NLP: Yelp Review to Rating

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Hello! In this project, we will be looking over Yelp reviews (data available here: [https://www.yelp.com/dataset (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 [2]:
```
# 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 [3]:
```
yelp = pd.read_json("./yelp_review_training_dataset.jsonl", lines = True)
yelp.head()
```

Out[3]:

	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 [4]:
```
yelp.shape
```

Out[4]:
```
(533581, 3)
```

EDA - Stars

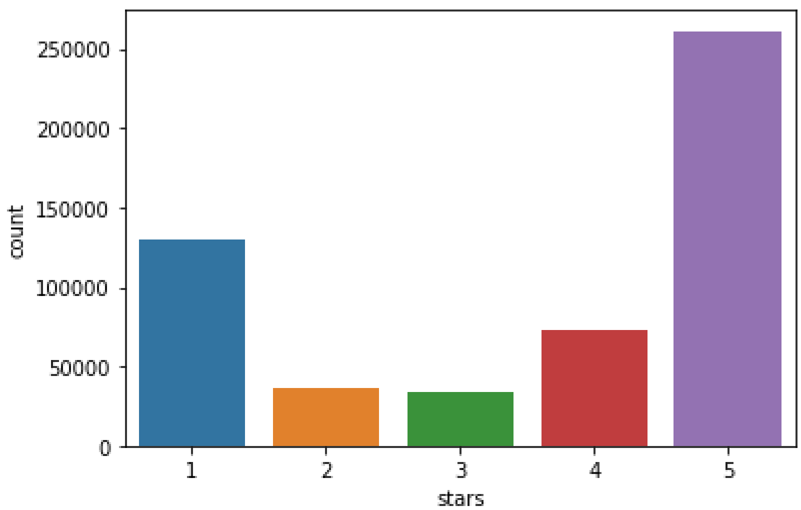
Not too much to go off of, but let's get a general understanding of our data. How many nulls do we have?

In [5]:
```
yelp.isna().sum()
```

Out[5]:
```
review_id    0
text         0
stars        0
dtype: int64
```

In [6]:
```
sns.countplot(yelp['stars'])
```

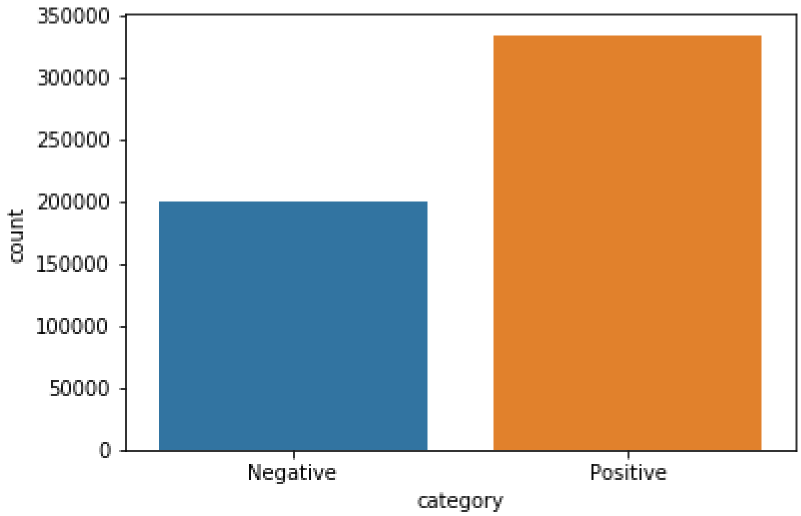
Out[6]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x20ac707f488>
```



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 [7]:
```
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 [8]:
```
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', 'd
idn', 'wasn', 'ain',
                        "doesn't", "isn't", "hasn't", 'shouldn', "weren't", "d
on't", "didn't",
                        "shouldn't", "wouldn't", "won't", "above", "below", "h
aven'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_SPA
CE_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()) # keepin
g 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)
```

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

In [ ]:

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

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 over 8g crook actual...	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: 50.7 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)
```

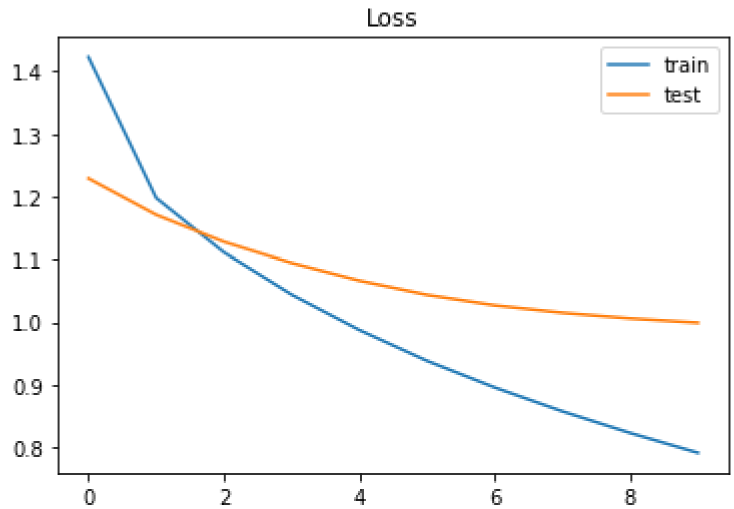
```
Train on 298804 samples, validate on 74702 samples
Epoch 1/10
298804/298804 [==============================] - 25s 85us/step - loss: 1.4230
- accuracy: 0.6991 - mean_absolute_error: 0.1534 - val_loss: 1.2289 - val_acc
uracy: 0.7439 - val_mean_absolute_error: 0.1336
Epoch 2/10
298804/298804 [==============================] - 13s 42us/step - loss: 1.1977
- accuracy: 0.7484 - mean_absolute_error: 0.1295 - val_loss: 1.1709 - val_acc
uracy: 0.7476 - val_mean_absolute_error: 0.1288
Epoch 3/10
298804/298804 [==============================] - 11s 37us/step - loss: 1.1111
- accuracy: 0.7622 - mean_absolute_error: 0.1246 - val_loss: 1.1279 - val_acc
uracy: 0.7488 - val_mean_absolute_error: 0.1282
Epoch 4/10
298804/298804 [==============================] - 12s 40us/step - loss: 1.0438
- accuracy: 0.7724 - mean_absolute_error: 0.1214 - val_loss: 1.0942 - val_acc
uracy: 0.7494 - val_mean_absolute_error: 0.1268
Epoch 5/10
298804/298804 [==============================] - 11s 38us/step - loss: 0.9872
- accuracy: 0.7822 - mean_absolute_error: 0.1183 - val_loss: 1.0659 - val_acc
uracy: 0.7482 - val_mean_absolute_error: 0.1289
Epoch 6/10
298804/298804 [==============================] - 12s 39us/step - loss: 0.9380
- accuracy: 0.7898 - mean_absolute_error: 0.1156 - val_loss: 1.0434 - val_acc
uracy: 0.7484 - val_mean_absolute_error: 0.1276
Epoch 7/10
298804/298804 [==============================] - 11s 38us/step - loss: 0.8954
- accuracy: 0.7981 - mean_absolute_error: 0.1129 - val_loss: 1.0267 - val_acc
uracy: 0.7496 - val_mean_absolute_error: 0.1260
Epoch 8/10
298804/298804 [==============================] - 12s 39us/step - loss: 0.8572
- accuracy: 0.8056 - mean_absolute_error: 0.1101 - val_loss: 1.0148 - val_acc
uracy: 0.7489 - val_mean_absolute_error: 0.1259
Epoch 9/10
298804/298804 [==============================] - 12s 39us/step - loss: 0.8226
- accuracy: 0.8137 - mean_absolute_error: 0.1073 - val_loss: 1.0057 - val_acc
uracy: 0.7491 - val_mean_absolute_error: 0.1252
Epoch 10/10
298804/298804 [==============================] - 12s 39us/step - loss: 0.7909
- accuracy: 0.8216 - mean_absolute_error: 0.1042 - val_loss: 0.9988 - val_acc
uracy: 0.7480 - val_mean_absolute_error: 0.1254
```

In [16]:

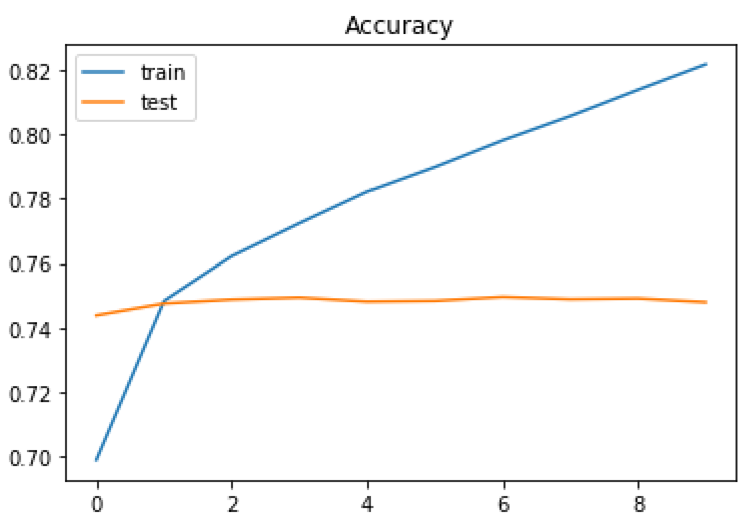
```python
score = baseline.evaluate(X_test, y_test,
                       batch_size=batch_size, verbose=1)
print('Test accuracy:', score[1])
```

```
160075/160075 [==============================] - 16s 101us/step
Test accuracy: 0.7500109076499939
```

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]:

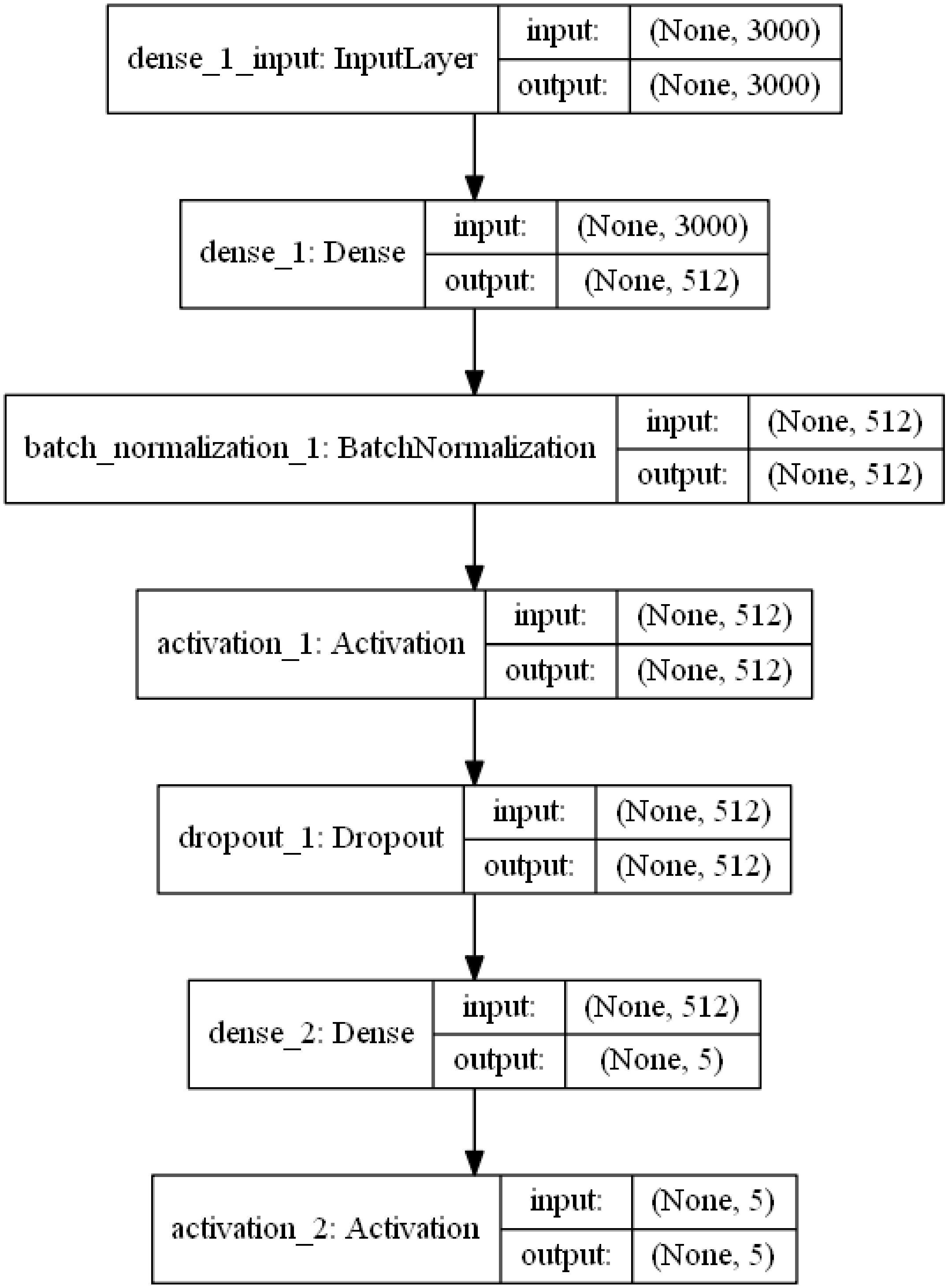
	1	2	3	4	5
1	34968	5141	1560	759	1364
2	1856	2690	1502	450	291
3	568	1580	3088	1902	598
4	275	605	2470	7667	4523
5	1220	727	1643	10983	71645

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

```
              precision    recall  f1-score   support

           1       0.90      0.80      0.85     43792
           2       0.25      0.40      0.31      6789
           3       0.30      0.40      0.34      7736
           4       0.35      0.49      0.41     15540
           5       0.91      0.83      0.87     86218

    accuracy                           0.75    160075
   macro avg       0.54      0.58      0.56    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: 25.3 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 284us/step - loss: 0.951
3 - accuracy: 0.7173 - mean_absolute_error: 0.1703 - val_loss: 0.7881 - val_a
ccuracy: 0.7471 - val_mean_absolute_error: 0.1216
Epoch 2/5
298804/298804 [==============================] - 82s 275us/step - loss: 0.772
2 - accuracy: 0.7532 - mean_absolute_error: 0.1183 - val_loss: 0.7453 - val_a
ccuracy: 0.7593 - val_mean_absolute_error: 0.1150
Epoch 3/5
298804/298804 [==============================] - 83s 279us/step - loss: 0.733
4 - accuracy: 0.7634 - mean_absolute_error: 0.1117 - val_loss: 0.7292 - val_a
ccuracy: 0.7641 - val_mean_absolute_error: 0.1133
Epoch 4/5
298804/298804 [==============================] - 83s 278us/step - loss: 0.710
7 - accuracy: 0.7705 - mean_absolute_error: 0.1088 - val_loss: 0.7232 - val_a
ccuracy: 0.7662 - val_mean_absolute_error: 0.1113
Epoch 5/5
298804/298804 [==============================] - 81s 271us/step - loss: 0.692
0 - accuracy: 0.7771 - mean_absolute_error: 0.1066 - val_loss: 0.7235 - val_a
ccuracy: 0.7673 - val_mean_absolute_error: 0.1049
```

LSTM #1: Evaluation

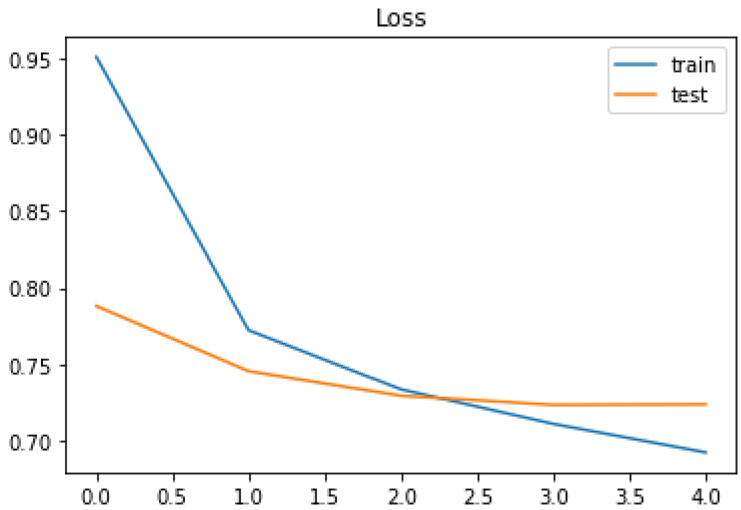
In [24]:
```
score = lstm.evaluate(X_test, y_test,
                       batch_size=batch_size, verbose=1)
print('Test accuracy:', score[1])
```

```
160075/160075 [==============================] - 10s 65us/step
Test accuracy: 0.7677151560783386
```

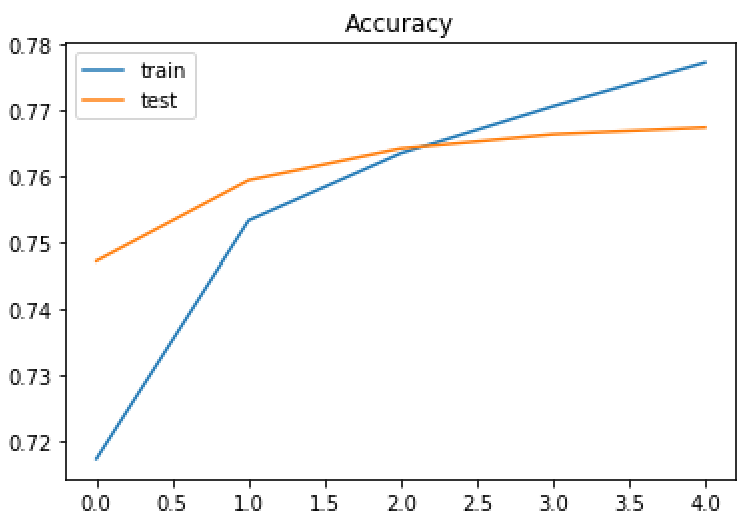
In [25]:
```
lstm.summary()
```

```
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]:

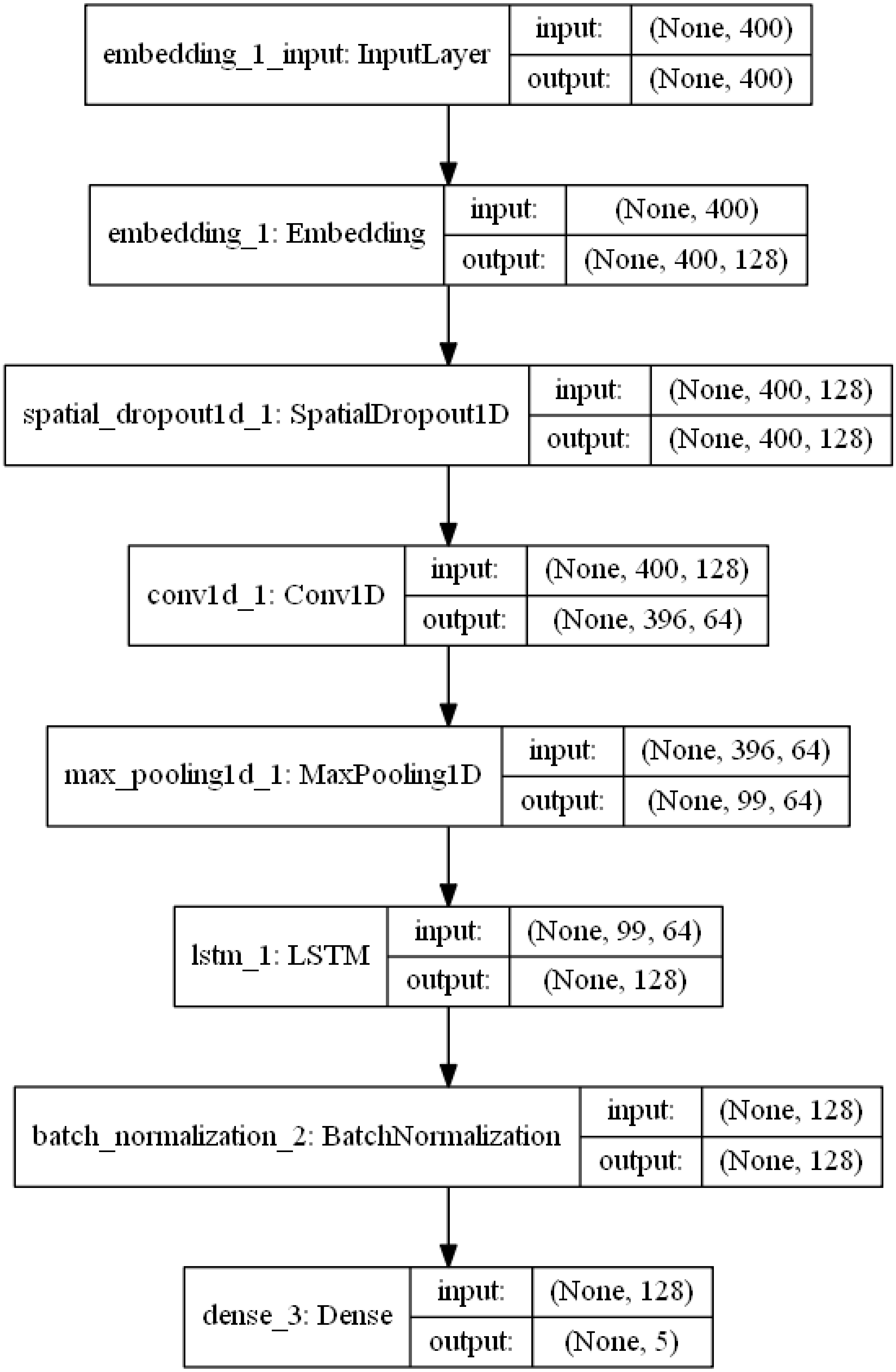
	1	2	3	4	5
1	36309	5855	1671	661	1073
2	1120	2918	1831	388	113
3	181	829	2347	1012	213
4	227	594	2953	7568	3272
5	1050	547	1461	12132	73750

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

```
              precision    recall  f1-score   support

           1       0.93      0.80      0.86     45569
           2       0.27      0.46      0.34      6370
           3       0.23      0.51      0.32      4582
           4       0.35      0.52      0.42     14614
           5       0.94      0.83      0.88     88940

    accuracy                           0.77    160075
   macro avg       0.54      0.62      0.56    160075
weighted avg       0.84      0.77      0.80    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 [34]:
```
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 [==============================] - 81s 272us/step - loss: 0.368
7 - accuracy: 0.9104 - mean_absolute_error: 0.1207 - val_loss: 0.3123 - val_a
ccuracy: 0.9252 - val_mean_absolute_error: 0.1119
Epoch 2/2
298804/298804 [==============================] - 80s 266us/step - loss: 0.270
6 - accuracy: 0.9337 - mean_absolute_error: 0.0870 - val_loss: 0.2934 - val_a
ccuracy: 0.9272 - val_mean_absolute_error: 0.0910
2
Train on 298804 samples, validate on 74702 samples
Epoch 1/2
298804/298804 [==============================] - 80s 269us/step - loss: 0.352
8 - accuracy: 0.9263 - mean_absolute_error: 0.1125 - val_loss: 0.3161 - val_a
ccuracy: 0.9327 - val_mean_absolute_error: 0.0865
Epoch 2/2
298804/298804 [==============================] - 78s 262us/step - loss: 0.277
2 - accuracy: 0.9369 - mean_absolute_error: 0.0844 - val_loss: 0.3112 - val_a
ccuracy: 0.9348 - val_mean_absolute_error: 0.0749
3
Train on 298804 samples, validate on 74702 samples
Epoch 1/3
298804/298804 [==============================] - 79s 263us/step - loss: 0.352
3 - accuracy: 0.9279 - mean_absolute_error: 0.1136 - val_loss: 0.3007 - val_a
ccuracy: 0.9365 - val_mean_absolute_error: 0.0858
Epoch 2/3
298804/298804 [==============================] - 78s 262us/step - loss: 0.268
5 - accuracy: 0.9400 - mean_absolute_error: 0.0803 - val_loss: 0.2787 - val_a
ccuracy: 0.9388 - val_mean_absolute_error: 0.0823
Epoch 3/3
298804/298804 [==============================] - 78s 261us/step - loss: 0.241
6 - accuracy: 0.9456 - mean_absolute_error: 0.0728 - val_loss: 0.3676 - val_a
ccuracy: 0.9381 - val_mean_absolute_error: 0.0642
4
Train on 298804 samples, validate on 74702 samples
Epoch 1/3
298804/298804 [==============================] - 79s 266us/step - loss: 0.548
9 - accuracy: 0.8588 - mean_absolute_error: 0.1882 - val_loss: 0.5471 - val_a
ccuracy: 0.8640 - val_mean_absolute_error: 0.1650
Epoch 2/3
298804/298804 [==============================] - 80s 269us/step - loss: 0.478
7 - accuracy: 0.8750 - mean_absolute_error: 0.1606 - val_loss: 0.5560 - val_a
ccuracy: 0.8526 - val_mean_absolute_error: 0.2064
Epoch 3/3
298804/298804 [==============================] - 80s 268us/step - loss: 0.444
0 - accuracy: 0.8858 - mean_absolute_error: 0.1482 - val_loss: 0.6031 - val_a
ccuracy: 0.8672 - val_mean_absolute_error: 0.1400
5
Train on 298804 samples, validate on 74702 samples
Epoch 1/4
298804/298804 [==============================] - 79s 264us/step - loss: 0.532
2 - accuracy: 0.8617 - mean_absolute_error: 0.1801 - val_loss: 0.5211 - val_a
ccuracy: 0.8629 - val_mean_absolute_error: 0.1901
Epoch 2/4
298804/298804 [==============================] - 79s 264us/step - loss: 0.452
7 - accuracy: 0.8832 - mean_absolute_error: 0.1522 - val_loss: 0.4804 - val_a
```

```
ccuracy: 0.8741 - val_mean_absolute_error: 0.1551
Epoch 3/4
298804/298804 [==============================] - 78s 262us/step - loss: 0.413
7 - accuracy: 0.8954 - mean_absolute_error: 0.1376 - val_loss: 0.4826 - val_a
ccuracy: 0.8758 - val_mean_absolute_error: 0.1482
Epoch 4/4
298804/298804 [==============================] - 78s 262us/step - loss: 0.378
3 - accuracy: 0.9066 - mean_absolute_error: 0.1240 - val_loss: 0.5026 - val_a
ccuracy: 0.8723 - val_mean_absolute_error: 0.1509
```

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

Testing

In [35]:

```
%%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
0.34496329845384976
0.7604185538029049
Wall time: 5min 37s
```

In [36]:
```
# Confusion matrix
cm = confusion_matrix(ps["pred"], y_test_true[0])
pd.DataFrame(cm, index=cols, columns=cols)
```

Out[36]:

	1	2	3	4	5
1	36471	6035	2066	914	1181
2	1031	2798	1718	555	204
3	118	500	1657	488	95
4	156	549	2482	5805	1948
5	1111	861	2340	13999	74993

In [37]:
```
print(classification_report(ps["pred"], y_test_true[0]))
```

```
              precision    recall  f1-score   support

           1       0.94      0.78      0.85     46667
           2       0.26      0.44      0.33      6306
           3       0.16      0.58      0.25      2858
           4       0.27      0.53      0.36     10940
           5       0.96      0.80      0.87     93304

    accuracy                           0.76    160075
   macro avg       0.52      0.63      0.53    160075
weighted avg       0.86      0.76      0.80    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 [38]:
```
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 [39]:
```
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 [40]:
```
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))])
```

```
[0.32784632203654535, 0.7670092144307356]
```

In [41]:
```
# 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[41]:

	1	2	3	4	5
1	36660	6184	2112	920	1182
2	1015	2869	1770	547	196
3	131	688	2300	1041	295
4	128	413	2466	6840	2638
5	953	589	1615	12413	74110

In [42]:
```python
print(classification_report(y_pred_true, y_test_true))
```

```
              precision    recall  f1-score   support

           1       0.93      0.80      0.86     45569
           2       0.27      0.46      0.34      6370
           3       0.23      0.51      0.32      4582
           4       0.35      0.52      0.42     14614
           5       0.94      0.83      0.88     88940

    accuracy                           0.77    160075
   macro avg       0.54      0.62      0.56    160075
weighted avg       0.84      0.77      0.80    160075
```

Challenges

Challenge 5

In [43]:
```python
c5 = pd.read_json("./yelp_challenge_5_with_answers.jsonl", lines = True)
print(c5.shape)
c5.head()
```

```
(500, 3)
```

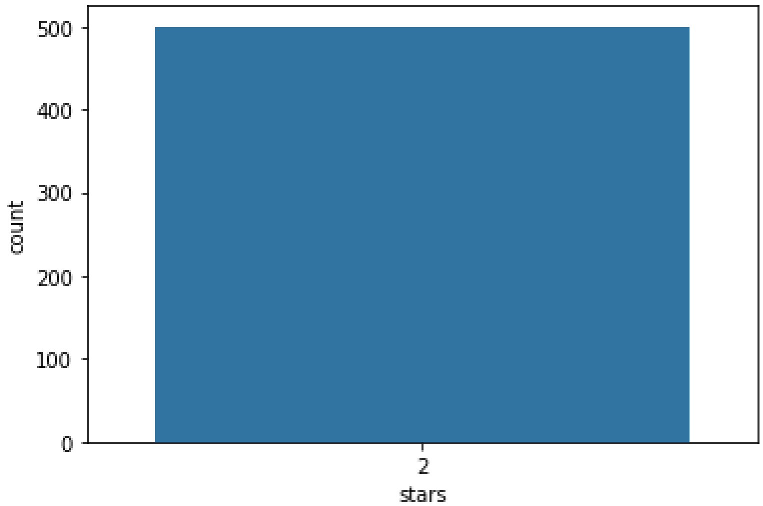
Out[43]:

	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 [44]:
```
sns.countplot(c5['stars'])
```

Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x20d387d96c8>



Pre-processing

In [45]:
```
c5['text'] = c5['text'].apply(clean_text)
c5.head()
```

Out[45]:

	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 [46]:
```
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 [47]:
```
# 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 98us/step
[2.34812021446228, 0.2639999985694885, 0.28951653838157654]
500/500 [==============================] - 0s 534us/step
[1.9364630460739136, 0.2800000011920929, 0.2655700445175171]
[0.952, 0.27]
```

Attempt Ensemble

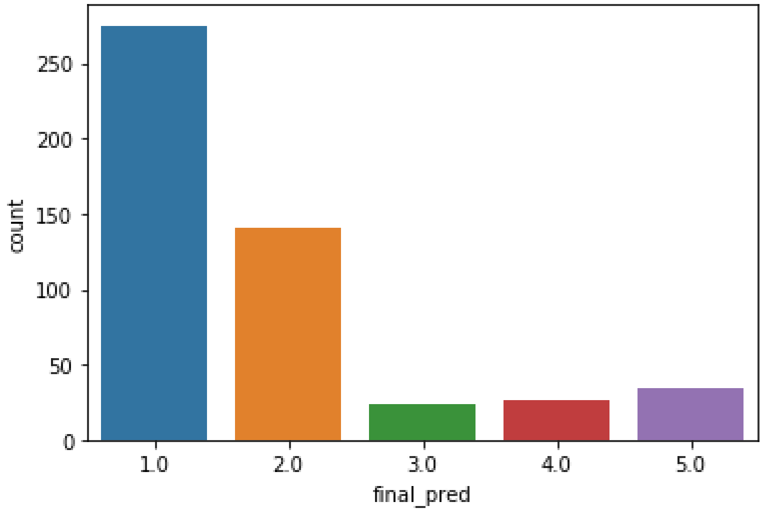
In [48]:
```
# Baseline
baseline_preds = pd.DataFrame(baseline.predict(X_baseline), columns=cols)
baseline_preds['baseline_pred'] = baseline_preds.idxmax(axis=1)

# 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))])
```

```
[0.91, 0.28]
```

Misc.

In [49]:
```
sns.countplot(all_preds["final_pred"])
```

Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x20dcf35d048>



Challenge 6

In [50]:
```
c6 = pd.read_json("./yelp_challenge_6_with_answers.jsonl", lines = True)
print(c6.shape)
c6.head()
```

```
(500, 3)
```

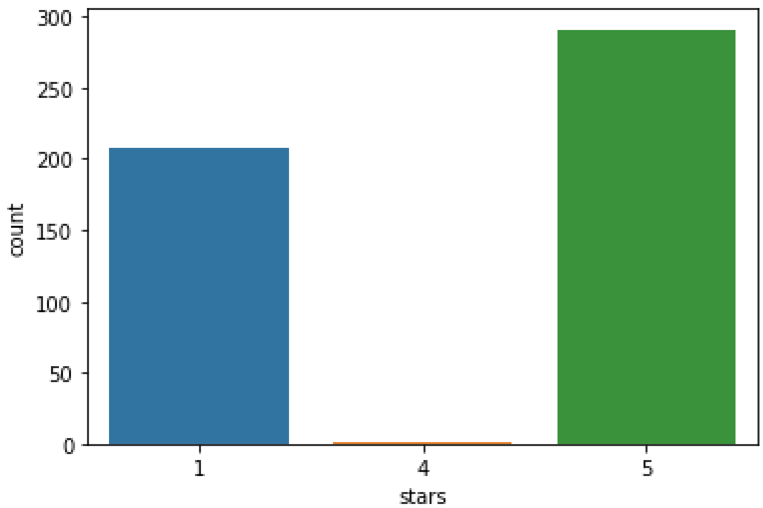
Out[50]:

	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 [51]:
```
sns.countplot(c6['stars'])
```

Out[51]: <matplotlib.axes._subplots.AxesSubplot at 0x20d6f035208>



Pre-processing

In [52]:
```
c6['text'] = c6['text'].apply(clean_text)
c6.head()
```

Out[52]:

	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 no intent visit place disgust next door...	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 [53]:
```
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 [54]:
```
# 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 76us/step
[2.789095220565796, 0.4339999854564667, 0.25485464930534363]
500/500 [==============================] - 0s 512us/step
[2.4458844165802, 0.4320000112056732, 0.2280576527118683]
[2.06, 0.468]
```

Attempt Ensemble

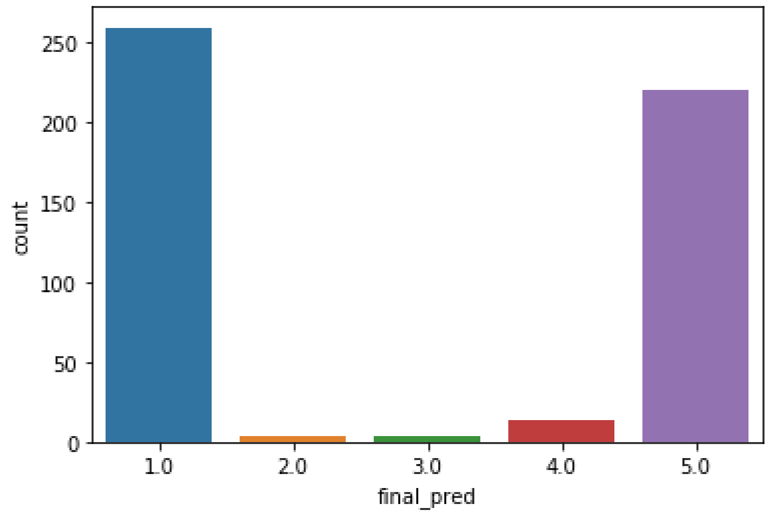
In [55]:
```
# Baseline
baseline_preds = pd.DataFrame(baseline.predict(X_baseline), columns=cols)
baseline_preds['baseline_pred'] = baseline_preds.idxmax(axis=1)

# 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))])
```

```
[2.04, 0.466]
```

Misc.

In [56]:
```
sns.countplot(all_preds["final_pred"])
```

Out[56]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x20dd1760d88>
```



Challenge 3

In [57]:
```
c3 = pd.read_json("./yelp_challenge_3_with_answers.jsonl", lines = True)
print(c3.shape)
c3.head()
```

```
(534, 3)
```

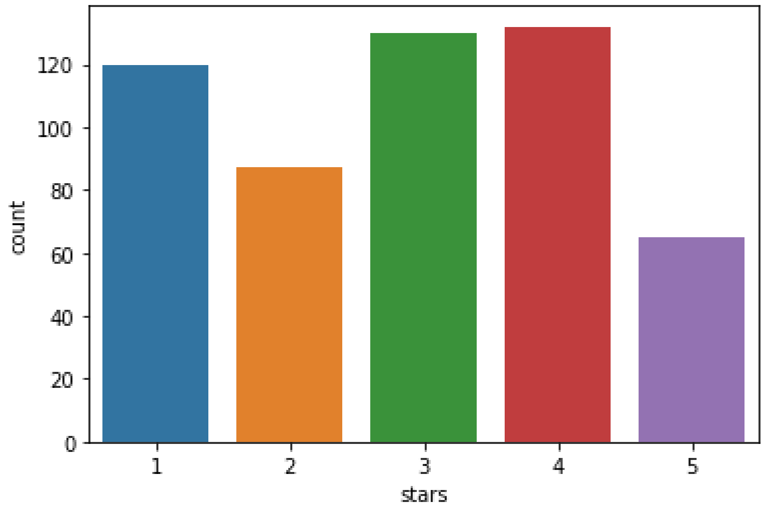
Out[57]:

	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 [58]:
```
sns.countplot(c3['stars'])
```

Out[58]: <matplotlib.axes._subplots.AxesSubplot at 0x20dd16f0c08>



Pre-processing

In [59]:
```
c3['text'] = c3['text'].apply(clean_text)
c3.head()
```

Out[59]:

	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	veri bad food avoid group 4 veri hungri came o...	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 [60]:
```
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 [61]:
```
# # 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 [62]:
```
# 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 77us/step
[1.443663603357608, 0.5524344444274902, 0.20500308275222778]
534/534 [==============================] - 0s 564us/step
[1.185322723138645, 0.5543071031570435, 0.18644575774669647]
[0.5973782771535581, 0.5112359550561798]
```

Attempt Ensemble

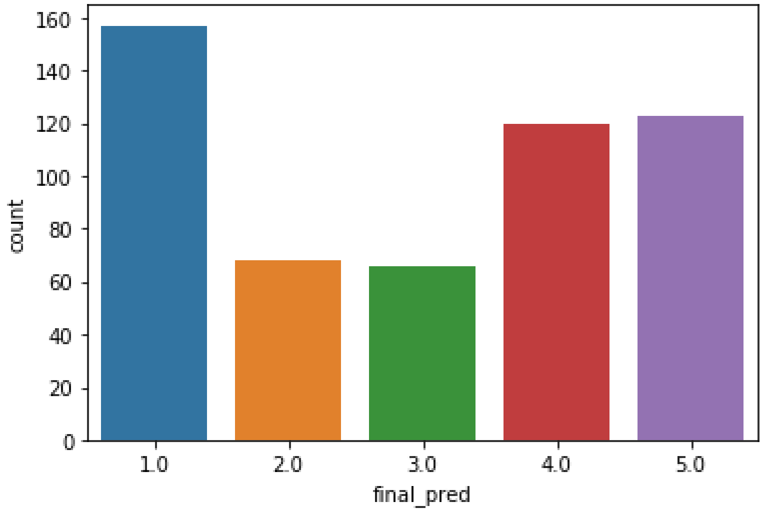
In [63]:
```
# Baseline
baseline_preds = pd.DataFrame(baseline.predict(X_baseline), columns=cols)
baseline_preds['baseline_pred'] = baseline_preds.idxmax(axis=1)

# 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))])
```

```
[0.5262172284644194, 0.5561797752808989]
```

Misc.

In [64]:
```
sns.countplot(all_preds["final_pred"])
```

Out[64]: <matplotlib.axes._subplots.AxesSubplot at 0x20dd18bd0c8>



Challenge 8

In [65]:
```
c8 = pd.read_json("./yelp_challenge_8_with_answers.jsonl", lines = True)
print(c8.shape)
c8.head()
```

```
(500, 3)
```

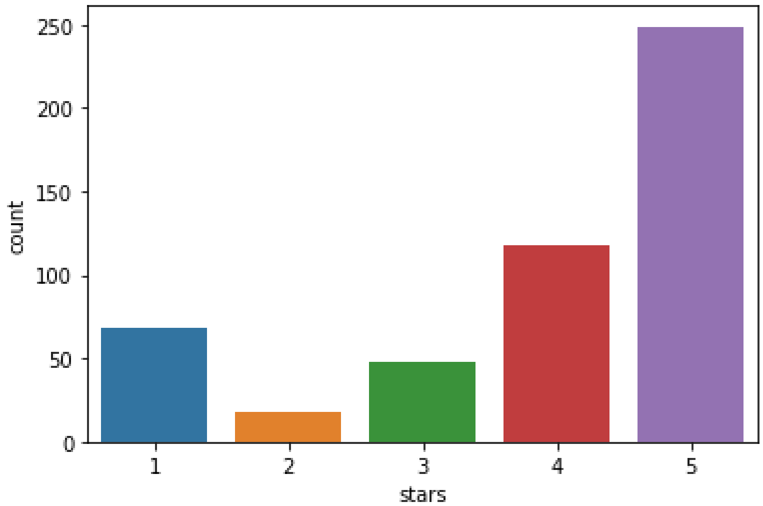
Out[65]:

	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 [66]:
```
sns.countplot(c8['stars'])
```

Out[66]: <matplotlib.axes._subplots.AxesSubplot at 0x20dd1868fc8>



Pre-processing

In [67]:
```
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[67]:

	review_id	text	stars
0	qOOv-A-vo3kMT0yi4jIllg	not 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	veri old dirti van	1

Load previous tokenizer

In [68]:
```
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 [69]:
```
# # 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 [70]:
```
# 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 76us/step
[1.25901877784729, 0.6380000114440918, 0.18588165938854218]
500/500 [==============================] - 0s 572us/step
[1.0685809507369994, 0.6380000114440918, 0.1606481522321701]
[0.634, 0.614]
```

Attempt Ensemble

In [71]:
```
# 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))])
```

```
[0.61, 0.628]
```

Misc.

In [72]:
```
sns.countplot(all_preds["final_pred"])
```

Out[72]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x20dd189e588>
```