FinalProjectCST383

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0.1 Project Pacific Analytics

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0.1.4 Feb 15, 2023

Project progress report

Purpose. The purpose of this assignment is to help keep you on track, and to allow us to help you make adjustments to your project before it is due.

Exploration of Names

[1]:
```
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib import rcParams
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.model_selection import cross_val_score
import graphviz
# cite https://stackoverflow.com/questions/74877602/
 ↪getting-a-warning-when-using-sklearn-neighbors-about-keepdims
from warnings import simplefilter
simplefilter(action='ignore', category=FutureWarning)

sns.set()
rcParams['figure.figsize'] = 8,6
sns.set_context('talk')   # 'talk' for slightly larger
```

[2]:
```
# code in this cell from:
# https://stackoverflow.com/questions/27934885/
↪how-to-hide-code-from-cells-in-ipython-notebook-visualized-with-nbviewer
from IPython.display import HTML

HTML('''<script>
code_show=true;
function code_toggle() {
 if (code_show){
 $('div.input').hide();
 } else {
 $('div.input').show();
 }
 code_show = !code_show
}
$( document ).ready(code_toggle);
</script>
<form action="javascript:code_toggle()"><input type="submit" value="Click here␣
↪to display/hide the code."></form>''')
```

[2]:
```
<IPython.core.display.HTML object>
```

[3]:
```
# The original CSV is too large for github. It is 31mb and github accepts 25mb␣
↪or less.
# The plan is to split the files and merge them on read.
# We found a website that can split CSVs online. https://www.splitcsv.com/
# Successfully split but ran in to problems
# For now we will host on Dropbox. Dropbox can handle larger files when not␣
↪using a webbrowser.
# Error, need to change domain to direct download. Went from dropbox.com to dl.
↪dropboxusercontent.com
df = pd.read_csv("http://dl.dropboxusercontent.com/s/0uzku9gb353n3nv/
↪NYC_Dog_Licensing_Dataset.csv")

dfBaby = pd.read_csv("https://archive.ics.uci.edu/ml/machine-learning-databases/
↪00591/name_gender_dataset.csv")
```

The choice of dataset is Animal (Dog) License Data from NYC from data.gov . The file is approximately 31 megabytes and holds 500,000 lines of data. It is hosted on a dropbox for ease of use.

We are going to predict the AnimalName. There are 8 columns of data, but we are most interested in the AnimalName.

The predictors we will be using are ZipCode and Birthyear.

Preprocessing, exploration, and visualization, and machine learning work are below.

[4]:
```
#Let us look at the information and general data of the chart.
df.info()
print(df.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 508196 entries, 0 to 508195
Data columns (total 8 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   AnimalName          507169 non-null  object
 1   AnimalGender        508175 non-null  object
 2   AnimalBirthYear     508196 non-null  int64
 3   BreedName           508196 non-null  object
 4   ZipCode             508187 non-null  float64
 5   LicenseIssuedDate   508196 non-null  object
 6   LicenseExpiredDate  508119 non-null  object
 7   Extract Year        508196 non-null  int64
dtypes: float64(1), int64(2), object(5)
memory usage: 31.0+ MB
       AnimalBirthYear        ZipCode   Extract Year
count    508196.000000  508187.000000  508196.000000
mean       2013.206304   10704.532395    2019.380810
std           4.847849    1096.178521       2.646618
min        1991.000000       0.000000    2016.000000
25%        2010.000000   10031.000000    2017.000000
50%        2014.000000   10468.000000    2018.000000
75%        2017.000000   11228.000000    2022.000000
max        2021.000000   99508.000000    2022.000000
```

data['Gender'].replace(0, 'Female',inplace=True) data['Gender'].replace(1, 'Male',inplace=True)

[5]:
```
#Let us look at the information and general data of the chart.
dfBaby.info()
print(dfBaby.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 147269 entries, 0 to 147268
Data columns (total 4 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   Name         147269 non-null  object
 1   Gender       147269 non-null  object
 2   Count        147269 non-null  int64
 3   Probability  147269 non-null  float64
dtypes: float64(1), int64(1), object(2)
memory usage: 4.5+ MB
              Count   Probability
count  1.472690e+05  1.472690e+05
```

```
mean   2.481161e+03  6.790295e-06
std    4.645472e+04  1.271345e-04
min    1.000000e+00  2.736740e-09
25%    5.000000e+00  1.368370e-08
50%    1.700000e+01  4.652460e-08
75%    1.320000e+02  3.612500e-07
max    5.304407e+06  1.451679e-02
```

[6]:
```
#sns.pairplot(df)
#df.plot()
```

[ ]:
```
```

How many Zipcodes are there?

[7]:
```
df['ZipCode'].value_counts().head(10)
```

[7]:
```
10025.0    11439
10023.0     9164
11215.0     8829
10024.0     8826
11201.0     8757
10011.0     8555
10128.0     8392
10009.0     8073
10314.0     7613
10312.0     7467
Name: ZipCode, dtype: int64
```

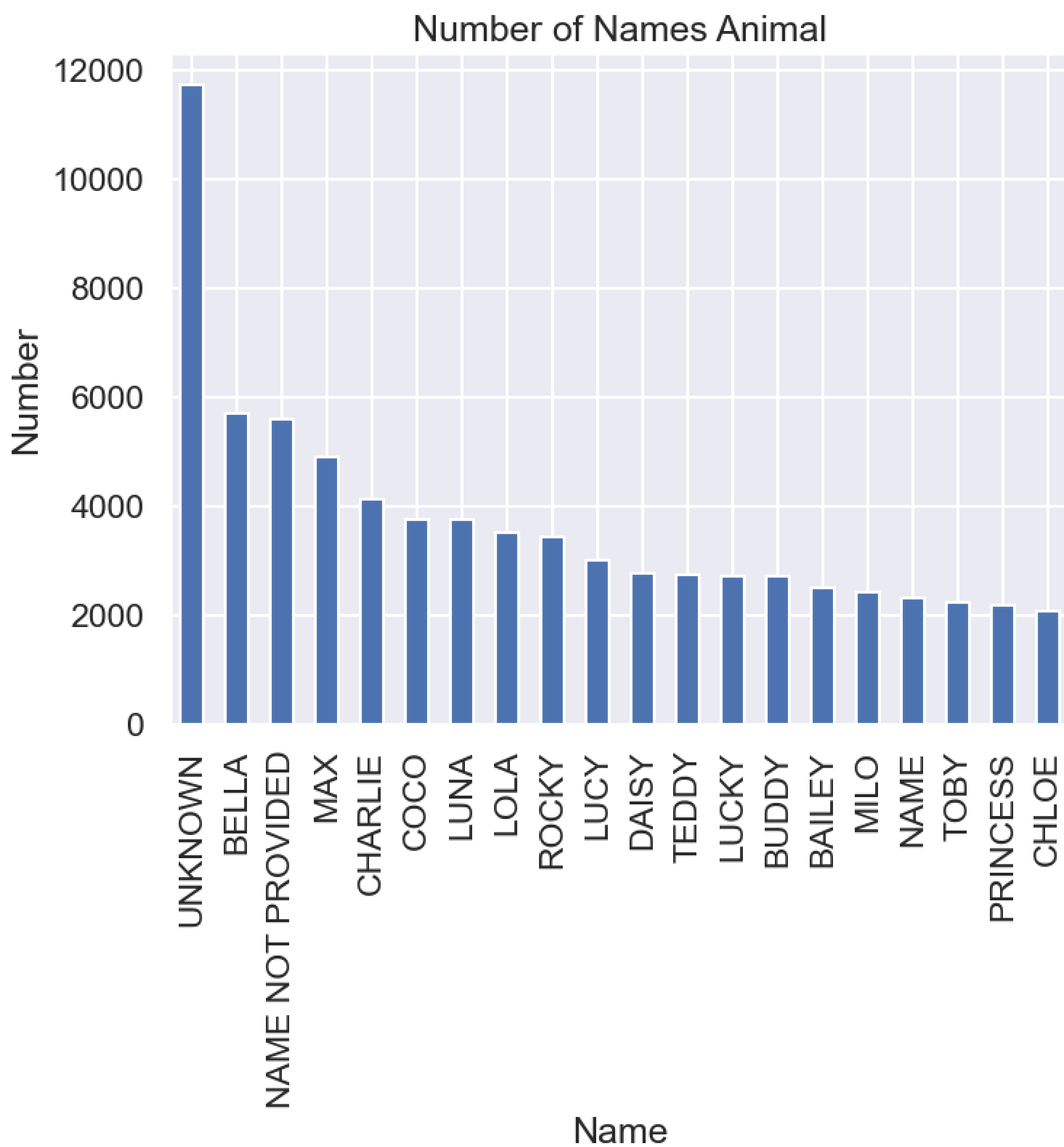
[8]:
```
df['ZipCode'].value_counts().size
```

[8]:
```
784
```

There are 740 zip codes.

What are the most popular animal names?

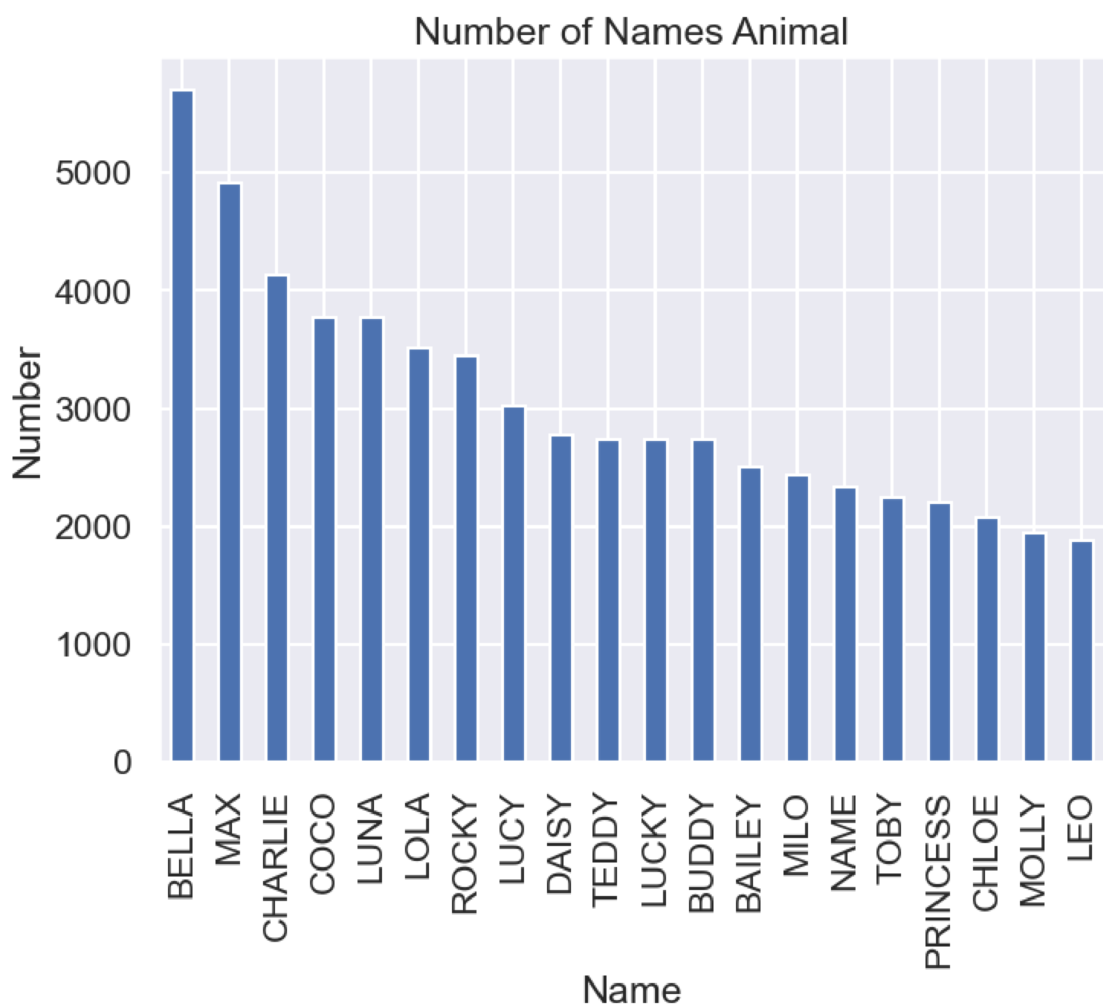
[9]:
```
#@ 1 Show the top 20 names
names = df['AnimalName'].value_counts().head(20)
names.plot.bar()
plt.xlabel("Name")
plt.ylabel("Number")
plt.title("Number of Names Animal");
```



We need to clean up the data. The most popular name is uknown and second most popular is name not provided.[

[10]:
```
#Drop junk names

df = df[df.AnimalName != 'UNKNOWN']
df = df[df.AnimalName != 'NAME NOT PROVIDED']


#@ 1 Show the top 20 names after dropping junk names
names = df['AnimalName'].value_counts().head(20)
```

```
names.plot.bar()
plt.xlabel("Name")
plt.ylabel("Number")
plt.title("Number of Names Animal");
```



Let us clean up the data further.

[11]:
```
# DATA PREPARATION
print(df.isnull().sum())
# na values:
# AnimalName: 1027
# AnimalGender: 21
# ZipCode: 9
# LicenseExpiredDate: 77
# while we could dropna on all values, we are only doing so on AnimalGender
```

```
# we plan to predict BreedName using AnimalGender and Extract Year, so others␣
↪are not required

# predicting AnimalName (or lack of name) using ZipCode and AnimalBirthYear␣
↪sounds very interesting; however,
# the feedback stated that predictions using zipcodes and dates is difficult,␣
↪so I think we should explore the
# relationship between these using plots instead. Such as

# easy way to show dropped columns
df_dropped = df[df['AnimalGender'].isna()]
print(df_dropped)

# drop rows that contain na in AnimalGender column
df = df[df['AnimalGender'].notna()]
#print(df.isnull().sum())
```

```
AnimalName            1027
AnimalGender            21
AnimalBirthYear          0
BreedName                0
ZipCode                  9
LicenseIssuedDate        0
LicenseExpiredDate      44
Extract Year             0
dtype: int64
       AnimalName AnimalGender  AnimalBirthYear  \
7356      SPARKEY          NaN             2005
16436      SHEBAH          NaN             1997
16684      SHEBAH          NaN             1997
17929      SHEBAH          NaN             1997
18002      SHEBAH          NaN             1997
47593       BUDDY          NaN             2005
57191       NANUK          NaN             2000
69701      SIDNEY          NaN             2003
110361     CHERRY          NaN             2002
112674      NANUK          NaN             2000
115288    SPARKEY          NaN             2005
123852      BUDDY          NaN             2005
142049     SIDNEY          NaN             2003
194786    SPARKEY          NaN             2005
198415      BUDDY          NaN             2005
210919      NANUK          NaN             2000
219012     SIDNEY          NaN             2003
261017     CHERRY          NaN             2002
261018     CHERRY          NaN             2002
261461      BUDDY          NaN             2005
```

439372	CHERRY	NaN	2002

	BreedName	ZipCode	LicenseIssuedDate \
7356	Yorkshire Terrier	11220.0	03/16/2015
16436	German Shepherd Dog	11218.0	07/10/2016
16684	German Shepherd Dog	11218.0	08/09/2017
17929	German Shepherd Dog	11218.0	10/01/2018
18002	German Shepherd Dog	11218.0	07/31/2019
47593	Cavalier King Charles Spaniel	10307.0	03/06/2016
57191	Maltese	11358.0	04/19/2016
69701	Shih Tzu	11358.0	06/10/2016
110361	Unknown	11209.0	12/17/2016
112674	Maltese	11358.0	04/19/2016
115288	Yorkshire Terrier	11220.0	01/16/2017
123852	Cavalier King Charles Spaniel	10307.0	03/08/2017
142049	Shih Tzu	11358.0	06/06/2017
194786	Yorkshire Terrier	11220.0	02/13/2018
198415	Cavalier King Charles Spaniel	10307.0	03/03/2018
210919	Maltese	11358.0	05/03/2018
219012	Shih Tzu	11358.0	06/11/2018
261017	Unknown	11209.0	03/02/2019
261018	Unknown	11209.0	12/24/2020
261461	Cavalier King Charles Spaniel	10307.0	04/02/2019
439372	MINI PINSCHER	11209.0	12/24/2020

	LicenseExpiredDate	Extract Year
7356	03/01/2017	2016
16436	08/30/2017	2016
16684	08/30/2018	2017
17929	08/30/2019	2018
18002	08/30/2020	2022
47593	04/30/2017	2016
57191	03/29/2017	2016
69701	07/30/2017	2016
110361	01/30/2019	2016
112674	03/29/2018	2017
115288	03/01/2018	2017
123852	04/30/2018	2017
142049	07/30/2018	2017
194786	03/01/2019	2018
198415	04/30/2019	2018
210919	03/29/2019	2018
219012	07/30/2019	2018
261017	01/30/2021	2022
261018	01/30/2022	2022
261461	04/30/2020	2022
439372	01/30/2022	2022

Experimenting with data.

[12]:
```
#Label enconding from

def Encoder(df):
          columnsToEncode = list(df.
 ↪select_dtypes(include=['category','object']))
          le = LabelEncoder()
          for feature in columnsToEncode:
              try:
                  df[feature] = le.fit_transform(df[feature])
              except:
                  print('Error encoding '+feature)
          return df
```

Machine Learning and Predictions,

[13]:
```
#preserve index values

df = df.drop('ZipCode', axis=1)

df['oldIndex'] = df.index
df['oldName'] = df.index

dfConvert = df.copy()

#get rid of strings
dfE = Encoder(df)

df = pd.read_csv("http://dl.dropboxusercontent.com/s/0uzku9gb353n3nv/
 ↪NYC_Dog_Licensing_Dataset.csv")

df = df[df.AnimalName != 'UNKNOWN']
df = df[df.AnimalName != 'NAME NOT PROVIDED']

df = df.drop('ZipCode', axis=1)


#show top 10
dfE.head(10)

X0 = dfE.iloc[:,[0] ].values #AnimalName
X1 = dfE.iloc[:,[0,2] ].values #AnimalName, AnimalBirthYear
X2 = dfE.iloc[:,[0,2,7] ].values #AnimalName, AnimalBirthYear, Extract Year
X3 = dfE.iloc[:,[0,2,7] ].values #AnimalName, AnimalBirthYear, Extract year
X4 = dfE.iloc[:,[0,2,3] ].values #AnimalName, AnimalBirthYear, BreedName
X5 = dfE.iloc[:,[0,7] ].values #AnimalName, AnimalBirthYear
X6 = dfE.iloc[:,[0,7,3] ].values #AnimalName, Extract Year, BreedName
```

```
X7 = dfE.iloc[:,[0,7,3] ].values #AnimalName, Extract Year, BreedName
X8 = dfE.iloc[:,[0,7] ].values #AnimalName, Extract Year
X9 = dfE.iloc[:,[0,2,4,7] ].values #AnimalName, AnimalBirthYear, BreedName,␣
 ↪Extract Year
X10 = dfE.iloc[:,[0,2,4,7] ].values #AnimalName, AnimalBirthYear, BreedName,␣
 ↪Extract Year

stringX = ["1","1","1","1","1","1","1","1","1","1","1"]
stringX[0]= "AnimalName"
stringX[1]="AnimalName, AnimalBirthYear"
stringX[2]="AnimalName, AnimalBirthYear, Extract Year"
stringX[3]="AnimalName, AnimalBirthYear, Extract Year"
stringX[4]="AnimalName, AnimalBirthYear, BreedName"
stringX[5]="AnimalName, AnimalBirthYear"
stringX[6]="AnimalName, Extract Year, BreedName"
stringX[7]="AnimalName, Extract Year, BreedName"
stringX[8]="AnimalName, Extract Year"
stringX[9]="AnimalName, AnimalBirthYear, BreedName, Extract Year"
stringX[10]="AnimalName, AnimalBirthYear, BreedName, Extract Year"



#y is animal gender
y = dfE.iloc[:,[1]].values.ravel()

#y2 is breed for curiosity
y2 = dfE.iloc[:,[2]].values.ravel()
```

[14]:
```
dfE.head(10)
```

[14]:

	AnimalName	AnimalGender	AnimalBirthYear	BreedName	LicenseIssuedDate	\
0	19476	0	2014	44	1780	
1	28351	1	2010	196	1780	
2	462	1	2014	120	1780	
3	21233	0	2013	32	1780	
4	15038	0	2009	777	1780	
5	11448	1	2006	1316	1780	
6	3683	1	2008	1316	1780	
7	4986	0	2012	697	1780	
8	10884	0	2007	414	1788	
9	16253	1	2009	217	1788	

	LicenseExpiredDate	Extract Year	oldIndex	oldName
0	2936	2016	0	0
1	3166	2016	1	1
2	2938	2016	2	2
3	2936	2016	3	3

```
4                3243         2016         4         4
5                3486         2016         5         5
6                3370         2016         6         6
7                3157         2016         7         7
8                1227         2016         8         8
9                2992         2016         9         9
```

[15]:
```
dfConvert.head(10)
```

[15]:
```
  AnimalName AnimalGender  AnimalBirthYear  \
0      PAIGE            F             2014
1       YOGI            M             2010
2        ALI            M             2014
3      QUEEN            F             2013
4       LOLA            F             2009
5        IAN            M             2006
6      BUDDY            M             2008
7  CHEWBACCA            F             2012
8   HEIDI-BO            F             2007
9    MASSIMO            M             2009

                             BreedName LicenseIssuedDate LicenseExpiredDate  \
0  American Pit Bull Mix / Pit Bull Mix        09/12/2014         09/12/2017
1                                 Boxer        09/12/2014         10/02/2017
2                               Basenji        09/12/2014         09/12/2019
3                      Akita Crossbreed        09/12/2014         09/12/2017
4                               Maltese        09/12/2014         10/09/2017
5                               Unknown        09/12/2014         10/30/2019
6                               Unknown        09/12/2014         10/20/2017
7           Labrador Retriever Crossbreed        09/12/2014         10/01/2019
8                   Dachshund Smooth Coat        09/13/2014         04/16/2017
9                        Bull Dog, French        09/13/2014         09/17/2017

   Extract Year  oldIndex  oldName
0          2016         0        0
1          2016         1        1
2          2016         2        2
3          2016         3        3
4          2016         4        4
5          2016         5        5
6          2016         6        6
7          2016         7        7
8          2016         8        8
9          2016         9        9
```

[16]:
```
dfBaby.head(10)
```

[16]:

	Name	Gender	Count	Probability
0	James	M	5304407	0.014517
1	John	M	5260831	0.014398
2	Robert	M	4970386	0.013603
3	Michael	M	4579950	0.012534
4	William	M	4226608	0.011567
5	Mary	F	4169663	0.011411
6	David	M	3787547	0.010366
7	Joseph	M	2695970	0.007378
8	Richard	M	2638187	0.007220
9	Charles	M	2433540	0.006660

[17]:

```
dfE.index.value_counts().sum()
```

[17]: 490848

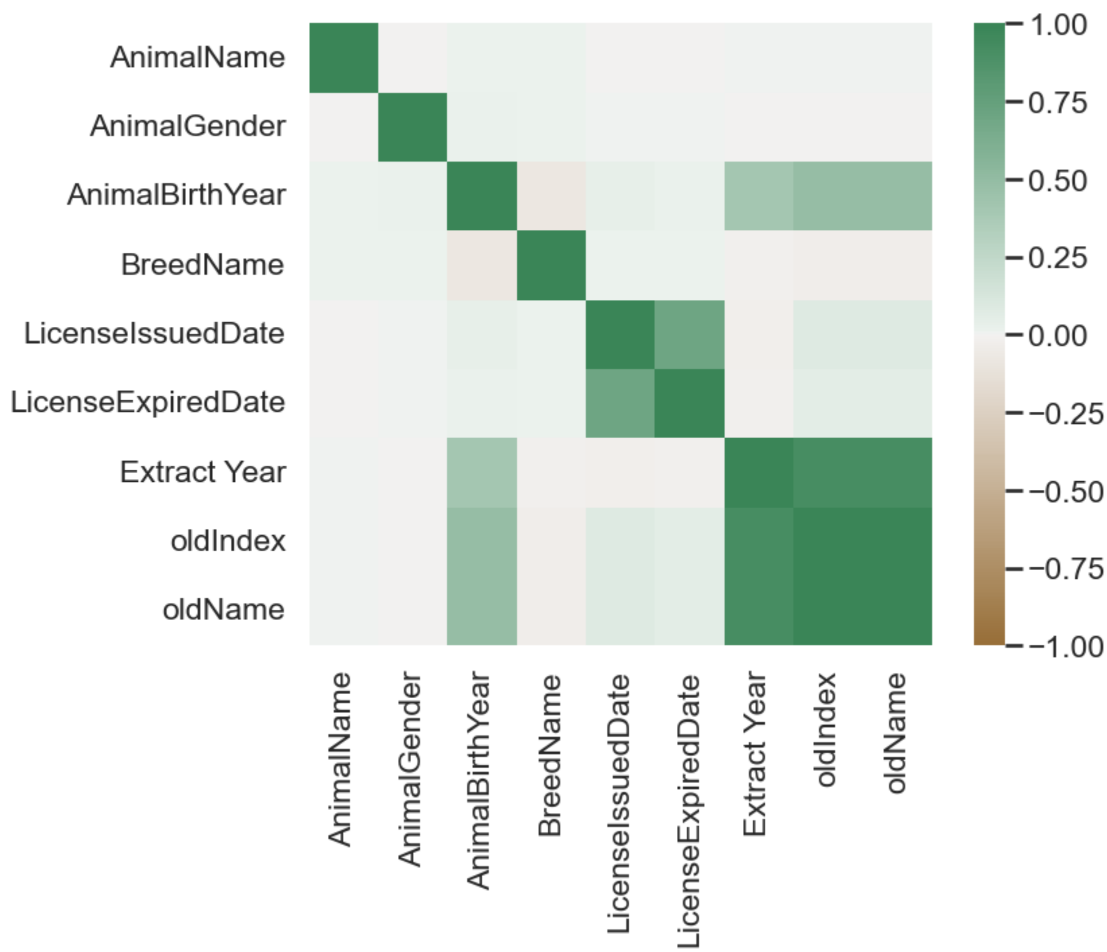
[18]:

```
dfBaby['Name'] = dfBaby['Name'].str.upper()
```

Convert to upper for baby names

[19]:

```
import matplotlib.pyplot as plt
import seaborn as sns

correlation_full_health = dfE.corr()

#cite https://seaborn.pydata.org/generated/seaborn.heatmap.html

axis_corr = sns.heatmap(
correlation_full_health,
vmin=-1, vmax=1, center=0,
cmap=sns.diverging_palette(50, 500, n=500),
square=True
)

plt.show()
```



[20]:
```
dfE.head(10)
```

[20]:
```
   AnimalName  AnimalGender  AnimalBirthYear  BreedName  LicenseIssuedDate  \
0       19476             0             2014         44               1780
1       28351             1             2010        196               1780
2         462             1             2014        120               1780
3       21233             0             2013         32               1780
4       15038             0             2009        777               1780
5       11448             1             2006       1316               1780
6        3683             1             2008       1316               1780
7        4986             0             2012        697               1780
8       10884             0             2007        414               1788
9       16253             1             2009        217               1788

   LicenseExpiredDate  Extract Year  oldIndex  oldName
0                2936          2016         0        0
1                3166          2016         1        1
```

2	2938	2016	2	2
3	2936	2016	3	3
4	3243	2016	4	4
5	3486	2016	5	5
6	3370	2016	6	6
7	3157	2016	7	7
8	1227	2016	8	8
9	2992	2016	9	9

[21]:

```
xTotal = [X0,X1,X2,X3,X4,X5,X6,X7,X8,X9,X10]
kTotal = [0 ,1 ,2 ,3 ,4 ,5 ,6 ,7 ,8 ,9 ,10]
neighborTotal = [0 , 0,0 ,0 ,0 ,0 ,0 ,0 ,0 ,0 ,0]

count = 0

results = ["1","1","1","1","1","1","1","1","1","1","1"]

for X in xTotal:

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25)

    scaler = StandardScaler()
    scaler.fit(X_train)
    X_train = scaler.transform(X_train)
    X_test = scaler.transform(X_test)

    for noK in range(1, 10):

        classifier = KNeighborsClassifier(n_neighbors = noK)
        classifier.fit(X_train, y_train)


        y_pred = classifier.predict(X_test)

        accuracy = accuracy_score(y_test,y_pred)

        if accuracy>neighborTotal[count]:
            neighborTotal[count]= accuracy

            kTotal[count] = noK


    results[count]= "Optimal Accuracy Score of␣
↪"+str(neighborTotal[count])+"Best K ("+str(kTotal[count])+")␣
↪"+str(stringX[count])
    count += 1
```

```
for result in results:
    print(result)
```

```
Optimal Accuracy Score of 0.8678042897190169Best K (5) AnimalName
Optimal Accuracy Score of 0.8675516656887672Best K (1) AnimalName,
AnimalBirthYear
Optimal Accuracy Score of 0.6420073016493905Best K (1) AnimalName,
AnimalBirthYear, Extract Year
Optimal Accuracy Score of 0.6423577156268335Best K (1) AnimalName,
AnimalBirthYear, Extract Year
Optimal Accuracy Score of 0.856036899406741Best K (1) AnimalName,
AnimalBirthYear, BreedName
Optimal Accuracy Score of 0.7034030901623313Best K (1) AnimalName,
AnimalBirthYear
Optimal Accuracy Score of 0.6287323163178825Best K (1) AnimalName, Extract Year,
BreedName
Optimal Accuracy Score of 0.6301095247408567Best K (1) AnimalName, Extract Year,
BreedName
Optimal Accuracy Score of 0.7047314036117087Best K (1) AnimalName, Extract Year
Optimal Accuracy Score of 0.5544771497490057Best K (7) AnimalName,
AnimalBirthYear, BreedName, Extract Year
Optimal Accuracy Score of 0.5546890279679249Best K (9) AnimalName,
AnimalBirthYear, BreedName, Extract Year
```

[22]:

```
xTotal = [X0,X1,X2,X3,X4,X5,X6,X7,X8,X9,X10]

count = 0

for X in xTotal:

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25)

    scaler = StandardScaler()
    scaler.fit(X_train)
    X_train = scaler.transform(X_train)
    X_test = scaler.transform(X_test)

    classifier = KNeighborsClassifier(n_neighbors = kTotal[count])
    classifier.fit(X_train, y_train)


    y_pred = classifier.predict(X_test)

    accuracy = accuracy_score(y_test,y_pred)

    print("Optimized Accuracy Score of "+str(count) + ": " +str(accuracy)+"␣
↪("+stringX[count]+")")
```

```
    count+=1
```

```
Optimized Accuracy Score of 0: 0.8636726644500945 (AnimalName)
Optimized Accuracy Score of 1: 0.8678450355303475 (AnimalName, AnimalBirthYear)
Optimized Accuracy Score of 2: 0.643963100593259 (AnimalName, AnimalBirthYear,
Extract Year)
Optimized Accuracy Score of 3: 0.6408990155811982 (AnimalName, AnimalBirthYear,
Extract Year)
Optimized Accuracy Score of 4: 0.8538366255948888 (AnimalName, AnimalBirthYear,
BreedName)
Optimized Accuracy Score of 5: 0.7048128952343699 (AnimalName, AnimalBirthYear)
Optimized Accuracy Score of 6: 0.6294575917595672 (AnimalName, Extract Year,
BreedName)
Optimized Accuracy Score of 7: 0.6326194667188213 (AnimalName, Extract Year,
BreedName)
Optimized Accuracy Score of 8: 0.7046743594758459 (AnimalName, Extract Year)
Optimized Accuracy Score of 9: 0.5543956581263446 (AnimalName, AnimalBirthYear,
BreedName, Extract Year)
Optimized Accuracy Score of 10: 0.5537437251450551 (AnimalName, AnimalBirthYear,
BreedName, Extract Year)
```

After finding the optimal predictors, we produce an accuracy score and classification report.

[23]:
```
X = X1

#Animal name animal birth year

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25)

scaler = StandardScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)

classifier = KNeighborsClassifier(n_neighbors = 1)
classifier.fit(X_train, y_train)


y_pred = classifier.predict(X_test)

print("accuracy_score:")
accuracy = accuracy_score(y_test,y_pred)
print(accuracy)
print(" ")
print("classification_report:")
classification = classification_report(y_test, y_pred)
print(classification)
```

```
accuracy_score:
0.8663374405111155

classification_report:
              precision    recall  f1-score   support

           0       0.86      0.85      0.85     56143
           1       0.88      0.88      0.88     66569

    accuracy                           0.87    122712
   macro avg       0.87      0.87      0.87    122712
weighted avg       0.87      0.87      0.87    122712
```

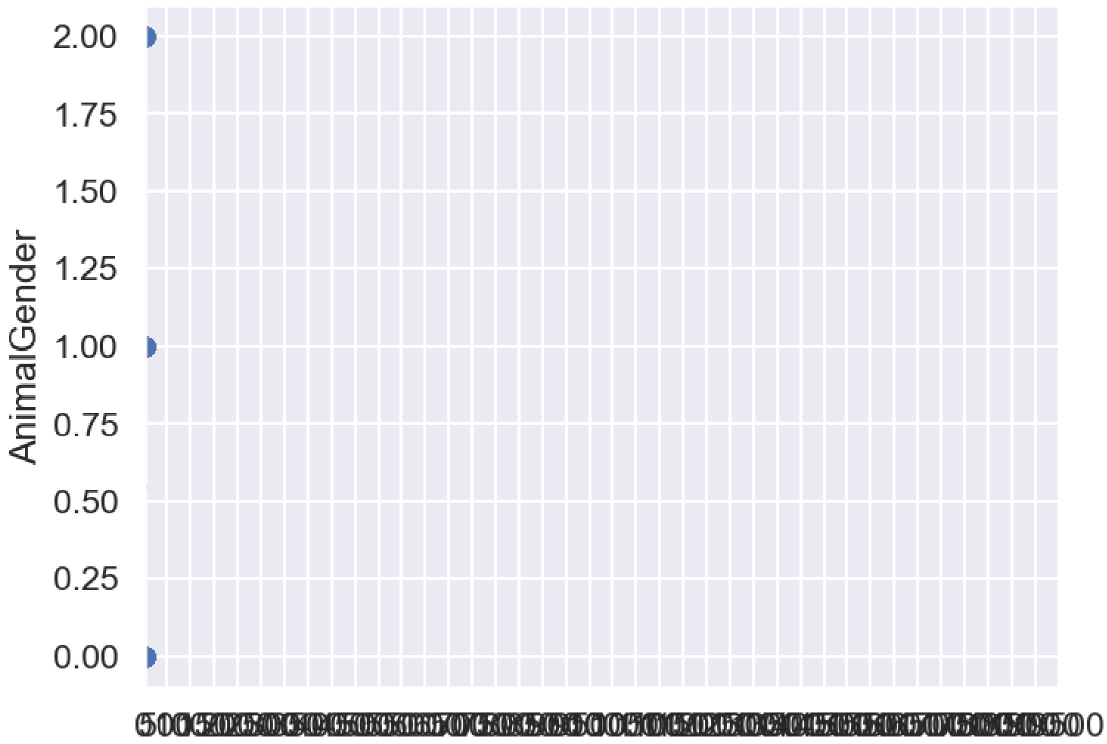
[24]:
```
df.head(10)
dfE.head(10)
```

[24]:
```
   AnimalName  AnimalGender  AnimalBirthYear  BreedName  LicenseIssuedDate  \
0       19476             0             2014         44               1780
1       28351             1             2010        196               1780
2         462             1             2014        120               1780
3       21233             0             2013         32               1780
4       15038             0             2009        777               1780
5       11448             1             2006       1316               1780
6        3683             1             2008       1316               1780
7        4986             0             2012        697               1780
8       10884             0             2007        414               1788
9       16253             1             2009        217               1788

   LicenseExpiredDate  Extract Year  oldIndex  oldName
0                2936          2016         0        0
1                3166          2016         1        1
2                2938          2016         2        2
3                2936          2016         3        3
4                3243          2016         4        4
5                3486          2016         5        5
6                3370          2016         6        6
7                3157          2016         7        7
8                1227          2016         8        8
9                2992          2016         9        9
```

[25]:
```
#get rid of strings
df = Encoder(df)

#drop infinites
df = df[np.isfinite(df).all(1)]
```

```
predictors = ['AnimalName', 'AnimalBirthYear']

target = 'AnimalGender'
X = df[predictors].values
y = df[target].values

#use random state 42 70/30 split
X_train, X_test, y_train, y_test=train_test_split(X,y,test_size=.
 ↪30,random_state=42)

#fit the linear model
regr=LinearRegression()
regr.fit(X_train, y_train)
#get prediction
predicted=regr.predict(X_test)

rmse=np.sqrt(((y_test - predicted)**2).mean())
print('RMSE 1: {:.2f}'.format(rmse))

length_of_first = len(df['AnimalName'])
#df['BreedName'].values.reshape((-1, length_of_first))
predicted.resize((length_of_first))

sns.regplot(x=predicted, y='AnimalGender', data=df)
plt.xticks(np.arange(0,20000,500))
plt.show()

df.info()
df.head(10)
```

```
RMSE 1: 0.50
```




```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 490869 entries, 0 to 508195
Data columns (total 7 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   AnimalName          490869 non-null  int64
 1   AnimalGender        490869 non-null  int64
 2   AnimalBirthYear     490869 non-null  int64
 3   BreedName           490869 non-null  int64
 4   LicenseIssuedDate   490869 non-null  int64
 5   LicenseExpiredDate  490869 non-null  int64
 6   Extract Year        490869 non-null  int64
dtypes: int64(7)
memory usage: 30.0 MB
```

[25]:

	AnimalName	AnimalGender	AnimalBirthYear	BreedName	LicenseIssuedDate	\
0	19476	0	2014	44	1780	
1	28351	1	2010	196	1780	
2	462	1	2014	120	1780	
3	21233	0	2013	32	1780	
4	15038	0	2009	777	1780	
5	11448	1	2006	1316	1780	
6	3683	1	2008	1316	1780	

```
7        4986              0             2012         697                1780
8       10884              0             2007         414                1788
9       16253              1             2009         217                1788

   LicenseExpiredDate  Extract Year
0                2936          2016
1                3166          2016
2                2938          2016
3                2936          2016
4                3243          2016
5                3486          2016
6                3370          2016
7                3157          2016
8                1227          2016
9                2992          2016
```

We'll have to figure out what the next steps are given that we have a horizontal line for our fit.

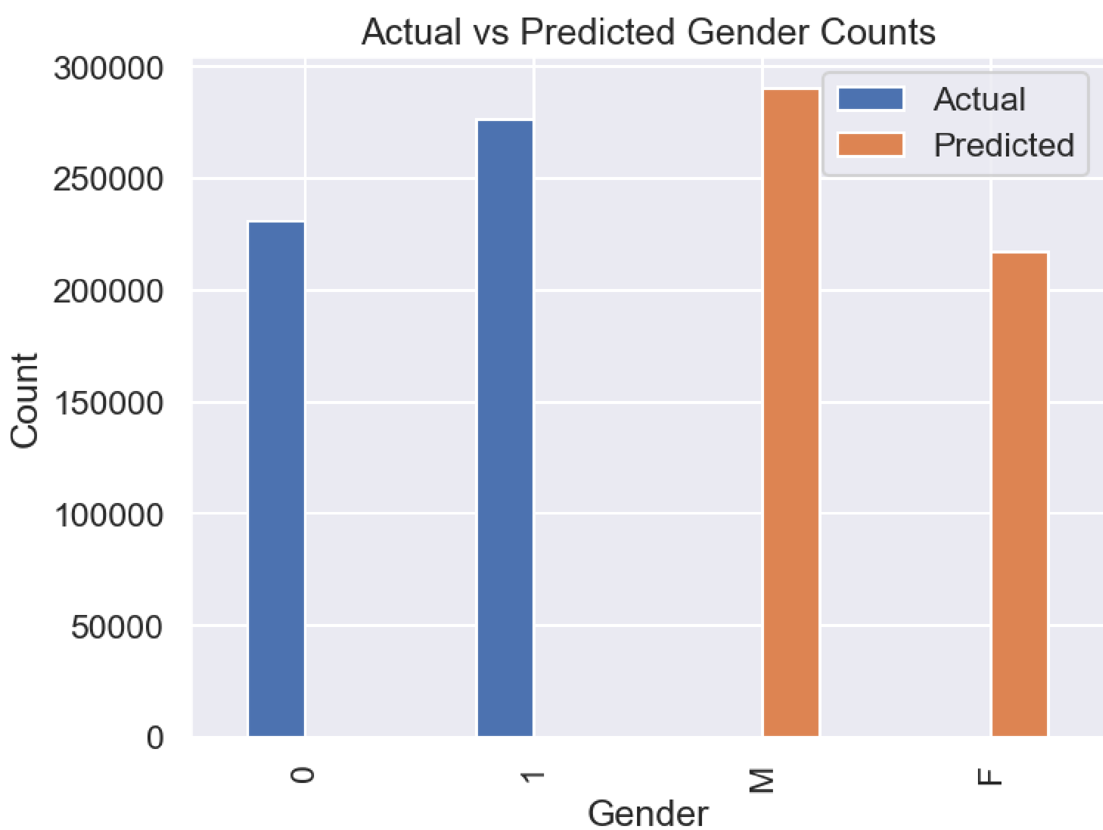
Code that makes a prediction of genders based of names using a decision tree. Then its plots the actual gender count to the predicted count if you think it would be good to add here it is but if not thats okay lol the code is kind of long tho

[26]:
```python
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt

# Load the data
df = pd.read_csv("http://dl.dropboxusercontent.com/s/0uzku9gb353n3nv/
 ↪NYC_Dog_Licensing_Dataset.csv")

# Filter out rows with NaN names and gender
df = df[['AnimalName', 'AnimalGender']].dropna()
df = df[df['AnimalGender'] != 'Unknown']

# Encode gender as numerical value
le = LabelEncoder()
df['AnimalGender'] = le.fit_transform(df['AnimalGender'])

# Split data into training and testing sets
train_size = int(len(df) * 0.8)
train_features = df['AnimalName'][:train_size]
train_labels = df['AnimalGender'][:train_size]
test_features = df['AnimalName'][train_size:]
test_labels = df['AnimalGender'][train_size:]

# Transform names to feature vectors using character frequency
char_freqs = {}
```

```
for name in train_features:
    for char in name:
        if char not in char_freqs:
            char_freqs[char] = 0
        char_freqs[char] += 1
char_freqs = {char: idx for idx, char in enumerate(sorted(char_freqs.keys()))}

train_feature_vectors = []
for name in train_features:
    freq_vec = [0] * len(char_freqs)
    for char in name:
        if char in char_freqs:
            freq_vec[char_freqs[char]] += 1
    train_feature_vectors.append(freq_vec)

test_feature_vectors = []
for name in test_features:
    freq_vec = [0] * len(char_freqs)
    for char in name:
        if char in char_freqs:
            freq_vec[char_freqs[char]] += 1
    test_feature_vectors.append(freq_vec)

# Train a decision tree classifier
clf = DecisionTreeClassifier()
clf.fit(train_feature_vectors, train_labels)

# Make predictions on the test set
predictions = clf.predict(test_feature_vectors)

# Calculate accuracy
accuracy = sum(predictions == test_labels) / len(test_labels)
print(f"Accuracy: {accuracy:.2f}")

# Predict genders for all names in the dataset
all_features = df['AnimalName']
all_feature_vectors = []
for name in all_features:
    freq_vec = [0] * len(char_freqs)
    for char in name:
        if char in char_freqs:
            freq_vec[char_freqs[char]] += 1
    all_feature_vectors.append(freq_vec)
all_predictions = clf.predict(all_feature_vectors)
predicted_genders = le.inverse_transform(all_predictions)

# Plot predicted gender distribution
```

```
gender_counts = df.groupby('AnimalGender').size()
predicted_gender_counts = pd.Series(predicted_genders).value_counts()
combined_counts = pd.concat([gender_counts, predicted_gender_counts], axis=1)
combined_counts.columns = ['Actual', 'Predicted']
combined_counts.plot(kind='bar')
plt.title('Actual vs Predicted Gender Counts')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()
```

```
Accuracy: 0.86
```



[27]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import LabelEncoder
import pandas as pd


# Filter out rows with NaN names and gender
df = df[['AnimalName', 'AnimalGender']].dropna()
df = df[df['AnimalGender'] != 'Unknown']

```

```
# Encode gender as numerical value
le = LabelEncoder()
df['AnimalGender'] = le.fit_transform(df['AnimalGender'])

# Transform names to feature vectors using character frequency
char_freqs = {}
for name in df['AnimalName']:
    for char in name:
        if char not in char_freqs:
            char_freqs[char] = 0
        char_freqs[char] += 1
char_freqs = {char: idx for idx, char in enumerate(sorted(char_freqs.keys()))}

feature_vectors = []
for name in df['AnimalName']:
    freq_vec = [0] * len(char_freqs)
    for char in name:
        if char in char_freqs:
            freq_vec[char_freqs[char]] += 1
    feature_vectors.append(freq_vec)

labels = df['AnimalGender']

# Split data into training and testing sets
train_size = int(len(df) * 0.8)
train_features = feature_vectors[:train_size]
train_labels = labels[:train_size]
test_features = feature_vectors[train_size:]
test_labels = labels[train_size:]

# Train and test the KNN classifier for different values of N
best_n = 0
best_accuracy = 0
for n in range(1, 21):
    clf = KNeighborsClassifier(n_neighbors=n)
    clf.fit(train_features, train_labels)
    predictions = clf.predict(test_features)
    accuracy = sum(predictions == test_labels) / len(test_labels)
    print(f"N={n}: Accuracy={accuracy:.2f}")
    if accuracy > best_accuracy:
        best_accuracy = accuracy
        best_n = n

# Print the optimal value of N
print(f"Optimal N: {best_n}")
```

```
---------------------------------------------------------------------------
```

```
KeyboardInterrupt                         Traceback (most recent call last)
/var/folders/95/nfpk8m1s6479lxrh28lnmvx40000gn/T/ipykernel_88010/1125926953.py␣
 ↪in <module>
     44     clf = KNeighborsClassifier(n_neighbors=n)
     45     clf.fit(train_features, train_labels)
---> 46     predictions = clf.predict(test_features)
     47     accuracy = sum(predictions == test_labels) / len(test_labels)
     48     print(f"N={n}: Accuracy={accuracy:.2f}")

~/opt/anaconda3/lib/python3.9/site-packages/sklearn/neighbors/_classification.p␣
 ↪in predict(self, X)
    212             Class labels for each data sample.
    213         """
--> 214         neigh_dist, neigh_ind = self.kneighbors(X)
    215         classes_ = self.classes_
    216         _y = self._y

~/opt/anaconda3/lib/python3.9/site-packages/sklearn/neighbors/_base.py in␣
 ↪kneighbors(self, X, n_neighbors, return_distance)
    750                 kwds = self.effective_metric_params_
    751
--> 752             chunked_results = list(

    753                 pairwise_distances_chunked(
    754                     X,

~/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/pairwise.py in␣
 ↪pairwise_distances_chunked(X, Y, reduce_func, metric, n_jobs, working_memory,␣
 ↪**kwds)
   1724         if reduce_func is not None:
   1725             chunk_size = D_chunk.shape[0]
-> 1726             D_chunk = reduce_func(D_chunk, sl.start)
   1727             _check_chunk_size(D_chunk, chunk_size)
   1728         yield D_chunk

~/opt/anaconda3/lib/python3.9/site-packages/sklearn/neighbors/_base.py in␣
 ↪_kneighbors_reduce_func(self, dist, start, n_neighbors, return_distance)
    632         """
    633         sample_range = np.arange(dist.shape[0])[:, None]
--> 634         neigh_ind = np.argpartition(dist, n_neighbors - 1, axis=1)
    635         neigh_ind = neigh_ind[:, :n_neighbors]
    636         # argpartition doesn't guarantee sorted order, so we sort again

<__array_function__ internals> in argpartition(*args, **kwargs)

~/opt/anaconda3/lib/python3.9/site-packages/numpy/core/fromnumeric.py in␣
 ↪argpartition(a, kth, axis, kind, order)
    837
```

```
    838     """
--> 839     return _wrapfunc(a, 'argpartition', kth, axis=axis, kind=kind,␣
 ↪order=order)
    840
    841

~/opt/anaconda3/lib/python3.9/site-packages/numpy/core/fromnumeric.py in␣
 ↪_wrapfunc(obj, method, *args, **kwds)
     55
     56     try:
---> 57         return bound(*args, **kwds)
     58     except TypeError:
     59         # A TypeError occurs if the object does have such a method in its

KeyboardInterrupt:
```

[ ]: