In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
```

In [2]:

```
iris_df = pd.read_csv('iris.data', header=None, names=['sepal length', 'sepal width', 'p
etal length', 'petal width', 'class'])
glass_df = pd.read_csv('glass.data', index_col=0, header=None, names=['Id', 'RI', 'Na',
'Mg', 'Al', 'Si', 'K', 'Ca', 'Ba', 'Fe', 'class'])
wine_df = pd.read_csv('wine.data', header=None, names=['class', 'Alcohol', 'Malic acid',
'Ash', 'Alcalinity of ash', 'Magnesium', 'Total phenols', 'Flavanoids', 'Nonflavanoid phe
nols', 'Proanthocyanins', 'Color intensity', 'Hue', 'OD280/OD315 of diluted wines', 'Pro
line'])
```

In [3]:

```
def split_df(df, test_size=None):
    X = df[[col for col in df if col != 'class']]
    y = df['class']
    return X, y
```

In [4]:

```
from sklearn.neighbors import KNeighborsClassifier
def knn(x, y, k = 5, weights = 'uniform', p = 2, metric = 'minkowski'):
    classifier = KNeighborsClassifier(n_neighbors = k, weights = weights, p = p, metric
= metric, n_jobs = -1)
    classifier.fit(x, y)
    return classifier
```

In [5]:

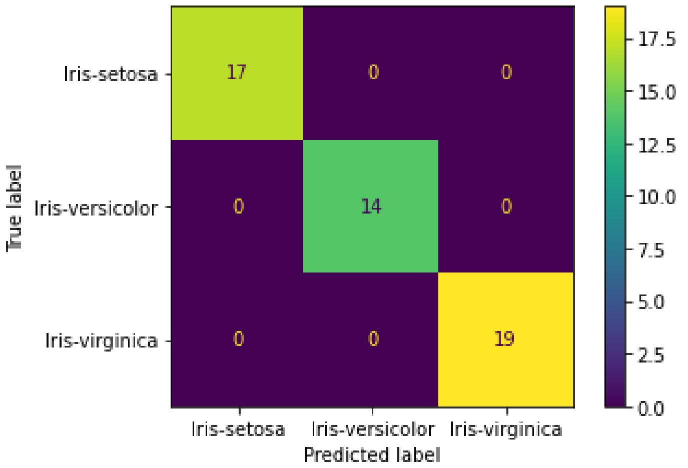
```
X, y = split_df(iris_df)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33)
clf = knn(X_train, y_train)
```

In [6]:

```
import sklearn.metrics as metrics
metrics.plot_confusion_matrix(clf, X_test, y_test)
```

Out[6]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1ff8830c2e0>
```



In [7]:

```
def get_stats(X_train, X_test, y_train, y_test):
    clr = knn(X_train, y_train)
    y_pred = clr.predict(X_test)
    print('classes:', y_test.unique())
    print('precision:', metrics.precision_score(y_test, y_pred, average=None))
    print('recall:', metrics.recall_score(y_test, y_pred, average=None))
    print('f-score:', metrics.f1_score(y_test, y_pred, average=None))
    print('accuracy:', metrics.accuracy_score(y_test, y_pred))
```

In [8]:

```
get_stats(X_train, X_test, y_train, y_test)
```

```
classes: ['Iris-virginica' 'Iris-versicolor' 'Iris-setosa']
precision: [1. 1. 1.]
recall: [1. 1. 1.]
f-score: [1. 1. 1.]
accuracy: 1.0
```

In [9]:

```
from sklearn.model_selection import cross_val_score, KFold, LeaveOneOut
def test_cv(X, y):
    for folds in [2,5,10]:
        clr = KNeighborsClassifier(n_jobs=-1)
        print(folds, 'folds:')
        print('\tno shuffle:', cross_val_score(clr, X, y, cv=KFold(folds), scoring='f1_w
eighted', n_jobs=-1).mean())
        print('\tshuffle:', cross_val_score(clr, X, y, cv=KFold(folds, shuffle=True), sc
oring='f1_weighted', n_jobs=-1).mean())
    print('leave one out:', cross_val_score(clr, X, y, cv=LeaveOneOut(), scoring='f1_wei
ghted', n_jobs=-1).mean())
```

In [10]:

```
test_cv(X, y)
```

```
2 folds:
 no shuffle: 0.15893470790378006
 shuffle: 0.9534017971758664
5 folds:
 no shuffle: 0.9465178096757045
 shuffle: 0.9665951005528244
10 folds:
 no shuffle: 0.9634920634920634
 shuffle: 0.959030303030303
leave one out: 0.9666666666666667
```

Dla zbiorów Iris, Glass i Wine mieszanie danych jest konieczne, ponieważ są one posortowane według klas, co powoduje, że w jednym foldzie mogą znaleźć się obiekty tylko 1 klasy.

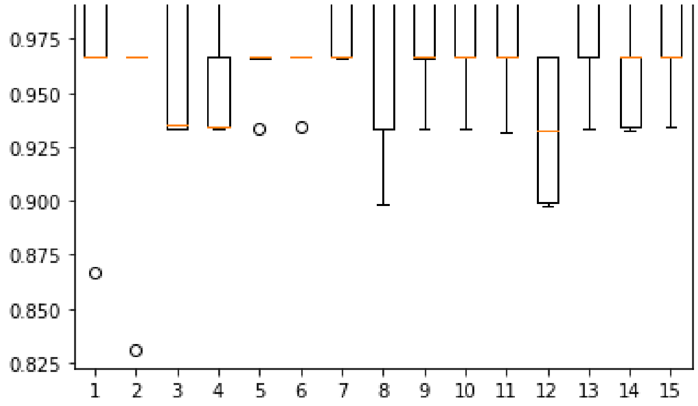
Wadami leave one out są jego koszt czasowy, duża wariancja wyników i to że każdy zbiór uczący jest prawie taki sam jak cały zbiór początkowy, co nie chroni przed przeuczeniem. Lepiej jest używać zwykłego folda.

In [11]:

```
def test_k_neighbors(X, y):
    _x = list(range(1,16))
    _y = []
    for k in _x:
        clr = KNeighborsClassifier(n_neighbors = k)
        _y.append(cross_val_score(clr, X, y, cv=KFold(shuffle=True), scoring='f1_weighte
d', n_jobs=-1))
    plt.boxplot(_y, labels = _x)
```

In [12]:

```
test_k_neighbors(X, y)
```



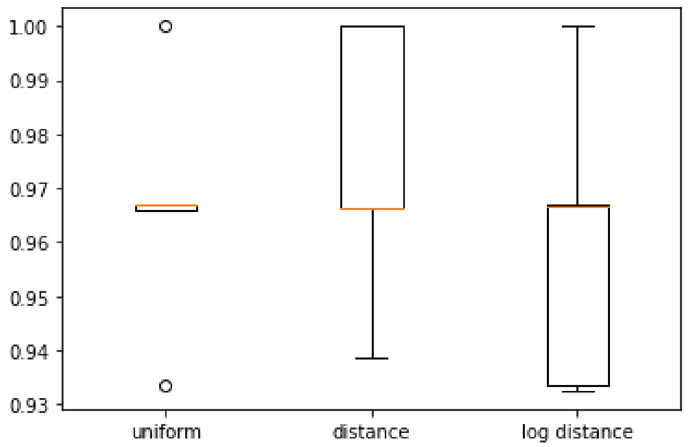
Często dla `k` parzystego dokładność jest gorsza niż dla nieparzystego, ponieważ dochodzi do sytuacji, gdzie wśród sąsiadów punktu jest tyle samo punktów jednej klasy, jak i drugiej.

In [13]:

```
def test_weights(X, y):
    _x = ['uniform', 'distance', 'log distance']
    _y = []
    def log_dist(x):
        return np.log(1 / 1 + x)
    for w in ['uniform', 'distance', log_dist]:
        clr = KNeighborsClassifier(weights = w)
        _y.append(cross_val_score(clr, X, y, cv=KFold(shuffle=True), scoring='f1_weighted', n_jobs=-1))
    plt.boxplot(_y, labels = _x)
```

In [14]:

```
test_weights(X, y)
```

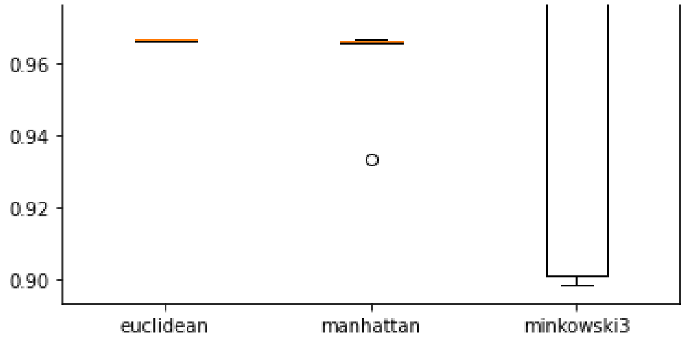


In [15]:

```
def test_metrics(X, y):
    _x = ['euclidean', 'manhattan', 'minkowski3']
    _y = []
    def log_dist(x):
        return np.log(1 / 1 + x)
    for p in [2,1,3]:
        clr = KNeighborsClassifier(p = p)
        _y.append(cross_val_score(clr, X, y, cv=KFold(shuffle=True), scoring='f1_weighted', n_jobs=-1))
    plt.boxplot(_y, labels = _x)
```

In [16]:

```
test_metrics(X, y)
```



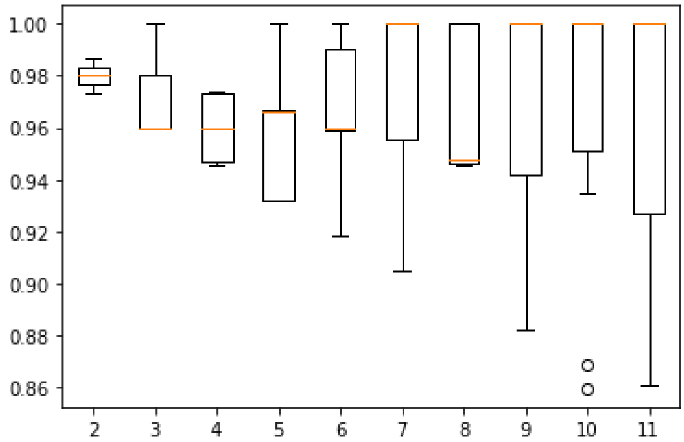
In [17]:

```
from sklearn.model_selection import StratifiedKFold
def test_k_neighbors_stratify(X, y, stratify=True):
    _x = list(range(2, 12))
    _y = []
    for k in _x:
        clr = KNeighborsClassifier()
        if stratify:
            _y.append(cross_val_score(clr, X, y, cv=StratifiedKFold(n_splits=k, shuffle=
True), scoring='f1_weighted', n_jobs=-1))
        else:
            _y.append(cross_val_score(clr, X, y, cv=KFold(n_splits=k, shuffle=True), sco
ring='f1_weighted', n_jobs=-1))
    plt.boxplot(_y, labels = _x)
```

Stratyfikacja

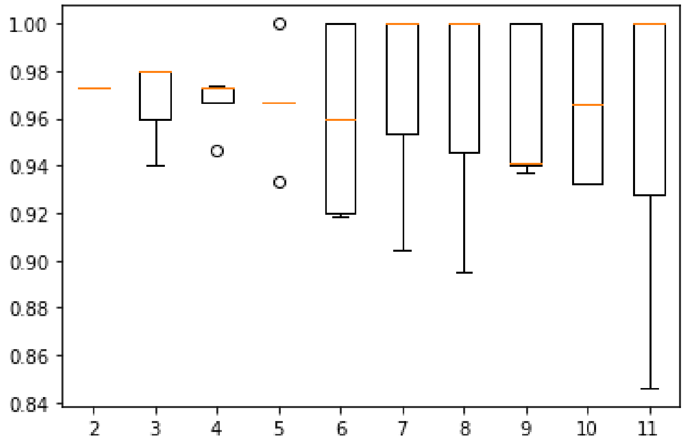
In [18]:

```
test_k_neighbors_stratify(X, y, False)
```



In [19]:

```
test_k_neighbors_stratify(X, y, True)
```



Glass

In [20]:

```
X, y = split_df(glass_df)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33)
```

In [21]:

```
get_stats(X_train, X_test, y_train, y_test)
```

```
classes: [1 3 2 7 6 5]
precision: [0.5        0.76923077 1.         0.         0.         0.66666667]
recall: [0.81818182 0.66666667 0.125      0.         0.         0.8       ]
f-score: [0.62068966 0.71428571 0.22222222 0.         0.         0.72727273]
accuracy: 0.6056338028169014
```

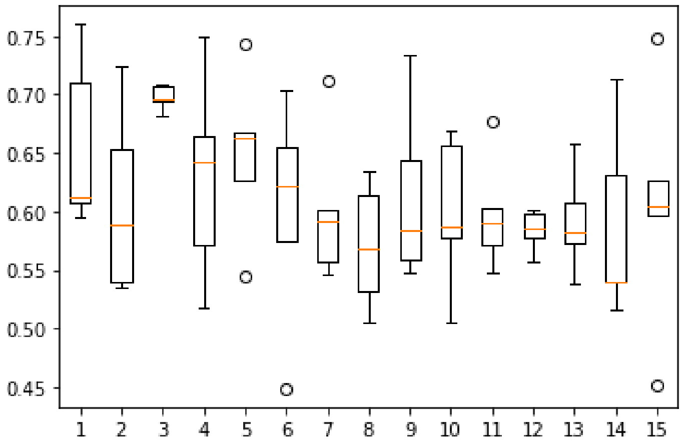
In [22]:

```
test_cv(X, y)
```

```
2 folds:
 no shuffle: 0.19378370100882605
 shuffle: 0.619312193700766
5 folds:
 no shuffle: 0.42109301134807503
 shuffle: 0.5926650235700344
10 folds:
 no shuffle: 0.6207481443755953
 shuffle: 0.6327032945431884
leave one out: 0.6728971962616822
```

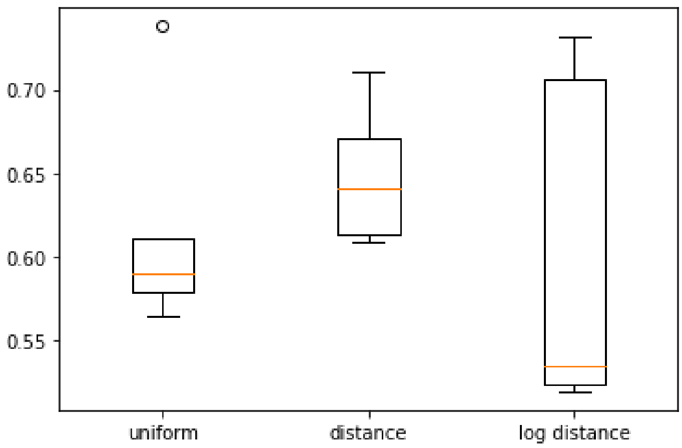
In [23]:

```
test_k_neighbors(X, y)
```



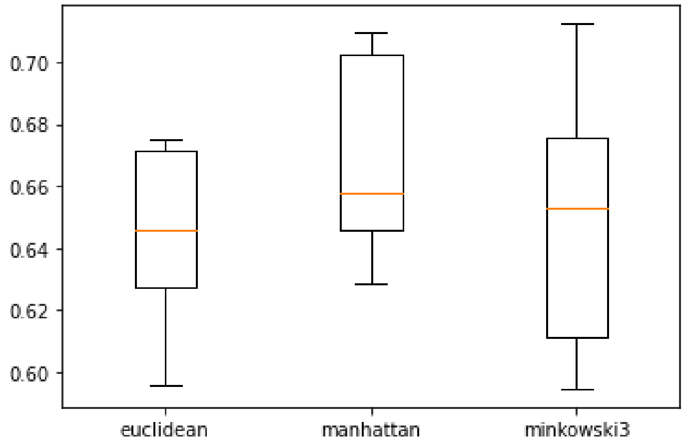
In [24]:

```
test_weights(X, y)
```



In [25]:

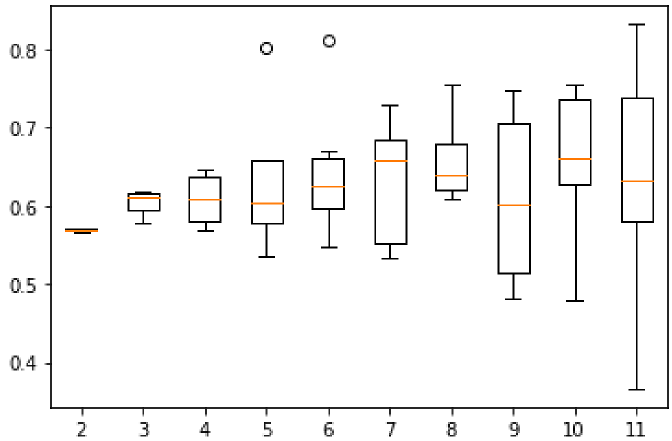
```
test_metrics(X, y)
```



Stratyfikacja

In [26]:

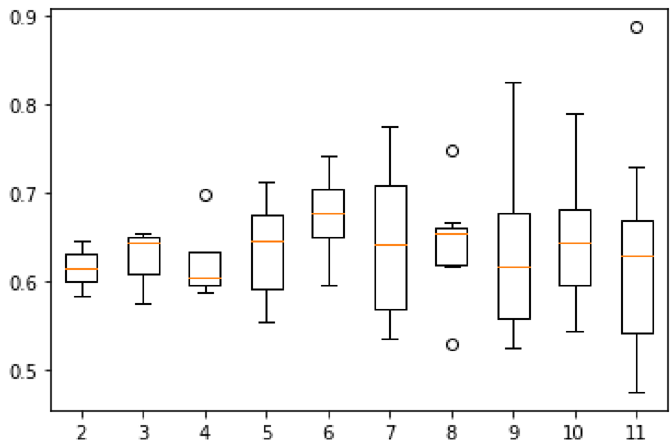
```
test_k_neighbors_stratify(X, y, False)
```



In [27]:

```
test_k_neighbors_stratify(X, y, True)
```

```
c:\users\kajetan\studia-mag\ai-venv\lib\site-packages\sklearn\model_selection\_split.py:6
66: UserWarning: The least populated class in y has only 9 members, which is less than n_
splits=10.
  warnings.warn(("The least populated class in y has only %d"
c:\users\kajetan\studia-mag\ai-venv\lib\site-packages\sklearn\model_selection\_split.py:6
66: UserWarning: The least populated class in y has only 9 members, which is less than n_
splits=11.
  warnings.warn(("The least populated class in y has only %d"
```



Wine

In [28]:

```
X, y = split_df(wine_df)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33)
```

In [29]:

```
get_stats(X_train, X_test, y_train, y_test)
```

```
classes: [2 1 3]
precision: [0.86363636 0.8        0.35294118]
recall: [0.95       0.61538462 0.46153846]
f-score: [0.9047619  0.69565217 0.4       ]
accuracy: 0.6949152542372882
```

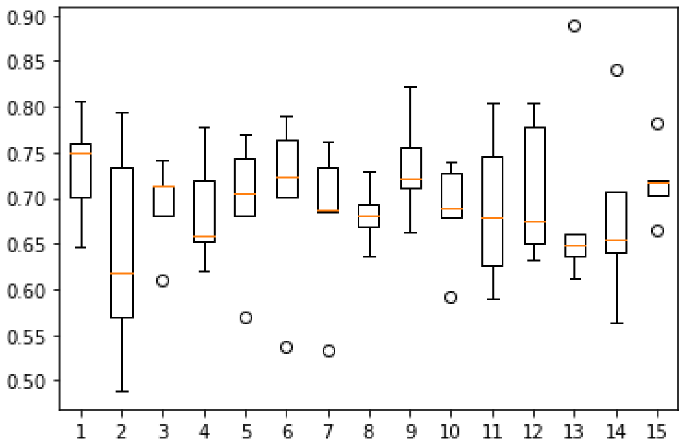
In [30]:

```
test_cv(X, y)
```

```
2 folds:
 no shuffle: 0.2554655517812037
 shuffle: 0.7059680830869044
5 folds:
 no shuffle: 0.673603653652538
 shuffle: 0.676222101263509
10 folds:
 no shuffle: 0.7309527506932836
 shuffle: 0.6811323643676584
leave one out: 0.6966292134831461
```

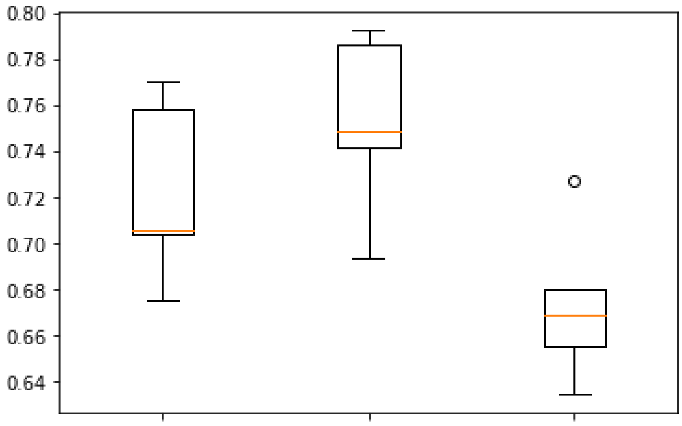
In [31]:

```
test_k_neighbors(X, y)
```



In [32]:

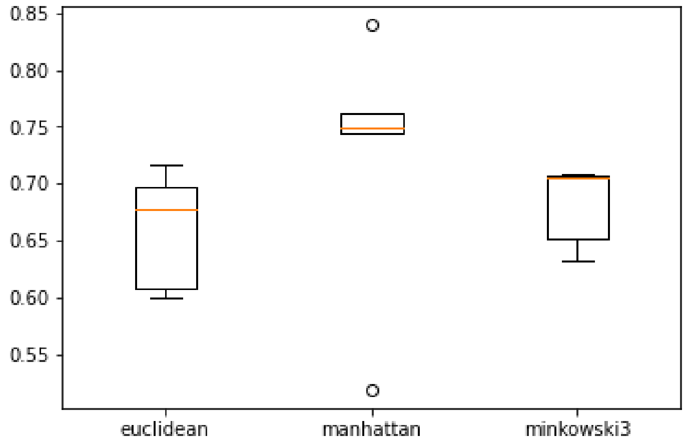
```
test_weights(X, y)
```



uniform distance log distance

In [33]:

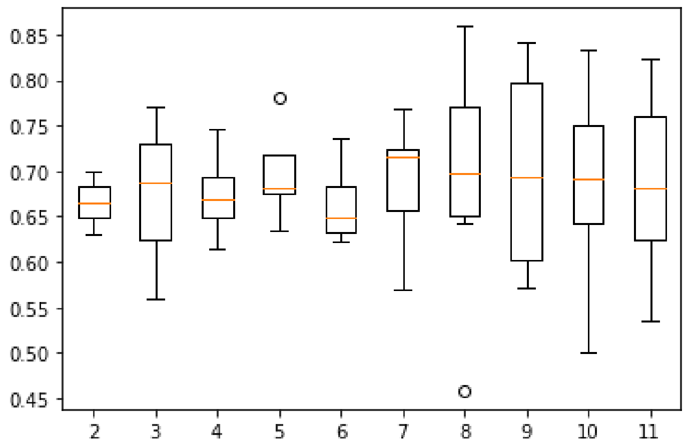
```
test_metrics(X, y)
```



Stratyfikacja

In [34]:

```
test_k_neighbors_stratify(X, y, False)
```



In [35]:

```
test_k_neighbors_stratify(X, y, True)
```