5. Assignments

1. Use bag of words upto 4 grams and compute the micro f1 score with Logistic regression(OvR)
2. Perform hyperparam tuning on alpha (or lambda) for Logistic regression to improve the performance using GridSearch
3. Try OneVsRestClassifier with Linear-SVM (SGDClassifier with loss-hinge)

In [0]:

```
#Taking 0.5 Million entries to a dataframe.
conn_r = sqlite3.connect('Copy of Titlemoreweight.db')
preprocessed_data = pd.read_sql_query("""SELECT question, Tags FROM QuestionsProcessed""", conn_r)
conn_r.close()
```

In [0]:

```
preprocessed_data=preprocessed_data[:100000]
```

In [9]:

```
preprocessed_data.head()
```

Out[9]:

	question	tags
0	dynam datagrid bind silverlight dynam datagrid...	c# silverlight data-binding
1	dynam datagrid bind silverlight dynam datagrid...	c# silverlight data-binding columns
2	java.lang.noclassdeffounderror javax servlet j...	jsp jstl
3	java.sql.sqlexcept microsoft odbc driver manag...	java jdbc
4	better way updat feed fb php sdk better way up...	facebook api facebook-php-sdk

In [10]:
```
print("number of data points in sample :", preprocessed_data.shape[0])
print("number of dimensions :", preprocessed_data.shape[1])
```

```
number of data points in sample : 100000
number of dimensions : 2
```

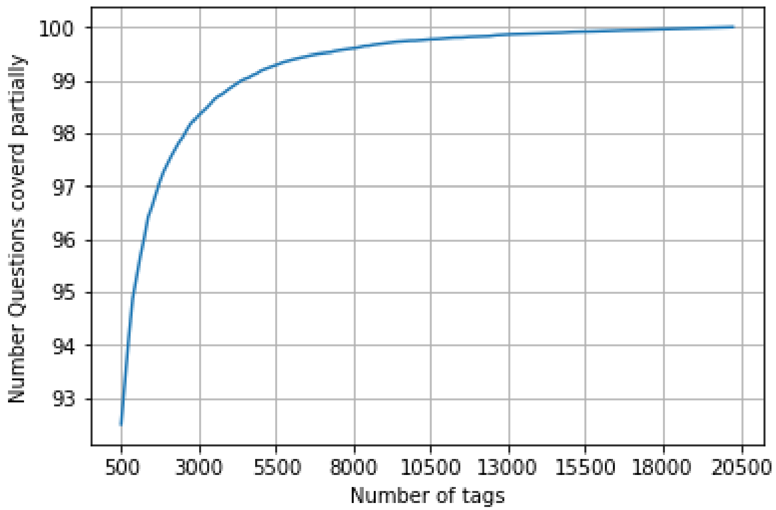
In [0]:
```
def tags_to_choose(n):
    t = multilabel_y.sum(axis=0).tolist()[0]
    sorted_tags_i = sorted(range(len(t)), key=lambda i: t[i], reverse=True)
    multilabel_yn=multilabel_y[:,sorted_tags_i[:n]]
    return multilabel_yn

def questions_explained_fn(n):
    multilabel_yn = tags_to_choose(n)
    x= multilabel_yn.sum(axis=1)
    return (np.count_nonzero(x==0))
```

In [0]:
```
vectorizer = CountVectorizer(tokenizer = lambda x: x.split(), binary='true')
multilabel_y = vectorizer.fit_transform(preprocessed_data['tags'])
```

In [0]:
```
questions_explained = []
total_tags=multilabel_y.shape[1]
total_qs=preprocessed_data.shape[0]
for i in range(500, total_tags, 100):
    questions_explained.append(np.round(((total_qs-questions_explained_fn(i))/total_qs)*100,3))
```

In [14]:
```
fig, ax = plt.subplots()
ax.plot(questions_explained)
xlabel = list(500+np.array(range(-50,450,50))*50)
ax.set_xticklabels(xlabel)
plt.xlabel("Number of tags")
plt.ylabel("Number Questions coverd partially")
plt.grid()
plt.show()
# you can choose any number of tags based on your computing power, mini
```

```
mun is 500(it covers 90% of the tags)
print("with ",5500,"tags we are covering ",questions_explained[50],"% o
f questions")
print("with ",500,"tags we are covering ",questions_explained[0],"% of
 questions")
```




```
with  5500 tags we are covering  99.481 % of questions
with  500 tags we are covering  92.5 % of questions
```

In [15]:

```
# we will be taking 500 tags
multilabel_yx = tags_to_choose(500)
print("number of questions that are not covered :", questions_explained
_fn(500),"out of ", total_qs)
```

```
number of questions that are not covered : 7500 out of  100000
```

In [0]:

```
total_size=preprocessed_data.shape[0]
train_size=int(0.80*total_size)

x_train=preprocessed_data.head(train_size)
x_test=preprocessed_data.tail(total_size - train_size)
```

```
y_train = multilabel_yx[0:train_size,:]
y_test = multilabel_yx[train_size:total_size,:]
```

In [17]:
```
print("Number of data points in train data :", y_train.shape)
print("Number of data points in test data :", y_test.shape)
```

```
Number of data points in train data : (80000, 500)
Number of data points in test data : (20000, 500)
```

Featurizing data with count vectorizer(BoW)

In [18]:
```
start = datetime.now()
vectorizer = CountVectorizer(min_df=0.00009, max_features=200000, token
izer=lambda x: x.split(), ngram_range=(1,4))
x_train_multilabel = vectorizer.fit_transform(x_train['question'])
x_test_multilabel = vectorizer.transform(x_test['question'])
print("Time taken to run this cell :", datetime.now() - start)
```

```
Time taken to run this cell : 0:01:23.851951
```

In [19]:
```
print("Dimensions of train data X:",x_train_multilabel.shape, "Y :",y_t
rain.shape)
print("Dimensions of test data X:",x_test_multilabel.shape,"Y:",y_test.
shape)
```

```
Dimensions of train data X: (80000, 101734) Y : (80000, 500)
Dimensions of test data X: (20000, 101734) Y: (20000, 500)
```

log regg one vs rest classifier and hyper param tunning

In [21]:
```
from sklearn.model_selection import GridSearchCV
param={'estimator__alpha': [10**-5, 10**-4, 10**-3, 10**-2, 10**-1, 10*
*0, 10**1]}
classifier = OneVsRestClassifier(SGDClassifier(loss='log', penalty='l1'
```

```
))
gsv = GridSearchCV(estimator = classifier, param_grid=param, cv=3, verb
ose=0, scoring='f1_micro',n_jobs=15)
gsv.fit(x_train_multilabel, y_train)

best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
print('value of alpha after hyperparameter tuning : ',best_alpha)
```

```
value of alpha after hyperparameter tuning :  0.001
```

Training a classifier with the best value of the hyperparameter

In [22]:

```
start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='log', alpha=best_a
lpha, penalty='l1'), n_jobs=-1)
classifier.fit(x_train_multilabel, y_train)
predictions = classifier.predict (x_test_multilabel)


print("Accuracy :",metrics.accuracy_score(y_test, predictions))
print("Hamming loss ",metrics.hamming_loss(y_test,predictions))


precision = precision_score(y_test, predictions, average='micro')
recall = recall_score(y_test, predictions, average='micro')
f1 = f1_score(y_test, predictions, average='micro')

print("Micro-average quality numbers")
print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(pr
ecision, recall, f1))

precision = precision_score(y_test, predictions, average='macro')
recall = recall_score(y_test, predictions, average='macro')
f1 = f1_score(y_test, predictions, average='macro')

print("Macro-average quality numbers")
```

```
print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(pr
ecision, recall, f1))

#print (metrics.classification_report(y_test, predictions))
print("Time taken to run this cell :", datetime.now() - start)
```

```
Accuracy : 0.1197
Hamming loss  0.0040428
Micro-average quality numbers
Precision: 0.4430, Recall: 0.3065, F1-measure: 0.3624
Macro-average quality numbers
Precision: 0.3185, Recall: 0.2214, F1-measure: 0.2374
Time taken to run this cell : 0:03:44.962072
```

Support Vector Classification(SGD Classifier with hinge loss)

hyper param

In [23]:

```
param={'estimator__alpha': [10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10**
1]}
classifier = OneVsRestClassifier(SGDClassifier(loss='hinge', penalty='l
1'))
gsv = GridSearchCV(estimator = classifier, param_grid=param, cv=3, verb
ose=0, scoring='f1_micro',n_jobs=15)
gsv.fit(x_train_multilabel, y_train)

best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
print('value of alpha after hyperparameter tuning : ',best_alpha)
```

```
value of alpha after hyperparameter tuning :  0.001
```

model with best hyper param

In [24]:

```
start = datetime.now()
#best_alpha = gsv.best_estimator_.get_params()['estimator__alpha']
classifier = OneVsRestClassifier(SGDClassifier(loss='hinge', alpha=best
_alpha, penalty='l1'), n_jobs=-1)
classifier.fit(x_train_multilabel, y_train)
predictions = classifier.predict (x_test_multilabel)


print("Accuracy :",metrics.accuracy_score(y_test, predictions))
print("Hamming loss ",metrics.hamming_loss(y_test,predictions))


precision = precision_score(y_test, predictions, average='micro')
recall = recall_score(y_test, predictions, average='micro')
f1 = f1_score(y_test, predictions, average='micro')

print("Micro-average quality numbers")
print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(pr
ecision, recall, f1))

precision = precision_score(y_test, predictions, average='macro')
recall = recall_score(y_test, predictions, average='macro')
f1 = f1_score(y_test, predictions, average='macro')

print("Macro-average quality numbers")
print("Precision: {:.4f}, Recall: {:.4f}, F1-measure: {:.4f}".format(pr
ecision, recall, f1))

#print (metrics.classification_report(y_test, predictions))
print("Time taken to run this cell :", datetime.now() - start)
```

```
Accuracy : 0.1168
Hamming loss  0.004063
Micro-average quality numbers
Precision: 0.4389, Recall: 0.3027, F1-measure: 0.3583
Macro-average quality numbers
Precision: 0.2867, Recall: 0.2268, F1-measure: 0.2271
Time taken to run this cell : 0:02:44.301788
```

Conclusion

```
We have choosen 'f1_micro' scoring metric because of the stated
 business statement.

Used bag of words upto 4 grams

For logistic regression , I have used 'SGDClassifier' instead of
 'LogisticRegression'. The reason is 'LogisticRegression' takes
 lots of time for hyperparameter tuning.
```

In [26]:

```python
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Classification model", "featurization","micro-f1","ma
cro-f1","hamming loss ","accuracy"]

x.add_row(["log reg(sgd classifier)", 'count vec', 0.36, 0.23, 0.004,0.
119])
x.add_row(["linear svm", 'count vec', 0.35, 0.22, 0.004,0.116])

print(x)
```

```
+-------------------------+---------------+----------+----------+------
---------+----------+
|   Classification model  | featurization | micro-f1 | macro-f1 | hammi
ng loss   | accuracy |
+-------------------------+---------------+----------+----------+------
---------+----------+
| log reg(sgd classifier) |   count vec   |   0.36   |   0.23   |
0.004     |  0.119   |
|        linear svm       |   count vec   |   0.35   |   0.22   |
0.004     |  0.116   |
+-------------------------+---------------+----------+----------+------
---------+----------+
```