NLP: Yelp Review to Rating

Authors: Tanvee Desai and Tanner Arrizabalaga

Hello! In this project, we will be looking over Yelp reviews (data available here: https://www.yelp.com/dataset (https://www.yelp.com/dataset)) and utilizing ML/DL to accurately predict what the reviews star rating is based solely on text.

This project is split into the following parts

- Libraries
- EDA
- Data Cleaning
  - Stop word removal, HTML parsing, punctuation removal, etc.
  - Creation of a cleaned *and* stemmed dataset
- Model Implementation
  - Simple BOW Model Neural Network
  - LSTM
  - Bidirectional LSTM
  - One vs. All LSTM Approach
- Exploring Challenges
  - Challenge 5
  - Challenge 6

Importing necessary libraries

In [1]:
```
# General Libraries
import json
import sys
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import itertools

# NLP
import nltk
import re
from nltk.corpus import stopwords
from bs4 import BeautifulSoup
from nltk.stem import PorterStemmer


# ML/DL
import tensorflow as tf
import pickle

from sklearn.preprocessing import LabelBinarizer, LabelEncoder
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.model_selection import train_test_split

from tensorflow import keras
from keras import Sequential
from keras.layers import Dense, Activation, Dropout, Embedding, Conv1D, MaxPoo
ling1D, LSTM, BatchNormalization, SpatialDropout1D, Bidirectional
from keras.preprocessing.sequence import pad_sequences
from keras.preprocessing import text, sequence
from keras import utils
from keras import regularizers
from keras.models import load_model
from keras.initializers import Constant
from keras.utils import plot_model
```

```
Using TensorFlow backend.
```

In [2]:
```
yelp = pd.read_json("./yelp_review_training_dataset.jsonl", lines = True)
yelp.head()
```

Out[2]:

	review_id	text	stars
0	Q1sbwvVQXV2734tPgoKj4Q	Total bill for this horrible service? Over $8G...	1
1	GJXCdrto3ASJOqKeVWPi6Q	I *adore* Travis at the Hard Rock's new Kelly ...	5
2	2TzJjDVDEuAW6MR5Vuc1ug	I have to say that this office really has it t...	5
3	yi0R0Ugj_xUx_Nek0-_Qig	Went in for a lunch. Steak sandwich was delici...	5
4	11a8sVPMUFtaC7_ABRkmtw	Today was my second out of three sessions I ha...	1

How large is the data?

In [3]:
```
yelp.shape
```

Out[3]:
```
(533581, 3)
```

EDA - Stars

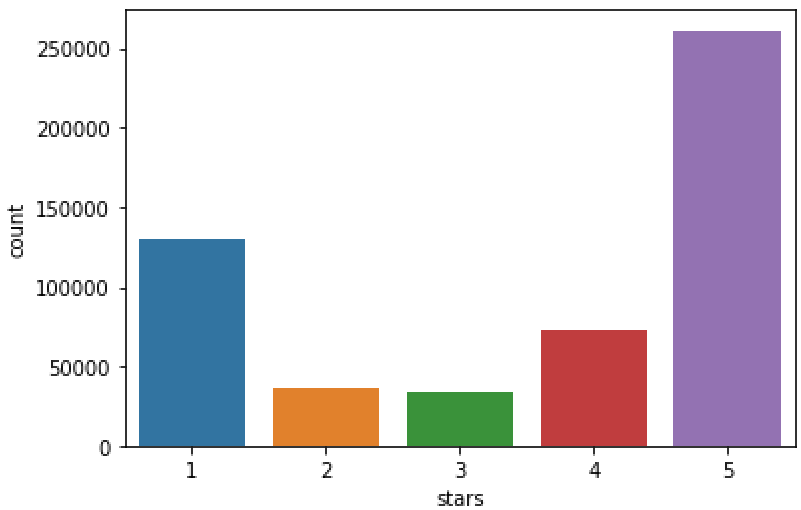
Not too much to go off of, but let's get a general understanding of our data. How many nulls do we have?

In [4]:
```
yelp.isna().sum()
```

Out[4]:
```
review_id    0
text         0
stars        0
dtype: int64
```

In [5]:
```
sns.countplot(yelp['stars'])
```

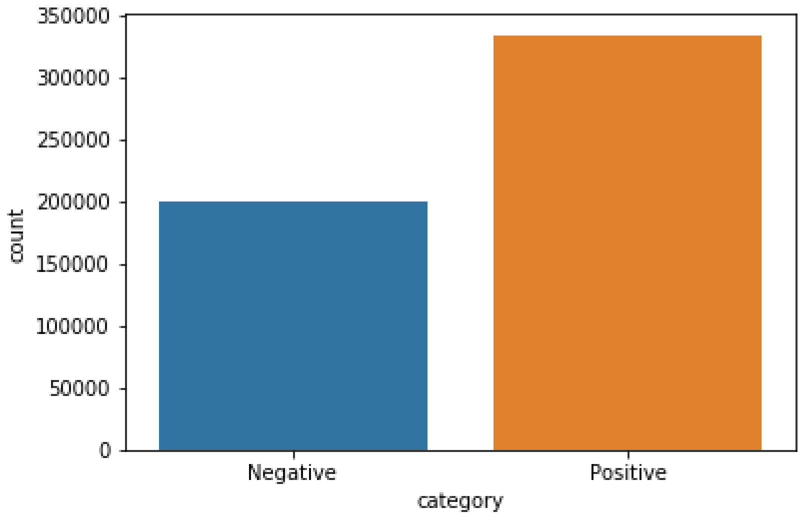
Out[5]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x259ba2b0e08>
```



One thing we can potentially look at is whether or not the reviews are balanced. Let's say >=4 is positive, and <4 is negative. If we do see a significant difference in positive and negative reviews, we can balance it before training.

In [6]:
```
def pos_or_neg(x):
    if x >= 4:
        return "Positive"
    else:
        return "Negative"

yelp['category'] = yelp['stars'].apply(pos_or_neg)

sns.countplot(yelp['category'])
num_pos = np.count_nonzero(yelp['category'] == 'Positive')
num_neg = np.count_nonzero(yelp['category'] == 'Negative')
print("Positive to negative review ratio: ", num_pos / num_neg)
```

```
Positive to negative review ratio:  1.6679183395916979
```



There are roughly 1 and 2/3 times as many positive reviews as negative reviews. We will first try no class balancing when building the model, but may turn to class balancing later on.

Data Cleaning - Text

In [7]:
```
REPLACE_BY_SPACE_RE = re.compile('[/(){}\[\]\|@,;]')
BAD_SYMBOLS_RE = re.compile('[^0-9a-z #+_]')
STOPWORDS = set(stopwords.words('english'))
print(STOPWORDS)

def adjust_stopwords(stopwords):
    words_to_keep = set(['nor', 'not', 'very', 'no', 'few', 'too', 'doesn', 'didn', 'wasn', 'ain',
                        "doesn't", "isn't", "hasn't", 'shouldn', "weren't", "don't", "didn't",
                        "shouldn't", "wouldn't", "won't", "above", "below", "haven't", "shan't", "weren"
                        "but", "wouldn", "mightn", "under", "mustn't", "over", "won", "aren", "wasn't",
                        "than"])
    return stopwords - words_to_keep

def clean_text(text):
    """
        text: a string

        return: modified initial string
    """
    new_text = BeautifulSoup(text, "lxml").text # HTML decoding
    new_text = new_text.lower() # lowercase text
    new_text = REPLACE_BY_SPACE_RE.sub(' ', new_text) # replace REPLACE_BY_SPACE_RE symbols by space in text
    new_text = BAD_SYMBOLS_RE.sub(' ', new_text) # delete symbols which are in BAD_SYMBOLS_RE from text

    ps = PorterStemmer()

#     new_text = ' '.join(ps.stem(word) for word in new_text.split()) # keeping all words, no stop word removal
    new_text = ' '.join(ps.stem(word) for word in new_text.split() if word not in STOPWORDS) # delete stopwords from text and stem
    return new_text

# STOPWORDS = adjust_stopwords(STOPWORDS)
print(STOPWORDS)
```

```
{'their', 'its', 'his', 're', "wouldn't", "you've", 'was', 'we', 'of', "you'r
e", 'a', 'do', 'while', 'been', 'into', 's', 'what', "should've", 'for', 'bef
ore', 'shan', 'o', 'mustn', 'because', 'or', "it's", 'they', 'and', 'off', 'o
ther', 'd', 'your', 'more', "shouldn't", 'during', 'who', "that'll", 'furthe
r', 'didn', 'so', 'from', 'all', 'wouldn', 'about', "mustn't", 'him', 'it',
'am', 'himself', 'doing', 'aren', 'an', 'are', 'being', 'now', 'shouldn', 'ov
er', 'to', 'you', 'y', 'than', 'just', 'with', "mightn't", 'yourselves', 'som
e', 'the', 'be', 'between', 'having', "wasn't", 'same', 'yours', 'down', "nee
dn't", 'were', 'he', 'll', 'how', 'doesn', 'but', 'this', 'ma', 'itself', 'th
emselves', 'once', 'had', 'those', 'is', 'not', 'm', 'ain', "couldn't", "yo
u'll", "aren't", 'mightn', 'by', 'any', 'where', 'own', 'on', 'hasn', 'both',
"doesn't", 'then', "shan't", 'until', 'under', 't', "isn't", 'through', 'was
n', 'did', 'them', 'won', 'up', "don't", 'such', 'after', 'here', 've', 'thes
e', "hasn't", "you'd", "she's", 'most', 'again', 'when', 'ours', 'too', 'abov
e', 'out', 'she', 'myself', 'each', 'below', 'have', 'why', 'will', 'in', 'wh
om', 'herself', 'at', "didn't", 'her', 'which', 'very', "weren't", 'only', 'i
f', 'ourselves', "hadn't", 'me', 'as', 'couldn', 'has', 'few', 'that', 'shoul
d', 'my', 'theirs', 'yourself', 'hers', 'our', 'no', 'can', 'haven', 'nor',
'needn', 'against', 'isn', 'there', 'i', 'does', "won't", "haven't", 'weren',
'hadn', 'don'}
```


```
{'their', 'its', 'his', 're', "wouldn't", "you've", 'was', 'we', 'of', "you'r
e", 'a', 'do', 'while', 'been', 'into', 's', 'what', "should've", 'for', 'bef
ore', 'shan', 'o', 'mustn', 'because', 'or', "it's", 'they', 'and', 'off', 'o
ther', 'd', 'your', 'more', "shouldn't", 'during', 'who', "that'll", 'furthe
r', 'didn', 'so', 'from', 'all', 'wouldn', 'about', "mustn't", 'him', 'it',
'am', 'himself', 'doing', 'aren', 'an', 'are', 'being', 'now', 'shouldn', 'ov
er', 'to', 'you', 'y', 'than', 'just', 'with', "mightn't", 'yourselves', 'som
e', 'the', 'be', 'between', 'having', "wasn't", 'same', 'yours', 'down', "nee
dn't", 'were', 'he', 'll', 'how', 'doesn', 'but', 'this', 'ma', 'itself', 'th
emselves', 'once', 'had', 'those', 'is', 'not', 'm', 'ain', "couldn't", "yo
u'll", "aren't", 'mightn', 'by', 'any', 'where', 'own', 'on', 'hasn', 'both',
"doesn't", 'then', "shan't", 'until', 'under', 't', "isn't", 'through', 'was
n', 'did', 'them', 'won', 'up', "don't", 'such', 'after', 'here', 've', 'thes
e', "hasn't", "you'd", "she's", 'most', 'again', 'when', 'ours', 'too', 'abov
e', 'out', 'she', 'myself', 'each', 'below', 'have', 'why', 'will', 'in', 'wh
om', 'herself', 'at', "didn't", 'her', 'which', 'very', "weren't", 'only', 'i
f', 'ourselves', "hadn't", 'me', 'as', 'couldn', 'has', 'few', 'that', 'shoul
d', 'my', 'theirs', 'yourself', 'hers', 'our', 'no', 'can', 'haven', 'nor',
'needn', 'against', 'isn', 'there', 'i', 'does', "won't", "haven't", 'weren',
'hadn', 'don'}
```

In [8]:
```
%%time
yelp['text'] = yelp['text'].apply(clean_text)
yelp.to_csv('cleaned_yelp_stemmed.csv')
```

```
C:\Users\Tanner\Anaconda3\envs\yelp\lib\site-packages\bs4\__init__.py:398: Us
erWarning: "https://www.consumeraffairs.com/news/mypillow-gets-a-rude-awakeni
ng-as-the-better-business-bureau-gives-it-an-f-010517.html" looks like a URL.
Beautiful Soup is not an HTTP client. You should probably use an HTTP client
like requests to get the document behind the URL, and feed that document to B
eautiful Soup.
  markup
C:\Users\Tanner\Anaconda3\envs\yelp\lib\site-packages\bs4\__init__.py:312: Us
erWarning: "." looks like a filename, not markup. You should probably open th
is file and pass the filehandle into Beautiful Soup.
  ' Beautiful Soup.' % self._decode_markup(markup)
C:\Users\Tanner\Anaconda3\envs\yelp\lib\site-packages\bs4\__init__.py:398: Us
erWarning: "http://www.marketwired.com/press-release/lease-of-spot-concord-pl
ace-cafe-terminated-tsx-venture-spp-1950108.htm

Unfortunate!" looks like a URL. Beautiful Soup is not an HTTP client. You sho
uld probably use an HTTP client like requests to get the document behind the
URL, and feed that document to Beautiful Soup.
  markup
C:\Users\Tanner\Anaconda3\envs\yelp\lib\site-packages\bs4\__init__.py:312: Us
erWarning: "..." looks like a filename, not markup. You should probably open
this file and pass the filehandle into Beautiful Soup.
  ' Beautiful Soup.' % self._decode_markup(markup)

Wall time: 10min 57s
```

In [9]:
```
text_1 = "\"Good morning, cocktails for you?\" \nWait...what? Oh...it's Vegas! \n\nDining here, you best not be dieting because this place is literally the definition of excess, but in a good way. I'm a sucker for benedicts so that was awesome. \nService was really great too and the staff was so welcoming. It was our first stop just after landing so really appreciate the service.\n\nBack in Hawaii this reminds me of Zippys or Anna Millers - that home feeling. Prices are a bit high, but for what you get it's totally worth it. Will remember this place if I ever return to Vegas in the future."
text_2 = "80 bucks, thirty minutes to fix my shattered iPhone screen. Verizon won't help you so go here"
text_3 = "Tr\u00e8s grand caf\u00e9, mais aussi calme et reposant, je m'y suis arr\u00eat\u00e9 alors que j'\u00e9tais dans le coin.\n\nOn peu y mang\u00e9 le midi, prendre une p\u00e2tisserie ou un caf\u00e9/th\u00e9. \n\nJ'ai prit un th\u00e9 qui \u00e9tait vraiment bon, et je me suis pos\u00e9 devant une des grandes baies vitr\u00e9es sur un coussin et j'ai relax\u00e9 compl\u00e8tement pendant 2 heures. \n\nMais c'est aussi une coop\u00e9rative d'artiste, avec une estrade etc.\n\nIl y a aussi un magasin Bio \u00e0 l'entr\u00e9e o\u00f9 vous retrouverez des savons, huile d'olive et plein d'autres produits."
text_4 = "Sadly, as of July 28, 2016, Silverstein bakery is permanently closed. I went there today in person and found the bad news posted on their door. :("
text_5 = "I went here  they were about to close but the cashier was especially helpful ..but I guess they were tired of work..."

clean_text(text_4)
```

Out[9]:
```
'sadli juli 28 2016 silverstein bakeri perman close went today person found bad news post door'
```

Model Implementation

Evaluation

1. Average Star Error (Average Absolute offset between predicted and true number of stars)

2. Accuracy (Exact Match -- Number of exactly predicted star ratings / total samples)

In [10]:
```
from keras.losses import mean_absolute_error, binary_crossentropy, categorical
_crossentropy

def my_custom_loss_ova(y_true, y_pred):
    mse = mean_absolute_error(y_true, y_pred)
    crossentropy = binary_crossentropy(y_true, y_pred)
    return mse + crossentropy

def my_custom_loss(y_true, y_pred):
    mse = mean_absolute_error(y_true, y_pred)
    crossentropy = categorical_crossentropy(y_true, y_pred)
    return mse + crossentropy

def MAE(y_true, y_pred):
    diffs = np.abs(y_true - y_pred)
    loss = np.mean(diffs)
    return loss

def Accuracy(y_true, y_pred):
    correct = y_true == y_pred
    cor_count = np.count_nonzero(correct)
    return cor_count / len(y_true)

def custom_loss(y_true, y_pred):
    return MAE(y_true, y_pred) + Accuracy(y_true, y_pred)
```

Train/Test Split (Unbalanced and balanced)

In [11]:
```
yelp = pd.read_csv('cleaned_yelp_stemmed.csv')
yelp.head()
```

Out[11]:

	Unnamed: 0	review_id	text	stars	category
0	0	Q1sbwvVQXV2734tPgoKj4Q	total bill horribl servic 8g crook actual nerv...	1	Negative
1	1	GJXCdrto3ASJOqKeVWPi6Q	ador travi hard rock new kelli cardena salon a...	5	Positive
2	2	2TzJjDVDEuAW6MR5Vuc1ug	say offic realli togeth organ friendli dr j ph...	5	Positive
3	3	yi0R0Ugj_xUx_Nek0-_Qig	went lunch steak sandwich delici caesar salad ...	5	Positive
4	4	11a8sVPMUFtaC7_ABRkmtw	today second three session paid although first...	1	Negative

In [12]:
```
X = yelp['text'].fillna('').values
y = yelp['stars']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, rand
om_state=42)
```

In [13]:
```
%%time
max_words = 3000
tokenizer = text.Tokenizer(num_words=max_words, char_level=False)

tokenizer.fit_on_texts(X_train)
X_train = tokenizer.texts_to_matrix(X_train)
X_test = tokenizer.texts_to_matrix(X_test)

encoder = LabelEncoder()
encoder.fit(y_train)
y_train = encoder.transform(y_train)
y_test = encoder.transform(y_test)

num_classes = np.max(y_train) + 1
y_train = utils.to_categorical(y_train, num_classes)
y_test = utils.to_categorical(y_test, num_classes)

print('X_train shape:', X_train.shape)
print('X_test shape:', X_test.shape)
print('y_train shape:', y_train.shape)
print('y_test shape:', y_test.shape)
```

```
X_train shape: (373506, 3000)
X_test shape: (160075, 3000)
y_train shape: (373506, 5)
y_test shape: (160075, 5)
Wall time: 48.1 s
```

Let's save the tokenizer as well for our test submission file script.

In [14]:
```
# # saving
# with open('tokenizer.pickle', 'wb') as handle:
#     pickle.dump(tokenizer, handle, protocol=pickle.HIGHEST_PROTOCOL)

# # loading
# with open('tokenizer.pickle', 'rb') as handle:
#     tokenizer = pickle.load(handle)
```

Baseline Sequential Model

Here, we are computing a single model, but in future we will optimize on several parameters, listed below

- Batch size
- Learning rate
- Gradient clipping
- Drop out
- Batch normalization
- Optimizers
- Regularization

After some tests, the main variations I noticed were from the learning rate, regularization, and the choice of the optimizer. With that being said, this baseline model will use **ADAM with a learning rate of .0001 and regularization (kernel, bias, and activity)**

In [15]:
```
batch_size = 512
epochs = 10

lr_schedule = keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate=.0001,
    decay_steps=10000,
    decay_rate=0.9)

optimizer = keras.optimizers.Adam(learning_rate=lr_schedule, beta_1=0.9, beta_
2=0.95, amsgrad=False)

baseline = Sequential()
baseline.add(Dense(512, input_shape=(max_words,), kernel_regularizer=regulariz
ers.l1_l2(l1=1e-5, l2=1e-4),
          bias_regularizer=regularizers.l2(1e-4),
          activity_regularizer=regularizers.l2(1e-5)))
baseline.add(BatchNormalization())
baseline.add(Activation('relu'))
baseline.add(Dropout(0.3))
baseline.add(Dense(5))
baseline.add(Activation('softmax'))

baseline.compile(loss=my_custom_loss,
              optimizer=optimizer,
              metrics=['accuracy', 'mean_absolute_error'])

history = baseline.fit(X_train, y_train,
                    batch_size=batch_size,
                    epochs=epochs,
                    verbose=1,
                    validation_split=0.2)
```

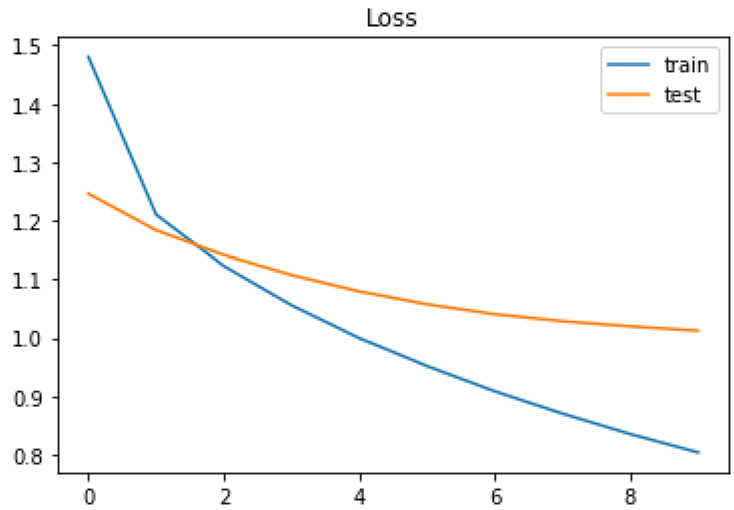
```
Train on 298804 samples, validate on 74702 samples
Epoch 1/10
298804/298804 [==============================] - 27s 91us/step - loss: 1.4803
- accuracy: 0.6812 - mean_absolute_error: 0.1601 - val_loss: 1.2459 - val_acc
uracy: 0.7400 - val_mean_absolute_error: 0.1342
Epoch 2/10
298804/298804 [==============================] - 12s 41us/step - loss: 1.2103
- accuracy: 0.7449 - mean_absolute_error: 0.1311 - val_loss: 1.1835 - val_acc
uracy: 0.7438 - val_mean_absolute_error: 0.1316
Epoch 3/10
298804/298804 [==============================] - 12s 39us/step - loss: 1.1226
- accuracy: 0.7605 - mean_absolute_error: 0.1261 - val_loss: 1.1413 - val_acc
uracy: 0.7459 - val_mean_absolute_error: 0.1291
Epoch 4/10
298804/298804 [==============================] - 12s 39us/step - loss: 1.0557
- accuracy: 0.7702 - mean_absolute_error: 0.1226 - val_loss: 1.1072 - val_acc
uracy: 0.7464 - val_mean_absolute_error: 0.1285
Epoch 5/10
298804/298804 [==============================] - 12s 40us/step - loss: 0.9993
- accuracy: 0.7790 - mean_absolute_error: 0.1197 - val_loss: 1.0793 - val_acc
uracy: 0.7476 - val_mean_absolute_error: 0.1284
Epoch 6/10
298804/298804 [==============================] - 12s 40us/step - loss: 0.9512
- accuracy: 0.7870 - mean_absolute_error: 0.1170 - val_loss: 1.0572 - val_acc
uracy: 0.7479 - val_mean_absolute_error: 0.1283
Epoch 7/10
298804/298804 [==============================] - 11s 38us/step - loss: 0.9080
- accuracy: 0.7964 - mean_absolute_error: 0.1141 - val_loss: 1.0403 - val_acc
uracy: 0.7466 - val_mean_absolute_error: 0.1280
Epoch 8/10
298804/298804 [==============================] - 11s 37us/step - loss: 0.8698
- accuracy: 0.8035 - mean_absolute_error: 0.1113 - val_loss: 1.0282 - val_acc
uracy: 0.7475 - val_mean_absolute_error: 0.1271
Epoch 9/10
298804/298804 [==============================] - 11s 37us/step - loss: 0.8348
- accuracy: 0.8116 - mean_absolute_error: 0.1084 - val_loss: 1.0194 - val_acc
uracy: 0.7463 - val_mean_absolute_error: 0.1267
Epoch 10/10
298804/298804 [==============================] - 11s 37us/step - loss: 0.8035
- accuracy: 0.8182 - mean_absolute_error: 0.1055 - val_loss: 1.0120 - val_acc
uracy: 0.7470 - val_mean_absolute_error: 0.1263
```

In [16]:

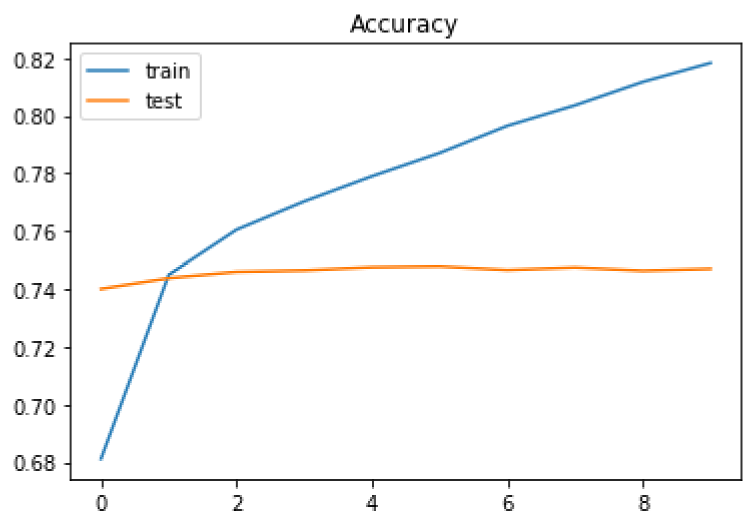
```
score = baseline.evaluate(X_test, y_test,
                          batch_size=batch_size, verbose=1)
print('Test accuracy:', score[1])
```

```
160075/160075 [==============================] - 10s 62us/step
Test accuracy: 0.747930645942688
```

In [17]:
```
plt.title('Loss')
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='test')
plt.legend()
plt.show()
```



In [18]:
```
plt.title('Accuracy')
plt.plot(history.history['accuracy'], label='train')
plt.plot(history.history['val_accuracy'], label='test')
plt.legend()
plt.show()
```



In [19]:
```
# Get model output
y_pred = baseline.predict(X_test)

cols = [1, 2, 3, 4, 5]

# Creating predictions table
baseline_ps = pd.DataFrame(data=y_pred, columns=cols)
y_pred_true = baseline_ps.idxmax(axis=1)

# Creating truth
baseline_truth = pd.DataFrame(data=y_test, columns=cols)
y_test_true = baseline_truth.idxmax(axis=1)

# Confusion matrix
cm = confusion_matrix(y_pred_true, y_test_true)
pd.DataFrame(cm, index=cols, columns=cols)
```

Out[19]:

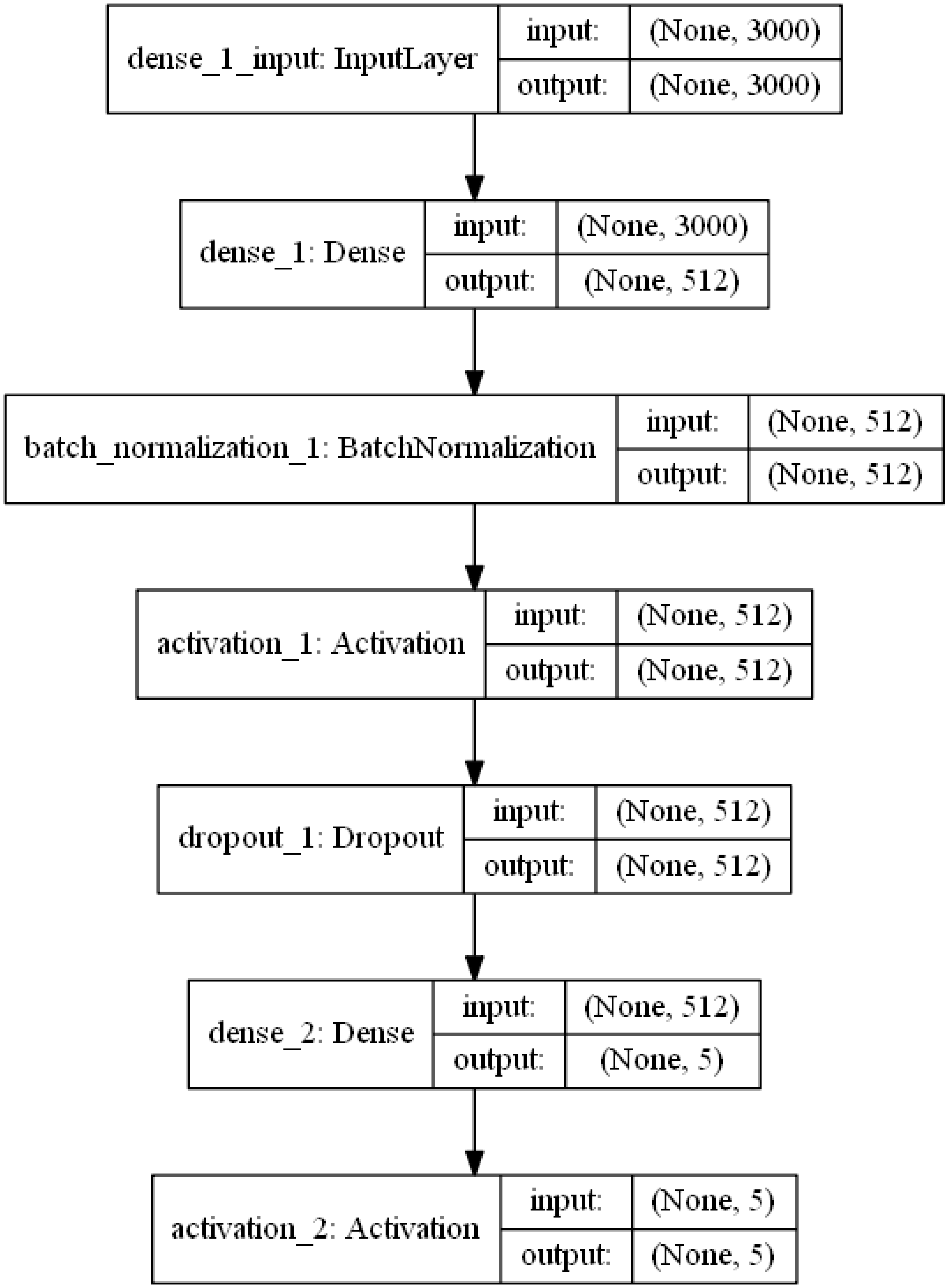
	1	2	3	4	5
1	34864	5157	1651	763	1356
2	1676	2570	1416	489	265
3	524	1389	2731	1626	541
4	363	731	2705	7742	4441
5	1460	896	1760	11141	71818

In [20]:
```
print(classification_report(y_pred_true, y_test_true))
```

```
              precision    recall  f1-score   support

           1       0.90      0.80      0.84     43791
           2       0.24      0.40      0.30      6416
           3       0.27      0.40      0.32      6811
           4       0.36      0.48      0.41     15982
           5       0.92      0.82      0.87     87075

    accuracy                           0.75    160075
   macro avg       0.53      0.58      0.55    160075
weighted avg       0.80      0.75      0.77    160075
```

In [21]:
```
plot_model(baseline, to_file='baseline.png', show_shapes=True)
```

Out[21]:



Let's save this model.

In [ ]:
```
# baseline.save('./models/baseline.h5')
```

Now training with several parameter changes

In [ ]:
```
batch_sizes = [128, 256, 512]
epochs = [5]
learning_rates = [.01, .001, .0001]
dropout = [False, True]
batch_norm = [False, True]
regularization = [True]
optimizers = ["SGD", "RMSProp", "ADAM"]

all_lists = [batch_sizes, epochs, learning_rates, dropout, batch_norm, regular
ization, optimizers]

params_to_test = list(itertools.product(*all_lists))
print(len(params_to_test))
```

In [ ]:
```
models = {}
histories = {}
scores = {}

for params in params_to_test:
    print(params)
    batch_size, epochs, learning_rate, dropout, batch_norm, regularization, op
t = params

    if opt == "SGD":
        optimizer = keras.optimizers.SGD(learning_rate=learning_rate, momentum
=0.0, nesterov=False)
    elif opt == "RMSProp":
        optimizer = keras.optimizers.RMSprop(learning_rate=learning_rate, rho=
0.9)
    elif opt == "ADAM":
        optimizer = keras.optimizers.Adam(learning_rate=learning_rate, beta_1=
0.9, beta_2=0.99, amsgrad=False)
    else:
        optimizer = keras.optimizers.Adadelta(learning_rate=learning_rate, rho
=0.95)

    model = Sequential()
    model.add(Dense(512, input_shape=(max_words,), kernel_regularizer=regulari
zers.l1_l2(l1=1e-5, l2=1e-4)))

    # Check Batch Normalization
    if batch_norm:
        model.add(BatchNormalization())

    model.add(Activation('relu'))

    # Check Dropout
    if dropout:
        model.add(Dropout(0.2))

    model.add(Dense(5))
    model.add(Activation('softmax'))

    model.compile(loss='categorical_crossentropy',
                  optimizer=optimizer,
                  metrics=['accuracy'])

    history = model.fit(X_train, y_train,
                        batch_size=batch_size,
                        epochs=epochs,
                        verbose=0,
                        validation_split=0.1)

    models[params] = model
    histories[params] = history

    score = model.evaluate(X_test, y_test, batch_size=batch_size, verbose=1)
    print(score)

    scores[params] = score
```

LSTM Model

Specific Data Prep

In [22]:
```
%%time
X = yelp['text'].fillna('').values
y = pd.get_dummies(yelp['stars']).values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, rando
m_state=42)
print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)

max_words = 3000
maxlen = 400

X_train = tokenizer.texts_to_sequences(X_train)
X_test = tokenizer.texts_to_sequences(X_test)

# For the LSTM, we are going to pad our sequences
X_train = pad_sequences(X_train, maxlen=maxlen)
X_test = pad_sequences(X_test, maxlen=maxlen)
```

```
(373506,) (373506, 5)
(160075,) (160075, 5)
Wall time: 25.8 s
```

LSTM #1

In [23]:
```
batch_size = 512
epochs = 5

lr_schedule = keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate=.001,
    decay_steps=10000,
    decay_rate=0.9)

optimizer = keras.optimizers.Adam(learning_rate=lr_schedule, beta_1=0.9, beta_
2=0.99, amsgrad=False, clipvalue=.3)

lstm = Sequential()
lstm.add(Embedding(max_words, 128, input_length=maxlen))
lstm.add(SpatialDropout1D(0.2))
lstm.add(Conv1D(64, 5, activation='relu', kernel_regularizer=regularizers.l1_l
2(l1=1e-5, l2=1e-4),
          bias_regularizer=regularizers.l2(1e-4)))
lstm.add(MaxPooling1D(pool_size=4))
lstm.add(LSTM(128, dropout=0.2, recurrent_dropout=0.2))
lstm.add(BatchNormalization())
lstm.add(Dense(5, activation='sigmoid'))

lstm.compile(loss=my_custom_loss,
             optimizer=optimizer,
             metrics=['accuracy', 'mean_absolute_error'])

history = lstm.fit(X_train, y_train,
                   batch_size=batch_size,
                   epochs=epochs,
                   verbose=1,
                   validation_split=0.2)
```

```
Train on 298804 samples, validate on 74702 samples
Epoch 1/5
298804/298804 [==============================] - 85s 286us/step - loss: 0.970
2 - accuracy: 0.7115 - mean_absolute_error: 0.1741 - val_loss: 0.8182 - val_a
ccuracy: 0.7407 - val_mean_absolute_error: 0.1252
Epoch 2/5
298804/298804 [==============================] - 82s 274us/step - loss: 0.805
8 - accuracy: 0.7446 - mean_absolute_error: 0.1233 - val_loss: 0.7838 - val_a
ccuracy: 0.7478 - val_mean_absolute_error: 0.1179
Epoch 3/5
298804/298804 [==============================] - 82s 276us/step - loss: 0.764
3 - accuracy: 0.7543 - mean_absolute_error: 0.1142 - val_loss: 0.7559 - val_a
ccuracy: 0.7551 - val_mean_absolute_error: 0.1121
Epoch 4/5
298804/298804 [==============================] - 82s 275us/step - loss: 0.740
3 - accuracy: 0.7622 - mean_absolute_error: 0.1112 - val_loss: 0.7556 - val_a
ccuracy: 0.7582 - val_mean_absolute_error: 0.1113
Epoch 5/5
298804/298804 [==============================] - 82s 275us/step - loss: 0.722
4 - accuracy: 0.7677 - mean_absolute_error: 0.1092 - val_loss: 0.7547 - val_a
ccuracy: 0.7576 - val_mean_absolute_error: 0.1075
```

LSTM #1: Evaluation

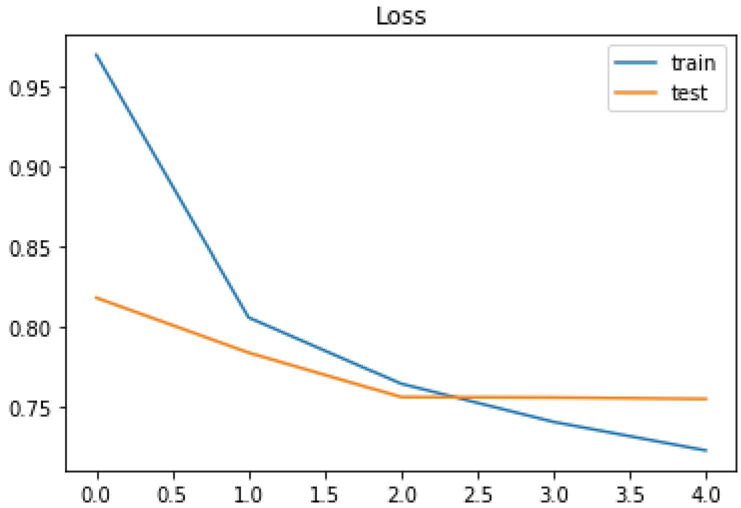
In [24]:
```
score = lstm.evaluate(X_test, y_test,
                       batch_size=batch_size, verbose=1)
print('Test accuracy:', score[1])
```

```
160075/160075 [==============================] - 10s 65us/step
Test accuracy: 0.7598188519477844
```

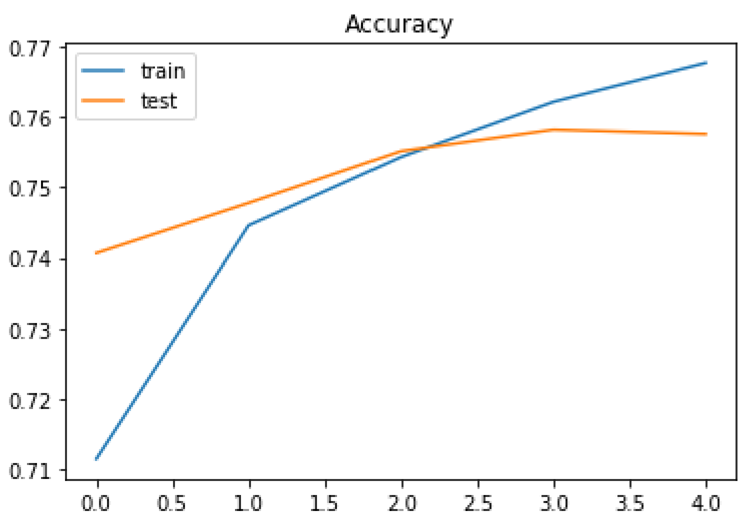
In [25]:
```
lstm.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
embedding_1 (Embedding)      (None, 400, 128)          384000    
_________________________________________________________________
spatial_dropout1d_1 (Spatial (None, 400, 128)          0         
_________________________________________________________________
conv1d_1 (Conv1D)            (None, 396, 64)           41024     
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 99, 64)            0         
_________________________________________________________________
lstm_1 (LSTM)                (None, 128)               98816     
_________________________________________________________________
batch_normalization_2 (Batch (None, 128)               512       
_________________________________________________________________
dense_3 (Dense)              (None, 5)                 645       
=================================================================
Total params: 524,997
Trainable params: 524,741
Non-trainable params: 256
_________________________________________________________________
```

In [26]:
```
plt.title('Loss')
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='test')
plt.legend()
plt.show()
```



In [27]:
```
plt.title('Accuracy')
plt.plot(history.history['accuracy'], label='train')
plt.plot(history.history['val_accuracy'], label='test')
plt.legend()
plt.show()
```



In [28]:
```
# Get model output
y_pred = lstm.predict(X_test)
y_pred

cols = [1, 2, 3, 4, 5]

# Creating predictions table
baseline_ps = pd.DataFrame(data=y_pred, columns=cols)
y_pred_true = baseline_ps.idxmax(axis=1)
y_pred_true

# Creating truth
baseline_truth = pd.DataFrame(data=y_test, columns=cols)
y_test_true = baseline_truth.idxmax(axis=1)
y_test_true

# Confusion matrix
cm = confusion_matrix(y_pred_true, y_test_true)
pd.DataFrame(cm, index=cols, columns=cols)
```

Out[28]:

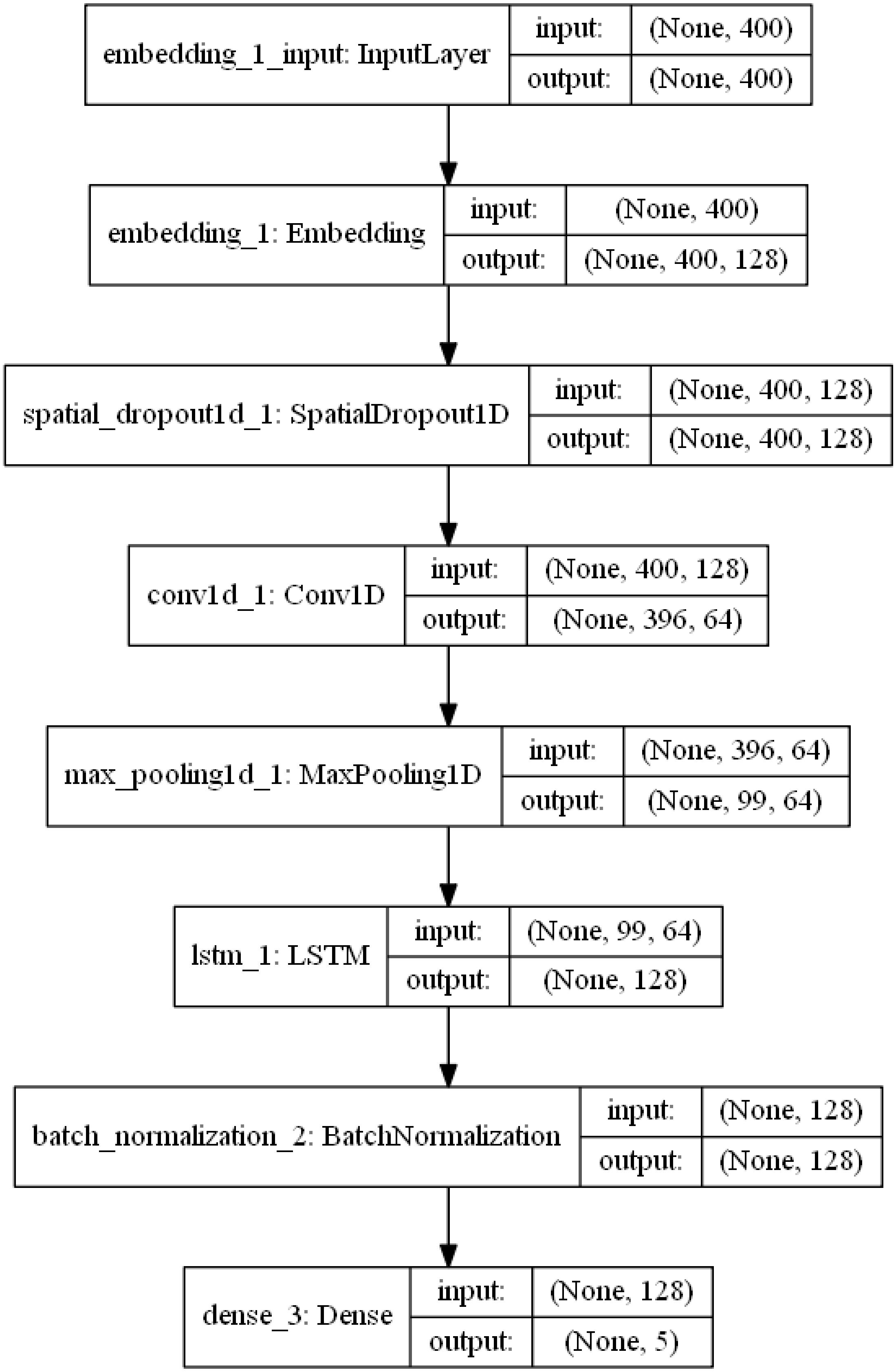
	1	2	3	4	5
1	35569	5399	1573	723	1140
2	1139	2459	1313	268	111
3	319	1213	2553	1087	195
4	353	791	2980	6941	2869
5	1507	881	1844	12742	74106

In [29]:
```
print(classification_report(y_pred_true, y_test_true))
```

```
              precision    recall  f1-score   support

           1       0.91      0.80      0.85     44404
           2       0.23      0.46      0.31      5290
           3       0.25      0.48      0.33      5367
           4       0.32      0.50      0.39     13934
           5       0.94      0.81      0.87     91080

    accuracy                           0.76    160075
   macro avg       0.53      0.61      0.55    160075
weighted avg       0.84      0.76      0.79    160075
```

In [30]:
```
plot_model(lstm, to_file='baseline.png', show_shapes=True)
```

Out[30]:



Let's save this model as well.

In [ ]:
```
# lstm.save('./models/lstm.h5')
```

LSTM #2

In [ ]:
```
batch_size = 128
epochs = 5

lr_schedule = keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate=.001,
    decay_steps=10000,
    decay_rate=0.9)

optimizer = keras.optimizers.Adam(learning_rate=lr_schedule, beta_1=0.9, beta_
2=0.99, amsgrad=False, clipvalue=.3)

lstm_v2 = Sequential()
lstm_v2.add(Embedding(max_words, 128, input_length=maxlen))
lstm_v2.add(SpatialDropout1D(0.3))
lstm_v2.add(Bidirectional(LSTM(128, dropout=0.3, recurrent_dropout=0.3)))
lstm_v2.add(Dense(128, activation='relu'))
lstm_v2.add(Dropout(0.2))
lstm_v2.add(Dense(128, activation='relu'))
lstm_v2.add(Dropout(0.2))
lstm_v2.add(Dense(5, activation='sigmoid'))

lstm_v2.compile(loss='categorical_crossentropy',
              optimizer=optimizer,
              metrics=['accuracy'])

history = lstm_v2.fit(X_train, y_train,
                    batch_size=batch_size,
                    epochs=epochs,
                    verbose=1,
                    validation_split=0.2)
```

LSTM #2: Evaluation

In [ ]:
```
score = lstm_v2.evaluate(X_test, y_test,
                       batch_size=batch_size, verbose=1)
print('Test accuracy:', score[1])
```

In [ ]:
```
lstm_v2.summary()
```

In [ ]:
```
plt.title('Loss')
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='test')
plt.legend()
plt.show()
```

In [ ]:
```
plt.title('Accuracy')
plt.plot(history.history['accuracy'], label='train')
plt.plot(history.history['val_accuracy'], label='test')
plt.legend()
plt.show()
```

Let's save this model as well.

In [ ]:
```
lstm.save('./models/lstm_v2.h5')
```

One vs. All Approach

In the one vs. all approach, it goes by the following idea:

- We will have N learners for the multi-class classification problem, where N is the number of classes
- For each learner L, we will train L on our training data X_{Train} and y_{Train}. However, y_{Train} consists of only one label, making it a binary classification problem instead of multinomial
  - For instance, learner L_1 will still use all of X_{Train}, but y_{Train} will now be transformed to be a binary vector v_i where i denotes the star rating we are attempting to predict
- Once we have concluded our training, we will then create an ensemble model (bagging) that does the following
  1. L_1, L_2, ..., L_5 all assign p_i to each record in X_{Test}, where p_i is the likelihood observation x_n belongs to class i
  2. From there, our prediction is the following: $P_n = argmax(p_1, p_2, p_3, p_4, p_5)$

After observing the challenge datasets 5 & 6, my partner and I believe this approach is a clever way to tackle the challenges while still having a strong model.

Sources: https://developers.google.com/machine-learning/crash-course/multi-class-neural-networks/one-vs-all (https://developers.google.com/machine-learning/crash-course/multi-class-neural-networks/one-vs-all)

In [31]:
```
yelp = pd.read_csv('cleaned_yelp_stemmed.csv')

X = yelp['text'].fillna('').values
y = pd.get_dummies(yelp['stars']).values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, rand
om_state=42)

# Loading
# with open('tokenizer.pickle', 'rb') as handle:
#     tokenizer = pickle.load(handle)

max_words = 3000
maxlen = 400

X_train = tokenizer.texts_to_sequences(X_train)
X_test = tokenizer.texts_to_sequences(X_test)
X_train = pad_sequences(X_train, maxlen=maxlen)
X_test = pad_sequences(X_test, maxlen=maxlen)

print('X_train shape:', X_train.shape)
print('X_test shape:', X_test.shape)
print('y_train shape:', y_train.shape)
print('y_test shape:', y_test.shape)
```

```
X_train shape: (373506, 400)
X_test shape: (160075, 400)
y_train shape: (373506, 5)
y_test shape: (160075, 5)
```

Buidling all models

In [32]:
```
stars = np.arange(1, 6)
models = {}
histories = {}
batch_size = 512

for star in stars:
    if star in [1, 2]:
        epochs = 2
    elif star in [3, 4]:
        epochs = 3
    else:
        epochs = 4

    print(star)
    y_train_sub = y_train[:, star - 1]

    lr_schedule = keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate=.001,
    decay_steps=10000,
    decay_rate=0.9)

    optimizer = keras.optimizers.Adam(learning_rate=lr_schedule, beta_1=0.9, b
eta_2=0.99, amsgrad=False, clipvalue=.3)

    sub_lstm = Sequential()
    sub_lstm.add(Embedding(max_words, 128, input_length=maxlen))
    sub_lstm.add(SpatialDropout1D(0.2))
    sub_lstm.add(Conv1D(64, 5, activation='relu', kernel_regularizer=regulariz
ers.l1_l2(l1=1e-5, l2=1e-4),
              bias_regularizer=regularizers.l2(1e-4)))
    sub_lstm.add(MaxPooling1D(pool_size=4))
    sub_lstm.add(LSTM(128))
    sub_lstm.add(BatchNormalization())
    sub_lstm.add(Dense(8))
    sub_lstm.add(Dense(1, activation='sigmoid'))

    sub_lstm.compile(loss=my_custom_loss_ova,
                  optimizer=optimizer,
                  metrics=['accuracy', 'mean_absolute_error'])

    history = sub_lstm.fit(X_train, y_train_sub,
                        batch_size=batch_size,
                        epochs=epochs,
                        verbose=1,
                        validation_split=0.2)

    models[star] = sub_lstm
    histories[star] = sub_lstm
```

```
1
Train on 298804 samples, validate on 74702 samples
Epoch 1/2
298804/298804 [==============================] - 79s 266us/step - loss: 0.369
7 - accuracy: 0.9086 - mean_absolute_error: 0.1216 - val_loss: 0.4489 - val_a
ccuracy: 0.8743 - val_mean_absolute_error: 0.1355
Epoch 2/2
298804/298804 [==============================] - 79s 266us/step - loss: 0.288
5 - accuracy: 0.9289 - mean_absolute_error: 0.0925 - val_loss: 0.3031 - val_a
ccuracy: 0.9253 - val_mean_absolute_error: 0.0925
2
Train on 298804 samples, validate on 74702 samples
Epoch 1/2
298804/298804 [==============================] - 79s 265us/step - loss: 0.365
4 - accuracy: 0.9239 - mean_absolute_error: 0.1191 - val_loss: 0.3355 - val_a
ccuracy: 0.9325 - val_mean_absolute_error: 0.0775
Epoch 2/2
298804/298804 [==============================] - 80s 268us/step - loss: 0.280
6 - accuracy: 0.9366 - mean_absolute_error: 0.0853 - val_loss: 0.4040 - val_a
ccuracy: 0.9073 - val_mean_absolute_error: 0.1553
3
Train on 298804 samples, validate on 74702 samples
Epoch 1/3
298804/298804 [==============================] - 80s 268us/step - loss: 0.348
0 - accuracy: 0.9279 - mean_absolute_error: 0.1112 - val_loss: 0.3232 - val_a
ccuracy: 0.9363 - val_mean_absolute_error: 0.0713
Epoch 2/3
298804/298804 [==============================] - 81s 271us/step - loss: 0.271
3 - accuracy: 0.9395 - mean_absolute_error: 0.0812 - val_loss: 0.4267 - val_a
ccuracy: 0.9067 - val_mean_absolute_error: 0.1677
Epoch 3/3
298804/298804 [==============================] - 79s 265us/step - loss: 0.244
7 - accuracy: 0.9451 - mean_absolute_error: 0.0736 - val_loss: 0.3127 - val_a
ccuracy: 0.9387 - val_mean_absolute_error: 0.0690
4
Train on 298804 samples, validate on 74702 samples
Epoch 1/3
298804/298804 [==============================] - 80s 268us/step - loss: 0.552
5 - accuracy: 0.8573 - mean_absolute_error: 0.1904 - val_loss: 0.5362 - val_a
ccuracy: 0.8644 - val_mean_absolute_error: 0.1602
Epoch 2/3
298804/298804 [==============================] - 79s 266us/step - loss: 0.481
9 - accuracy: 0.8740 - mean_absolute_error: 0.1620 - val_loss: 0.5839 - val_a
ccuracy: 0.8680 - val_mean_absolute_error: 0.1408
Epoch 3/3
298804/298804 [==============================] - 80s 269us/step - loss: 0.448
7 - accuracy: 0.8846 - mean_absolute_error: 0.1502 - val_loss: 0.5643 - val_a
ccuracy: 0.8480 - val_mean_absolute_error: 0.2029
5
Train on 298804 samples, validate on 74702 samples
Epoch 1/4
298804/298804 [==============================] - 81s 271us/step - loss: 0.545
7 - accuracy: 0.8570 - mean_absolute_error: 0.1860 - val_loss: 0.5329 - val_a
ccuracy: 0.8642 - val_mean_absolute_error: 0.2003
Epoch 2/4
298804/298804 [==============================] - 80s 266us/step - loss: 0.471
9 - accuracy: 0.8763 - mean_absolute_error: 0.1602 - val_loss: 0.4889 - val_a
```

```
ccuracy: 0.8711 - val_mean_absolute_error: 0.1623
Epoch 3/4
298804/298804 [==============================] - 80s 267us/step - loss: 0.434
2 - accuracy: 0.8888 - mean_absolute_error: 0.1458 - val_loss: 0.4988 - val_a
ccuracy: 0.8720 - val_mean_absolute_error: 0.1519
Epoch 4/4
298804/298804 [==============================] - 79s 266us/step - loss: 0.397
9 - accuracy: 0.9009 - mean_absolute_error: 0.1314 - val_loss: 0.5104 - val_a
ccuracy: 0.8709 - val_mean_absolute_error: 0.1505
```

Building an ensemble model (maximization between learners) for all trained models

Testing

In [33]:

```
%%time
# Evaluating the models above (TEST)
y_test_und = pd.DataFrame(y_test)
y_test_true = pd.DataFrame(y_test_und.columns[np.where(y_test_und!=0)[1]]) + 1

# Unload models
lstm_1, lstm_2, lstm_3, lstm_4, lstm_5 = models[1], models[2], models[3], mode
ls[4], models[5]

## Predicting the probability for each observation each model
print("Predicting 1 star")
one_star_ps = lstm_1.predict(X_test)
print("Predicting 2 star")
two_star_ps = lstm_2.predict(X_test)
print("Predicting 3 star")
three_star_ps = lstm_3.predict(X_test)
print("Predicting 4 star")
four_star_ps = lstm_4.predict(X_test)
print("Predicting 5 star")
five_star_ps = lstm_5.predict(X_test)

data = [one_star_ps.flatten(), two_star_ps.flatten(), three_star_ps.flatten(),
four_star_ps.flatten(), five_star_ps.flatten()]
cols = [1, 2, 3, 4, 5]
ps = pd.DataFrame(data=data, index=cols).T

ps["pred"] = ps.idxmax(axis=1)
ps.head()

print(MAE(ps["pred"], y_test_true[0]))
print(Accuracy(ps["pred"], y_test_true[0]))
```

```
Predicting 1 star
Predicting 2 star
Predicting 3 star
Predicting 4 star
Predicting 5 star
0.3562642511322817
0.7501358738091519
Wall time: 5min 43s
```

In [34]:
```
# Confusion matrix
cm = confusion_matrix(ps["pred"], y_test_true[0])
pd.DataFrame(cm, index=cols, columns=cols)
```

Out[34]:

	1	2	3	4	5
1	34351	4408	1326	600	1117
2	2859	4550	3057	1380	1004
3	35	123	737	135	20
4	663	1100	3918	10021	5861
5	979	562	1225	9625	70419

In [35]:
```
print(classification_report(ps["pred"], y_test_true[0]))
```

```
              precision    recall  f1-score   support

           1       0.88      0.82      0.85     41802
           2       0.42      0.35      0.39     12850
           3       0.07      0.70      0.13      1050
           4       0.46      0.46      0.46     21563
           5       0.90      0.85      0.87     82810

    accuracy                           0.75    160075
   macro avg       0.55      0.64      0.54    160075
weighted avg       0.79      0.75      0.77    160075
```

Saving the models

In [ ]:
```
# lstm_1.save("./models/one_star.h5")
# lstm_2.save("./models/two_star.h5")
# lstm_3.save("./models/three_star.h5")
# lstm_4.save("./models/four_star.h5")
# lstm_5.save("./models/five_star.h5")
```

Ensemble on Test Set

In [36]:
```
yelp = pd.read_csv('cleaned_yelp_stemmed.csv')

X = yelp['text'].fillna('').values
y = pd.get_dummies(yelp['stars'])

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, rand
om_state=42)
print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)

max_words = 3000
maxlen = 400

# with open('tokenizer.pickle', 'rb') as handle:
#     tokenizer = pickle.load(handle)

print(y_test)

necc_cols = [1, 2, 3, 4, 5]
for col in necc_cols:
    if col not in y_test.columns:
        y_test[col] = 0

y_test = y_test[necc_cols]
y_test = y_test.values

X_baseline = tokenizer.texts_to_matrix(X_test)
X_lstm = tokenizer.texts_to_sequences(X_test)
X_lstm = pad_sequences(X_lstm, maxlen=maxlen)
```

```
(373506,) (373506, 5)
(160075,) (160075, 5)
        1  2  3  4  5
255947  0  0  0  0  1
261035  0  0  0  0  1
355633  0  0  0  0  1
205506  0  0  0  0  1
97222   0  0  0  1  0
...    .. .. .. .. ..
491832  0  0  0  0  1
311959  0  0  0  0  1
140524  1  0  0  0  0
125037  0  0  1  0  0
200135  0  0  0  1  0

[160075 rows x 5 columns]
```

In [ ]:
```
# # Trying our pretrained models
# # Optimizer
# lr_schedule = keras.optimizers.schedules.ExponentialDecay(initial_learning_r
ate=.001, decay_steps=10000, decay_rate=0.9)
# optimizer = keras.optimizers.Adam(learning_rate=lr_schedule, beta_1=0.9, bet
a_2=0.99, amsgrad=False, clipvalue=.3)

# # Baseline
# baseline = load_model('./models/baseline.h5')

# baseline.compile(loss='categorical_crossentropy',
#                optimizer=optimizer,
#                metrics=['accuracy'])

# # LSTM
# lstm = load_model('./models/lstm.h5')

# lstm.compile(loss='categorical_crossentropy',
#                optimizer=optimizer,
#                metrics=['accuracy'])


# # One vs. all
# lstm_1 = load_model('./models/one_star.h5')

# lstm_1.compile(loss='binary_crossentropy',
#                    optimizer=optimizer,
#                    metrics=['accuracy'])

# lstm_2 = load_model('./models/two_star.h5')

# lstm_2.compile(loss='binary_crossentropy',
#                    optimizer=optimizer,
#                    metrics=['accuracy'])

# lstm_3 = load_model('./models/three_star.h5')

# lstm_3.compile(loss='binary_crossentropy',
#                    optimizer=optimizer,
#                    metrics=['accuracy'])

# lstm_4 = load_model('./models/four_star.h5')

# lstm_4.compile(loss='binary_crossentropy',
#                    optimizer=optimizer,
#                    metrics=['accuracy'])

# lstm_5 = load_model('./models/five_star.h5')

# lstm_5.compile(loss='binary_crossentropy',
#                    optimizer=optimizer,
#                    metrics=['accuracy'])
```

In [37]:
```
cols = [1, 2, 3, 4, 5]
# Baseline
print("Baseline")
baseline_preds = pd.DataFrame(baseline.predict(X_baseline), columns=cols)
baseline_preds['baseline_pred'] = baseline_preds.idxmax(axis=1)

# LSTM
print("LSTM")
lstm_preds = pd.DataFrame(lstm.predict(X_lstm), columns=cols)
lstm_preds['lstm_pred'] = lstm_preds.idxmax(axis=1)

# One vs. all
print("OVA")
one_star_ps = lstm_1.predict(X_lstm)
two_star_ps = lstm_2.predict(X_lstm)
three_star_ps = lstm_3.predict(X_lstm)
four_star_ps = lstm_4.predict(X_lstm)
five_star_ps = lstm_5.predict(X_lstm)

data = [one_star_ps.flatten(), two_star_ps.flatten(), three_star_ps.flatten(),
four_star_ps.flatten(), five_star_ps.flatten()]
ova_preds = pd.DataFrame(data=data, index=cols).T

ova_preds["ova_pred"] = ova_preds.idxmax(axis=1)

all_preds = pd.DataFrame([baseline_preds['baseline_pred'], lstm_preds['lstm_pr
ed'], ova_preds['ova_pred']]).T
all_preds["final_pred"] = all_preds.mode(axis=1)[0]
```

```
Baseline
LSTM
OVA
```

In [38]:
```
print([MAE(all_preds["final_pred"], pd.DataFrame(data=y_test, columns=cols).id
xmax(axis=1)), Accuracy(all_preds["final_pred"], pd.DataFrame(data=y_test, col
umns=cols).idxmax(axis=1))])
```

```
[0.34630017179447137, 0.7610057785413088]
```

In [39]:
```
# Confusion matrix
cm = confusion_matrix(all_preds["final_pred"], pd.DataFrame(data=y_test, colum
ns=cols).idxmax(axis=1))
pd.DataFrame(cm, index=cols, columns=cols)
```

Out[39]:

	1	2	3	4	5
1	35798	5430	1818	892	1335
2	1489	3254	2009	798	417
3	145	690	1864	703	157
4	310	671	3058	8141	3751
5	1145	698	1514	11227	72761

In [40]:
```
print(classification_report(y_pred_true, y_test_true))
```

```
              precision    recall  f1-score   support

           1       0.91      0.80      0.85     44404
           2       0.23      0.46      0.31      5290
           3       0.25      0.48      0.33      5367
           4       0.32      0.50      0.39     13934
           5       0.94      0.81      0.87     91080

    accuracy                           0.76    160075
   macro avg       0.53      0.61      0.55    160075
weighted avg       0.84      0.76      0.79    160075
```

Challenges

Challenge 5

In [41]:
```
c5 = pd.read_json("./yelp_challenge_5_with_answers.jsonl", lines = True)
print(c5.shape)
c5.head()
```

```
(500, 3)
```

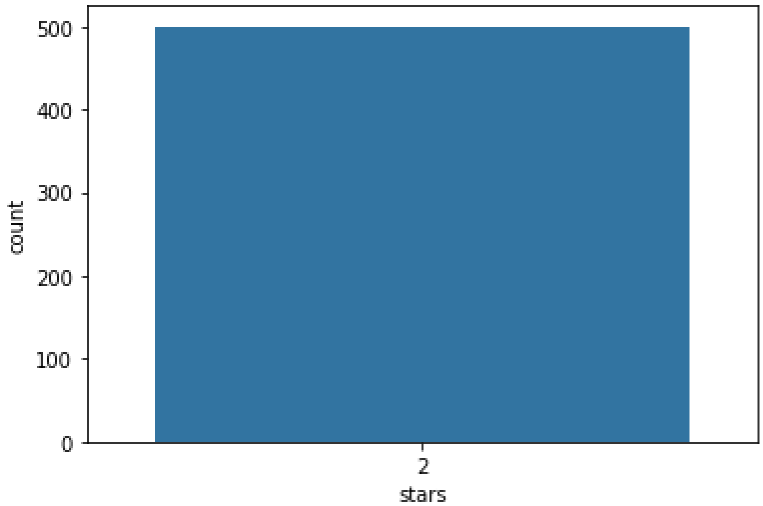
Out[41]:

	review_id	text	stars
0	50	I went to this campus for 1 semester. I was in...	2
1	51	I have rated it a two star based on its compar...	2
2	52	Just like most of the reviews, we ordered and ...	2
3	53	I only go here if it is an emergency. I HATE i...	2
4	54	Rude staff. I got 60 feeder fish and about 15 ...	2

Quick EDA

In [42]:
```
sns.countplot(c5['stars'])
```

Out[42]: <matplotlib.axes._subplots.AxesSubplot at 0x25a298c48c8>



Pre-processing

In [43]:
```
c5['text'] = c5['text'].apply(clean_text)
c5.head()
```

Out[43]:

	review_id	text	stars
0	50	went campu 1 semest busi inform system campu o...	2
1	51	rate two star base comparison shop find staff ...	2
2	52	like review order paid half front door advanc ...	2
3	53	go emerg hate one door enter exit loss prevent...	2
4	54	rude staff got 60 feeder fish 15 dead cashier ...	2

Load previous tokenizer

In [44]:
```
X = c5['text'].fillna('').values
y = pd.get_dummies(c5['stars'])

# with open('tokenizer.pickle', 'rb') as handle:
#     tokenizer = pickle.load(handle)

max_words

necc_cols = [1, 2, 3, 4, 5]
for col in necc_cols:
    if col not in y.columns:
        y[col] = 0

y = y[necc_cols]
y = y.values

X_baseline = tokenizer.texts_to_matrix(X)
X_lstm = tokenizer.texts_to_sequences(X)
X_lstm = pad_sequences(X_lstm, maxlen=400)
```

Load and compile models

In [ ]:
```
# # Baseline
# baseline = load_model('./models/baseline.h5')

# baseline.compile(loss='categorical_crossentropy',
#                 optimizer=optimizer,
#                 metrics=['accuracy'])

# # LSTM
# lstm = load_model('./models/lstm.h5')

# lstm.compile(loss='categorical_crossentropy',
#                 optimizer=optimizer,
#                 metrics=['accuracy'])


# # One vs. all
# lstm_1 = load_model('./models/one_star.h5')

# lstm_1.compile(loss='binary_crossentropy',
#                     optimizer=optimizer,
#                     metrics=['accuracy'])

# lstm_2 = load_model('./models/two_star.h5')

# lstm_2.compile(loss='binary_crossentropy',
#                     optimizer=optimizer,
#                     metrics=['accuracy'])

# lstm_3 = load_model('./models/three_star.h5')

# lstm_3.compile(loss='binary_crossentropy',
#                     optimizer=optimizer,
#                     metrics=['accuracy'])

# lstm_4 = load_model('./models/four_star.h5')

# lstm_4.compile(loss='binary_crossentropy',
#                     optimizer=optimizer,
#                     metrics=['accuracy'])

# lstm_5 = load_model('./models/five_star.h5')

# lstm_5.compile(loss='binary_crossentropy',
#                     optimizer=optimizer,
#                     metrics=['accuracy'])
```

Evaluate Models

In [45]:
```
# Baseline
print(baseline.evaluate(X_baseline, y))

# LSTM
print(lstm.evaluate(X_lstm, y))

# One vs. All
one_star_ps = lstm_1.predict(X_lstm)
two_star_ps = lstm_2.predict(X_lstm)
three_star_ps = lstm_3.predict(X_lstm)
four_star_ps = lstm_4.predict(X_lstm)
five_star_ps = lstm_5.predict(X_lstm)

data = [one_star_ps.flatten(), two_star_ps.flatten(), three_star_ps.flatten(),
four_star_ps.flatten(), five_star_ps.flatten()]
cols = [1, 2, 3, 4, 5]
ps = pd.DataFrame(data=data, index=cols).T

ps["ova_pred"] = ps.idxmax(axis=1)

print([MAE(ps["ova_pred"], pd.DataFrame(data=y, columns=cols).idxmax(axis=1)),
Accuracy(ps["ova_pred"], pd.DataFrame(data=y, columns=cols).idxmax(axis=1))])
```

```
500/500 [==============================] - 0s 84us/step
[2.4071271114349364, 0.27000001072883606, 0.29180610179901123]
500/500 [==============================] - 0s 600us/step
[2.0676476106643675, 0.2240000069141388, 0.260670930147171]
[0.754, 0.45]
```

Attempt Ensemble

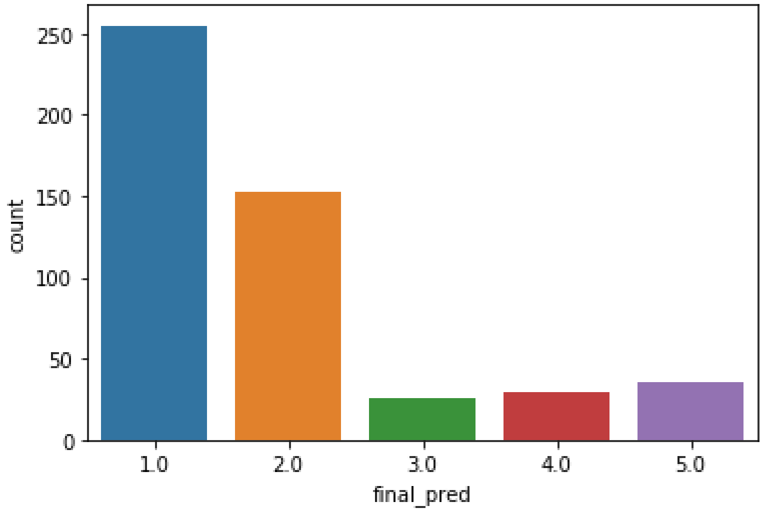
In [47]:
```
# Baseline
baseline_preds = pd.DataFrame(baseline.predict(X_baseline), columns=cols)
baseline_preds['baseline_pred'] = baseline_preds.idxmax(axis=1)

# LSTM
lstm_preds = pd.DataFrame(lstm.predict(X_lstm), columns=cols)
lstm_preds['lstm_pred'] = lstm_preds.idxmax(axis=1)

# One vs. all
ova_preds = ps

all_preds = pd.DataFrame([baseline_preds['baseline_pred'], lstm_preds['lstm_pr
ed'], ova_preds['ova_pred']]).T
all_preds["final_pred"] = all_preds.mode(axis=1)[0]

print([MAE(all_preds["final_pred"], pd.DataFrame(data=y, columns=cols).idxmax(
axis=1)), Accuracy(all_preds["final_pred"], pd.DataFrame(data=y, columns=cols)
.idxmax(axis=1))])
```

```
[0.898, 0.306]
```

Misc.

In [48]:
```
sns.countplot(all_preds["final_pred"])
```

Out[48]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x259cebb6cc8>
```



Challenge 6

In [49]:
```
c6 = pd.read_json("./yelp_challenge_6_with_answers.jsonl", lines = True)
print(c6.shape)
c6.head()
```

```
(500, 3)
```

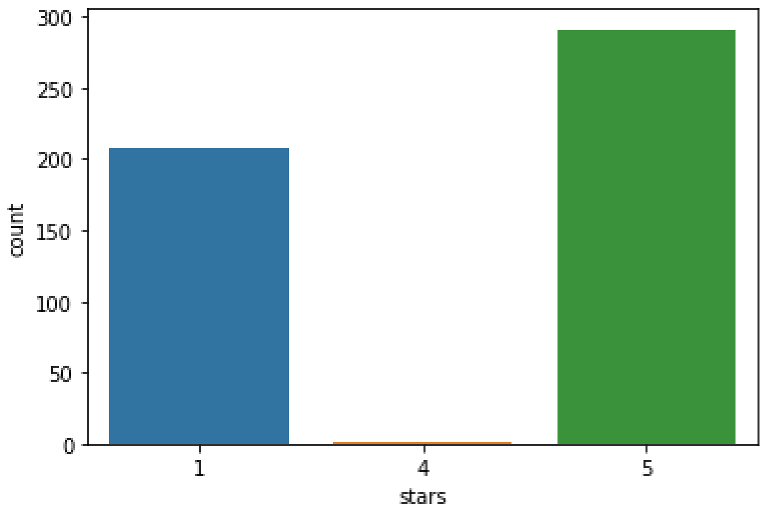
Out[49]:

	review_id	text	stars
0	60	Amazing for Trees\n\n$20 for a 5 gallon . I wi...	5
1	61	How the hell can Taco Bell be closed before mi...	5
2	62	I actually had no intention of visiting this p...	5
3	63	Yesterday around 3:30 pm I was driving west on...	5
4	64	DR FITZMAURICE did surgery on both hands on th...	5

Quick EDA

In [50]:
```
sns.countplot(c6['stars'])
```

Out[50]: <matplotlib.axes._subplots.AxesSubplot at 0x25cfd501b48>



Pre-processing

In [51]:
```
c6['text'] = c6['text'].apply(clean_text)
c6.head()
```

Out[51]:

	review_id	text	stars
0	60	amaz tree 20 5 gallon never go low home depot ...	5
1	61	hell taco bell close midnight illeg mean pract...	5
2	62	actual intent visit place disgust next door ho...	5
3	63	yesterday around 3 30 pm drive west pinnacl re...	5
4	64	dr fitzmauric surgeri hand day 8 plu year ago ...	5

Load previous tokenizer

In [52]:
```
X = c6['text'].fillna('').values
y = pd.get_dummies(c6['stars'])

# with open('tokenizer.pickle', 'rb') as handle:
#     tokenizer = pickle.load(handle)

max_words

necc_cols = [1, 2, 3, 4, 5]
for col in necc_cols:
    if col not in y.columns:
        y[col] = 0

y = y[necc_cols]
y = y.values

X_baseline = tokenizer.texts_to_matrix(X)
X_lstm = tokenizer.texts_to_sequences(X)
X_lstm = pad_sequences(X_lstm, maxlen=400)
```

Load and compile models

In [ ]:
```
# # Baseline
# baseline = load_model('./models/baseline.h5')

# baseline.compile(loss='categorical_crossentropy',
#                 optimizer=optimizer,
#                 metrics=['accuracy'])

# # LSTM
# lstm = load_model('./models/lstm.h5')

# lstm.compile(loss='categorical_crossentropy',
#                 optimizer=optimizer,
#                 metrics=['accuracy'])


# # One vs. all
# lstm_1 = load_model('./models/one_star.h5')

# lstm_1.compile(loss='binary_crossentropy',
#                     optimizer=optimizer,
#                     metrics=['accuracy'])

# lstm_2 = load_model('./models/two_star.h5')

# lstm_2.compile(loss='binary_crossentropy',
#                     optimizer=optimizer,
#                     metrics=['accuracy'])

# lstm_3 = load_model('./models/three_star.h5')

# lstm_3.compile(loss='binary_crossentropy',
#                     optimizer=optimizer,
#                     metrics=['accuracy'])

# lstm_4 = load_model('./models/four_star.h5')

# lstm_4.compile(loss='binary_crossentropy',
#                     optimizer=optimizer,
#                     metrics=['accuracy'])

# lstm_5 = load_model('./models/five_star.h5')

# lstm_5.compile(loss='binary_crossentropy',
#                     optimizer=optimizer,
#                     metrics=['accuracy'])
```

Evaluate Models

In [53]:
```
# Baseline
print(baseline.evaluate(X_baseline, y))

# LSTM
print(lstm.evaluate(X_lstm, y))

# One vs. All
one_star_ps = lstm_1.predict(X_lstm)
two_star_ps = lstm_2.predict(X_lstm)
three_star_ps = lstm_3.predict(X_lstm)
four_star_ps = lstm_4.predict(X_lstm)
five_star_ps = lstm_5.predict(X_lstm)

data = [one_star_ps.flatten(), two_star_ps.flatten(), three_star_ps.flatten(),
four_star_ps.flatten(), five_star_ps.flatten()]
cols = [1, 2, 3, 4, 5]
ps = pd.DataFrame(data=data, index=cols).T

ps["ova_pred"] = ps.idxmax(axis=1)

print([MAE(ps["ova_pred"], pd.DataFrame(data=y, columns=cols).idxmax(axis=1)),
Accuracy(ps["ova_pred"], pd.DataFrame(data=y, columns=cols).idxmax(axis=1))])
```

```
500/500 [==============================] - 0s 90us/step
[2.8102550601959226, 0.4320000112056732, 0.255241334438324]
500/500 [==============================] - 0s 548us/step
[2.5306867599487304, 0.4300000071525574, 0.22644712030887604]
[2.108, 0.376]
```

Attempt Ensemble

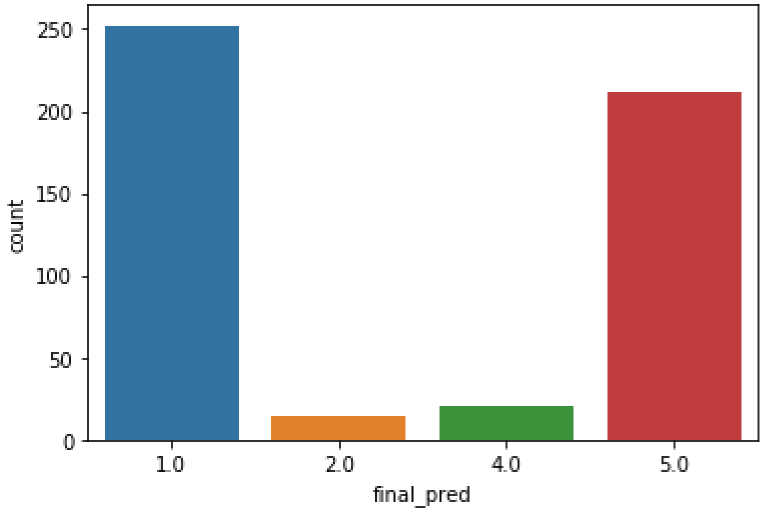
In [54]:
```
# Baseline
baseline_preds = pd.DataFrame(baseline.predict(X_baseline), columns=cols)
baseline_preds['baseline_pred'] = baseline_preds.idxmax(axis=1)

# LSTM
lstm_preds = pd.DataFrame(lstm.predict(X_lstm), columns=cols)
lstm_preds['lstm_pred'] = lstm_preds.idxmax(axis=1)

# One vs. all
ova_preds = ps

all_preds = pd.DataFrame([baseline_preds['baseline_pred'], lstm_preds['lstm_pr
ed'], ova_preds['ova_pred']]).T
all_preds["final_pred"] = all_preds.mode(axis=1)[0]

print([MAE(all_preds["final_pred"], pd.DataFrame(data=y, columns=cols).idxmax(
axis=1)), Accuracy(all_preds["final_pred"], pd.DataFrame(data=y, columns=cols)
.idxmax(axis=1))])
```

```
[2.042, 0.452]
```

Misc.

In [55]:
```
sns.countplot(all_preds["final_pred"])
```

Out[55]: <matplotlib.axes._subplots.AxesSubplot at 0x25d0477a808>



Challenge 3

In [56]:
```
c3 = pd.read_json("./yelp_challenge_3_with_answers.jsonl", lines = True)
print(c3.shape)
c3.head()
```

(534, 3)

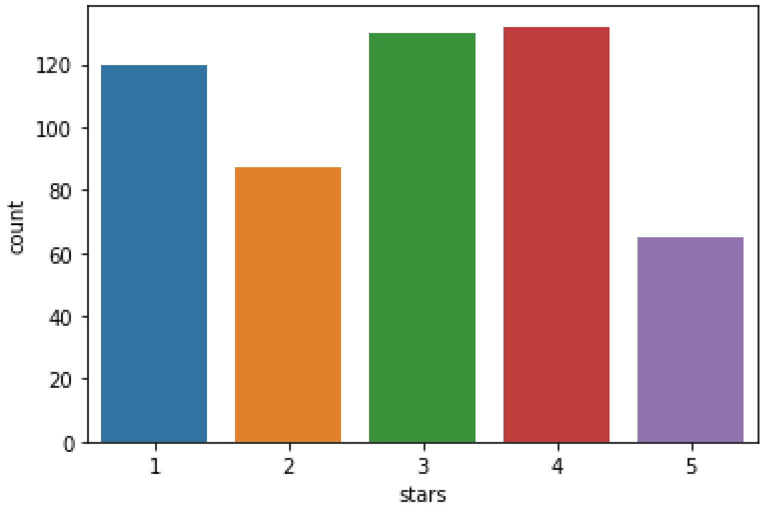
Out[56]:

	review_id	text	stars
0	30	We stopped here for lunch today and were pleas...	4
1	31	We went for a quick lunch here - it's all reas...	3
2	32	Very bad food, avoid it. We were a group of 4 ...	2
3	33	Bring a friend or two to help open the door. I...	3
4	34	Ukai serves some of the best sushi and sashimi...	4

Quick EDA

In [57]:
```
sns.countplot(c3['stars'])
```

Out[57]: <matplotlib.axes._subplots.AxesSubplot at 0x25d04690108>



Pre-processing

In [58]:
```
c3['text'] = c3['text'].apply(clean_text)
c3.head()
```

Out[58]:

	review_id	text	stars
0	30	stop lunch today pleasantli surpris great ambi...	4
1	31	went quick lunch reason well price good food n...	3
2	32	bad food avoid group 4 hungri came order batat...	2
3	33	bring friend two help open door think weigh 40...	3
4	34	ukai serv best sushi sashimi london bar nobu i...	4

Load previous tokenizer

In [59]:
```
X = c3['text'].fillna('').values
y = pd.get_dummies(c3['stars'])

# with open('tokenizer.pickle', 'rb') as handle:
#     tokenizer = pickle.load(handle)

max_words

necc_cols = [1, 2, 3, 4, 5]
for col in necc_cols:
    if col not in y.columns:
        y[col] = 0

y = y[necc_cols]
y = y.values

X_baseline = tokenizer.texts_to_matrix(X)
X_lstm = tokenizer.texts_to_sequences(X)
X_lstm = pad_sequences(X_lstm, maxlen=400)
```

Load and compile models

In [ ]:
```
# # Baseline
# baseline = load_model('./models/baseline.h5')

# baseline.compile(loss='categorical_crossentropy',
#                optimizer=optimizer,
#                metrics=['accuracy'])

# # LSTM
# lstm = load_model('./models/lstm.h5')

# lstm.compile(loss='categorical_crossentropy',
#                optimizer=optimizer,
#                metrics=['accuracy'])


# # One vs. all
# lstm_1 = load_model('./models/one_star.h5')

# lstm_1.compile(loss='binary_crossentropy',
#                    optimizer=optimizer,
#                    metrics=['accuracy'])

# lstm_2 = load_model('./models/two_star.h5')

# lstm_2.compile(loss='binary_crossentropy',
#                    optimizer=optimizer,
#                    metrics=['accuracy'])

# lstm_3 = load_model('./models/three_star.h5')

# lstm_3.compile(loss='binary_crossentropy',
#                    optimizer=optimizer,
#                    metrics=['accuracy'])

# lstm_4 = load_model('./models/four_star.h5')

# lstm_4.compile(loss='binary_crossentropy',
#                    optimizer=optimizer,
#                    metrics=['accuracy'])

# lstm_5 = load_model('./models/five_star.h5')

# lstm_5.compile(loss='binary_crossentropy',
#                    optimizer=optimizer,
#                    metrics=['accuracy'])
```

Evaluate Models

In [60]:
```
# Baseline
print(baseline.evaluate(X_baseline, y))

# LSTM
print(lstm.evaluate(X_lstm, y))

# One vs. All
one_star_ps = lstm_1.predict(X_lstm)
two_star_ps = lstm_2.predict(X_lstm)
three_star_ps = lstm_3.predict(X_lstm)
four_star_ps = lstm_4.predict(X_lstm)
five_star_ps = lstm_5.predict(X_lstm)

data = [one_star_ps.flatten(), two_star_ps.flatten(), three_star_ps.flatten(),
four_star_ps.flatten(), five_star_ps.flatten()]
cols = [1, 2, 3, 4, 5]
ps = pd.DataFrame(data=data, index=cols).T

ps["ova_pred"] = ps.idxmax(axis=1)

print([MAE(ps["ova_pred"], pd.DataFrame(data=y, columns=cols).idxmax(axis=1)),
Accuracy(ps["ova_pred"], pd.DataFrame(data=y, columns=cols).idxmax(axis=1))])
```

```
534/534 [==============================] - 0s 82us/step
[1.4426695729016366, 0.5599250793457031, 0.2019977569580078]
534/534 [==============================] - 0s 538us/step
[1.2576780779084908, 0.533707857131958, 0.1886107474565506]
[0.5767790262172284, 0.5187265917602997]
```

Attempt Ensemble

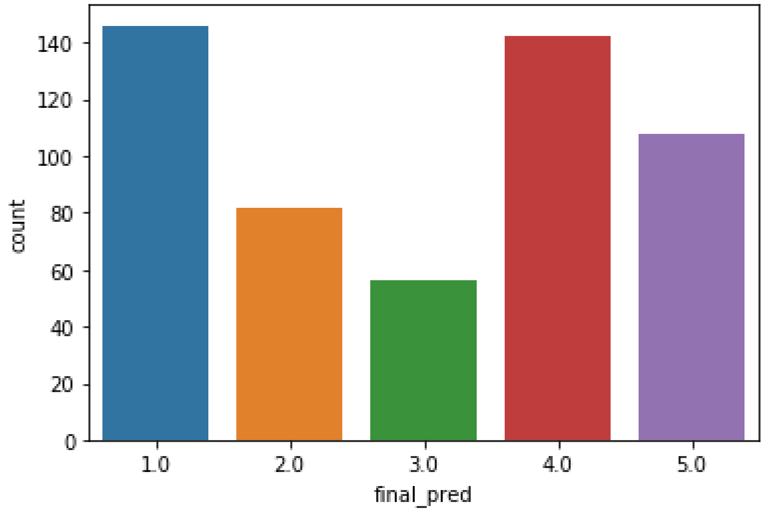
In [61]:
```
# Baseline
baseline_preds = pd.DataFrame(baseline.predict(X_baseline), columns=cols)
baseline_preds['baseline_pred'] = baseline_preds.idxmax(axis=1)

# LSTM
lstm_preds = pd.DataFrame(lstm.predict(X_lstm), columns=cols)
lstm_preds['lstm_pred'] = lstm_preds.idxmax(axis=1)

# One vs. all
ova_preds = ps

all_preds = pd.DataFrame([baseline_preds['baseline_pred'], lstm_preds['lstm_pr
ed'], ova_preds['ova_pred']]).T
all_preds["final_pred"] = all_preds.mode(axis=1)[0]

print([MAE(all_preds["final_pred"], pd.DataFrame(data=y, columns=cols).idxmax(
axis=1)), Accuracy(all_preds["final_pred"], pd.DataFrame(data=y, columns=cols)
.idxmax(axis=1))])
```

```
[0.5599250936329588, 0.5468164794007491]
```

Misc.

In [62]:
```
sns.countplot(all_preds["final_pred"])
```

Out[62]: <matplotlib.axes._subplots.AxesSubplot at 0x25d0467ed88>



Challenge 8

In [63]:
```
c8 = pd.read_json("./yelp_challenge_8_with_answers.jsonl", lines = True)
print(c8.shape)
c8.head()
```

(500, 3)

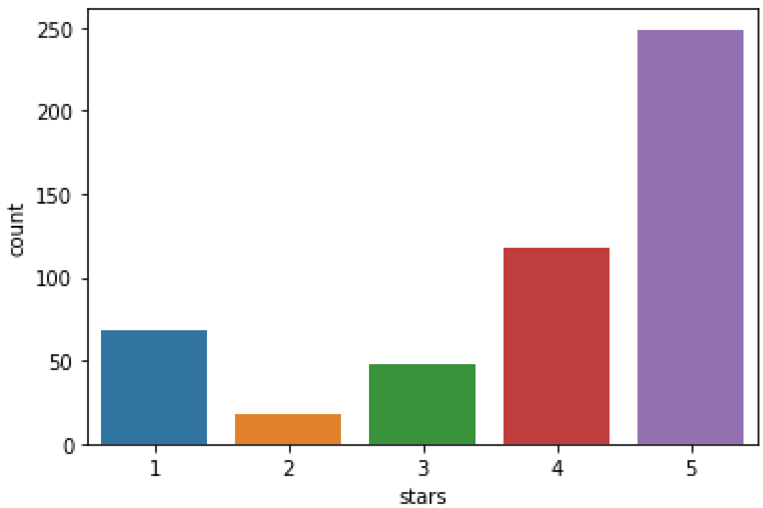
Out[63]:

	review_id	text	stars
0	qOOv-A-vo3kMT0yi4jIllg	Not bad for fast food.	4
1	uqxkO6B6w_sIDSAGr0k_0A	Une institution du café	4
2	0o_gGSU0m_4QyNLWEHKgug	J ai vraiment aimé !!!!	4
3	BKAj-fKWW5G3yt3xAkbUCQ	They have good poutine.	4
4	fAhp8IwuGNT0ywKmsCs6VQ	Very old and dirty vans.	1

Quick EDA

In [64]:
```
sns.countplot(c8['stars'])
```

Out[64]: <matplotlib.axes._subplots.AxesSubplot at 0x25d0480cc48>



Pre-processing

In [65]:
```
c8['text'] = c8['text'].apply(clean_text)
c8.head()
```

```
C:\Users\Tanner\Anaconda3\envs\yelp\lib\site-packages\bs4\__init__.py:398: UserWarning: "https://casetext.com/case/united-states-v-butterbaugh-2" looks like a URL. Beautiful Soup is not an HTTP client. You should probably use an HTTP client like requests to get the document behind the URL, and feed that document to Beautiful Soup.
  markup
```

Out[65]:

	review_id	text	stars
0	qOOv-A-vo3kMT0yi4jIllg	bad fast food	4
1	uqxkO6B6w_sIDSAGr0k_0A	une institut du caf	4
2	0o_gGSU0m_4QyNLWEHKgug	j ai vraiment aim	4
3	BKAj-fKWW5G3yt3xAkbUCQ	good poutin	4
4	fAhp8IwuGNT0ywKmsCs6VQ	old dirti van	1

Load previous tokenizer

In [66]:
```
X = c8['text'].fillna('').values
y = pd.get_dummies(c8['stars'])

# with open('tokenizer.pickle', 'rb') as handle:
#     tokenizer = pickle.load(handle)

max_words

necc_cols = [1, 2, 3, 4, 5]
for col in necc_cols:
    if col not in y.columns:
        y[col] = 0

y = y[necc_cols]
y = y.values

X_baseline = tokenizer.texts_to_matrix(X)
X_lstm = tokenizer.texts_to_sequences(X)
X_lstm = pad_sequences(X_lstm, maxlen=400)
```

Load and compile models

In [ ]:
```
# # Baseline
# baseline = load_model('./models/baseline.h5')

# baseline.compile(loss='categorical_crossentropy',
#                 optimizer=optimizer,
#                 metrics=['accuracy'])

# # LSTM
# lstm = load_model('./models/lstm.h5')

# lstm.compile(loss='categorical_crossentropy',
#                 optimizer=optimizer,
#                 metrics=['accuracy'])


# # One vs. all
# lstm_1 = load_model('./models/one_star.h5')

# lstm_1.compile(loss='binary_crossentropy',
#                     optimizer=optimizer,
#                     metrics=['accuracy'])

# lstm_2 = load_model('./models/two_star.h5')

# lstm_2.compile(loss='binary_crossentropy',
#                     optimizer=optimizer,
#                     metrics=['accuracy'])

# lstm_3 = load_model('./models/three_star.h5')

# lstm_3.compile(loss='binary_crossentropy',
#                     optimizer=optimizer,
#                     metrics=['accuracy'])

# lstm_4 = load_model('./models/four_star.h5')

# lstm_4.compile(loss='binary_crossentropy',
#                     optimizer=optimizer,
#                     metrics=['accuracy'])

# lstm_5 = load_model('./models/five_star.h5')

# lstm_5.compile(loss='binary_crossentropy',
#                     optimizer=optimizer,
#                     metrics=['accuracy'])
```

Evaluate Models

In [67]:
```
# Baseline
print(baseline.evaluate(X_baseline, y))

# LSTM
print(lstm.evaluate(X_lstm, y))

# One vs. All
one_star_ps = lstm_1.predict(X_lstm)
two_star_ps = lstm_2.predict(X_lstm)
three_star_ps = lstm_3.predict(X_lstm)
four_star_ps = lstm_4.predict(X_lstm)
five_star_ps = lstm_5.predict(X_lstm)

data = [one_star_ps.flatten(), two_star_ps.flatten(), three_star_ps.flatten(),
four_star_ps.flatten(), five_star_ps.flatten()]
cols = [1, 2, 3, 4, 5]
ps = pd.DataFrame(data=data, index=cols).T

ps["ova_pred"] = ps.idxmax(axis=1)

print([MAE(ps["ova_pred"], pd.DataFrame(data=y, columns=cols).idxmax(axis=1)),
Accuracy(ps["ova_pred"], pd.DataFrame(data=y, columns=cols).idxmax(axis=1))])
```

```
500/500 [==============================] - 0s 78us/step
[1.2850014667510987, 0.6359999775886536, 0.18668590486049652]
500/500 [==============================] - 0s 550us/step
[1.120063006401062, 0.6320000290870667, 0.1618264764547348]
[0.618, 0.59]
```

Attempt Ensemble

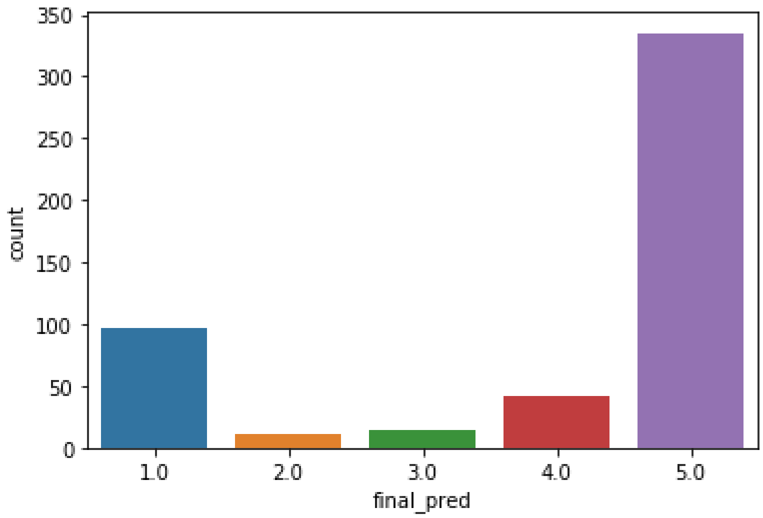
In [68]:
```
# Baseline
baseline_preds = pd.DataFrame(baseline.predict(X_baseline), columns=cols)
baseline_preds['baseline_pred'] = baseline_preds.idxmax(axis=1)

# LSTM
lstm_preds = pd.DataFrame(lstm.predict(X_lstm), columns=cols)
lstm_preds['lstm_pred'] = lstm_preds.idxmax(axis=1)

# One vs. all
ova_preds = ps

all_preds = pd.DataFrame([baseline_preds['baseline_pred'], lstm_preds['lstm_pr
ed'], ova_preds['ova_pred']]).T
all_preds["final_pred"] = all_preds.mode(axis=1)[0]

print([MAE(all_preds["final_pred"], pd.DataFrame(data=y, columns=cols).idxmax(
axis=1)), Accuracy(all_preds["final_pred"], pd.DataFrame(data=y, columns=cols)
.idxmax(axis=1))])
```

```
[0.556, 0.632]
```

Misc.

In [69]:
```
sns.countplot(all_preds["final_pred"])
```

Out[69]: <matplotlib.axes._subplots.AxesSubplot at 0x25a2d7cd848>



In [ ]: