In [1]:

```
import pandas as pd
import numpy as np
from sklearn.model_selection import KFold
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn import linear_model
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn import metrics
import seaborn as sns
from sklearn.cluster import KMeans, DBSCAN
from scipy.cluster.hierarchy import linkage, dendrogram, fcluster
import matplotlib.pyplot as plt
```

In [2]:

```
# TASK 2: DATA COLLECTION
```

In [3]:
```
data_mat = pd.read_csv('student-mat.csv')
data_mat.head(20)
```

Out[3]:

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	famre
0	GP	F	18	U	GT3	A	4	4	at_home	teacher	...	4
1	GP	F	17	U	GT3	T	1	1	at_home	other	...	5
2	GP	F	15	U	LE3	T	1	1	at_home	other	...	4
3	GP	F	15	U	GT3	T	4	2	health	services	...	3
4	GP	F	16	U	GT3	T	3	3	other	other	...	4
5	GP	M	16	U	LE3	T	4	3	services	other	...	5
6	GP	M	16	U	LE3	T	2	2	other	other	...	4
7	GP	F	17	U	GT3	A	4	4	other	teacher	...	4
8	GP	M	15	U	LE3	A	3	2	services	other	...	4
9	GP	M	15	U	GT3	T	3	4	other	other	...	5
10	GP	F	15	U	GT3	T	4	4	teacher	health	...	3
11	GP	F	15	U	GT3	T	2	1	services	other	...	5
12	GP	M	15	U	LE3	T	4	4	health	services	...	4
13	GP	M	15	U	GT3	T	4	3	teacher	other	...	5
14	GP	M	15	U	GT3	A	2	2	other	other	...	4
15	GP	F	16	U	GT3	T	4	4	health	other	...	4
16	GP	F	16	U	GT3	T	4	4	services	services	...	3
17	GP	F	16	U	GT3	T	3	3	other	other	...	5
18	GP	M	17	U	GT3	T	3	2	services	services	...	5
19	GP	M	16	U	LE3	T	4	3	health	other	...	3

20 rows × 33 columns

In [4]:
```
data_por = pd.read_csv('student-por.csv')
data_por.head()
#print(data_por)
```

Out[4]:

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	famrel
0	GP	F	18	U	GT3	A	4	4	at_home	teacher	...	4
1	GP	F	17	U	GT3	T	1	1	at_home	other	...	5
2	GP	F	15	U	LE3	T	1	1	at_home	other	...	4
3	GP	F	15	U	GT3	T	4	2	health	services	...	3
4	GP	F	16	U	GT3	T	3	3	other	other	...	4

5 rows × 33 columns

In [5]:
```
# TASK 3: DATA PREPARATION
```

In [6]:
```
# Remove any unnecessary attributes from the datasets.
data_mat_df = pd.DataFrame(data=data_mat)
data_por_df = pd.DataFrame(data=data_por)

#data_mat_updated = data_mat_df.drop(columns=['famsize','Pstatus','Mjo
b','Fjob','reason','guardian','famsup','activities','nursery','highe
r','freetime','goout','health','romantic','famrel'])
#data_por_updated = data_por_df.drop(columns=['famsize','Pstatus','Mjo
b','Fjob','reason','guardian','famsup','activities','nursery','highe
r','freetime','goout','health','romantic','famrel'])
#data_por_updated = data_por_df.drop(columns=['famsize','Pstatus','Med
u','Fedu','Mjob','Fjob','reason','guardian','nursery','higher','romanti
c','famrel'])
```

In [7]:
```
# Merge both datasets together.

data_merged = data_mat_df.merge(data_por_df, on=["school","sex","age","a
ddress",
                                                                "famsize","Ps
tatus","Medu","Fedu",
                                                               "Mjob","Fjob",
"reason","nursery",
                                                               "internet"],su
ffixes=('_mat', '_por'))


data_merged = data_merged.drop(columns=["nursery","famsize","Pstatus","r
eason","guardian_por","guardian_mat",
                                       "famrel_por","famrel_mat","romant
ic_por","romantic_mat","goout_por",
                                       "goout_mat","Mjob","Fjob","higher
_por","higher_mat","paid_por",
                                       "paid_mat","famsup_por","famsup_m
at","failures_por","failures_mat"])
#print(data_merged)
data_merged.head(20)
```

Out[7]:

	school	sex	age	address	Medu	Fedu	traveltime_mat	studytime_mat	schoolsup_m
0	GP	F	18	U	4	4	2	2	yes
1	GP	F	17	U	1	1	1	2	no
2	GP	F	15	U	1	1	1	2	yes
3	GP	F	15	U	4	2	1	3	no
4	GP	F	16	U	3	3	1	2	no
5	GP	M	16	U	4	3	1	2	no
6	GP	M	16	U	2	2	1	2	no
7	GP	F	17	U	4	4	2	2	yes
8	GP	M	15	U	3	2	1	2	no
9	GP	M	15	U	3	4	1	2	no
10	GP	F	15	U	4	4	1	2	no
11	GP	F	15	U	2	1	3	3	no
12	GP	M	15	U	4	4	1	1	no
13	GP	M	15	U	4	3	2	2	no
14	GP	M	15	U	2	2	1	3	no
15	GP	F	16	U	4	4	1	1	no
16	GP	F	16	U	4	4	1	3	no
17	GP	F	16	U	3	3	3	2	yes
18	GP	M	17	U	3	2	1	1	no
19	GP	M	16	U	4	3	1	1	no

20 rows × 31 columns

In [8]:

```
# TASK 4: DATA EXPLORATION
```

In [9]:

```
data_merged.groupby(['sex']).describe()
```

Out[9]:

	Dalc_mat								Dalc_por		...	traveltim	
	count	**mean**	**std**	**min**	**25%**	**50%**	**75%**	**max**	**count**	**mean**	**...**	**75%**	**r**
sex													
F	198.0	1.262626	0.605991	1.0	1.0	1.0	1.0	5.0	198.0	1.267677	...	2.0	4
M	184.0	1.701087	1.067554	1.0	1.0	1.0	2.0	5.0	184.0	1.701087	...	2.0	4

2 rows × 184 columns

In [10]:
```
data_merged[data_merged['sex'] == 'F'].mean()
```

Out[10]:
```
age               16.606061
Medu               2.696970
Fedu               2.515152
traveltime_mat     1.404040
studytime_mat      2.272727
freetime_mat       3.015152
Dalc_mat           1.262626
Walc_mat           1.964646
health_mat         3.388889
absences_mat       5.787879
G1_mat            10.459596
G2_mat            10.282828
G3_mat             9.838384
traveltime_por     1.409091
studytime_por      2.272727
freetime_por       3.030303
Dalc_por           1.267677
Walc_por           1.979798
health_por         3.383838
absences_por       3.717172
G1_por            12.545455
G2_por            12.691919
G3_por            13.085859
dtype: float64
```

In [11]:
```
data_merged[data_merged['sex'] == 'M'].mean()
```

Out[11]:
```
age               16.565217
Medu               2.923913
Fedu               2.619565
traveltime_mat     1.483696
studytime_mat      1.777174
freetime_mat       3.445652
Dalc_mat           1.701087
Walc_mat           2.619565
health_mat         3.782609
absences_mat       4.815217
G1_mat            11.293478
G2_mat            11.173913
G3_mat            10.978261
traveltime_por     1.483696
studytime_por      1.788043
freetime_por       3.445652
Dalc_por           1.701087
Walc_por           2.625000
health_por         3.782609
absences_por       3.625000
G1_por            11.646739
G2_por            11.750000
G3_por            11.902174
dtype: float64
```

In [12]:
```
data_merged.head(5)
#data_merged.keys()
```

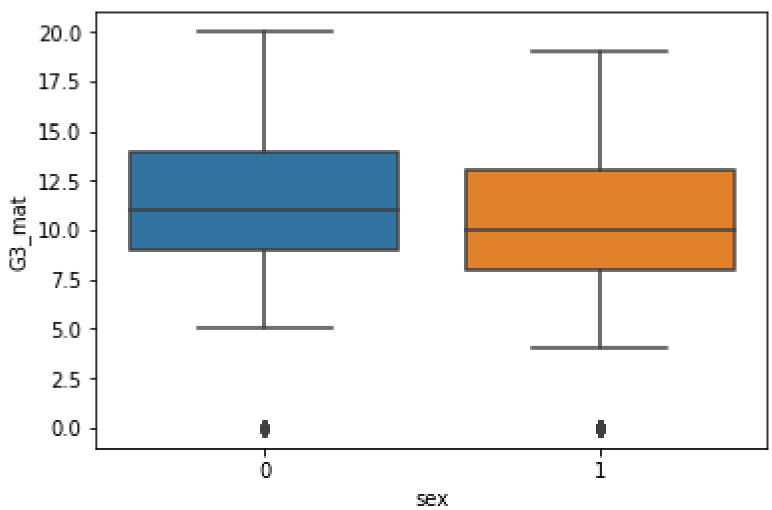
Out[12]:

	school	sex	age	address	Medu	Fedu	traveltime_mat	studytime_mat	schoolsup_ma
0	GP	F	18	U	4	4	2	2	yes
1	GP	F	17	U	1	1	1	2	no
2	GP	F	15	U	1	1	1	2	yes
3	GP	F	15	U	4	2	1	3	no
4	GP	F	16	U	3	3	1	2	no

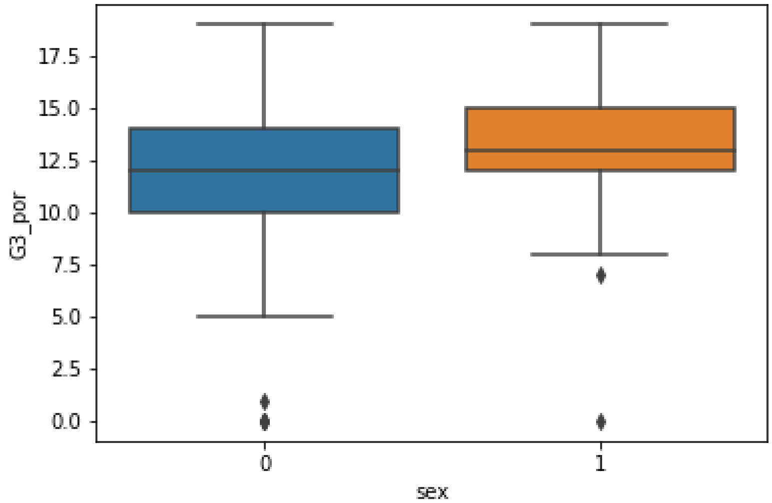
5 rows × 31 columns

In [13]:
```
data_merged['sex'] = data_merged.apply(lambda row: 1 if (row['sex']=='F'
) else 0, axis = 1)
#data_merged.head(50)
```

In [14]:
```
ax = sns.boxplot(y='G3_mat', x='sex', data=data_merged)
```



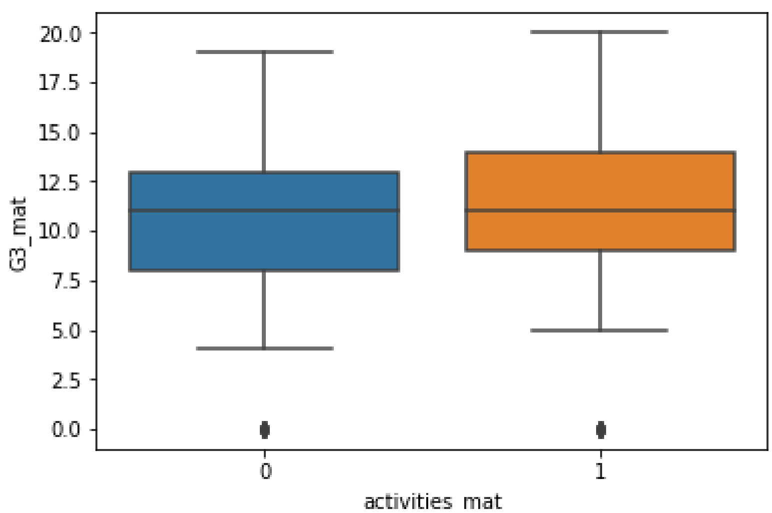
In [15]:
```
ax = sns.boxplot(y='G3_por', x='sex', data=data_merged)
```



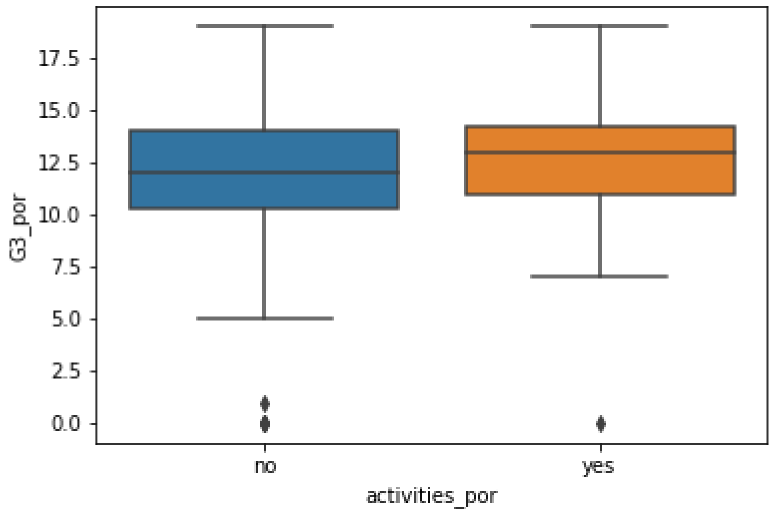
In [16]:
```
#When looking at the final grades for both math and porteguese according
to their gender. For math grades the males
#had a better average final grade than the females. For the porteguese g
rades, the females had a higher average than the
#males.
```

In [17]:
```
data_merged['activities_mat'] = data_merged.apply(lambda row: 1 if (row[
'activities_mat']=='yes') else 0, axis = 1)
```

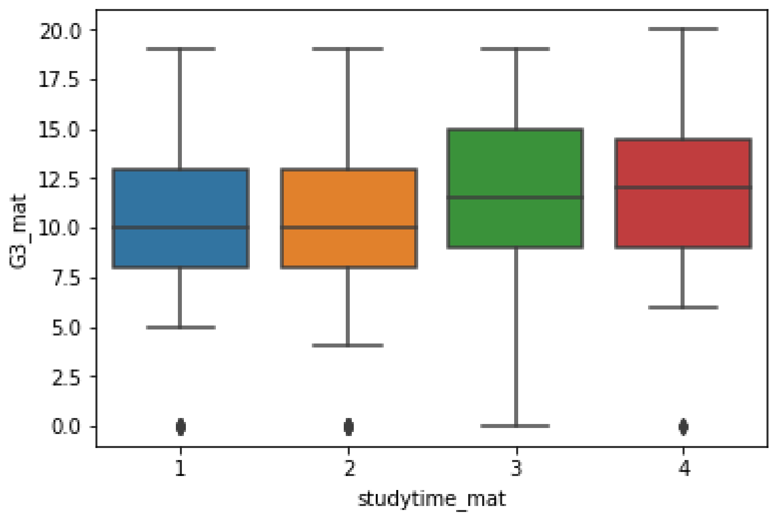
In [18]:
```
ax = sns.boxplot(y='G3_mat', x='activities_mat', data=data_merged)
```



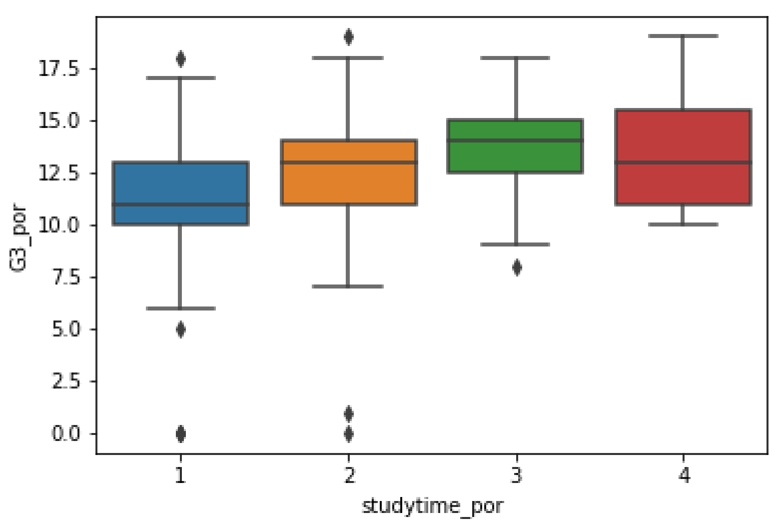
In [19]:
```
ax = sns.boxplot(y='G3_por', x='activities_por', data=data_merged)
```



In [20]:
```
ax = sns.boxplot(y='G3_mat', x='studytime_mat', data=data_merged)
```

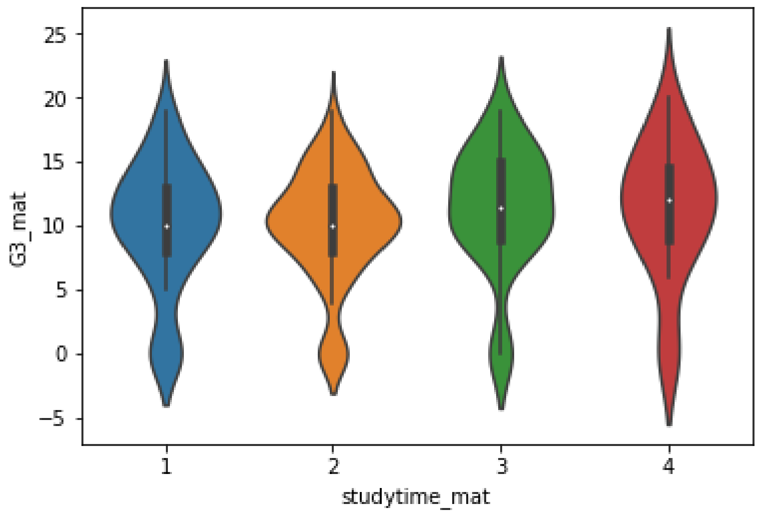


In [21]:
```
ax = sns.boxplot(y='G3_por', x='studytime_por', data=data_merged)
```



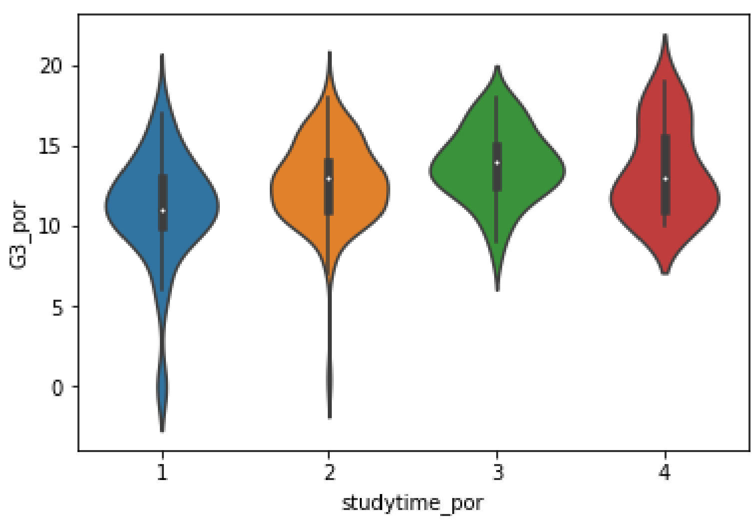
In [22]:
```
ax = sns.violinplot(x='studytime_mat', y='G3_mat', data=data_merged, ci=
None)
```

```
/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:1706: Futur
eWarning: Using a non-tuple sequence for multidimensional indexing is d
eprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future t
his will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



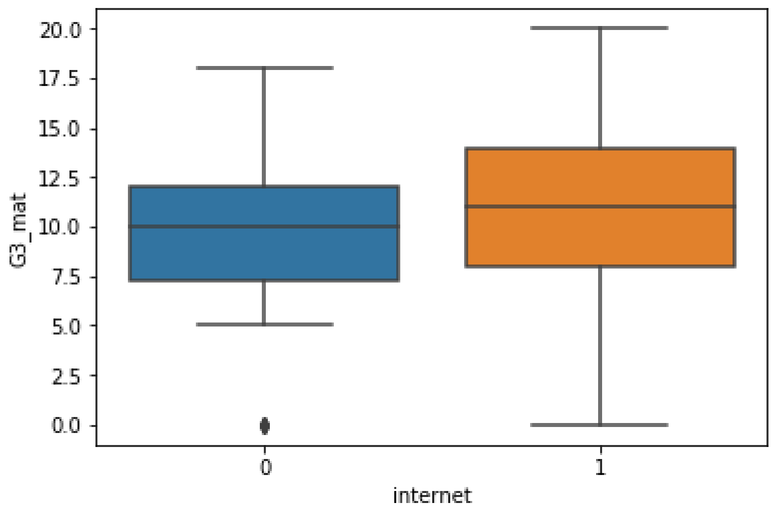
In [23]:
```
ax = sns.violinplot(x='studytime_por', y='G3_por', data=data_merged, ci=
None)
```

```
/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:1706: Futur
eWarning: Using a non-tuple sequence for multidimensional indexing is d
eprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future t
his will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

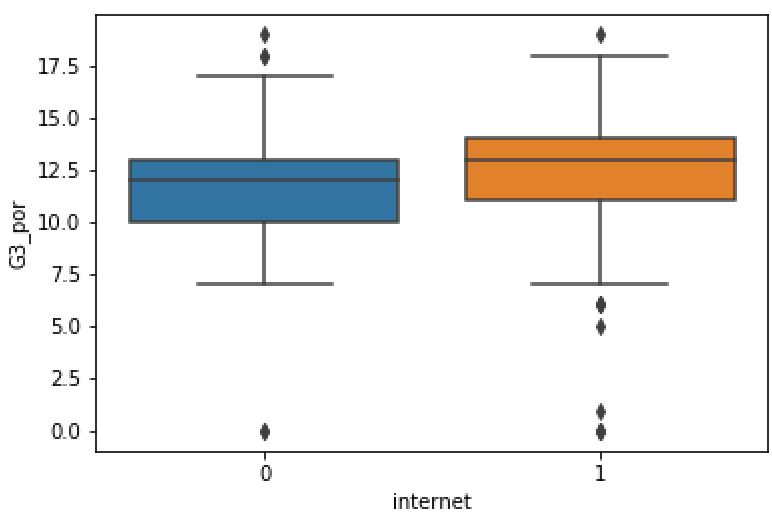


In [24]:
```
data_merged['internet'] = data_merged.apply(lambda row: 1 if (row['inter
net']=='yes') else 0, axis = 1)
```

In [25]:
```
ax = sns.boxplot(y='G3_mat', x='internet', data=data_merged)
```



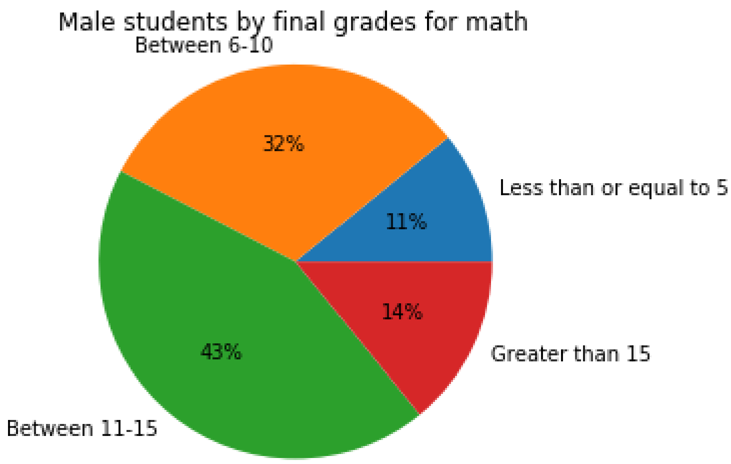
In [26]:
```
ax = sns.boxplot(y='G3_por', x='internet', data=data_merged)
```



In [27]:
```
data_merged_males = data_merged[data_merged['sex'] == 0]
data_merged_females = data_merged[data_merged['sex'] == 1]
```

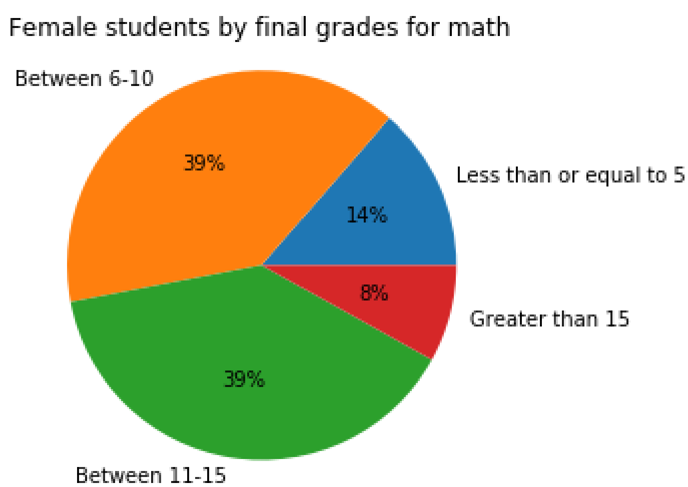
In [28]:
```
# Pie Chart for final math grade ranges for male students

a = data_merged_males[data_merged_males.G3_mat <= 5]['G3_mat'].count()
b = data_merged_males[(data_merged_males.G3_mat > 5) & (data_merged_male
s.G3_mat <= 10)]['G3_mat'].count()
c = data_merged_males[(data_merged_males.G3_mat > 10) & (data_merged_mal
es.G3_mat <= 15)]['G3_mat'].count()
d = data_merged_males[data_merged_males.G3_mat > 15]['G3_mat'].count()
plt.pie([a, b, c, d], autopct='%1.0f%%', labels = ['Less than or equal t
o 5', 'Between 6-10',
                                'Between 11-15', 'Greater than 15'])
plt.title('Male students by final grades for math')
plt.axis('equal')
```

Out[28]:
```
(-1.1271387085047244,
 1.1012923194526059,
 -1.1005860724441208,
 1.1123075213265348)
```



In [29]:
```
# Pie Chart for final math grade ranges for female students
a = data_merged_females[data_merged_females.G3_mat <= 5]['G3_mat'].count
()
b = data_merged_females[(data_merged_females.G3_mat > 5) & (data_merged_
females.G3_mat <= 10)]['G3_mat'].count()
c = data_merged_females[(data_merged_females.G3_mat > 10) & (data_merged
_females.G3_mat <= 15)]['G3_mat'].count()
d = data_merged_females[data_merged_females.G3_mat > 15]['G3_mat'].count
()
plt.pie([a, b, c, d], autopct='%1.0f%%', labels = ['Less than or equal t
o 5', 'Between 6-10',
                                'Between 11-15', 'Greater than 15'])
plt.title('Female students by final grades for math')
plt.axis('equal')
```

Out[29]:
```
(-1.122337174883346,
 1.1010636874613766,
 -1.121614035577209,
 1.1169884601798985)
```



In [30]:
```
#Attributes to use
#Internet
#Studytime
#Activites
#sex
```

In [31]:
```
x_train, x_test, y_train, y_test = train_test_split(data_mat[[ 'age','Me
du','Fedu','traveltime', 'studytime','failures', 'famrel',
                                                              'freetime'
, 'goout','Dalc', 'Walc',"health", 'absences','G1', 'G2','G3']], data_ma
t['G3'],
                                                    test_size = 0.25, ra
ndom_state = 0)
x_train, x_val, y_train, y_val = train_test_split(x_train, y_train, test
_size = 0.2, random_state = 0)
```

In [32]:

```
scaler = StandardScaler()
scaler.fit(x_train)
x_train_scale = scaler.transform(x_train)
x_test_scale = scaler.transform(x_test)
x_test_scale_df = pd.DataFrame(x_test_scale, columns=x_test.columns)
x_train_scale_df = pd.DataFrame(x_train_scale, columns=x_train.columns)
```

In [33]:

```
model = linear_model.LinearRegression()
fitted_model = model.fit(X = x_train_scale_df[[ 'age', 'Medu','Fedu','tr
aveltime', 'studytime','failures', 'famrel','freetime',
                                                 'goout','Dalc', 'Walc',
"health", 'absences','G1', 'G2']],
                         y = x_train_scale_df['G3'])
score = fitted_model.score(X = x_train_scale_df[[ 'age', 'Medu','Fedu',
'traveltime', 'studytime','failures', 'famrel','freetime',
                                                 'goout','Dalc', 'Walc',
"health", 'absences','G1', 'G2']],
                           y = x_train_scale_df['G3'])
print(score)
print(fitted_model)
predicted = fitted_model.predict(X = x_test_scale_df[[ 'age', 'Medu','Fe
du','traveltime', 'studytime','failures', 'famrel','freetime',
                                                 'goout','Dalc', 'Walc',
"health", 'absences','G1', 'G2']])
print(predicted)
print(fitted_model.coef_)
```

```
0.8667354920170355
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=F
alse)
[ 0.90715774  0.17470885 -0.12918381  1.19814325  1.42476824  0.3623943
7
  0.53734614  0.0822588  -0.52290503  1.03900528 -0.60401038  0.8113355
6
  0.25869046 -0.60902427  1.10877207  0.95370939  0.63572055 -0.2832158
9
 -0.19829639  1.09185672 -0.95511851 -1.55672538 -0.86748789  1.1046025
3
  0.33405877  1.39685441 -0.1932772   2.19768587 -2.42394271  0.6019067
 -2.63634902 -0.79805452 -0.53120403 -1.14569754  0.59579569 -0.0824339
1
  0.55314588  1.90322236 -0.4161394   0.31464271 -1.46231415  1.9289984
2
 -0.72873445 -0.44314386  0.00702654 -2.8055975   0.28013164 -1.4687589
5
  0.2454916  -0.59396256 -0.20010491  1.91233183  0.34068998 -0.6904058
2
  0.40550928 -0.53819416 -0.29972452  0.55306188  1.08386248  0.7872962
3
  0.62047956  0.59260489  0.82229912  1.18198172 -0.49963326  1.294844
  1.83323243  0.34124177 -1.52986678 -0.27527291 -0.33602415  0.7798839
7
 -0.79613313 -1.60362294  0.12014744 -0.46764254  0.09523266  1.7983152
8
 -1.08492778 -0.08777118 -0.39234676 -0.74897231 -0.18899658  0.5813137
6
 -0.20431842  0.0802354   0.04080468  1.0314921   1.77565258 -0.7222360
5
 -0.55354322 -2.62662144 -0.57457115  0.94394118 -0.9574847  -0.2870452
7
  1.98345593 -0.02306405  0.42046162]
[-0.04547697  0.03125151 -0.04042362  0.02093456  0.01835104 -0.0266450
1
  0.02730096  0.01008406  0.00627269 -0.01940812  0.04655953  0.0423335
8
  0.05610459  0.0747147   0.86108522]
```

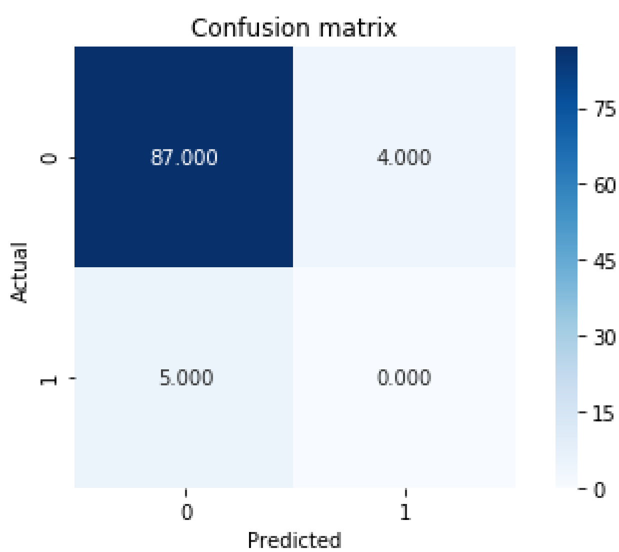
In [34]:

```
x_train, x_test, y_train, y_test = train_test_split(data_merged[[ 'age',
'activities_mat','internet','sex','Fedu','traveltime_mat','traveltime_po
r',
                                                                 'studyt
ime_mat', 'studytime_por','freetime_mat','freetime_por','Dalc_mat','Dalc
_por',
                                                                 'Walc_m
at', 'Walc_por','health_mat',"health_por",'absences_mat','absences_por',
                                                                 'G1_ma
t','G1_por','G3_mat','G3_por']], data_merged['school'],
                                                     test_size = 0.25, ra
ndom_state = 0)
x_train, x_val, y_train, y_val = train_test_split(x_train, y_train, test
_size = 0.2, random_state = 0)
```

In [35]:
```
scaler = StandardScaler()
scaler.fit(x_train)
x_train_scale = scaler.transform(x_train)
x_test_scale = scaler.transform(x_test)
x_test_scale_df = pd.DataFrame(x_test_scale, columns=x_test.columns)
x_train_scale_df = pd.DataFrame(x_train_scale, columns=x_train.columns)
```

In [36]:
```
classifier = KNeighborsClassifier(n_neighbors = 3)
classifier.fit(x_train_scale, y_train)

y_pred = classifier.predict(x_test_scale)
#all_data_pred=classifier.predict(all_data)
conf_matrix = metrics.confusion_matrix(y_test, y_pred)
print(conf_matrix)

sns.heatmap(conf_matrix, annot = True, fmt = ".3f", square = True, cmap
= plt.cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Confusion matrix')
plt.tight_layout()
```

```
[[87  4]
 [ 5  0]]
```



In [37]:
```
print(metrics.accuracy_score(y_test, y_pred)) # accuracy
print(1 - metrics.accuracy_score(y_test, y_pred)) # error
print(metrics.precision_score(y_test, y_pred, average = None)) # precisi
on
print(metrics.recall_score(y_test, y_pred, average = None)) # recall
print(metrics.f1_score(y_test, y_pred, average = None)) # F1 score
```

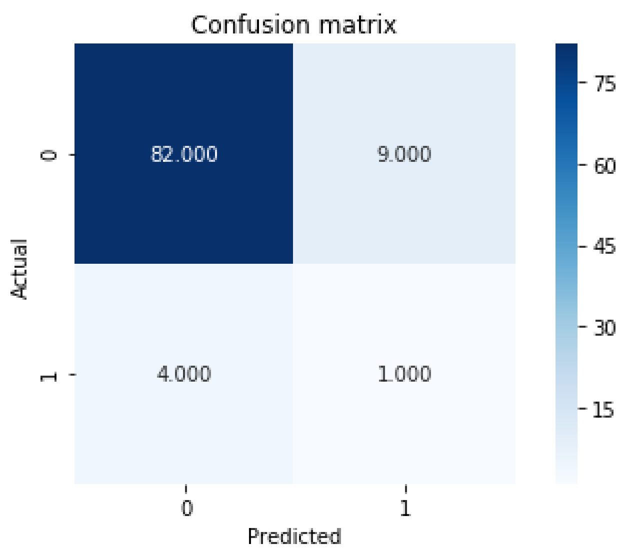
```
0.90625
0.09375
[0.94565217 0.        ]
[0.95604396 0.        ]
[0.95081967 0.        ]
```

In [38]:
```
#Classifying using Naive Bayes
classifier = GaussianNB()
classifier.fit(x_train_scale, y_train)
```

Out[38]: GaussianNB(priors=None)

In [39]:
```
y_pred = classifier.predict(x_test_scale)
#all_data_pred=classifier.predict(all_data)
conf_matrix = metrics.confusion_matrix(y_test, y_pred)
print(conf_matrix)

sns.heatmap(conf_matrix, annot = True, fmt = ".3f", square = True, cmap
= plt.cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Confusion matrix')
plt.tight_layout()
```

```
[[82  9]
 [ 4  1]]
```



In [40]:
```
print(metrics.accuracy_score(y_test, y_pred)) # accuracy
print(1 - metrics.accuracy_score(y_test, y_pred)) # error
print(metrics.precision_score(y_test, y_pred, average = None)) # precisi
on
print(metrics.recall_score(y_test, y_pred, average = None)) # recall
print(metrics.f1_score(y_test, y_pred, average = None)) # F1 score
```

```
0.8645833333333334
0.13541666666666663
[0.95348837 0.1       ]
[0.9010989 0.2       ]
[0.92655367 0.13333333]
```

In [41]:
```
# CLASSIFIER: Linear SVM
# Initialize linear SVM classifier
classifier = SVC(kernel = 'linear')
classifier.fit(x_train, y_train)
```

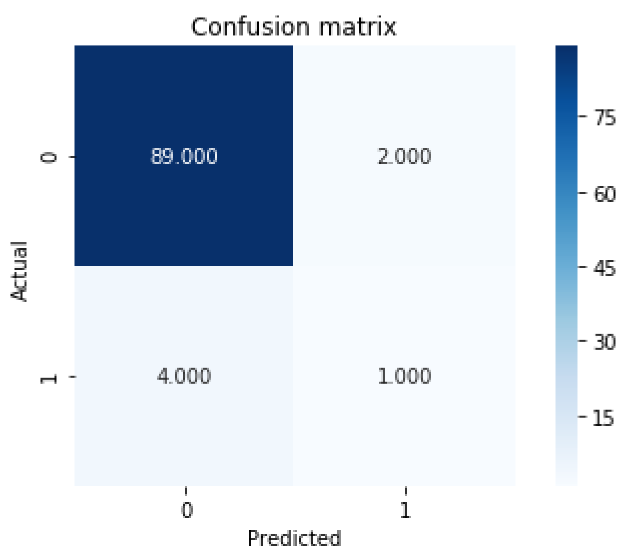
Out[41]:
```
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='linea
r',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

In [42]:
```
# Predict class labels using linear SVM classifier
y_pred = classifier.predict(x_test)
```

In [43]:
```
# Compute confusion matrix
conf_matrix = metrics.confusion_matrix(y_test, y_pred)
print(conf_matrix)
```

```
[[89  2]
 [ 4  1]]
```

In [44]:
```
# Plot confusion matrix
sns.heatmap(conf_matrix, annot = True, fmt = ".3f", square = True, cmap
= plt.cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Confusion matrix')
plt.tight_layout()
```



In [45]:
```
# Compute evaluation metrics
print(metrics.accuracy_score(y_test, y_pred)) # accuracy
print(1 - metrics.accuracy_score(y_test, y_pred)) # error
print(metrics.precision_score(y_test, y_pred, average = None)) # precisi
on
print(metrics.recall_score(y_test, y_pred, average = None)) # recall
print(metrics.f1_score(y_test, y_pred, average = None)) # F1 score
```

```
0.9375
0.0625
[0.95698925 0.33333333]
[0.97802198 0.2       ]
[0.9673913 0.25      ]
```

In [46]:
```
# CLASSIFIER: Kernel SVM
# Initialize kernel SVM classifier
classifier = SVC(kernel = 'poly')
classifier.fit(x_train, y_train)
```

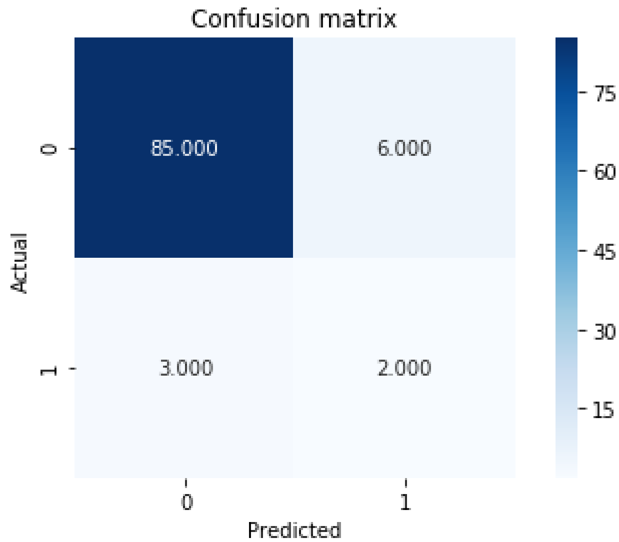
Out[46]:
```
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='poly',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

In [47]:
```
# Predict class labels using kernel SVM classifier
y_pred = classifier.predict(x_test)
```

In [48]:
```
# Compute confusion matrix
conf_matrix = metrics.confusion_matrix(y_test, y_pred)
print(conf_matrix)
```

```
[[85  6]
 [ 3  2]]
```

In [49]:
```
# Plot confusion matrix
sns.heatmap(conf_matrix, annot = True, fmt = ".3f", square = True, cmap
= plt.cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Confusion matrix')
plt.tight_layout()
```



In [50]:
```
# Compute evaluation metrics
print(metrics.accuracy_score(y_test, y_pred)) # accuracy
print(1 - metrics.accuracy_score(y_test, y_pred)) # error
print(metrics.precision_score(y_test, y_pred, average = None)) # precisi
on
print(metrics.recall_score(y_test, y_pred, average = None)) # recall
print(metrics.f1_score(y_test, y_pred, average = None)) # F1 score
```

```
0.90625
0.09375
[0.96590909 0.25      ]
[0.93406593 0.4       ]
[0.94972067 0.30769231]
```