In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

In [2]:
```
file_handler = open("car_data.csv", "r")
car_data = pd.read_csv('car_data.csv')
file_handler.close()
```

In [3]:
```
car_data.head()
```

Out[3]:

	buying	maint	doors	persons	lug_boot	safety	acceptability
0	vhigh	vhigh	2	2	small	low	unacc
1	vhigh	vhigh	2	2	small	med	unacc
2	vhigh	vhigh	2	2	small	high	unacc
3	vhigh	vhigh	2	2	med	low	unacc
4	vhigh	vhigh	2	2	med	med	unacc

In [4]:
```
buying = {'vhigh': 3, 'high': 2, 'med': 1, 'low': 0}
car_data.buying = [buying[item] for item in car_data.buying]
maint = {'vhigh': 3, 'high': 2, 'med': 1, 'low': 0}
car_data.maint = [maint[item] for item in car_data.maint]
doors = {'2': 2, '3': 3, '4': 4, '5more': 5}
car_data.doors = [doors[item] for item in car_data.doors]
persons = {'2': 2, '4': 4, 'more': 6}
car_data.persons = [persons[item] for item in car_data.persons]
lug_boot = {'big': 2, 'med': 1, 'small': 0}
car_data.lug_boot = [lug_boot[item] for item in car_data.lug_boot]
safety = {'high': 2, 'med': 1, 'low': 0}
car_data.safety = [safety[item] for item in car_data.safety]
acceptability = {'vgood': 1, 'good': 1, 'acc': 1, 'unacc': 0}
car_data.acceptability = [acceptability[item] for item in car_data.acceptability]
car_data.head()
```

Out[4]:

	buying	maint	doors	persons	lug_boot	safety	acceptability
0	3	3	2	2	0	0	0
1	3	3	2	2	0	1	0
2	3	3	2	2	0	2	0
3	3	3	2	2	1	0	0
4	3	3	2	2	1	1	0

In [5]:
```
x = car_data.values[:,[0,1,2,3,4,5]]
y = car_data.values[:,6]
```

In [6]:
```
from sklearn.preprocessing import StandardScaler
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, train_size =

# Standardizing the features
sc_X = StandardScaler()
sc_X.fit(x_train)
x_train = sc_X.transform(x_train)
x_test = sc_X.transform(x_test)
```

In [7]:
```
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state=0)
classifier.fit(x_train, y_train)
```

Out[7]:
```
LogisticRegression(random_state=0)
```

In [8]:
```
y_pred = classifier.predict(x_test)
y_pred[0:30]
```

Out[8]:
```
array([0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0,
       0, 0, 0, 1, 0, 1, 0, 0], dtype=int64)
```

In [9]:
```
from sklearn.metrics import confusion_matrix
cnf_matrix = confusion_matrix(y_test, y_pred)
cnf_matrix
```

Out[9]:
```
array([[214,  20],
       [ 31,  81]], dtype=int64)
```

In [10]:
```
import warnings
warnings.filterwarnings('ignore')
from sklearn import metrics
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print("Precision:",metrics.precision_score(y_test, y_pred, pos_label='positive', averag
print("Recall:",metrics.recall_score(y_test, y_pred, pos_label='positive', average='wei
```

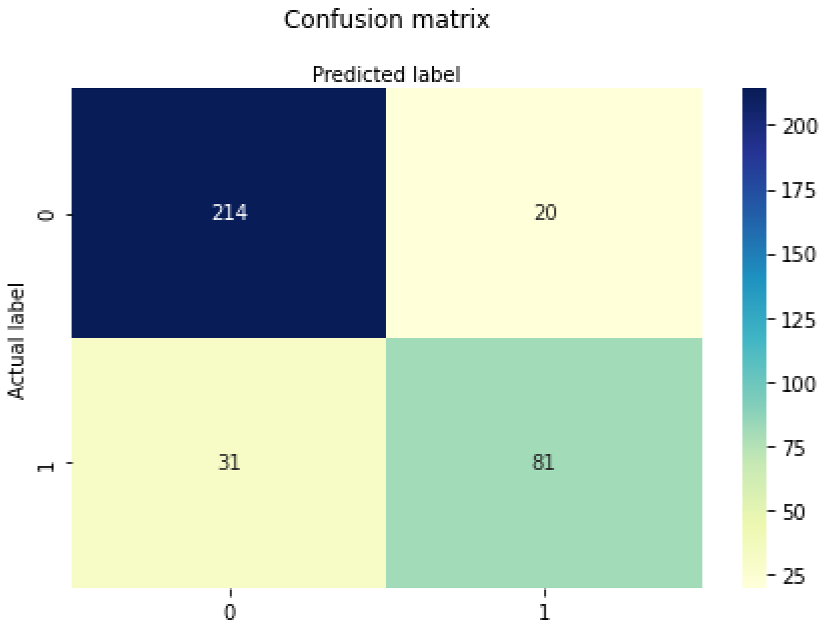
```
Accuracy: 0.8526011560693642
Precision: 0.8503283783610166
Recall: 0.8526011560693642
```

In [11]:
```
class_names=[0,1]
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)

sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

```
Text(0.5, 257.44, 'Predicted label')
```

Out[11]:



In [12]:

```
from sklearn.metrics import make_scorer, accuracy_score, precision_score, recall_score
from sklearn.model_selection import KFold
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_validate
from sklearn.linear_model import LinearRegression
```

In [13]:

```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
metrics = ['accuracy', 'precision', 'recall']
sum = 0
for kfoldloop in (2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20):
    cv = KFold(n_splits=kfoldloop, random_state=1, shuffle=True)
    scores = cross_validate(lr, x_train, y_train, scoring=metrics, cv=cv, n_jobs=-1)
    sorted(scores.keys())
    ['fit_time', 'score_time', 'test_accuracy', 'test_precision', 'test_recall']
    print("K = ", kfoldloop)
    print("Accuracy:", np.mean(scores['test_accuracy']))
    print("Precision:", np.mean(scores['test_precision']))
    print("Recall:", np.mean(scores['test_recall']))
```

```
K =  2
Accuracy: 0.8654124457308249
Precision: 0.7853302292065076
Recall: 0.7383960047003526
K =  3
Accuracy: 0.8675893615014618
Precision: 0.795201605546433
Recall: 0.7369151825892267
K =  4
Accuracy: 0.8668530619083522
Precision: 0.7939483749237689
Recall: 0.732819776410984
K =  5
Accuracy: 0.8682885993826192
Precision: 0.7996396396396396
Recall: 0.7365593158175299
K =  6
```

```
Accuracy: 0.8675512892904198
Precision: 0.7989898567717889
Recall: 0.7329737224801668
K =  7
Accuracy: 0.8646655093355601
Precision: 0.7933329486176726
Recall: 0.7276699902876026
K =  8
Accuracy: 0.8697531590267509
Precision: 0.7981994702169629
Recall: 0.7372997598162072
K =  9
Accuracy: 0.8697290363957031
Precision: 0.8031977747942077
Recall: 0.7368773334550132
K =  10
Accuracy: 0.8690021895527057
Precision: 0.8063315239785828
Recall: 0.7307122170614979
K =  11
Accuracy: 0.8697720057720058
Precision: 0.8066027128648163
Recall: 0.737105760130966
K =  12
Accuracy: 0.8733570714642679
Precision: 0.8083306226944242
Recall: 0.7462431161207093
K =  13
Accuracy: 0.8726109897860913
Precision: 0.8094079865916649
Recall: 0.7411035170083967
K =  14
Accuracy: 0.8719557086904024
Precision: 0.8079127023677212
Recall: 0.740260609668612
K =  15
Accuracy: 0.8726663549945458
Precision: 0.8116502509215155
Recall: 0.7442057175883809
K =  16
Accuracy: 0.8725691659983961
Precision: 0.8063278096560592
Recall: 0.7461379134366812
K =  17
Accuracy: 0.8718936535770586
Precision: 0.8112617790569062
Recall: 0.7486244862629416
K =  18
Accuracy: 0.8711931343510292
Precision: 0.8068294611378771
Recall: 0.7426381201955592
K =  19
Accuracy: 0.8719258191139949
Precision: 0.8047020575146482
Recall: 0.7428173589271987
K =  20
Accuracy: 0.8726915113871636
Precision: 0.8091241918201302
Recall: 0.7443298774239177
```

In [14]:

```
from sklearn.naive_bayes import GaussianNB
gb = GaussianNB()
metrics = ['accuracy', 'precision', 'recall']
sum = 0
```

```
for kfoldloop in (2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20):
    cv = KFold(n_splits=kfoldloop, random_state=1, shuffle=True)
    scores = cross_validate(gb, x_train, y_train, scoring=metrics, cv=cv, n_jobs=-1)
    sorted(scores.keys())
    ['fit_time', 'score_time', 'test_accuracy', 'test_precision', 'test_recall']
    print("K = ", kfoldloop)
    print("Accuracy:", np.mean(scores['test_accuracy']))
    print("Precision:", np.mean(scores['test_precision']))
    print("Recall:", np.mean(scores['test_recall']))
```

```
K =  2
Accuracy: 0.8806078147612156
Precision: 0.868367968333714
Recall: 0.6959949079514297
K =  3
Accuracy: 0.890020120091798
Precision: 0.8877208827456217
Recall: 0.7146828877211172
K =  4
Accuracy: 0.8907388791153557
Precision: 0.8859986825946349
Recall: 0.7165263107812351
K =  5
Accuracy: 0.8878381206508659
Precision: 0.8844734994734994
Recall: 0.7067422363574678
K =  6
Accuracy: 0.8900056465273857
Precision: 0.8866097142591708
Recall: 0.7141182918213894
K =  7
Accuracy: 0.8892844324316405
Precision: 0.886588570277605
Recall: 0.7131170614569998
K =  8
Accuracy: 0.889295436214545
Precision: 0.8870698413412417
Recall: 0.7097937552213869
K =  9
Accuracy: 0.8892850069320658
Precision: 0.8847554074742565
Recall: 0.7196484076523648
K =  10
Accuracy: 0.8885778333854656
Precision: 0.8893675692499221
Recall: 0.7092556565383881
K =  11
Accuracy: 0.8892987012987014
Precision: 0.8881661186646524
Recall: 0.714174298827411 6
K =  12
Accuracy: 0.8914792603698151
Precision: 0.8902029582258218
Recall: 0.7201430919530222
K =  13
Accuracy: 0.8914653500264504
Precision: 0.8910469226996972
Recall: 0.7206283804272798
K =  14
Accuracy: 0.8914804016844834
Precision: 0.8926676699096365
Recall: 0.7156151679764519
K =  15
Accuracy: 0.88789932990494
```

```
Precision: 0.8901208251755658
Recall: 0.7109801798971731
K =  16
Accuracy: 0.8892675755145683
Precision: 0.8869056274822529
Recall: 0.7137700511688583
K =  17
Accuracy: 0.889305134881414
Precision: 0.887973779227669
Recall: 0.7170283304210294
K =  18
Accuracy: 0.8900091136933241
Precision: 0.886814080370638
Recall: 0.714024428360782
K =  19
Accuracy: 0.8892694063926941
Precision: 0.88747955600245
Recall: 0.7098663713457091
K =  20
Accuracy: 0.8900828157349897
Precision: 0.888516855306716
Recall: 0.7141490560523068
```

In [15]:

```
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(x_train, y_train)
y_nbpred  =  classifier.predict(x_test)
y_nbpred[0:30]
```

Out[15]:

```
array([0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 1, 0, 0], dtype=int64)
```

In [16]:

```
import warnings
warnings.filterwarnings('ignore')
from sklearn import metrics
print("Accuracy:",metrics.accuracy_score(y_test, y_nbpred))
print("Precision:",metrics.precision_score(y_test, y_nbpred, pos_label='positive', aver
print("Recall:",metrics.recall_score(y_test, y_nbpred, pos_label='positive', average='w
```

```
Accuracy: 0.8757225433526011
Precision: 0.8767891263874993
Recall: 0.8757225433526011
```

In [17]:

```
from sklearn.metrics import confusion_matrix,accuracy_score
cnf_matrix2 = confusion_matrix(y_test, y_nbpred)
cnf_matrix2
```

Out[17]:

```
array([[224,  10],
       [ 33,  79]], dtype=int64)
```

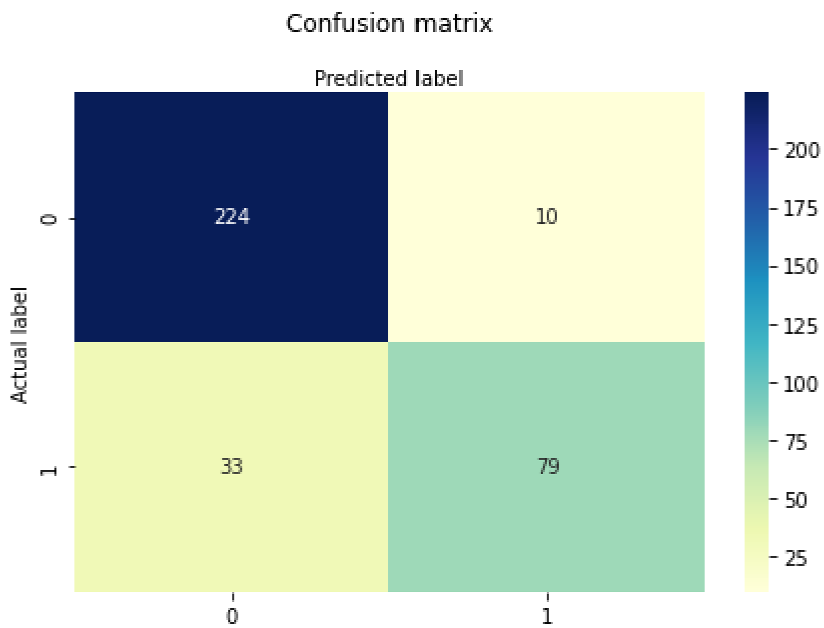
In [18]:

```
class_names=[0,1]
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)

sns.heatmap(pd.DataFrame(cnf_matrix2), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
```

```
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[18]: Text(0.5, 257.44, 'Predicted label')

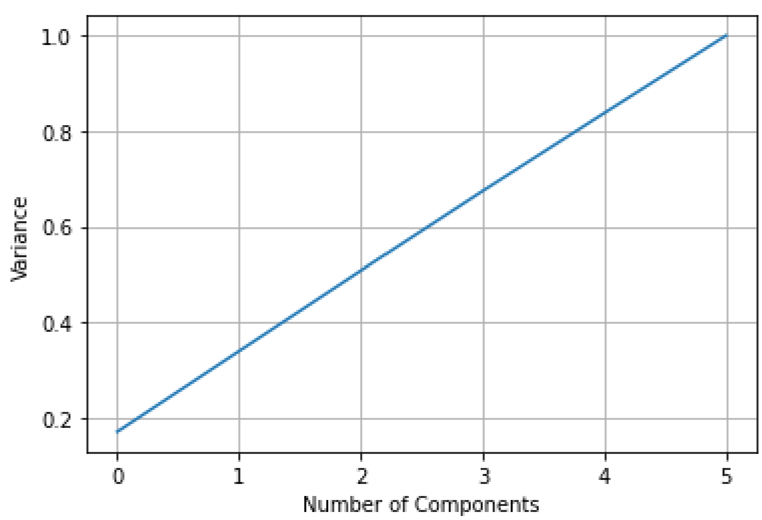


In [19]:

```
from sklearn.decomposition import PCA
pca = PCA(n_components=6)
pca.fit(x_train)
xpca = pca.transform(x_train)
```

In [20]:

```
plt.plot(np.cumsum((pca.explained_variance_ratio_)))
plt.xlabel('Number of Components')
plt.ylabel('Variance')
plt.grid()
```

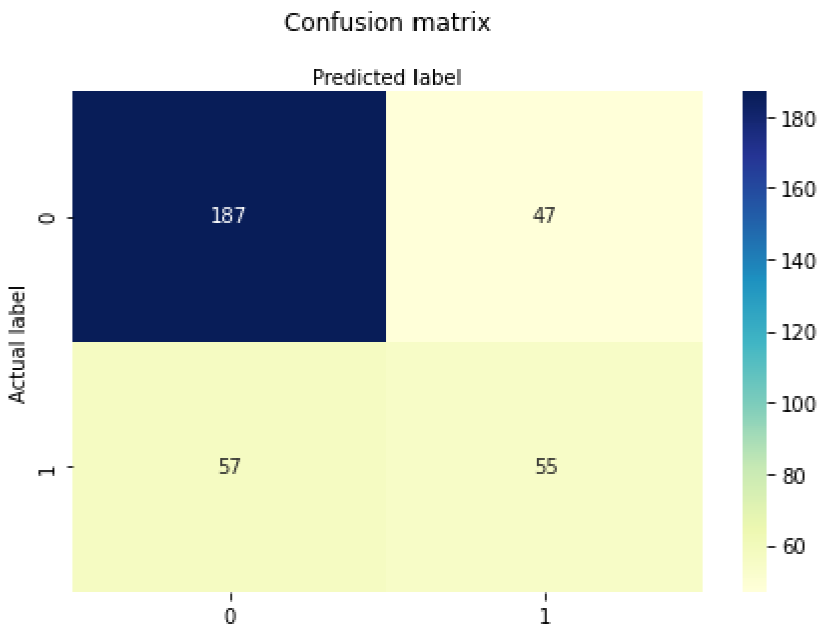


In [21]:

```
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state=0)
classifier.fit(xpca, y_train)
```

```
y_pred_pca = classifier.predict(x_test)
y_pred_pca[0:30]
class_names=[0,1]
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
from sklearn.metrics import confusion_matrix
cnf_matrix_pca = confusion_matrix(y_test, y_pred_pca)
cnf_matrix_pca
sns.heatmap(pd.DataFrame(cnf_matrix_pca), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
from sklearn import metrics
print("Accuracy:",metrics.accuracy_score(y_test, y_pred_pca))
print("Precision:",metrics.precision_score(y_test, y_pred_pca, pos_label='positive', av
print("Recall:",metrics.recall_score(y_test, y_pred_pca, pos_label='positive', average=
```

```
Accuracy: 0.6994219653179191
Precision: 0.6928561342095826
Recall: 0.6994219653179191
```



In [22]:

```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
lda = LinearDiscriminantAnalysis(n_components=1)
lda_t = lda.fit_transform(x_train,y_train)
y_pred_lda = lda.predict(x_test)
y_pred_lda[0:30]
```

Out[22]:

```
array([0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0,
       0, 0, 0, 1, 0, 1, 0, 1], dtype=int64)
```

In [23]:

```
from sklearn import metrics
print("Accuracy:",metrics.accuracy_score(y_test, y_pred_lda))
print("Precision:",metrics.precision_score(y_test, y_pred_lda, pos_label='positive', av
print("Recall:",metrics.recall_score(y_test, y_pred_lda, pos_label='positive', average=
```

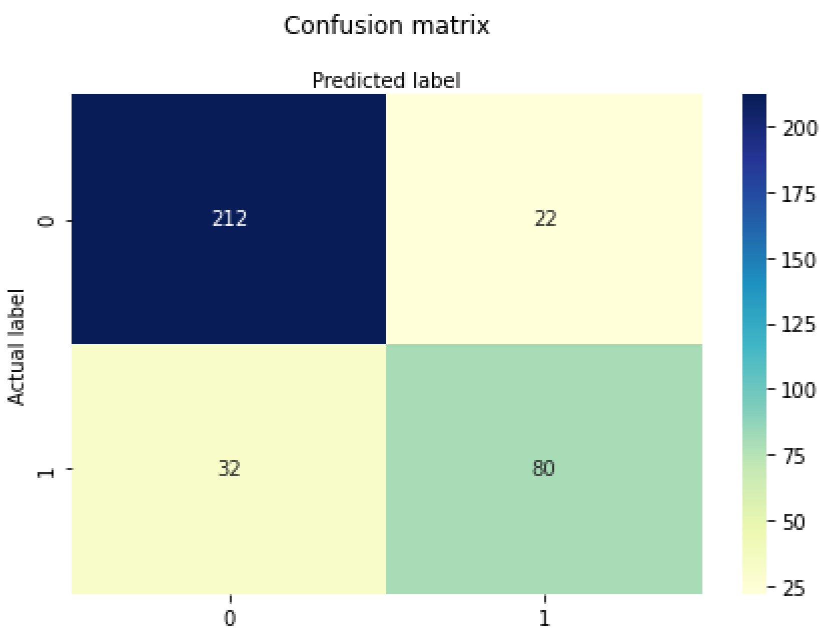
```
Accuracy: 0.8439306358381503
Precision: 0.8414873198402832
Recall: 0.8439306358381503
```

In [24]:

```
cnf_matrix3 = confusion_matrix(y_test, y_pred_lda)
class_names=[0,1] # name of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix3), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[24]:

```
Text(0.5, 257.44, 'Predicted label')
```



In [25]:

```
x1 = car_data.values[:, 0]
x2 = car_data.values[:, 1]
x3 = car_data.values[:, 2]
x4 = car_data.values[:, 3]
x5 = car_data.values[:, 4]
x6 = car_data.values[:, 5]
y  = car_data.values[:, 6]
```

In [26]:

```
def mean_squared_error (y, y_bar):
    difference = y - y_bar
    squared_difference = difference**2
    summation = squared_difference.sum()
    MSE = summation/len(y)
    return MSE
```

In [27]:

```
def gradient_decsent(x, y, lr, i_iter):
    theta0 = 0
    theta1 = 0
    losses = []
    thetas = []
    for i in range (i_iter):
        y_bar = theta1*x + theta0
        loss = mean_squared_error(y, y_bar)
        theta0 = theta0 - (lr*-2*(y-y_bar).sum()/len(y))
        theta1 = theta1 - (lr*-2*(x.dot(y-y_bar)).sum()/len(y))
        losses.append(loss)
        thetas.append((theta0, theta1))
    return thetas, losses
```

In [28]:

```
thetas1, losses1 = gradient_decsent(x1, y, 0.1, 100)
thetas2, losses2 = gradient_decsent(x2, y, 0.1, 100)
thetas3, losses3 = gradient_decsent(x3, y, 0.1, 100)
thetas4, losses4 = gradient_decsent(x4, y, 0.1, 100)
thetas5, losses5 = gradient_decsent(x5, y, 0.1, 100)
thetas6, losses6 = gradient_decsent(x6, y, 0.1, 100)
```

In [29]:

```
print("y_bar=",thetas1[99][1],"x1 +",thetas1[99][0])
print("y_bar=",thetas2[99][1],"x2 +",thetas2[99][0])
print("y_bar=",thetas3[99][1],"x3 +",thetas3[99][0])
print("y_bar=",thetas4[99][1],"x4 +",thetas4[99][0])
print("y_bar=",thetas5[99][1],"x5 +",thetas5[99][0])
print("y_bar=",thetas6[99][1],"x6 +",thetas6[99][0])
```

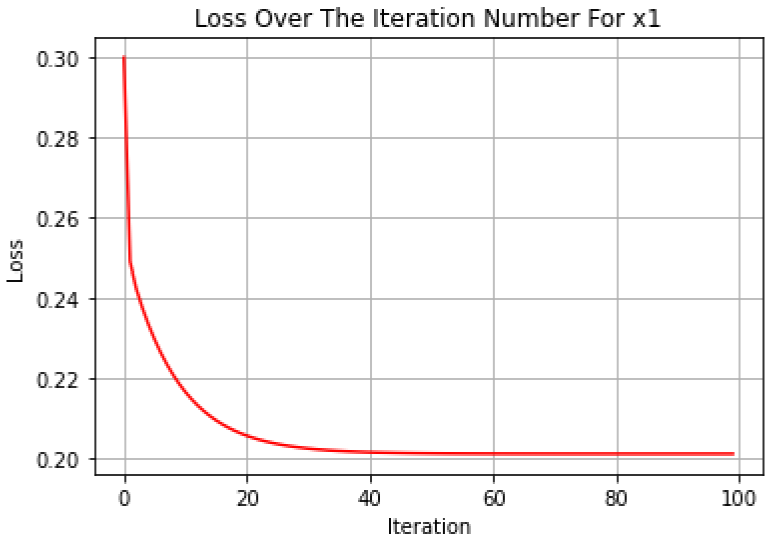
```
y_bar= -0.08340895323185711 x1 + 0.4246359694020135
y_bar= -0.07416488533971391 x2 + 0.4107795147140705
y_bar= -2.2587848519177108e+26 x3 + -5.89397245690261e+25
y_bar= -1.6291205036951662e+45 x4 + -3.516696109088365e+44
y_bar= 0.07144905610395608 x5 + 0.22821543835151284
y_bar= 0.2593262001798127 x6 + 0.04052848609098093
```

In [30]:

```
x_axis = np.arange(0., 100, 1)
plt.grid()
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.title('Loss Over The Iteration Number For x1')
plt.plot(x_axis,losses1,color='red')
```

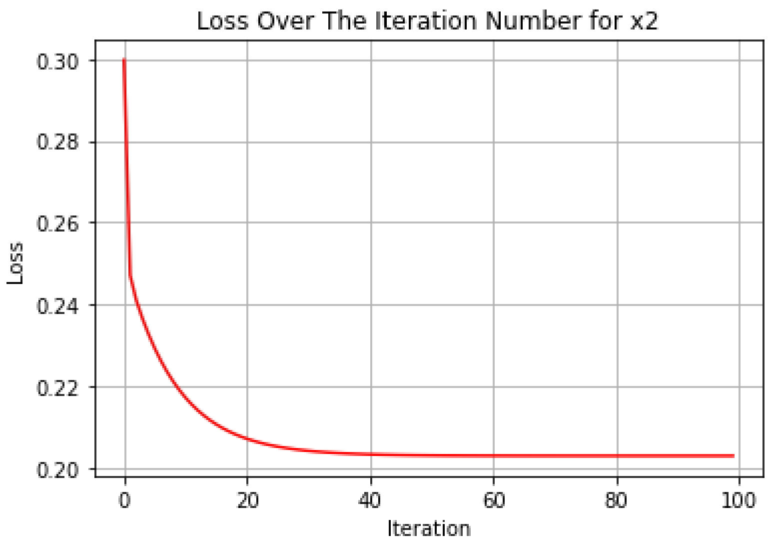
Out[30]:

```
[<matplotlib.lines.Line2D at 0x2463a23e040>]
```



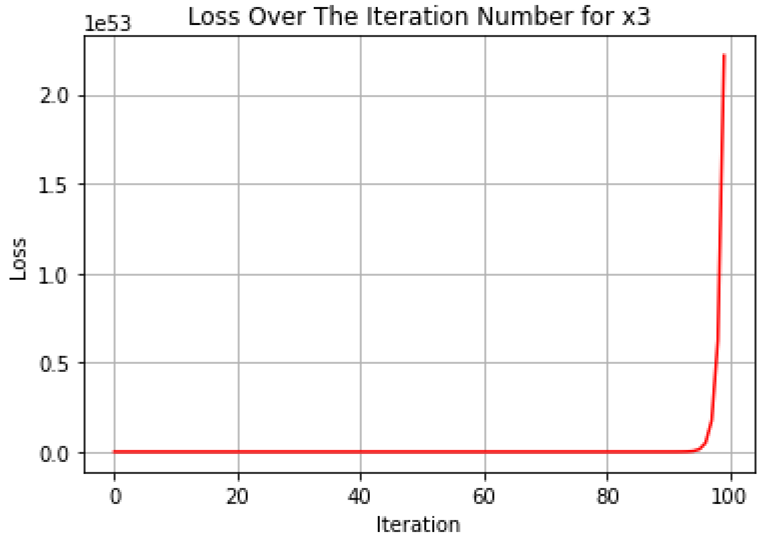
In [31]:
```
x_axis = np.arange(0., 100, 1)
plt.grid()
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.title('Loss Over The Iteration Number for x2')
plt.plot(x_axis,losses2,color='red')
```

Out[31]: [<matplotlib.lines.Line2D at 0x2463a28cd60>]



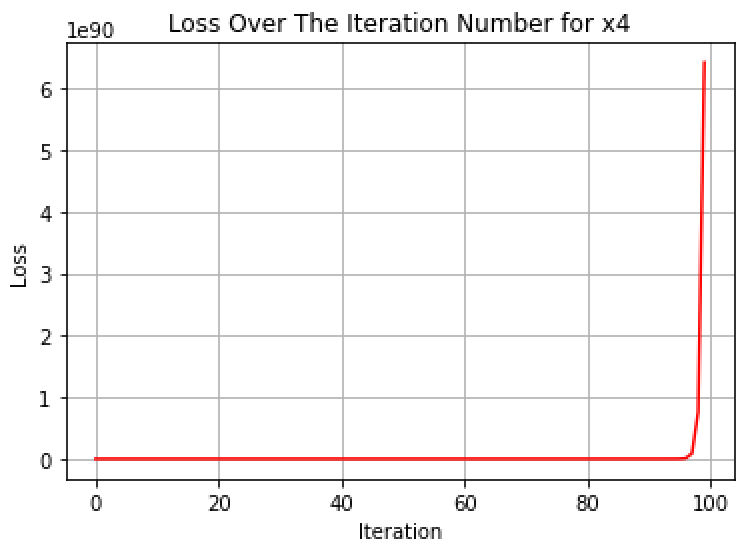
In [32]:
```
x_axis = np.arange(0., 100, 1)
plt.grid()
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.title('Loss Over The Iteration Number for x3')
plt.plot(x_axis,losses3,color='red')
```

Out[32]: [<matplotlib.lines.Line2D at 0x2463a2f2430>]



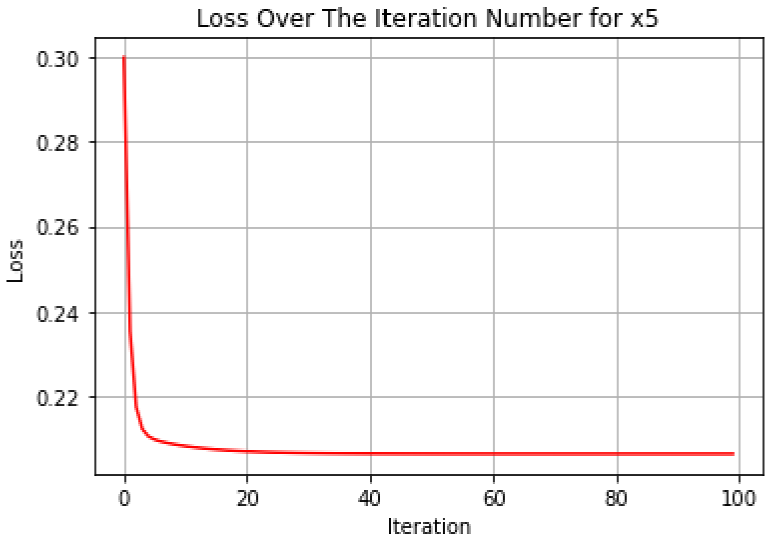
In [33]:
```
x_axis = np.arange(0., 100, 1)
plt.grid()
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.title('Loss Over The Iteration Number for x4')
plt.plot(x_axis,losses4,color='red')
```

Out[33]:
```
[<matplotlib.lines.Line2D at 0x2463a34c7c0>]
```



In [34]:
```
x_axis = np.arange(0., 100, 1)
plt.grid()
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.title('Loss Over The Iteration Number for x5')
plt.plot(x_axis,losses5,color='red')
```

Out[34]:
```
[<matplotlib.lines.Line2D at 0x2463a3ac8b0>]
```

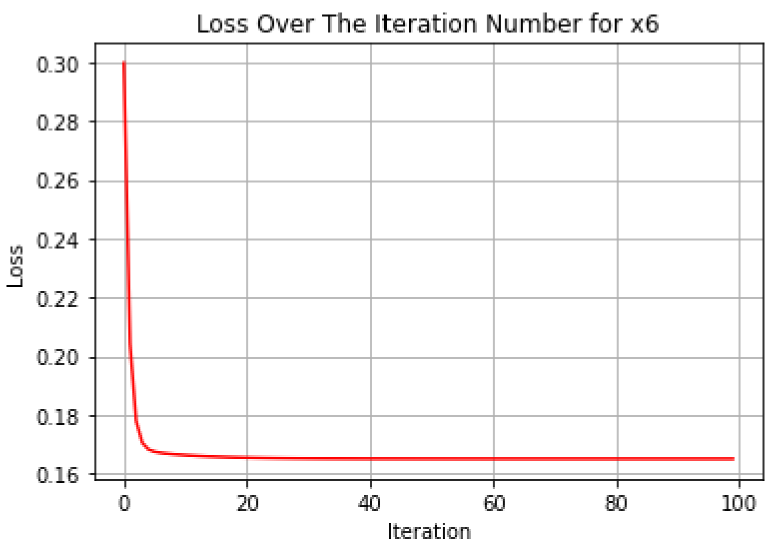


In [35]:

```
x_axis = np.arange(0., 100, 1)
plt.grid()
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.title('Loss Over The Iteration Number for x6')
plt.plot(x_axis,losses6,color='red')
```

Out[35]:

```
[<matplotlib.lines.Line2D at 0x2463a405bb0>]
```



In [36]:

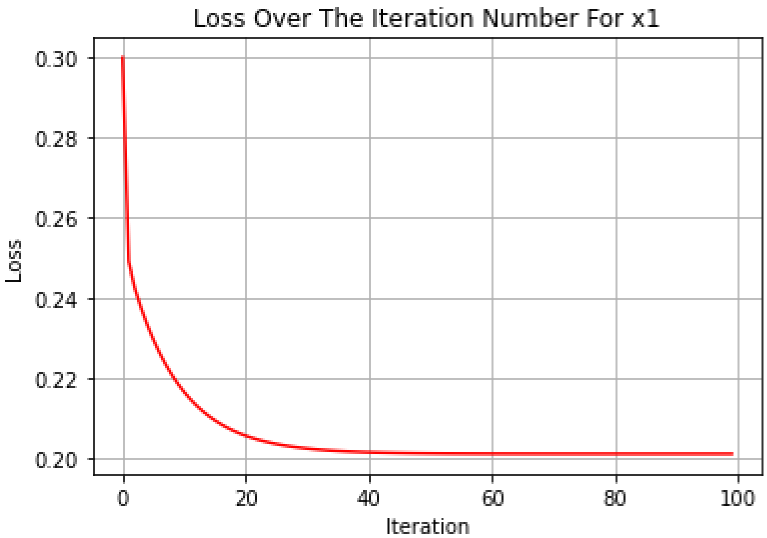
```
print("final loss for the first column:", losses1[99])
print("final loss for the second column:", losses2[99])
print("final loss for the third column:", losses3[99])
print("final loss for the fourth column:", losses4[99])
print("final loss for the fifth column:", losses5[99])
print("final loss for the sixth column:", losses6[99])
```

```
final loss for the first column: 0.20113036015205932
final loss for the second column: 0.20296290031600558
final loss for the third column: 2.216040706950132e+53
final loss for the fourth column: 6.423806551336502e+90
final loss for the fifth column: 0.20652963888568068
final loss for the sixth column: 0.16499707812768777
```

In [37]:
```
thetas2, losses2 = gradient_decsent(x2, y, 0.01, 100)
thetas3, losses3 = gradient_decsent(x3, y, 0.01, 100)
thetas4, losses4 = gradient_decsent(x4, y, 0.01, 100)
thetas5, losses5 = gradient_decsent(x5, y, 0.01, 100)
thetas6, losses6 = gradient_decsent(x6, y, 0.01, 100)

x_axis = np.arange(0., 100, 1)
plt.grid()
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.title('Loss Over The Iteration Number For x1')
plt.plot(x_axis,losses1,color='red')
```

Out[37]:
```
[<matplotlib.lines.Line2D at 0x2463a46dd60>]
```



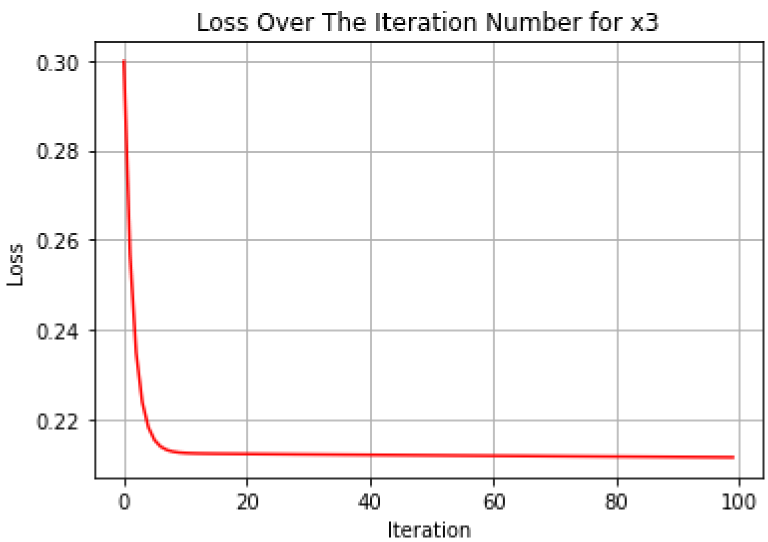
In [38]:
```
x_axis = np.arange(0., 100, 1)
plt.grid()
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.title('Loss Over The Iteration Number for x2')
plt.plot(x_axis,losses2,color='red')
```

Out[38]:
```
[<matplotlib.lines.Line2D at 0x2463a4c8d90>]
```

In [39]:

```
x_axis = np.arange(0., 100, 1)
plt.grid()
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.title('Loss Over The Iteration Number for x3')
plt.plot(x_axis,losses3,color='red')
```

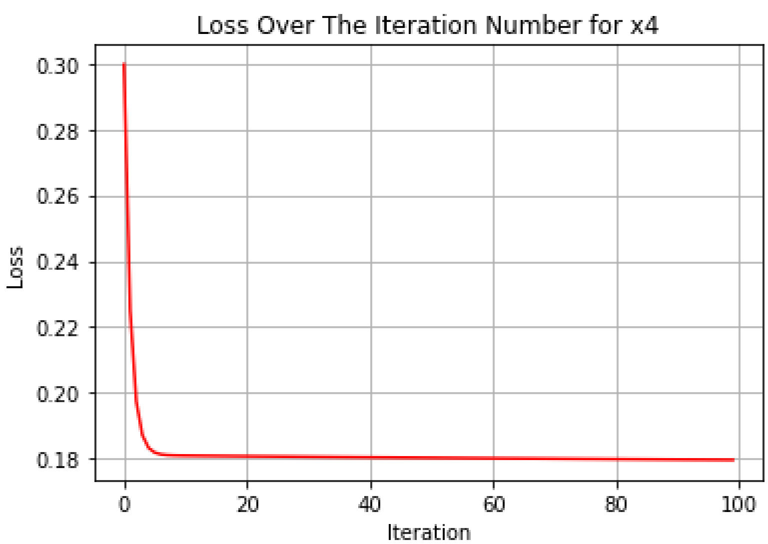
Out[39]: [<matplotlib.lines.Line2D at 0x2463a52f280>]



In [40]:

```
x_axis = np.arange(0., 100, 1)
plt.grid()
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.title('Loss Over The Iteration Number for x4')
plt.plot(x_axis,losses4,color='red')
```

Out[40]: [<matplotlib.lines.Line2D at 0x2463a57dc40>]

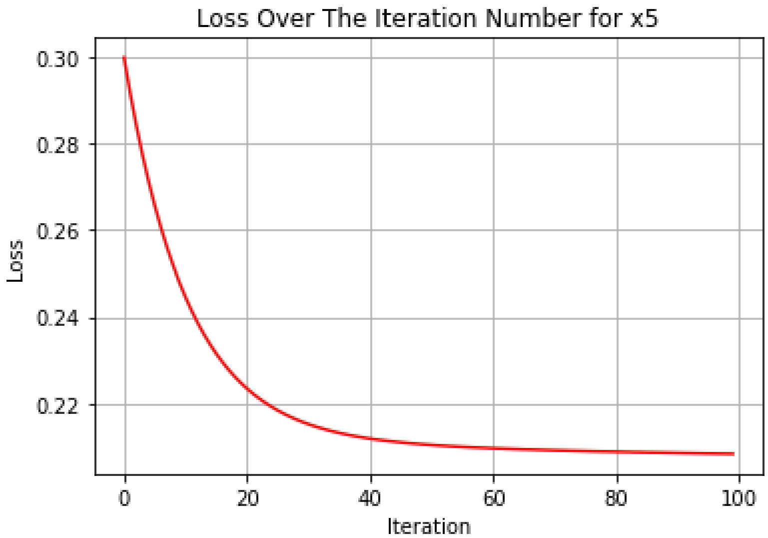


In [41]:

```
x_axis = np.arange(0., 100, 1)
plt.grid()
plt.xlabel('Iteration')
```

```
plt.ylabel('Loss')
plt.title('Loss Over The Iteration Number for x5')
plt.plot(x_axis,losses5,color='red')
```

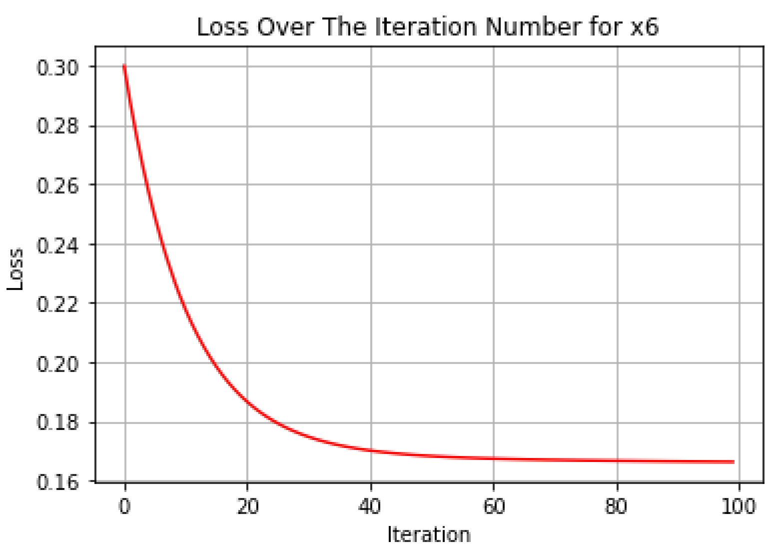
Out[41]: [<matplotlib.lines.Line2D at 0x2463a5deca0>]



In [42]:

```
x_axis = np.arange(0., 100, 1)
plt.grid()
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.title('Loss Over The Iteration Number for x6')
plt.plot(x_axis,losses6,color='red')
```

Out[42]: [<matplotlib.lines.Line2D at 0x2463b607dc0>]



In [43]:

```
print("final loss for the first column:", losses1[99])
print("final loss for the second column:", losses2[99])
print("final loss for the third column:", losses3[99])
print("final loss for the fourth column:", losses4[99])
print("final loss for the fifth column:", losses5[99])
print("final loss for the sixth column:", losses6[99])
```

```
final loss for the first column: 0.20113036015205932
final loss for the second column: 0.2178840718943801
final loss for the third column: 0.21149317775625842
final loss for the fourth column: 0.17956480646029002
final loss for the fifth column: 0.20844060449792876
final loss for the sixth column: 0.16631268945694924
```

In [ ]: