Application of Deep Learning to Text and Image Data

Module 1, Lab 3: Building an End-to-End Neural Network Solution

In the previous lab, you used a neural network with image data to predict the category that an item belonged to. In this lab, you will process text data by building an end-to-end neural network solution. The solution will incorporate all the data processing techniques that you have learned so far.

You will learn how to do the following:

- Import and preprocess data.
- Create a neural network with multiple layers.
- Train text data with your neural network.
- Validate your model as you train.
- Change different parameters to improve your neural network.

Austin Animal Center Dataset

In this lab, you will work with historical pet adoption data in the Austin Animal Center Shelter Intakes and Outcomes dataset. The target field of the dataset (**Outcome Type**) is the outcome of adoption: 1 for adopted and 0 for not adopted. Multiple features are used in the dataset.

Dataset schema:

- **Pet ID:** Unique ID of the pet
- **Outcome Type:** State of pet at the time of recording the outcome (0 = not placed, 1 = placed). This is the field to predict.
- **Sex upon Outcome:** Sex of pet at outcome
- **Name:** Name of pet
- **Found Location:** Found location of pet before it entered the shelter
- **Intake Type:** Circumstances that brought the pet to the shelter
- **Intake Condition:** Health condition of the pet when it entered the shelter
- **Pet Type:** Type of pet
- **Sex upon Intake:** Sex of pet when it entered the shelter
- **Breed:** Breed of pet
- **Color:** Color of pet
- **Age upon Intake Days:** Age (days) of pet when it entered the shelter
- **Age upon Outcome Days:** Age (days) of pet at outcome

You will be presented with two kinds of exercises throughout the notebook: activities and challenges.

No coding is needed for an activity. You try to understand a concept, answer questions, or run a code cell.	Challenges are where you can practice your coding skills.

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Data processing

The first step is to process the dataset.

```
# Install libraries
!pip install -U -q -r requirements.txt

ERROR: pip's dependency resolver does not currently take into account
all the packages that are installed. This behaviour is the source of
the following dependency conflicts.
autovizwidget 0.21.0 requires pandas<2.0.0,>=0.20.1, but you have
pandas 2.0.3 which is incompatible.
hdijupyterutils 0.21.0 requires pandas<2.0.0,>=0.17.1, but you have
pandas 2.0.3 which is incompatible.
sparkmagic 0.21.0 requires pandas<2.0.0,>=0.17.1, but you have pandas
2.0.3 which is incompatible.
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pandas 2.0.3 which is incompatible.
sparkmagic 0.21.0 requires pandas<2.0.0,>=0.17.1, but you have pandas
2.0.3 which is incompatible.

# Import the dependencies
import boto3
import os
from os import path
```

```python
import pandas as pd

%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import re, string
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.utils import shuffle
import torch
from torch import nn
import Stemmer

from MLUDTI_M1_Lab3_neural_network import NeuralNetwork
```

```
Matplotlib is building the font cache; this may take a moment.
Matplotlib is building the font cache; this may take a moment.
```

First, read the dataset into a DataFrame and look at it. The data might look familiar because it was used in the labs of the Machine Learning through Application course.

```python
df = pd.read_csv("data/austin-animal-center-dataset.csv")

print("The shape of the dataset is:", df.shape)
```

```
The shape of the dataset is: (95485, 13)
The shape of the dataset is: (95485, 13)
```

```python
# Print the first five rows of the dataset
df.head()
```

```
    Pet ID  Outcome Type Sex upon Outcome        Name  \
0  A794011           1.0    Neutered Male       Chunk
1  A776359           1.0    Neutered Male       Gizmo
2  A674754           0.0      Intact Male         NaN
3  A689724           1.0    Neutered Male  *Donatello
4  A680969           1.0    Neutered Male       *Zeus

                        Found Location      Intake Type Intake
Condition  \
0                          Austin (TX)  Owner Surrender
Normal
1    7201 Levander Loop in Austin (TX)            Stray
Normal
2        12034 Research in Austin (TX)            Stray
Nursing
```

```
3     2300 Waterway Bnd in Austin (TX)            Stray
Normal
4  4701 Staggerbrush Rd in Austin (TX)            Stray
Nursing

  Pet Type Sex upon Intake                    Breed
Color  \
0      Cat   Neutered Male   Domestic Shorthair Mix   Brown
Tabby/White
1      Dog     Intact Male  Chihuahua Shorthair Mix
White/Brown
2      Cat     Intact Male   Domestic Shorthair Mix        Orange
Tabby
3      Cat     Intact Male   Domestic Shorthair Mix
Black
4      Cat     Intact Male   Domestic Shorthair Mix  White/Orange
Tabby

   Age upon Intake Days  Age upon Outcome Days
0                   730                    730
1                   365                    365
2                     6                      6
3                    60                     60
4                     7                     60

    Pet ID  Outcome Type Sex upon Outcome        Name  \
0  A794011           1.0    Neutered Male       Chunk
1  A776359           1.0    Neutered Male       Gizmo
2  A674754           0.0      Intact Male         NaN
3  A689724           1.0    Neutered Male  *Donatello
4  A680969           1.0    Neutered Male       *Zeus

                        Found Location      Intake Type Intake
Condition  \
0                           Austin (TX)  Owner Surrender
Normal
1    7201 Levander Loop in Austin (TX)            Stray
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Nursing
3     2300 Waterway Bnd in Austin (TX)            Stray
Normal
4  4701 Staggerbrush Rd in Austin (TX)            Stray
Nursing

  Pet Type Sex upon Intake                    Breed
Color  \
0      Cat   Neutered Male   Domestic Shorthair Mix   Brown
Tabby/White
1      Dog     Intact Male  Chihuahua Shorthair Mix
```

```
White/Brown
2      Cat     Intact Male   Domestic Shorthair Mix        Orange
Tabby
3      Cat     Intact Male   Domestic Shorthair Mix
Black
4      Cat     Intact Male   Domestic Shorthair Mix  White/Orange
Tabby

   Age upon Intake Days  Age upon Outcome Days
0                   730                    730
1                   365                    365
2                     6                      6
3                    60                     60
4                     7                     60
```

EDA

Now, perform the basic steps of exploratory data analysis (EDA) and look for insights to inform later ML modeling choices.

```
# Print the data types and nonnull values for each column
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 95485 entries, 0 to 95484
Data columns (total 13 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Pet ID                 95485 non-null  object
 1   Outcome Type           95485 non-null  float64
 2   Sex upon Outcome       95484 non-null  object
 3   Name                   59138 non-null  object
 4   Found Location         95485 non-null  object
 5   Intake Type            95485 non-null  object
 6   Intake Condition       95485 non-null  object
 7   Pet Type               95485 non-null  object
 8   Sex upon Intake        95484 non-null  object
 9   Breed                  95485 non-null  object
 10  Color                  95485 non-null  object
 11  Age upon Intake Days   95485 non-null  int64
 12  Age upon Outcome Days  95485 non-null  int64
dtypes: float64(1), int64(2), object(10)
memory usage: 9.5+ MB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 95485 entries, 0 to 95484
Data columns (total 13 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Pet ID                 95485 non-null  object
```

```
 1   Outcome Type           95485 non-null  float64
 2   Sex upon Outcome       95484 non-null  object
 3   Name                   59138 non-null  object
 4   Found Location         95485 non-null  object
 5   Intake Type            95485 non-null  object
 6   Intake Condition       95485 non-null  object
 7   Pet Type               95485 non-null  object
 8   Sex upon Intake        95484 non-null  object
 9   Breed                  95485 non-null  object
 10  Color                  95485 non-null  object
 11  Age upon Intake Days   95485 non-null  int64
 12  Age upon Outcome Days  95485 non-null  int64
dtypes: float64(1), int64(2), object(10)
memory usage: 9.5+ MB
```

```
# Print the column names
print(df.columns)
```

```
Index(['Pet ID', 'Outcome Type', 'Sex upon Outcome', 'Name', 'Found
Location',
       'Intake Type', 'Intake Condition', 'Pet Type', 'Sex upon
Intake',
       'Breed', 'Color', 'Age upon Intake Days', 'Age upon Outcome
Days'],
      dtype='object')
Index(['Pet ID', 'Outcome Type', 'Sex upon Outcome', 'Name', 'Found
Location',
       'Intake Type', 'Intake Condition', 'Pet Type', 'Sex upon
Intake',
       'Breed', 'Color', 'Age upon Intake Days', 'Age upon Outcome
Days'],
      dtype='object')
```

```
# Create lists that identify the numerical, categorical, and text
features, and the target/label
numerical_features = ["Age upon Intake Days", "Age upon Outcome Days"]

categorical_features = [
    "Sex upon Outcome",
    "Intake Type",
    "Intake Condition",
    "Pet Type",
    "Sex upon Intake",
]

text_features = ["Found Location", "Breed", "Color"]

model_features = numerical_features + categorical_features +
text_features
model_target = "Outcome Type"
```

Note: The **Pet ID** and **Name** features were omitted because they are irrelevant to the outcome.

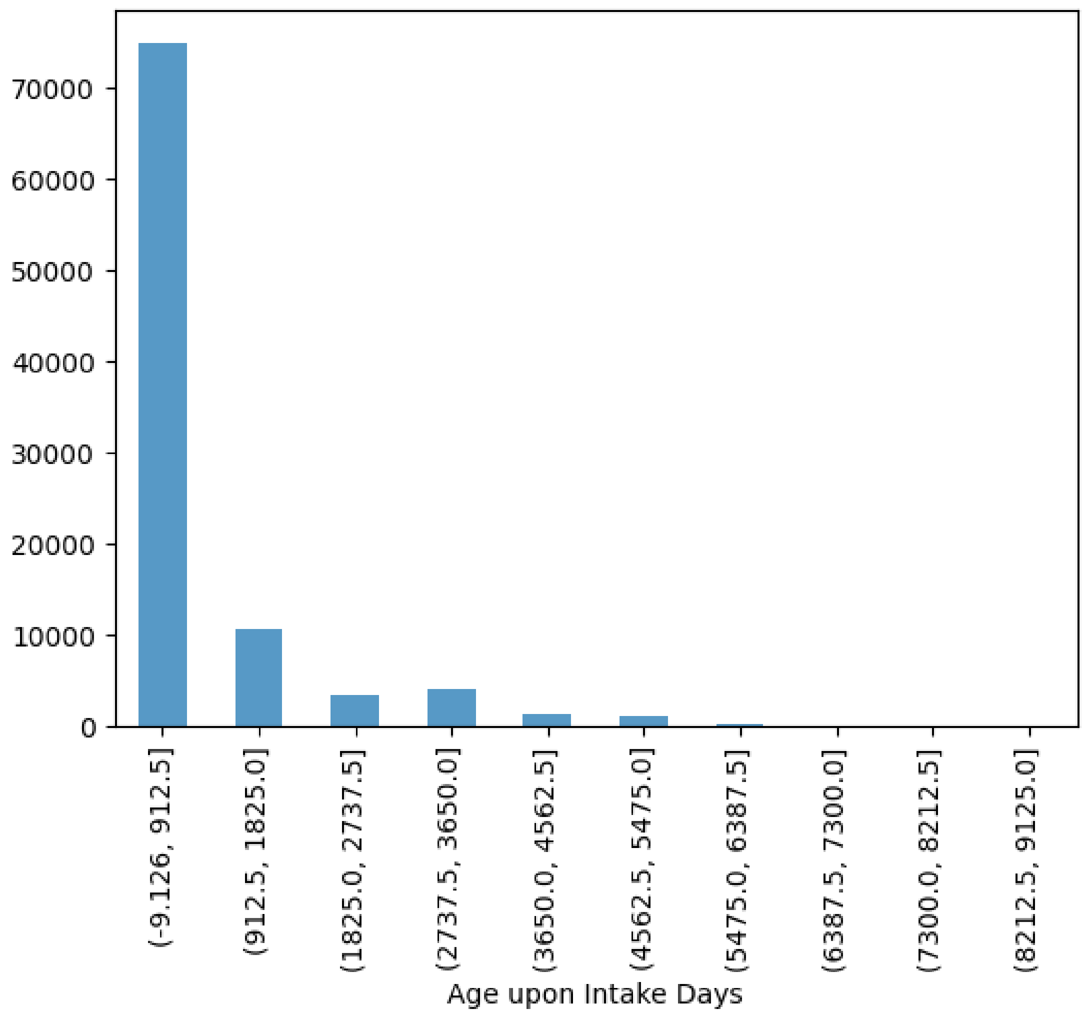
Cleaning the data

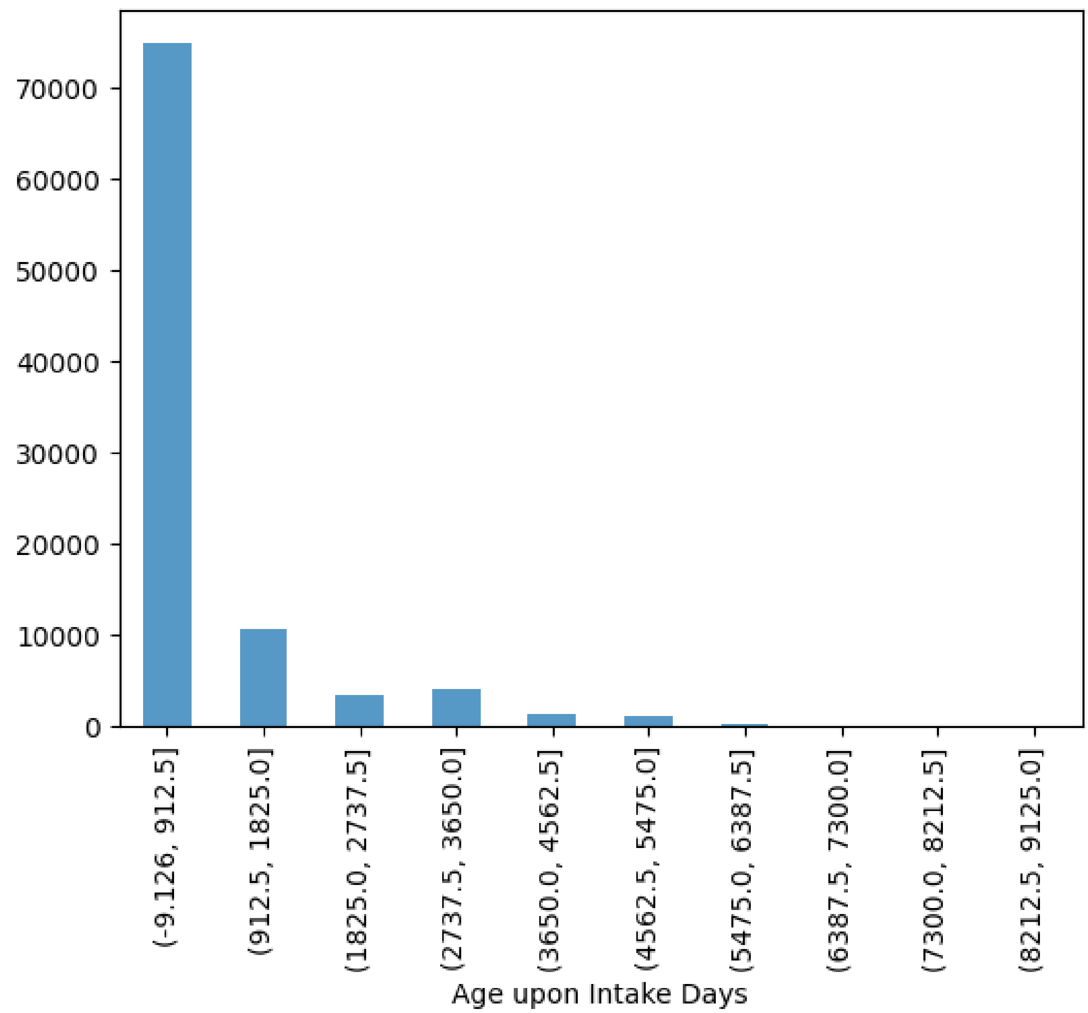
Cleaning numerical features

Take a moment to examine the numerical features. Remember that the `value_counts()` function can give a view of the numerical features by placing feature values in respective bins. The function can also be used for plotting.

```
for c in numerical_features:
    print(c)
    print(df[c].value_counts(bins=10, sort=False))
    df[c].value_counts(bins=10, sort=False).plot(kind="bar",
alpha=0.75, rot=90)
    plt.show()
```

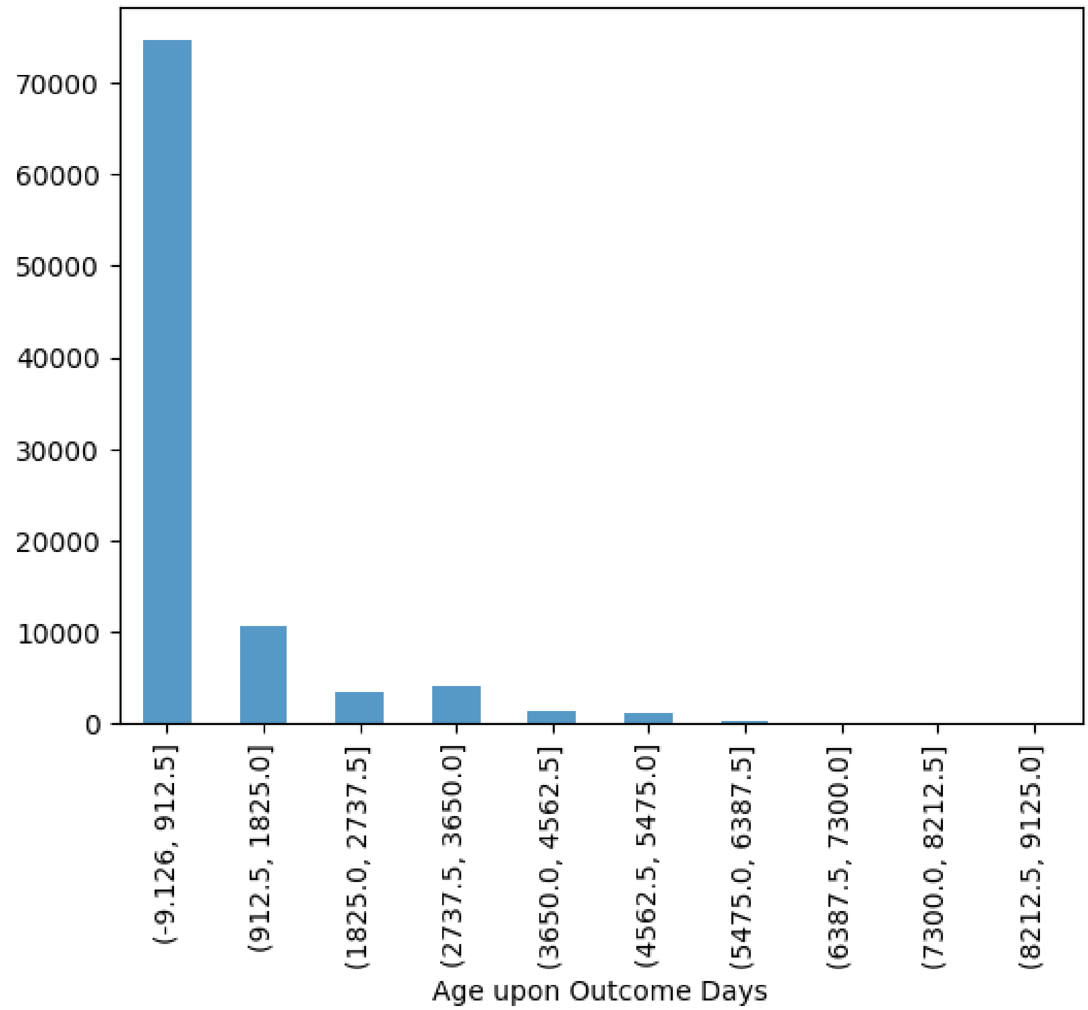
```
Age upon Intake Days
Age upon Intake Days
(-9.126, 912.5]     74835
(912.5, 1825.0]     10647
(1825.0, 2737.5]     3471
(2737.5, 3650.0]     3998
(3650.0, 4562.5]     1234
(4562.5, 5475.0]     1031
(5475.0, 6387.5]      183
(6387.5, 7300.0]       79
(7300.0, 8212.5]        5
(8212.5, 9125.0]        2
Name: count, dtype: int64
Age upon Intake Days
Age upon Intake Days
(-9.126, 912.5]     74835
(912.5, 1825.0]     10647
(1825.0, 2737.5]     3471
(2737.5, 3650.0]     3998
(3650.0, 4562.5]     1234
(4562.5, 5475.0]     1031
(5475.0, 6387.5]      183
(6387.5, 7300.0]       79
(7300.0, 8212.5]        5
(8212.5, 9125.0]        2
Name: count, dtype: int64
```

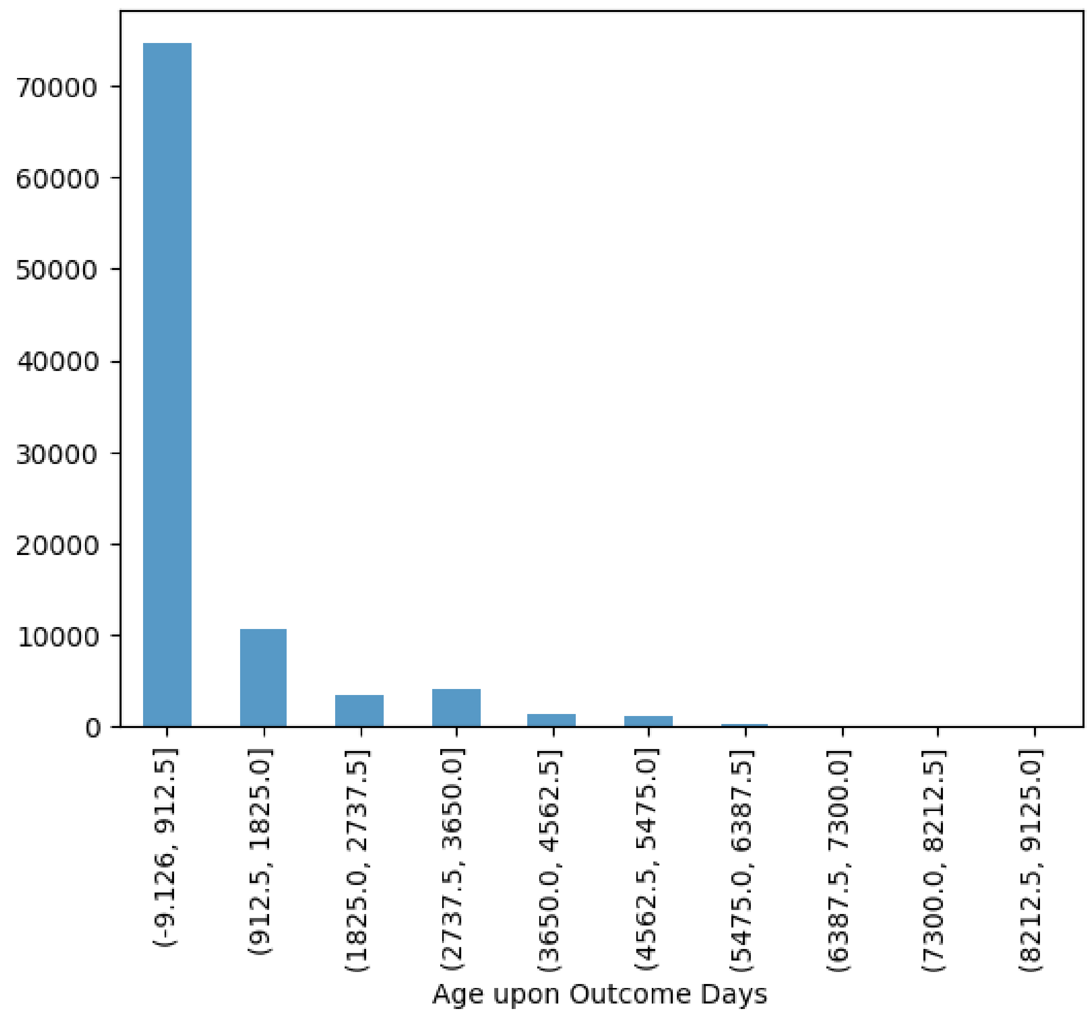

70000
60000
50000
40000
30000
20000
10000
0
(-9.126, 912.5]
(912.5, 1825.0]
(1825.0, 2737.5]
(2737.5, 3650.0]
(3650.0, 4562.5]
(4562.5, 5475.0]
(5475.0, 6387.5]
(6387.5, 7300.0]
(7300.0, 8212.5]
(8212.5, 9125.0]
Age upon Intake Days




```
Age upon Outcome Days
Age upon Outcome Days
(-9.126, 912.5]     74642
(912.5, 1825.0]     10699
(1825.0, 2737.5]     3465
(2737.5, 3650.0]     4080
(3650.0, 4562.5]     1263
(4562.5, 5475.0]     1061
(5475.0, 6387.5]      187
(6387.5, 7300.0]       81
(7300.0, 8212.5]        5
(8212.5, 9125.0]        2
Name: count, dtype: int64
Age upon Outcome Days
Age upon Outcome Days
(-9.126, 912.5]     74642
(912.5, 1825.0]     10699
(1825.0, 2737.5]     3465
```

```
(2737.5, 3650.0]     4080
(3650.0, 4562.5]     1263
(4562.5, 5475.0]     1061
(5475.0, 6387.5]      187
(6387.5, 7300.0]       81
(7300.0, 8212.5]        5
(8212.5, 9125.0]        2
Name: count, dtype: int64
```





If any outliers are identified as likely wrong values, dropping them could improve the histograms for the numerical values and could later improve overall model performance.

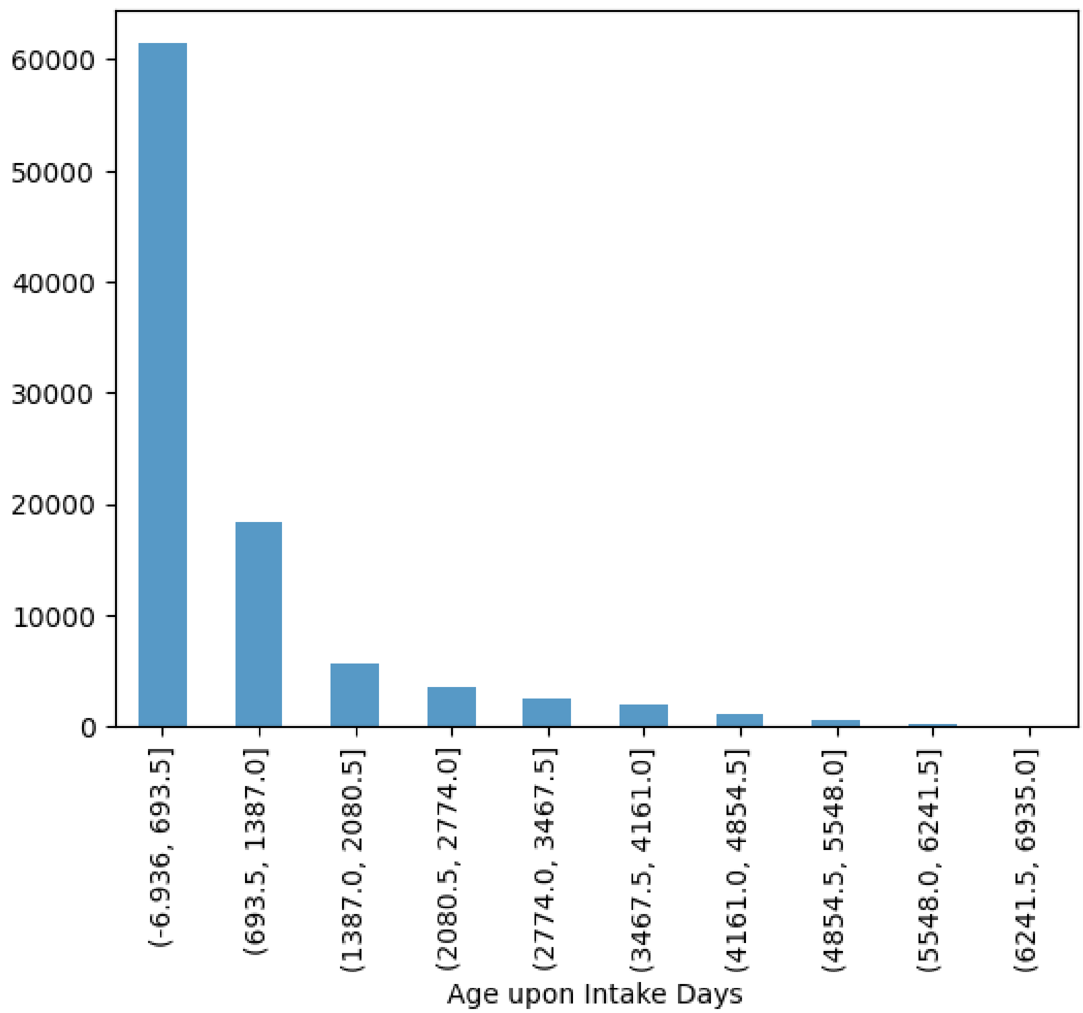
Remove any values in the upper 10 percent for the feature, and then plot the features.

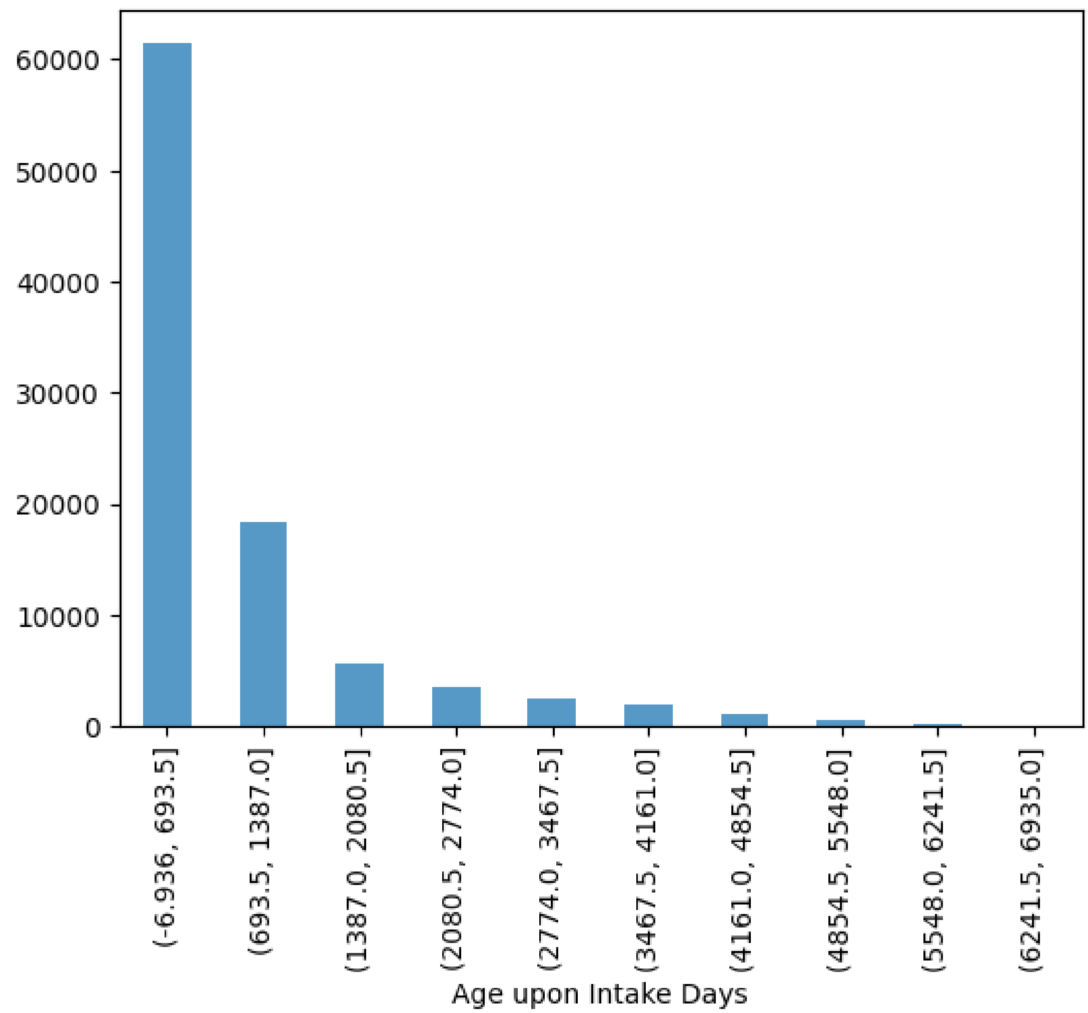
```
for c in numerical_features:
    # Drop values beyond 90% of max()
    dropIndexes = df[df[c] > df[c].max() * 9 / 10].index
    df.drop(dropIndexes, inplace=True)

for c in numerical_features:
    print(c)
    print(df[c].value_counts(bins=10, sort=False))
    df[c].value_counts(bins=10, sort=False).plot(kind="bar",
alpha=0.75, rot=90)
    plt.show()

Age upon Intake Days
Age upon Intake Days
```

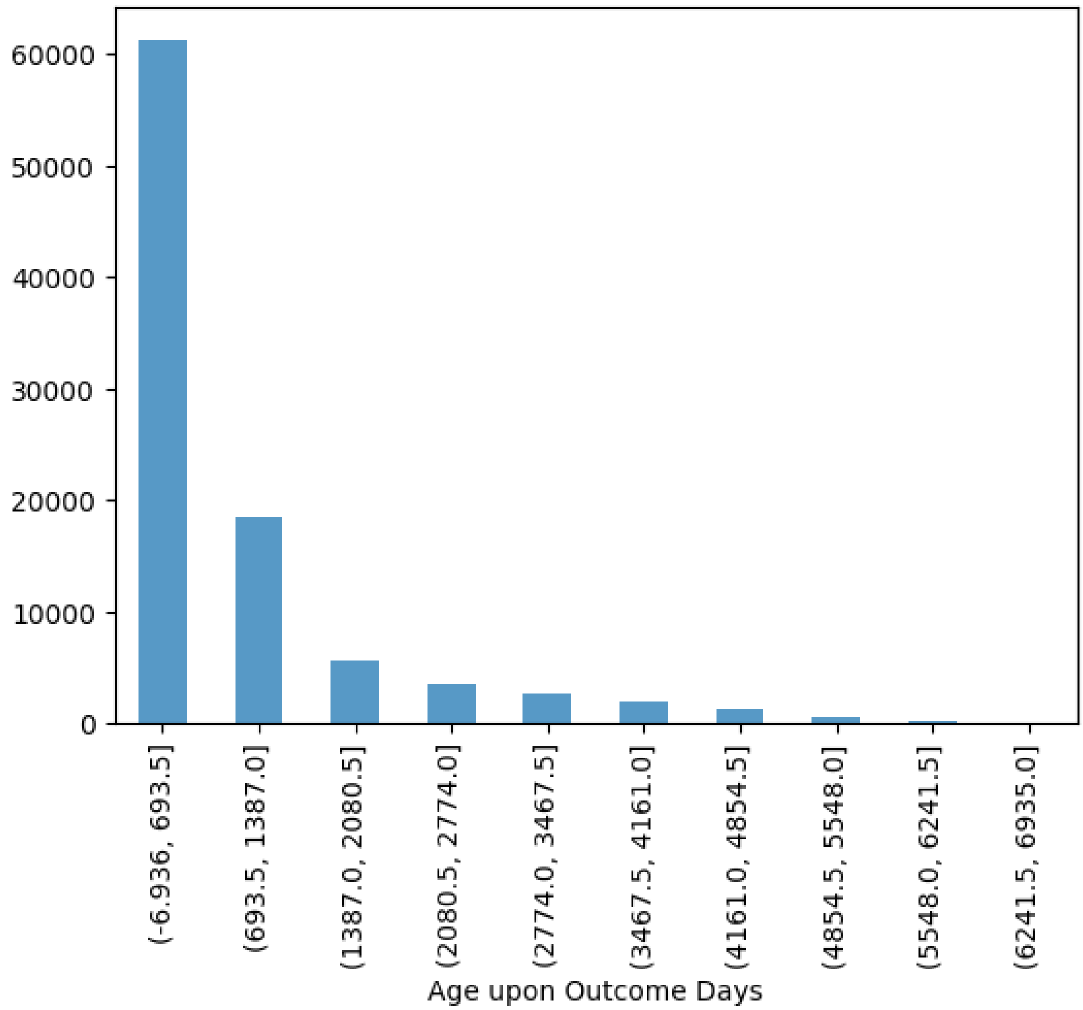
```
(-6.936, 693.5]     61425
(693.5, 1387.0]     18400
(1387.0, 2080.5]     5657
(2080.5, 2774.0]     3471
(2774.0, 3467.5]     2557
(3467.5, 4161.0]     1962
(4161.0, 4854.5]     1148
(4854.5, 5548.0]      596
(5548.0, 6241.5]      183
(6241.5, 6935.0]       63
Name: count, dtype: int64
Age upon Intake Days
Age upon Intake Days
(-6.936, 693.5]     61425
(693.5, 1387.0]     18400
(1387.0, 2080.5]     5657
(2080.5, 2774.0]     3471
(2774.0, 3467.5]     2557
(3467.5, 4161.0]     1962
(4161.0, 4854.5]     1148
(4854.5, 5548.0]      596
(5548.0, 6241.5]      183
(6241.5, 6935.0]       63
Name: count, dtype: int64
```

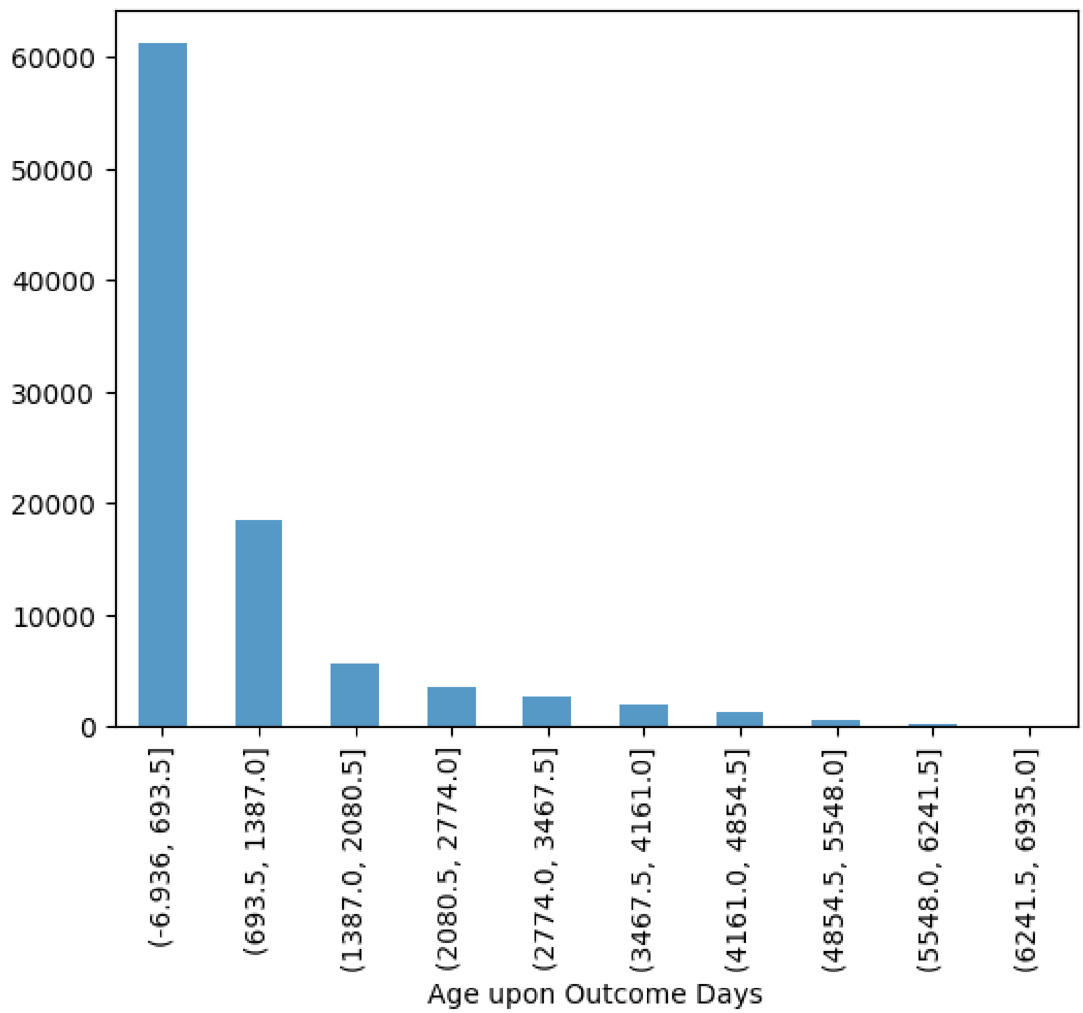

60000
50000
40000
30000
20000
10000
0
(-6.936, 693.5]
(693.5, 1387.0]
(1387.0, 2080.5]
(2080.5, 2774.0]
(2774.0, 3467.5]
(3467.5, 4161.0]
(4161.0, 4854.5]
(4854.5, 5548.0]
(5548.0, 6241.5]
(6241.5, 6935.0]
Age upon Intake Days




```
Age upon Outcome Days
Age upon Outcome Days
(-6.936, 693.5]     61208
(693.5, 1387.0]     18490
(1387.0, 2080.5]     5643
(2080.5, 2774.0]     3465
(2774.0, 3467.5]     2600
(3467.5, 4161.0]     2004
(4161.0, 4854.5]     1196
(4854.5, 5548.0]      604
(5548.0, 6241.5]      187
(6241.5, 6935.0]       65
Name: count, dtype: int64
Age upon Outcome Days
Age upon Outcome Days
(-6.936, 693.5]     61208
(693.5, 1387.0]     18490
(1387.0, 2080.5]     5643
```

```
(2080.5, 2774.0]      3465
(2774.0, 3467.5]      2600
(3467.5, 4161.0]      2004
(4161.0, 4854.5]      1196
(4854.5, 5548.0]       604
(5548.0, 6241.5]       187
(6241.5, 6935.0]        65
Name: count, dtype: int64
```





Cleaning text features

Take a moment to examine the text features.

```
# Prepare cleaning functions
import re, string

stop_words = ["a", "an", "the", "this", "that", "is", "it", "to",
"and", "in"]

stemmer = Stemmer.Stemmer('english')

def preProcessText(text):
    # Lowercase text, and strip leading and trailing white space
    text = text.lower().strip()

    # Remove HTML tags
    text = re.compile("<.*?>").sub("", text)
```

```
    # Remove punctuation
    text = re.compile("[%s]" % re.escape(string.punctuation)).sub(" ",
text)

    # Remove extra white space
    text = re.sub("\s+", " ", text)

    return text


def lexiconProcess(text, stop_words, stemmer):
    filtered_sentence = []
    words = text.split(" ")
    for w in words:
        if w not in stop_words:
            filtered_sentence.append(stemmer.stemWord(w))
    text = " ".join(filtered_sentence)

    return text


def cleanSentence(text, stop_words, stemmer):
    return lexiconProcess(preProcessText(text), stop_words, stemmer)
```

Note: The text cleaning process can take a while to complete, depending on the size of the text data.

```
# Clean the text features
for c in text_features:
    print("Text cleaning: ", c)
    df[c] = [cleanSentence(item, stop_words, stemmer) for item in
df[c].values]

Text cleaning:  Found Location
Text cleaning:  Found Location
Text cleaning:  Breed
Text cleaning:  Breed
Text cleaning:  Color
Text cleaning:  Color
```

Train, validation, and test datasets

Now that the data has been cleaned, you need to split the full dataset into training and test subsets by using sklearn's train_test_split() function. With this function, you can specify the following:

- The proportion of the dataset to include in the test split as a number between 0.0-1.0 with a default of 0.25.
- An integer that controls the shuffling that is applied to the data before the split. Passing an integer allows for reproducible output across multiple function calls.

To help reduce sampling bias, the original dataset is shuffled before the split. After the initial split, the training data is further split into training and validation subsets.

```
from sklearn.model_selection import train_test_split

train_data, test_data = train_test_split(
    df, test_size=0.15, shuffle=True, random_state=23
)

train_data, val_data = train_test_split(
    train_data, test_size=0.15, shuffle=True, random_state=23
)

# Print the shapes of the training, validation, and test datasets
print(
    "Train - Validation - Test dataset shapes: ",
    train_data.shape,
    val_data.shape,
    test_data.shape,
)
```

```
Train - Validation - Test dataset shapes:  (68970, 13) (12172, 13)
(14320, 13)
Train - Validation - Test dataset shapes:  (68970, 13) (12172, 13)
(14320, 13)
```

Data processing with a pipeline and ColumnTransformer

In a typical ML workflow, you need to apply data transformations, such as imputation and scaling, at least twice: first on the training dataset by using `.fit()` and `.transform()` when preparing the data to train the model, and then by using `.transform()` on any new data that you want to predict on (validation or test). Sklearn's Pipeline is a tool that simplifies this process by enforcing the implementation and order of data processing steps.

In this section, you will build separate pipelines to handle the numerical, categorical, and text features. Then, you will combine them into a composite pipeline along with an estimator. To do this, you will use a LogisticRegression classifier.

You will need multiple pipelines to ensure that all the data is handled correctly:

- **Numerical features pipeline:** Impute missing values with the mean by using sklearn's `SimpleImputer`, followed by `MinMaxScaler`. If different processing is desired for different numerical features, different pipelines should be built as described for the text features pipeline.

- **Categoricals pipeline:** Impute with a placeholder value (this won't have an effect because you already encoded the `nan` values), and encode with sklearn's `OneHotEncoder`. If computing memory is an issue, it is a good idea to check the number of unique values for the categoricals to get an estimate of how many dummy features one-hot encoding will create. Note the `handle_unknown` parameter, which tells the encoder to ignore (rather than throw an error for) any unique value that might show in the validation or test set that was not present in the initial training set.

- **Text features pipeline:** With memory usage in mind, build three more pipelines, one for each of the text features. The current sklearn implementation requires a separate transformer for each text feature (unlike the numericals and categoricals).

Finally, the selective preparations of the dataset features are then put together into a collective ColumnTransformer, which is used in a pipeline along with an estimator. This ensures that the transforms are performed automatically in all situations. This includes on the raw data when fitting the model, when making predictions, when evaluating the model on a validation dataset through cross-validation, or when making predictions on a test dataset in the future.

```
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer

### COLUMN_TRANSFORMER ###
##########################

# Preprocess the numerical features
numerical_processor = Pipeline(
    [
        ("num_imputer", SimpleImputer(strategy="mean")),
        (
            "num_scaler",
            MinMaxScaler(),
        ),
    ]
)

# Preprocess the categorical features
categorical_processor = Pipeline(
    [
        (
            "cat_imputer",
            SimpleImputer(strategy="constant", fill_value="missing"),
        ),  # Shown in case it is needed. No effect here because you 
already imputed with 'nan' strings.
        (
            "cat_encoder",
            OneHotEncoder(handle_unknown="ignore"),
        ),  # handle_unknown tells it to ignore (rather than throw an 
error for) any value that was not present in the initial training set.
    ]
)
```

```
# Preprocess first text feature
text_processor_0 = Pipeline(
    [("text_vectorizer_0", CountVectorizer(binary=True,
max_features=50))]
)

# Preprocess second text feature
text_processor_1 = Pipeline(
    [("text_vectorizer_1", CountVectorizer(binary=True,
max_features=50))]
)

# Preprocess third text feature
text_processor_2 = Pipeline(
    [("text_vectorizer_2", CountVectorizer(binary=True,
max_features=50))]
)

# Combine all data preprocessors (add more if you choose to define
more)
# For each processor/step, specify: a name, the actual process, and
the features to be processed.
data_processor = ColumnTransformer(
    [
        ("numerical_processing", numerical_processor,
numerical_features),
        ("categorical_processing", categorical_processor,
categorical_features),
        ("text_processing_0", text_processor_0, text_features[0]),
        ("text_processing_1", text_processor_1, text_features[1]),
        ("text_processing_2", text_processor_2, text_features[2]),
    ]
)

# Visualize the data processing pipeline
from sklearn import set_config

set_config(display="diagram")
data_processor
```

```
ColumnTransformer(transformers=[('numerical_processing',
                                 Pipeline(steps=[('num_imputer',
                                                  SimpleImputer()),
                                                 ('num_scaler',
                                                  MinMaxScaler())]),
                                 ['Age upon Intake Days',
                                  'Age upon Outcome Days']),
                                ('categorical_processing',
                                 Pipeline(steps=[('cat_imputer',
```

```
SimpleImputer(fill_value='missing',

strategy='constant')),
                                                          ('cat_encoder',

OneHotEncoder(handle_unknown='ignore'))])...
                                      ('text_processing_0',
                                       Pipeline(steps=[('text_vectorizer_0',

CountVectorizer(binary=True,

max_features=50))]),
                                       'Found Location'),
                                      ('text_processing_1',
                                       Pipeline(steps=[('text_vectorizer_1',

CountVectorizer(binary=True,

max_features=50))]),
                                       'Breed'),
                                      ('text_processing_2',
                                       Pipeline(steps=[('text_vectorizer_2',

CountVectorizer(binary=True,

max_features=50))]),
                                       'Color')])

ColumnTransformer(transformers=[('numerical_processing',
                                       Pipeline(steps=[('num_imputer',
                                                         SimpleImputer()),
                                                        ('num_scaler',
                                                         MinMaxScaler())]),
                                       ['Age upon Intake Days',
                                        'Age upon Outcome Days']),
                                      ('categorical_processing',
                                       Pipeline(steps=[('cat_imputer',

SimpleImputer(fill_value='missing',

strategy='constant')),
                                                          ('cat_encoder',

OneHotEncoder(handle_unknown='ignore'))])...
                                      ('text_processing_0',
                                       Pipeline(steps=[('text_vectorizer_0',

CountVectorizer(binary=True,

max_features=50))]),
                                       'Found Location'),
```

```
                                ('text_processing_1',
                                 Pipeline(steps=[('text_vectorizer_1',

CountVectorizer(binary=True,

max_features=50))]),
                                 'Breed'),
                                ('text_processing_2',
                                 Pipeline(steps=[('text_vectorizer_2',

CountVectorizer(binary=True,

max_features=50))]),
                                 'Color')])

# Prepare data for training
X_train = train_data[model_features]
y_train = train_data[model_target].values

# Get validation data to validate the network
X_val = val_data[model_features]
y_val = val_data[model_target].values

# Get test data to test the network for submission to the leaderboard
X_test = test_data[model_features]
y_test = test_data[model_target].values

print("Dataset shapes before processing: ", X_train.shape,
X_val.shape, X_test.shape)

X_train = data_processor.fit_transform(X_train).toarray()
X_val = data_processor.transform(X_val).toarray()
X_test = data_processor.transform(X_test).toarray()

print("Dataset shapes after processing: ", X_train.shape, X_val.shape,
X_test.shape)

Dataset shapes before processing:  (68970, 10) (12172, 10) (14320, 10)
Dataset shapes before processing:  (68970, 10) (12172, 10) (14320, 10)
Dataset shapes after processing:  (68970, 171) (12172, 171) (14320,
171)
Dataset shapes after processing:  (68970, 171) (12172, 171) (14320,
171)
```

Training and validation of a neural network

Now, run the following code cell to interact with the neural network to gain insight into how neural networks train.

Architect the neural network by updating the number of layers (maximum of 4) and the number of neurons per layer (maximum of 3) to solve the classification problem that displays when you run the following cell. The background colors show the neural network's predicted classification regions for the true data (circles).

Note that upon retraining the network, the weights are randomly initialized, and the gradients are reset to 0. In the visual representation, each green circle corresponds to an epoch. Each red circle corresponds to that layer's weight update gradient (from backpropagation).

To develop a better understanding, train the model for different architectures. Note that the model gets stuck sometimes—initialization is important!

```
NeuralNetwork()
```

```
<MLUDTI_M1_Lab3_neural_network.NeuralNetwork at 0x7f9b3a8dfa30>
```


```
<MLUDTI_M1_Lab3_neural_network.NeuralNetwork at 0x7f9b3a8dfa30>
```


Now you need to build a PyTorch neural network and use it to fit to the training data. As part of the training, you need to use the validation data to check performance at the end of each training iteration.

```
# Define the hyperparamaters
batch_size = 16
num_epochs = 15
learning_rate = 0.001
device = torch.device("cuda:0" if torch.cuda.is_available() else
"cpu")

# Convert the data into PyTorch tensors

X_train = torch.tensor(X_train, dtype=torch.float32).to(device)
X_val = torch.tensor(X_val, dtype=torch.float32).to(device)
X_test = torch.tensor(X_test, dtype=torch.float32).to(device)

y_train = torch.tensor(y_train, dtype=torch.long).to(device)
y_val = torch.tensor(y_val, dtype=torch.long).to(device)
y_test = torch.tensor(y_test, dtype=torch.long).to(device)

# Use PyTorch DataLoaders to load the data in batches
train_dataset = torch.utils.data.TensorDataset(X_train, y_train)
train_loader = torch.utils.data.DataLoader(train_dataset,
                                           batch_size=batch_size,
                                           drop_last=True)

val_dataset = torch.utils.data.TensorDataset(X_val, y_val)
val_loader = torch.utils.data.DataLoader(val_dataset,
                                         batch_size=batch_size,
                                         drop_last=True)
```

```
# Create a multilayer perceptron by using the Sequential module. Add
the following in sequence:
# Two hidden layers of size 64
# Dropout layers attached to the hidden layers
# ReLU activation functions
# One output layer

############### CODE HERE ###############



############### END OF CODE ###############


def xavier_init_weights(m):
    if type(m) == nn.Linear:
        torch.nn.init.xavier_uniform_(m.weight)


net.apply(xavier_init_weights)
```

```
----------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
last)
Cell In[18], line 19
     15     if type(m) == nn.Linear:
     16         torch.nn.init.xavier_uniform_(m.weight)
---> 19 net.apply(xavier_init_weights)

NameError: name 'net' is not defined
```


```
----------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
last)
Cell In[18], line 19
     15     if type(m) == nn.Linear:
     16         torch.nn.init.xavier_uniform_(m.weight)
---> 19 net.apply(xavier_init_weights)

NameError: name 'net' is not defined
```


```
# Define the loss function and the optimizer
# Choose cross-entropy loss for this classification problem
loss = nn.CrossEntropyLoss()

# Optimize with stochastic gradient descent. You can experiment with
other optimizers.
optimizer = torch.optim.SGD(net.parameters(), lr=learning_rate)
```

```
import time

#####################
# Network training and validation

# Start the outer epoch loop (epoch = full pass through the dataset)
for epoch in range(num_epochs):
    start = time.time()

    training_loss, validation_loss = 0.0, 0.0

    # Training loop (with autograd and trainer steps)
    # This loop trains the neural network
    # Weights are updated here
    net.train()  # Activate training mode (dropouts and so on)
    for data, target in train_loader:
        # Zero the parameter gradients
        optimizer.zero_grad()
        data = data.to(device)
        target = target.to(device)
        # Forward + backward + optimize
        output = net(data)
        L = loss(output, target)
        L.backward()
        optimizer.step()
        # Add batch loss
        training_loss += L.item()

    net.eval()  # Activate eval mode (don't use dropouts and so on)
    for data, target in val_loader:
        data = data.to(device)
        target = target.to(device)
        output = net(data)
        L = loss(output, target)
        # Add batch loss
        validation_loss += L.item()

    # Take the average losses
    training_loss = training_loss / len(train_loader)
    val_loss = validation_loss / len(val_loader)

    end = time.time()
    print(
        "Epoch %s. Train_loss %f Validation_loss %f Seconds %f"
        % (epoch, training_loss, val_loss, end - start)
    )
```

Testing the neural network

Now you can evaluate the performance of the trained network on the test set.

```
from sklearn.metrics import classification_report

# Activate eval mode (don't use dropouts and so on)
net.eval()

# Get test predictions
predictions = net(X_test)

# Print performance of the test data
print(
    classification_report(
        y_test.cpu().numpy(),
predictions.argmax(axis=1).cpu().detach().numpy()
    )
)
```

Improvement ideas

You can improve this neural network by tuning network parameters such as the following:

- Architecture
- Number of layers
- Number of hidden neurons
- Choice of activation function
- Weight initialization
- Dropout
- Choice of optimizer function
- Learning rate
- Batch size
- Number of epochs

As you make changes, closely monitor the loss function and the accuracy on both training and validation to identify what changes improve your model.

Conclusion

In this notebook, you built a basic neural network to process text data.

Next Lab: Introducing CNNs

In the next lab in this module you will learn how to build a convolutional neural network to process hand written numbers.