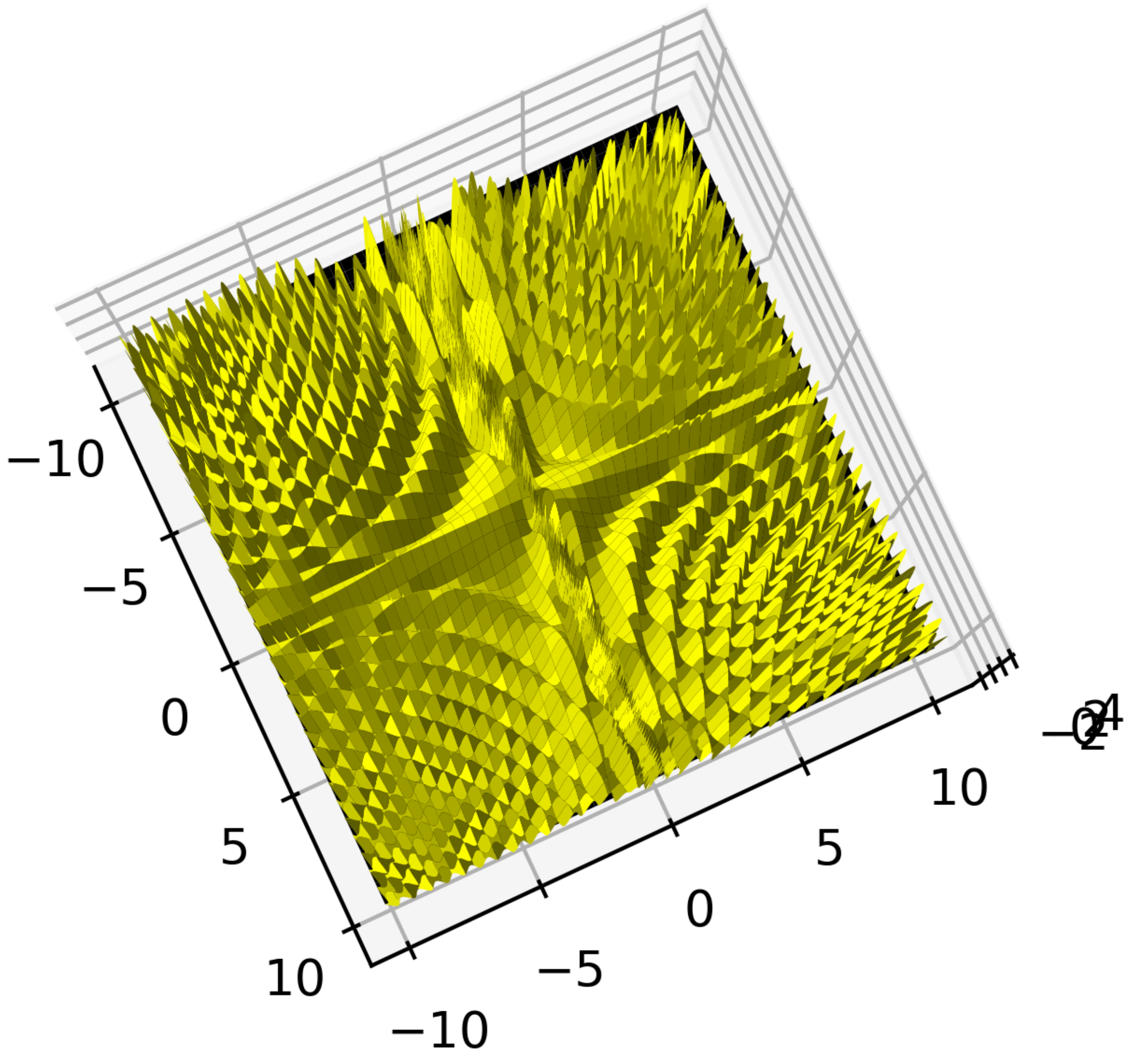
Here we are going to get acquainted with an algorithm called KNN (k-nearest neighbors). Join us. Usually, there is an explanation related to that part at the bottom of each code.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

def true_label (x,y):
    import numpy as np
    c=2*np.sin(x/y)+2*np.cos(x*y)+0.15
    if c>0.5:
        return True
    else:
        return False

def true_Vfunction (x,y):
    import numpy as np
    c=2*np.sin(x/y)+2*np.cos(x*y)+0.15
    return c
```

importing and dfinitons

We defined the function by which partitions the coordinate plane into two parts.

In [2]:
```
from mpl_toolkits import mplot3d
import numpy
from matplotlib import pyplot

Xfroshow=np.linspace(-10,10,500)
Yfroshow=np.linspace(-10,10,500)
Xfroshow2,Yfroshow2=np.meshgrid(Xfroshow,Yfroshow)
Zforshow=2*np.sin(Xfroshow2/Yfroshow2)+2*np.cos(Xfroshow2*Yfroshow2)+0.15


fig = plt.figure(dpi=380)
wf = plt.axes(projection ='3d')
#wf.plot_wireframe(Xfroshow2, Yfroshow2, Zforshow, color ='green')
wf.plot_surface(Xfroshow, Yfroshow2, 0*Zforshow+0.5,alpha=1,color='black')
wf.plot_surface(Xfroshow2, Yfroshow2, Zforshow,alpha=1,color ='yellow')

wf.view_init(85,-25)
#wf.view_init(90,90)
pyplot.show()

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



The partition of the page is done with the help of the above surface.

In [3]:
```
rndx=20*np.random.rand(1980)-10
rndy=20*np.random.rand(1980)-10
zrnd=[]
for i in range (0,len(rndx)):
    if true_label(rndx[i],rndy[i])==True:
        zrnd.append(True)
    else:
        zrnd.append(False)
Rrndx=[]
Rrndy=[]
Brndx=[]
Brndy=[]
for i in range (0,len(rndx)):
    if zrnd[i]==True:
      Rrndx.append(rndx[i])
      Rrndy.append(rndy[i])
    else:
      Brndx.append(rndx[i])
      Brndy.append(rndy[i])
```

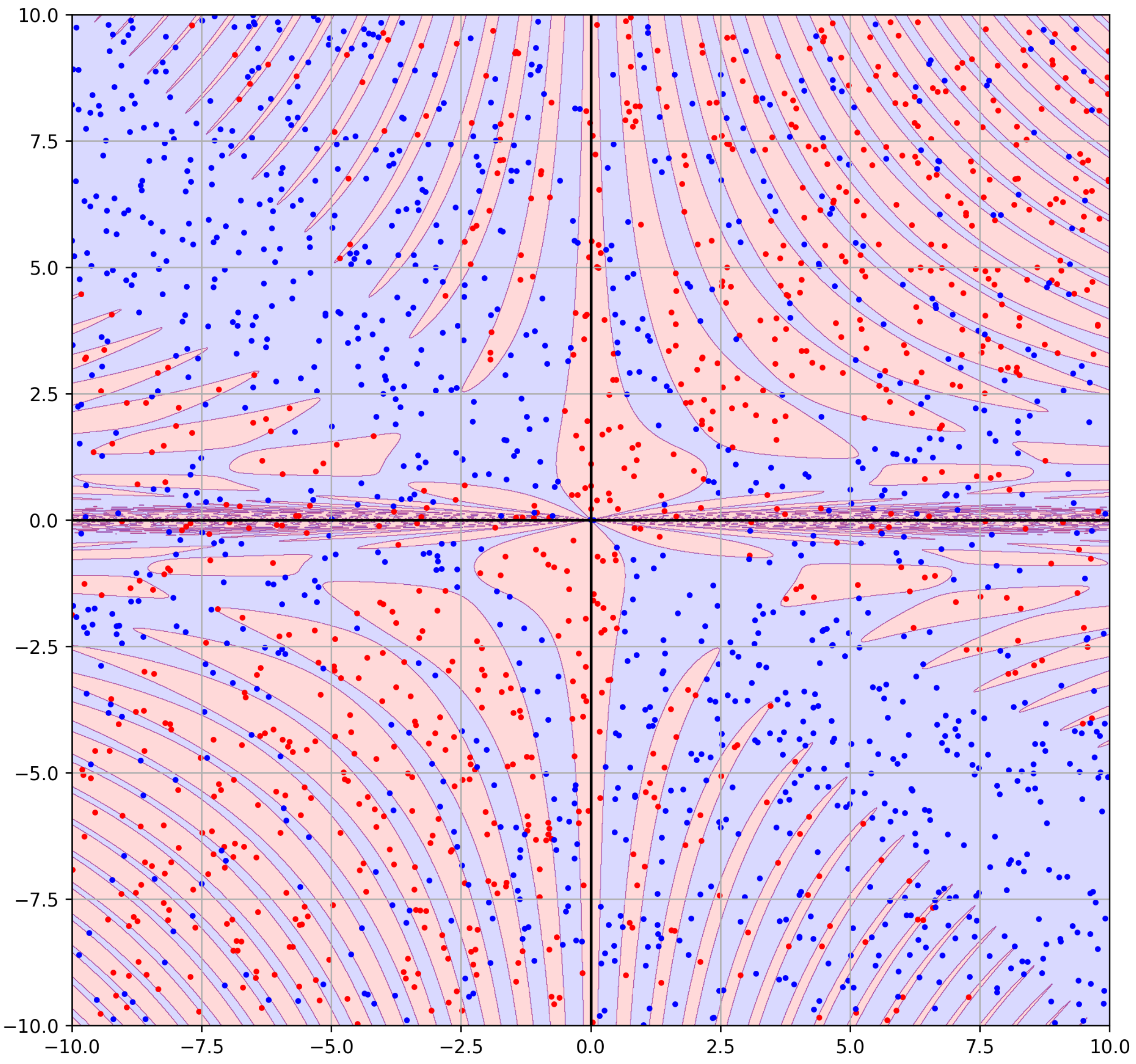
Get n random and classify them by true label.

In [4]:
```
N=1550

x=np.linspace(-10,10,N)
y=np.linspace(-10,10,N)
X,Y=np.meshgrid(x,y)
Z1=2*np.sin(X/Y)+2*np.cos(X*Y)+0.15
z=Z1

for i in range (0,np.shape(z)[0]):
  for j in range (0,np.shape(z)[1]):
    if (z[i][j]>0.5):
        z[i][j]=20
    else:
        z[i][j]=False
```

It is just for visualizing the partition of the plane to red and blue, and the next one is to visualize data and our true function.

In [5]:

```
plt.figure(figsize=(10,10),dpi=250)
plt.contourf(x,y,z,colors=['blue','red'],alpha=0.15)
plt.scatter(Rrndx, Rrndy,color='red',s=4.5)
plt.scatter(Brndx, Brndy,color='blue',s=4.5)

#delta=0.01
#x_for_plot,y_for_plot=np.meshgrid(np.arange(-10,10,delta),np.arange(-10,10,delta))
#plt.contour(x_for_plot,y_for_plot,2*np.sin(x_for_plot/y_for_plot)+2*np.cos(x_for_plot*y_for_plot)+0.15,[0.5],alpha=1,linewidth
plt.axhline(0,color='black') # x = 0
plt.axvline(0,color='black') # y = 0
plt.xlim(-10,10)
plt.ylim(-10,10)
plt.grid()
plt.title('')
plt.show()
```



Here, we have a visualization of the true label and also the labels of data.

In [6]:

```
X=[]
for i in range (0,len(rndx)):
    X.append([rndx[i],rndy[i]])

#for i in range (0,len(zrnd))
#    if zrnd[i]==True
#        Y.aappend()
```

Modify the structure in order to use the algorithm

In [7]:

```
X_trian,X_test,y_trian,y_test=train_test_split(X,zrnd)
```

In this part, we divided the collection into two parts. The first part is for training and the second part is as a validation set. We will explain about the test set later.

In [8]:
```
KS=[]
from sklearn.neighbors import KNeighborsClassifier
for i in range (1,300):
    knn=KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_trian,y_trian)
    KS.append(knn.score(X_test,y_test))
```

From hyperparameter 1 to 300, we apply the k-nearest neighbor algorithm to our data.

In [9]:
```
np.max(KS)
```

Out[9]:
```
0.7171717171717171
```

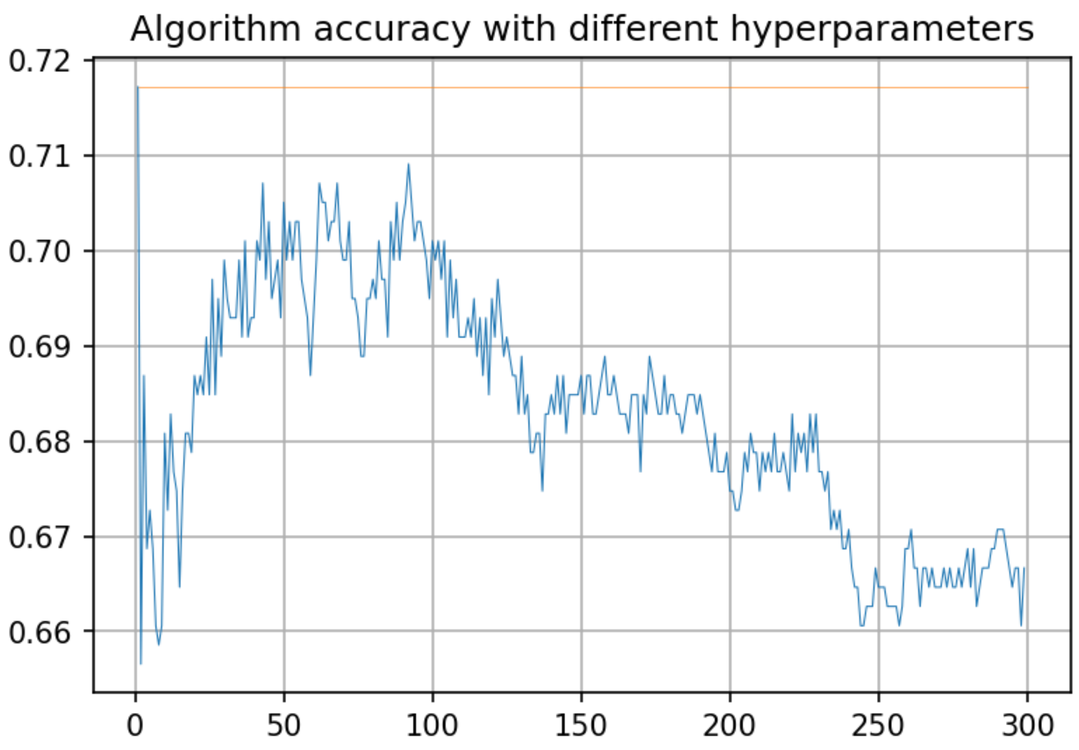
To see the most accuracy we took.

In [10]:
```
KS.index(np.max(KS))
```

Out[10]:
```
0
```

To see which hyperparameter got the most accuracy.

In [11]:
```
plt.figure(dpi=150)
plt.plot(np.arange(1,300,1),KS,lw=0.5)
plt.plot([1,300],[np.max(KS),np.max(KS)],lw=0.3)
plt.grid()
plt.title('Algorithm accuracy with different hyperparameters')
plt.show()
```



In [12]:
```
rndxtest=20*np.random.rand(1500)-10
rndytest=20*np.random.rand(1500)-10
zrndtest=[]
for i in range (0,len(rndxtest)):
    if true_label(rndxtest[i],rndytest[i])==True:
        zrndtest.append(True)
    else:
        zrndtest.append(False)
Rrndxtest=[]
Rrndytest=[]
Brndxtest=[]
Brndytest=[]
for i in range (0,len(rndxtest)):
    if zrndtest[i]==True:
      Rrndxtest.append(rndxtest[i])
      Rrndytest.append(rndytest[i])
    else:
      Brndxtest.append(rndxtest[i])
      Brndytest.append(rndytest[i])
```

```
Xtest=[]
for i in range (0,len(rndxtest)):
    Xtest.append([rndxtest[i],rndytest[i]])
```

Since we have the true labeling function, we can generate the test set randomly. So we do this for random data.

In [13]:
```
knn=KNeighborsClassifier(n_neighbors=KS.index(np.max(KS))+1)
knn.fit(X_trian,y_trian)
Euclidean_ac=knn.score(Xtest,zrndtest)
print(Euclidean_ac)
```

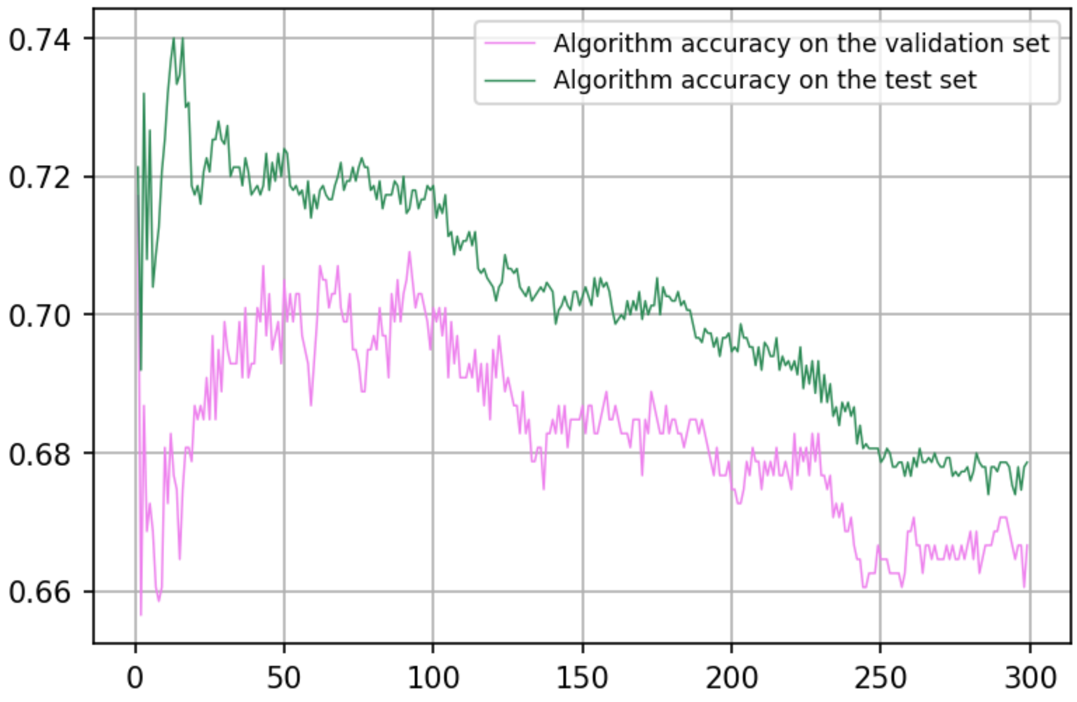
```
0.7213333333333334
```

We have already found the optimal hyperparameter for the validation set. Now we would like to check the accuracy of this hyperparameter on the test set.

In [14]:
```
KSTEST=[]
for i in range (1,300):
    knn=KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_trian,y_trian)
    KSTEST.append(knn.score(Xtest,zrndtest))
```

We only do visualization on the test set as we did before on the validation set.

In [15]:
```
plt.figure(dpi=150)
plt.plot(np.arange(1,300,1),KS,lw=0.7,label='Algorithm accuracy on the validation set',color='violet')
plt.plot(np.arange(1,300,1),KSTEST,lw=0.7,label='Algorithm accuracy on the test set',color='seagreen')
#plt.plot([1,300],[np.max(KS),np.max(KS)],lw=0.3)
plt.grid()
plt.legend(fontsize='small')
plt.show()
```



Now we can see the accuracy of different hyperparameters on the validation set and the test set on a graph.

In [16]:
```
KS_manhattan=[]
for i in range (1,300):
    knn = KNeighborsClassifier(n_neighbors=i, metric='manhattan')
    knn.fit(X_trian,y_trian)
    KS_manhattan.append(knn.score(X_test,y_test))
```

We do the same operation with the Manhattan metric.

In [17]:
```
np.max(KS_manhattan)
```

Out[17]:
```
0.7151515151515152
```

To see the most accuracy we took.

In [18]:
```
KS_manhattan.index(np.max(KS_manhattan))
```

```
Out[18]: 0
```

To see which hyperparameter got the most accuracy.

```
In [19]: knn=KNeighborsClassifier(n_neighbors=KS_manhattan.index(np.max(KS_manhattan))+1,metric='manhattan')
         knn.fit(X_trian,y_trian)
         Manhattan_ac=knn.score(Xtest,zrndtest)
         print(Manhattan_ac)
```

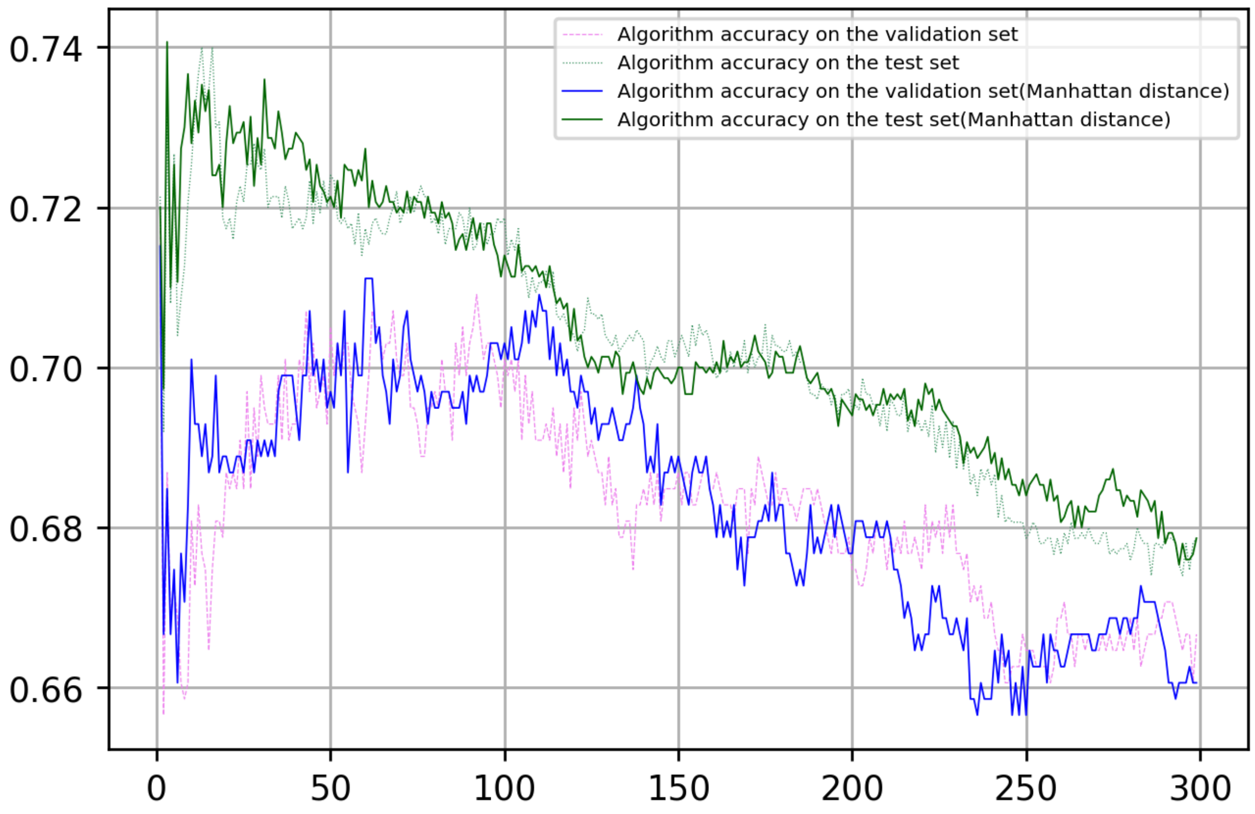
```
0.72
```

We have already found the optimal hyperparameter for the validation set(Manhattan Distance). Now we would like to check the accuracy of this hyperparameter on the test set.

```
In [20]: KSTEST_M=[]
         for i in range (1,300):
             knn=KNeighborsClassifier(n_neighbors=i,metric='manhattan')
             knn.fit(X_trian,y_trian)
             KSTEST_M.append(knn.score(Xtest,zrndtest))
```

We only do visualization on the test set as we did before on the validation set.

```
In [21]: plt.figure(dpi=250)
         plt.plot(np.arange(1,300,1),KS,lw=0.35,label='Algorithm accuracy on the validation set',color='violet',ls='--')
         plt.plot(np.arange(1,300,1),KSTEST,lw=0.35,label='Algorithm accuracy on the test set',color='seagreen',ls=':')
         plt.plot(np.arange(1,300,1),KS_manhattan,lw=0.5,color='blue',label='Algorithm accuracy on the validation set(Manhattan distance
         plt.plot(np.arange(1,300,1),KSTEST_M,lw=0.5,label='Algorithm accuracy on the test set(Manhattan distance)',color='darkgreen')
         #plt.plot([1,300],[np.max(KS),np.max(KS)],lw=0.3)
         plt.grid()
         plt.legend(fontsize='xx-small')
         plt.show()
```



Now we can see the accuracy of different hyperparameters on the validation set and the test set on a graph. (according to manhatan distance and also euclidean Distance at the same time)

```
In [22]: KS_cosine=[]
         for i in range (1,300):
             knn = KNeighborsClassifier(n_neighbors=i, metric='cosine')
             knn.fit(X_trian,y_trian)
             KS_cosine.append(knn.score(X_test,y_test))
```

We do the same operation with the Cosine metric.

```
In [23]: np.max(KS_cosine)
```

```
Out[23]: 0.7191919191919192
```

To see the most accuracy we took.

In [24]:
```
KS_cosine.index(np.max(KS_cosine))
```
Out[24]:
```
8
```

To see which hyperparameter got the most accuracy.

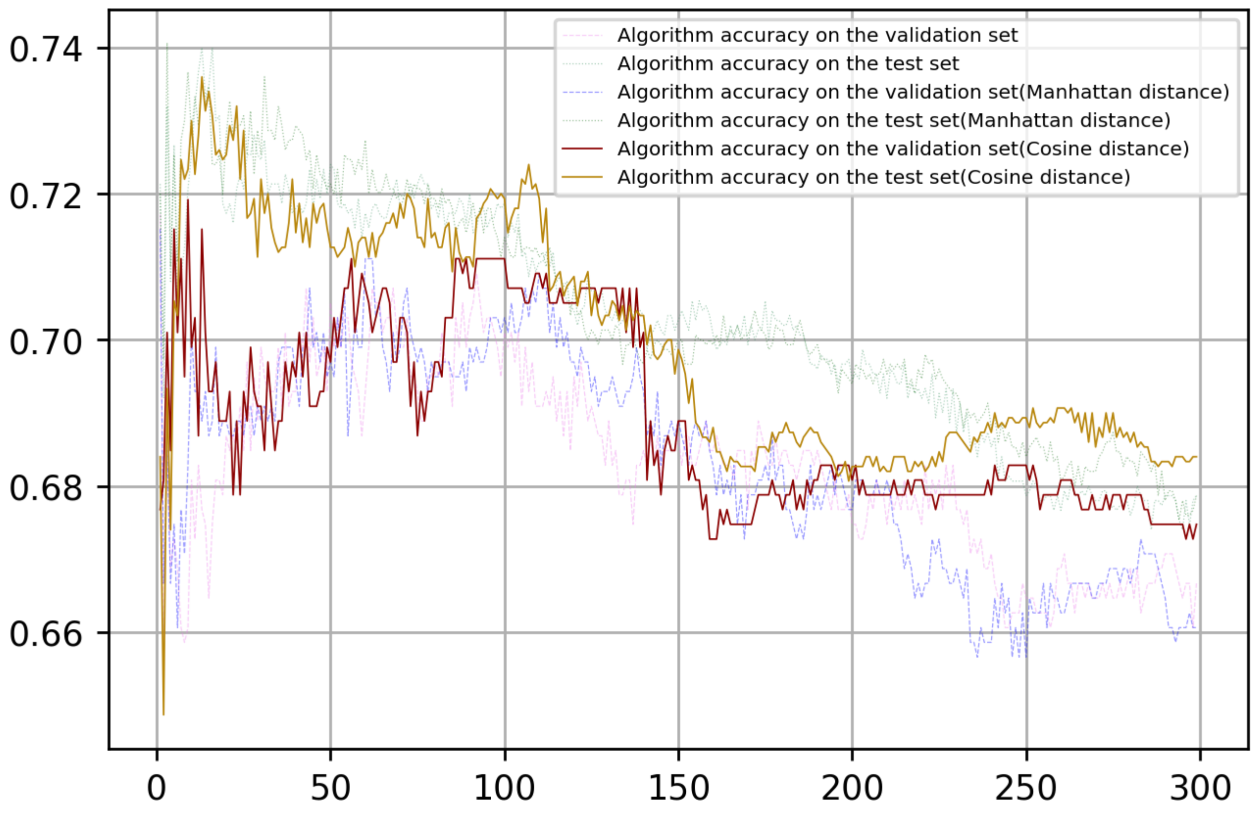
In [25]:
```
knn=KNeighborsClassifier(n_neighbors=KS_cosine.index(np.max(KS_cosine))+1,metric='cosine')
knn.fit(X_trian,y_trian)
Cosine_ac=knn.score(Xtest,zrndtest)
print(Cosine_ac)
```
```
0.7233333333333334
```

We have already found the optimal hyperparameter for the validation set(Cosine Distance). Now we would like to check the accuracy of this hyperparameter on the test set.

In [26]:
```
KSTEST_C=[]
for i in range (1,300):
    knn=KNeighborsClassifier(n_neighbors=i,metric='cosine')
    knn.fit(X_trian,y_trian)
    KSTEST_C.append(knn.score(Xtest,zrndtest))
```

We only do visualization on the test set as we did before on the validation set.

In [27]:
```
plt.figure(dpi=250)
a=0.4
plt.plot(np.arange(1,300,1),KS,lw=0.35,label='Algorithm accuracy on the validation set',color='violet',ls='--',alpha=a)
plt.plot(np.arange(1,300,1),KSTEST,lw=0.35,label='Algorithm accuracy on the test set',color='seagreen',ls=':',alpha=a)
plt.plot(np.arange(1,300,1),KS_manhattan,lw=0.35,color='blue',label='Algorithm accuracy on the validation set(Manhattan distanc
plt.plot(np.arange(1,300,1),KSTEST_M,lw=0.35,label='Algorithm accuracy on the test set(Manhattan distance)',color='darkgreen',l
plt.plot(np.arange(1,300,1),KS_cosine,lw=0.5,color='darkred',label='Algorithm accuracy on the validation set(Cosine distance)')
plt.plot(np.arange(1,300,1),KSTEST_C,lw=0.5,label='Algorithm accuracy on the test set(Cosine distance)',color='darkgoldenrod')
#plt.plot([1,300],[np.max(KS),np.max(KS)],lw=0.3)
plt.grid()
plt.legend(fontsize='xx-small')
plt.show()
```



we can see the accuracy of different hyperparameters on the validation set and the test set on a graph. (according to manhatan distance , euclidean Distance and also cosine distance at the same time)

In [28]:
```
KS_jaccard=[]
for i in range (1,300):
    knn = KNeighborsClassifier(n_neighbors=i, metric='jaccard')
    knn.fit(X_trian,y_trian)
    KS_jaccard.append(knn.score(X_test,y_test))
```

We do the same operation with the Jaccard Distance.

In [29]:
```
np.max(KS_jaccard)
```

Out[29]:
```
0.5636363636363636
```

To see the most accuracy we took.

In [30]:
```
KS_jaccard.index(np.max(KS_jaccard))
```

Out[30]:
```
0
```

To see which hyperparameter got the most accuracy.

In [31]:
```
knn=KNeighborsClassifier(n_neighbors=KS_jaccard.index(np.max(KS_jaccard))+1,metric='jaccard')
knn.fit(X_trian,y_trian)
Jaccard_ac=knn.score(Xtest,zrndtest)
print(Jaccard_ac)
```

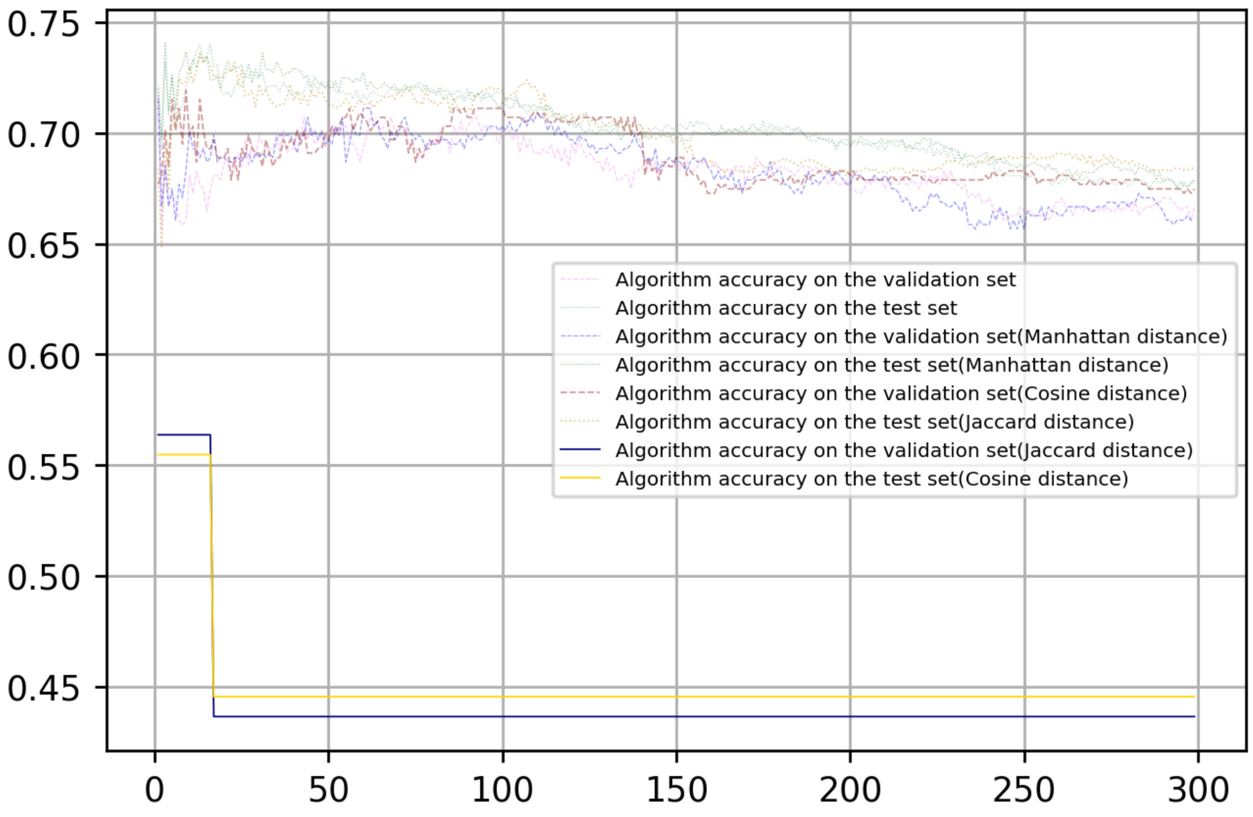
```
0.5546666666666666
```

We have already found the optimal hyperparameter for the validation set(Cosine Distance). Now we would like to check the accuracy of this hyperparameter on the test set.

In [32]:
```
KSTEST_J=[]
for i in range (1,300):
    knn=KNeighborsClassifier(n_neighbors=i,metric='jaccard')
    knn.fit(X_trian,y_trian)
    KSTEST_J.append(knn.score(Xtest,zrndtest))
```

We only do visualization on the test set as we did before on the validation set.

In [33]:
```
plt.figure(dpi=250)
a=0.4
plt.plot(np.arange(1,300,1),KS,lw=0.35,label='Algorithm accuracy on the validation set',color='violet',ls='--',alpha=a)
plt.plot(np.arange(1,300,1),KSTEST,lw=0.35,label='Algorithm accuracy on the test set',color='seagreen',ls=':',alpha=a)
plt.plot(np.arange(1,300,1),KS_manhattan,lw=0.35,color='blue',label='Algorithm accuracy on the validation set(Manhattan distanc
plt.plot(np.arange(1,300,1),KSTEST_M,lw=0.35,label='Algorithm accuracy on the test set(Manhattan distance)',color='darkgreen',l
plt.plot(np.arange(1,300,1),KS_cosine,lw=0.5,color='darkred',label='Algorithm accuracy on the validation set(Cosine distance)',
plt.plot(np.arange(1,300,1),KSTEST_C,lw=0.5,label='Algorithm accuracy on the test set(Jaccard distance)',color='darkgoldenrod',
plt.plot(np.arange(1,300,1),KS_jaccard,lw=0.5,color='navy',label='Algorithm accuracy on the validation set(Jaccard distance)')
plt.plot(np.arange(1,300,1),KSTEST_J,lw=0.5,label='Algorithm accuracy on the test set(Cosine distance)',color='gold')
#plt.plot([1,300],[np.max(KS),np.max(KS)],lw=0.3)
plt.grid()
plt.legend(fontsize='xx-small')
plt.show()
```



we can see the accuracy of different hyperparameters on the validation set and the test set on a graph. (according to manhatan distance , euclidean Distance, cosine distance and also Jaccard distance at the same time)

In [34]:
```
KS_hamming=[]
for i in range (1,300):
    knn = KNeighborsClassifier(n_neighbors=i, metric='hamming')
    knn.fit(X_trian,y_trian)
    KS_hamming.append(knn.score(X_test,y_test))
```

We do the same operation with the Hamming Distance.

In [35]:
```
np.max(KS_hamming)
```

Out[35]:
```
0.5636363636363636
```

To see the most accuracy we took.

In [36]:
```
KS_hamming.index(np.max(KS_hamming))
```

Out[36]:
```
0
```

To see which hyperparameter got the most accuracy.

In [37]:
```
knn=KNeighborsClassifier(n_neighbors=KS_hamming.index(np.max(KS_hamming))+1,metric='hamming')
knn.fit(X_trian,y_trian)
Hamming_ac=knn.score(Xtest,zrndtest)
print(Hamming_ac)
```

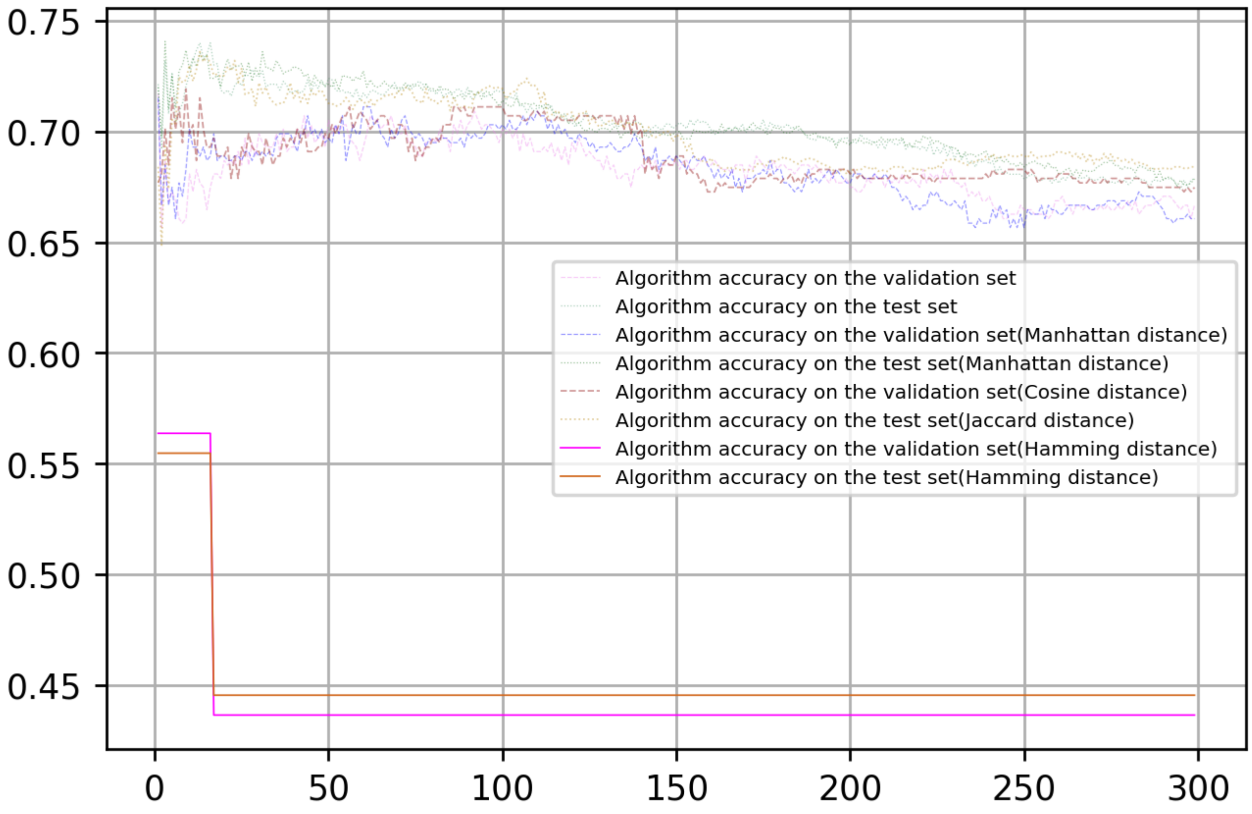
```
0.5546666666666666
```

We have already found the optimal hyperparameter for the validation set(Cosine Distance). Now we would like to check the accuracy of this hyperparameter on the test set.

In [38]:
```
KSTEST_H=[]
for i in range (1,300):
    knn=KNeighborsClassifier(n_neighbors=i,metric='hamming')
    knn.fit(X_trian,y_trian)
    KSTEST_H.append(knn.score(Xtest,zrndtest))
```

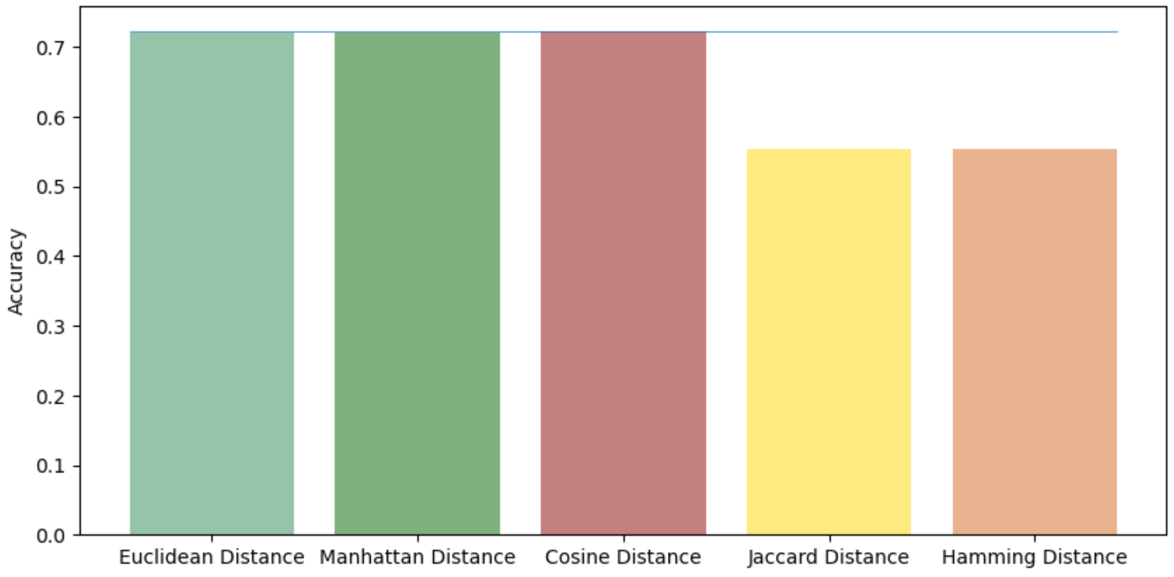
We only do visualization on the test set as we did before on the validation set.

In [39]:
```
plt.figure(dpi=250)
a=0.4
plt.plot(np.arange(1,300,1),KS,lw=0.35,label='Algorithm accuracy on the validation set',color='violet',ls='--',alpha=a)
plt.plot(np.arange(1,300,1),KSTEST,lw=0.35,label='Algorithm accuracy on the test set',color='seagreen',ls=':',alpha=a)
plt.plot(np.arange(1,300,1),KS_manhattan,lw=0.35,color='blue',label='Algorithm accuracy on the validation set(Manhattan distanc
plt.plot(np.arange(1,300,1),KSTEST_M,lw=0.35,label='Algorithm accuracy on the test set(Manhattan distance)',color='darkgreen',l
plt.plot(np.arange(1,300,1),KS_cosine,lw=0.5,color='darkred',label='Algorithm accuracy on the validation set(Cosine distance)',
plt.plot(np.arange(1,300,1),KSTEST_C,lw=0.5,label='Algorithm accuracy on the test set(Jaccard distance)',color='darkgoldenrod',
plt.plot(np.arange(1,300,1),KS_hamming,lw=0.5,color='fuchsia',label='Algorithm accuracy on the validation set(Hamming distance)
plt.plot(np.arange(1,300,1),KSTEST_H,lw=0.5,label='Algorithm accuracy on the test set(Hamming distance)',color='chocolate')
#plt.plot([1,300],[np.max(KS),np.max(KS)],lw=0.3)
plt.grid()
plt.legend(fontsize='xx-small')
plt.show()
```



we can see the accuracy of different hyperparameters on the validation set and the test set on a graph. (according to manhatan distance , euclidean Distance, cosine distance and also Hamming distance at the same time)

In [40]:
```
labels = ['Euclidean Distance', 'Manhattan Distance', 'Cosine Distance', 'Jaccard Distance', 'Hamming Distance']
y_pos = np.arange(len(labels))
acc=[Euclidean_ac, Manhattan_ac, Cosine_ac, Jaccard_ac, Hamming_ac]
maximum=np.max(acc)
plt.figure(figsize=(10,5),dpi=100)
plt.plot([-0.4,4.4],[maximum,maximum],lw=0.5)
plt.bar(y_pos, acc, align='center', alpha=0.5,color=['seagreen','darkgreen','darkred','gold','chocolate'])
plt.xticks(y_pos, labels)
plt.ylabel('Accuracy')

plt.show()
```



You can see the output accuracy of the algorithm based on different meters.