HW4

April 14, 2020

1 HW4

1.1 Part I

Use the **PopDivas_data.csv** on GitHub to build a prediction model.

1. Explore the Data
   - What patterns/relationships do you notice?
2. Choose/Build Your Model (*Decision Tree* OR *KNN*)
   - Why did you choose this type of model?
   - Which variables are you including in your model?
   - Choose a model validation technique and explain why you chose it.
   - Which variables did you standardize and Why?

3. Evaluate Your Model
   - State how it did (and what evidence/metric do you have to support that?)

1.2 Part II

Use the **YouTubeKidsVideo.csv** on GitHub to build a Naive Bayes Classifier. This dataset looks at the titles/descriptions of YouTube videos that are (1) and are not (0) meant for kids. The variable KidsVideo is 1 if the video is meant for kids, and 0 if it is not. The other variables are 1 if that word (e.g. “toy”, “girl”…etc) is in the title/description of the video, and 0 if it is not.

1. Explore the Data
   - What patterns/relationships do you notice?
2. Build your model
   - Which variables are you including in your model?
   - Choose a model validation technique and explain why you chose it.
3. Evaluate Your Model
   - How did it do? What evidence/metric do you have to support that?

2 Part I

[87]:
```python
import warnings
warnings.filterwarnings('ignore')

import pandas as pd
import numpy as np
```

```
from plotnine import *
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.neighbors import KNeighborsClassifier, KNeighborsRegressor
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB

from sklearn import metrics
from sklearn.preprocessing import StandardScaler, LabelBinarizer
from sklearn.model_selection import KFold # k-fold cv
from sklearn.model_selection import cross_val_score # cross validation metrics
from sklearn.model_selection import cross_val_predict # cross validation metrics
from sklearn.metrics import accuracy_score, confusion_matrix, mean_squared_error
#from sklearn.metrics import plot_confusion_matrix

from sklearn.model_selection import GridSearchCV

%precision %.7g
%matplotlib inline
```

[88]:
```
divas = pd.read_csv('data/PopDivas_data.csv')
print(divas.head())
print(divas.info())
print(divas.isnull().sum())
print(divas.describe())
```

```
   Unnamed: 0 artist_name  danceability   energy  key  loudness  mode  \
0           1     Beyoncé         0.386  0.28800    1   -18.513     1
1           2     Beyoncé         0.484  0.36300    5    -8.094     0
2           3     Beyoncé         0.537  0.24700    2   -17.750     1
3           4     Beyoncé         0.672  0.69600    4    -6.693     0
4           5     Beyoncé         0.000  0.00515    9   -22.612     0

   speechiness  acousticness  instrumentalness  liveness  valence  \
0       0.0602         0.533           0.01670    0.1410    0.399
1       0.0368         0.645           0.00000    0.1250    0.201
2       0.0793         0.199           0.00001    0.4230    0.170
3       0.1770         0.200           0.02750    0.0736    0.642
4       0.0000         0.524           0.95000    0.1140    0.000

   duration_ms                   track_name
0        43850    balance (mufasa interlude)
1       226479                       BIGGER
2        46566  the stars (mufasa interlude)
3       162353               FIND YOUR WAY BACK
4        13853    uncle scar (scar interlude)
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 14 columns):
Unnamed: 0          1599 non-null int64
artist_name         1599 non-null object
danceability        1599 non-null float64
energy              1599 non-null float64
key                 1599 non-null int64
loudness            1599 non-null float64
mode                1599 non-null int64
speechiness         1599 non-null float64
acousticness        1599 non-null float64
instrumentalness    1599 non-null float64
liveness            1599 non-null float64
valence             1599 non-null float64
duration_ms         1599 non-null int64
track_name          1599 non-null object
dtypes: float64(8), int64(4), object(2)
memory usage: 175.0+ KB
None
Unnamed: 0          0
artist_name         0
danceability        0
energy              0
key                 0
loudness            0
mode                0
speechiness         0
acousticness        0
instrumentalness    0
liveness            0
valence             0
duration_ms         0
track_name          0
dtype: int64
        Unnamed: 0  danceability       energy          key    loudness  \
count  1599.000000   1599.000000  1599.000000  1599.000000  1599.00000
mean    800.000000      0.602417     0.645139     5.329581    -6.59192
std     461.735855      0.161994     0.199446     3.506414     3.25770
min       1.000000      0.000000     0.005150     0.000000   -27.63100
25%     400.500000      0.494000     0.517500     2.000000    -7.33900
50%     800.000000      0.628000     0.684000     6.000000    -5.82500
75%    1199.500000      0.718000     0.797000     8.000000    -4.76400
max    1599.000000      0.932000     0.994000    11.000000    -1.35700

              mode  speechiness  acousticness  instrumentalness     liveness  \
count  1599.000000  1599.000000   1599.000000       1599.000000  1599.000000
mean      0.602877     0.120019      0.205701          0.015319     0.232994
std       0.489455     0.135377      0.261146          0.094224     0.208165
```

```
min       0.000000     0.000000      0.000025          0.000000      0.016200
25%       0.000000     0.040100      0.016200          0.000000      0.097800
50%       1.000000     0.061500      0.082500          0.000002      0.149000
75%       1.000000     0.151000      0.302500          0.000081      0.310000
max       1.000000     0.960000      0.977000          0.955000      0.993000

           valence   duration_ms
count  1599.000000  1.599000e+03
mean      0.480844  2.215496e+05
std       0.233011  6.732088e+04
min       0.000000  8.619000e+03
25%       0.293000  1.997860e+05
50%       0.467000  2.229860e+05
75%       0.664000  2.491995e+05
max       0.971000  1.187253e+06
```

[89]:
```python
print(divas['artist_name'].unique())
print(divas['key'].unique())
```

```
['Beyoncé' 'Britney Spears' 'Christina Aguilera' 'Lady Gaga' 'Rihanna'
 'Ariana Grande']
[ 1  5  2  4  9  7  6  0  8  3 10 11]
```

[90]:
```python
divas['artist_name'] = divas['artist_name'].astype('category')

label_binary = LabelBinarizer()
lb_results = label_binary.fit_transform(divas["artist_name"])
column_names = label_binary.classes_
# lb_results.shape
# column_names

lb_df = pd.DataFrame(lb_results, columns = column_names)
#print(lb_df)

divas = divas.join(lb_df, lsuffix='index', rsuffix='index')

print(divas.head(20))
#combined.drop(combined.columns[9], axis=1, inplace=True)
column_names = divas.columns[15:]
```

```
    Unnamed: 0 artist_name  danceability   energy  key  loudness  mode  \
0            1     Beyoncé         0.386  0.28800    1   -18.513     1
1            2     Beyoncé         0.484  0.36300    5    -8.094     0
2            3     Beyoncé         0.537  0.24700    2   -17.750     1
3            4     Beyoncé         0.672  0.69600    4    -6.693     0
4            5     Beyoncé         0.000  0.00515    9   -22.612     0
5            6     Beyoncé         0.932  0.77500    7    -5.345     0
6            7     Beyoncé         0.563  0.47000    6   -13.470     1
```

7	8	Beyoncé	0.790	0.69300	0	-5.767	1
8	9	Beyoncé	0.489	0.35300	8	-17.619	1
9	10	Beyoncé	0.484	0.45700	8	-9.458	0
10	11	Beyoncé	0.494	0.41100	6	-15.021	0
11	12	Beyoncé	0.608	0.70900	7	-6.175	1
12	13	Beyoncé	0.000	0.55800	0	-17.238	1
13	14	Beyoncé	0.804	0.82300	0	-3.667	0
14	15	Beyoncé	0.603	0.60200	6	-7.083	1
15	16	Beyoncé	0.000	0.18600	0	-17.370	1
16	17	Beyoncé	0.731	0.67400	2	-6.704	1
17	18	Beyoncé	0.628	0.28700	9	-16.666	0
18	19	Beyoncé	0.647	0.73200	2	-5.846	1
19	20	Beyoncé	0.255	0.32000	8	-19.821	1

	speechiness	acousticness	instrumentalness	liveness	valence	\
0	0.0602	0.5330	0.016700	0.1410	0.399	
1	0.0368	0.6450	0.000000	0.1250	0.201	
2	0.0793	0.1990	0.000010	0.4230	0.170	
3	0.1770	0.2000	0.027500	0.0736	0.642	
4	0.0000	0.5240	0.950000	0.1140	0.000	
5	0.1150	0.0184	0.015700	0.3180	0.584	
6	0.1470	0.0306	0.661000	0.2830	0.186	
7	0.0605	0.0420	0.026700	0.0790	0.855	
8	0.6640	0.4910	0.000022	0.2290	0.175	
9	0.2040	0.7380	0.000000	0.5360	0.342	
10	0.7710	0.7030	0.000000	0.1560	0.403	
11	0.3740	0.1190	0.000000	0.3370	0.709	
12	0.0000	0.7560	0.000000	0.5330	0.000	
13	0.0745	0.0984	0.000004	0.2460	0.489	
14	0.2300	0.0490	0.000000	0.2790	0.595	
15	0.0000	0.7830	0.000140	0.3330	0.000	
16	0.0801	0.0057	0.000025	0.1090	0.730	
17	0.6600	0.6750	0.000000	0.4260	0.535	
18	0.0891	0.0846	0.000000	0.5970	0.548	
19	0.0533	0.8260	0.021900	0.2610	0.302	

	duration_ms	track_name	\
0	43850	balance (mufasa interlude)	
1	226479	BIGGER	
2	46566	the stars (mufasa interlude)	
3	162353	FIND YOUR WAY BACK	
4	13853	uncle scar (scar interlude)	
5	155990	DON'T JEALOUS ME	
6	16768	danger (young simba & young nala interlude)	
7	190108	JA ARA E	
8	29582	run away (scar & young simba interlude)	
9	107204	NILE	
10	53793	new lesson (timon, pumbaa & young simba interl…	

```
11       272068                 MOOD 4 EVA (feat. Oumou Sangaré)
12         8619               reunited (nala & simba interlude)
13       152563                                           WATER
14       248472                                 BROWN SKIN GIRL
15        14827                  come home (nala interlude)
16       198952                              KEYS TO THE KINGDOM
17        31391           follow me (simba & rafiki interlude)
18       222529                                         ALREADY
19        45293                    remember (mufasa interlude)

    Ariana Grande  Beyoncé  Britney Spears  Christina Aguilera  Lady Gaga  \
0               0        1               0                   0          0
1               0        1               0                   0          0
2               0        1               0                   0          0
3               0        1               0                   0          0
4               0        1               0                   0          0
5               0        1               0                   0          0
6               0        1               0                   0          0
7               0        1               0                   0          0
8               0        1               0                   0          0
9               0        1               0                   0          0
10              0        1               0                   0          0
11              0        1               0                   0          0
12              0        1               0                   0          0
13              0        1               0                   0          0
14              0        1               0                   0          0
15              0        1               0                   0          0
16              0        1               0                   0          0
17              0        1               0                   0          0
18              0        1               0                   0          0
19              0        1               0                   0          0

    Rihanna
0         0
1         0
2         0
3         0
4         0
5         0
6         0
7         0
8         0
9         0
10        0
11        0
12        0
13        0
14        0
```

```
15          0
16          0
17          0
18          0
19          0
```

[91]:

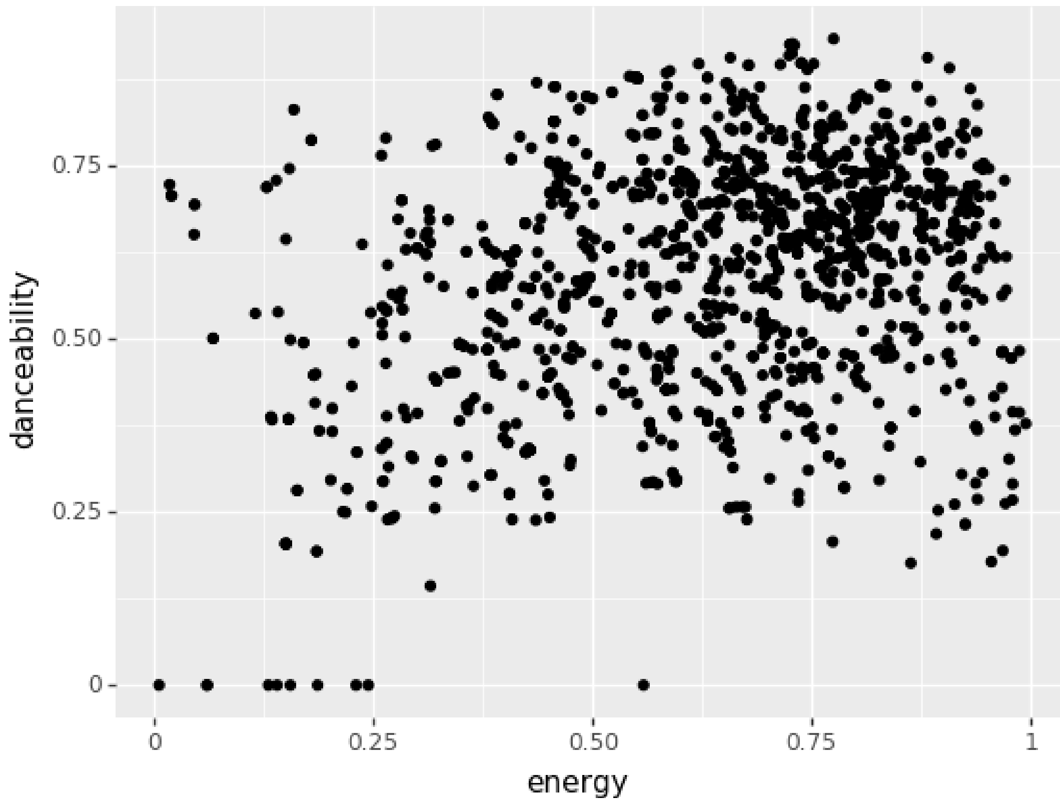
```
divas.head()
```

[91]:

```
   Unnamed: 0 artist_name  danceability   energy  key  loudness  mode  \
0           1     Beyoncé         0.386  0.28800    1   -18.513     1
1           2     Beyoncé         0.484  0.36300    5    -8.094     0
2           3     Beyoncé         0.537  0.24700    2   -17.750     1
3           4     Beyoncé         0.672  0.69600    4    -6.693     0
4           5     Beyoncé         0.000  0.00515    9   -22.612     0

   speechiness  acousticness  instrumentalness  liveness  valence  \
0       0.0602         0.533           0.01670    0.1410    0.399
1       0.0368         0.645           0.00000    0.1250    0.201
2       0.0793         0.199           0.00001    0.4230    0.170
3       0.1770         0.200           0.02750    0.0736    0.642
4       0.0000         0.524           0.95000    0.1140    0.000

   duration_ms                    track_name  Ariana Grande  Beyoncé  \
0        43850    balance (mufasa interlude)              0        1
1       226479                        BIGGER              0        1
2        46566  the stars (mufasa interlude)              0        1
3       162353                FIND YOUR WAY BACK          0        1
4        13853    uncle scar (scar interlude)             0        1

   Britney Spears  Christina Aguilera  Lady Gaga  Rihanna
0               0                   0          0        0
1               0                   0          0        0
2               0                   0          0        0
3               0                   0          0        0
4               0                   0          0        0
```

[92]:

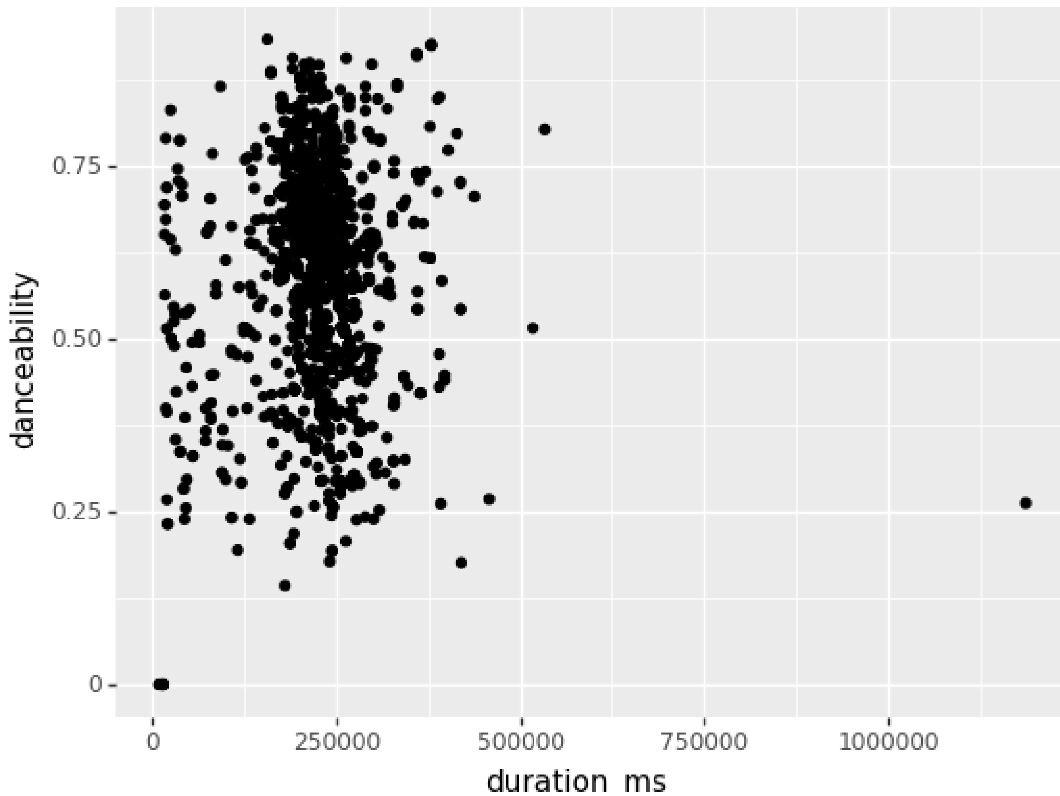
```
(ggplot(divas, aes(x = "energy", y = "danceability"))
        +geom_point())
```



[92]: <ggplot: (-9223371894412295976)>

1a - Seems like there is generally a positive relationship between energy and dancability due to the large cluster in the top right corner

[93]:
```
(ggplot(divas, aes(x = "duration_ms", y = "danceability"))
        +geom_point())
```



[93]: <ggplot: (-9223371894413343008)>

data is too bunched up to view in this view

[94]:
```
divas['duration_s'] = divas['duration_ms'] / 1000

# get rid of interlude songs
divas = divas[divas['duration_s'] > 60]
print(divas.shape)
```

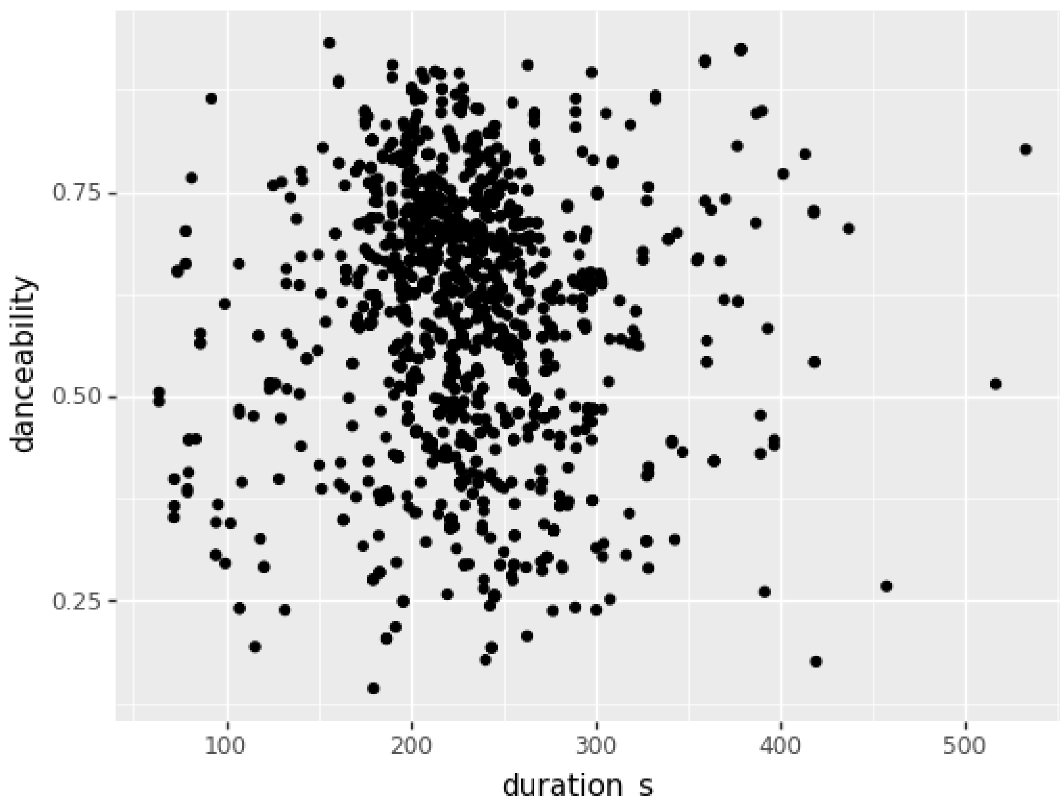
```
(1539, 21)
```

[95]:
```
#(divas['duration_s'] > 600).sum()
print(divas.loc[divas['duration_s'] > 600])

# got rid of that mix because it would likely throw off the model
divas = divas[divas['duration_s'] < 600]
```

```
     Unnamed: 0 artist_name  danceability  energy  key  loudness  mode  \
268         269     Beyoncé         0.262   0.971   11    -3.827     0

     speechiness  acousticness  instrumentalness  …  valence  duration_ms  \
```

```
268         0.383          0.108                0.0  …    0.289      1187253

                                            track_name Ariana Grande  Beyoncé  \
268  Destiny's Child Medley - Audio from The Beyonc…             0        1

     Britney Spears  Christina Aguilera  Lady Gaga  Rihanna  duration_s
268               0                   0          0        0    1187.253

[1 rows x 21 columns]
```

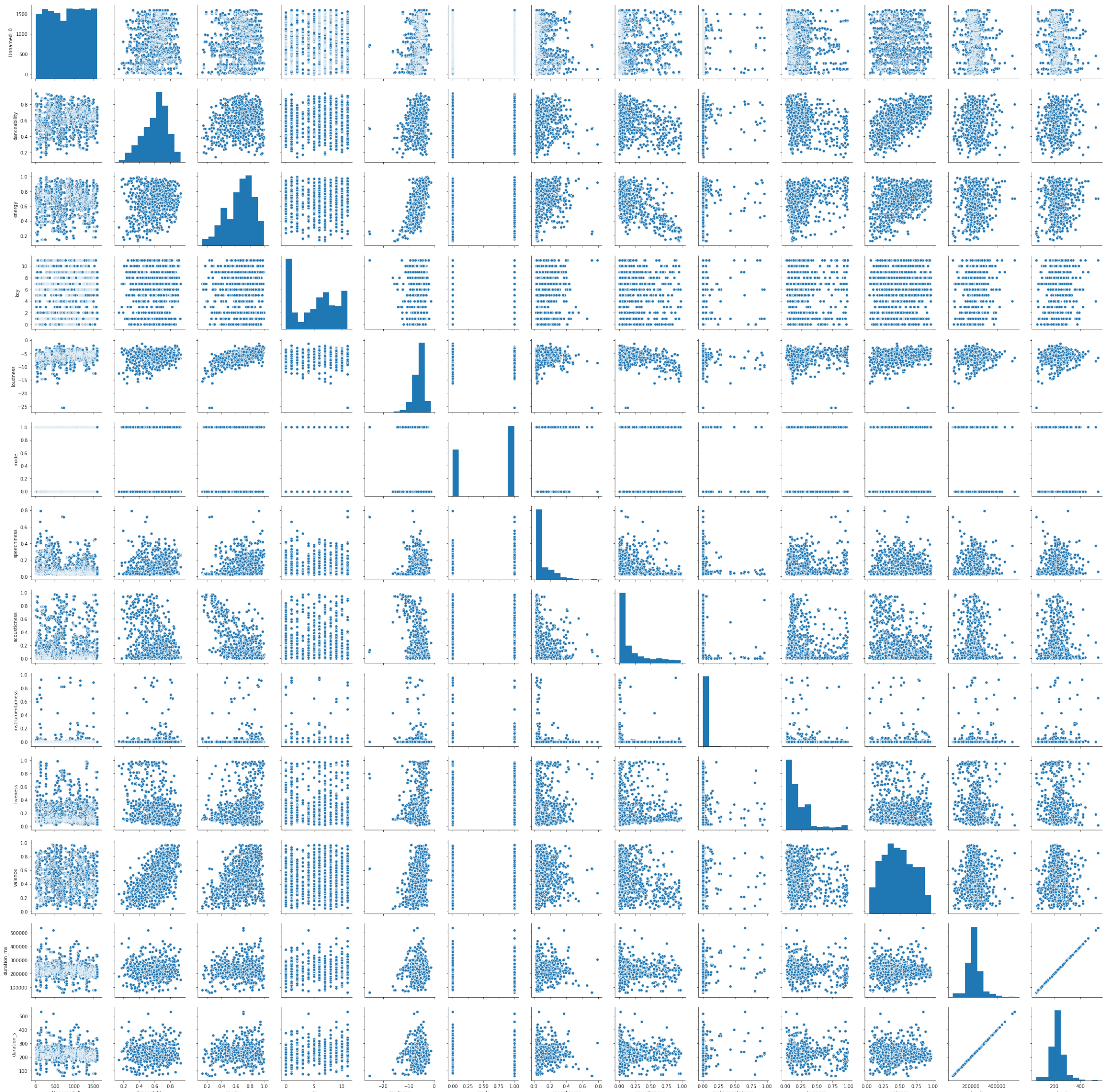
[8]:
```
(ggplot(divas, aes(x = "duration_s", y = "danceability"))
        +geom_point())
```



[8]: <ggplot: (-9223371894318240052)>

1b - converted to seconds so that its easier to interpret. also removed the destinys child medley so that it wouldnt throw off the model

[16]:
```
g = sns.pairplot(divas)
```



1c - at a glance valence also looks like it has a positve relationship, as well as loudness a little bit.

[113]:
```
predictors = ["valence","duration_s","loudness"]

predictors[2:2] = column_names

#print(predictors)
X = divas[predictors]
y = divas["danceability"]

X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.2)

knn = KNeighborsRegressor()
```

```python
ks = {"n_neighbors": range(1,30)}

# use grid search to find best parameters
grid = GridSearchCV(knn,ks, scoring = "r2", cv = 5)

zscore = StandardScaler()
zscore.fit(X_train)

Xs_train = zscore.transform(X_train)
Xs_test = zscore.transform(X_test)

knnmod = grid.fit(X_train, y_train)

knnmod.best_estimator_.get_params()["n_neighbors"]
```

[113]: 1

[114]:
```python
poss_k = [1,2,3,4,5,6,7,8,9,10]
acc = {}

for k in poss_k:
    kf = KFold(n_splits = 5)
    knn2 = KNeighborsRegressor(n_neighbors = k)

    acc[k] = np.mean(cross_val_score(knn2, X_train, y_train, cv = kf))

print(acc)

chosen_k = max(acc, key=acc.get)
print(chosen_k)

knn_final = KNeighborsRegressor(n_neighbors = chosen_k)
knn_final.fit(X_train,y_train)

knn_final.score(X_test,y_test)
```

```
{1: 0.3247511583538543, 2: 0.30816326432983165, 3: 0.2830303003513635, 4:
0.25626460996674727, 5: 0.23821537517322752, 6: 0.20528739606340496, 7:
0.18350167613503354, 8: 0.15760007469868254, 9: 0.14593655363540706, 10:
0.1396864875637521}
1
```

[114]: 0.535546400750241

Write your responses here

2 - I chose KNN as the model to use because I believe artists draw a lot of inspiration from other

artists and there might be an interesting relationship between these artists since they were kind of around at the same time and I think knn is an interesting model that might be able to capture this relationship.

[109]:
```
train_pred = knnmod.predict(X_train)
test_pred = knnmod.predict(X_test)

print('training r2 is:', knnmod.score(X_train, y_train)) #training R2
print('testing r2 is:', knnmod.score(X_test, y_test)) #testing R2

print('\ntrain mse is: ', mean_squared_error(y_train,train_pred))
print('test mse is: ', mean_squared_error(y_test,test_pred))
```

```
training r2 is: 0.9999997641015631
testing r2 is: 0.19972686224014524

train mse is:  5.691056910568755e-09
test mse is:  0.017059165584415583
```

[115]:
```
train_pred = knn_final.predict(X_train)
test_pred = knn_final.predict(X_test)

print('training r2 is:', knn_final.score(X_train, y_train)) #training R2
print('testing r2 is:', knn_final.score(X_test, y_test)) #testing R2

print('\ntrain mse is: ', mean_squared_error(y_train,train_pred))
print('test mse is: ', mean_squared_error(y_test,test_pred))
```

```
training r2 is: 0.9999997915786427
testing r2 is: 0.535546400750241

train mse is:  4.878048780487634e-09
test mse is:  0.011231870129870132
```

Write your responses here

The model didnt do too terrible according to the r2 in the k-fold model. The initial model seemed very overfitted to the training data which is why i decided to make a k-fold model as well. I standardized all variables because I couldnt figure out how to choose specific ones. I kept getting errors on the zscore fit method.

3 Part II

Use the YouTubeKidsVideo.csv on GitHub to build a Naive Bayes Classifier. This dataset looks at the titles/descriptions of YouTube videos that are (1) and are not (0) meant for kids. The variable KidsVideo is 1 if the video is meant for kids, and 0 if it is not. The other variables are 1 if that word (e.g. “toy”, “girl”…etc) is in the title/description of the video, and 0 if it is not.

`Explore the Data`

```
    What patterns/relationships do you notice?
Build your model
    Which variables are you including in your model?
    Choose a model validation technique and explain why you chose it.
Evaluate Your Model
    How did it do? What evidence/metric do you have to support that?
```

[31]:

```python
vids = pd.read_csv('data/YouTubeKidsVideo.csv')
print(vids.head())
print(vids.info())
print(vids.isnull().sum())
print(vids.describe())
```

```
   kidsVideo  cat  toy  sad  girl  is
0          1    1    0    0     0   0
1          1    1    0    0     0   0
2          1    1    1    0     0   0
3          1    1    1    0     0   0
4          1    0    0    0     0   0
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 6 columns):
kidsVideo    2000 non-null int64
cat          2000 non-null int64
toy          2000 non-null int64
sad          2000 non-null int64
girl         2000 non-null int64
is           2000 non-null int64
dtypes: int64(6)
memory usage: 93.9 KB
None
kidsVideo    0
cat          0
toy          0
sad          0
girl         0
is           0
dtype: int64
         kidsVideo          cat          toy          sad         girl  \
count  2000.000000  2000.000000  2000.00000  2000.000000  2000.000000
mean      0.500000     0.488000     0.30450     0.234000     0.236000
std       0.500125     0.499981     0.46031     0.423478     0.424728
min       0.000000     0.000000     0.00000     0.000000     0.000000
25%       0.000000     0.000000     0.00000     0.000000     0.000000
50%       0.500000     0.000000     0.00000     0.000000     0.000000
75%       1.000000     1.000000     1.00000     0.000000     0.000000
max       1.000000     1.000000     1.00000     1.000000     1.000000
```

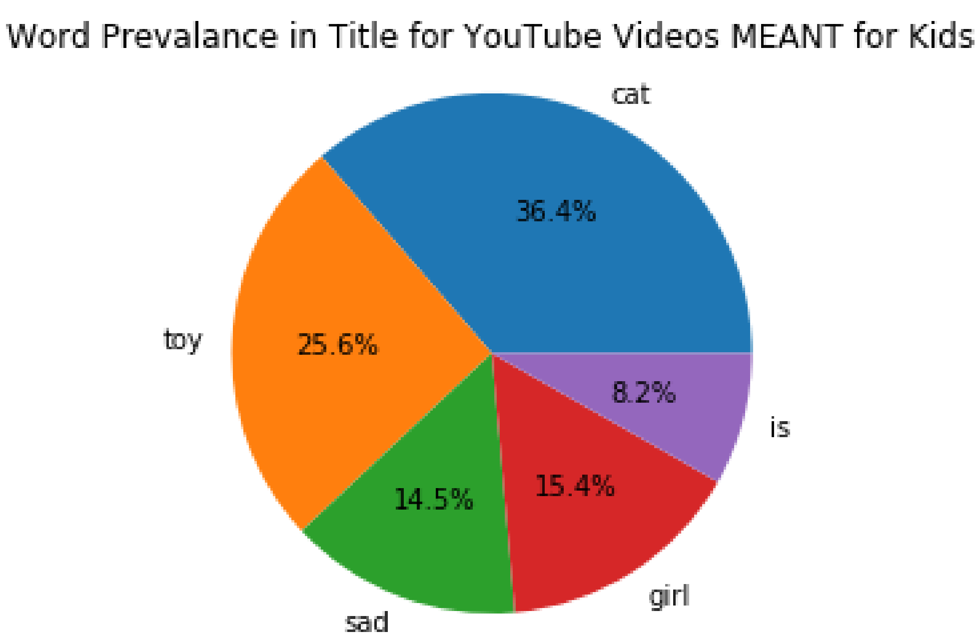
```
                is
count  2000.000000
mean      0.145000
std       0.352189
min       0.000000
25%       0.000000
50%       0.000000
75%       0.000000
max       1.000000
```

[32]:
```
kids = vids[vids['kidsVideo'] == 1]
not_kids = vids[vids['kidsVideo'] == 0]

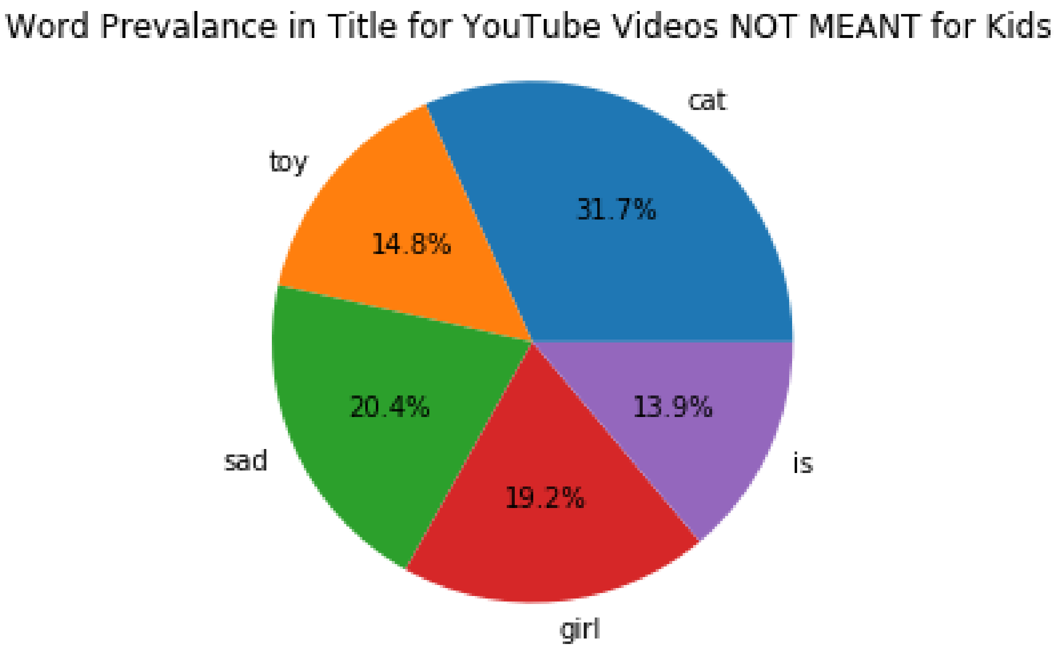
print(kids.shape)
print(not_kids.shape)
```

```
(1000, 6)
(1000, 6)
```

[33]:
```
Data = {'total': [kids['cat'].sum(),kids['toy'].sum(),kids['sad'].
 ↪sum(),kids['girl'].sum(),kids['is'].sum()]}
df = pd.DataFrame(Data,columns=['total'])
my_labels = 'cat','toy','sad', 'girl', 'is'
plt.pie(df,labels=my_labels,autopct='%1.1f%%')
plt.title('Word Prevalance in Title for YouTube Videos MEANT for Kids')
plt.axis('equal')
plt.show()
```



[34]:
```
Data = {'total': [not_kids['cat'].sum(),not_kids['toy'].sum(),not_kids['sad'].
 ↪sum(),not_kids['girl'].sum(),not_kids['is'].sum()]}
df = pd.DataFrame(Data,columns=['total'])
my_labels = 'cat','toy','sad', 'girl', 'is'
plt.pie(df,labels=my_labels,autopct='%1.1f%%')
plt.title('Word Prevalance in Title for YouTube Videos NOT MEANT for Kids')
plt.axis('equal')
plt.show()
```



data shows that there are more titles with the word toy in the title in videos meant for kids. The opposite is true in the case for videos not meant for children, rather sad is a more common word in titles not meant for kids.

[118]:
```
predictors = ['toy', 'sad']

X = vids[predictors]
y = vids["kidsVideo"]



kf = KFold(n_splits = 4)
nb = GaussianNB()
acc = []
predictedVals = []
for train, test in kf.split(X,y):
    X_train = X.iloc[train]
```

```
    X_test = X.iloc[test]
    y_train = y[train]
    y_test = y[test]



    nb.fit(X_train,y_train)
    acc.append(nb.score(X_test,y_test))
    cnf_matrix = confusion_matrix(y_test, y_test)
    print(cnf_matrix)
```

```
[[500]]
[[500]]
[[500]]
[[500]]
```

Write your responses here

i used the two most prevelant words in the model because they were the most distinct keywords in titles. I chose accuracy as the metric to use in assessing the model because it is a very common metric to determines the overall predicted accuracy of the model.

[117]:
```
print(acc)
print(np.mean(acc))
```

```
[0.46, 0.454, 0.68, 0.666]
0.5650000000000001
```

Write your responses here

The model doesnt do too well given a score close to .50 indicating that the model is accurate and useful in half of the time.

[ ]:
```
get_ipython().system("jupyter nbconvert --output-dir='output/' --to pdf knn_nb.
 ↪ipynb")
get_ipython().system("jupyter nbconvert --output-dir='output/' --to markdown␣
 ↪knn_nb.ipynb")
get_ipython().system("jupyter nbconvert --output-dir='output/' --to html knn_nb.
 ↪ipynb")
get_ipython().system("jupyter nbconvert --output-dir='output/' --to python␣
 ↪knn_nb.ipynb")
```

```
This application is used to convert notebook files (*.ipynb) to various other
formats.

WARNING: THE COMMANDLINE INTERFACE MAY CHANGE IN FUTURE RELEASES.

Options
```

```
-------

Arguments that take values are actually convenience aliases to full
Configurables, whose aliases are listed on the help line. For more information
on full configurables, see '--help-all'.

--debug

    set log level to logging.DEBUG (maximize logging output)

--generate-config

    generate default config file

-y

    Answer yes to any questions instead of prompting.

--execute

    Execute the notebook prior to export.

--allow-errors

    Continue notebook execution even if one of the cells throws an error and
include the error message in the cell output (the default behaviour is to abort
conversion). This flag is only relevant if '--execute' was specified, too.

--stdin

    read a single notebook file from stdin. Write the resulting notebook with
default basename 'notebook.*'

--stdout

    Write notebook output to stdout instead of files.

--inplace

    Run nbconvert in place, overwriting the existing notebook (only
    relevant when converting to notebook format)

--clear-output

    Clear output of current file and save in place,
```

```
    overwriting the existing notebook.

--no-prompt

    Exclude input and output prompts from converted document.

--no-input

    Exclude input cells and output prompts from converted document.
    This mode is ideal for generating code-free reports.
--log-level=<Enum> (Application.log_level)

    Default: 30

    Choices: (0, 10, 20, 30, 40, 50, 'DEBUG', 'INFO', 'WARN', 'ERROR',
'CRITICAL')

    Set the log level by value or name.

--config=<Unicode> (JupyterApp.config_file)

    Default: ''

    Full path of a config file.

--to=<Unicode> (NbConvertApp.export_format)

    Default: 'html'

    The export format to be used, either one of the built-in formats

    ['asciidoc', 'custom', 'html', 'latex', 'markdown', 'notebook', 'pdf',

    'python', 'rst', 'script', 'slides'] or a dotted object name that represents

    the import path for an `Exporter` class

--template=<Unicode> (TemplateExporter.template_file)

    Default: ''

    Name of the template file to use

--writer=<DottedObjectName> (NbConvertApp.writer_class)

    Default: 'FilesWriter'

    Writer class used to write the  results of the conversion
```

```
--post=<DottedOrNone> (NbConvertApp.postprocessor_class)
    Default: ''
    PostProcessor class used to write the results of the conversion
--output=<Unicode> (NbConvertApp.output_base)
    Default: ''
    overwrite base name use for output files. can only be used when converting
    one notebook at a time.
--output-dir=<Unicode> (FilesWriter.build_directory)
    Default: ''
    Directory to write output(s) to. Defaults to output to the directory of each
    notebook. To recover previous default behaviour (outputting to the current
    working directory) use . as the flag value.
--reveal-prefix=<Unicode> (SlidesExporter.reveal_url_prefix)
    Default: ''
    The URL prefix for reveal.js (version 3.x). This defaults to the reveal CDN,
    but can be any url pointing to a copy  of reveal.js.
    For speaker notes to work, this must be a relative path to a local  copy of
    reveal.js: e.g., "reveal.js".
    If a relative path is given, it must be a subdirectory of the current
    directory (from which the server is run).
    See the usage documentation
    (https://nbconvert.readthedocs.io/en/latest/usage.html#reveal-js-html-
    slideshow) for more details.
--nbformat=<Enum> (NotebookExporter.nbformat_version)
```

```
    Default: 4

    Choices: [1, 2, 3, 4]

    The nbformat version to write. Use this to downgrade notebooks.

To see all available configurables, use `--help-all`

Examples
--------

    The simplest way to use nbconvert is

    > jupyter nbconvert mynotebook.ipynb

    which will convert mynotebook.ipynb to the default format (probably HTML).

    You can specify the export format with `--to`.
    Options include ['asciidoc', 'custom', 'html', 'latex', 'markdown',
'notebook', 'pdf', 'python', 'rst', 'script', 'slides'].

    > jupyter nbconvert --to latex mynotebook.ipynb

    Both HTML and LaTeX support multiple output templates. LaTeX includes
    'base', 'article' and 'report'.  HTML includes 'basic' and 'full'. You
    can specify the flavor of the format used.

    > jupyter nbconvert --to html --template basic mynotebook.ipynb

    You can also pipe the output to stdout, rather than a file

    > jupyter nbconvert mynotebook.ipynb --stdout

    PDF is generated via latex

    > jupyter nbconvert mynotebook.ipynb --to pdf

    You can get (and serve) a Reveal.js-powered slideshow

    > jupyter nbconvert myslides.ipynb --to slides --post serve

    Multiple notebooks can be given at the command line in a couple of
    different ways:

    > jupyter nbconvert notebook*.ipynb
    > jupyter nbconvert notebook1.ipynb notebook2.ipynb
```

```
    or you can specify the notebooks list in a config file, containing::

        c.NbConvertApp.notebooks = ["my_notebook.ipynb"]

    > jupyter nbconvert --config mycfg.py
```

```
[NbConvertApp] WARNING | pattern 'knn_nb.ipynb' matched no files
This application is used to convert notebook files (*.ipynb) to various other
formats.

WARNING: THE COMMANDLINE INTERFACE MAY CHANGE IN FUTURE RELEASES.

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    generate default config file

-y

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    Execute the notebook prior to export.

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    Full path of a config file.

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    The export format to be used, either one of the built-in formats

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```

```
    'python', 'rst', 'script', 'slides'] or a dotted object name that represents
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--template=<Unicode> (TemplateExporter.template_file)
    Default: ''
    Name of the template file to use
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    Default: 'FilesWriter'
    Writer class used to write the  results of the conversion
--post=<DottedOrNone> (NbConvertApp.postprocessor_class)
    Default: ''
    PostProcessor class used to write the results of the conversion
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    Default: ''
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    working directory) use . as the flag value.
--reveal-prefix=<Unicode> (SlidesExporter.reveal_url_prefix)
    Default: ''
    The URL prefix for reveal.js (version 3.x). This defaults to the reveal CDN,
    but can be any url pointing to a copy  of reveal.js.
```

```
    For speaker notes to work, this must be a relative path to a local  copy of

    reveal.js: e.g., "reveal.js".

    If a relative path is given, it must be a subdirectory of the current

    directory (from which the server is run).

    See the usage documentation

    (https://nbconvert.readthedocs.io/en/latest/usage.html#reveal-js-html-

    slideshow) for more details.

--nbformat=<Enum> (NotebookExporter.nbformat_version)

    Default: 4

    Choices: [1, 2, 3, 4]

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```
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    > jupyter nbconvert notebook*.ipynb
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    or you can specify the notebooks list in a config file, containing::

        c.NbConvertApp.notebooks = ["my_notebook.ipynb"]

    > jupyter nbconvert --config mycfg.py

[NbConvertApp] WARNING | pattern 'knn_nb.ipynb' matched no files
```