Import Necessary Libraries In [34]: import pandas as pd import seaborn as sns import numpy as np from sklearn.metrics import accuracy\_score from matplotlib import pyplot as plt from sklearn.model\_selection import train\_test\_split from sklearn.neighbors import KNeighborsClassifier from sklearn.model\_selection import cross\_val\_score Data collection In [3]: zoodata=pd.read\_csv('Zoo.csv') zoodata animal Out[3]: hair feathers eggs milk airborne aquatic predator toothed backbone bre name 0 aardvark 1 0 0 1 0 0 1 1 1 antelope 0 0 1 0 0 0 1 1 1 1 2 bass 0 0 1 0 0 1 1 1 1 3 1 0 0 1 0 0 1 1 1 bear 0 0 0 1 4 boar 1 0 1 1 1 96 wallaby 1 0 0 1 0 0 0 1 1 97 0 1 0 1 0 0 0 0 wasp 98 wolf 0 0 1 0 0 1 1 1 0 0 99 0 0 0 0 0 0 worm 1 100 wren 1 1 0 1 0 0 0 1 101 rows × 18 columns In [4]: zoodata.head() Out[4]: animal feathers eggs milk airborne aquatic predator toothed backbone breat name 0 0 1 1 1 0 aardvark 1 0 0 1 0 0 1 antelope 1 0 0 1 1 2 0 0 1 0 0 1 1 1 1 bass 3 0 0 0 0 1 bear 1 1 4 0 0 1 0 0 1 1 1 1 boar In [5]: zoodata.describe() Out[5]: hair feathers eggs milk airborne aquatic predator count 101.000000 101.000000 101.000000 101.000000 101.000000 101.000000 101.000000 0.425743 0.198020 0.405941 0.356436 mean 0.584158 0.237624 0.554455 0.496921 0.400495 0.495325 0.493522 0.427750 0.481335 0.499505 std min 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 25% 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 **75**% 1.000000 0.000000 1.000000 1.000000 0.000000 1.000000 1.000000 1.000000 1.000000 1.000000 max 1.000000 1.000000 1.000000 1.000000 In [10]: import warnings warnings.filterwarnings('ignore') In [11]: sns.factorplot('type', data=zoodata, kind="count", size = 5, aspect = 2) <seaborn.axisgrid.FacetGrid at 0x19ede65f430> 40 35 30 25 20 15 10 5 type In [14]: zoodata.plot(kind='density', subplots=True, layout=(4,5), figsize=(13,20), 2.00 eggs milk 175 75 1.0 1.0 .50 1.0 .50 125 0.8 0.8 0.8 25 100 0.6 .00 0.6 0.6 d.75 0.4 0.4 50 0.2 0.2 0.2 d.25 .25 0.0 1.4 7.00 predator 1.2 toothed breathes 2.0 175 1.2 1.0 1.0 150 1.0 0.8 1.5 0.8 25 0.8 0.0 0.0 Density 0.6 100 backbone 0.6 1.0 d.75 0.4 0.4 0.4 0.50 0.5 0.2 0.2 0.2 0.25 0.0 0.0 0.0 0.0 fins 0.200 3.5 tail domestic 2.5 2.0 0.175 3.0 1.50 0.150 2.0 2.5 125 1.5 0.125 2.0 2.5 2.5 .00 1.5 0.100 1.0 0.75 0.075 1.0 1.0 **d**.50 0.050 0.5 0.5 0.5 catsize 0.25 type 1.0 .20 Density 9.0 .10 0.4 .05 0.2 0.0 In [15]: zoodata.plot(kind='box', subplots=True, layout=(4,5), figsize=(13,20), sha plt.show() 0.8 0.8 0.8 0.8 0.8 0.6 0.6 0.6 0.6 0.6 0.4 0.4 0.4 0.4 0.2 0.2 0.2 0.2 0.2 0.0 0.0 0.0 0.0 0.0 feathers eggs milk airborne 1.0 1.0 1.0 1.0 1.0 0.8 0.6 0.6 0.6 0.6 0.6 0.4 0.4 0.4 0.4 0.4 0.2 0.2 0.2 0.2 0.2 0.0 0.0 0.0 aquatic predator toothed backbone breathes 1.0 1.0 8 1.0 1.0 7 0.8 0.8 0.8 0.8 6 0.6 0.6 0.4 0.4 0.4 0.2 0.2 0.2 0.2 1 0.0 0.0 0.0 0.8 0.6 0.2 2 0.0 catsize Finding correlation between the variables in data In [16]: cor = zoodata.corr(method='pearson') In [17]: cor.style.background\_gradient(cmap='coolwarm') Out[17]: hair feathers eggs milk airborne aquatic predator tooth 1.000000 -0.427851 -0.817382 0.878503 -0.198431 -0.473554 -0.154769 0.4925 hair feathers -0.427851 1.000000 0.419248 -0.410761 0.656553 -0.058552 -0.104430 -0.6136 -0.817382 -0.938848 0.376646 0.419248 1.000000 0.376244 0.011605 -0.6421 eggs milk 0.878503 -0.410761 -0.938848 1.000000 -0.366765 -0.362613 -0.029721 0.6281 airborne -0.198431 0.656553 -0.366765 1.000000 -0.172638 -0.295181 -0.5943 0.376646 aquatic -0.473554 -0.058552 0.376244 -0.362613 -0.172638 1.000000 0.375978 0.0531 0.1294 -0.104430 -0.295181 -0.154769 0.011605 -0.029721 0.375978 1.000000 predator toothed 0.492531 -0.613631 -0.642150 0.628168 -0.594311 0.053150 0.129452 1.0000 0.5750 backbone -0.340420 -0.104718 0.022463 0.051022 0.191681 0.231403 0.384958 breathes 0.441149 0.254588 -0.382777 0.423527 0.286039 -0.637506 -0.262931 -0.0656 -0.104245 venomous -0.145739 0.098689 -0.242449 0.008528 0.087915 0.115391 -0.0623 fins -0.280313 -0.223541 0.164796 -0.156328 -0.251157 0.604492 0.190302 0.3642 -0.360638 -0.099723 0.394009 -0.206686 -0.224918 0.214196 0.043712 -0.1934 legs -0.221090 0.3103 tail 0.048973 0.292569 0.210026 0.009482 -0.034642 0.018947 domestic 0.031586 -0.155610 0.163928 0.063274 -0.224308 -0.309794 0.0694 0.207208 -0.349768 catsize 0.455020 -0.135934 -0.514650 0.574906 -0.111866 0.144790 0.3440 -0.562384 0.661825 -0.197520 -0.723683 0.022677 0.061179 -0.4715 0.326639 type KNN Finding optimal number of K In [18]: X = zoodata.iloc[:,1:17]y = zoodata.iloc[:,17] In [21]: X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, r In [23]:  $k_values = np.arange(1, 25)$  $train_accuracy = []$ test\_accuracy = [] In [26]: for i, k in enumerate(k\_values): knn = KNeighborsClassifier(n\_neighbors=k) knn.fit(X\_train,y\_train) train\_accuracy.append(knn.score(X\_train, y\_train)) test\_accuracy.append(knn.score(X\_test, y\_test)) In [28]: plt.figure(figsize=[13,8]) plt.plot(k\_values, test\_accuracy, label = 'Testing Accuracy') plt.plot(k\_values, train\_accuracy, label = 'Training Accuracy') plt.legend() plt.title('-value VS Accuracy') plt.xlabel('Number of Neighbors') plt.ylabel('Accuracy') plt.xticks(k\_values) plt.show() -value VS Accuracy Testing Accuracy 1.00 Training Accuracy 0.95 0.90 0.85 0.80 0.75 0.70 16 10 12 13 14 Applying the algorithm In [29]: knn = KNeighborsClassifier(n\_neighbors=5) In [30]: knn.fit(X\_train, y\_train) y\_pred\_KNeighborsClassifier = knn.predict(X\_test) In [31]: scores = [] cv\_scores = [] In [32]: score = accuracy\_score(y\_pred\_KNeighborsClassifier,y\_test) scores.append(score) In [35]: score\_knn=cross\_val\_score(knn, X,y, cv=10) In [36]: score\_knn.mean() Out[36]: 0.8809090909090909 In [37]: score\_knn.std()\*2 0.12072782037115655Out[37]: In [38]: cv\_score = score\_knn.mean() In [39]: cv\_scores.append(cv\_score) In [40]: cv\_scores Out[40]: [0.8809090909090909] In [ ]: