
# Personalized cancer diagnosis

# 1. Business Problem

## 1.1 Data Description

In this competition you will develop algorithms to classify genetic mutations based on clinical evidence (text).

There are nine different classes a genetic mutation can be classified on.

This is not a trivial task since interpreting clinical evidence is very challenging even for human specialists. Therefore, modeling the clinical evidence (text) will be critical for the success of your approach.

Both, training and test, data sets are provided via two different files. One (training/test_variants) provides the information about the genetic mutations, whereas the other (training/test_text) provides the clinical evidence (text) that our human experts used to classify the genetic mutations. Both are linked via the ID field.

Therefore the genetic mutation (row) with ID=15 in the file training_variants, was classified using the clinical evidence (text) from the row with ID=15 in the file training_text

Finally, to make it more exciting!! Some of the test data is machine-generated to prevent hand labeling. You will submit all the results of your classification algorithm, and we will ignore the machine-generated samples.

**source:** https://www.kaggle.com/c/msk-redefining-cancer-treatment/data

### 1.1.1 File descriptions

- **training_variants** - a comma separated file containing the description of the genetic mutations used for training. Fields are ID (the id of the row used to link the mutation to the clinical evidence), Gene (the gene where this genetic mutation is located), Variation (the aminoacid change for this mutations), Class (1-9 the class this genetic mutation has been classified on)
- **training_text** - a double pipe (||) delimited file that contains the clinical evidence (text) used to classify genetic mutations. Fields are ID (the id of the row used to link the clinical evidence to the genetic mutation), Text (the clinical evidence used to classify the genetic mutation)

- **test_variants** - a comma separated file containing the description of the genetic mutations used for training. Fields are ID (the id of the row used to link the mutation to the clinical evidence), Gene (the gene where this genetic mutation is located), Variation (the aminoacid change for this mutations)
- **test_text** - a double pipe (||) delimited file that contains the clinical evidence (text) used to classify genetic mutations. Fields are ID (the id of the row used to link the clinical evidence to the genetic mutation), Text (the clinical evidence used to classify the genetic mutation)
- **submissionSample** - a sample submission file in the correct format

### 1.2. Real-world/Business objectives and constraints.

- No low-latency requirement.
- Interpretability is important.
- Errors can be very costly.
- Probability of a data-point belonging to each class is needed.

### 1.3 Evaluation

Submissions are evaluated on **Multi Class Log Loss** between the predicted probability and the observed target.

Source: https://www.kaggle.com/c/msk-redefining-cancer-treatment#evaluation

# 2. Mapping Real world problem into ML problem

## 2.1 Type of Machine Learning

There are nine different classes a genetic mutation can be classified into => Multi class classification problem

### 2.2 Performance Metric

- malticlass log loss
- confusion Matrix

### 2.3 Train, CV and Test Data

Split the dataset randomly into three parts train, cross validation and test with 64%,16%, 20% of data respectively

# 3. Exploratory Data Analysis

In [2]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from tqdm import tqdm
```

In [ ]:

```

```

In [3]:
```
#reading training_variants file
variant_df=pd.read_csv("training/training_variants")
print("Let's see 1st five data from training variants")
variant_df.head()
```

```
Let's see 1st five data from training variants
```

Out[3]:

| | ID | Gene | Variation | Class |
|---|---|---|---|---|
| **0** | 0 | FAM58A | Truncating Mutations | 1 |
| **1** | 1 | CBL | W802* | 2 |
| **2** | 2 | CBL | Q249E | 2 |
| **3** | 3 | CBL | N454D | 3 |
| **4** | 4 | CBL | L399V | 4 |

In [4]:
```
print("Number of data points in training variants:",variant_df.shape[0])
print("Number of features in training variants:",variant_df.shape[1])
print("All features:: ",variant_df.columns.values)
```

```
Number of data points in training variants: 3321
Number of features in training variants: 4
All features::  ['ID' 'Gene' 'Variation' 'Class']
```

In [5]:
```
#reading training text
text_df=pd.read_csv("training/training_text",sep="\|\|",engine="python",names=["ID","TE
text_df.head()
```

Out[5]:

| | ID | TEXT |
|---|---|---|
| **0** | 0 | Cyclin-dependent kinases (CDKs) regulate a var... |
| **1** | 1 | Abstract Background Non-small cell lung canc... |
| **2** | 2 | Abstract Background Non-small cell lung canc... |
| **3** | 3 | Recent evidence has demonstrated that acquired... |
| **4** | 4 | Oncogenic mutations in the monomeric Casitas B... |

## 3.1 Basic Analysis

In [6]:
```
print("Number of data points in training variants:",text_df.shape[0])
print("Number of features in training variants:",text_df.shape[1])
print("All features:: ",text_df.columns.values)
```

```
Number of data points in training variants: 3321
Number of features in training variants: 2
All features::  ['ID' 'TEXT']
```

### observation:

- both datasets have same number of datapoints
- variant datasets has 4 features and text_df has 2 features
- both datasets have a common column which is "ID"

In [7]:
```
import nltk
import re
```

```
import os
```

In [8]:
```
stopword=nltk.corpus.stopwords.words("english")
```

In [9]:
```
# Let remove stopwords and clean text
def nlp_preprocessing(text):
#     print(type(text))
    if type(text) is str:
        # replace every special char with space
        text=re.sub("[^a-zA-Z0-9\n]"," ",text)
        # replace multiple space with single space
        text=re.sub("\s+"," ",text)
        # convert text to lower case
        text=text.lower()
        #removing all stopwords from text
        text=" ".join([word for word in text.split() if word not in stopword and len(wo
    return text
```

In [10]:
```
# saving the concated file
if not os.path.isfile("training/merged_data.csv"):
    text_df["TEXT"]=[nlp_preprocessing(text) for text in tqdm(text_df["TEXT"])]
    #Lets merge both dataset by Id key
    df=variant_df.merge(text_df,how='inner',on="ID")
    df.to_csv("training/merged_data.csv",index=False)

else:
    df=pd.read_csv("training/merged_data.csv")
df.head()
```

Out[10]:

| | ID | Gene | Variation | Class | TEXT |
|---|---|---|---|---|---|
| **0** | 0 | FAM58A | Truncating Mutations | 1 | cyclin dependent kinases cdks regulate variety... |
| **1** | 1 | CBL | W802* | 2 | abstract background non small cell lung cancer... |
| **2** | 2 | CBL | Q249E | 2 | abstract background non small cell lung cancer... |
| **3** | 3 | CBL | N454D | 3 | recent evidence demonstrated acquired uniparen... |
| **4** | 4 | CBL | L399V | 4 | oncogenic mutations monomeric casitas b lineag... |

In [11]:
```
# Checking any NULL value exist
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3321 entries, 0 to 3320
Data columns (total 5 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   ID         3321 non-null   int64 
 1   Gene       3321 non-null   object
 2   Variation  3321 non-null   object
 3   Class      3321 non-null   int64 
 4   TEXT       3316 non-null   object
dtypes: int64(2), object(3)
memory usage: 129.9+ KB
```

In [12]:
```
df[df.isnull().any(axis=1)]
```

Out[12]:

| | ID | Gene | Variation | Class | TEXT |
|---|---|---|---|---|---|
| **1109** | 1109 | FANCA | S1088F | 1 | NaN |
| **1277** | 1277 | ARID5B | Truncating Mutations | 1 | NaN |
| **1407** | 1407 | FGFR3 | K508M | 6 | NaN |
| **1639** | 1639 | FLT1 | Amplification | 6 | NaN |
| **2755** | 2755 | BRAF | G596C | 7 | NaN |

**Observation:** It seems that there are some null value which present in TEXT feature

- We can fill NULL value with concatation of gene and variation columns

In [13]:
```
#filling NULL value with concatation of gene and variation columns
df.loc[df["TEXT"].isnull(),"TEXT"]=df.Gene+" "+df.Variation
```

In [14]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3321 entries, 0 to 3320
Data columns (total 5 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   ID         3321 non-null   int64 
 1   Gene       3321 non-null   object
 2   Variation  3321 non-null   object
 3   Class      3321 non-null   int64 
 4   TEXT       3321 non-null   object
dtypes: int64(2), object(3)
memory usage: 129.9+ KB
```

In [15]:
```
#split dataset into train,test and validation set
X=df
y=df['Class']
```

In [16]:
```
from sklearn.model_selection import train_test_split
import seaborn as sns
import warnings
from sklearn.metrics import log_loss,plot_confusion_matrix,confusion_matrix
warnings.filterwarnings(action="ignore")
```

In [17]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.2, random
```

In [18]:
```
# data distribution
print("Number of train data points:",X_train.shape[0])
print("Number of validation data points:",X_cv.shape[0])
print("Number of test data points:",X_test.shape[0])
```

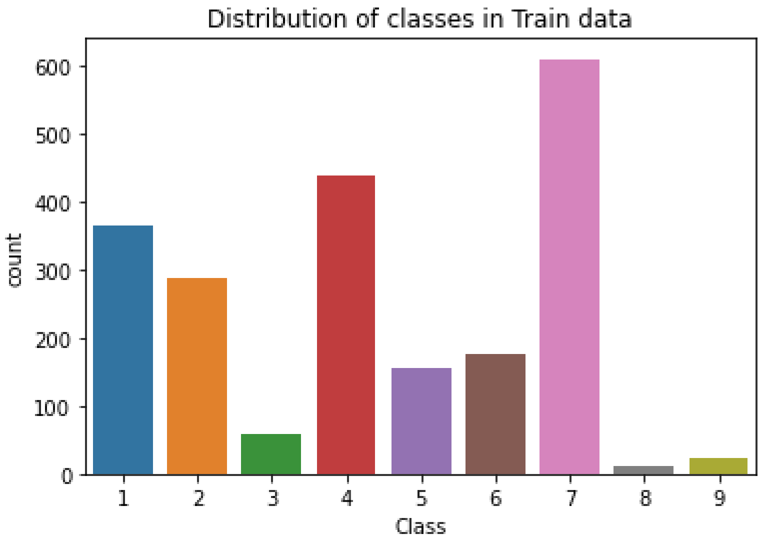
```
Number of train data points: 2124
Number of validation data points: 532
Number of test data points: 665
```

In [19]:
```
# plotting distribution of Y
train_y_sort=X_train['Class'].value_counts(normalize=True,sort=True)
test_y_sort=X_test['Class'].value_counts(normalize=True,sort=True)
cv_y_sort=X_cv['Class'].value_counts(normalize=True,sort=True)
```

In [ ]:

In [20]:

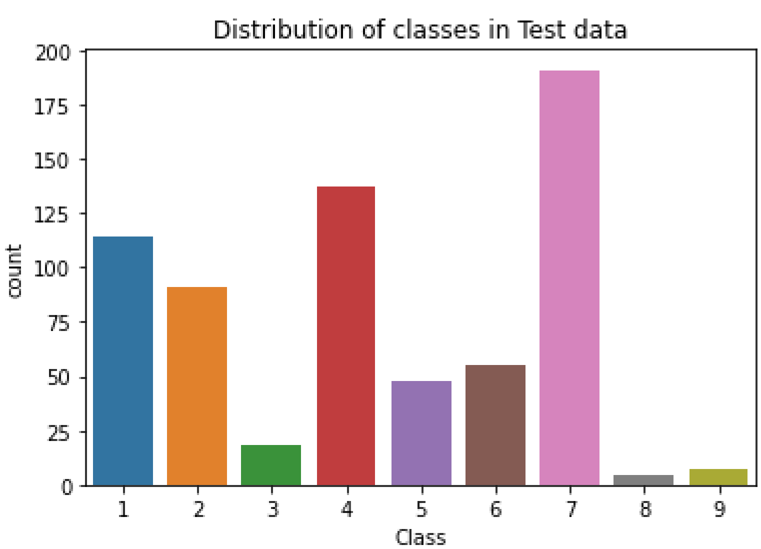
```
sns.countplot(x=y_train)
plt.title("Distribution of classes in Train data")
plt.show()
# sorted_y=np.argsort(train_y_sort,order="dsc")
for i in range(len(train_y_sort)):
    print("Number of data point in class {0} :: {1}%".format(train_y_sort.index[i],roun
```




```
Number of data point in class 7 :: 28.67%
Number of data point in class 4 :: 20.67%
Number of data point in class 1 :: 17.09%
Number of data point in class 2 :: 13.61%
Number of data point in class 6 :: 8.29%
Number of data point in class 5 :: 7.3%
Number of data point in class 3 :: 2.68%
Number of data point in class 9 :: 1.13%
Number of data point in class 8 :: 0.56%
```

In [21]:

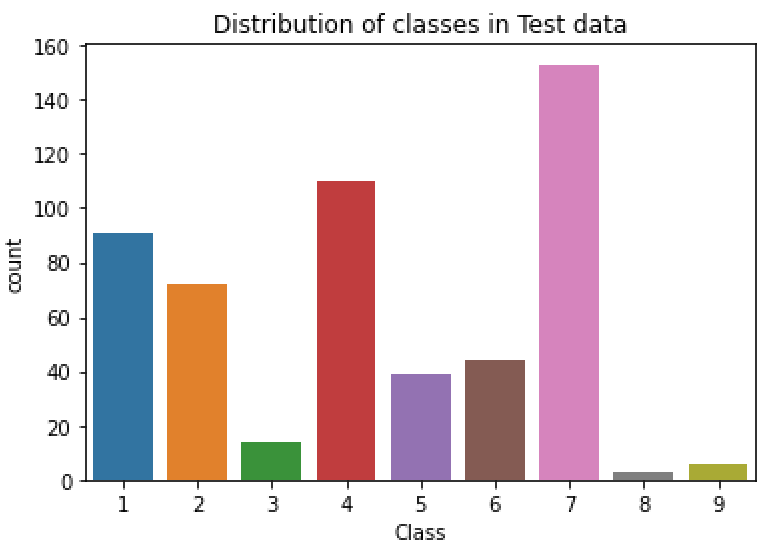
```
sns.countplot(x=y_test)
plt.title("Distribution of classes in Test data")
plt.show()
# sorted_y=np.argsort(train_y_sort,order="dsc")
for i in range(len(test_y_sort)):
    print("Number of data point in class {0} :: {1}%".format(test_y_sort.index[i],round
```



```
Number of data point in class 7 :: 28.72%
Number of data point in class 4 :: 20.6%
Number of data point in class 1 :: 17.14%
Number of data point in class 2 :: 13.68%
Number of data point in class 6 :: 8.27%
Number of data point in class 5 :: 7.22%
Number of data point in class 3 :: 2.71%
Number of data point in class 9 :: 1.05%
Number of data point in class 8 :: 0.6%
```

In [22]:

```
sns.countplot(x=y_cv)
plt.title("Distribution of classes in Test data")
plt.show()
# sorted_y=np.argsort(train_y_sort,order="dsc")
for i in range(len(cv_y_sort)):
    print("Number of data point in class {0} :: {1}%".format(cv_y_sort.index[i],round(c
```




```
Number of data point in class 7 :: 28.76%
Number of data point in class 4 :: 20.68%
Number of data point in class 1 :: 17.11%
Number of data point in class 2 :: 13.53%
Number of data point in class 6 :: 8.27%
Number of data point in class 5 :: 7.33%
Number of data point in class 3 :: 2.63%
Number of data point in class 9 :: 1.13%
Number of data point in class 8 :: 0.56%
```

In [23]:

```
rand_probs=np.random.rand(1,9)
rand_probs=rand_probs/sum(rand_probs.flatten())
rand_probs.flatten()
```

Out[23]:

```
array([0.12479829, 0.12392318, 0.03663268, 0.12003061, 0.10259138,
       0.13960845, 0.16832089, 0.10720818, 0.07688636])
```

In [ ]:

In [24]:

```
# source: https://onestopdataanalysis.com/confusion-matrix-python/
def plot_confusion_matrix(data, labels,title="Confution Matrix"):
    """Plot confusion matrix using heatmap.

    Args:
        data (list of list): List of lists with confusion matrix data.
        labels (list): Labels which will be plotted across x and y axis.
        output_filename (str): Path to output file.
```

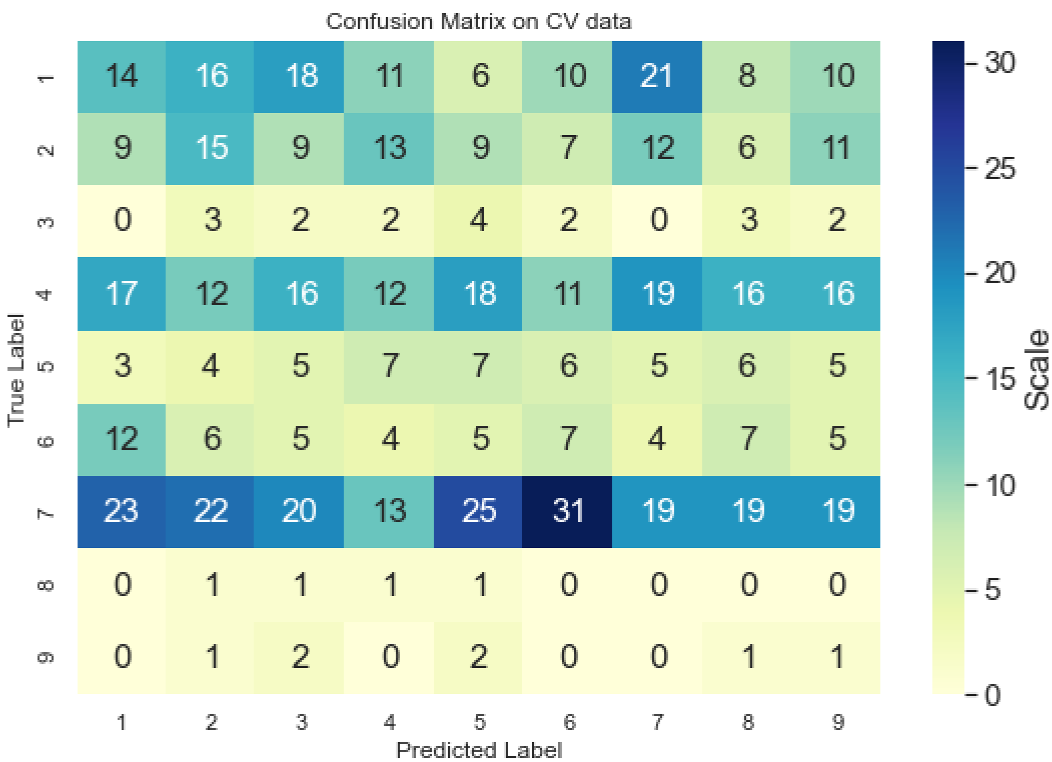
```
    """
    sns.set(color_codes=True)
    plt.figure(1, figsize=(9, 6))

    plt.title(title)

    sns.set(font_scale=1.4)
    ax = sns.heatmap(data, annot=True, cmap="YlGnBu", cbar_kws={'label': 'Scale'})

    ax.set_xticklabels(labels)
    ax.set_yticklabels(labels)

    ax.set(ylabel="True Label", xlabel="Predicted Label")

#     plt.savefig(output_filename, bbox_inches='tight', dpi=300)
    plt.show()
```

In [25]:

```
# Lets see random Model for classification
# benifit of Random Model that we will have idea that how worst our model can be
# we need to generate 9 number and the sum of it would be 1
cv_pred_y=np.zeros((y_cv.shape[0],9))
test_pred_y=np.zeros((y_test.shape[0],9))
##################################################
for i in range(y_cv.shape[0]):
    rand_probs=np.random.rand(1,9)
    rand_probs=rand_probs/sum(rand_probs.flatten())
    cv_pred_y[i]=rand_probs.flatten()
print("Log Loss on Cross validation data using Random Model::",log_loss(y_cv,cv_pred_y)

pred_y=np.argmax(cv_pred_y,axis=1)
matrix=confusion_matrix(y_cv,pred_y+1)
plot_confusion_matrix(matrix,labels=[1,2,3,4,5,6,7,8,9],title="Confusion Matrix on CV d
##################################################
print("-"*50)
for i in range(y_test.shape[0]):
    rand_probs=np.random.rand(1,9)
    rand_probs=rand_probs/sum(rand_probs.flatten())
    test_pred_y[i]=rand_probs.flatten()
print("Log Loss on Test data using Random Model::",log_loss(y_test,test_pred_y))
pred_y=np.argmax(test_pred_y,axis=1)
matrix=confusion_matrix(y_test,pred_y+1)
plot_confusion_matrix(matrix,labels=[1,2,3,4,5,6,7,8,9],title="Confusion Matrix on CV d
```

```
Log Loss on Cross validation data using Random Model:: 2.4574981433768444
```


```
-------------------------------------------------------
Log Loss on Test data using Random Model:: 2.505014793998099
```




### Observation:

- Now we know that our log loss for other model must not be greater than Random model log loss.

## 3.3 Univariate Analysis

In [26]:
```
from sklearn.linear_model import SGDClassifier
```

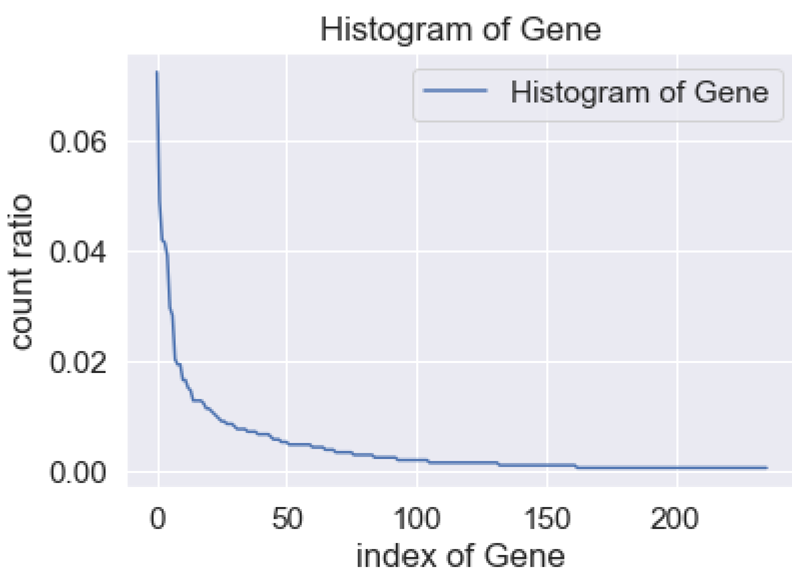
```
from sklearn.calibration import CalibratedClassifierCV
from sklearn.model_selection import GridSearchCV
```

In [27]:
```
# Let's See that How useful Gene Feature is ?
# Gene is a categorical feature so we can convert this feature into vector two way.
#     1. One hot encoding
#     2.Respose coding
```

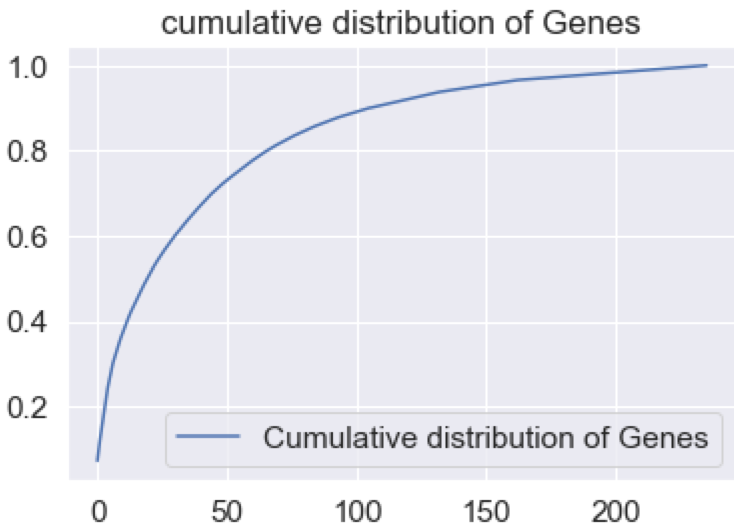
In [28]:
```
print("Number of unique Gene::",len(X_train['Gene'].unique()))
```

```
Number of unique Gene:: 236
```

In [29]:
```
unique_gene_count=X_train['Gene'].value_counts(normalize=True,sort=True)
plt.plot(unique_gene_count.values,label="Histogram of Gene")
plt.title("Histogram of Gene")
plt.xlabel("index of Gene")
plt.ylabel("count ratio")
# plt.xticks([0,50,100,150,200,250])
plt.legend()
plt.show()
```




In [30]:
```
#Plotting Cummulative Distribution of Gene
c = np.cumsum(unique_gene_count.values)
plt.plot(c,label='Cumulative distribution of Genes')
plt.title("cumulative distribution of Genes")
plt.legend()
plt.show()
```



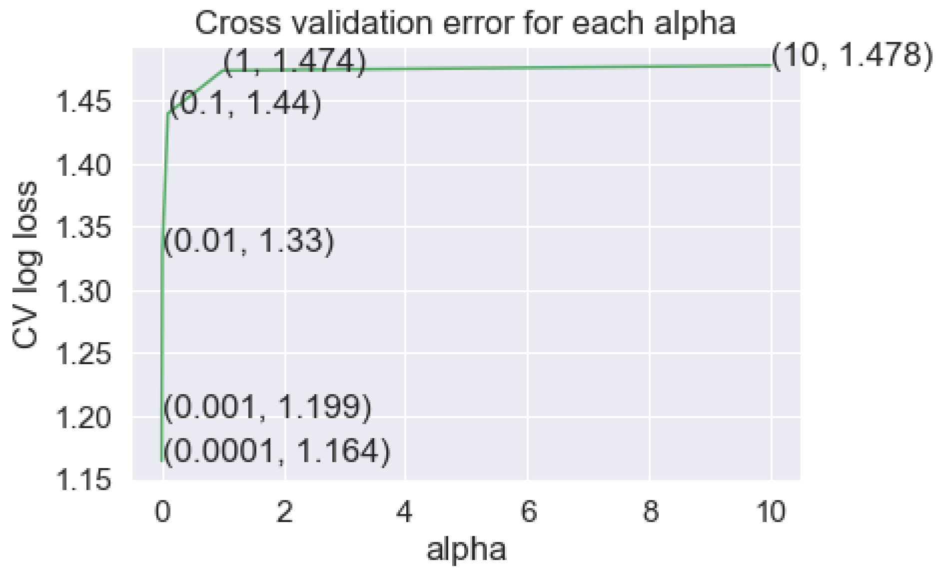

### 3.3.1 Gene Feature Analysis

In [31]:
```
# convert Gene Feature into vector using CountVectorizer
from sklearn.feature_extraction.text import CountVectorizer
vectorizer=CountVectorizer()
train_gene=vectorizer.fit_transform(X_train['Gene'])
test_gene=vectorizer.transform(X_test["Gene"])
cv_gene=vectorizer.transform(X_cv["Gene"])
```

In [32]:
```
# We will train a model with Gene feature and we will check that how valuable this feat
# for predicting class
model=SGDClassifier(penalty="l2",loss="log")
alpha=[10**i for i in range(-4,2)]
cv_error_lt=[]
for i in alpha:
    model=SGDClassifier(alpha=i,penalty="l2",loss="log",n_jobs=-1)
    model.fit(train_gene,y_train)
    clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
    clf.fit(train_gene,y_train)
    pred=clf.predict_proba(cv_gene)
    loss_val=log_loss(y_cv,pred)
    cv_error_lt.append(loss_val)
    print("For the calue of alpha {0} log loss ::{1}".format(i,loss_val))
```

```
For the calue of alpha 0.0001 log loss ::1.1644767172867667
For the calue of alpha 0.001 log loss ::1.1992505696666693
For the calue of alpha 0.01 log loss ::1.330374291242205
For the calue of alpha 0.1 log loss ::1.439568815381793
For the calue of alpha 1 log loss ::1.4737208008334826
For the calue of alpha 10 log loss ::1.4777835735517502
```

In [33]:
```
fig, ax = plt.subplots()

ax.plot(alpha,cv_error_lt,c='g')
plt.title("Cross validation error for each alpha")
for i, txt in enumerate(np.round(cv_error_lt,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],cv_error_lt[i]))
plt.xlabel("alpha")
plt.ylabel("CV log loss")

plt.show()
```




In [34]:
```
#Train with best alpha after cross validation
best_alpha=alpha[np.argmin(cv_error_lt)]
model=SGDClassifier(alpha=best_alpha,penalty="l2",loss="log",n_jobs=-1)
model.fit(train_gene,y_train)
clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
clf.fit(train_gene,y_train)
print("log loss with best alpha on Training data:",log_loss(y_train,clf.predict_proba(t
print("log loss with best alpha on Test data:",log_loss(y_test,clf.predict_proba(test_g
print("log loss with best alpha on CV data:",log_loss(y_cv,clf.predict_proba(cv_gene)))
```

```
log loss with best alpha on Training data: 0.9806488644554413
log loss with best alpha on Test data: 1.2410632302598306
log loss with best alpha on CV data: 1.1633193109441078
```

**Ques:** Is the Gene feature stable across all the data sets (Test, Train, Cross validation)

**Ans:** Yes, All datasets (Train,Test and CVs) are stable that's why CV and test error are not significantaly more than Train error

In [35]:
```
print("Ques:: How many data points of CV and Test are covered by 236 unique Genes of Tr
cv_coverage=X_cv[X_cv['Gene'].isin(list(set(X_train["Gene"])))].shape[0]
test_coverage=X_test[X_test['Gene'].isin(list(set(X_train["Gene"])))].shape[0]
print("Number of {0} out of {1} in CV data:: {2}".format(str(cv_coverage),str(X_cv.shap
print("Number of {0} out of {1} in Test data:: {2}".format(test_coverage,X_test.shape[0
```

```
Ques:: How many data points of CV and Test are covered by 236 unique Genes of Train data
sets??
Number of 523 out of 532 in CV data:: 98.30827067669173
Number of 642 out of 665 in Test data:: 96.54135338345866
```

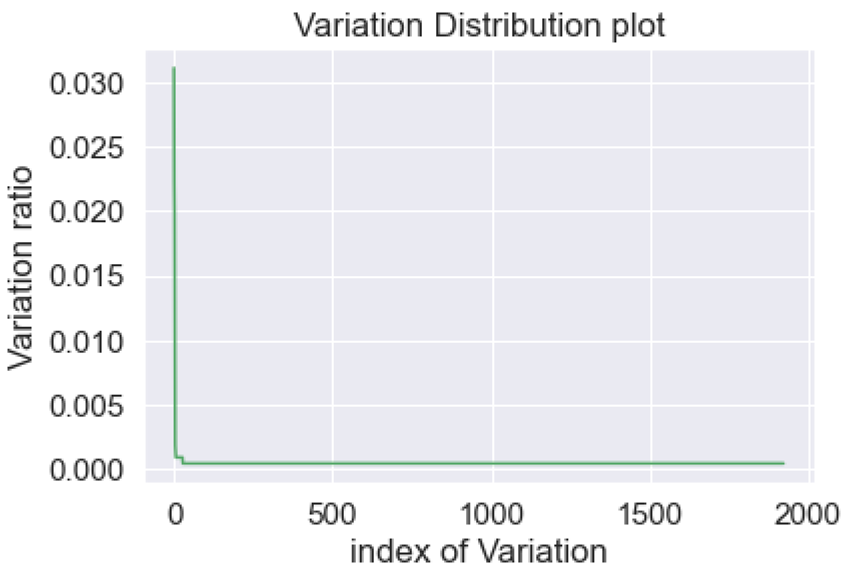
**Observation**

- Here we train our model with only Gene feature
- We observe that Loss with Gene feture is significantly less than random Model
- Hence this Gene Feture is very useful to classify the Classes.

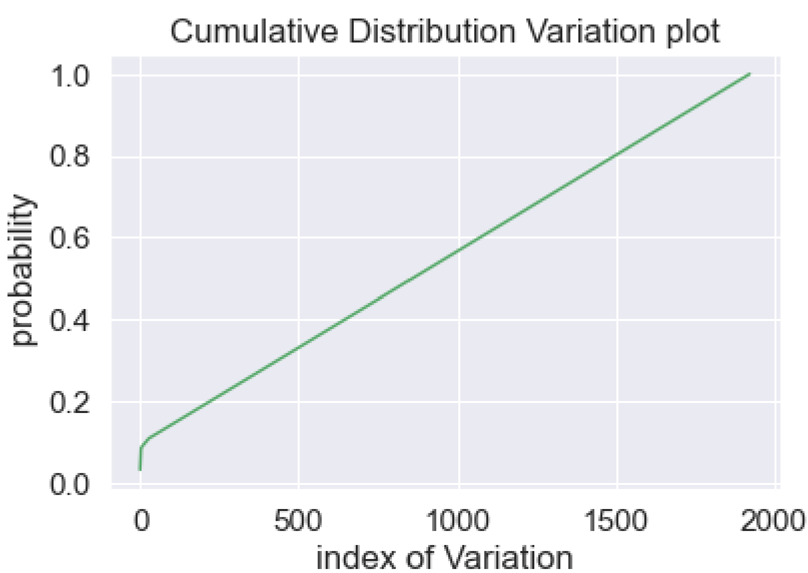
## 3.3.1 Variation Feature Analysis

In [36]:
```
unique_variation=X_train.Variation.value_counts(normalize=True,sort=True)
plt.plot(unique_variation.values,c='g')
plt.title("Variation Distribution plot")
```

```
plt.xlabel("index of Variation")
plt.ylabel("Variation ratio")
plt.show()
```




In [37]:
```
c=np.cumsum(unique_variation.values)
plt.plot(c,c='g')
plt.title("Cumulative Distribution Variation plot")
plt.xlabel("index of Variation")
plt.ylabel(" probability")
plt.show()
```




In [38]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer2=CountVectorizer()
train_var=vectorizer2.fit_transform(X_train['Variation'])
test_var=vectorizer2.transform(X_test["Variation"])
cv_var=vectorizer2.transform(X_cv["Variation"])
```

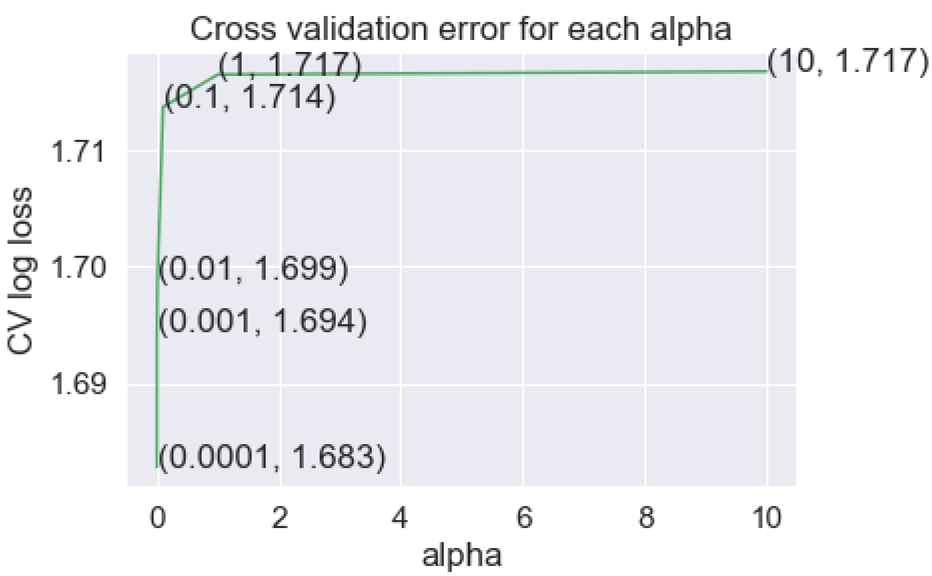
In [39]:
```
# We will train a model with Variation feature and we will check that how valuable this
# for predicting class
model=SGDClassifier(penalty="l2",loss="log")
alpha=[10**i for i in range(-4,2)]
cv_error_lt=[]
```

```
for i in alpha:
    model=SGDClassifier(alpha=i,penalty="l2",loss="log",n_jobs=-1)
    model.fit(train_var,y_train)
    clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
    clf.fit(train_var,y_train)
    pred=clf.predict_proba(cv_var)
    loss_val=log_loss(y_cv,pred)
    cv_error_lt.append(loss_val)
    print("For the calue of alpha {0} log loss ::{1}".format(i,loss_val))
```

```
For the calue of alpha 0.0001 log loss ::1.682792066580981
For the calue of alpha 0.001 log loss ::1.6943974749000452
For the calue of alpha 0.01 log loss ::1.699011401695639
For the calue of alpha 0.1 log loss ::1.7137569342913428
For the calue of alpha 1 log loss ::1.716554744400735
For the calue of alpha 10 log loss ::1.716820212131253
```

In [40]:

```
fig, ax = plt.subplots()

ax.plot(alpha,cv_error_lt,c='g')
plt.title("Cross validation error for each alpha")
for i, txt in enumerate(np.round(cv_error_lt,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],cv_error_lt[i]))
plt.xlabel("alpha")
plt.ylabel("CV log loss")

plt.show()
```




In [41]:

```
#Train with best alpha after cross validation
best_alpha=alpha[np.argmin(cv_error_lt)]
model=SGDClassifier(alpha=best_alpha,penalty="l2",loss="log",n_jobs=-1)
model.fit(train_var,y_train)
clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
clf.fit(train_var,y_train)
print("log loss with best alpha on Training data:",log_loss(y_train,clf.predict_proba(t
print("log loss with best alpha on Test data:",log_loss(y_test,clf.predict_proba(test_v
print("log loss with best alpha on CV data:",log_loss(y_cv,clf.predict_proba(cv_var)))
```

```
log loss with best alpha on Training data: 0.7394873310745763
log loss with best alpha on Test data: 1.7115699178990391
log loss with best alpha on CV data: 1.681227636005181
```

In [42]:
```
print("Ques:: How many data points of CV and Test are covered by 236 unique Genes of Tr
cv_coverage=X_cv[X_cv['Variation'].isin(list(set(X_train["Variation"])))].shape[0]
test_coverage=X_test[X_test['Variation'].isin(list(set(X_train["Variation"])))].shape[0
print("Number of {0} out of {1} in CV data:: {2}".format(str(cv_coverage),str(X_cv.shap
print("Number of {0} out of {1} in Test data:: {2}".format(test_coverage,X_test.shape[0
```

```
Ques:: How many data points of CV and Test are covered by 236 unique Genes of Train data
sets??
Number of 53 out of 532 in CV data:: 9.962406015037594
Number of 67 out of 665 in Test data:: 10.075187969924812
```

In [ ]:

### 3.3.3 Univariate Analysis on Text Feature

- How many unique words are present in train data?
- How are word frequencies distributed?
- How to featurize text field?
- Is the text feature useful in predicitng y_i?
- Is the text feature stable across train, test and CV datasets?

In [43]:
```
# How many unique words are present in train data?
def get_unique_words(data):
    unique_words=set()
    for text in data:
        unique_words.update(text.split())
    return unique_words
train_text_unique_words=get_unique_words(X_train['TEXT'])
print("unique words in train data:: {0}".format(len(train_text_unique_words)))
```

```
unique words in train data:: 117072
```

In [44]:
```
# How are word frequencies distributed?
# or Is the text feature stable across train, test and CV datasets?
cv_text_unique_words=get_unique_words(X_cv["TEXT"])
cv_text_coverage=len(cv_text_unique_words & train_text_unique_words)
test_text_unique_words=get_unique_words(X_test.TEXT)
test_text_coverage=len(np.intersect1d(list(test_text_unique_words),list(train_text_uniq
print("In CV data,{0} out of {1} :: {2}%".format(cv_text_coverage,len(cv_text_unique_wo

print("In test data,{0} out of {1} :: {2}%".format(test_text_coverage,len(test_text_uni
```

```
In CV data,49387 out of 60261 :: 81.95516171321418%
In test data,57521 out of 72325 :: 79.53128240580712%
```

**How to featurize text field?**

- We can featurize this text data following way:
    - Bag of words
    - TFIDF
    - W2V
    - TFIDF-W2V
    - Response Coding

In [45]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
bow=CountVectorizer(min_df=5)
train_text=bow.fit_transform(X_train["TEXT"])
```

```
test_text=bow.transform(X_test['TEXT'])
cv_text=bow.transform(X_cv.TEXT)
```

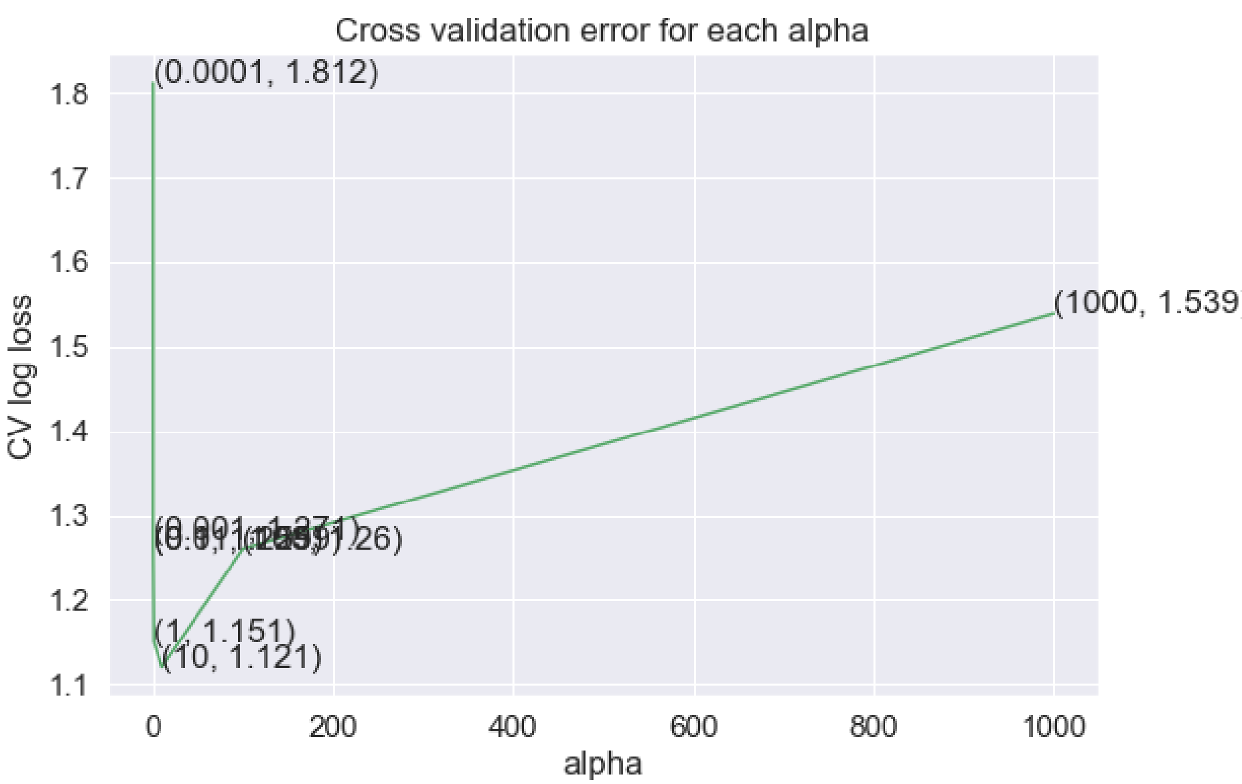
In [46]:

```
alpha=[10**i for i in range(-4,4)]
cv_error_lt=[]
for i in alpha:
    model=SGDClassifier(alpha=i,penalty="l2",loss="log",n_jobs=-1)
    model.fit(train_text,y_train)
    clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
    clf.fit(train_text,y_train)
    pred=clf.predict_proba(cv_text)
    loss_val=log_loss(y_cv,pred)
    cv_error_lt.append(loss_val)
    print("For the calue of alpha {0} log loss ::{1}".format(i,loss_val))
```

```
For the calue of alpha 0.0001 log loss ::1.811913517465497
For the calue of alpha 0.001 log loss ::1.2708476393213184
For the calue of alpha 0.01 log loss ::1.259488073007061
For the calue of alpha 0.1 log loss ::1.2592537460927968
For the calue of alpha 1 log loss ::1.1505620832559467
For the calue of alpha 10 log loss ::1.120598754741693
For the calue of alpha 100 log loss ::1.2604169056211851
For the calue of alpha 1000 log loss ::1.5385463870910967
```

In [47]:

```
fig, ax = plt.subplots(figsize=(9,6))

ax.plot(alpha,cv_error_lt,c='g')
plt.title("Cross validation error for each alpha")
for i, txt in enumerate(np.round(cv_error_lt,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],cv_error_lt[i]))
plt.xlabel("alpha")
plt.ylabel("CV log loss")

plt.show()
```



In [48]:
```
#Train with best alpha after cross validation
best_alpha=alpha[np.argmin(cv_error_lt)]
model=SGDClassifier(alpha=best_alpha,penalty="l2",loss="log",n_jobs=-1)
model.fit(train_text,y_train)
clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
clf.fit(train_text,y_train)
print("log loss with best alpha on Training data:",log_loss(y_train,clf.predict_proba(t
print("log loss with best alpha on Test data:",log_loss(y_test,clf.predict_proba(test_t
print("log loss with best alpha on CV data:",log_loss(y_cv,clf.predict_proba(cv_text)))
```

```
log loss with best alpha on Training data: 0.8687973204148157
log loss with best alpha on Test data: 1.2655685102146783
log loss with best alpha on CV data: 1.1241182671962198
```

### Ques: Is the text feature useful in predicitng y_i?

**Ans:** Yes,It seems like useful.

# 4. Machine Learning Models

In [49]:
```
tfidf=TfidfVectorizer(min_df=5)
train_text_tf=tfidf.fit_transform(X_train["TEXT"])
test_text_tf=tfidf.transform(X_test['TEXT'])
cv_text_tf=tfidf.transform(X_cv.TEXT)
```

In [50]:
```
from scipy.sparse import hstack
```

In [51]:
```
# Concating Feature Gene Vectors,Variation Vector and BOW of text Feature
############### Created Datasets with BOW ################
train_bow_df=hstack((train_gene,train_var,train_text))
test_bow_df=hstack((test_gene,test_var,test_text))
cv_bow_df=hstack((cv_gene,cv_var,cv_text))

############# Created Datasets with TFIDF ###############
train_df_tfidf=hstack((train_gene,train_var,train_text_tf))
test_df_tfidf=hstack((test_gene,test_var,test_text_tf))
cv_df_tfidf=hstack((cv_gene,cv_var,cv_text_tf))
```

## 4.1 Base Model with Naive Bayes

In [52]:
```
from sklearn.naive_bayes import MultinomialNB
from xgboost import XGBClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier,StackingClassifier
```

### 4.1.1 Multi Nomial Naive bayes with BOW

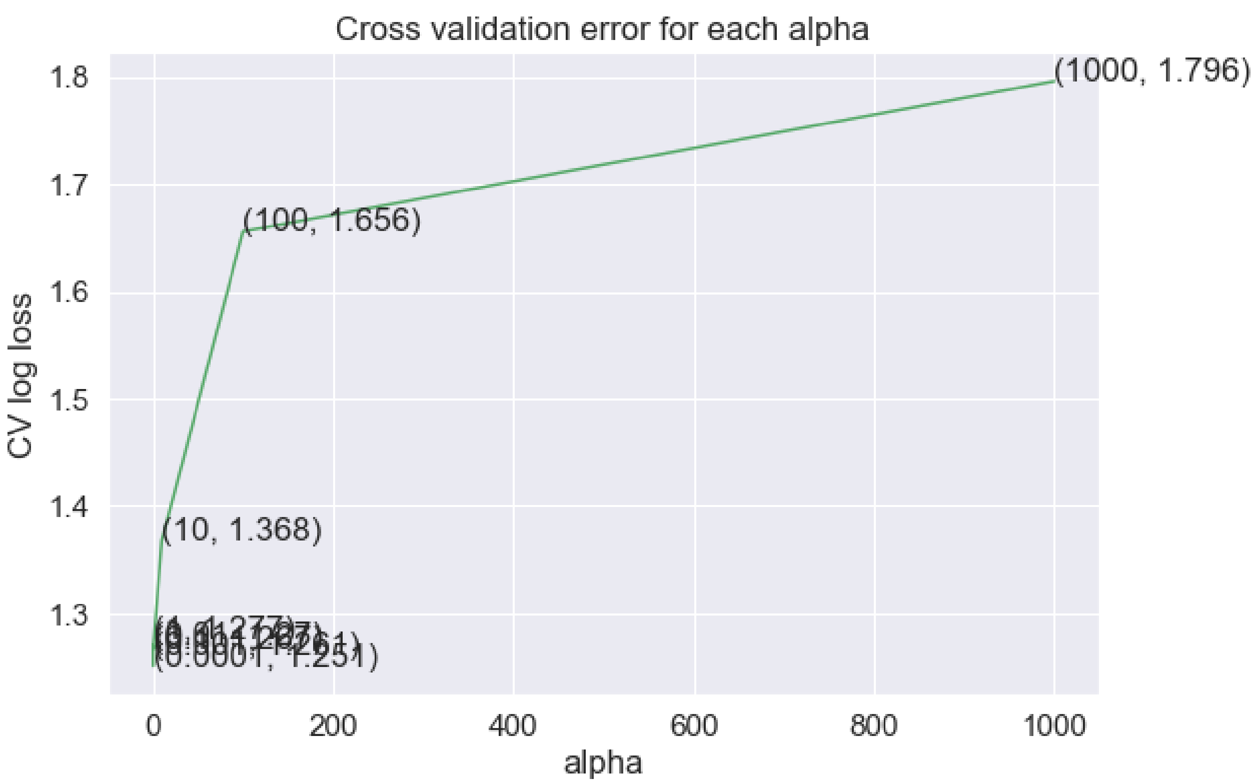
In [53]:
```
## MultiNomailNB with BOW
alpha=[10**i for i in range(-4,4)]
cv_error_lt=[]
for i in alpha:
    model=MultinomialNB(alpha=i)
    model.fit(train_bow_df,y_train)
    clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
    clf.fit(train_bow_df,y_train)
    pred=clf.predict_proba(cv_bow_df)
    loss_val=log_loss(y_cv,pred)
```

```
    cv_error_lt.append(loss_val)
    print("For the calue of alpha {0} log loss ::{1}".format(i,loss_val))
```

```
For the calue of alpha 0.0001 log loss ::1.25122306728042
For the calue of alpha 0.001 log loss ::1.26072944861013
For the calue of alpha 0.01 log loss ::1.2699572943672874
For the calue of alpha 0.1 log loss ::1.2669874331788413
For the calue of alpha 1 log loss ::1.276947587493194
For the calue of alpha 10 log loss ::1.367869821462335
For the calue of alpha 100 log loss ::1.6558116779164127
For the calue of alpha 1000 log loss ::1.795707909391549
```

In [54]:

```
fig, ax = plt.subplots(figsize = (9, 6))
ax.plot(alpha,cv_error_lt,c='g')
plt.title("Cross validation error for each alpha")
for i, txt in enumerate(np.round(cv_error_lt,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],cv_error_lt[i]))
plt.xlabel("alpha")
plt.ylabel("CV log loss")

plt.show()
```

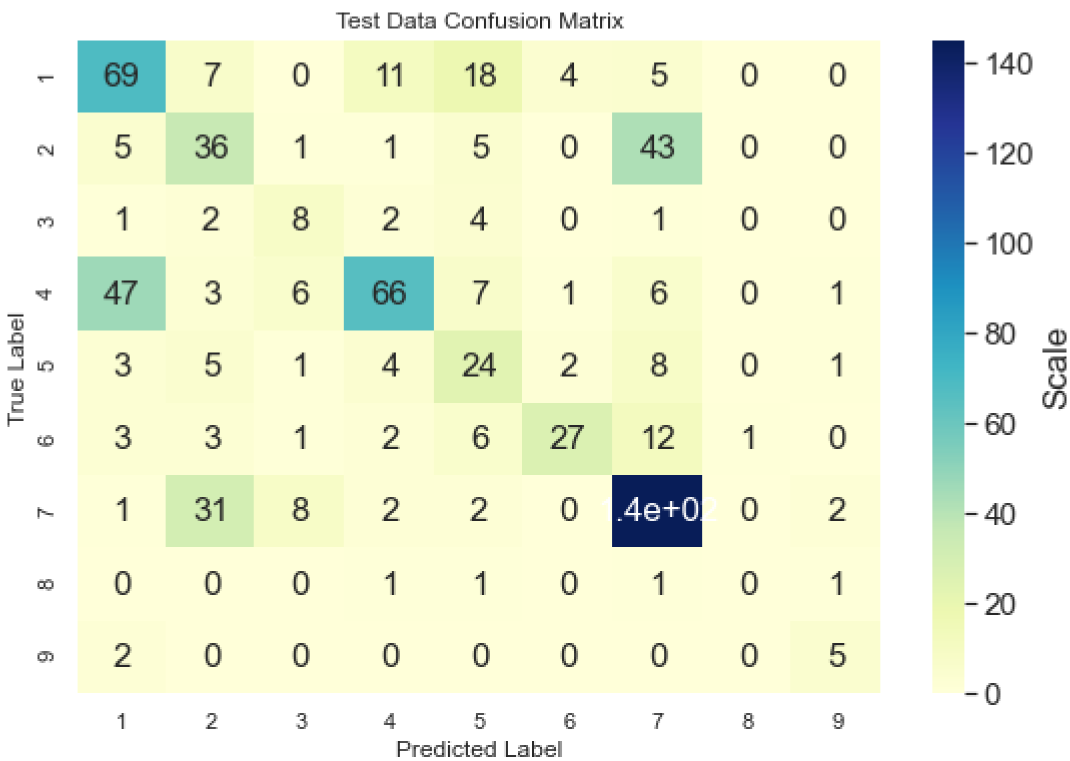



In [55]:

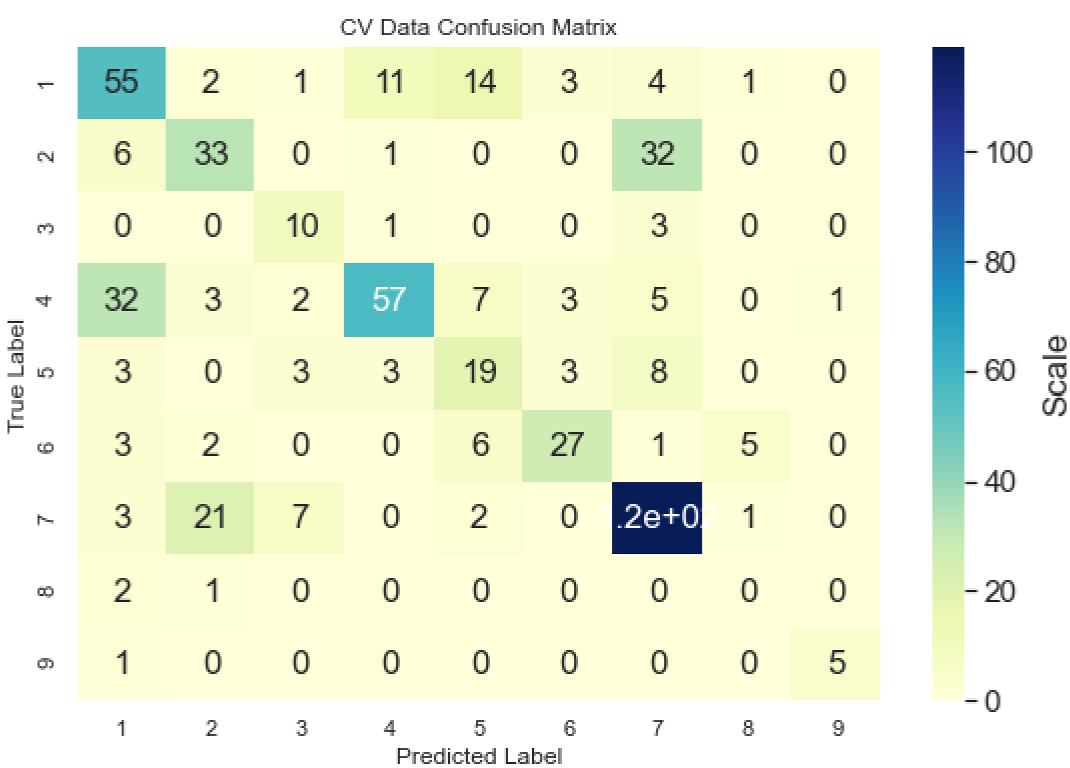
```
#Train with best alpha after cross validation
best_alpha=alpha[np.argmin(cv_error_lt)]
model=MultinomialNB(alpha=best_alpha)
model.fit(train_bow_df,y_train)
clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
clf.fit(train_bow_df,y_train)
print("log loss with best alpha on Training data:",log_loss(y_train,clf.predict_proba(t
print("log loss with best alpha on Test data:",log_loss(y_test,clf.predict_proba(test_b
print("log loss with best alpha on CV data:",log_loss(y_cv,clf.predict_proba(cv_bow_df)
```

```
log loss with best alpha on Training data: 0.9621995694726143
log loss with best alpha on Test data: 1.3734535234609273
log loss with best alpha on CV data: 1.25122306728042
```

In [56]:
```
pred=clf.predict(test_bow_df)
matrix=confusion_matrix(y_test,pred)
plot_confusion_matrix(matrix,labels=[1,2,3,4,5,6,7,8,9],title="Test Data Confusion Matr
```




In [57]:
```
pred=clf.predict(cv_bow_df)
matrix=confusion_matrix(y_cv,pred)
plot_confusion_matrix(matrix,labels=[1,2,3,4,5,6,7,8,9],title="CV Data Confusion Matrix
```

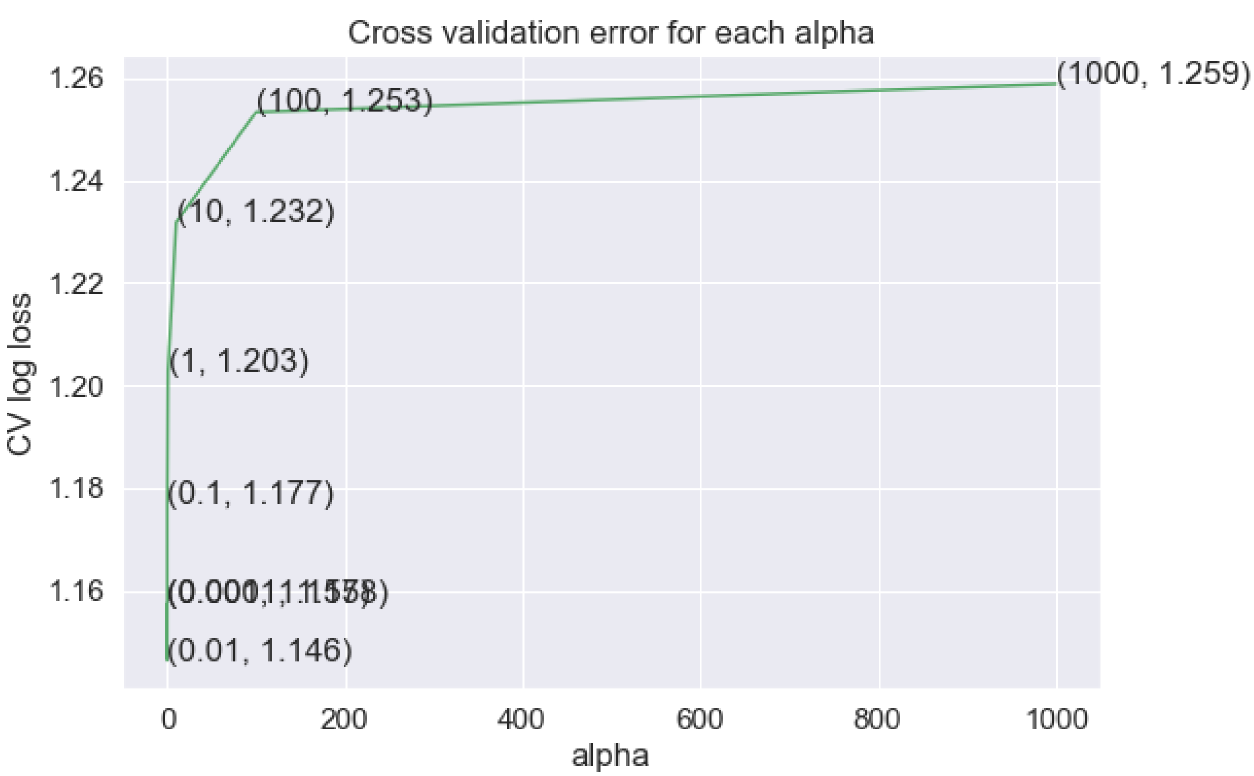



## 4.1.2 MultiNomailNB with TFIDF

In [58]:
```
## MultiNomailNB with TFIDF
alpha=[10**i for i in range(-4,4)]
cv_error_lt=[]
for i in alpha:
    model=MultinomialNB(alpha=i)
    model.fit(train_df_tfidf,y_train)
    clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
    clf.fit(train_df_tfidf,y_train)
    pred=clf.predict_proba(cv_df_tfidf)
    loss_val=log_loss(y_cv,pred)
    cv_error_lt.append(loss_val)
    print("For the calue of alpha {0} log loss ::{1}".format(i,loss_val))
```

```
For the calue of alpha 0.0001 log loss ::1.157509561832669
For the calue of alpha 0.001 log loss ::1.1574628344616684
For the calue of alpha 0.01 log loss ::1.1464000451301044
For the calue of alpha 0.1 log loss ::1.1769781228619376
For the calue of alpha 1 log loss ::1.2029265897768597
For the calue of alpha 10 log loss ::1.2318058986646945
For the calue of alpha 100 log loss ::1.2533809365787343
For the calue of alpha 1000 log loss ::1.2588090573918358
```

In [59]:
```
fig, ax = plt.subplots(figsize = (9, 6))
ax.plot(alpha,cv_error_lt,c='g')
plt.title("Cross validation error for each alpha")
for i, txt in enumerate(np.round(cv_error_lt,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],cv_error_lt[i]))
plt.xlabel("alpha")
plt.ylabel("CV log loss")

plt.show()
```



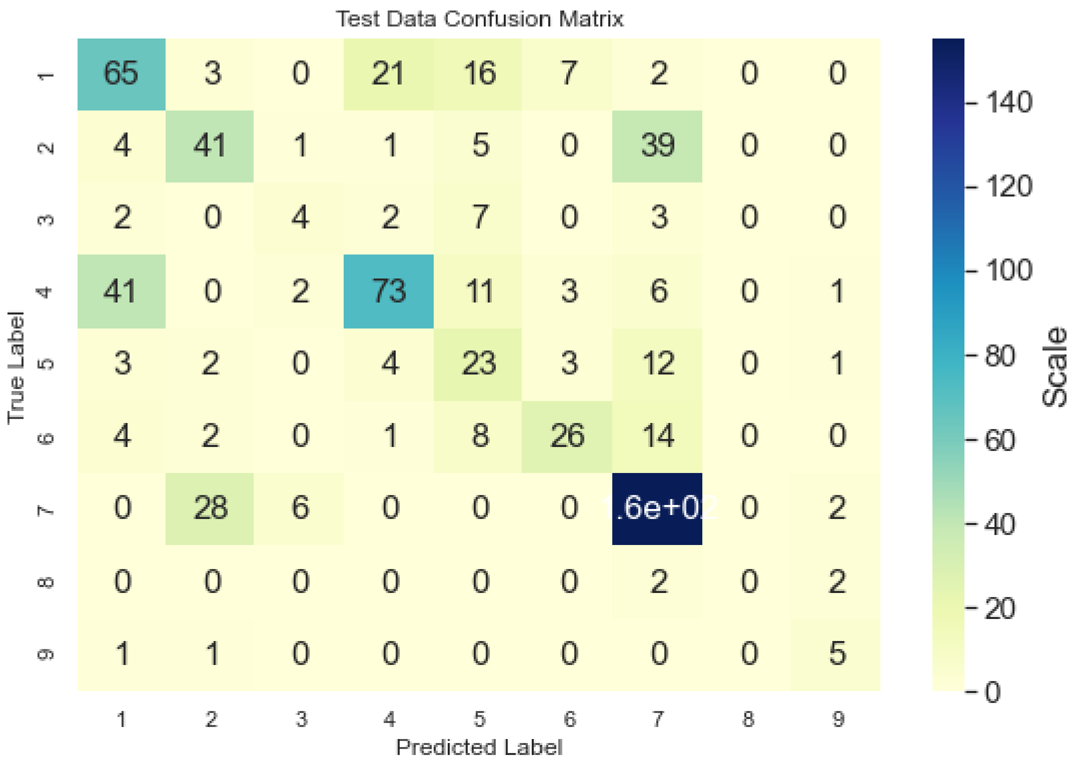

In [60]:
```
#Train with best alpha after cross validation
best_alpha=alpha[np.argmin(cv_error_lt)]
model=MultinomialNB(alpha=best_alpha)
```

```
model.fit(train_df_tfidf,y_train)
clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
clf.fit(train_df_tfidf,y_train)
print("log loss with best alpha on Training data:",log_loss(y_train,clf.predict_proba(t
print("log loss with best alpha on Test data:",log_loss(y_test,clf.predict_proba(test_d
print("log loss with best alpha on CV data:",log_loss(y_cv,clf.predict_proba(cv_df_tfid
```

```
log loss with best alpha on Training data: 0.617024879981238
log loss with best alpha on Test data: 1.2667904480846968
log loss with best alpha on CV data: 1.1464000451301044
```

In [61]:

```
pred=clf.predict(test_df_tfidf)
matrix=confusion_matrix(y_test,pred)
plot_confusion_matrix(matrix,labels=[1,2,3,4,5,6,7,8,9],title="Test Data Confusion Matr
```




# 4.2 Logistic Regression

## 4.2.1 Logistic Regression with balancing (BOW)

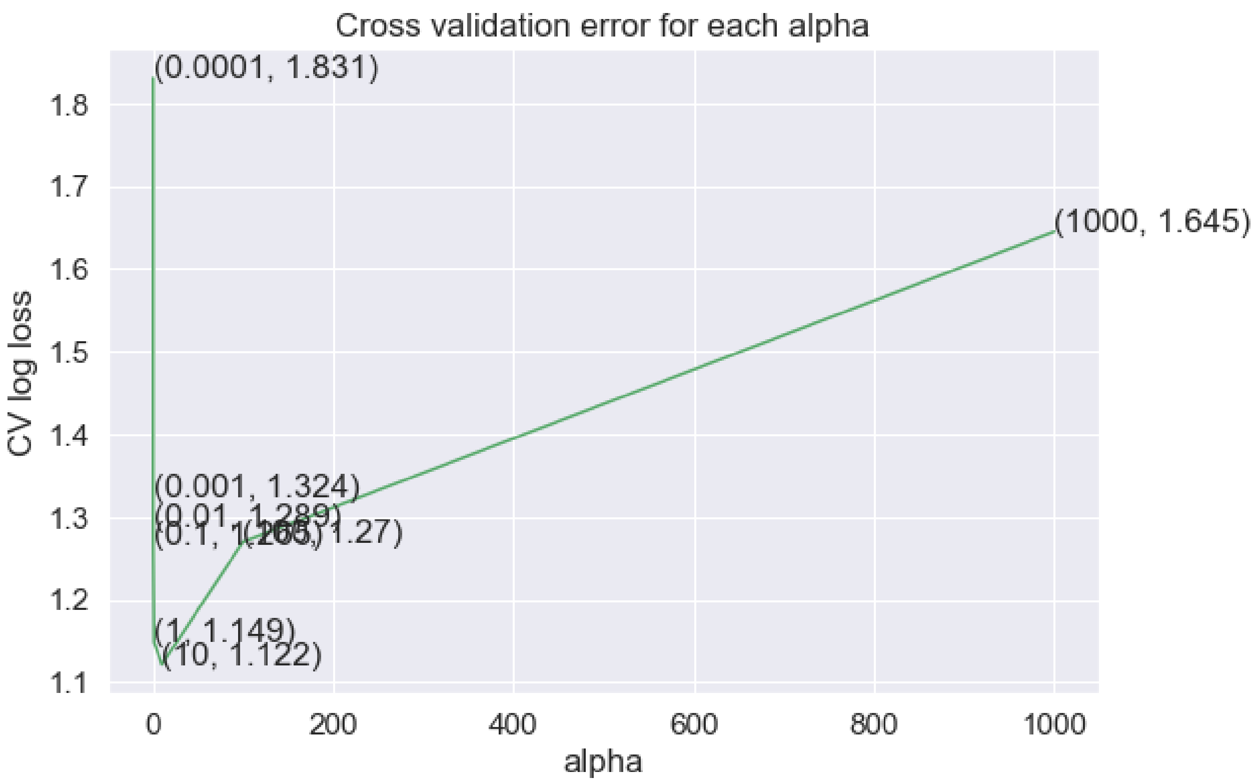
In [62]:

```
## SGDClassifier with BOW
alpha=[10**i for i in range(-4,4)]
cv_error_lt=[]
for i in alpha:
    model=SGDClassifier(alpha=i,class_weight="balanced",penalty="l2",loss="log",n_jobs=
    model.fit(train_bow_df,y_train)
    clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
    clf.fit(train_bow_df,y_train)
    pred=clf.predict_proba(cv_bow_df)
    loss_val=log_loss(y_cv,pred)
    cv_error_lt.append(loss_val)
    print("For the calue of alpha {0} log loss ::{1}".format(i,loss_val))
```

```
For the calue of alpha 0.0001 log loss ::1.8308895156109954
For the calue of alpha 0.001 log loss ::1.3239746657346012
For the calue of alpha 0.01 log loss ::1.2885768501389008
```

```
For the calue of alpha 0.1 log loss ::1.2654770146098346
For the calue of alpha 1 log loss ::1.148653462917311
For the calue of alpha 10 log loss ::1.1215705827035258
For the calue of alpha 100 log loss ::1.2698867104835383
For the calue of alpha 1000 log loss ::1.6447705452770334
```

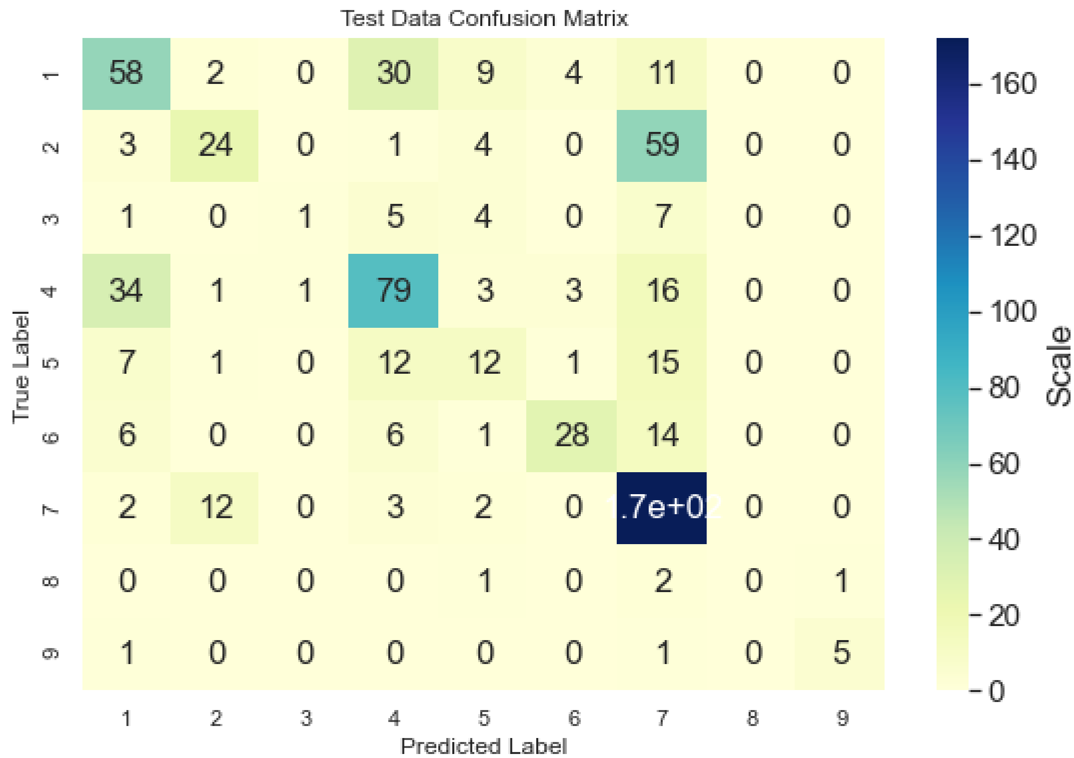
In [63]:
```python
fig, ax = plt.subplots(figsize = (9, 6))
ax.plot(alpha,cv_error_lt,c='g')
plt.title("Cross validation error for each alpha")
for i, txt in enumerate(np.round(cv_error_lt,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],cv_error_lt[i]))
plt.xlabel("alpha")
plt.ylabel("CV log loss")

plt.show()
```




In [64]:
```python
#Train with best alpha after cross validation
best_alpha=alpha[np.argmin(cv_error_lt)]
model=SGDClassifier(alpha=best_alpha,class_weight="balanced",penalty="l2",loss="log",n_
model.fit(train_bow_df,y_train)
clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
clf.fit(train_bow_df,y_train)
print("log loss with best alpha on Training data:",log_loss(y_train,clf.predict_proba(t
print("log loss with best alpha on Test data:",log_loss(y_test,clf.predict_proba(test_b
print("log loss with best alpha on CV data:",log_loss(y_cv,clf.predict_proba(cv_bow_df)
```

```
log loss with best alpha on Training data: 0.8705518524169856
log loss with best alpha on Test data: 1.2683110164605904
log loss with best alpha on CV data: 1.1125304886110914
```

In [65]:
```python
pred=clf.predict(test_bow_df)
matrix=confusion_matrix(y_test,pred)
plot_confusion_matrix(matrix,labels=[1,2,3,4,5,6,7,8,9],title="Test Data Confusion Matr
```

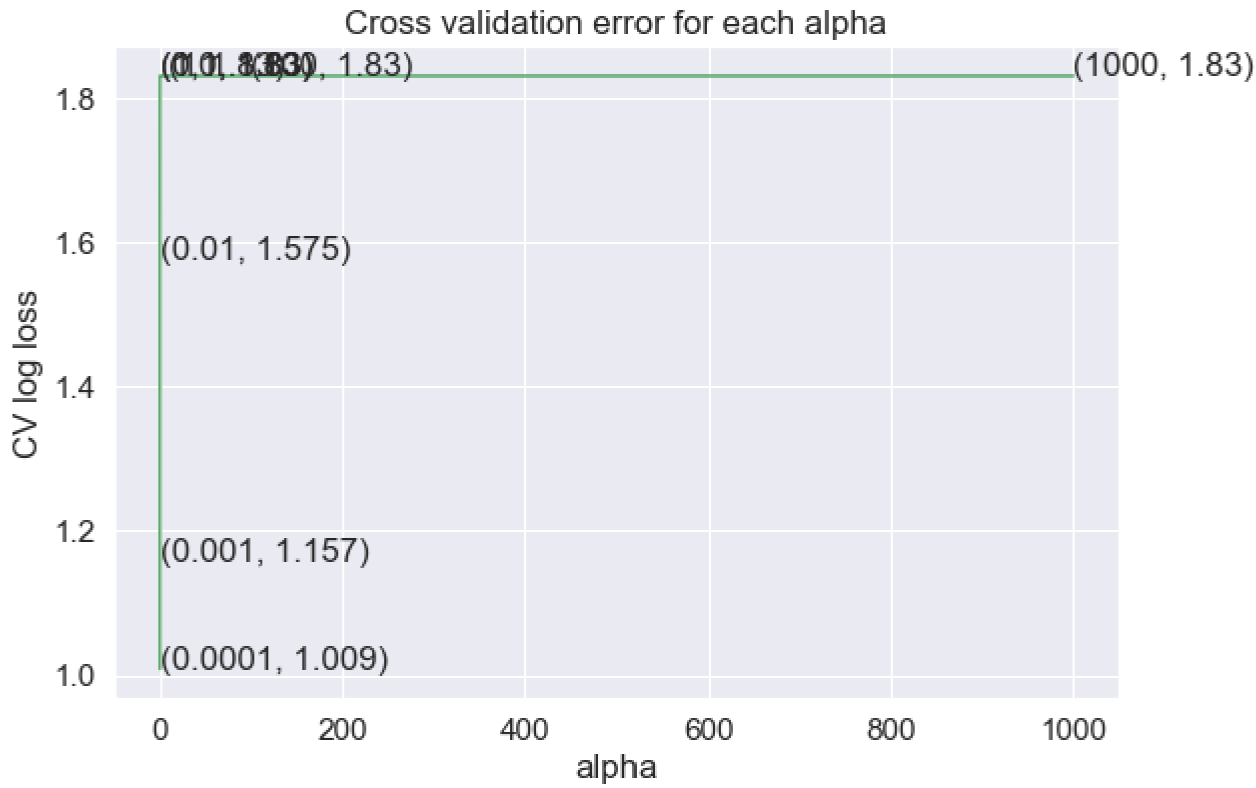



## 4.2.1 Logistic Regression with balancing (TFIDF)

In [66]:
```
## SGDClassifier with TFIDF
alpha=[10**i for i in range(-4,4)]
cv_error_lt=[]
for i in alpha:
    model=SGDClassifier(alpha=i,class_weight="balanced",penalty="l1",loss="log",n_jobs=
    model.fit(train_df_tfidf,y_train)
    clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
    clf.fit(train_df_tfidf,y_train)
    pred=clf.predict_proba(cv_df_tfidf)
    loss_val=log_loss(y_cv,pred)
    cv_error_lt.append(loss_val)
    print("For the calue of alpha {0} log loss ::{1}".format(i,loss_val))
```

```
For the calue of alpha 0.0001 log loss ::1.0086640195395389
For the calue of alpha 0.001 log loss ::1.1571240351008227
For the calue of alpha 0.01 log loss ::1.5752317669345255
For the calue of alpha 0.1 log loss ::1.8303536160966096
For the calue of alpha 1 log loss ::1.830353615966804
For the calue of alpha 10 log loss ::1.830353615964826
For the calue of alpha 100 log loss ::1.8303536159647842
For the calue of alpha 1000 log loss ::1.8303536159647815
```

In [67]:
```
fig, ax = plt.subplots(figsize = (9, 6))
ax.plot(alpha,cv_error_lt,c='g')
plt.title("Cross validation error for each alpha")
for i, txt in enumerate(np.round(cv_error_lt,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],cv_error_lt[i]))
plt.xlabel("alpha")
plt.ylabel("CV log loss")

plt.show()
```



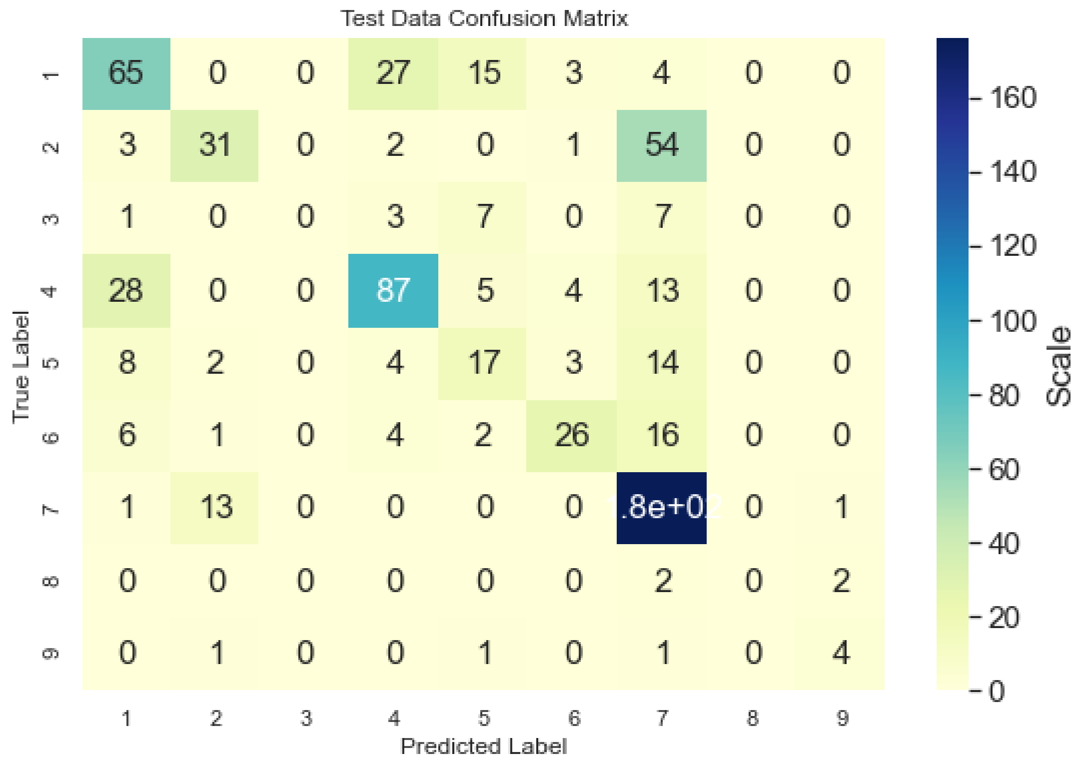

In [68]:

```
#Train with best alpha after cross validation
best_alpha=alpha[np.argmin(cv_error_lt)]
model=SGDClassifier(alpha=best_alpha,class_weight="balanced",penalty="l1",loss="log",n_
model.fit(train_df_tfidf,y_train)
clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
clf.fit(train_df_tfidf,y_train)
print("log loss with best alpha on Training data:",log_loss(y_train,clf.predict_proba(t
print("log loss with best alpha on Test data:",log_loss(y_test,clf.predict_proba(test_d
print("log loss with best alpha on CV data:",log_loss(y_cv,clf.predict_proba(cv_df_tfid
```

```
log loss with best alpha on Training data: 0.4977533363193307
log loss with best alpha on Test data: 1.138695193228391
log loss with best alpha on CV data: 1.008984836312022
```

In [69]:

```
pred=clf.predict(test_df_tfidf)
matrix=confusion_matrix(y_test,pred)
plot_confusion_matrix(matrix,labels=[1,2,3,4,5,6,7,8,9],title="Test Data Confusion Matr
```




## 4.3 Support Vector Machine

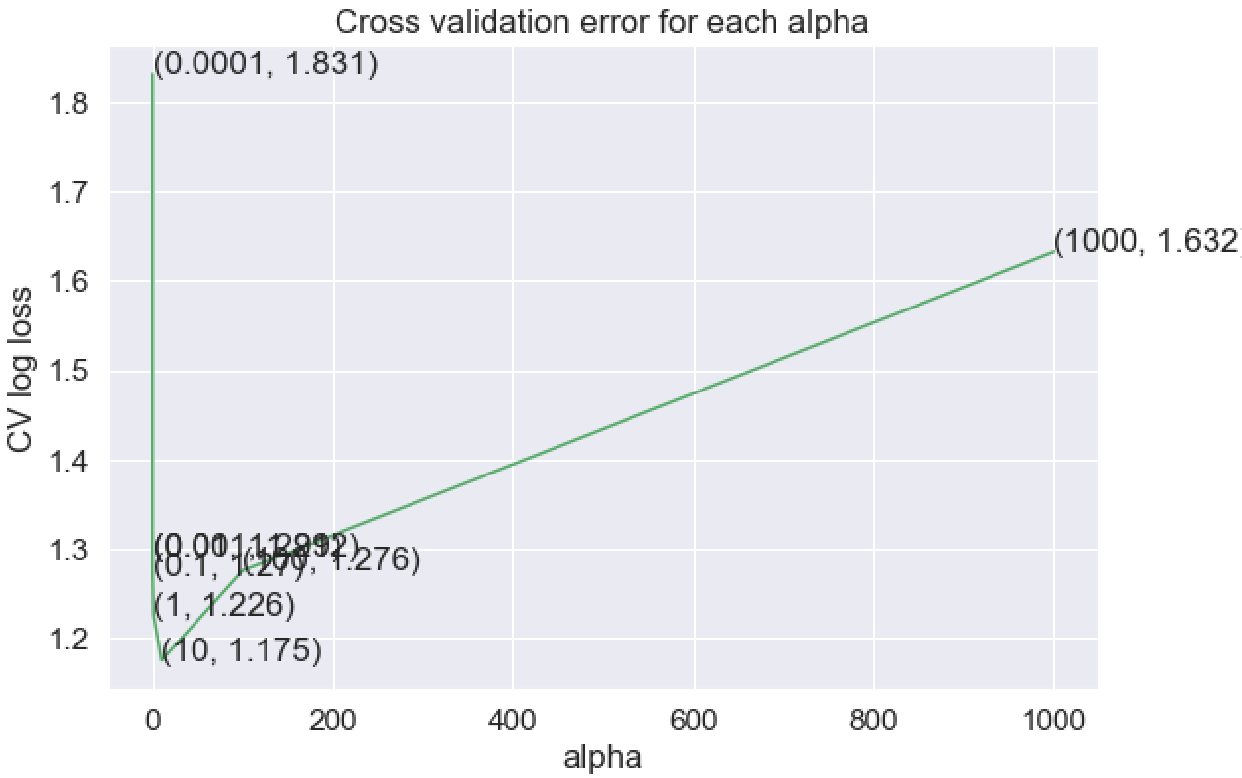
### 4.3.1 Support Vector Machine with balanced(BOW)

In [70]:
```
## SGDClassifier with BOW
alpha=[10**i for i in range(-4,4)]
cv_error_lt=[]
for i in alpha:
    model=SGDClassifier(alpha=i,class_weight="balanced",penalty="l2",loss="hinge",n_job
    model.fit(train_bow_df,y_train)
    clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
    clf.fit(train_bow_df,y_train)
    pred=clf.predict_proba(cv_bow_df)
    loss_val=log_loss(y_cv,pred)
    cv_error_lt.append(loss_val)
    print("For the calue of alpha {0} log loss ::{1}".format(i,loss_val))
```

```
For the calue of alpha 0.0001 log loss ::1.8308895156109954
For the calue of alpha 0.001 log loss ::1.2918445209996223
For the calue of alpha 0.01 log loss ::1.2909905810269657
For the calue of alpha 0.1 log loss ::1.2703936905733353
For the calue of alpha 1 log loss ::1.2260821546046268
For the calue of alpha 10 log loss ::1.1753710622865579
For the calue of alpha 100 log loss ::1.2756177402587823
For the calue of alpha 1000 log loss ::1.6320886081413049
```

In [71]:
```
fig, ax = plt.subplots(figsize = (9, 6))
ax.plot(alpha,cv_error_lt,c='g')
plt.title("Cross validation error for each alpha")
for i, txt in enumerate(np.round(cv_error_lt,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],cv_error_lt[i]))
plt.xlabel("alpha")
plt.ylabel("CV log loss")
```

```
plt.show()
```



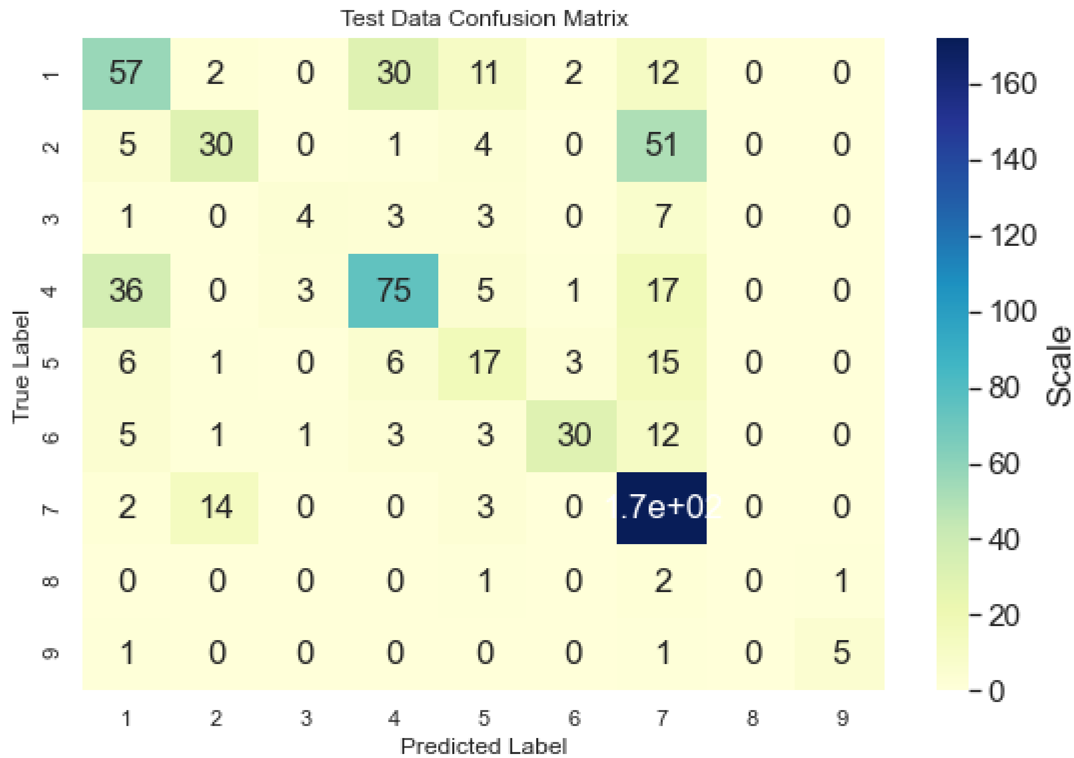

In [72]:

```
#Train with best alpha after cross validation
best_alpha=alpha[np.argmin(cv_error_lt)]
model=SGDClassifier(alpha=best_alpha,class_weight="balanced",penalty="l2",loss="hinge",
model.fit(train_bow_df,y_train)
clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
clf.fit(train_bow_df,y_train)
print("log loss with best alpha on Training data:",log_loss(y_train,clf.predict_proba(t
print("log loss with best alpha on Test data:",log_loss(y_test,clf.predict_proba(test_b
print("log loss with best alpha on CV data:",log_loss(y_cv,clf.predict_proba(cv_bow_df)
```

```
log loss with best alpha on Training data: 0.8666208356329617
log loss with best alpha on Test data: 1.304183233352549
log loss with best alpha on CV data: 1.16799820223793
```

In [73]:

```
pred=clf.predict(test_bow_df)
matrix=confusion_matrix(y_test,pred)
plot_confusion_matrix(matrix,labels=[1,2,3,4,5,6,7,8,9],title="Test Data Confusion Matr
```

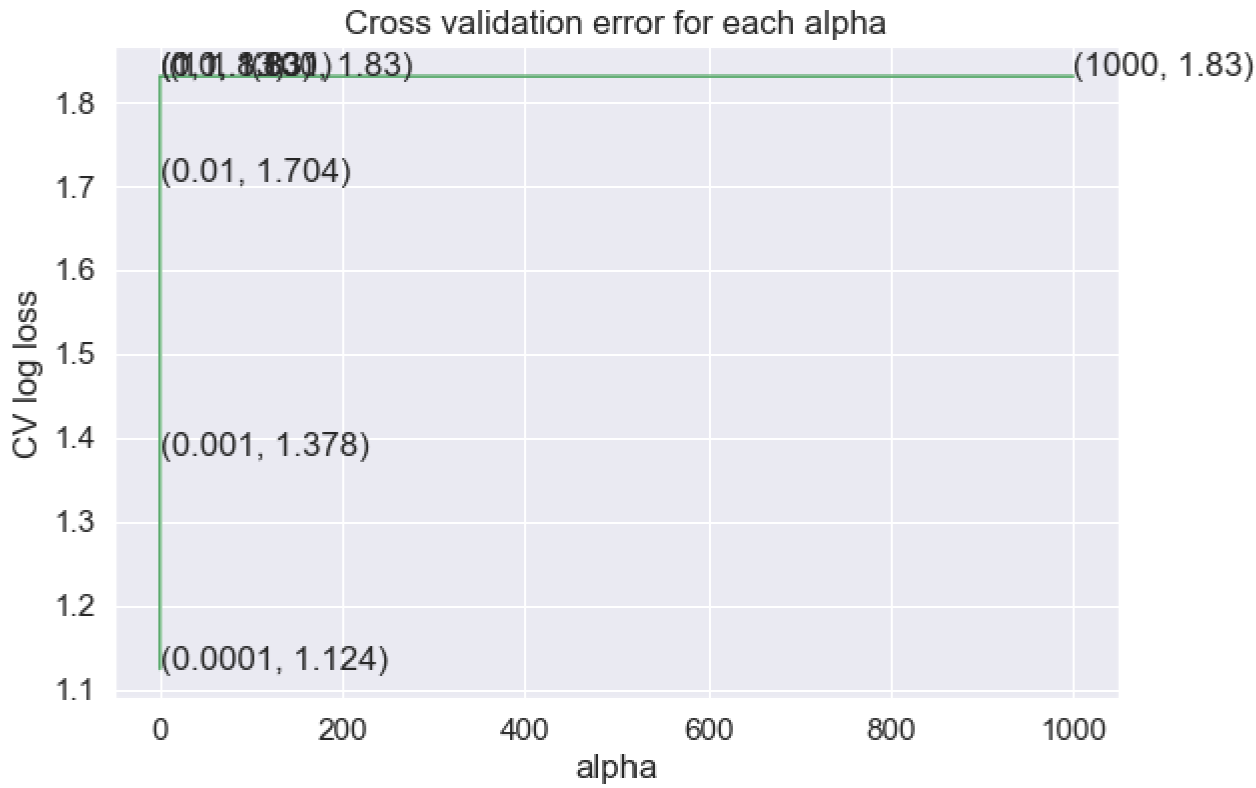



## 4.3.2 Support Vector Machine with balanced(TFIDF)

In [74]:
```
## SGDClassifier with TFIDF
alpha=[10**i for i in range(-4,4)]
cv_error_lt=[]
for i in alpha:
    model=SGDClassifier(alpha=i,class_weight="balanced",penalty="l1",loss="hinge",n_job
    model.fit(train_df_tfidf,y_train)
    clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
    clf.fit(train_df_tfidf,y_train)
    pred=clf.predict_proba(cv_df_tfidf)
    loss_val=log_loss(y_cv,pred)
    cv_error_lt.append(loss_val)
    print("For the calue of alpha {0} log loss ::{1}".format(i,loss_val))
```

```
For the calue of alpha 0.0001 log loss ::1.1244874698224663
For the calue of alpha 0.001 log loss ::1.377710048303911
For the calue of alpha 0.01 log loss ::1.7043738072292607
For the calue of alpha 0.1 log loss ::1.8307708099537774
For the calue of alpha 1 log loss ::1.830353615973257
For the calue of alpha 10 log loss ::1.8303536159651947
For the calue of alpha 100 log loss ::1.8303536159647957
For the calue of alpha 1000 log loss ::1.830353615964784
```

In [75]:
```
fig, ax = plt.subplots(figsize = (9, 6))
ax.plot(alpha,cv_error_lt,c='g')
plt.title("Cross validation error for each alpha")
for i, txt in enumerate(np.round(cv_error_lt,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],cv_error_lt[i]))
plt.xlabel("alpha")
plt.ylabel("CV log loss")

plt.show()
```



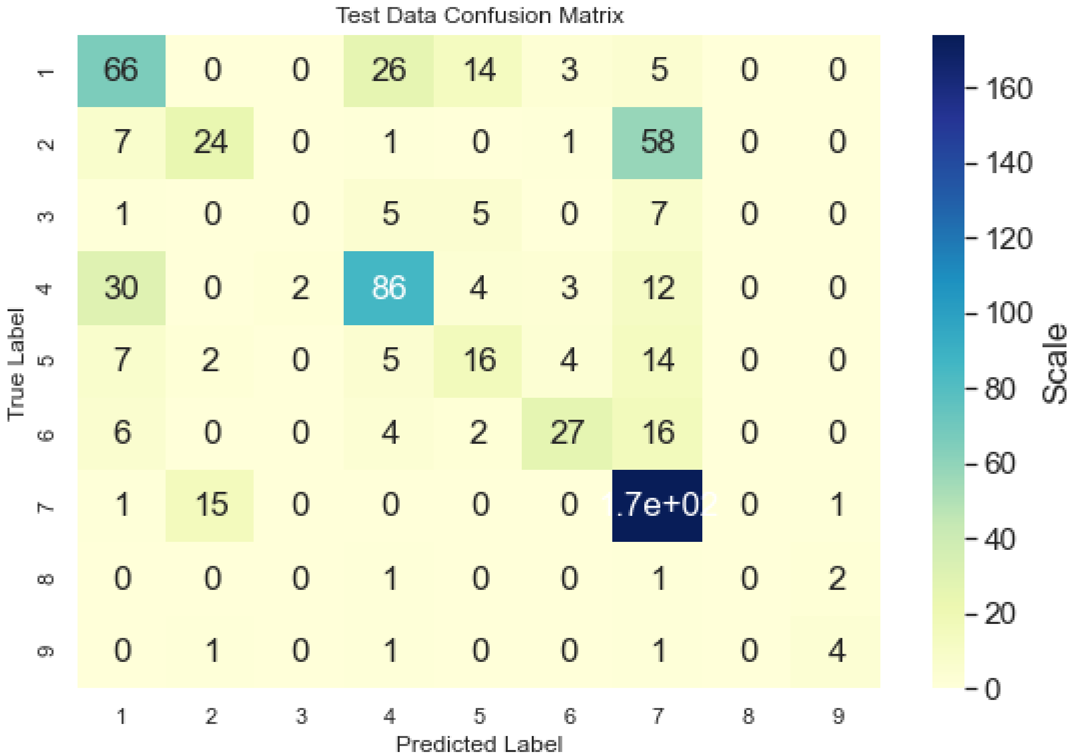

In [76]:

```
#Train with best alpha after cross validation
best_alpha=alpha[np.argmin(cv_error_lt)]
model=SGDClassifier(alpha=best_alpha,class_weight="balanced",penalty="l1",loss="hinge",
model.fit(train_df_tfidf,y_train)
clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
clf.fit(train_df_tfidf,y_train)
print("log loss with best alpha on Training data:",log_loss(y_train,clf.predict_proba(t
print("log loss with best alpha on Test data:",log_loss(y_test,clf.predict_proba(test_d
print("log loss with best alpha on CV data:",log_loss(y_cv,clf.predict_proba(cv_df_tfid
```

```
log loss with best alpha on Training data: 0.5515814377001828
log loss with best alpha on Test data: 1.229546475366088
log loss with best alpha on CV data: 1.1181082953117663
```

In [77]:

```
pred=clf.predict(test_df_tfidf)
matrix=confusion_matrix(y_test,pred)
plot_confusion_matrix(matrix,labels=[1,2,3,4,5,6,7,8,9],title="Test Data Confusion Matr
```




## 4.4 KNN classifier

### 4.4.1 KNeighborsClassifier with BOW

In [78]:

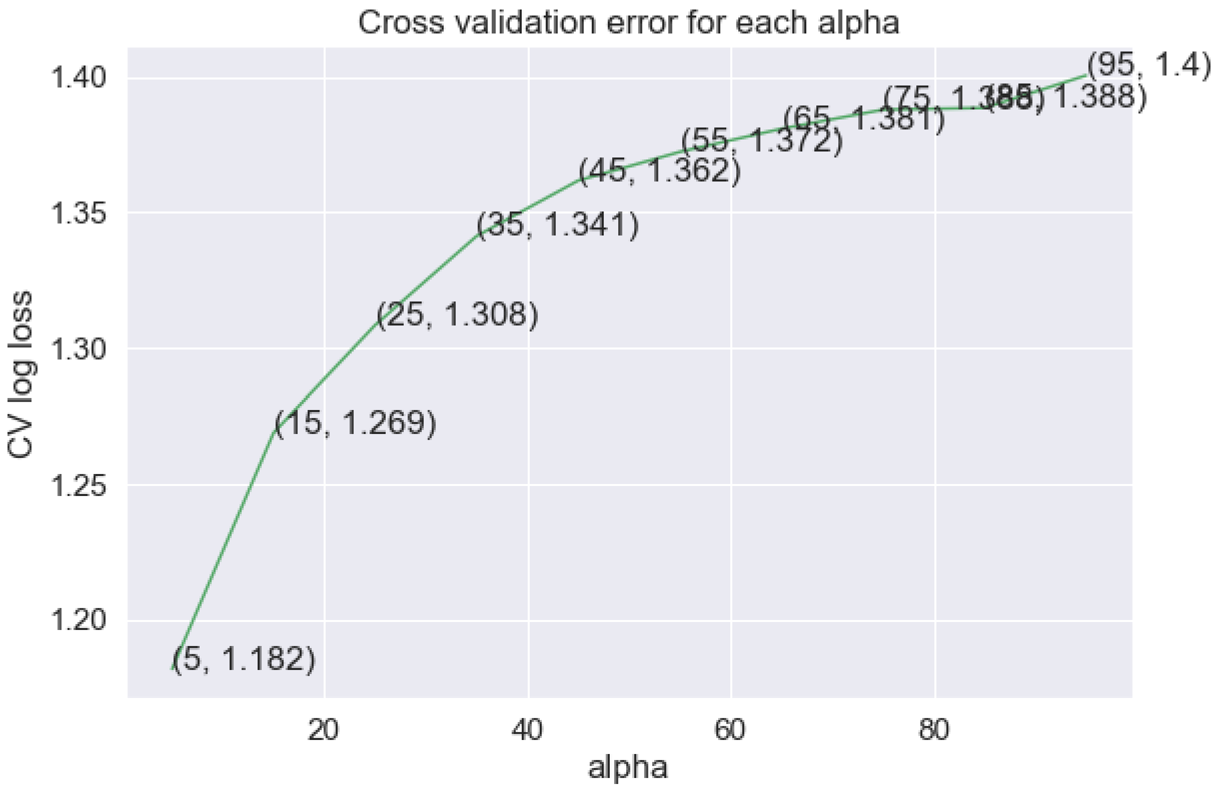
```
## KNeighborsClassifier with BOW
alpha=[i for i in np.arange(5,100,10)]
cv_error_lt=[]
for i in alpha:
    model=KNeighborsClassifier(n_neighbors=i,n_jobs=-1)
    model.fit(train_bow_df,y_train)
    clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
    clf.fit(train_bow_df,y_train)
    pred=clf.predict_proba(cv_bow_df)
    loss_val=log_loss(y_cv,pred)
    cv_error_lt.append(loss_val)
    print("For the calue of alpha {0} log loss ::{1}".format(i,loss_val))
```

```
For the calue of alpha 5 log loss ::1.1817411514622922
For the calue of alpha 15 log loss ::1.2688476489641012
For the calue of alpha 25 log loss ::1.3083650255672536
For the calue of alpha 35 log loss ::1.3412013412661934
For the calue of alpha 45 log loss ::1.3616566724368497
For the calue of alpha 55 log loss ::1.3722842130523774
For the calue of alpha 65 log loss ::1.3807949892896338
For the calue of alpha 75 log loss ::1.3878249884123937
For the calue of alpha 85 log loss ::1.3884865940950297
For the calue of alpha 95 log loss ::1.4004500202465593
```

In [79]:

```
fig, ax = plt.subplots(figsize = (9, 6))
ax.plot(alpha,cv_error_lt,c='g')
plt.title("Cross validation error for each alpha")
for i, txt in enumerate(np.round(cv_error_lt,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],cv_error_lt[i]))
plt.xlabel("alpha")
plt.ylabel("CV log loss")
```

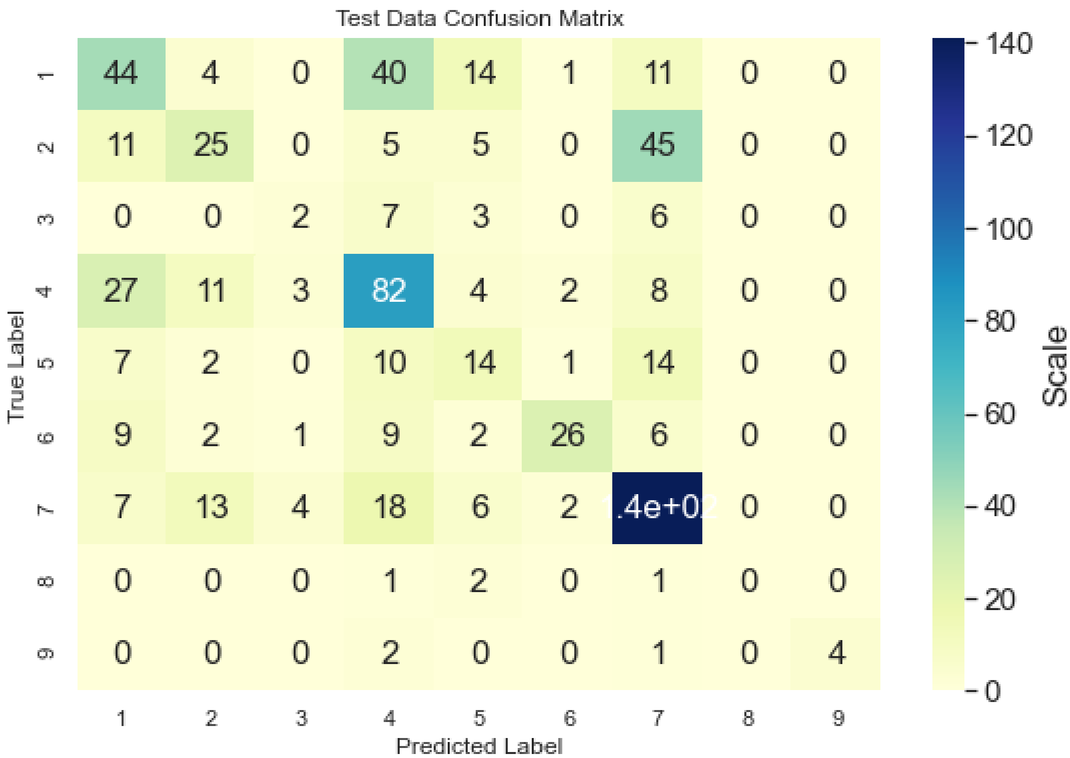
```
plt.show()
```




In [80]:
```
#Train with best alpha after cross validation
best_alpha=alpha[np.argmin(cv_error_lt)]
model=KNeighborsClassifier(n_neighbors=best_alpha,n_jobs=-1)
model.fit(train_bow_df,y_train)
clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
clf.fit(train_bow_df,y_train)
print("log loss with best alpha on Training data:",log_loss(y_train,clf.predict_proba(t
print("log loss with best alpha on Test data:",log_loss(y_test,clf.predict_proba(test_b
print("log loss with best alpha on CV data:",log_loss(y_cv,clf.predict_proba(cv_bow_df)
```

```
log loss with best alpha on Training data: 0.9359228435861102
log loss with best alpha on Test data: 1.335061592592927
log loss with best alpha on CV data: 1.1817411514622922
```

In [81]:
```
pred=clf.predict(test_bow_df)
matrix=confusion_matrix(y_test,pred)
plot_confusion_matrix(matrix,labels=[1,2,3,4,5,6,7,8,9],title="Test Data Confusion Matr
```

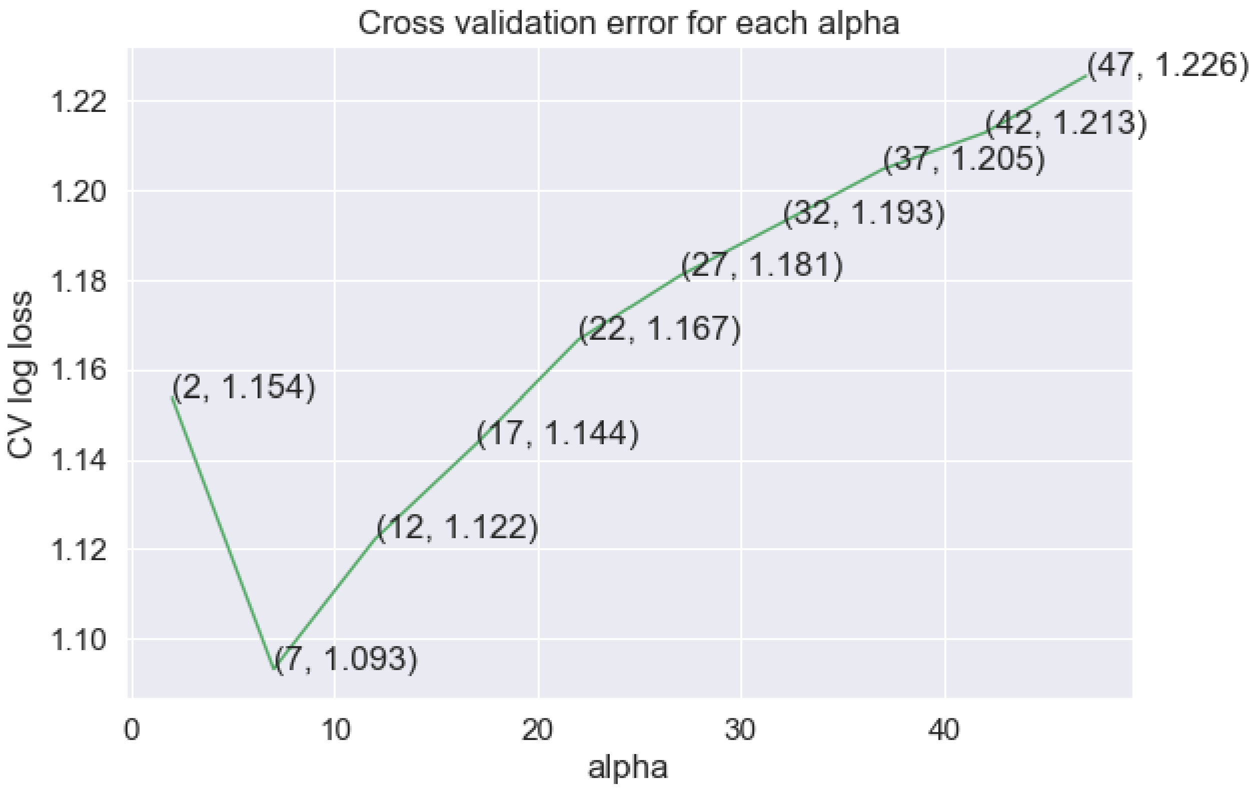



### 4.4.2 KNeighborsClassifier with TFIDF

In [82]:
```
## KNeighborsClassifier with TFIDF
alpha=[i for i in np.arange(2,50,5)]
cv_error_lt=[]
for i in alpha:
    model=KNeighborsClassifier(n_neighbors=i,n_jobs=-1)
    model.fit(train_df_tfidf,y_train)
    clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
    clf.fit(train_df_tfidf,y_train)
    pred=clf.predict_proba(cv_df_tfidf)
    loss_val=log_loss(y_cv,pred)
    cv_error_lt.append(loss_val)
    print("For the calue of alpha {0} log loss ::{1}".format(i,loss_val))
```

```
For the calue of alpha 2 log loss ::1.1537566048101764
For the calue of alpha 7 log loss ::1.0932047355388939
For the calue of alpha 12 log loss ::1.1222713551903087
For the calue of alpha 17 log loss ::1.1435571721342734
For the calue of alpha 22 log loss ::1.166600201136215
For the calue of alpha 27 log loss ::1.1809428689428187
For the calue of alpha 32 log loss ::1.1927427547319651
For the calue of alpha 37 log loss ::1.2047347415124332
For the calue of alpha 42 log loss ::1.2128444024233427
For the calue of alpha 47 log loss ::1.225543296670065
```

In [83]:
```
fig, ax = plt.subplots(figsize = (9, 6))
ax.plot(alpha,cv_error_lt,c='g')
plt.title("Cross validation error for each alpha")
for i, txt in enumerate(np.round(cv_error_lt,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],cv_error_lt[i]))
plt.xlabel("alpha")
plt.ylabel("CV log loss")

plt.show()
```



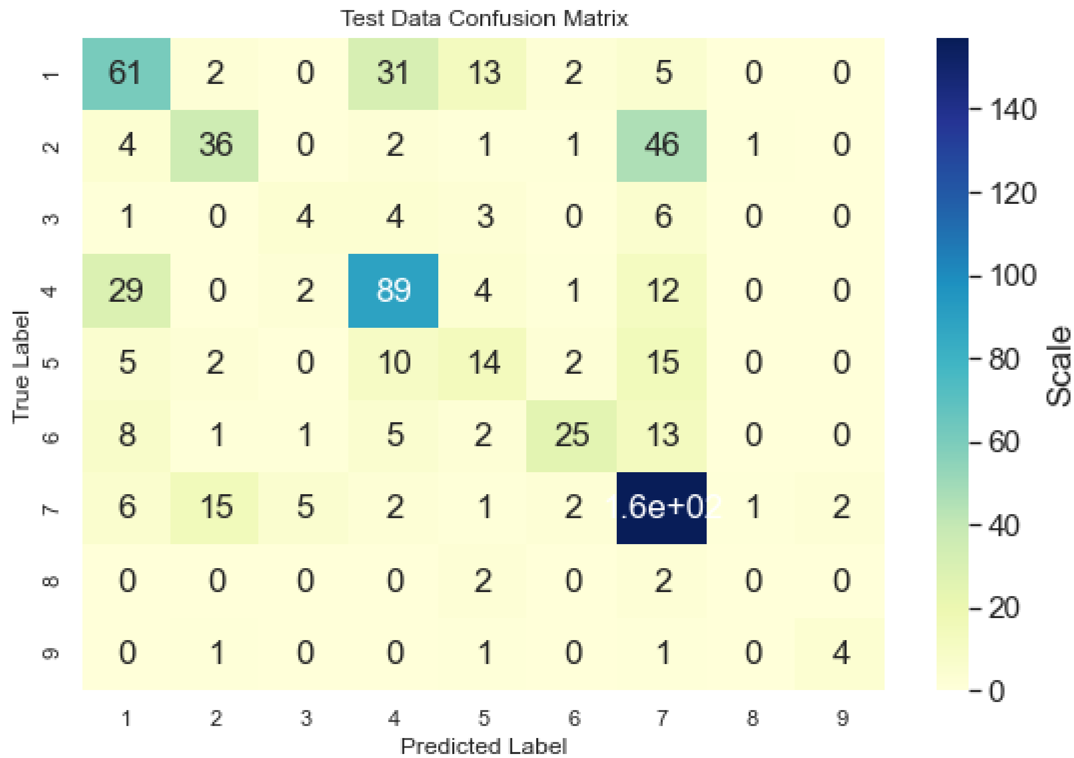

In [84]:

```
#Train with best alpha after cross validation
best_alpha=alpha[np.argmin(cv_error_lt)]
model=KNeighborsClassifier(n_neighbors=best_alpha,n_jobs=-1)
model.fit(train_df_tfidf,y_train)
clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
clf.fit(train_df_tfidf,y_train)
print("log loss with best alpha on Training data:",log_loss(y_train,clf.predict_proba(t
print("log loss with best alpha on Test data:",log_loss(y_test,clf.predict_proba(test_d
print("log loss with best alpha on CV data:",log_loss(y_cv,clf.predict_proba(cv_df_tfid
```

```
log loss with best alpha on Training data: 0.9067838511242281
log loss with best alpha on Test data: 1.185056564398821
log loss with best alpha on CV data: 1.0932047355388939
```

In [85]:

```
pred=clf.predict(test_df_tfidf)
matrix=confusion_matrix(y_test,pred)
plot_confusion_matrix(matrix,labels=[1,2,3,4,5,6,7,8,9],title="Test Data Confusion Matr
```




# 4.5 RandomForestClassifier

## 4.5.1 RandomForestClassifier with BOW

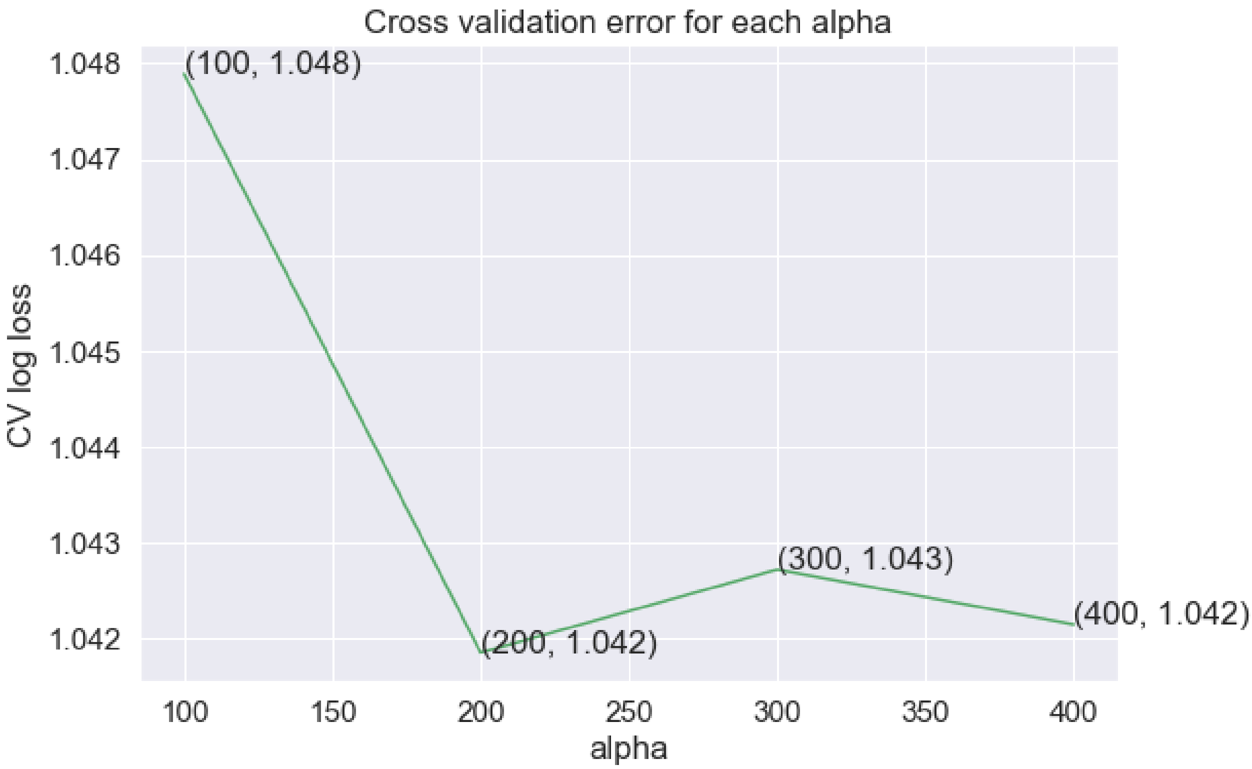
In [89]:

```
## RandomForestClassifier with BOW
alpha=[i for i in np.arange(100,500,100)]
cv_error_lt=[]
for i in alpha:
    model=RandomForestClassifier(n_estimators=i,n_jobs=-1)
    model.fit(train_bow_df,y_train)
    clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
    clf.fit(train_bow_df,y_train)
    pred=clf.predict_proba(cv_bow_df)
    loss_val=log_loss(y_cv,pred)
    cv_error_lt.append(loss_val)
    print("For the calue of alpha {0} log loss ::{1}".format(i,loss_val))
```

```
For the calue of alpha 100 log loss ::1.0478866049718734
For the calue of alpha 200 log loss ::1.0418572813888172
For the calue of alpha 300 log loss ::1.0427213854279753
For the calue of alpha 400 log loss ::1.0421512617859232
```

In [90]:

```
fig, ax = plt.subplots(figsize = (9, 6))
ax.plot(alpha,cv_error_lt,c='g')
plt.title("Cross validation error for each alpha")
for i, txt in enumerate(np.round(cv_error_lt,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],cv_error_lt[i]))
plt.xlabel("alpha")
plt.ylabel("CV log loss")

plt.show()
```



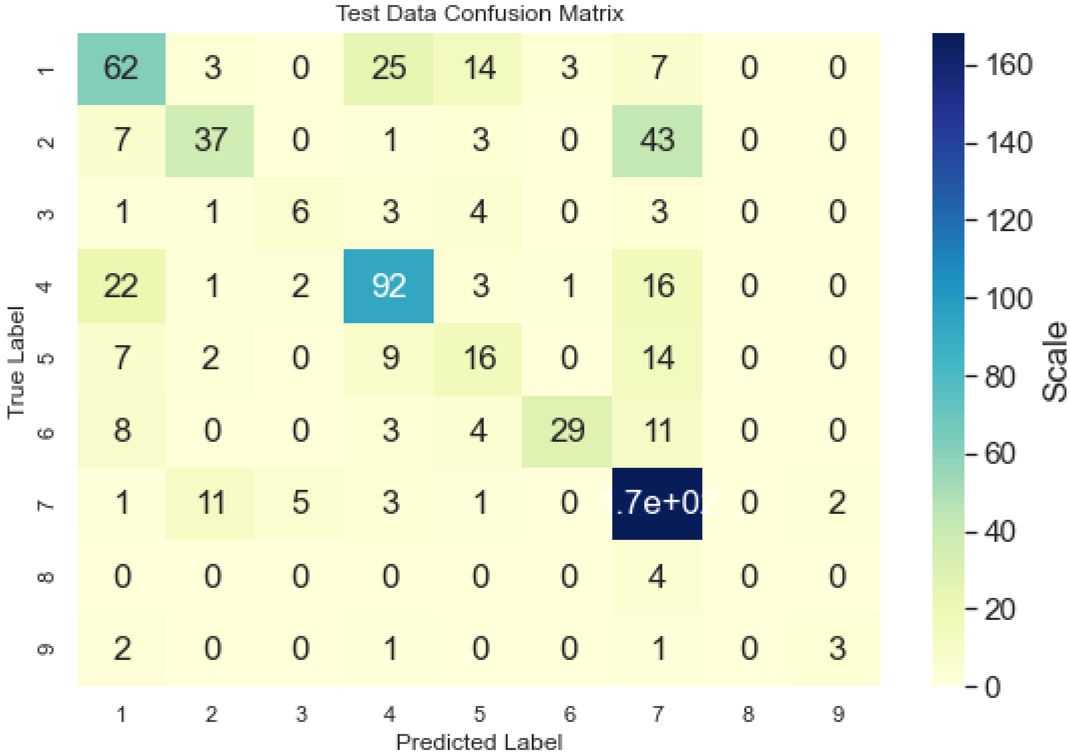

In [91]:

```
#Train with best alpha after cross validation
best_alpha=alpha[np.argmin(cv_error_lt)]
model=RandomForestClassifier(n_estimators=best_alpha,n_jobs=-1)
model.fit(train_bow_df,y_train)
clf=CalibratedClassifierCV(base_estimator=model,method="sigmoid")
clf.fit(train_bow_df,y_train)
print("log loss with best alpha on Training data:",log_loss(y_train,clf.predict_proba(t
print("log loss with best alpha on Test data:",log_loss(y_test,clf.predict_proba(test_b
print("log loss with best alpha on CV data:",log_loss(y_cv,clf.predict_proba(cv_bow_df)
```

```
log loss with best alpha on Training data: 0.3658493725516728
log loss with best alpha on Test data: 1.1753902710301987
log loss with best alpha on CV data: 1.0385190224433274
```

In [92]:

```
pred=clf.predict(test_bow_df)
matrix=confusion_matrix(y_test,pred)
plot_confusion_matrix(matrix,labels=[1,2,3,4,5,6,7,8,9],title="Test Data Confusion Matr
```




In [ ]:

# Conclusion

In [105…

```
from tabulate import tabulate
columns=["model","text vector","test loss","cv loss"]
summary=[["MultiNomialNB","BOW",1.37,1.25]
         ,["MultiNomialNB","TFIDF",1.26,1.14]
         ,["Logistic Regression with balancing","BOW",1.27,1.11]
         ,["Logistic Regression with balancing","TFIDF",1.13,1.01]
         ,["SVM with balancing","BOW",1.30,1.17]
         ,["SVM with balancing","TFIDF",1.23,1.11]
         ,["KNeighborsClassifier","BOW",1.33,1.18]
         ,["KNeighborsClassifier","TFIDF",1.18,1.09]
         ,["RandomForestClassifier","BOW",1.17,1.03]
        ]
summary_df=pd.DataFrame(summary,columns=columns)
#https://www.geeksforgeeks.org/display-the-pandas-dataframe-in-table-style/
print(tabulate(summary_df,headers="keys",tablefmt = 'psql'))
```

```
+----+------------------------------------+---------------+-------------+-----------+
|    | model                              | text vector   |   test loss |   cv loss |
|----+------------------------------------+---------------+-------------+-----------|
|  0 | MultiNomialNB                      | BOW           |        1.37 |      1.25 |
|  1 | MultiNomialNB                      | TFIDF         |        1.26 |      1.14 |
|  2 | Logistic Regression with balancing | BOW           |        1.27 |      1.11 |
|  3 | Logistic Regression with balancing | TFIDF         |        1.13 |      1.01 |
|  4 | SVM with balancing                 | BOW           |        1.3  |      1.17 |
|  5 | SVM with balancing                 | TFIDF         |        1.23 |      1.11 |
|  6 | KNeighborsClassifier               | BOW           |        1.33 |      1.18 |
|  7 | KNeighborsClassifier               | TFIDF         |        1.18 |      1.09 |
|  8 | RandomForestClassifier             | BOW           |        1.17 |      1.03 |
+----+------------------------------------+---------------+-------------+-----------+
```

In [ ]:

In [ ]:

In [ ]:

In [ ]: