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

In [85]:
```
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 [0]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

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 [88]:
```
catWiki['class'] = 'cat'
dogWiki['class'] = 'dog'
data = catWiki
data = data.append(dogWiki)
data.head()
```

Out[88]:

	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 [89]:
```
data.columns
```

Out[89]:
```
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 [94]:
```
#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)
```

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

In [95]:
```
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 [96]:
```
#data.to_csv('/content/csvfiles/Boths_cats_and_dogs.csv')
data.head()
```

Out[96]:

	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 [98]:
```
data
```

Out[98]:

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

290 rows × 3 columns

Word Counts with CountVectorizer The CountVectorizer provides a simple way to both tokenize a collection of text documents and build a vocabulary of known words, but also to encode new documents using that vocabulary.

You can use it as follows:

Create an instance of the CountVectorizer class. Call the fit() function in order to learn a vocabulary from one or more documents. Call the transform() function on one or more documents as needed to encode each as a vector. An encoded vector is returned with a length of the entire vocabulary and an integer count for the number of times each word appeared in the document.

Feature Engineering

In [174]:
```
from sklearn.feature_extraction.text import CountVectorizer
# list of text documents
text = data['text']
# create the transform
vectorizer = CountVectorizer(min_df=5, max_features=37)
# tokenize and build vocab
vectorizer.fit(text)
# summarize
print(vectorizer.vocabulary_)
# encode document
vector = vectorizer.transform(text)
# summarize encoded vector
print(vector.shape)
print(type(vector))
print(vector.toarray())
```

```
{'cat': 7, 'domestic': 11, 'species': 31, 'domesticated': 12, 'often': 24, 'f
eral': 14, 'human': 17, 'cats': 8, 'humans': 18, 'breeds': 6, 'body': 4, 'pre
y': 29, 'like': 20, 'social': 30, 'female': 13, 'two': 33, 'known': 19, 'pe
t': 27, 'pets': 28, 'first': 15, 'also': 0, 'may': 23, 'years': 36, 'animal
s': 1, 'behavior': 3, 'main': 21, 'article': 2, 'one': 25, 'many': 22, 'stud
y': 32, 'health': 16, 'dog': 9, 'breed': 5, 'people': 26, 'dogs': 10, 'wolf':
34, 'wolves': 35}
(290, 37)
<class 'scipy.sparse.csr.csr_matrix'>
[[0 0 0 ... 0 0 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]]
```

In [175]:
```
print(vectorizer.vocabulary_)
```

```
{'cat': 7, 'domestic': 11, 'species': 31, 'domesticated': 12, 'often': 24, 'f
eral': 14, 'human': 17, 'cats': 8, 'humans': 18, 'breeds': 6, 'body': 4, 'pre
y': 29, 'like': 20, 'social': 30, 'female': 13, 'two': 33, 'known': 19, 'pe
t': 27, 'pets': 28, 'first': 15, 'also': 0, 'may': 23, 'years': 36, 'animal
s': 1, 'behavior': 3, 'main': 21, 'article': 2, 'one': 25, 'many': 22, 'stud
y': 32, 'health': 16, 'dog': 9, 'breed': 5, 'people': 26, 'dogs': 10, 'wolf':
34, 'wolves': 35}
```

In [176]:
```
type(vector)
```

Out[176]:
```
scipy.sparse.csr.csr_matrix
```

In [177]:
```
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 [178]:
```
#CNN accepst data in 3D
# reshape the data.
X_train= X_train.reshape(232,37,1)
X_test = X_test.reshape(58,37,1)
type(X_train)
```

Out[178]:
```
numpy.ndarray
```

In [0]:
```
epochs = 50
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 [180]:
```
model.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_14 (Conv1D)           (None, 36, 32)            96
_________________________________________________________________
batch_normalization_14 (Batc (None, 36, 32)            128
_________________________________________________________________
dropout_21 (Dropout)         (None, 36, 32)            0
_________________________________________________________________
conv1d_15 (Conv1D)           (None, 35, 64)            4160
_________________________________________________________________
batch_normalization_15 (Batc (None, 35, 64)            256
_________________________________________________________________
dropout_22 (Dropout)         (None, 35, 64)            0
_________________________________________________________________
flatten_7 (Flatten)          (None, 2240)              0
_________________________________________________________________
dense_14 (Dense)             (None, 64)                143424
_________________________________________________________________
dropout_23 (Dropout)         (None, 64)                0
_________________________________________________________________
dense_15 (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 [182]:
```
history = model.fit(X_train,y_train,epochs=epochs,validation_data=(X_test,y_test),verbose=1)
```

```
Epoch 1/50
8/8 [==============================] - 0s 25ms/step - loss: 0.9941 - accurac
y: 0.5647 - val_loss: 0.6821 - val_accuracy: 0.5862
Epoch 2/50
8/8 [==============================] - 0s 13ms/step - loss: 1.0717 - accurac
y: 0.5086 - val_loss: 0.6785 - val_accuracy: 0.6034
Epoch 3/50
8/8 [==============================] - 0s 11ms/step - loss: 0.8451 - accurac
y: 0.6078 - val_loss: 0.6737 - val_accuracy: 0.6724
Epoch 4/50
8/8 [==============================] - 0s 13ms/step - loss: 0.8299 - accurac
y: 0.6293 - val_loss: 0.6683 - val_accuracy: 0.6897
Epoch 5/50
8/8 [==============================] - 0s 12ms/step - loss: 0.7251 - accurac
y: 0.6379 - val_loss: 0.6630 - val_accuracy: 0.6897
Epoch 6/50
8/8 [==============================] - 0s 12ms/step - loss: 0.7169 - accurac
y: 0.6379 - val_loss: 0.6573 - val_accuracy: 0.6897
Epoch 7/50
8/8 [==============================] - 0s 13ms/step - loss: 0.7878 - accurac
y: 0.6724 - val_loss: 0.6510 - val_accuracy: 0.7069
Epoch 8/50
8/8 [==============================] - 0s 13ms/step - loss: 0.6766 - accurac
y: 0.6552 - val_loss: 0.6442 - val_accuracy: 0.6897
Epoch 9/50
8/8 [==============================] - 0s 12ms/step - loss: 0.5880 - accurac
y: 0.6983 - val_loss: 0.6374 - val_accuracy: 0.7069
Epoch 10/50
8/8 [==============================] - 0s 11ms/step - loss: 0.6005 - accurac
y: 0.6853 - val_loss: 0.6306 - val_accuracy: 0.7069
Epoch 11/50
8/8 [==============================] - 0s 12ms/step - loss: 0.5932 - accurac
y: 0.7155 - val_loss: 0.6236 - val_accuracy: 0.7069
Epoch 12/50
8/8 [==============================] - 0s 11ms/step - loss: 0.5124 - accurac
y: 0.7198 - val_loss: 0.6164 - val_accuracy: 0.7241
Epoch 13/50
8/8 [==============================] - 0s 12ms/step - loss: 0.4588 - accurac
y: 0.7931 - val_loss: 0.6090 - val_accuracy: 0.7241
Epoch 14/50
8/8 [==============================] - 0s 12ms/step - loss: 0.4409 - accurac
y: 0.7629 - val_loss: 0.6011 - val_accuracy: 0.7414
Epoch 15/50
8/8 [==============================] - 0s 11ms/step - loss: 0.4639 - accurac
y: 0.7672 - val_loss: 0.5934 - val_accuracy: 0.7414
Epoch 16/50
8/8 [==============================] - 0s 12ms/step - loss: 0.5034 - accurac
y: 0.7672 - val_loss: 0.5855 - val_accuracy: 0.7414
Epoch 17/50
8/8 [==============================] - 0s 11ms/step - loss: 0.4307 - accurac
y: 0.7672 - val_loss: 0.5774 - val_accuracy: 0.7414
Epoch 18/50
8/8 [==============================] - 0s 12ms/step - loss: 0.4251 - accurac
y: 0.7328 - val_loss: 0.5693 - val_accuracy: 0.7414
Epoch 19/50
8/8 [==============================] - 0s 12ms/step - loss: 0.4087 - accurac
y: 0.7888 - val_loss: 0.5612 - val_accuracy: 0.7414
```

```
Epoch 20/50
8/8 [==============================] - 0s 11ms/step - loss: 0.4052 - accurac
y: 0.7845 - val_loss: 0.5532 - val_accuracy: 0.7414
Epoch 21/50
8/8 [==============================] - 0s 12ms/step - loss: 0.4943 - accurac
y: 0.7457 - val_loss: 0.5450 - val_accuracy: 0.7586
Epoch 22/50
8/8 [==============================] - 0s 12ms/step - loss: 0.4783 - accurac
y: 0.7414 - val_loss: 0.5364 - val_accuracy: 0.7931
Epoch 23/50
8/8 [==============================] - 0s 11ms/step - loss: 0.4069 - accurac
y: 0.7802 - val_loss: 0.5277 - val_accuracy: 0.7931
Epoch 24/50
8/8 [==============================] - 0s 11ms/step - loss: 0.3335 - accurac
y: 0.8319 - val_loss: 0.5193 - val_accuracy: 0.7931
Epoch 25/50
8/8 [==============================] - 0s 12ms/step - loss: 0.3849 - accurac
y: 0.7931 - val_loss: 0.5106 - val_accuracy: 0.7931
Epoch 26/50
8/8 [==============================] - 0s 11ms/step - loss: 0.4154 - accurac
y: 0.7759 - val_loss: 0.5014 - val_accuracy: 0.7931
Epoch 27/50
8/8 [==============================] - 0s 13ms/step - loss: 0.3691 - accurac
y: 0.8147 - val_loss: 0.4921 - val_accuracy: 0.7931
Epoch 28/50
8/8 [==============================] - 0s 12ms/step - loss: 0.4306 - accurac
y: 0.7845 - val_loss: 0.4828 - val_accuracy: 0.8103
Epoch 29/50
8/8 [==============================] - 0s 11ms/step - loss: 0.3635 - accurac
y: 0.8103 - val_loss: 0.4742 - val_accuracy: 0.8103
Epoch 30/50
8/8 [==============================] - 0s 11ms/step - loss: 0.3619 - accurac
y: 0.8017 - val_loss: 0.4657 - val_accuracy: 0.8448
Epoch 31/50
8/8 [==============================] - 0s 11ms/step - loss: 0.3878 - accurac
y: 0.7974 - val_loss: 0.4571 - val_accuracy: 0.8621
Epoch 32/50
8/8 [==============================] - 0s 11ms/step - loss: 0.3203 - accurac
y: 0.8319 - val_loss: 0.4484 - val_accuracy: 0.8621
Epoch 33/50
8/8 [==============================] - 0s 11ms/step - loss: 0.3318 - accurac
y: 0.8190 - val_loss: 0.4401 - val_accuracy: 0.8621
Epoch 34/50
8/8 [==============================] - 0s 11ms/step - loss: 0.3768 - accurac
y: 0.8017 - val_loss: 0.4318 - val_accuracy: 0.8621
Epoch 35/50
8/8 [==============================] - 0s 11ms/step - loss: 0.3319 - accurac
y: 0.8190 - val_loss: 0.4229 - val_accuracy: 0.8621
Epoch 36/50
8/8 [==============================] - 0s 11ms/step - loss: 0.3590 - accurac
y: 0.8319 - val_loss: 0.4142 - val_accuracy: 0.8621
Epoch 37/50
8/8 [==============================] - 0s 11ms/step - loss: 0.3679 - accurac
y: 0.7931 - val_loss: 0.4060 - val_accuracy: 0.8621
Epoch 38/50
8/8 [==============================] - 0s 12ms/step - loss: 0.3769 - accurac
y: 0.7845 - val_loss: 0.3972 - val_accuracy: 0.8621
```

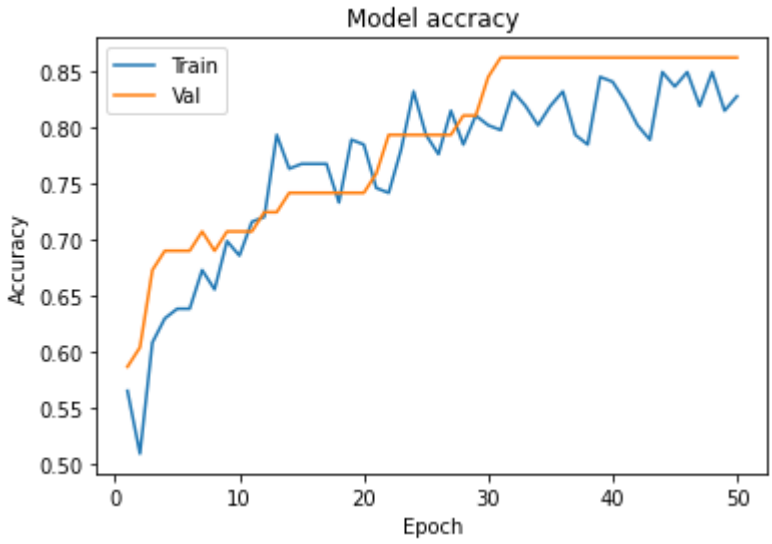
```
Epoch 39/50
8/8 [==============================] - 0s 11ms/step - loss: 0.3637 - accurac
y: 0.8448 - val_loss: 0.3888 - val_accuracy: 0.8621
Epoch 40/50
8/8 [==============================] - 0s 12ms/step - loss: 0.3205 - accurac
y: 0.8405 - val_loss: 0.3809 - val_accuracy: 0.8621
Epoch 41/50
8/8 [==============================] - 0s 12ms/step - loss: 0.3481 - accurac
y: 0.8233 - val_loss: 0.3738 - val_accuracy: 0.8621
Epoch 42/50
8/8 [==============================] - 0s 12ms/step - loss: 0.3806 - accurac
y: 0.8017 - val_loss: 0.3670 - val_accuracy: 0.8621
Epoch 43/50
8/8 [==============================] - 0s 11ms/step - loss: 0.4154 - accurac
y: 0.7888 - val_loss: 0.3597 - val_accuracy: 0.8621
Epoch 44/50
8/8 [==============================] - 0s 12ms/step - loss: 0.2916 - accurac
y: 0.8491 - val_loss: 0.3529 - val_accuracy: 0.8621
Epoch 45/50
8/8 [==============================] - 0s 12ms/step - loss: 0.2989 - accurac
y: 0.8362 - val_loss: 0.3468 - val_accuracy: 0.8621
Epoch 46/50
8/8 [==============================] - 0s 12ms/step - loss: 0.2845 - accurac
y: 0.8491 - val_loss: 0.3418 - val_accuracy: 0.8621
Epoch 47/50
8/8 [==============================] - 0s 12ms/step - loss: 0.3230 - accurac
y: 0.8190 - val_loss: 0.3367 - val_accuracy: 0.8621
Epoch 48/50
8/8 [==============================] - 0s 11ms/step - loss: 0.3317 - accurac
y: 0.8491 - val_loss: 0.3316 - val_accuracy: 0.8621
Epoch 49/50
8/8 [==============================] - 0s 11ms/step - loss: 0.3606 - accurac
y: 0.8147 - val_loss: 0.3265 - val_accuracy: 0.8621
Epoch 50/50
8/8 [==============================] - 0s 10ms/step - loss: 0.3441 - accurac
y: 0.8276 - val_loss: 0.3219 - val_accuracy: 0.8621
```

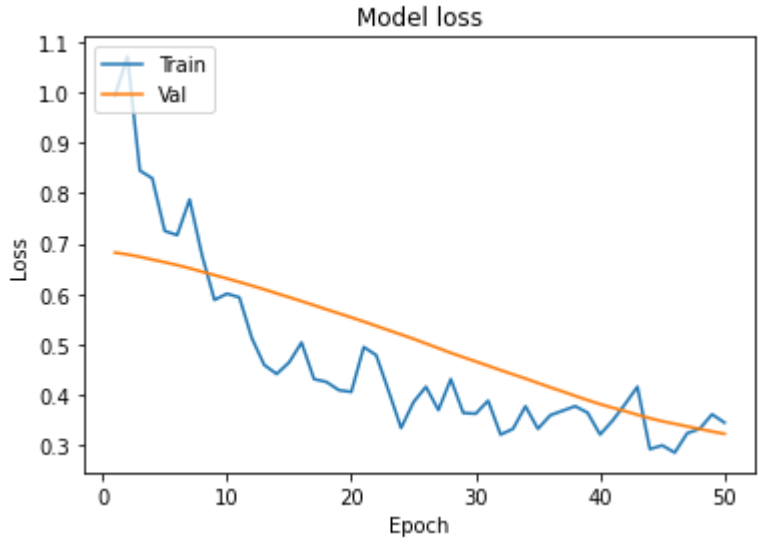
In [0]:

```
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 [184]:
```
plot_learningCurve(history,epochs)
```





In [185]:
```
#for testing  given samples

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

Out[185]:

	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 [187]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
# list of text documents
text = testData['content']

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

```
(10, 37)
<class 'scipy.sparse.csr.csr_matrix'>
[[0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0
  0]
 [0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0
  1]
 [0 0 1 0 0 0 0 1 1 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 1 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 1 0
  0]
 [0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0
  1]
 [0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 1 0 1 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 1 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0
  0]
 [1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0
  0]
 [0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0
  0]]
```

In [188]:
```
highD_vector.shape
```

Out[188]:
```
(10, 37)
```

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

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

In [190]:
```
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')
```

```
[0.83267546]Dog
[0.8564848]Dog
[0.17554471]cat
[0.5843016]Dog
[0.6556908]Dog
[0.6569063]Dog
[0.5942156]Dog
[0.47187203]cat
[0.37833437]cat
[0.3591253]cat
```

In [0]:
```

```