7020466-TanShuFei-A2-Task1

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0.0.1 CSCI 316 - A2 Individual Task 1- 23/02/2022

- Implement a Naïve Bayesian classifier to predict the age of abalone in Python from scratch.

0.1 1. Import Libaries

[2]:
```python
# Import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
sns.set(style="whitegrid")
```

0.2 2. Import Abalone Dataset

[3]:
```python
# Column name of each header
colsName = ['Sex', 'Length', 'Diameter', 'Height', 'Whole weight',
            'Shucked weight', 'Vescera weight', 'Shell weight',
            'Rings']

# Read in data from .data file
adf = pd.read_csv('./abalone.data',sep=',',names=colsName)

# Display data
adf.head()
```

[3]:
```
  Sex  Length  Diameter  Height  Whole weight  Shucked weight  Vescera weight  \
0   M   0.455     0.365   0.095        0.5140          0.2245          0.1010
1   M   0.350     0.265   0.090        0.2255          0.0995          0.0485
2   F   0.530     0.420   0.135        0.6770          0.2565          0.1415
3   M   0.440     0.365   0.125        0.5160          0.2155          0.1140
4   I   0.330     0.255   0.080        0.2050          0.0895          0.0395

   Shell weight  Rings
0         0.150     15
```

```
1          0.070      7
2          0.210      9
3          0.155     10
4          0.055      7
```

[4]:
```
adf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4177 entries, 0 to 4176
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Sex             4177 non-null   object
 1   Length          4177 non-null   float64
 2   Diameter        4177 non-null   float64
 3   Height          4177 non-null   float64
 4   Whole weight    4177 non-null   float64
 5   Shucked weight  4177 non-null   float64
 6   Vescera weight  4177 non-null   float64
 7   Shell weight    4177 non-null   float64
 8   Rings           4177 non-null   int64
dtypes: float64(7), int64(1), object(1)
memory usage: 293.8+ KB
```

0.3 3. Create a new column called 'Age'

Judging an abalone's age using the Rings column: - less than 6 rings: $<$ 7.5 years old = 'young' - 6 to 13 rings: 7.5 to 14.5 years old = 'adult' - more than 13 rings: $>$ 14.5 years old = 'old'

[6]:
```
# create a list of conditions
conditions = [
    (adf['Rings'] >= 1) & (adf['Rings'] <= 5),
    (adf['Rings'] >= 6) & (adf['Rings'] <= 13),
    (adf['Rings'] >= 14) & (adf['Rings'] <= 30)]

# create a list of the values we want to assign for each condition
values = ['Young', 'Adult', 'Old']

# create column name and select condition + values
adf['Age'] = np.select(conditions, values)

# Display data
adf.head() # Age column added successfully
```

[6]:
```
  Sex  Length  Diameter  Height  Whole weight  Shucked weight  Vescera weight  \
0   M   0.455     0.365   0.095        0.5140          0.2245          0.1010
1   M   0.350     0.265   0.090        0.2255          0.0995          0.0485
2   F   0.530     0.420   0.135        0.6770          0.2565          0.1415
```

```
3   M   0.440    0.365   0.125       0.5160         0.2155         0.1140
4   I   0.330    0.255   0.080       0.2050         0.0895         0.0395

   Shell weight  Rings    Age
0         0.150     15    Old
1         0.070      7  Adult
2         0.210      9  Adult
3         0.155     10  Adult
4         0.055      7  Adult
```

- Age column with ‘Young’ ‘Adult & ’Old’ successfully added to database

0.3.1 Data in ‘Age’

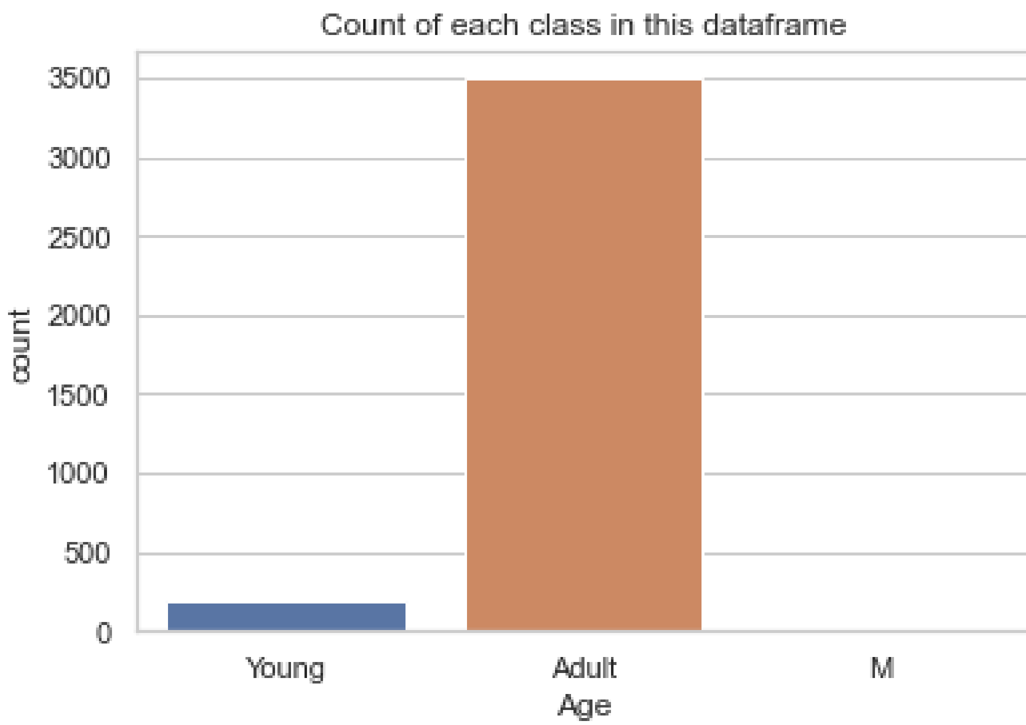
[7]:
```
# Show the total number of each cover types in this dataframe
print(adf.groupby('Age').size())
```

```
Age
Adult    3498
Old       490
Young     189
dtype: int64
```

0.3.2 Visualize ‘Age’

[8]:
```
# visualize the count of each 'Cover_Type' in this dataframe
plt.title('Count of each class in this dataframe')
sns.set_style('whitegrid')
sns.countplot(x=adf['Age'], order= ['Young','Adult','M'])

plt.show()
```



- There's significantly more Adult abalones than the rest of the age

---

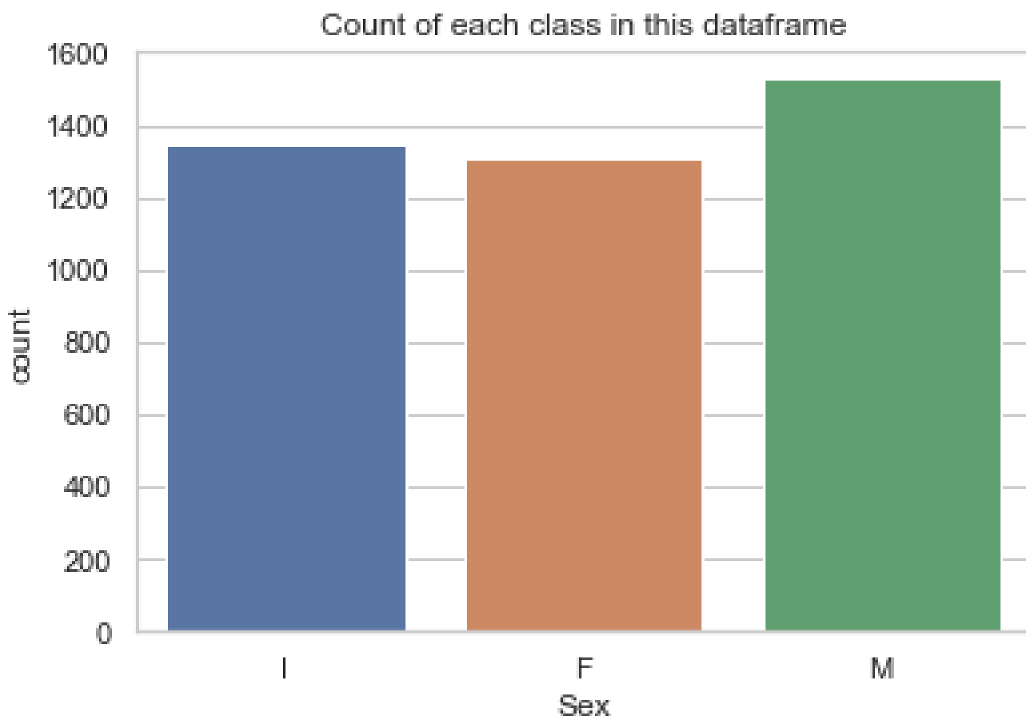
0.4 4. Encode Column 'Age' To dtype int64

[9]:
```python
# show the total number of each cover types in this dataframe
adf.groupby('Sex').size()
```

[9]:
```
Sex
F    1307
I    1342
M    1528
dtype: int64
```

[10]:
```python
# visualize the count of each 'Cover_Type' in this dataframe
plt.title('Count of each class in this dataframe')
sns.set_style('whitegrid')
sns.countplot(x=adf['Sex'], order= ['I','F','M'])

plt.show()
```



- Amount of Males abalones is the highest at 1528
- Female & Infant abalones are almost the same amount

- Encode Sex column to int64 for easier processing

[11]:
```
# Encode Sex column
encode_data = {"Sex":{"I":1, "F":2, "M":3}}
adf = adf.replace(encode_data)
adf
```

[11]:
```
      Sex  Length  Diameter  Height  Whole weight  Shucked weight  \
0       3   0.455     0.365   0.095        0.5140          0.2245
1       3   0.350     0.265   0.090        0.2255          0.0995
2       2   0.530     0.420   0.135        0.6770          0.2565
3       3   0.440     0.365   0.125        0.5160          0.2155
4       1   0.330     0.255   0.080        0.2050          0.0895
…     …     …       …      …          …              …
4172    2   0.565     0.450   0.165        0.8870          0.3700
4173    3   0.590     0.440   0.135        0.9660          0.4390
4174    3   0.600     0.475   0.205        1.1760          0.5255
4175    2   0.625     0.485   0.150        1.0945          0.5310
4176    3   0.710     0.555   0.195        1.9485          0.9455

      Vescera weight  Shell weight  Rings    Age
```

```
0             0.1010        0.1500     15    Old
1             0.0485        0.0700      7  Adult
2             0.1415        0.2100      9  Adult
3             0.1140        0.1550     10  Adult
4             0.0395        0.0550      7  Adult
…              …             …    …     …
4172          0.2390        0.2490     11  Adult
4173          0.2145        0.2605     10  Adult
4174          0.2875        0.3080      9  Adult
4175          0.2610        0.2960     10  Adult
4176          0.3765        0.4950     12  Adult

[4177 rows x 10 columns]
```

[12]:
```python
adf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4177 entries, 0 to 4176
Data columns (total 10 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Sex             4177 non-null   int64
 1   Length          4177 non-null   float64
 2   Diameter        4177 non-null   float64
 3   Height          4177 non-null   float64
 4   Whole weight    4177 non-null   float64
 5   Shucked weight  4177 non-null   float64
 6   Vescera weight  4177 non-null   float64
 7   Shell weight    4177 non-null   float64
 8   Rings           4177 non-null   int64
 9   Age             4177 non-null   object
dtypes: float64(7), int64(2), object(1)
memory usage: 326.5+ KB
```

0.5 5. Check for NULL, empty or zero values in dataset

0.5.1 Number of NULL in each dataset

[9]:
```python
# Check each columns for how many null data
print("Missing values for each column:\n")
print(adf.isnull().sum())
```

```
Missing values for each column:

Sex               0
Length            0
Diameter          0
```

```
Height            0
Whole weight      0
Shucked weight    0
Vescera weight    0
Shell weight      0
Rings             0
Age               0
dtype: int64
```

0.5.2 Number of non-zeros in each column

[10]:
```python
adf.astype(bool).sum(axis=0)
```

[10]:
```
Sex               4177
Length            4177
Diameter          4177
Height            4175
Whole weight      4177
Shucked weight    4177
Vescera weight    4177
Shell weight      4177
Rings             4177
Age               4177
dtype: int64
```

- Column 'Height' contains 4175 / 4177 value.
- Hence there's 2 values that is zeros in the dataset.

0.5.3 Replace zeros values in 'Height' cols to mean

[11]:
```python
adf['Height'] = adf['Height'].replace(0, adf['Height'].mean())
```

0.5.4 All data have equal numer of dataset now

[12]:
```python
# Check again.
# Height is now int 4177
adf.astype(bool).sum(axis=0)
```

[12]:
```
Sex               4177
Length            4177
Diameter          4177
Height            4177
Whole weight      4177
Shucked weight    4177
Vescera weight    4177
Shell weight      4177
Rings             4177
```

```
Age                4177
dtype: int64
```

[13]:
```
adf.head()
```

[13]:
```
   Sex  Length  Diameter  Height  Whole weight  Shucked weight  \
0    3   0.455     0.365   0.095        0.5140          0.2245
1    3   0.350     0.265   0.090        0.2255          0.0995
2    2   0.530     0.420   0.135        0.6770          0.2565
3    3   0.440     0.365   0.125        0.5160          0.2155
4    1   0.330     0.255   0.080        0.2050          0.0895

   Vescera weight  Shell weight  Rings    Age
0          0.1010         0.150     15    Old
1          0.0485         0.070      7  Adult
2          0.1415         0.210      9  Adult
3          0.1140         0.155     10  Adult
4          0.0395         0.055      7  Adult
```

0.6 6. Randomize Dataset

[14]:
```
# Set reset_index drop to True to prevent creating a new cols
# with old index entries
adf = adf.sample(frac=1).reset_index(drop=True)
adf.head()
```

[14]:
```
   Sex  Length  Diameter  Height  Whole weight  Shucked weight  \
0    3   0.415     0.345   0.135        0.3865           0.128
1    2   0.530     0.425   0.130        0.7585           0.325
2    2   0.470     0.365   0.120        0.5820           0.290
3    2   0.560     0.455   0.125        0.9430           0.344
4    2   0.680     0.570   0.205        1.8420           0.625

   Vescera weight  Shell weight  Rings    Age
0           0.070         0.148     13  Adult
1           0.197         0.205      8  Adult
2           0.092         0.146      8  Adult
3           0.129         0.375     21    Old
4           0.408         0.650     20    Old
```

0.7 7. Naives Bayes Classifier Function From Scratch

[15]:
```python
# Bayes Theorem form
# P(y|X) = P(X|y) * P(y) / P(X)

class NaiveBayesClassifier():
    #-----------------------------------------
    # Constructor
    def fit(self, features, target):
        self.classes = np.unique(target)
        self.count = len(self.classes)
        self.feature_nums = features.shape[1]
        self.rows = features.shape[0]
        self.calc_prior(features, target)
        self.calc_statistics(features, target)
    #-----------------------------------------
    # Calculate mean, variance for each column & convert to numpy array
    def calc_statistics(self, features, target):
        self.mean = features.groupby(target).apply(np.mean).to_numpy()
        self.var = features.groupby(target).apply(np.var).to_numpy()
        return self.mean, self.var
    #-----------------------------------------
    # Density function of the normal distribution
    def gaussian_density(self, class_idx, x):
        '''
        Calculate probability from gaussian density func.
        Assume probability of specific target & class is normally distributed

        Probability density function:
        (1/√2pi* ) * exp((-1/2)*((x- )^2)/(2* ²)),
        where  =mean,  ²=variance,  =sqrt of variance(SD)
        '''
        mean = self.mean[class_idx]
        var = self.var[class_idx]

        numerator = np.exp( (-1/2) * ((x - mean)**2) / (2 * var) )
        denominator = np.sqrt(2 * np.pi * var)
        prob = numerator / denominator

        return prob
    #-----------------------------------------
    # Prior probability P(y)
    # Calculate prior probabilities
    def calc_prior(self, features, target):
        self.prior = (features.groupby(target).apply(lambda x:len(x)) / self.
↪rows).to_numpy()
        return self.prior
```

```
    #-------------------------------------
    # Calculate posterior probability for each class
    def calc_posterior(self, x):
        posteriors = []

        for i in range(self.count): # From i to 3
            # use log to make it more numerically stable
            prior = np.log(self.prior[i])
            # use log to make it more numerically stable
            conditional = np.sum(np.log(self.gaussian_density(i, x)))
            posterior = prior + conditional
            posteriors.append(posterior)

        # return class with highest posterior probability
        return self.classes[np.argmax(posteriors)]
    #-------------------------------------
    # Calculate prediction
    def predict(self, features):
        preds = [self.calc_posterior(f) for f in features.to_numpy()]
        return preds
    #-------------------------------------
    # Calculate accuracy after getting prediction
    def accuracy(self, y_test, y_pred):
        accuracy = np.sum(y_test == y_pred) / len(y_test)
        return accuracy
    #-------------------------------------
    # Display data
    def visualize(self, y_true, y_pred, target):

        fig, ax = plt.subplots(1, 2, figsize=(13,5))
        fig.suptitle('True vs Predicted Comparison\n\n', fontsize=20)

        tr = pd.DataFrame(data=y_true, columns=[target])
        pr = pd.DataFrame(data=y_pred, columns=[target])

        plot1=sns.countplot(x=target, data=tr, ax=ax[0],␣
↪palette='coolwarm',alpha=0.7)
        plot2=sns.countplot(x=target, data=pr, ax=ax[1],␣
↪palette='coolwarm',alpha=0.7)

        ax[0].tick_params(labelsize=12)
        ax[1].tick_params(labelsize=12)

        ax[0].set_title("True values", fontsize=18)
        ax[1].set_title("Predicted values", fontsize=18)

        ax[0].set_ylim([0,1100])
```

```
    ax[1].set_ylim([0,1100])

    plt.show()
#-----------------------------------------
```

0.8 8. Split Data Into 70% Training & 30% Test

[16]:
```
# Set features and target
# X stores everything else except 'Age', Y stores 'Age'
X, y = adf.iloc[:, :-1], adf.iloc[:, -1]

# Randomize data
arr_rand = np.random.rand(X.shape[0]) # Random float
split = arr_rand < np.percentile(arr_rand, 70) # Returns bool

# Declare x & y training and testing set
X_train = X[split]
y_train = y[split]

X_test =  X[~split]
y_test = y[~split]

# Display int in train & test after split
print("X_train y_train: ",X_train.shape, y_train.shape)
print("X_test y_test: ", X_test.shape, y_test.shape)
```

```
X_train y_train:  (2924, 9) (2924,)
X_test y_test:  (1253, 9) (1253,)
```

[17]:
```
# Build the Naives Bayes classifier object
x = NaiveBayesClassifier()

# Use naive bayes model to fit training data
x.fit(X_train, y_train)

# Generate predicted classes for test data
# Stores 'Young', 'Adult', 'Old' from test data
predictions = x.predict(X_test)
```

```
/Users/tanshufei/opt/anaconda3/envs/py36-test/lib/python3.9/site-
packages/numpy/core/fromnumeric.py:3438: FutureWarning: In a future version,
DataFrame.mean(axis=None) will return a scalar mean over the entire DataFrame.
To retain the old behavior, use 'frame.mean(axis=0)' or just 'frame.mean()'
  return mean(axis=axis, dtype=dtype, out=out, **kwargs)
```

0.9 9. Create a Dummy Classifier for Comparison (Optional)

- DummyClassifier makes predictions that ignore the input features.
- Makes predictions without trying to find patterns in the data.
- Looks at what label is most frequent in the training dataset and makes predictions based on that label.

[18]:
```
# Import library
from sklearn.dummy import DummyClassifier

# Build a 'dummy' classifier for comparison
# Establish random_state for reproducibility
dummy = DummyClassifier(random_state=1)
#dummy = DummyClassifier(strategy='stratified')

# Fit with X_train y_train:  (2924, 9) (2924,)
dumb = dummy.fit(X_train, y_train)

# Perform classification on X_test
dumb_pred = dumb.predict(X_test)

# Return probability estimates for the X_test
dumb_pred_prob = dumb.predict_proba(X_test)
```

0.10 10. Naives Bayes Classifier VS Dummy Classifier Accuracy

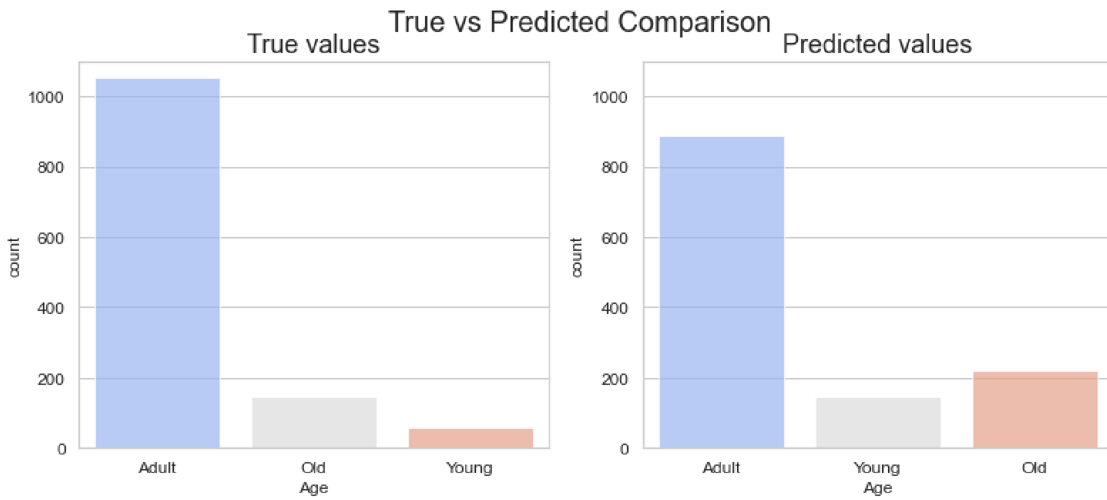
[19]:
```
# Compare the results from y_test and X_test
# Returns accuracy in percentage
print("Accuracy (Naives Bayes Classifier) : ", x.accuracy(y_test, predictions))
print("Accuracy %: ", "%.2f" % ((x.accuracy(y_test, predictions))  * 100), "%")
print()
print("Accuracy (Dummy Classifier): ",dumb.score(dumb_pred, y_test))
print("Accuracy %: ", "%.2f" % ((dumb.score(dumb_pred, y_test))  * 100), "%")
```

```
Accuracy (Naives Bayes Classifier) :  0.8411811652035116
Accuracy %:  84.12 %

Accuracy (Dummy Classifier):  0.839584996009577
Accuracy %:  83.96 %
```

0.10.1 Side-By-Side Comparison

[20]:
```
x.visualize(y_test, predictions, 'Age')
```



- The adult for true values is almost 150 more than the predicted values.
- The Old age for the predicted values is also almost approximately 35 more for the predicted values.
- The Young value varies the highest as the true values is approximately 75 and 175 for the Young in the predicted values.

0.10.2 Naive Bayes Break-Down for Test Values

[21]:
```
# Break down of y_test's 1253 data after split
print("Naive Bayes y_test Class Counts:")
print(y_test.value_counts(), end="\n\n")

print("Naive Bayes y_test Class Proportions:")
print(y_test.value_counts()/len(y_test))
```

```
Naive Bayes y_test Class Counts:
Adult    1052
Old       145
Young      56
Name: Age, dtype: int64

Naive Bayes y_test Class Proportions:
Adult    0.839585
Old      0.115722
Young    0.044693
Name: Age, dtype: float64
```

0.10.3 Naive Bayes Break-Down for Train Values

[22]:
```
# Break down of y_train's 2924 data after split
print("Naive Bayes y_Train Class Counts:")
print(y_train.value_counts(), end="\n\n")

print("Naive Bayes y_Train Class Proportions:")
print(y_train.value_counts(normalize=True), end="\n\n")
```

```
Naive Bayes y_Train Class Counts:
Adult    2446
Old       345
Young     133
Name: Age, dtype: int64

Naive Bayes y_Train Class Proportions:
Adult    0.836525
Old      0.117989
Young    0.045486
Name: Age, dtype: float64
```

0.11 11. Naives Bayes Classifier VS Dummy Classifier Confustion Matrix

0.11.1 Dummy Classifier

[23]:
```
# Import libraries
import sklearn
from sklearn.metrics import *
```

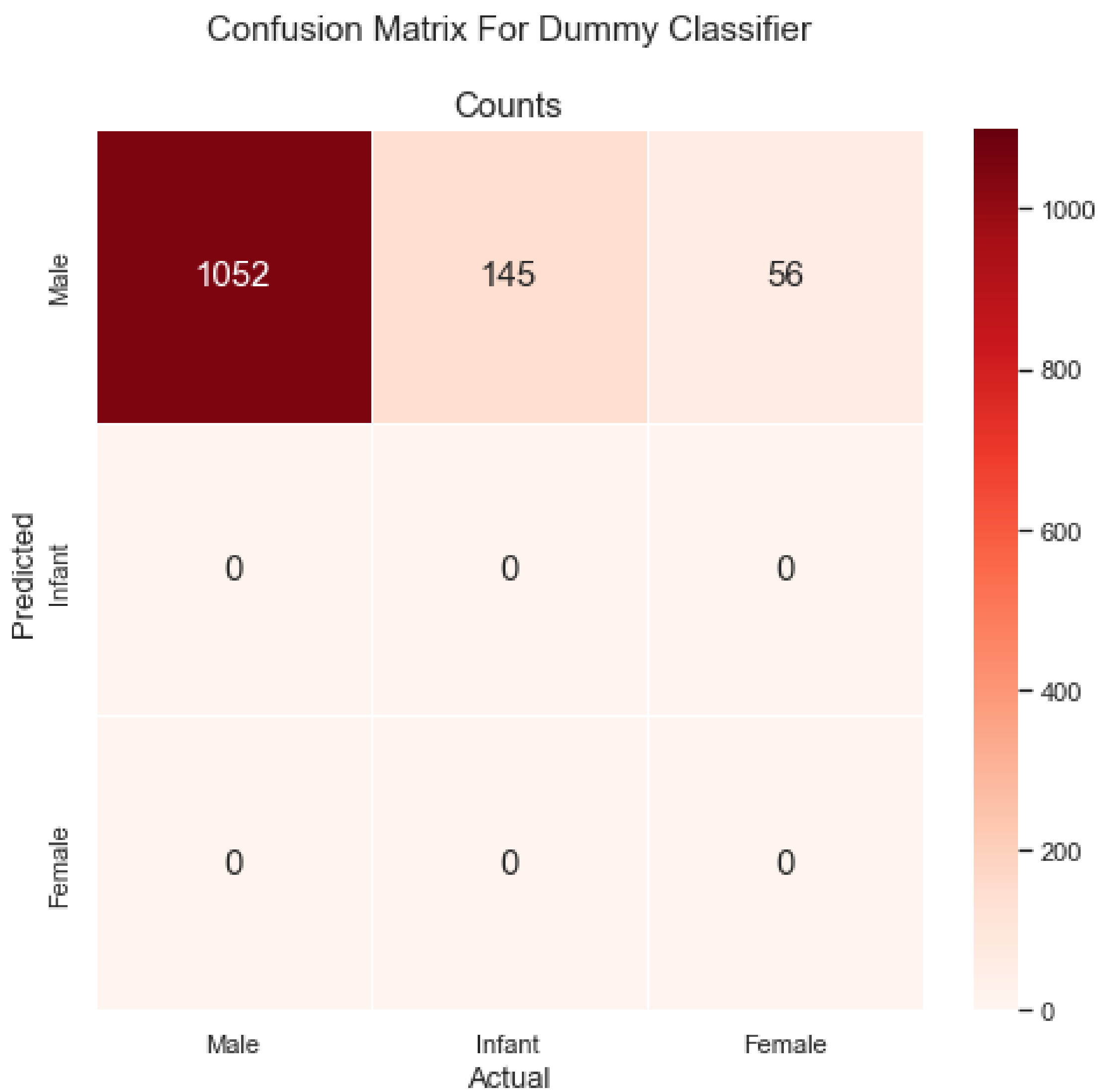
[24]:
```
cm_dummy = confusion_matrix(y_test, dumb_pred)
cm_dummy_df = pd.DataFrame(cm_dummy)

fig,ax = plt.subplots(figsize=(8,7))
sns.heatmap(cm_dummy_df.T, annot=True, annot_kws={'size':15}, cmap='Reds',
           vmin=0, vmax=1100, fmt='.0f',␣
 ↪linewidths=1,linecolor='white',cbar=True,
           ␣
 ↪xticklabels=['Male','Infant','Female'],yticklabels=['Male','Infant','Female'])
plt.ylabel('Predicted', fontsize=13)
plt.xlabel('Actual', fontsize=13)

ax.set_xticklabels(['Male','Infant','Female'], fontsize=11)
ax.set_yticklabels(['Male','Infant','Female'], fontsize=11)

plt.title('Confusion Matrix For Dummy Classifier\n\nCounts', fontsize=15)
```

```
plt.show()
```



- Large bulk of data is coming from Adult, mostly Males to be true-positive.
- Infants and Female is incorrectly identified

0.11.2 Number of data in each category

[25]:
```
y_train.value_counts(normalize=True)
```

[25]:
```
Adult    0.836525
Old      0.117989
Young    0.045486
Name: Age, dtype: float64
```

- dummy classifier seems to be classifying the bulk of our data as Males.
- We have a lot more Adults as compared to Young and Old.
- So the dummy classifier is predicting more Adults, Males in general to Young & Old.

0.11.3 Naive Bayes Classifier

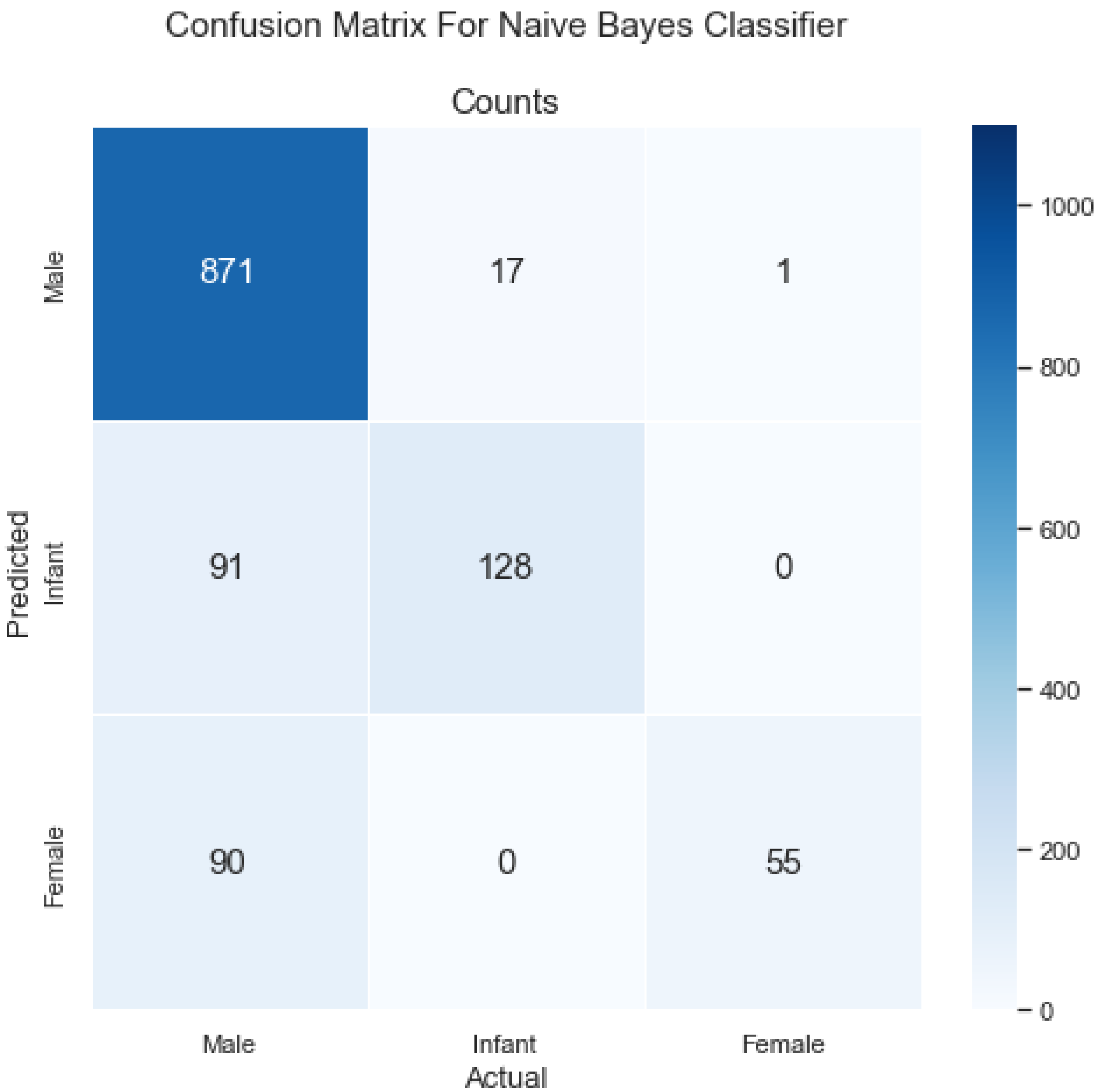
[26]:
```
import sklearn
from sklearn.metrics import *
```

[27]:
```
cm_naive = confusion_matrix(y_test, predictions)
cm_naive_df = pd.DataFrame(cm_naive)

fig,ax = plt.subplots(figsize=(8,7))
sns.heatmap(cm_naive_df.T, annot=True, annot_kws={'size':15}, cmap='Blues',
           vmin=0, vmax=1100, fmt='.0f',␣
 ↪linewidths=1,linecolor='white',cbar=True,
                                             ␣
 ↪xticklabels=['Male','Infant','Female'],yticklabels=['Male','Infant','Female'])
plt.ylabel('Predicted', fontsize=13)
plt.xlabel('Actual', fontsize=13)

ax.set_xticklabels(['Male','Infant','Female'], fontsize=11)
ax.set_yticklabels(['Male','Infant','Female'], fontsize=11)

plt.title('Confusion Matrix For Naive Bayes Classifier\n\nCounts', fontsize=15)
plt.show()
```



- The confusion matrix model correctly predicted the Age of Males 848 times. (True-Negative)
- There're most Adults than Infant and Females hence inbalance in figures from dataset
- Correctly predicted Ages of Infant 123 times.
- Correctly predicted Ages of Female 62 times. (True-Positive)
- 220 data has been incorrectly identified.

0.11.4 Comparison

- The dummy classifier performed better with 1031 data in the True-Positive, as compared to 848 in the Naive Bayes Classifier.
- But Naive Bayes Classifier correctly predicted 123 Infants and 62 Females as compared to 0 on both using the Dummy Classifier.