# eda

April 19, 2023

[1]:
```python
# Import neccessary Libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.feature_selection import SelectKBest, chi2
from sklearn.preprocessing import LabelEncoder
import nltk
from nltk.corpus import stopwords
from wordcloud import WordCloud
from textblob import TextBlob
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.decomposition import LatentDirichletAllocation
```

[2]:
```python
# Data Ingestion
pets_prepared_df = pd.read_csv('/Users/vaishnavikennedy/Downloads/data/
↪pets_prepared.csv')
breed_labels_df =  pd.read_csv('/Users/vaishnavikennedy/Downloads/data/
↪breed_labels.csv')
state_labels_df = pd.read_csv('/Users/vaishnavikennedy/Downloads/data/
↪state_labels.csv')
color_labels_df = pd.read_csv('/Users/vaishnavikennedy/Downloads/data/
↪color_labels.csv')
pets_prepared_df.head(5)
```

[2]:
```
        PetID  AdoptionSpeed  Type         Name  Age  Breed1  Breed2  Gender  \
0   86e1089a3              2     2       Nibble    3     299       0       1
1   6296e909a              0     2  No Name Yet    1     265       0       1
2   3422e4906              3     1      Brisco    1     307       0       1
3   5842f1ff5              2     1         Miko    4     307       0       2
4   850a43f90              2     1       Hunter    1     307       0       1

   Color1  Color2  …  HealthName  VaccinatedName  DewormedName  \
0       1       7  …     Healthy              No            No
1       1       2  …     Healthy        Not Sure      Not Sure
2       2       7  …     Healthy             Yes           Yes
3       1       2  …     Healthy             Yes           Yes
```

```
4       1       0  …     Healthy            No            No

   SterilizedName            BreedName         BreedBinsName     StateName  \
0              No                Tabby                 Tabby      Selangor
1        Not Sure  Domestic Medium Hair  Domestic Medium Hair  Kuala Lumpur
2              No          Mixed Breed           Mixed Breed      Selangor
3              No          Mixed Breed           Mixed Breed  Kuala Lumpur
4              No          Mixed Breed           Mixed Breed      Selangor

   StateBinsName  ColorName  AdoptedName
0       Selangor      Black            Y
1   Kuala Lumpur      Black            Y
2       Selangor      Brown            Y
3   Kuala Lumpur      Black            Y
4       Selangor      Black            Y

[5 rows x 49 columns]
```

[3]:
```python
# Data Basic Info
pets_prepared_df.info()
```

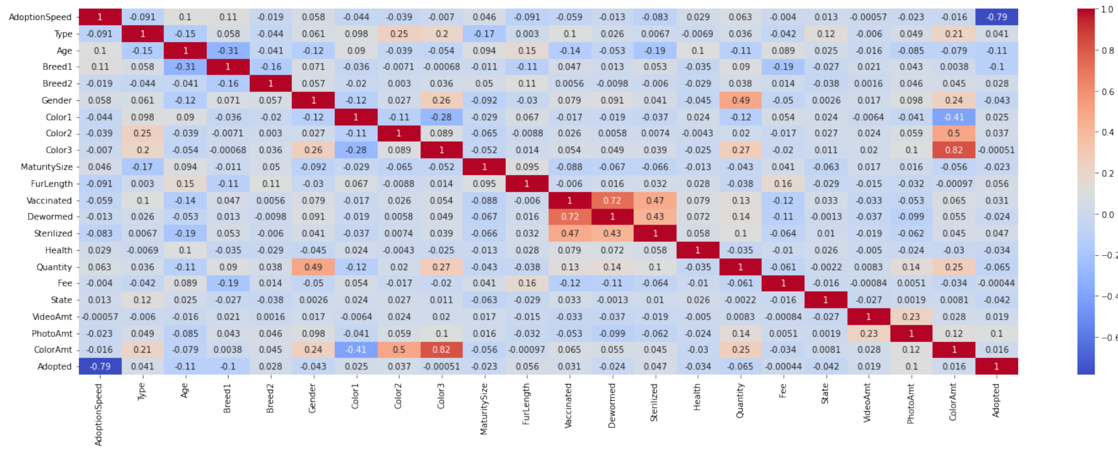
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14993 entries, 0 to 14992
Data columns (total 49 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   PetID            14993 non-null  object
 1   AdoptionSpeed    14993 non-null  int64
 2   Type             14993 non-null  int64
 3   Name             14993 non-null  object
 4   Age              14993 non-null  int64
 5   Breed1           14993 non-null  int64
 6   Breed2           14993 non-null  int64
 7   Gender           14993 non-null  int64
 8   Color1           14993 non-null  int64
 9   Color2           14993 non-null  int64
 10  Color3           14993 non-null  int64
 11  MaturitySize     14993 non-null  int64
 12  FurLength        14993 non-null  int64
 13  Vaccinated       14993 non-null  int64
 14  Dewormed         14993 non-null  int64
 15  Sterilized       14993 non-null  int64
 16  Health           14993 non-null  int64
 17  Quantity         14993 non-null  int64
 18  Fee              14993 non-null  int64
 19  State            14993 non-null  int64
 20  RescuerID        14993 non-null  object
 21  VideoAmt         14993 non-null  int64
```

```
 22  PhotoAmt          14993 non-null  int64
 23  Description       14981 non-null  object
 24  AgeBins           14993 non-null  object
 25  FeeBins           14993 non-null  object
 26  BreedBins         14993 non-null  object
 27  StateBins         14993 non-null  object
 28  VideoAmtBins      14993 non-null  object
 29  PhotoAmtBins      14993 non-null  object
 30  QuantityBins      14993 non-null  object
 31  BreedPure         14993 non-null  object
 32  ColorAmt          14993 non-null  int64
 33  NameorNO          14993 non-null  object
 34  Adopted           14993 non-null  int64
 35  TypeName          14993 non-null  object
 36  GenderName        14993 non-null  object
 37  MaturitySizeName  14993 non-null  object
 38  FurLengthName     14993 non-null  object
 39  HealthName        14993 non-null  object
 40  VaccinatedName    14993 non-null  object
 41  DewormedName      14993 non-null  object
 42  SterilizedName    14993 non-null  object
 43  BreedName         14988 non-null  object
 44  BreedBinsName     14993 non-null  object
 45  StateName         14993 non-null  object
 46  StateBinsName     14993 non-null  object
 47  ColorName         14993 non-null  object
 48  AdoptedName       14993 non-null  object
dtypes: int64(22), object(27)
memory usage: 5.6+ MB
```

***MISSING VALUES, DTYPE, SHAPE, TARGET***

```
- Missing Values : 0
- Dtypes : integer(22) and Object(27 features)
- Shape : Rows 14993, Columns : 49
- Target : AdoptionSpeed
```

[4]:
```
# Correlation matrix
corr_matrix=pets_prepared_df.corr()
plt.figure(figsize=(25,8))  # correlation matrix using a heatmap
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm")
plt.show()
```




***FEATURE INTERACTION - CORRELATION , REDUNDANT, UNIQUE ID VALUES***

- correlated_features= [‘Color3’,‘Vaccinated’, ‘Dewormed’], evident from heatmap correlated features
- From the data dictionary, it is eveident that below list of fields “drop_fields” are redundant or is used to derive bins or represented in another form or is unique set of identities such as PetID,Rescuer ID,Name etc..
- drop_fields=[‘PetID’,‘Name’, ‘State’,‘Age’,‘Fee’,‘Breed1’, ‘Breed2’,‘RescuerID’, ‘VideoAmt’, ‘PhotoAmt’, ‘Description’, ‘TypeName’, ‘GenderName’, ‘MaturitySizeName’, ‘FurLengthName’,‘HealthName’, ‘VaccinatedName’, ‘DewormedName’, ‘SterilizedName’,‘BreedName’, ‘StateBinsName’,‘StateName’,‘Quantity’,‘AdoptedName’] I will use these featured to configure drop_fields in the ML pipeline since presence of such columns can possiblydecrease performance. However, not depend on the correlation alone. will handle this in the ML pipeline along with feature importance

[5]:
```python
# Remove Redundant Columns and unwanted columns
drop_fields=["PetID","Name","Age","Breed1","Breed2","VideoAmt","PhotoAmt","Fee","State",
 "RescuerID","Description","TypeName","GenderName","MaturitySizeName",
 "FurLengthName","HealthName","DewormedName","Color1","Color2","Color3",
               "VaccinatedName","BreedName","StateName","Quantity","AdoptedName",
               "StateBinsName","SterilizedName"]
pets_prepared_df=pets_prepared_df.drop(columns=drop_fields,axis=1)
```

[6]:
```python
# Duplicates
duplicates_count = pets_prepared_df.duplicated().sum()
pets_prepared_df = pets_prepared_df.drop_duplicates(keep='first')
```

***DUPLICATES IN DF***

```
Number of Duplicate rows is 649
```

Remove these in the ML pipeline since they affect the performance of the value (drop by kee

[7]:
```
# Statistical Exploration
pets_prepared_df.describe()
```

[7]:

| | AdoptionSpeed | Type | Gender | MaturitySize | FurLength |
|---|---|---|---|---|---|
| count | 14344.000000 | 14344.000000 | 14344.000000 | 14344.000000 | 14344.000000 |
| mean | 2.515198 | 1.469116 | 1.778862 | 1.859314 | 1.472602 |
| std | 1.182641 | 0.499063 | 0.686853 | 0.555508 | 0.603115 |
| min | 0.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 |
| 25% | 2.000000 | 1.000000 | 1.000000 | 2.000000 | 1.000000 |
| 50% | 2.000000 | 1.000000 | 2.000000 | 2.000000 | 1.000000 |
| 75% | 4.000000 | 2.000000 | 2.000000 | 2.000000 | 2.000000 |
| max | 4.000000 | 2.000000 | 3.000000 | 4.000000 | 3.000000 |

| | Vaccinated | Dewormed | Sterilized | Health | ColorAmt |
|---|---|---|---|---|---|
| count | 14344.000000 | 14344.000000 | 14344.000000 | 14344.000000 | 14344.000000 |
| mean | 1.735011 | 1.561350 | 1.912507 | 1.038274 | 2.002858 |
| std | 0.668709 | 0.697103 | 0.572511 | 0.203844 | 0.771308 |
| min | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 |
| 25% | 1.000000 | 1.000000 | 2.000000 | 1.000000 | 1.000000 |
| 50% | 2.000000 | 1.000000 | 2.000000 | 1.000000 | 2.000000 |
| 75% | 2.000000 | 2.000000 | 2.000000 | 1.000000 | 3.000000 |
| max | 3.000000 | 3.000000 | 3.000000 | 3.000000 | 3.000000 |

| | Adopted |
|---|---|
| count | 14344.000000 |
| mean | 0.717652 |
| std | 0.450157 |
| min | 0.000000 |
| 25% | 0.000000 |
| 50% | 1.000000 |
| 75% | 1.000000 |
| max | 1.000000 |

***OUTLIER ANALYSIS***

- .50% row indicates the 50 th percentile of the featurte, that is, MEDIAN of each column. As we can see mean and the median values are not significantly different. This implies data is NOT SKEWED
- For almost all the features, Max value is not very much higher than 75% and this indicates not much of Outliers
- However since most of the features are almost like categorical features,we need to handle outliers based on finding rare categories by calulating frequency of each category.

***FEATURE SCALING***

- Since the range of values of the features is between 0-5 and doesnt vary much. There is no neccessary for feature scaling.

### *FIRST LEVEL DATA DISTRIBUTION INSIGHTS*

- Most animals have an adoption speed of 2, indicating a moderate adoption rate.More animals of Type 1 are up for adoption compared to Type 2.Most animals have a maturity size of 2, with fewer animals at the extremes.Most animals have fur length of 1 or 2, with relatively fewer having fur length 3. vaccination status of most of the pets are known and relatively less pet's vaccination status is unknown.Most of the pets are in good health and are sterlized as well. When it comes to colour of the pet most of the pets have 2 colours and the distribution is even.There are more adopted pets and less unadopted pets in the petcenter.

[8]:
```python
# Feature engineering - Adding new feature
pets_df = pd.read_csv('/Users/vaishnavikennedy/Downloads/data/pets_prepared.
 ↪csv')
rescuer_popularity = pets_df['RescuerID'].value_counts()
pets_df['RescuerPopularity'] = pets_df['RescuerID'].map(rescuer_popularity)
```

### *FEATURE ENGINEERING ADDED NEW FEATURE - RESCUERPOPULARITY*

- New feature added called as RescuerPopularity and on seeing the distribution we need to normalise the feature while creating in the ML pipeline such as rescuer_popularity = pets_df['RescuerID'].value_counts()

[9]:
```python
#Variance of Feature
pets_prepared_df.var()
```

```
/var/folders/mq/r38gxv852m588tryt1t04wlw0000gn/T/ipykernel_8587/1525901733.py:2:
FutureWarning: Dropping of nuisance columns in DataFrame reductions (with
'numeric_only=None') is deprecated; in a future version this will raise
TypeError.  Select only valid columns before calling the reduction.
  pets_prepared_df.var()
```

[9]:
```
AdoptionSpeed    1.398640
Type             0.249064
Gender           0.471767
MaturitySize     0.308589
FurLength        0.363748
Vaccinated       0.447171
Dewormed         0.485952
Sterilized       0.327769
Health           0.041553
ColorAmt         0.594916
Adopted          0.202642
dtype: float64
```

### *FEATURE SELECTION : VARIANCE OF THE FEATURE*

- AdoptionSpeed has the highest variance,this variability is expected since it is target variable. ColorAmt has the second highest variance.Type, MaturitySize, FurLength, Gender,Adopted and Health have low variance

### *LABEL ENCODING AND FEATURE INPUT*

-As a data prep step, Label encoding and using selectKbest model for looking into good features that could be Feature Input to Model

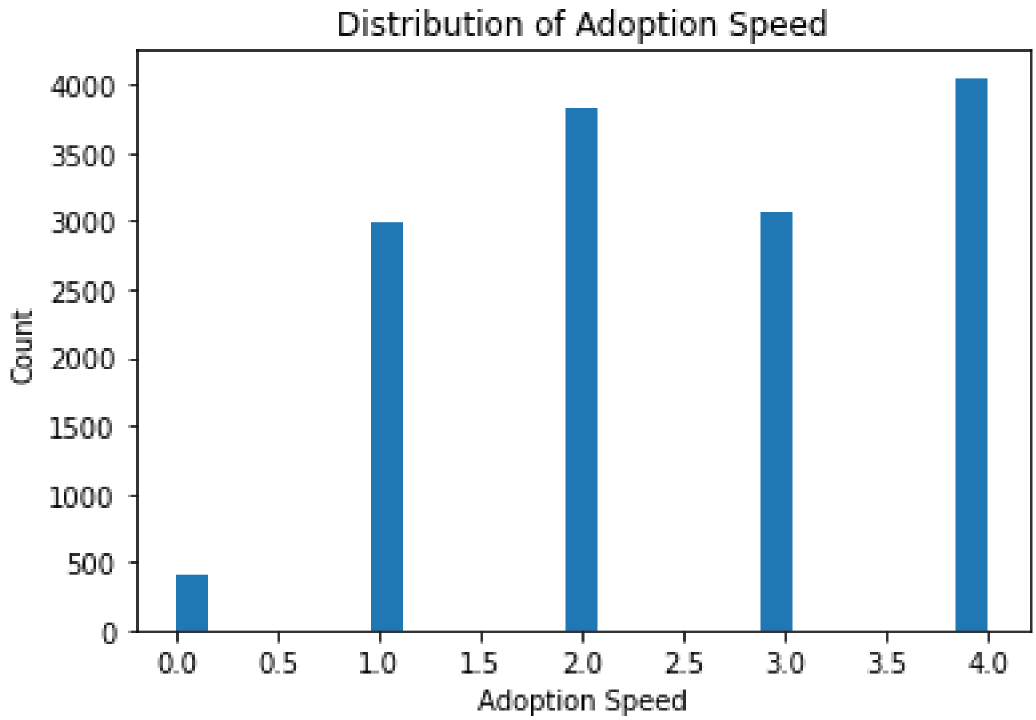
[10]:
```
#LabelEncoding
categorical_cols = pets_prepared_df.select_dtypes(include=['object']).columns.
 ↪tolist()
for col in categorical_cols:
    le = LabelEncoder()
    pets_prepared_df[col] = le.fit_transform(pets_prepared_df[col])
```

[11]:
```
#Feature Input - Feature Selection
k = 20
x = pets_prepared_df.drop(columns=['AdoptionSpeed'])
y = pets_prepared_df['AdoptionSpeed']
selector = SelectKBest(chi2, k=k)
selector.fit(x, y)
select_features = x.columns[selector.get_support()]
```

#### ***GOOD FEATURE INPUTS TOP 20***

- Top 20 good features for prediction are ['Type', 'Gender', 'MaturitySize', 'FurLength', 'Vaccinated', 'Dewormed', 'Sterilized', 'AgeBins', 'FeeBins', 'BreedBins', 'StateBins', 'VideoAmtBins', 'PhotoAmtBins', 'QuantityBins', 'BreedPure', 'ColorAmt', 'NameorNO', 'Adopted', 'BreedBinsName', 'ColorName']

[12]:
```
#Distribution of Target Variable
plt.hist(pets_prepared_df['AdoptionSpeed'], bins=25)
plt.xlabel('Adoption Speed')
plt.ylabel('Count')
plt.title('Distribution of Adoption Speed')
plt.show()
pets_prepared_df['AdoptionSpeed'].value_counts()
```




[12]:
```
4    4050
2    3835
3    3076
1    2980
0     403
Name: AdoptionSpeed, dtype: int64
```

***DISTRIBUTION OF TARGET : DATA IMBALANCE IN THE TARGET VARIABLE***

- It is evident from above histogram that the target variable class is imbalnced. The 0 class of the adoptionspeed is very low. Have to handle this imbalance in target variable in ML pipeline to resample the training dataset.

[13]:
```
# Import necessary libraries
# Load the data into a pandas dataframe
data = pd.read_csv('/Users/vaishnavikennedy/Downloads/data/pets_prepared.csv')
# Basic text preprocessing
data['Description'] = data['Description'].fillna('') # Fill NaN values with␣
↪empty string
data['Description'] = data['Description'].str.lower() # Convert text to␣
↪lowercase
data['Description'] = data['Description'].str.replace('[^a-zA-Z0-9\s]', '') #␣
↪Remove special characters
```

```
stop_words = set(stopwords.words('english')) # Create a set of stop words
data['Description'] = data['Description'].apply(lambda x: ' '.join(word for␣
↪word in x.split() if word not in stop_words)) # Remove stop words
data['Description'] = data['Description'].apply(nltk.word_tokenize) # Tokenize␣
↪the text data
# Word frequency analysis
word_count = pd.Series(np.concatenate(data['Description'])).value_counts()
common_words = word_count[:30]
rare_words = word_count[-30:]
# Word cloud
wordcloud = WordCloud(width = 800, height = 800, background_color ='white',␣
↪min_font_size = 10).generate_from_frequencies(word_count)
plt.figure(figsize = (8, 8), facecolor = None)
plt.imshow(wordcloud)
plt.axis("off")
plt.tight_layout(pad = 0)
plt.show()
# Sentiment analysis
data['polarity'] = data['Description'].apply(lambda x: TextBlob(' '.join(x)).
↪sentiment.polarity)
data['sentiment'] = pd.cut(data['polarity'], bins=3, labels=['Negative',␣
↪'Neutral', 'Positive'])
print("the distribution of the sentiments in the DF is \n ",data['sentiment'].
↪value_counts() )
# Topic modeling
vectorizer = CountVectorizer(max_features=1000, ngram_range=(1,2),␣
↪stop_words='english')
X = vectorizer.fit_transform(data['Description'].apply(lambda x: ' '.join(x)))
lda = LatentDirichletAllocation(n_components=10, random_state=42)
lda.fit(X)
features = vectorizer.get_feature_names()
print("The top words in each topic set is : ")
for topic_idx, topic in enumerate(lda.components_):
    print("Topic #%d:" % topic_idx)
    print(" ".join([features[i] for i in topic.argsort()[:-10 - 1:-1]]))
```

```
/var/folders/mq/r38gxv852m588tryt1t04wlw0000gn/T/ipykernel_8587/598330043.py:7:
FutureWarning: The default value of regex will change from True to False in a
future version.
  data['Description'] = data['Description'].str.replace('[^a-zA-Z0-9\s]', '') #
Remove special characters
```


```
the distribution of the sentiments in the DF is
  Neutral     11586
Positive     3367
Negative       40
Name: sentiment, dtype: int64
The top words in each topic set is :
Topic #0:
home puppy pls forever looking adopt contact interested forever home cute
Topic #1:
cat kitten trained playful active food litter healthy toilet white
Topic #2:
dan saya kucing dia yang di untuk ni yg adopt
Topic #3:
```

```
cat home old cats months kittens months old care loving adopt
Topic #4:
adoption contact interested free female old kindly male months location
Topic #5:
home good dog loving dogs owner good home family looking new
Topic #6:
fee rm adoption adoption fee vaccination spaying neutering long adopter caging
Topic #7:
puppies mother dog adopt birth help home puppy gave area
Topic #8:
loves little like hes play home love shes people playful
Topic #9:
dog care owner adopt house love im dont want good
```

```
/Users/vaishnavikennedy/opt/anaconda3/lib/python3.9/site-
packages/sklearn/utils/deprecation.py:87: FutureWarning: Function
get_feature_names is deprecated; get_feature_names is deprecated in 1.0 and will
be removed in 1.2. Please use get_feature_names_out instead.
  warnings.warn(msg, category=FutureWarning)
```

***ASSUMPTIONS SUPPORTING EDA: DESCRIPTION FEATURE DROPPING***

- The above EDA shows the wordcloud and the words are the common words that one can expect in any pet adoption description. On conducting sentimennt analysis , it is found that majoriy of the description is neutral about 11587 rows, Positive is 3367 rows and negative sentiment of 30. There is huge imbalnce in this feature. Also, looking at set of top words in each topic set obtained from topic modelling , also shows very commonly used words. Hence this feature can be completely dropped and may not be included in the ML pipeline.Another challengfe is mix of language.

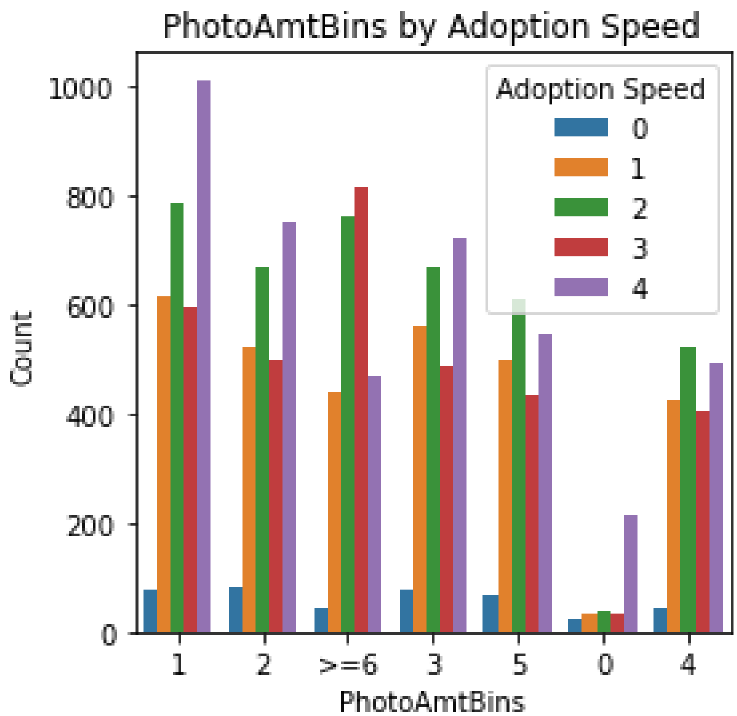
***FEATURE IMPORTANCE CONDUCTED : TOP10 IMPACTFUL FEATURES : OBTAINED FROPM THE BEST MODEL : INSIGHT INTO ADOPTER PREFERENCE***

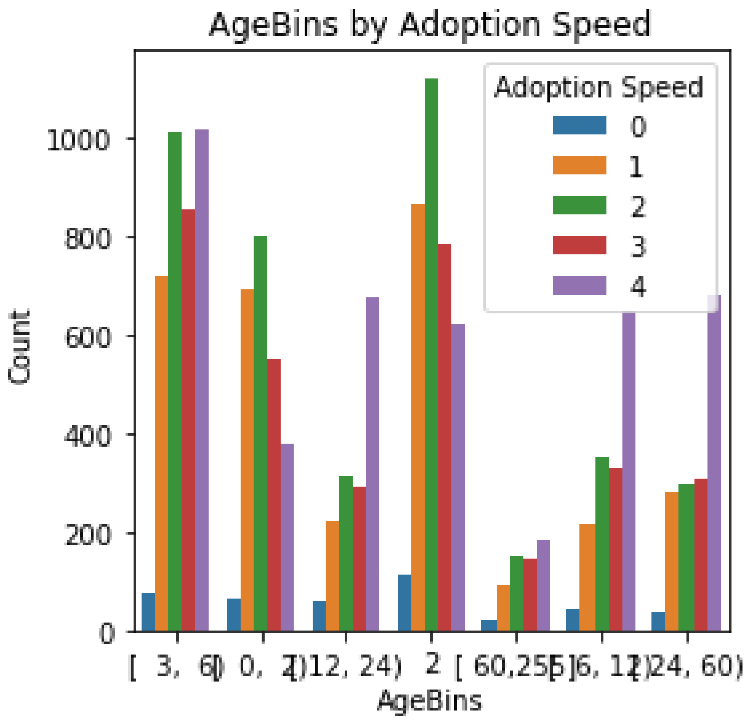
- Top 10 Features after modelling that is found impactful features for adopter's preference ['Adopted', 'PhotoAmtBins', 'AgeBins', 'RescuerPopularity', 'StateBins', 'ColorName', 'Gender', 'ColorAmt', 'FurLength', 'Dewormed'] The feature importance obtained during the ML pipeline with best model CAtboost and best parameters

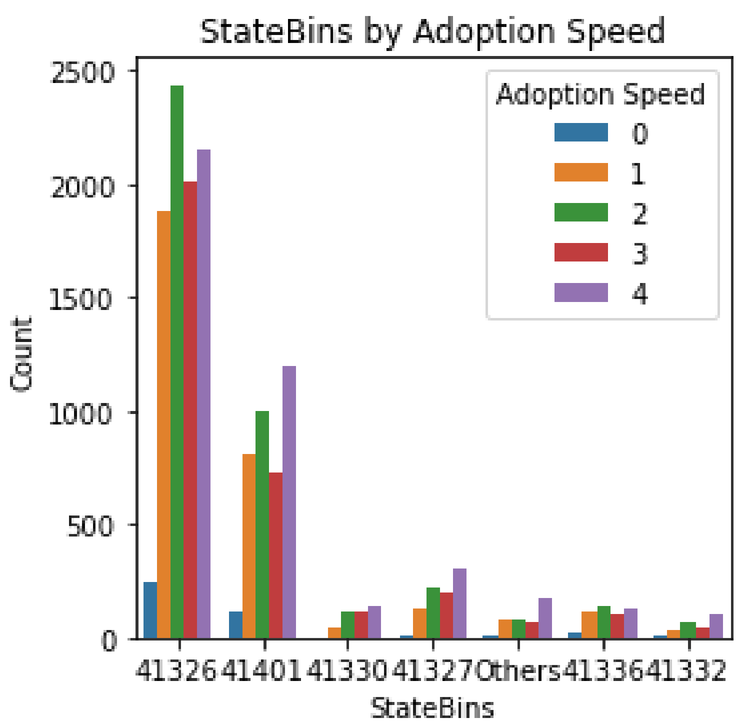
***THE BELOW COUNT PLOT WILL BE USED FOR MAKING RECOMMENDATION IN THE ML PIPELINE THAT WILL BE ADOPTERS PREFERENCE BASED ON THE ABOVE FEATURE IMPORTANCE OBTAINED AFTER MODELLING FROM THE BEST MODEL BEST PARAMETER***

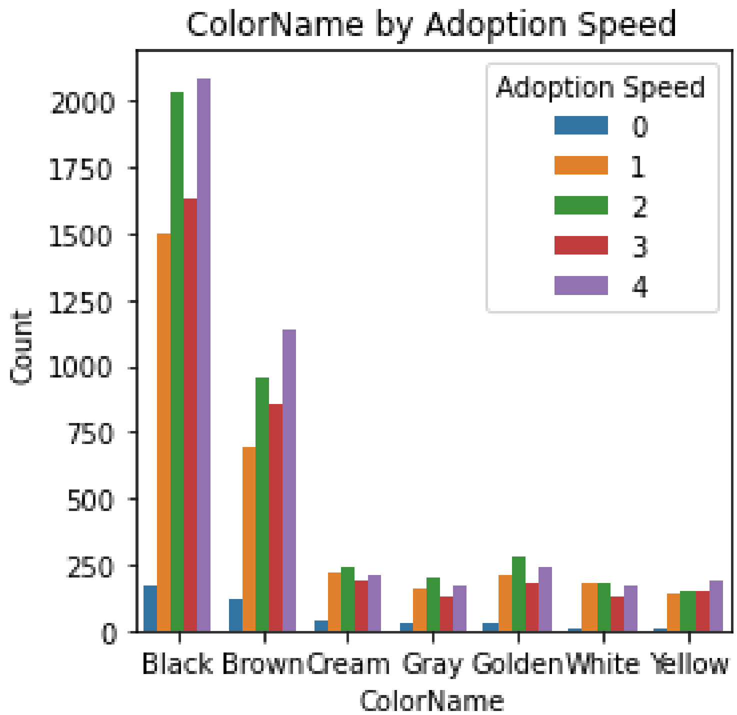
[14]:
```python
# Select the above 10 impactful columns  and prepare recommendation
cols = ['PhotoAmtBins', 'AgeBins', 'StateBins', 'ColorName', 'Gender',␣
↪'ColorAmt', 'FurLength', 'Dewormed']
# Plot the distribution of each feature by adoption speed
for col in cols:
    plt.figure(figsize=(4, 4))
```

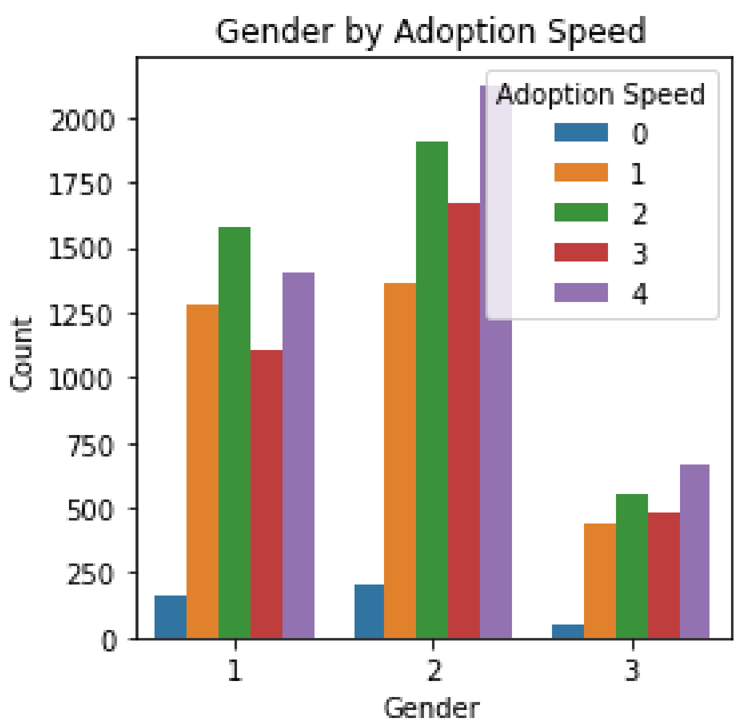
```
    sns.countplot(x=col, hue='AdoptionSpeed', data=data)
    plt.title(f'{col} by Adoption Speed')
    plt.xlabel(col)
    plt.ylabel('Count')
    plt.legend(title='Adoption Speed', loc='upper right')
    plt.show()
```

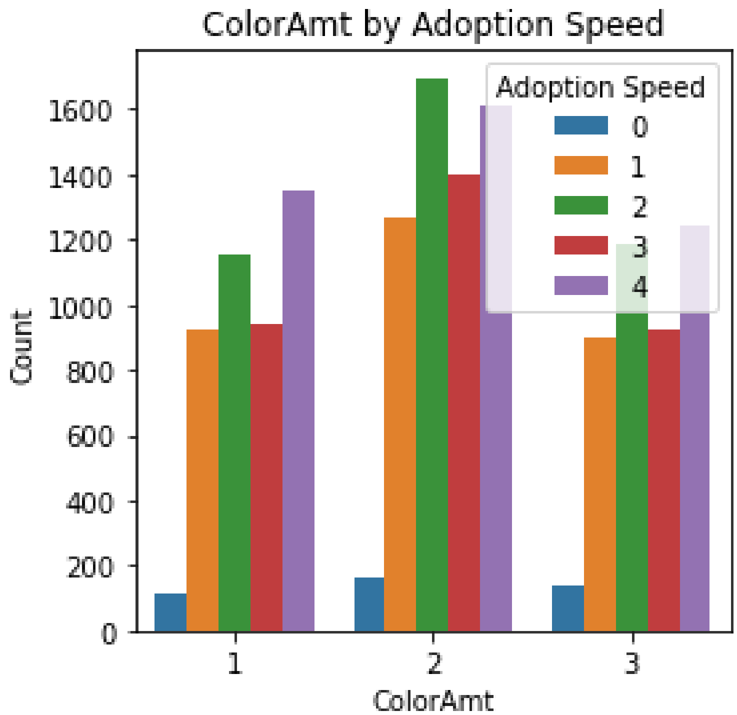


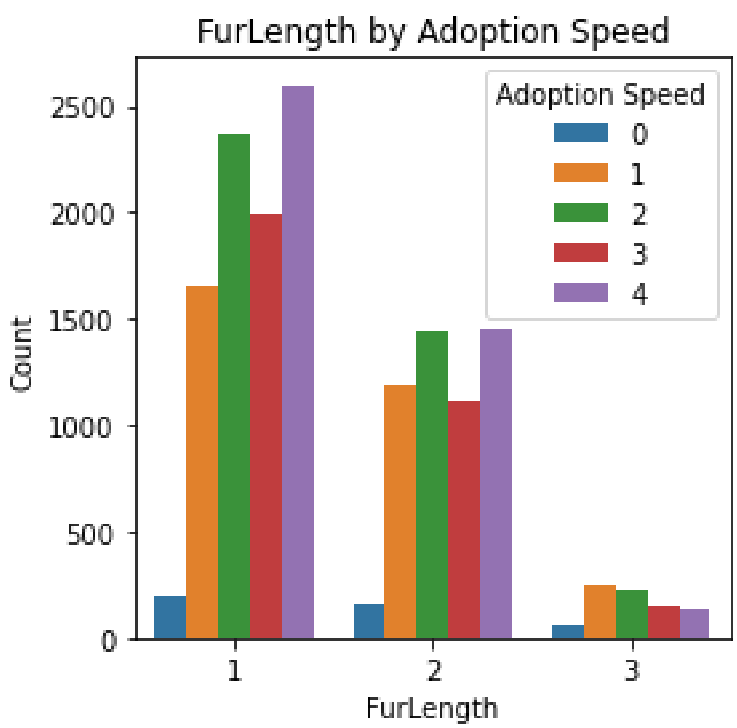

AgeBins by Adoption Speed
Adoption Speed
0
1
2
3
4
Count
0
200
400
600
800
1000
AgeBins

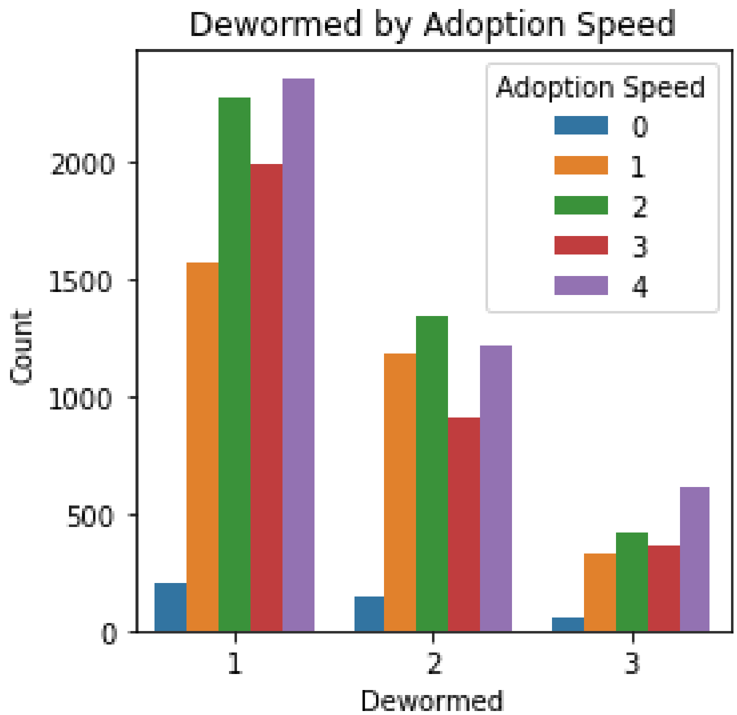

StateBins by Adoption Speed
Adoption Speed
0
1
2
3
4
Count
0
500
1000
1500
2000
2500
41326
41401
41330
41327
Others
41336
41332
StateBins


ColorName by Adoption Speed
Adoption Speed
0
1
2
3
4
2000
1750
1500
1250
1000
750
500
250
0
Count
Black
Brown
Cream
Gray
Golden
White
Yellow
ColorName


Gender by Adoption Speed
Adoption Speed
0
1
2
3
4
2000
1750
1500
1250
1000
750
500
250
0
Count
1
2
3
Gender


ColorAmt by Adoption Speed
Adoption Speed
0
1
2
3
4
Count
0
200
400
600
800
1000
1200
1400
1600
1
2
3
ColorAmt


FurLength by Adoption Speed
Adoption Speed
0
1
2
3
4
Count
0
500
1000
1500
2000
2500
1
2
3
FurLength




***RECOMMENDATION FOR PHOTOAMT***

- Pets with a higher number of photos in their profile tend to get adopted more quickly. The adoption speed increases with an increase in the number of photos up to 5 photos. Pets with 6 or more photos show no significant increase in adoption speed compared to pets with 5 photos.

***RECOMMENDATION FOR AGEBINS***

- The adoption speed of pets in the age range of 0-2 years varies widely, with around 700 pets adopted at a speed of 1 but only around 300 pets adopted at a speed of 4.

***RECOMMENDATION FOR STATEBINS***

- The majority of pets in the dataset are located in state with pincode 41326 followed by 41401 and Others.The adoption speed distribution is relatively consistent across different states, with the majority of pets being adopted at a speed of 2 or 4, regardless of their location

***RECOMMENDATION FOR COLORNAME***

- Black is the most common color for adopted pets, followed by brown and cream.Pets with cream-colored fur are more likely to be adopted faster

***RECOMMENDATION FOR GENDER***

- Adoption rates are MORE OR LESS same for male and female pets.The mixed group is very low comparitively

***RECOMMENDATION FOR COLOAMT***

- Animals with one color tend to have a higher adoption rate compared to those with more than one color. the adoption rate tends to decrease as the number of colors on an animal increases.

***RECOMMENDATION FOR FURLENGTH***

- Pets with fur length 1 tend to have higher adoption rates across all adoption speeds compared to pets with fur length 2 or 3.Pets with fur length 1 tend to have higher adoption rates across all adoption speeds compared to pets with fur length 2 or 3.

***RECOMMENDATION FOR DEWORMED***

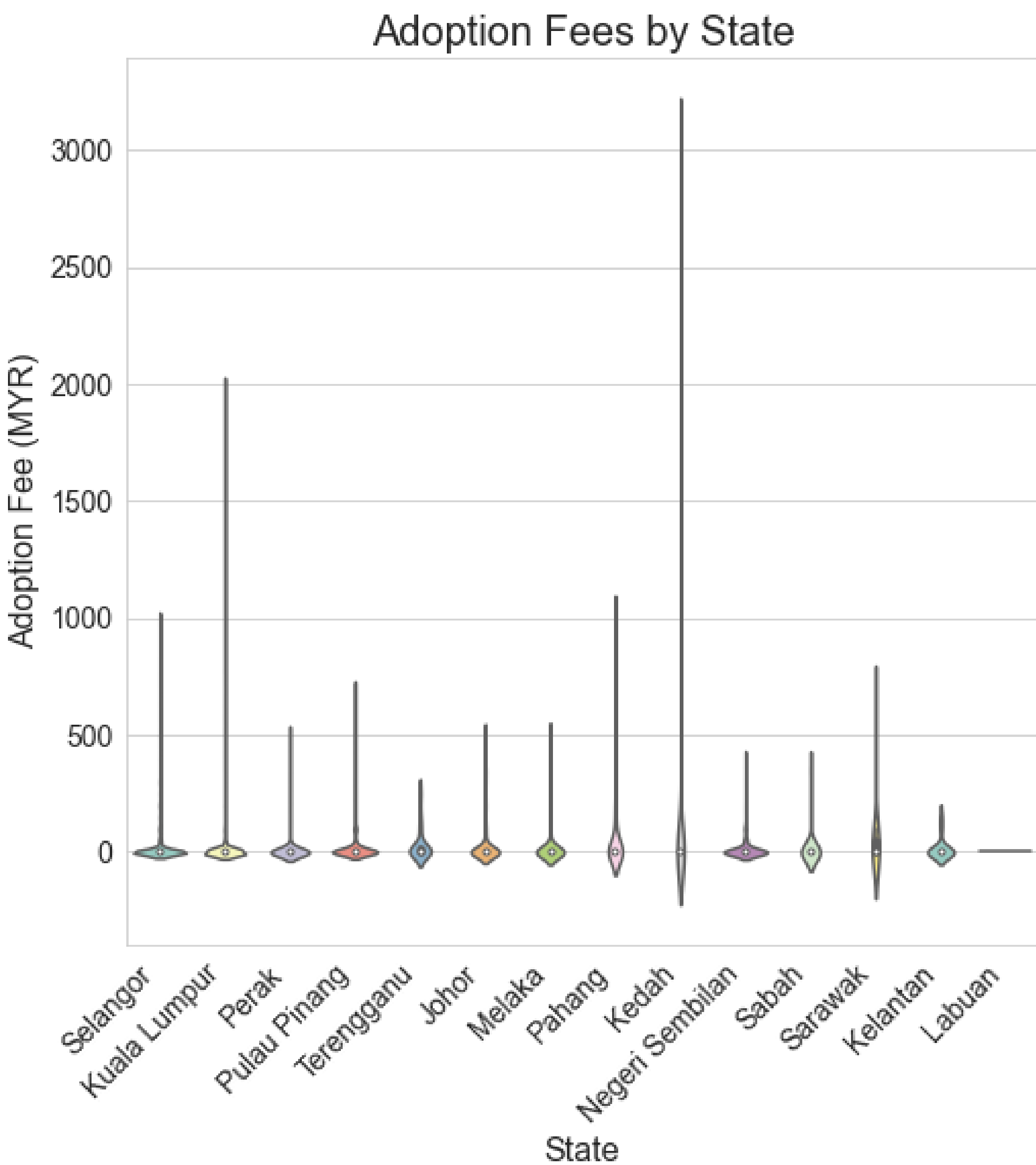
-Pets that are dewormed have a higher chance of being adopted quickly

[15]:
```
summary = data.groupby('State')['Fee'].agg(['mean', 'median', 'std', 'min',␣
↪'max'])
summary
```

[15]:

| State | mean | median | std | min | max |
|---|---|---|---|---|---|
| 41324 | 16.576642 | 0.0 | 70.661551 | 0 | 500 |
| 41325 | 29.563636 | 0.0 | 286.147474 | 0 | 3000 |
| 41326 | 22.638283 | 0.0 | 76.073489 | 0 | 1000 |
| 41327 | 16.400949 | 0.0 | 55.393501 | 0 | 700 |
| 41330 | 13.745238 | 0.0 | 63.797894 | 0 | 500 |
| 41332 | 14.233202 | 0.0 | 47.765434 | 0 | 400 |
| 41335 | 31.294118 | 0.0 | 117.633291 | 0 | 1000 |
| 41336 | 28.641026 | 0.0 | 82.860312 | 0 | 500 |
| 41342 | 63.846154 | 0.0 | 164.799801 | 0 | 600 |
| 41345 | 15.954545 | 0.0 | 74.610402 | 0 | 350 |
| 41361 | 26.923077 | 0.0 | 59.178998 | 0 | 250 |
| 41367 | 16.666667 | 0.0 | 44.986771 | 0 | 150 |
| 41401 | 19.101691 | 0.0 | 75.535827 | 0 | 2000 |
| 41415 | 0.000000 | 0.0 | 0.000000 | 0 | 0 |

[16]:
```
# Adoption Fee by State
sns.set_style("whitegrid")
plt.figure(figsize=(8,8))
sns.violinplot(x="StateName", y="Fee", data=data, palette="Set3")
plt.title("Adoption Fees by State", fontsize=20)
plt.xlabel("State", fontsize=16)
plt.ylabel("Adoption Fee (MYR)", fontsize=16)
plt.xticks(rotation=45, ha='right', fontsize=14)
plt.yticks(fontsize=14)
plt.show()
```

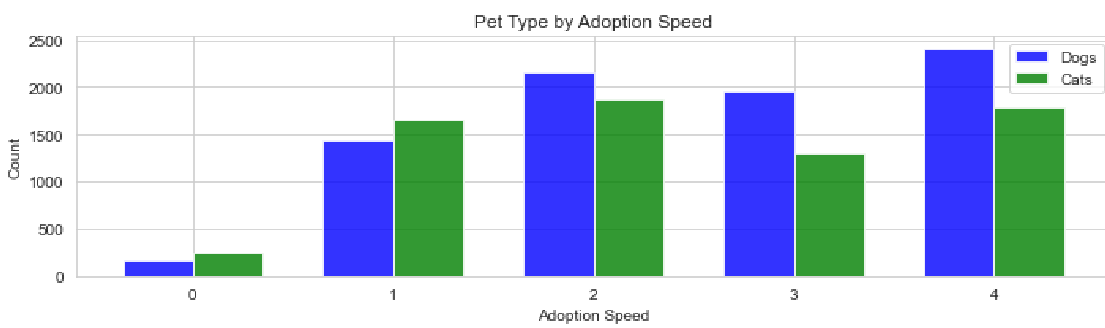



***FEES VARIATION BY STATE FOR DEWORMED***

-For most states, the median adoption fee is 0 dollars, indicating that a significant portion of adoptions are free.he maximum adoption fees across states also vary significantly, ranging from 150 dollars in state 41367 to 3000 dollars in state 41325.The standard deviation of adoption fees also varies greatly among states, ranging from 44.99 dollars in state 41367 to 286.15 dollars in state 41325. This suggests that there is a lot of variation in the adoption fees charged within each state.

[17]:
```
# Create a data frame with the counts of dogs and cats by adoption speed
dog_counts = data[data['Type'] == 1].groupby(['AdoptionSpeed'])['PetID'].count()
```

```
cat_counts = data[data['Type'] == 2].groupby(['AdoptionSpeed'])['PetID'].count()
data = pd.DataFrame({'Dogs': dog_counts, 'Cats': cat_counts})
# Create a grouped bar chart
fig, ax = plt.subplots(figsize=(10,3))
bar_width = 0.35
opacity = 0.8
index = np.arange(len(data.index))
rects1 = ax.bar(index, data['Dogs'], bar_width,
                alpha=opacity, color='b', label='Dogs')
rects2 = ax.bar(index + bar_width, data['Cats'], bar_width,
                alpha=opacity, color='g', label='Cats')
ax.set_xlabel('Adoption Speed')
ax.set_ylabel('Count')
ax.set_title('Pet Type by Adoption Speed')
ax.set_xticks(index + bar_width / 2)
ax.set_xticklabels(('0', '1', '2', '3', '4'))
ax.legend()
plt.tight_layout()
plt.show()
```

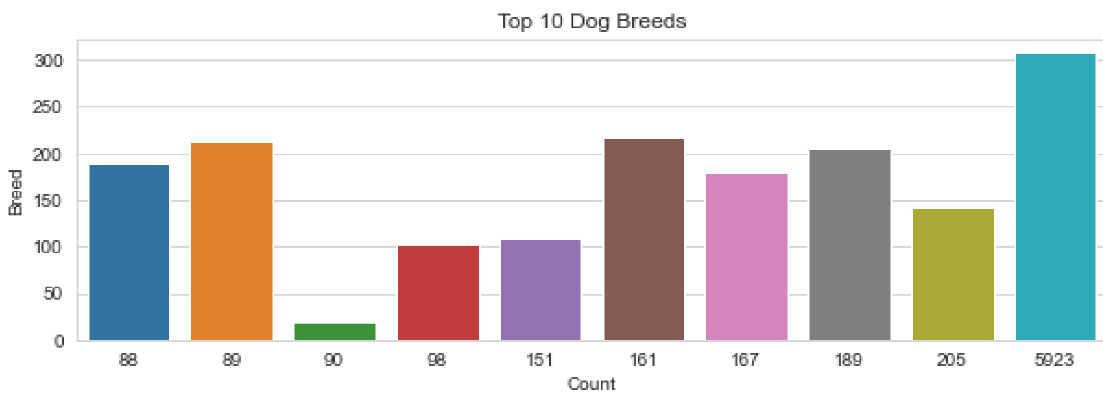


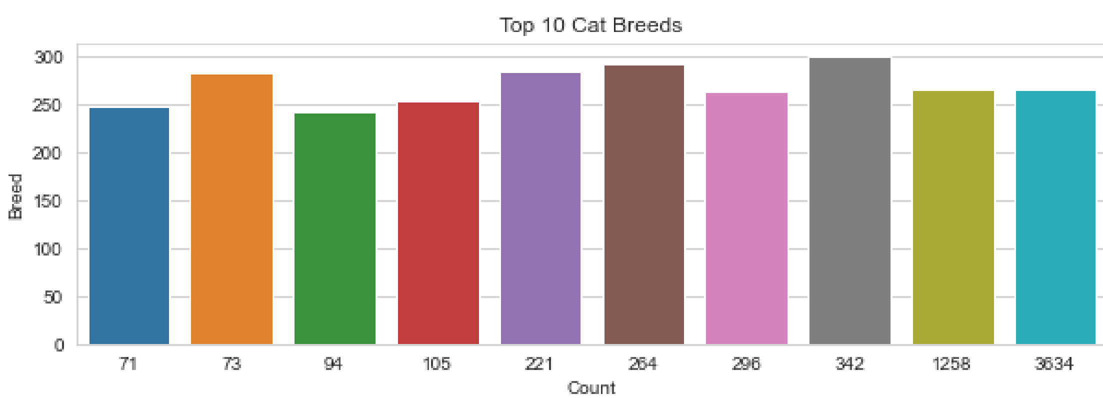

### *CAT VS DOG*

-Dogs have a higher count than cats across almost all adoption speeds.Adoption speed 3 has the lowest counts for both cats and dogs.

[18]:
```
# Load the prepared pets dataset
df = pd.read_csv('/Users/vaishnavikennedy/Downloads/data/pets_prepared.csv')
# Filter by type
dog_df = df[df['Type'] == 1]
cat_df = df[df['Type'] == 2]
# Get the top breeds for each type
dog_breeds = dog_df['Breed1'].value_counts().head(10)
cat_breeds = cat_df['Breed1'].value_counts().head(10)
# Plot the top dog breeds
plt.figure(figsize=(10,3))
sns.barplot(x=dog_breeds.values, y=dog_breeds.index)
```

```
plt.title('Top 10 Dog Breeds')
plt.xlabel('Count')
plt.ylabel('Breed')
plt.show()
# Plot the top cat breeds
plt.figure(figsize=(10,3))
sns.barplot(x=cat_breeds.values, y=cat_breeds.index)
plt.title('Top 10 Cat Breeds')
plt.xlabel('Count')
plt.ylabel('Breed')
plt.show()
```




***Top Dog breed***

- Top Dog breeds in the Df is : 5923 followed by : 161.the least found breed is 90

***Top Cat breed***

- Top Cat breeds in the Df is : 342 followed by : 264. the least found breed is 94