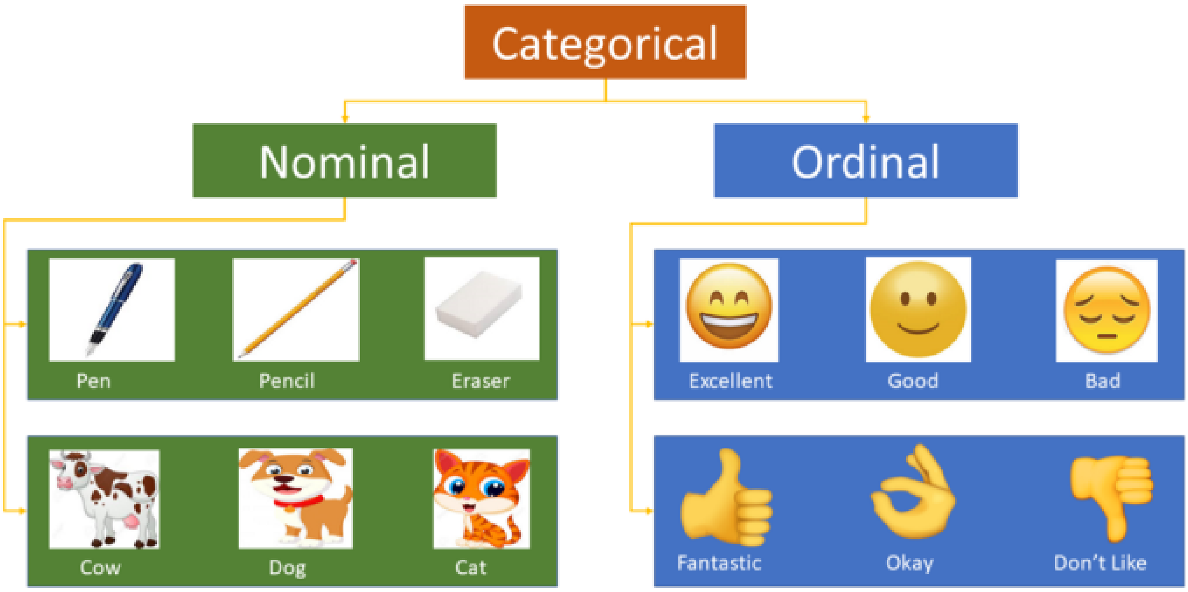
For reference :

https://matplotlib.org/gallery.html (https://matplotlib.org/gallery.html)

http://www.matplotlib.org (http://www.matplotlib.org)

https://github.com/rougier/matplotlib-tutorial (https://github.com/rougier/matplotlib-tutorial)

3 - Categorical variables



In [26]:
```
import pandas as pd
df = pd.read_csv("house_price_data.csv")
```

In [27]:
```
dataset_2 = df.copy()
```

In [39]:
```
dataset_2 = dataset_2[["LotFrontage", "Foundation" ,"LotArea","GarageCars","Garag

# you can add these 2 categorical columns to your dataset_2 and try to encode the
# dataset_2[["CentralAir", , "ExterQual"]]
```

In [40]:
```
dataset_2
```

Out[40]:

	LotFrontage	Foundation	LotArea	GarageCars	GarageArea	SalePrice
0	65.0	PConc	8450	2	548	208500
1	80.0	CBlock	9600	2	460	181500
2	68.0	PConc	11250	2	608	223500
3	60.0	BrkTil	9550	3	642	140000
4	84.0	PConc	14260	3	836	250000
...	...	...	...	...	...	...
1455	62.0	PConc	7917	2	460	175000
1456	85.0	CBlock	13175	2	500	210000
1457	66.0	Stone	9042	1	252	266500
1458	68.0	CBlock	9717	1	240	142125
1459	75.0	CBlock	9937	1	276	147500

1460 rows × 6 columns

In [30]:
```
dataset_2["Foundation"].unique()
```

Out[30]:
```
array(['PConc', 'CBlock', 'BrkTil', 'Wood', 'Slab', 'Stone'], dtype=object)
```

In [37]:
```
#dataset_2["CentralAir"].unique()
```

In [38]:
```
#dataset_2["ExterQual"].unique()
```

In [46]:
```
X = dataset_2.drop("SalePrice", axis = 1)
```

In [48]:
```
dataset_2
```

Out[48]:

	LotFrontage	Foundation	LotArea	GarageCars	GarageArea	SalePrice
0	65.0	PConc	8450	2	548	208500
1	80.0	CBlock	9600	2	460	181500
2	68.0	PConc	11250	2	608	223500
3	60.0	BrkTil	9550	3	642	140000
4	84.0	PConc	14260	3	836	250000
...	...	...	...	...	...	...
1455	62.0	PConc	7917	2	460	175000
1456	85.0	CBlock	13175	2	500	210000
1457	66.0	Stone	9042	1	252	266500
1458	68.0	CBlock	9717	1	240	142125
1459	75.0	CBlock	9937	1	276	147500

1460 rows × 6 columns

In [33]:
```
dataset_2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   LotFrontage  1201 non-null   float64
 1   CentralAir   1460 non-null   object 
 2   Foundation   1460 non-null   object 
 3   ExterQual    1460 non-null   object 
 4   LotArea      1460 non-null   int64  
 5   GarageCars   1460 non-null   int64  
 6   GarageArea   1460 non-null   int64  
 7   SalePrice    1460 non-null   int64  
dtypes: float64(1), int64(4), object(3)
memory usage: 91.4+ KB
```

OneHot Encoding :

We will be using these 2 classes to encode the categorical variables :

In [56]:
```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
```

In [59]:
```
ct = ColumnTransformer(transformers = [("Encoder", OneHotEncoder(), [1])], remair
```

In [60]:
```
X  = ct.fit_transform(X)
```

In [67]:
```
import numpy as np
X = np.array(X)
X[0]
```

Out[67]:
```
array([0.00e+00, 0.00e+00, 1.00e+00, 0.00e+00, 0.00e+00, 0.00e+00,
       6.50e+01, 8.45e+03, 2.00e+00, 5.48e+02])
```

Label Encoder :

Eeach category is assigned a value from 1 through the number of categories for the feature.

In [ ]:
```
dataset_3 = df.copy()
```

In [85]:
```
dataset_3 = dataset_2[["LotFrontage", "CentralAir" ,"LotArea","GarageCars","Garag
```

In [84]:
```
dataset_3["CentralAir"].unique()
```

Out[84]:
```
array([1, 0])
```

In [77]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
dataset_3["CentralAir"] = le.fit_transform(dataset_2["CentralAir"])
```

In [78]:
```
dataset_3
```

Out[78]:

	LotFrontage	CentralAir	LotArea	GarageCars	GarageArea	SalePrice
0	65.0	1	8450	2	548	208500
1	80.0	1	9600	2	460	181500
2	68.0	1	11250	2	608	223500
3	60.0	1	9550	3	642	140000
4	84.0	1	14260	3	836	250000
...	...	...	...	...	...	...
1455	62.0	1	7917	2	460	175000
1456	85.0	1	13175	2	500	210000
1457	66.0	1	9042	1	252	266500
1458	68.0	1	9717	1	240	142125
1459	75.0	1	9937	1	276	147500

1460 rows × 6 columns

Pandas has get_dummies()

re-importing the data

In [87]:
```
df = pd.read_csv("house_price_data.csv")
dataset_3 = df.copy()
dataset_3 = dataset_3[["LotFrontage", "CentralAir" ,"LotArea","GarageCars","Garag
dataset_3
```

Out[87]:

	LotFrontage	CentralAir	LotArea	GarageCars	GarageArea	SalePrice
0	65.0	Y	8450	2	548	208500
1	80.0	Y	9600	2	460	181500
2	68.0	Y	11250	2	608	223500
3	60.0	Y	9550	3	642	140000
4	84.0	Y	14260	3	836	250000
...	...	...	...	...	...	...
1455	62.0	Y	7917	2	460	175000
1456	85.0	Y	13175	2	500	210000
1457	66.0	Y	9042	1	252	266500
1458	68.0	Y	9717	1	240	142125
1459	75.0	Y	9937	1	276	147500

1460 rows × 6 columns

In [92]:
```
dataset_3 = pd.get_dummies(dataset_3, "CentralAir")
dataset_3
```

Out[92]:

	LotFrontage	LotArea	GarageCars	GarageArea	SalePrice	CentralAir_N	CentralAir_Y
0	65.0	8450	2	548	208500	0	1
1	80.0	9600	2	460	181500	0	1
2	68.0	11250	2	608	223500	0	1
3	60.0	9550	3	642	140000	0	1
4	84.0	14260	3	836	250000	0	1
...	...	...	...	...	...	...	...
1455	62.0	7917	2	460	175000	0	1
1456	85.0	13175	2	500	210000	0	1
1457	66.0	9042	1	252	266500	0	1
1458	68.0	9717	1	240	142125	0	1
1459	75.0	9937	1	276	147500	0	1

1460 rows × 7 columns

Ordinal Encoding

The encoding of variables retains the ordinal nature of the variable

In [98]:
```
dataset_4 = df.copy()
dataset_4 = dataset_4[["LotFrontage", "ExterQual" ,"LotArea","GarageCars","Garage
dataset_4
```

Out[98]:

	LotFrontage	ExterQual	LotArea	GarageCars	GarageArea	SalePrice
0	65.0	Gd	8450	2	548	208500
1	80.0	TA	9600	2	460	181500
2	68.0	Gd	11250	2	608	223500
3	60.0	TA	9550	3	642	140000
4	84.0	Gd	14260	3	836	250000
...	...	...	...	...	...	...
1455	62.0	TA	7917	2	460	175000
1456	85.0	TA	13175	2	500	210000
1457	66.0	Ex	9042	1	252	266500
1458	68.0	TA	9717	1	240	142125
1459	75.0	Gd	9937	1	276	147500

1460 rows × 6 columns

In [95]:
```
dataset_4["ExterQual"].unique()
```

Out[95]:
```
array(['Gd', 'TA', 'Ex', 'Fa'], dtype=object)
```

In [97]:
```
dict_4 = {'Gd':3, 'TA':2, 'Ex':4, 'Fa':1}
dataset_4["Quality"] = dataset_4["ExterQual"].map(dict_4)
dataset_4
```

Out[97]:

	LotFrontage	ExterQual	LotArea	GarageCars	GarageArea	SalePrice	Quality
0	65.0	Gd	8450	2	548	208500	3
1	80.0	TA	9600	2	460	181500	2
2	68.0	Gd	11250	2	608	223500	3
3	60.0	TA	9550	3	642	140000	2
4	84.0	Gd	14260	3	836	250000	3
...	...	...	...	...	...	...	...
1455	62.0	TA	7917	2	460	175000	2
1456	85.0	TA	13175	2	500	210000	2
1457	66.0	Ex	9042	1	252	266500	4
1458	68.0	TA	9717	1	240	142125	2
1459	75.0	Gd	9937	1	276	147500	3

1460 rows × 7 columns

In [ ]:

In [ ]:

4 - Logistic Regression

Import the libraries

In [144]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Get the data

In [145]:
```
df = pd.read_csv('diabetes_data.csv')
dataset = df.copy()
```

Check the head of the data

In [146]:
```
dataset.head()
```

Out[146]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	A
0	6	148	72	35	0	33.6	0.627	
1	1	85	66	29	0	26.6	0.351	
2	8	183	64	0	0	23.3	0.672	
3	1	89	66	23	94	28.1	0.167	
4	0	137	40	35	168	43.1	2.288	

In [147]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               768 non-null    int64  
 1   Glucose                   768 non-null    int64  
 2   BloodPressure             768 non-null    int64  
 3   SkinThickness             768 non-null    int64  
 4   Insulin                   768 non-null    int64  
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
 8   Outcome                   768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

In [148]:
```
dataset.describe()
```

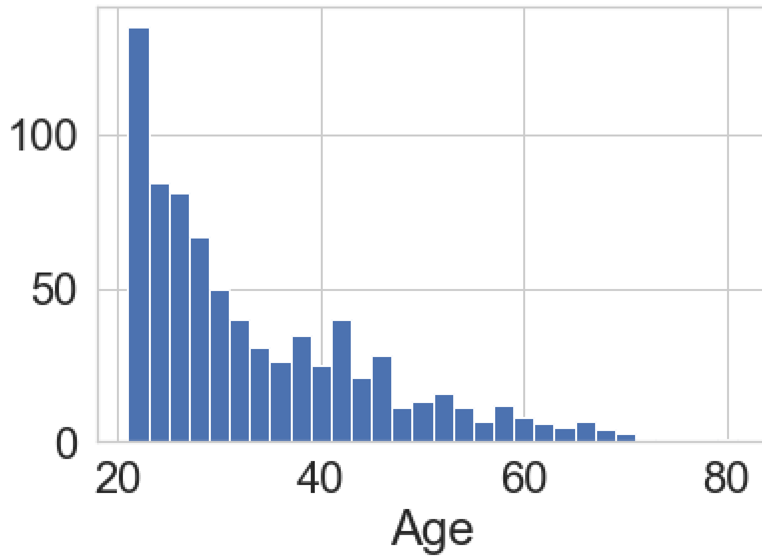
Out[148]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPe
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	

Explore the data using seaborn library

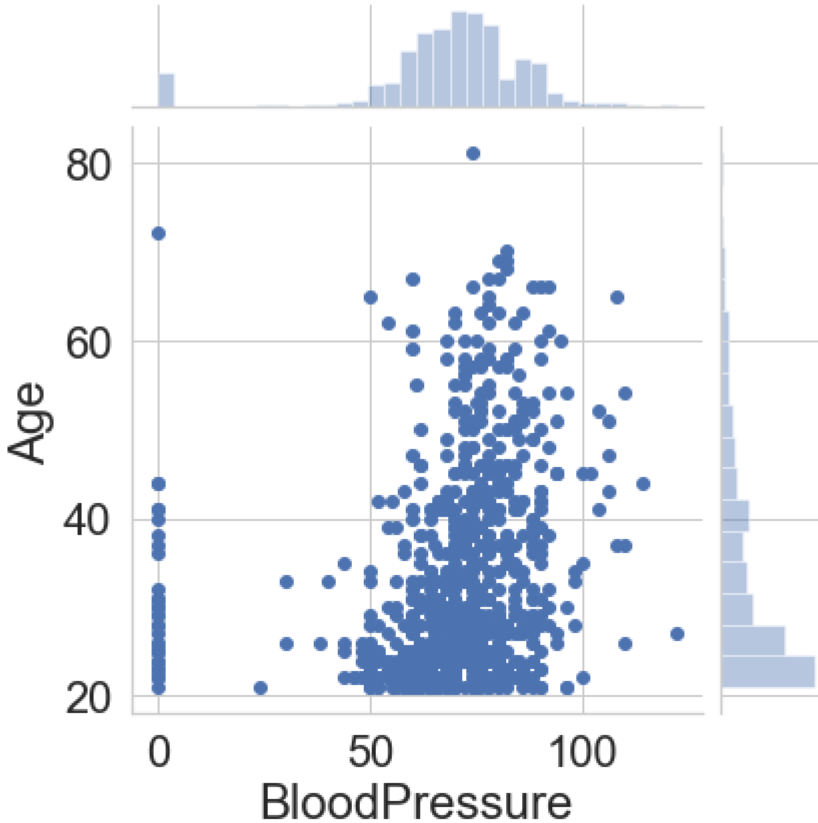
In [149]:
```
sns.set_style('whitegrid')

dataset['Age'].hist(bins=30)
plt.xlabel('Age')
```

Out[149]: Text(0.5, 0, 'Age')



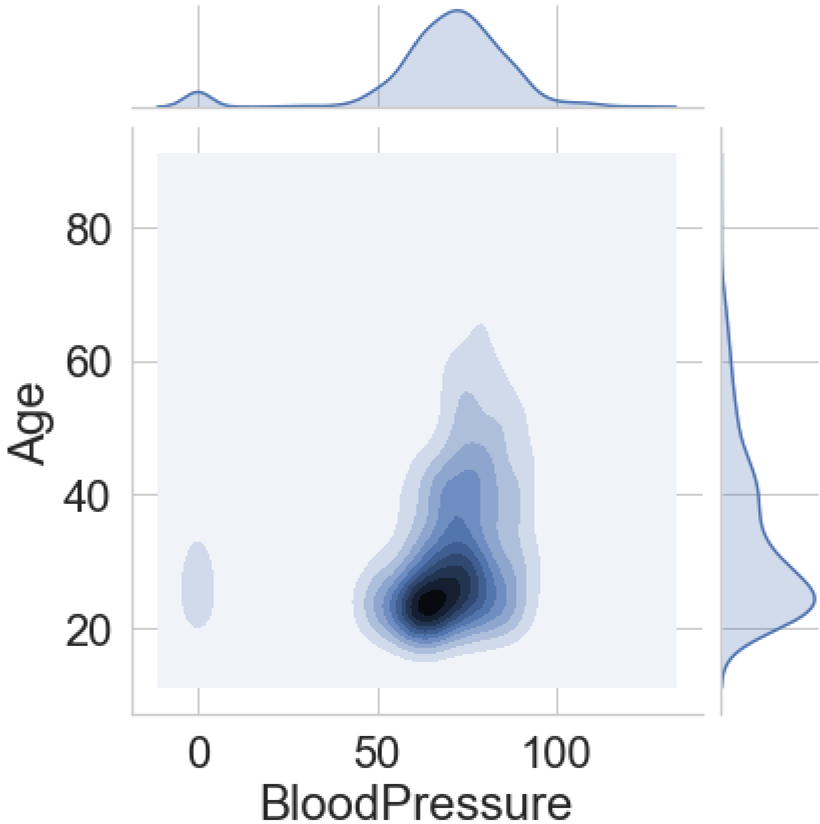
In [150]:
```
sns.set_style('whitegrid')

sns.jointplot(data = dataset, x = 'BloodPressure', y = 'Age')
```

Out[150]: <seaborn.axisgrid.JointGrid at 0x117c41c8>



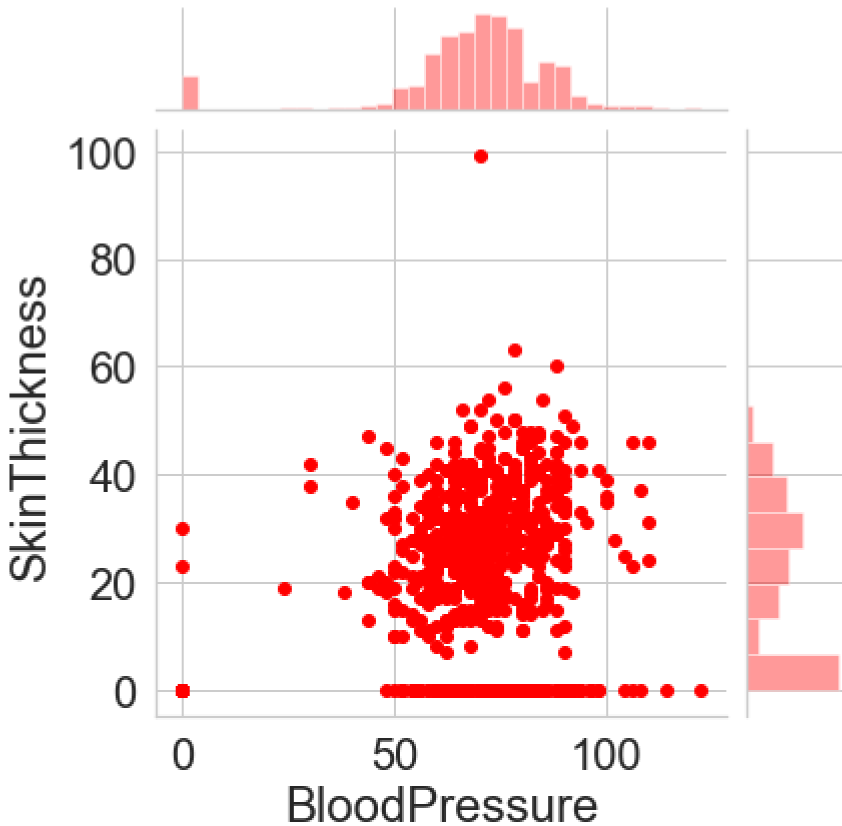
In [151]:
```
sns.jointplot(data = dataset, x = 'BloodPressure', y = 'Age', kind = 'kde')
```

Out[151]: <seaborn.axisgrid.JointGrid at 0x117c0548>



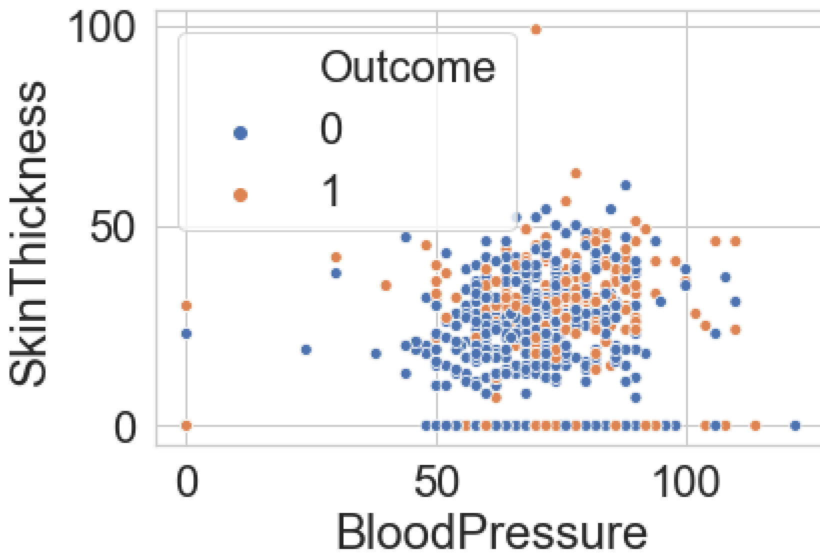
In [152]:
```
sns.set_style('whitegrid')

sns.jointplot(data = dataset, x = 'BloodPressure', y = 'SkinThickness' , color =
```

Out[152]: <seaborn.axisgrid.JointGrid at 0x13b61048>



In [153]:
```
sns.scatterplot(data = dataset, x = 'BloodPressure', y = 'SkinThickness' , hue =
```

Out[153]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x13efa208>
```



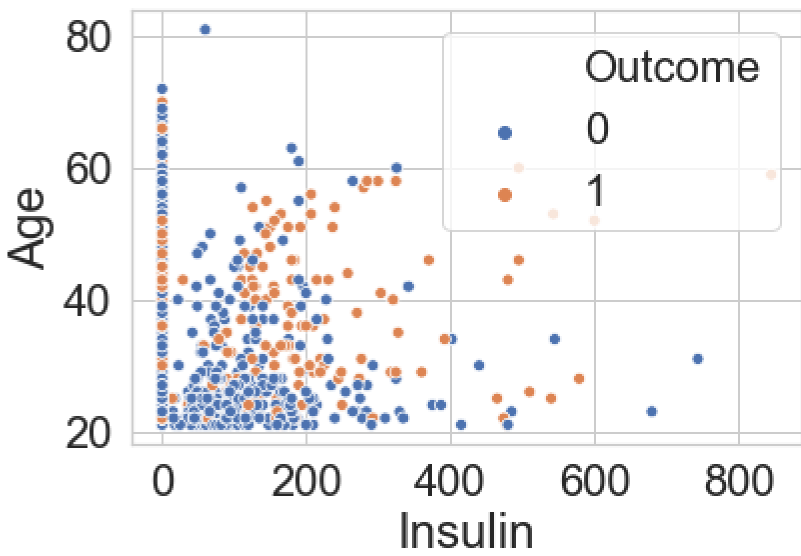
In [154]:
```
dataset.head()
```

Out[154]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	A
0	6	148	72	35	0	33.6	0.627	
1	1	85	66	29	0	26.6	0.351	
2	8	183	64	0	0	23.3	0.672	
3	1	89	66	23	94	28.1	0.167	
4	0	137	40	35	168	43.1	2.288	

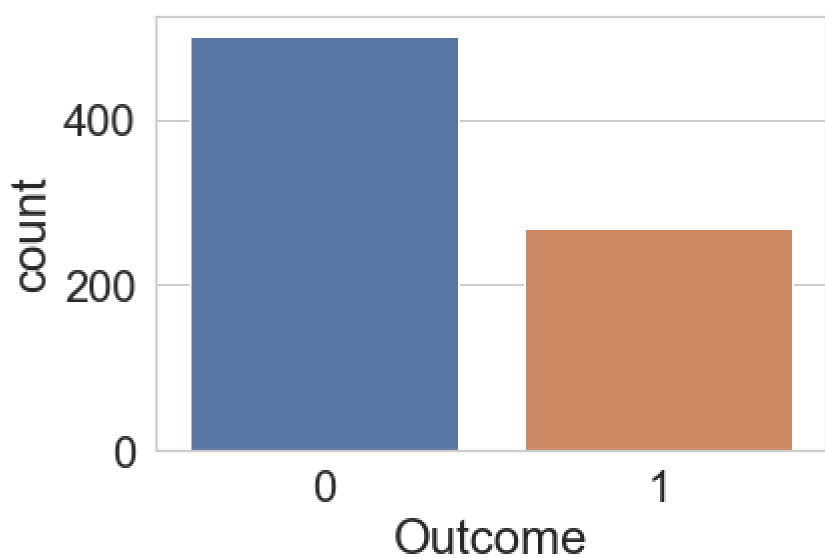
In [155]:
```
sns.scatterplot(data = dataset, x = 'Insulin', y = 'Age' , hue = 'Outcome')
```

Out[155]: <matplotlib.axes._subplots.AxesSubplot at 0x1413fbc8>



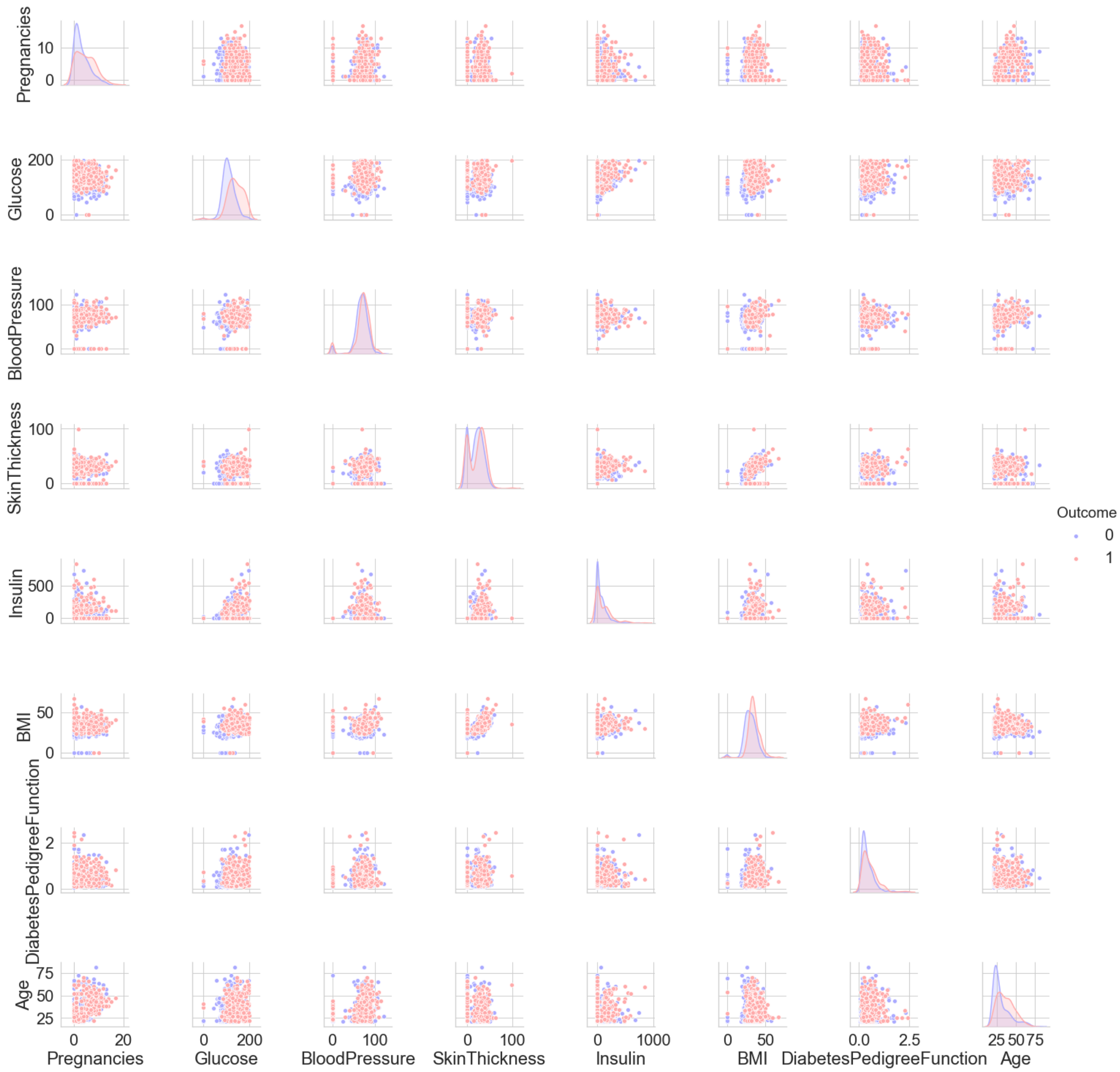
In [156]:
```
sns.countplot(dataset['Outcome'])
```

Out[156]: <matplotlib.axes._subplots.AxesSubplot at 0x141a98c8>



In [157]:
```
# Creating a paiplot for all variables
sns.pairplot(dataset,hue='Outcome',palette='bwr')
```

Out[157]: <seaborn.axisgrid.PairGrid at 0x141f8908>



Create and Train the model

In [158]:
```
dataset.head(3)
```

Out[158]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction
0	6	148	72	35	0	33.6	0.627
1	1	85	66	29	0	26.6	0.351
2	8	183	64	0	0	23.3	0.672

In [159]:
```
dataset.columns
```

Out[159]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

In [176]:
```
# Define X and y and convert them to arrays

#X = dataset[['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insuli

X = dataset.drop('Outcome', axis = 1).values
y = dataset["Outcome"].values
```

Feature Scaling:

In [177]:
```
'''
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X = sc.fit_transform(X)
'''
```

Out[177]:
```
'\nfrom sklearn.preprocessing import StandardScaler\nsc = StandardScaler()\nX =
sc.fit_transform(X)\n'
```

In [ ]:
```

```

Split the data into Train and Test sets

In [178]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2 , random_
```

Create and train the model

In [179]:
```
from sklearn.linear_model import LogisticRegression
```

In [180]:
```
log_reg = LogisticRegression()
```

In [181]:
```
log_reg.fit(X_train,y_train)
```

```
C:\Users\pc\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:940:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-
learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on)
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

Out[181]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

Evaluate the model

In [182]:
```
#Generate predictions with the model
y_pred = log_reg.predict(X_test)
```

In [183]:
```
#Compare y_pred and y_test

df_results = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
df_results.head(15)
```

Out[183]:

	Actual	Predicted
0	1	1
1	0	0
2	0	0
3	1	1
4	0	0
5	0	0
6	1	1
7	1	1
8	0	0
9	0	0
10	1	1
11	1	1
12	0	0
13	0	0
14	0	0

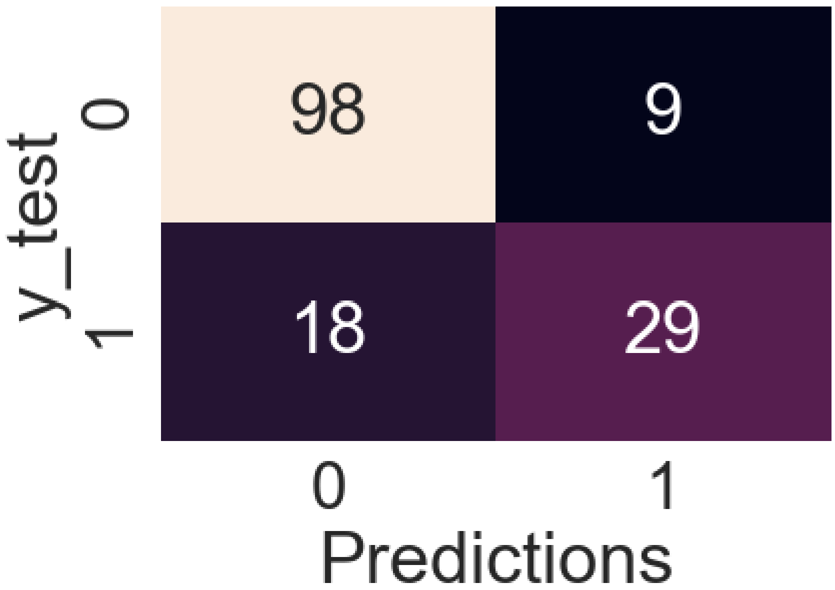
In [184]:
```
# Confusion matrix
from sklearn.metrics import confusion_matrix
```

In [185]:
```
cm = confusion_matrix(y_test,y_pred)
cm
```

Out[185]:
```
array([[98,  9],
       [18, 29]], dtype=int64)
```

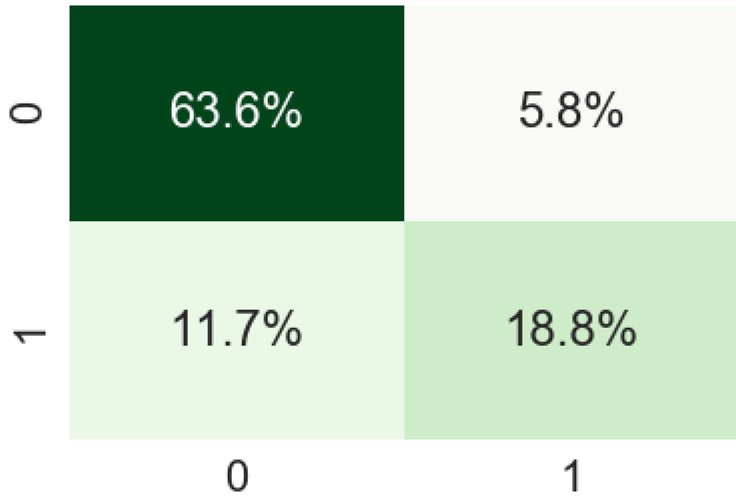
In [186]:
```
sns.set( font_scale=3)
sns.heatmap(cm , annot = True, cbar= False)
plt.xlabel('Predictions')
plt.ylabel('y_test')
```

Out[186]: Text(9.5, 0.5, 'y_test')



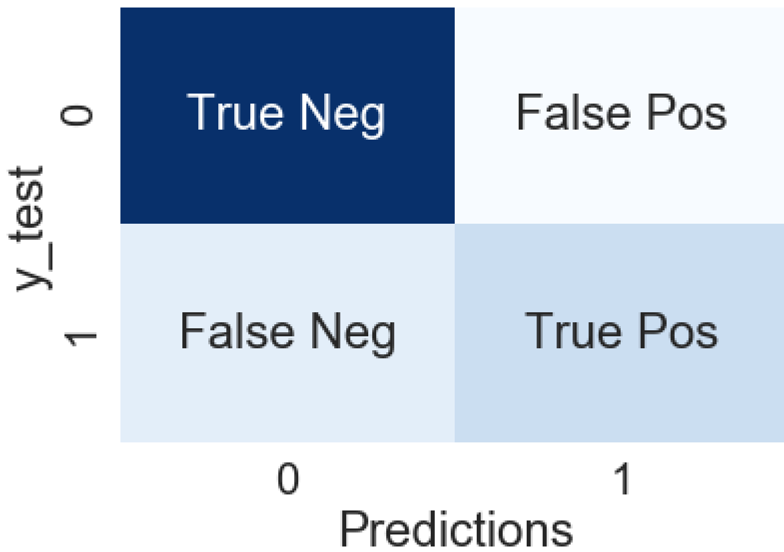
In [187]:
```
sns.set( font_scale=2)
sns.heatmap(cm/np.sum(cm), annot=True, fmt='.1%', cmap='Greens', cbar = False)
```

Out[187]: <matplotlib.axes._subplots.AxesSubplot at 0x17165348>



In [188]:
```
sns.set( font_scale=2)
labels =np.array([['True Neg','False Pos'],['False Neg','True Pos']])
sns.heatmap(cm, annot=labels,fmt='', cmap='Blues', cbar = False)

plt.xlabel('Predictions')
plt.ylabel('y_test')
```

Out[188]:
```
Text(20.5, 0.5, 'y_test')
```



In [ ]:

In [189]:
```
# Create a classification report for the model
from sklearn.metrics import classification_report
```

In [190]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.84      0.92      0.88       107
           1       0.76      0.62      0.68        47

    accuracy                           0.82       154
   macro avg       0.80      0.77      0.78       154
weighted avg       0.82      0.82      0.82       154
```

In [ ]:

In [ ]:

In [ ]: