In [0]:
```
import nltk
nltk.download('all')
```

In [2]:
```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Flatten,Dense, Dropout, BatchNormalization
from tensorflow.keras.layers import Conv1D,MaxPool1D
from tensorflow.keras.preprocessing.image import ImageDataGenerator

from tensorflow.keras.optimizers import Adam

import re,string,unicodedata
from bs4 import BeautifulSoup
from sklearn.preprocessing import LabelBinarizer

from nltk.corpus import stopwords
from nltk.stem.porter import PorterStemmer
from wordcloud import WordCloud,STOPWORDS
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import word_tokenize,sent_tokenize
import re,string,unicodedata
from nltk.tokenize.toktok import ToktokTokenizer
from nltk.stem import LancasterStemmer,WordNetLemmatizer

print(tf.__version__)
```

```
2.2.0
```

In [3]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: Futu
reWarning: pandas.util.testing is deprecated. Use the functions in the public
API at pandas.testing instead.
  import pandas.util.testing as tm
```

In [0]:
```
catWiki = pd.read_csv("/content/catWiki.txt", sep='\n', header=None)
dogWiki = pd.read_csv("/content/dogWiki.txt", sep='\n', header=None)

catWiki.columns = ['text']
dogWiki.columns = ['text']
```

In [6]:
```
catWiki['class'] = 'cat'
dogWiki['class'] = 'dog'
data = catWiki
data = data.append(dogWiki)
data.head()
```

Out[6]:

	text	class
0	The cat (Felis catus) is a domestic species of...	cat
1	The cat is similar in anatomy to the other fel...	cat
2	Female domestic cats can have kittens from spr...	cat
3	Cats were first domesticated in the Near East ...	cat
4	As of 2017, the domestic cat was the second-mo...	cat

In [7]:
```
data.columns
```

Out[7]:
```
Index(['text', 'class'], dtype='object')
```

In [0]:
```
#Tokenization of text
tokenizer=ToktokTokenizer()
#Setting English stopwords
stopword_list=nltk.corpus.stopwords.words('english')
```

In [0]:
```
#Removing the html strips
def strip_html(text):
    soup = BeautifulSoup(text, "html.parser")
    return soup.get_text()

#Removing the square brackets
def remove_between_square_brackets(text):
    return re.sub('\[[^]]*\]', '', text)

#Removing the noisy text
def denoise_text(text):
    text = strip_html(text)
    text = remove_between_square_brackets(text)
    return text

#Apply function on text column
data['text']=data['text'].apply(denoise_text)
```

In [0]:
```
#Define function for removing special characters
def remove_special_characters(text, remove_digits=True):
    pattern=r'[^a-zA-z0-9\s]'
    text=re.sub(pattern,'',text)
    return text

#Apply function on text column
data['text']=data['text'].apply(denoise_text)
```

In [11]:
```
#set stopwords to english
stop=set(stopwords.words('english'))
print(stop)

#removing the stopwords
def remove_stopwords(text, is_lower_case=False):
    tokens = tokenizer.tokenize(text)
    tokens = [token.strip() for token in tokens]
    if is_lower_case:
        filtered_tokens = [token for token in tokens if token not in stopword_
list]
    else:
        filtered_tokens = [token for token in tokens if token.lower() not in s
topword_list]
    filtered_text = ' '.join(filtered_tokens)
    return filtered_text


#Apply function on text column
data['text']=data['text'].apply(remove_stopwords)
```

```
{'been', 'where', "won't", 'her', 'what', 'same', "wasn't", 'how', 'such', 't
he', 'up', "wouldn't", 'have', "haven't", 'this', "that'll", 'you', "don't",
'she', 'myself', 'my', 'few', "should've", 'wasn', 'over', 'own', 'those', 'h
adn', 'o', 'herself', 'not', "shouldn't", 'shouldn', 'above', 'ain', 'hasn',
'then', 'nor', 'after', 'is', 'some', 'of', 'its', 'themselves', 'me', 'are',
'yourselves', 'both', 'should', 'theirs', "it's", 'too', 'now', 'himself', "s
he's", 'aren', "couldn't", 'by', 'if', 'in', 'but', 'was', "shan't", 'shan',
'our', 'an', "you've", 'all', 'only', 's', 'has', 'wouldn', 'd', 'any', 'whil
e', 'doesn', 'itself', "mustn't", 'didn', 'needn', 'very', 'these', 'your',
'we', 'before', 'be', 'm', 'who', 't', 'when', 'once', 'their', 'isn', 'throu
gh', "hadn't", 'it', 'between', 'do', "mightn't", 'doing', 'they', 'to', 'm
a', 've', 'no', 'ours', 'that', 'y', 'under', 'other', 'mightn', 'am', "are
n't", 'mustn', 'having', 'did', 'a', 'can', 'whom', 'again', 'he', "you'd",
'or', "doesn't", 'were', "didn't", 'so', 'his', 'further', 'more', "hasn't",
'won', 'with', 'into', 'on', 'why', 'them', 'and', 'i', 'most', 'from', 'jus
t', 'does', 'ourselves', 'being', 'as', 'him', 'yourself', 'll', 'for', "yo
u're", 're', 'weren', 'because', 'don', 'haven', 'off', 'here', 'there', 'wil
l', "isn't", 'below', 'out', 'yours', 'hers', "needn't", 'down', 'than', "wer
en't", 'at', 'couldn', 'about', 'which', 'until', 'against', 'had', "you'll",
'during', 'each'}
```

In [12]:
```
from sklearn.preprocessing import LabelBinarizer
#labeling the data
lb=LabelBinarizer()
#transformed label data
label_data=lb.fit_transform(data['class'])
#label_data
print(label_data.shape)

# labeling convert the classes as cat as "0" and Dog as "1"
```

```
(290, 1)
```

In [14]:
```
data.head()
```

Out[14]:

	text	class
0	cat (Felis catus) domestic species small car...	cat
1	cat similar anatomy felid species : strong fle...	cat
2	Female domestic cats kittens spring late autum...	cat
3	Cats first domesticated Near East around 7500 ...	cat
4	2017 , domestic cat second-most popular pet Un...	cat

In [0]:
```
data['label'] = label_data
```

In [16]:
```
data.tail()
```

Out[16]:

	text	class	label
166	Art	dog	1
167	Main article : Cultural depictions dogs Wester...	dog	1
168	Cultural depictions dogs art extend back thous...	dog	1
169	Education appreciation	dog	1
170	American Kennel Club reopened museum called " ...	dog	1

#Word Frequencies with TfidfVectorizer

Word counts are a good starting point, but are very basic.

One issue with simple counts is that some words like “the” will appear many times and their large counts will not be very meaningful in the encoded vectors.

An alternative is to calculate word frequencies, and by far the most popular method is called TF-IDF. This is an acronym than stands for “Term Frequency – Inverse Document” Frequency which are the components of the resulting scores assigned to each word.

Term Frequency: This summarizes how often a given word appears within a document.

Inverse Document Frequency: This downscales words that appear a lot across documents.

The **TfidfVectorizer** will tokenize documents, learn the vocabulary and inverse document frequency weightings, and allow you to encode new documents.

Feature Engineering

In [17]:
```
"""
Feature Engineering
Next, we will take the preprocessed texts as input and calculate their TF-IDF's. We will retain 10 features per text.

"""

from sklearn.feature_extraction.text import TfidfVectorizer
# list of text documents
text = data['text']
# create the transform
vectorizer = TfidfVectorizer(min_df=5, max_features=37)
# tokenize and build vocab
vectorizer.fit(text)
# summarize
#print(vectorizer.vocabulary_)
#print(vectorizer.idf_)
# encode document
vector = vectorizer.transform(text)
# summarize encoded vector
print(vector.shape)
print(vector.toarray())
```

```
(290, 37)
[[0.         0.         0.         ... 0.         0.         0.        ]
 [0.         0.         0.         ... 0.         0.         0.        ]
 [0.         0.         0.         ... 0.         0.         0.        ]
 ...
 [0.         0.         0.         ... 0.         0.         0.34439175]
 [0.         0.         0.         ... 0.         0.         0.        ]
 [0.         0.         0.         ... 0.         0.         0.        ]]
```

In [18]:
```
print(vectorizer.vocabulary_)
```

```
{'cat': 7, 'domestic': 11, 'species': 31, 'domesticated': 12, 'often': 24, 'feral': 14, 'human': 17, 'cats': 8, 'humans': 18, 'breeds': 6, 'body': 4, 'prey': 29, 'like': 20, 'social': 30, 'female': 13, 'two': 33, 'known': 19, 'pet': 27, 'pets': 28, 'first': 15, 'also': 0, 'may': 23, 'years': 36, 'animals': 1, 'behavior': 3, 'main': 21, 'article': 2, 'one': 25, 'many': 22, 'study': 32, 'health': 16, 'dog': 9, 'breed': 5, 'people': 26, 'dogs': 10, 'wolf': 34, 'wolves': 35}
```

In [19]:
```
type(vector)
```

Out[19]:
```
scipy.sparse.csr.csr_matrix
```

In [20]:
```
from sklearn.model_selection import train_test_split

# Split data to target (y) and features (X)
X = vector.toarray()
y = (np.array(data['label']))

# Here we split data to training and testing parts
X_train , X_test, y_train, y_test = train_test_split(X,y,test_size=0.2, random
_state= 0, stratify =y)
print("Train dataset shape: {0}, \nTest dataset shape: {1}".format(X_train.sha
pe, X_test.shape))
```

```
Train dataset shape: (232, 37),
Test dataset shape: (58, 37)
```

In [0]:
```
#CNN accepst data in 3D
# we have to reshape teh data.
X_train= X_train.reshape(232,37,1)
X_test = X_test.reshape(58,37,1)
```

In [0]:
```
epochs = 60
model = Sequential()
model.add(Conv1D(filters=32,kernel_size=2, activation='relu', input_shape = (3
7,1)))
model.add(BatchNormalization())
model.add(Dropout(0.2))

model.add(Conv1D(filters=64,kernel_size=2, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))

model.add(Flatten())
model.add(Dense(64,activation='relu'))
model.add(Dropout(0.5))


model.add(Dense(1,activation='sigmoid'))
```

In [92]:
```
model.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv1d_10 (Conv1D)           (None, 36, 32)            96        
_________________________________________________________________
batch_normalization_10 (Batc (None, 36, 32)            128       
_________________________________________________________________
dropout_15 (Dropout)         (None, 36, 32)            0         
_________________________________________________________________
conv1d_11 (Conv1D)           (None, 35, 64)            4160      
_________________________________________________________________
batch_normalization_11 (Batc (None, 35, 64)            256       
_________________________________________________________________
dropout_16 (Dropout)         (None, 35, 64)            0         
_________________________________________________________________
flatten_5 (Flatten)          (None, 2240)              0         
_________________________________________________________________
dense_10 (Dense)             (None, 64)                143424    
_________________________________________________________________
dropout_17 (Dropout)         (None, 64)                0         
_________________________________________________________________
dense_11 (Dense)             (None, 1)                 65        
=================================================================
Total params: 148,129
Trainable params: 147,937
Non-trainable params: 192
_________________________________________________________________
```

In [0]:
```
model.compile(optimizer=Adam(lr=0.00005),loss='binary_crossentropy',metrics=[
'accuracy'])
```

In [94]:
```
history = model.fit(X_train,y_train,epochs=epochs,validation_data=(X_test,y_te
st),verbose=1)
```

```
Epoch 1/60
8/8 [==============================] - 0s 28ms/step - loss: 0.9919 - accurac
y: 0.5991 - val_loss: 0.6868 - val_accuracy: 0.7586
Epoch 2/60
8/8 [==============================] - 0s 12ms/step - loss: 1.1141 - accurac
y: 0.5603 - val_loss: 0.6845 - val_accuracy: 0.7931
Epoch 3/60
8/8 [==============================] - 0s 14ms/step - loss: 0.9217 - accurac
y: 0.6250 - val_loss: 0.6827 - val_accuracy: 0.8103
Epoch 4/60
8/8 [==============================] - 0s 13ms/step - loss: 0.7741 - accurac
y: 0.6638 - val_loss: 0.6808 - val_accuracy: 0.8103
Epoch 5/60
8/8 [==============================] - 0s 12ms/step - loss: 0.7652 - accurac
y: 0.7026 - val_loss: 0.6791 - val_accuracy: 0.8103
Epoch 6/60
8/8 [==============================] - 0s 12ms/step - loss: 0.6875 - accurac
y: 0.7198 - val_loss: 0.6775 - val_accuracy: 0.8448
Epoch 7/60
8/8 [==============================] - 0s 13ms/step - loss: 0.7718 - accurac
y: 0.6810 - val_loss: 0.6756 - val_accuracy: 0.8448
Epoch 8/60
8/8 [==============================] - 0s 12ms/step - loss: 0.6540 - accurac
y: 0.6724 - val_loss: 0.6734 - val_accuracy: 0.8448
Epoch 9/60
8/8 [==============================] - 0s 14ms/step - loss: 0.6791 - accurac
y: 0.7112 - val_loss: 0.6712 - val_accuracy: 0.8448
Epoch 10/60
8/8 [==============================] - 0s 13ms/step - loss: 0.6365 - accurac
y: 0.7328 - val_loss: 0.6689 - val_accuracy: 0.8448
Epoch 11/60
8/8 [==============================] - 0s 12ms/step - loss: 0.5445 - accurac
y: 0.7500 - val_loss: 0.6668 - val_accuracy: 0.8448
Epoch 12/60
8/8 [==============================] - 0s 12ms/step - loss: 0.6192 - accurac
y: 0.7414 - val_loss: 0.6646 - val_accuracy: 0.8621
Epoch 13/60
8/8 [==============================] - 0s 15ms/step - loss: 0.5229 - accurac
y: 0.7241 - val_loss: 0.6615 - val_accuracy: 0.8621
Epoch 14/60
8/8 [==============================] - 0s 12ms/step - loss: 0.6126 - accurac
y: 0.7284 - val_loss: 0.6583 - val_accuracy: 0.8621
Epoch 15/60
8/8 [==============================] - 0s 13ms/step - loss: 0.4582 - accurac
y: 0.7716 - val_loss: 0.6550 - val_accuracy: 0.8621
Epoch 16/60
8/8 [==============================] - 0s 13ms/step - loss: 0.4662 - accurac
y: 0.7672 - val_loss: 0.6514 - val_accuracy: 0.8621
Epoch 17/60
8/8 [==============================] - 0s 12ms/step - loss: 0.4375 - accurac
y: 0.7716 - val_loss: 0.6475 - val_accuracy: 0.8621
Epoch 18/60
8/8 [==============================] - 0s 13ms/step - loss: 0.5194 - accurac
y: 0.7845 - val_loss: 0.6437 - val_accuracy: 0.8621
Epoch 19/60
8/8 [==============================] - 0s 13ms/step - loss: 0.4065 - accurac
y: 0.8190 - val_loss: 0.6400 - val_accuracy: 0.8621
```

```
Epoch 20/60
8/8 [==============================] - 0s 14ms/step - loss: 0.3864 - accurac
y: 0.7974 - val_loss: 0.6362 - val_accuracy: 0.8621
Epoch 21/60
8/8 [==============================] - 0s 13ms/step - loss: 0.4890 - accurac
y: 0.7586 - val_loss: 0.6323 - val_accuracy: 0.8621
Epoch 22/60
8/8 [==============================] - 0s 13ms/step - loss: 0.5373 - accurac
y: 0.7672 - val_loss: 0.6283 - val_accuracy: 0.8621
Epoch 23/60
8/8 [==============================] - 0s 13ms/step - loss: 0.3708 - accurac
y: 0.7888 - val_loss: 0.6243 - val_accuracy: 0.8621
Epoch 24/60
8/8 [==============================] - 0s 13ms/step - loss: 0.4030 - accurac
y: 0.8147 - val_loss: 0.6193 - val_accuracy: 0.8621
Epoch 25/60
8/8 [==============================] - 0s 12ms/step - loss: 0.4794 - accurac
y: 0.7802 - val_loss: 0.6141 - val_accuracy: 0.8621
Epoch 26/60
8/8 [==============================] - 0s 13ms/step - loss: 0.4689 - accurac
y: 0.7500 - val_loss: 0.6087 - val_accuracy: 0.8621
Epoch 27/60
8/8 [==============================] - 0s 12ms/step - loss: 0.3873 - accurac
y: 0.8190 - val_loss: 0.6033 - val_accuracy: 0.8621
Epoch 28/60
8/8 [==============================] - 0s 12ms/step - loss: 0.4557 - accurac
y: 0.7500 - val_loss: 0.5982 - val_accuracy: 0.8621
Epoch 29/60
8/8 [==============================] - 0s 12ms/step - loss: 0.4187 - accurac
y: 0.7500 - val_loss: 0.5928 - val_accuracy: 0.8621
Epoch 30/60
8/8 [==============================] - 0s 14ms/step - loss: 0.4007 - accurac
y: 0.8060 - val_loss: 0.5868 - val_accuracy: 0.8621
Epoch 31/60
8/8 [==============================] - 0s 14ms/step - loss: 0.3246 - accurac
y: 0.8362 - val_loss: 0.5805 - val_accuracy: 0.8621
Epoch 32/60
8/8 [==============================] - 0s 12ms/step - loss: 0.3946 - accurac
y: 0.7931 - val_loss: 0.5738 - val_accuracy: 0.8621
Epoch 33/60
8/8 [==============================] - 0s 12ms/step - loss: 0.3118 - accurac
y: 0.8448 - val_loss: 0.5668 - val_accuracy: 0.8621
Epoch 34/60
8/8 [==============================] - 0s 12ms/step - loss: 0.3621 - accurac
y: 0.8060 - val_loss: 0.5596 - val_accuracy: 0.8621
Epoch 35/60
8/8 [==============================] - 0s 12ms/step - loss: 0.3216 - accurac
y: 0.8405 - val_loss: 0.5524 - val_accuracy: 0.8621
Epoch 36/60
8/8 [==============================] - 0s 12ms/step - loss: 0.2861 - accurac
y: 0.8534 - val_loss: 0.5447 - val_accuracy: 0.8621
Epoch 37/60
8/8 [==============================] - 0s 12ms/step - loss: 0.4019 - accurac
y: 0.8276 - val_loss: 0.5366 - val_accuracy: 0.8621
Epoch 38/60
8/8 [==============================] - 0s 12ms/step - loss: 0.4026 - accurac
y: 0.8190 - val_loss: 0.5278 - val_accuracy: 0.8621
```

```
Epoch 39/60
8/8 [==============================] - 0s 14ms/step - loss: 0.3421 - accurac
y: 0.8276 - val_loss: 0.5190 - val_accuracy: 0.8621
Epoch 40/60
8/8 [==============================] - 0s 12ms/step - loss: 0.2875 - accurac
y: 0.8578 - val_loss: 0.5113 - val_accuracy: 0.8621
Epoch 41/60
8/8 [==============================] - 0s 13ms/step - loss: 0.3659 - accurac
y: 0.8233 - val_loss: 0.5028 - val_accuracy: 0.8621
Epoch 42/60
8/8 [==============================] - 0s 13ms/step - loss: 0.3524 - accurac
y: 0.8147 - val_loss: 0.4942 - val_accuracy: 0.8621
Epoch 43/60
8/8 [==============================] - 0s 12ms/step - loss: 0.3996 - accurac
y: 0.8060 - val_loss: 0.4847 - val_accuracy: 0.8621
Epoch 44/60
8/8 [==============================] - 0s 12ms/step - loss: 0.3165 - accurac
y: 0.8750 - val_loss: 0.4747 - val_accuracy: 0.8621
Epoch 45/60
8/8 [==============================] - 0s 13ms/step - loss: 0.3560 - accurac
y: 0.7931 - val_loss: 0.4648 - val_accuracy: 0.8621
Epoch 46/60
8/8 [==============================] - 0s 12ms/step - loss: 0.2918 - accurac
y: 0.8319 - val_loss: 0.4543 - val_accuracy: 0.8621
Epoch 47/60
8/8 [==============================] - 0s 13ms/step - loss: 0.3158 - accurac
y: 0.8233 - val_loss: 0.4438 - val_accuracy: 0.8621
Epoch 48/60
8/8 [==============================] - 0s 13ms/step - loss: 0.4144 - accurac
y: 0.7716 - val_loss: 0.4336 - val_accuracy: 0.8621
Epoch 49/60
8/8 [==============================] - 0s 13ms/step - loss: 0.3053 - accurac
y: 0.8578 - val_loss: 0.4232 - val_accuracy: 0.8621
Epoch 50/60
8/8 [==============================] - 0s 13ms/step - loss: 0.2754 - accurac
y: 0.8621 - val_loss: 0.4136 - val_accuracy: 0.8621
Epoch 51/60
8/8 [==============================] - 0s 12ms/step - loss: 0.4098 - accurac
y: 0.7716 - val_loss: 0.4044 - val_accuracy: 0.8621
Epoch 52/60
8/8 [==============================] - 0s 12ms/step - loss: 0.2787 - accurac
y: 0.8664 - val_loss: 0.3944 - val_accuracy: 0.8621
Epoch 53/60
8/8 [==============================] - 0s 14ms/step - loss: 0.3124 - accurac
y: 0.8578 - val_loss: 0.3854 - val_accuracy: 0.8621
Epoch 54/60
8/8 [==============================] - 0s 13ms/step - loss: 0.3664 - accurac
y: 0.8103 - val_loss: 0.3773 - val_accuracy: 0.8276
Epoch 55/60
8/8 [==============================] - 0s 15ms/step - loss: 0.3105 - accurac
y: 0.8190 - val_loss: 0.3688 - val_accuracy: 0.8276
Epoch 56/60
8/8 [==============================] - 0s 14ms/step - loss: 0.3248 - accurac
y: 0.8448 - val_loss: 0.3602 - val_accuracy: 0.8276
Epoch 57/60
8/8 [==============================] - 0s 13ms/step - loss: 0.3370 - accurac
y: 0.8190 - val_loss: 0.3520 - val_accuracy: 0.8276
```

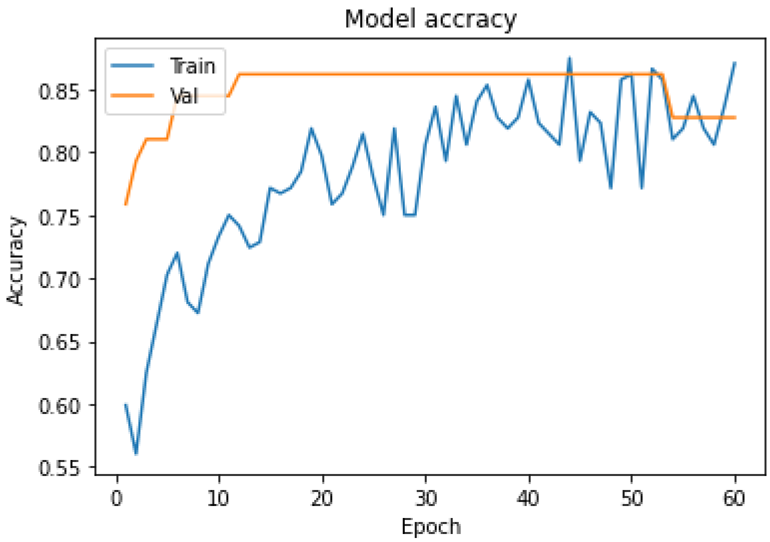
```
Epoch 58/60
8/8 [==============================] - 0s 14ms/step - loss: 0.3303 - accurac
y: 0.8060 - val_loss: 0.3437 - val_accuracy: 0.8276
Epoch 59/60
8/8 [==============================] - 0s 14ms/step - loss: 0.3155 - accurac
y: 0.8362 - val_loss: 0.3355 - val_accuracy: 0.8276
Epoch 60/60
8/8 [==============================] - 0s 13ms/step - loss: 0.2739 - accurac
y: 0.8707 - val_loss: 0.3279 - val_accuracy: 0.8276
```

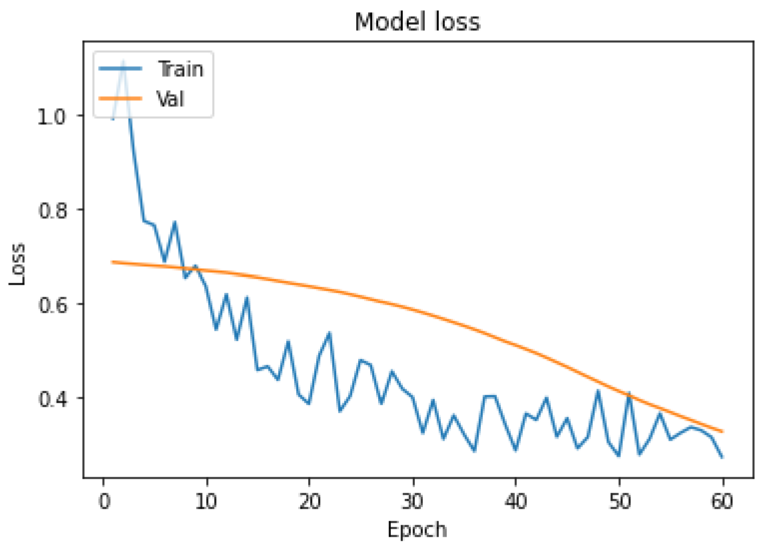
In [0]:

```
def plot_learningCurve(history,epoch):
  #plot training and validation accuracy values
  epoch_range = range(1,epoch+1)
  plt.plot(epoch_range, history.history['accuracy'])
  plt.plot(epoch_range, history.history['val_accuracy'])
  plt.title('Model accracy')
  plt.ylabel('Accuracy')
  plt.xlabel("Epoch")
  plt.legend(['Train','Val'],loc ='upper left')
  plt.show()

  #plot training & valdiation loss values
  plt.plot(epoch_range, history.history['loss'])
  plt.plot(epoch_range, history.history['val_loss'])
  plt.title('Model loss')
  plt.ylabel('Loss')
  plt.xlabel("Epoch")
  plt.legend(['Train','Val'],loc ='upper left')
  plt.show()
```

In [96]:
```
plot_learningCurve(history,epochs)
```





In [97]:
```
#for testing my samples

testData = pd.read_csv("/content/testSentences.txt", sep='\n', header=None)
testData.columns = ['content']
testData
```

Out[97]:

	content
0	This animal is similar to the other felid spec...
1	This animal is similar to the wolf and fox.
2	This animal can detect a drug when hidden.
3	One type of animal acts as a guard of things.
4	Whiskers coughed up a hairball today.
5	This animal can understand a hand signal if pr...
6	He has a kitten.
7	This animal will catch a mouse when it seems i...
8	He carried a python across the street.
9	Python programming with machine learning has n...

In [0]:
```
#set stopwords to english
stop=set(stopwords.words('english'))


#removing the stopwords
def remove_stopwords(text, is_lower_case=False):
    tokens = tokenizer.tokenize(text)
    tokens = [token.strip() for token in tokens]
    if is_lower_case:
        filtered_tokens = [token for token in tokens if token not in stopword_
list]
    else:
        filtered_tokens = [token for token in tokens if token.lower() not in s
topword_list]
    filtered_text = ' '.join(filtered_tokens)
    return filtered_text

#Apply function on text column
testData['content']=testData['content'].apply(remove_stopwords)
```

In [99]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
# list of text documents
text = testData['content']

# create the transform
vectorizer = TfidfVectorizer(min_df=0, max_features=37)
# tokenize and build vocab
vectorizer.fit(text)
# summarize
print(vectorizer.vocabulary_)
print(vectorizer.idf_)
# encode document
highD_vector = vectorizer.transform(text)
# summarize encoded vector
print(highD_vector.shape)
print(highD_vector.toarray())
highD_vector =highD_vector.toarray()
```

```
{'animal': 2, 'similar': 27, 'felid': 9, 'species': 28, 'wolf': 36, 'fox': 1
0, 'detect': 7, 'drug': 8, 'hidden': 14, 'one': 21, 'type': 33, 'acts': 1, 'g
uard': 11, 'things': 30, 'whiskers': 35, 'coughed': 6, 'hairball': 12, 'toda
y': 31, 'understand': 34, 'hand': 13, 'signal': 26, 'properly': 23, 'traine
d': 32, 'kitten': 16, 'catch': 5, 'mouse': 19, 'seems': 25, 'impossible': 15,
'carried': 4, 'python': 24, 'across': 0, 'street': 29, 'programming': 22, 'ma
chine': 18, 'learning': 17, 'nothing': 20, 'animals': 3}
[2.70474809 2.70474809 1.45198512 2.70474809 2.70474809 2.70474809
 2.70474809 2.70474809 2.70474809 2.70474809 2.70474809 2.70474809
 2.70474809 2.70474809 2.70474809 2.70474809 2.70474809 2.70474809
 2.70474809 2.70474809 2.70474809 2.70474809 2.70474809 2.70474809
 2.29928298 2.70474809 2.70474809 2.29928298 2.70474809 2.70474809
 2.70474809 2.70474809 2.70474809 2.70474809 2.70474809 2.70474809
 2.70474809]
(10, 37)
[[0.         0.         0.30937949 0.         0.         0.
  0.         0.         0.         0.57631002 0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.48991617 0.57631002 0.
  0.         0.         0.         0.         0.         0.
  0.        ]
 [0.         0.         0.30937949 0.         0.         0.
  0.         0.         0.         0.         0.57631002 0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.48991617 0.         0.
  0.         0.         0.         0.         0.         0.
  0.57631002]
 [0.         0.         0.29604467 0.         0.         0.
  0.         0.55147002 0.55147002 0.         0.         0.
  0.         0.         0.55147002 0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.        ]
 [0.         0.43485723 0.23344364 0.         0.         0.
  0.         0.         0.         0.         0.         0.43485723
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.43485723 0.         0.
  0.         0.         0.         0.         0.         0.
  0.43485723 0.         0.         0.43485723 0.         0.
  0.        ]
 [0.         0.         0.         0.         0.         0.
  0.5        0.         0.         0.         0.         0.
  0.5        0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.5        0.         0.         0.         0.5
  0.        ]
 [0.         0.         0.23344364 0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.43485723 0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.43485723
  0.         0.         0.43485723 0.         0.         0.
  0.         0.         0.43485723 0.         0.43485723 0.
  0.        ]
```

```
 [0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         1.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.        ]
 [0.         0.         0.25923797 0.         0.         0.48290674
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.48290674 0.         0.
  0.         0.48290674 0.         0.         0.         0.
  0.         0.48290674 0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.        ]
 [0.5182909  0.         0.         0.         0.5182909  0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.44059462 0.         0.         0.         0.         0.5182909
  0.         0.         0.         0.         0.         0.
  0.        ]
 [0.         0.         0.         0.41802399 0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.41802399
  0.41802399 0.         0.41802399 0.         0.41802399 0.
  0.35535858 0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.        ]]
```

In [100]:
```
highD_vector.shape
```

Out[100]:
```
(10, 37)
```

In [0]:
```
import numpy as np

flatten=highD_vector.flatten()
input_array = flatten.reshape([10, 37,1])
```

In [102]:

```
prediction = model.predict(input_array)
probability =prediction

for i in range(10):
  output =probability[i]
  print(output, sep='', end='')
  print("Dog") if output > 0.5 else print("cat")



# Save model
#model.save('classification_model.h5')
```

```
[0.8785318]Dog
[0.86361]Dog
[0.03198174]cat
[0.537996]Dog
[0.7973918]Dog
[0.52897847]Dog
[0.74985474]Dog
[0.4151338]cat
[0.38029507]cat
[0.53706473]Dog
```

In [0]: