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DNA_project / DNA_project_EDA.ipynb

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In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
sns.set()
import matplotlib.pyplot as plt
import os
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from keras.models import Sequential
from keras.layers import Dense
from keras.utils.np_utils import to_categorical
from keras.optimizers import Adam
```

```
Using TensorFlow backend.
```

In [2]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
# data source:https://www.kaggle.com/c/msk-redefining-cancer-treatment/data?select=stage1_solu
tion_filtered.csv.7z
```

In [4]:
```
path='/Users/huashi/Downloads/msk-redefining-cancer-treatment/data/'
```

In [5]:
```
# load the text train data  and text data
train_text= pd.read_csv(path+'training_text', sep='\|\|', header=None, skiprows=1, names=["ID"
,"Text"])

train_variants= pd.read_csv(path+'training_variants')
```

In [6]:
```
# check the shape of each dataset
train_text.shape
```

Out[6]:
```
(3321, 2)
```

In [7]:
```
train_variants.shape
```

Out[7]:
```
(3321, 4)
```

In [8]:
```
# before we remove those missing
#text data we need to merge variants data and text data
```

```
train = pd.merge(train_variants,train_text, how='left', on='ID')
```

In [9]:
```
train.isnull().sum() # there are five missing data in text column
```

Out[9]:
```
ID           0
Gene         0
Variation    0
Class        0
Text         5
dtype: int64
```

In [10]:
```
# remove missing values
df_train=train.dropna(axis=0).copy()
df_train.shape
```

Out[10]:
```
(3316, 5)
```

In [11]:
```
df_train.head()
```

Out[11]:

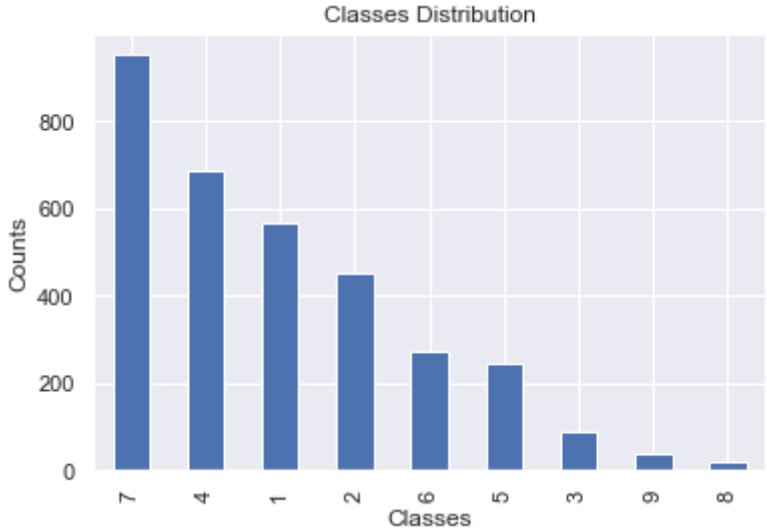
	ID	Gene	Variation	Class	Text
0	0	FAM58A	Truncating Mutations	1	Cyclin-dependent kinases (CDKs) regulate a var...
1	1	CBL	W802*	2	Abstract Background Non-small cell lung canc...
2	2	CBL	Q249E	2	Abstract Background Non-small cell lung canc...
3	3	CBL	N454D	3	Recent evidence has demonstrated that acquired...
4	4	CBL	L399V	4	Oncogenic mutations in the monomeric Casitas B...

EDA

- 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)

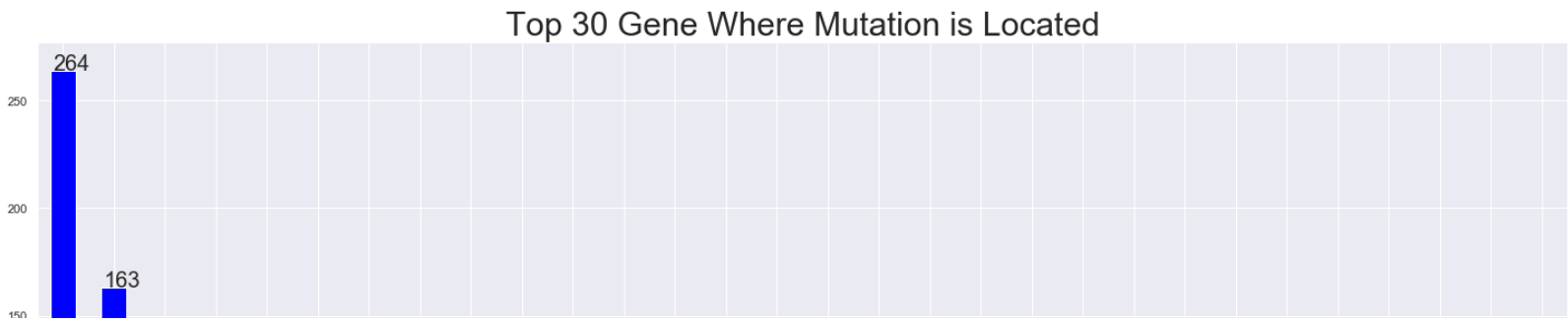
Class

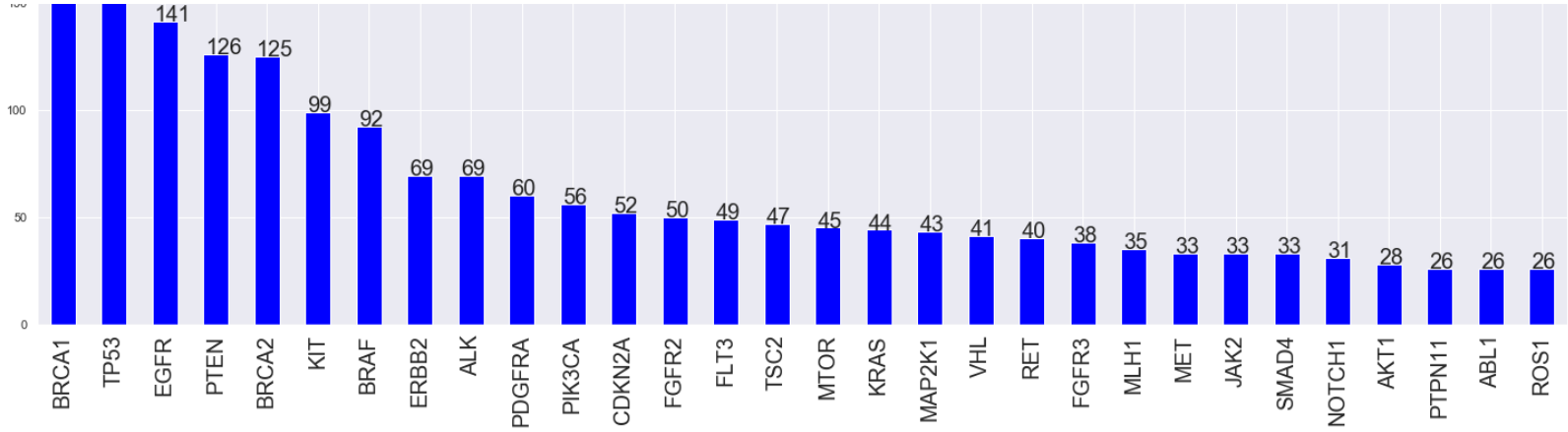
In [75]:
```
df_train.Class.value_counts().plot(kind="bar",title='Classes Distribution')
plt.xlabel('Classes')
plt.ylabel('Counts')
plt.show()
```



Gene

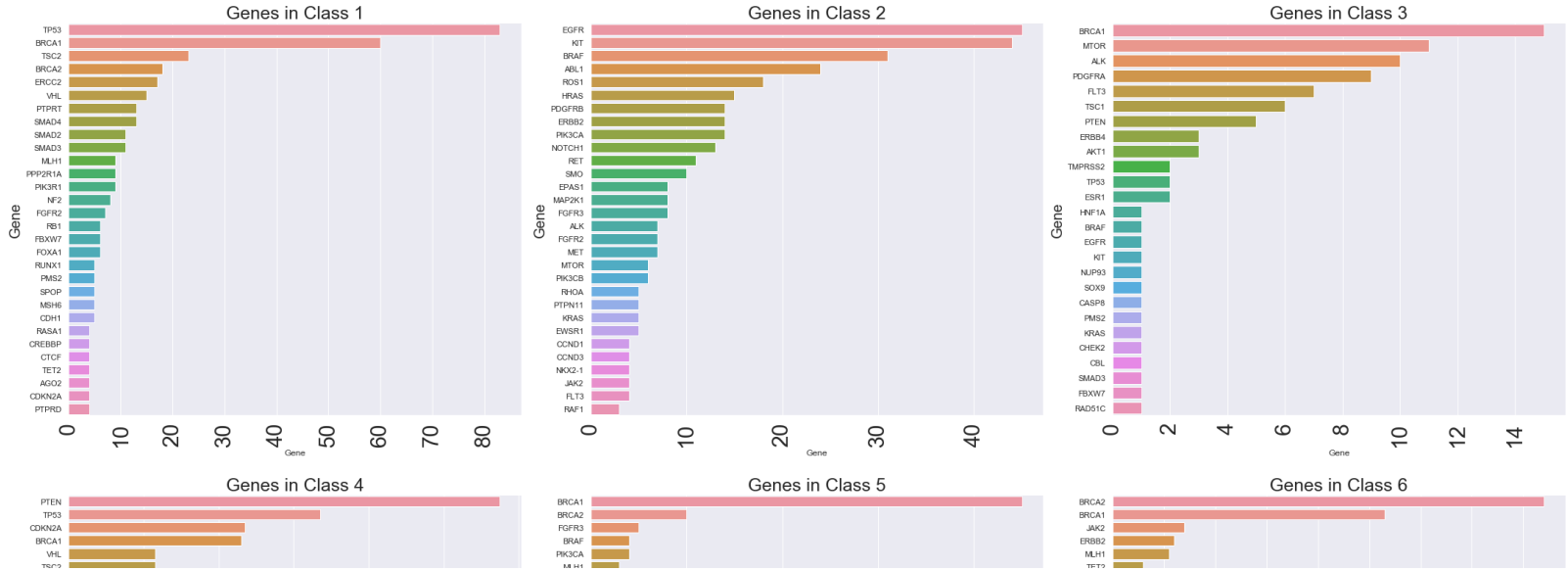
In [80]:
```
# Plot top 30 the frequency of the gene where this genetic mutation is located
df_train.Gene.value_counts()[:30].plot(kind='bar',figsize=(25,10),color='blue')
plt.xticks(fontsize=20)
plt.title("Top 30 Genes Where Mutation is Located",fontsize=30)
for i in range(0,30):
    plt.text(i-0.2,df_train.Gene.value_counts()[:30][i],"{}".format(df_train.Gene.value_counts
()[:30][i]),fontsize=20)
```

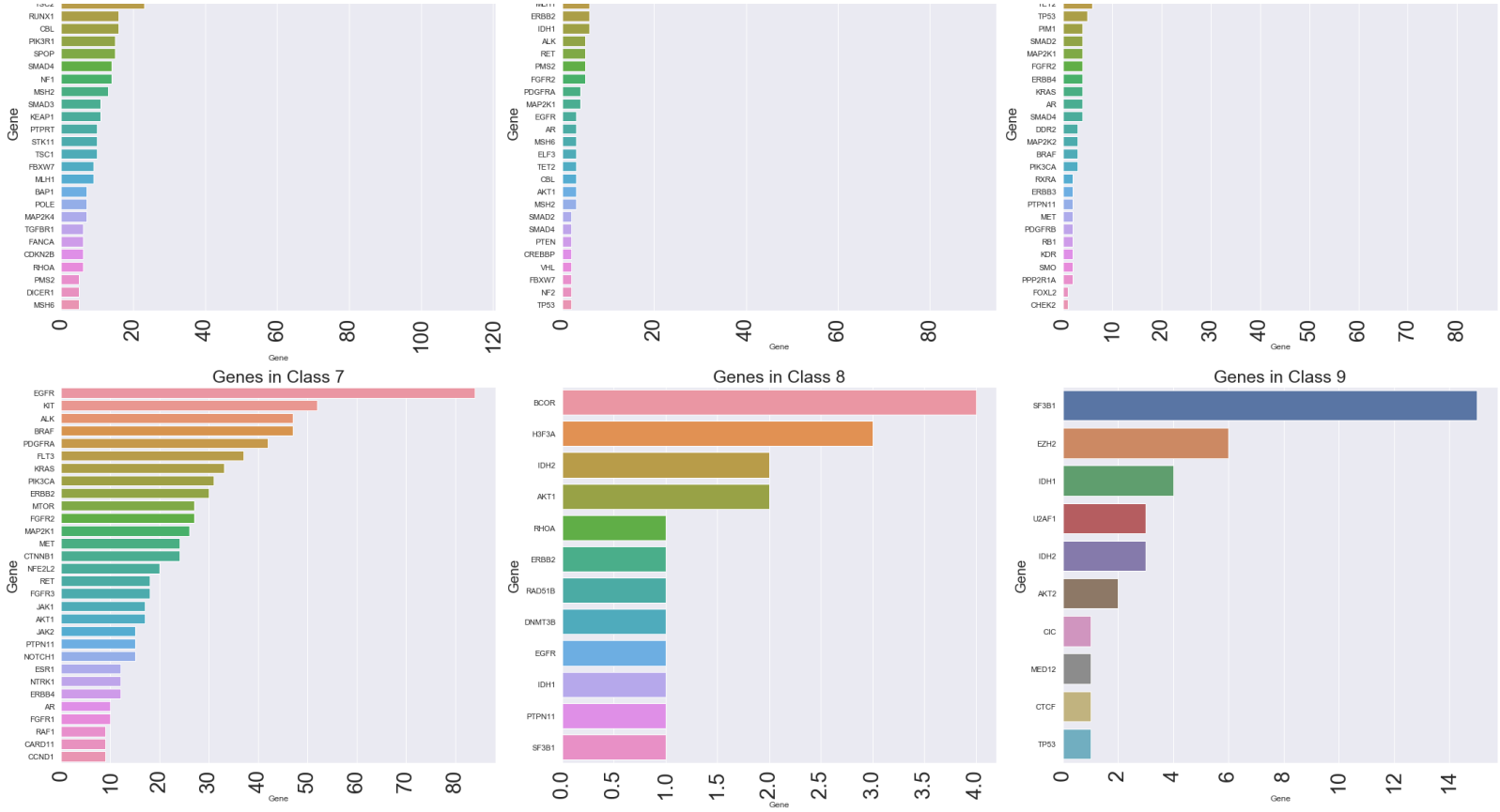




In [115]:

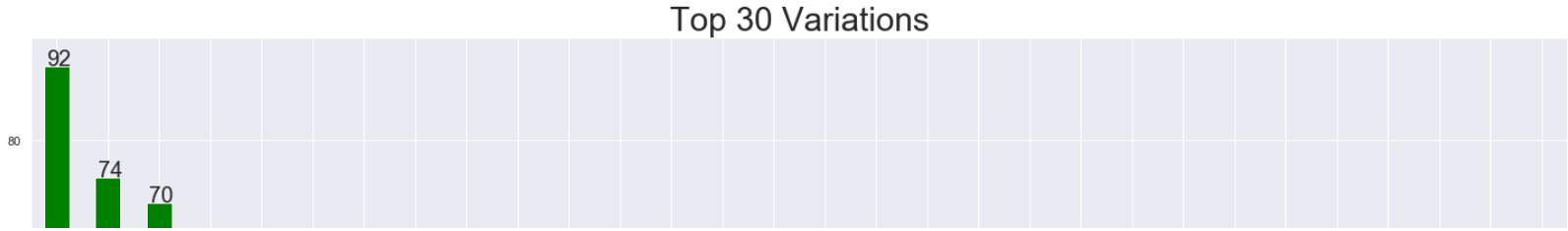
```
# Gene & Class
plt.figure(figsize=(30,27))
for i in range(0,9):
    class_df=pd.DataFrame(df_train[df_train.Class==i+1].Gene.value_counts()).reset_index()[:30
]
    plt.subplot(3,3,i+1)
    sns.barplot(class_df['Gene'],class_df['index'])
    plt.xticks(rotation=90,size=30)
    plt.ylabel("Gene",fontsize=20)
    plt.title('Genes in Class {}'.format(list(set(df_train.Class))[i]),fontsize=25)
plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=1.0)
plt.show()
```

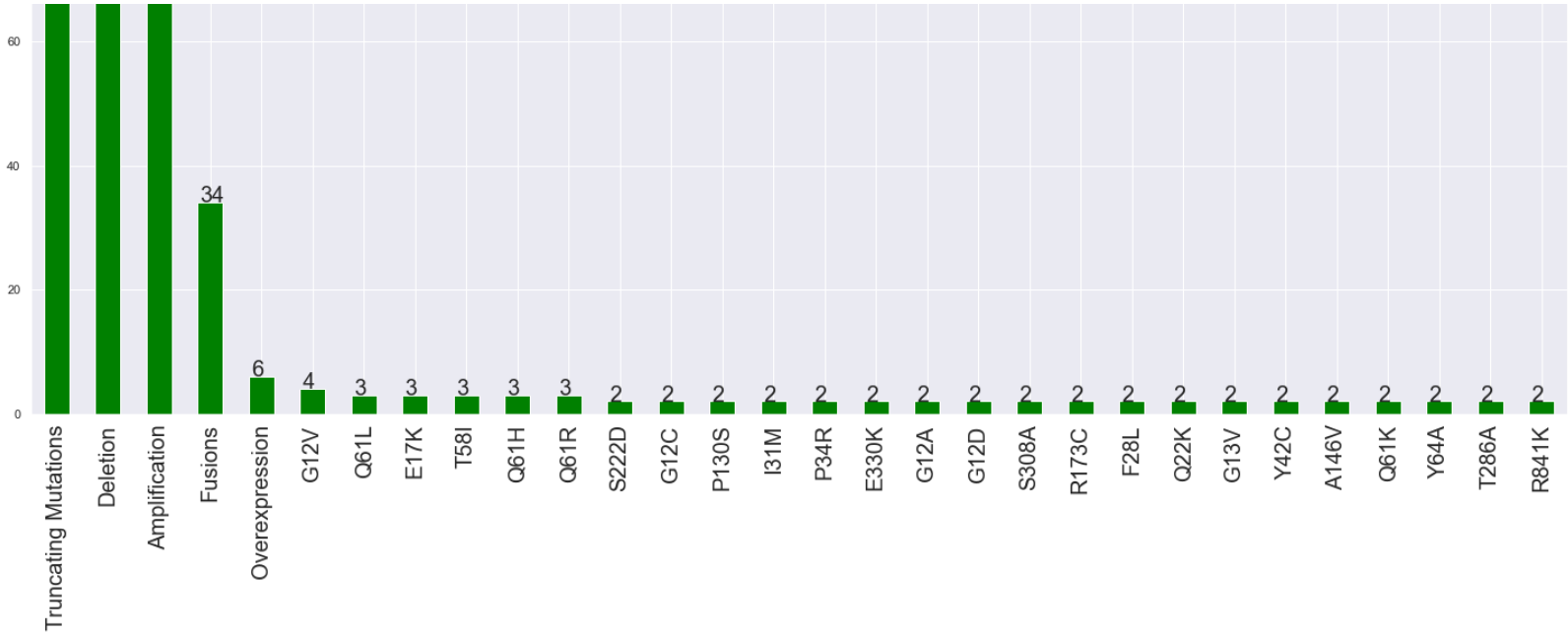




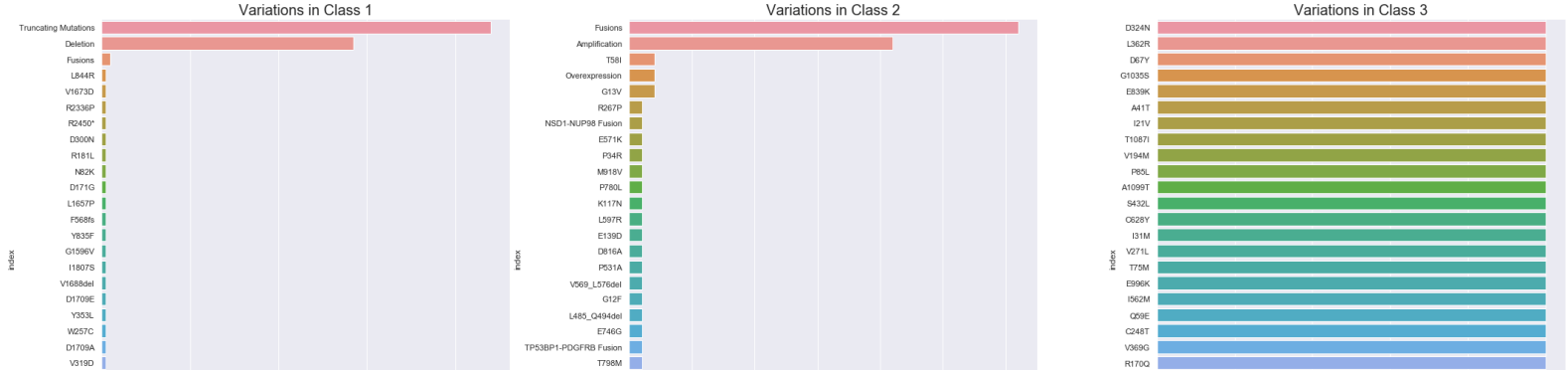
Variation

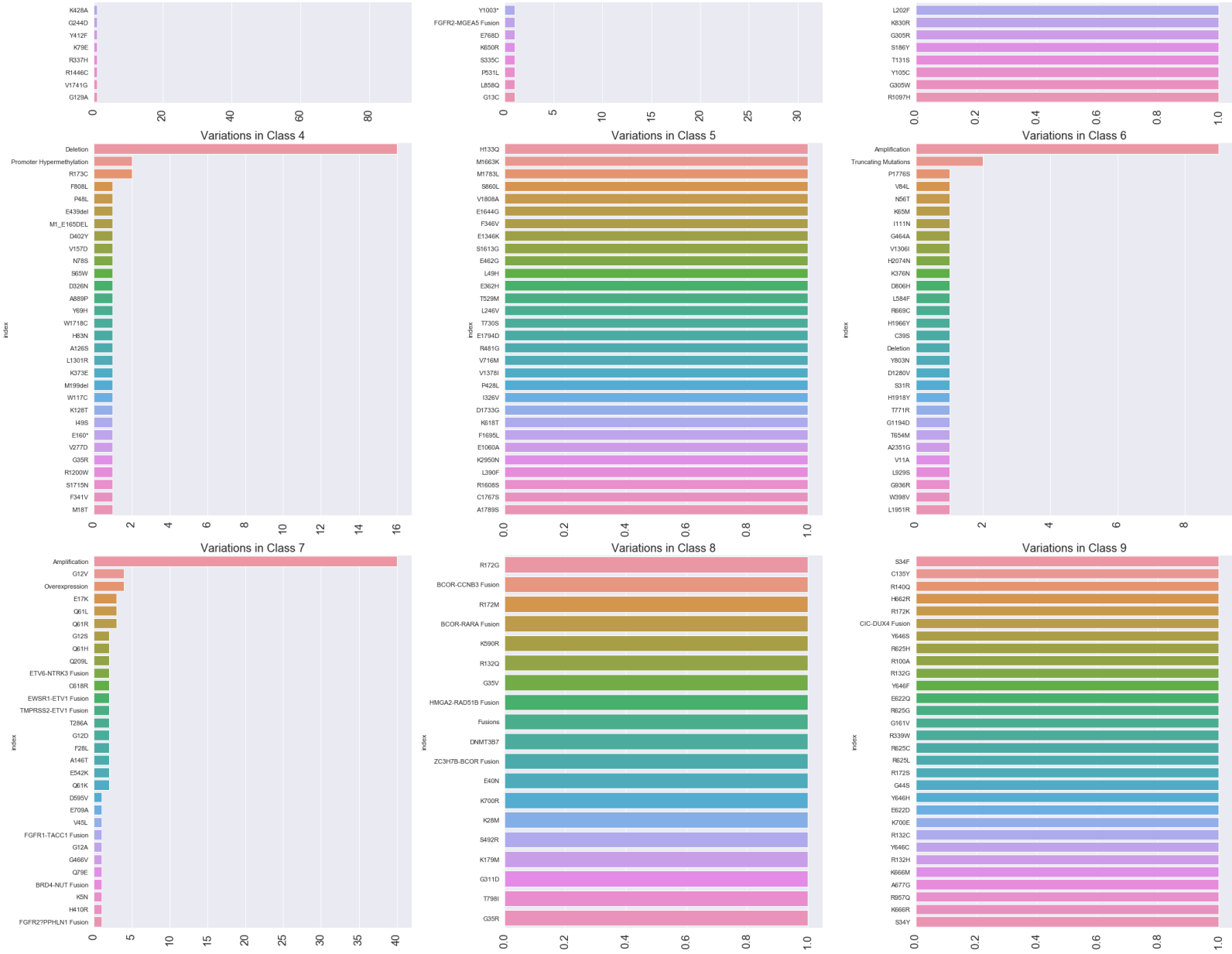
In [86]:
```
df_train.Variation.value_counts()[:30].plot(kind='bar',figsize=(25,10),color='green')
plt.xticks(fontsize=20)
plt.title("Top 30 Variations",fontsize=30)
for i in range(0,30):
    plt.text(i-0.2,df_train.Variation.value_counts()[:30][i],"{}".format(df_train.Variation.value_counts()[:30][i]),fontsize=20)
```





In [112]:
```
# Gene & Class
plt.figure(figsize=(30,30))
for i in range(0,9):
    class_df=pd.DataFrame(df_train[df_train.Class==i+1].Variation.value_counts()).reset_index
()[:30]
    plt.subplot(3,3,i+1)
    sns.barplot(class_df['Variation'],class_df['index'])
    plt.xticks(rotation=90,size=19)
    plt.xlabel("")
    plt.title('Variations in Class {}'.format(list(set(df_train.Class))[i]),fontsize=20)
plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=1.0)
plt.show()
```





Data Engineering

In [198]:
```
import re, string
from nltk.corpus import stopwords
import nltk
```

In [187]:
```
# Create functions for tokenization, stemming, Lelemmatization and
# finally combine all functions together to obtain cleaned_text_date for train and test data


sw_list = stopwords.words('english')
sw_list += list(string.punctuation)
sw_list += ["'''", '"""', '...', '``', '‘', '“', '’', '”', '‘', '’',"'", '©',
'said',"'s", "also",'one',"n't",'com', 'satirewire', '-', '—', "et al",
'—', '_','et al ',"/"]
sw_set = set(sw_list)

# tokenization
def process_review(review):
    tokens = nltk.word_tokenize(review) # tokenization
    stopwords_removed = [token.lower() for token in tokens if token.lower() not in sw_set]# st
op workds removal
    return stopwords_removed

# Stemming
from nltk.stem import PorterStemmer
ps = PorterStemmer()
# create a function stemming() and loop through each word in a review
def stemming(review):
    stemmed_review=[]
    for w in review:
        stemmed_review.append(ps.stem(w))
    return stemmed_review

# import libraries
from nltk.stem.wordnet import WordNetLemmatizer
lemmatizer = WordNetLemmatizer()

# create a function  and loop through each word in  a review
def lemmatization(review):
    lemma_list=[]
    for word in review:
        lemma_word=lemmatizer.lemmatize(word,pos='v')
        lemma_list.append(lemma_word)
    return lemma_list

# Conbime all functions above and obtian cleaned text data
def data_preprocessing(review):
```

```
    #tokenization, stop words removal, punctuation marks removel
    processed_review=list(map(process_review,review))
    # stemming
    stemming_reviews=list(map(stemming,processed_review))
    # lemmatization
    lemma_reviews=list(map(lemmatization,stemming_reviews))
    return lemma_reviews
```

In [192]:
```
cleaned_train_text=data_preprocessing(df_train['Text'])
```

In [157]:
```
import pickle
pickle_out1=open('cleaned_train_text', 'wb')
pickle.dump(cleaned_train_text, pickle_out1)
pickle_out1.close()
pickle_out2.close()
```

In [12]:
```
import pickle
pickle_in_train = open("cleaned_train_text","rb")
cleaned_train_text = pickle.load(pickle_in_train)
```

N-grams

In [42]:
```
df_train['cleaned_text']=[" ".join(i) for i in cleaned_train_text]
```

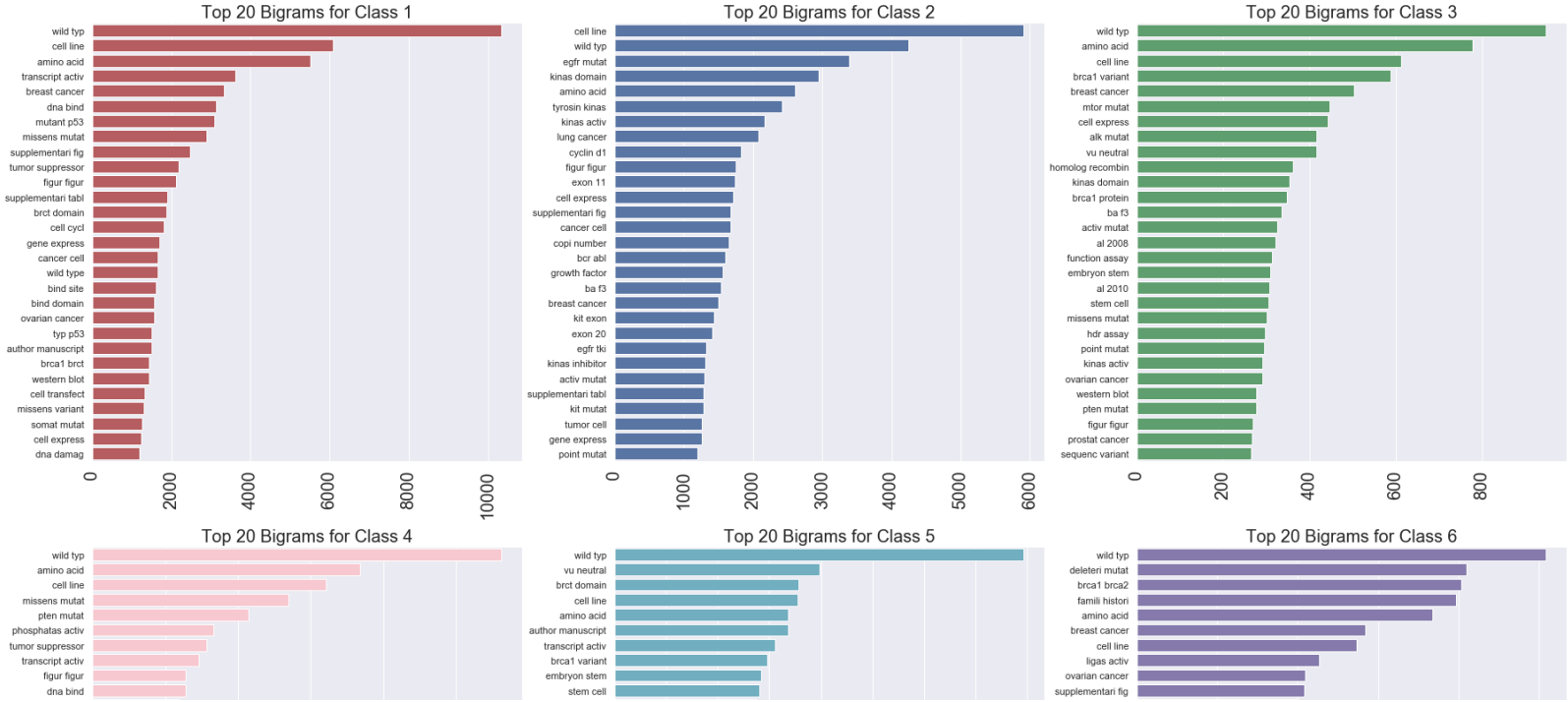
In [122]:
```
from sklearn.feature_extraction.text import CountVectorizer
def get_top_n_bigram(corpus, n=None):
    vec = CountVectorizer(ngram_range=(2, 2), stop_words='english').fit(corpus)
    bag_of_words = vec.transform(corpus)
    sum_words = bag_of_words.sum(axis=0)
    words_freq = [(word, sum_words[0, idx]) for word, idx in vec.vocabulary_.items()]
    words_freq =sorted(words_freq, key = lambda x: x[1], reverse=True)
    return words_freq[:n]
#source:https://towardsdatascience.com/a-complete-exploratory-data-analysis-and-visualization-
for-text-data-29fb1b96fb6a
```

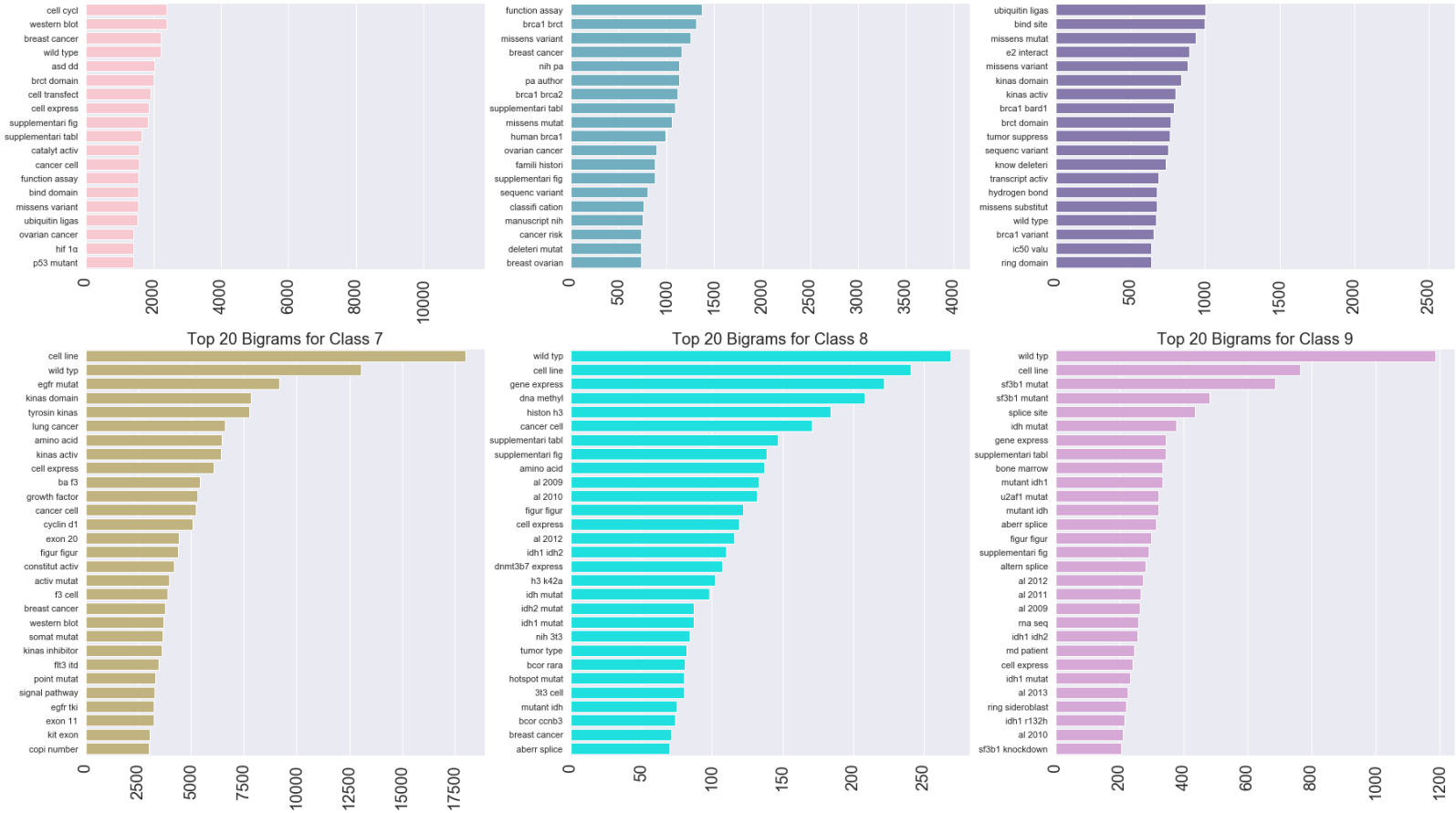
In [124]:
```
# Apply the function above foe each class
class1 = get_top_n_bigram(df_train[df_train['Class']==1]['cleaned_text'], 30)
class2=  get_top_n_bigram(df_train[df_train['Class']==2]['cleaned_text'], 30)
class3 = get_top_n_bigram(df_train[df_train['Class']==3]['cleaned_text'], 30)
```

```
class4 = get_top_n_bigram(df_train[df_train['Class']==4]['cleaned_text'], 30)
class5 = get_top_n_bigram(df_train[df_train['Class']==5]['cleaned_text'], 30)
class6 = get_top_n_bigram(df_train[df_train['Class']==6]['cleaned_text'], 30)
class7 = get_top_n_bigram(df_train[df_train['Class']==7]['cleaned_text'], 30)
class8 = get_top_n_bigram(df_train[df_train['Class']==8]['cleaned_text'], 30)
class9 = get_top_n_bigram(df_train[df_train['Class']==9]['cleaned_text'], 30)
```

In [179]:
```
classes_data=[class1[1:],class2[1:],class3[1:],class4[1:],classfive,
              class6[1:],class7[1:],class8[1:],class9[1:]]
colors=['r','b','g','pink','c','m','y','aqua','plum']
```

In [180]:
```
plt.figure(figsize=(25,25))
for i in range(0,9):
    plt.subplot(3,3,i+1)
    x=[x[0] for x in classes_data[i]]
    y=[x[1] for x in  classes_data[i]]
    sns.barplot(y,x,color=colors[i])
    plt.xticks(rotation=90,fontsize=20)
    plt.title("Top 20 Bigrams for Class {}".format(i+1),fontsize=20)
plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=1.0)
plt.show()
```





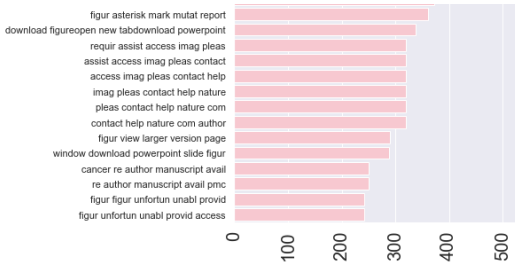
In [202]:
```
# Trigrams
def get_top_n_ngram(corpus, n=None,k=None):
    vec = CountVectorizer(ngram_range=(k,k )).fit(corpus)
    bag_of_words = vec.transform(corpus)
    sum_words = bag_of_words.sum(axis=0)
    words_freq = [(word, sum_words[0, idx]) for word, idx in vec.vocabulary_.items()]
    words_freq =sorted(words_freq, key = lambda x: x[1], reverse=True)
    return words_freq[:n]
#source:https://towardsdatascience.com/a-complete-exploratory-data-analysis-and-visualization-for-text-data-29fb1b96fb6a
```

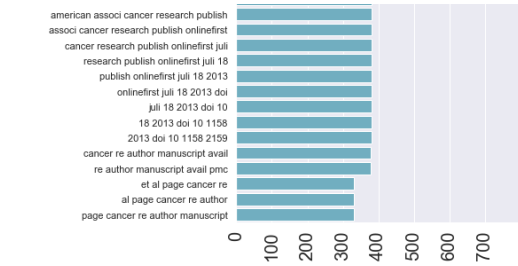
In [203]:
```
# Apply the function above foe each class
class1t = get_top_n_ngram(df_train[df_train['Class']==1]['cleaned_text'], 30,5)
class2t = get_top_n_ngram(df_train[df_train['Class']==2]['cleaned_text'], 30,5)
class3t = get_top_n_ngram(df_train[df_train['Class']==3]['cleaned_text'], 30,5)
class4t = get_top_n_ngram(df_train[df_train['Class']==4]['cleaned_text'], 30,5)
```

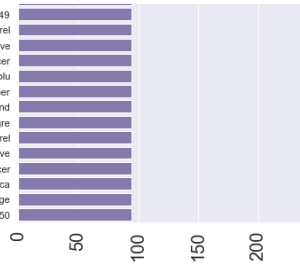
```
class5t = get_top_n_ngram(df_train[df_train['Class']==5]['cleaned_text'], 30,5)
class6t = get_top_n_ngram(df_train[df_train['Class']==6]['cleaned_text'], 30,5)
class7t = get_top_n_ngram(df_train[df_train['Class']==7]['cleaned_text'], 30,5)
class8t = get_top_n_ngram(df_train[df_train['Class']==8]['cleaned_text'], 30,5)
class9t = get_top_n_ngram(df_train[df_train['Class']==9]['cleaned_text'], 30,5)
```

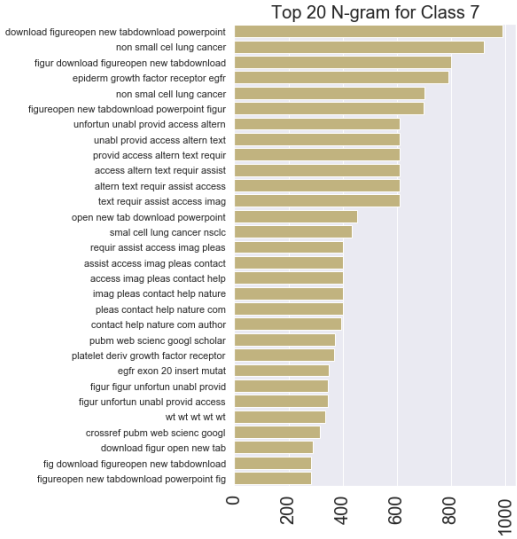
In [205]:

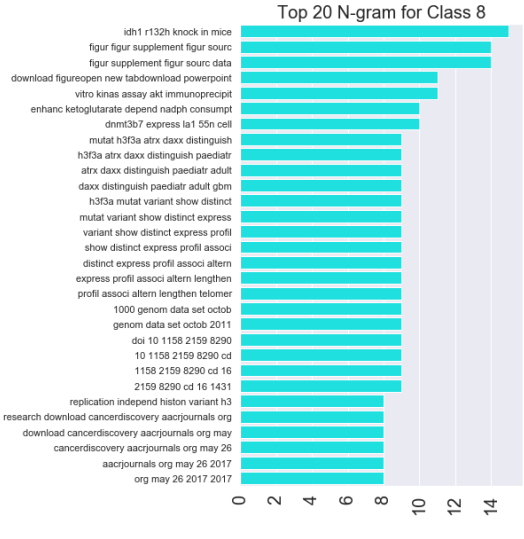
```
classest_data=[class1t,class2t,class3t,class4t,class5t,
               class6t,class7t,class8t,class9t]
plt.figure(figsize=(25,25))
# good reviews bigrams
for i in range(0,9):
    plt.subplot(3,3,i+1)
    x=[x[0] for x in classest_data[i]]
    y=[x[1] for x in  classest_data[i]]
    sns.barplot(y,x,color=colors[i])
    plt.xticks(rotation=90,fontsize=20)
    plt.title("Top 20 N-gram for Class {}".format(i+1),fontsize=20)
plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=1.0)
plt.show()
```

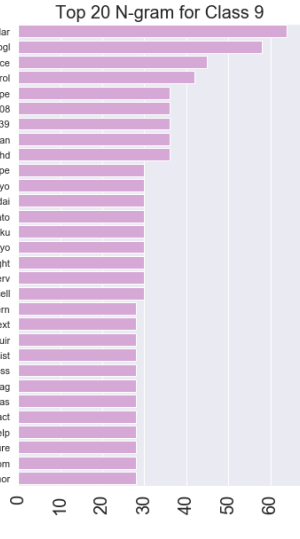












In [43]:
```
#declare inputs and target
inputs=df_train[['ID', 'Gene', 'Variation','cleaned_text']]
target=df_train.Class
```

Resampling

In [44]:
```
from sklearn.utils import resample
```

In [45]:
```
training  = pd.DataFrame()
training[list(inputs.columns)]=inputs
training['target']=target
training.head()
```

Out[45]:

	ID	Gene	Variation	cleaned_text	target
0	0	FAM58A	Truncating Mutations	cyclin-depend kinas cdk regul varieti fundamen...	1

1	1	CBL	W802*	abstract background non-smal cell lung cancer ...	2
2	2	CBL	Q249E	abstract background non-smal cell lung cancer ...	2
3	3	CBL	N454D	recent evid demonstr acquir uniparent disomi a...	3
4	4	CBL	L399V	oncogen mutat monomer casita b-lineag lymphoma...	4

In [46]:
```
# separate minority and majority classes
classes_list=[]
for i in range(0,9):
    class_i= training[training.target==i+1]
    classes_list.append(class_i)
    print("Class {}: ".format(i+1)+str(len(class_i)))
# we can see class 7 is the majority class and  class 3,8,9 contain very small size of samples
```

```
Class 1: 566
Class 2: 452
Class 3: 89
Class 4: 686
Class 5: 242
Class 6: 273
Class 7: 952
Class 8: 19
Class 9: 37
```

In [47]:
```
# upsample minority
def oversampling(majority,minority):
    minority_upsampled = resample(minority,
                                  replace=True, # sample with replacement
                                  n_samples=len(majority), # match number in majority class
                                  random_state=365) # reproducible results
    return minority_upsampled
```

In [48]:
```
# since class 7 is our majority group we need to remove it from our classes list
classes_list.pop(-3)# remove class 7 dataset
```

Out[48]:

	ID	Gene	Variation	cleaned_text	target
28	28	TERT	C228T	sequenc studi identifi mani recurr code mutat ...	7
31	31	TERT	Promoter Mutations	sequenc studi identifi mani recurr code mutat ...	7
34	34	TERT	C250T	sequenc studi identifi mani recurr code mutat ...	7

67	67	RHEB	Y35C	gene encod compon pi3k-akt-mtor signal axi fre...	7
68	68	RHEB	Y35N	gene encod compon pi3k-akt-mtor signal axi fre...	7
...	...	...	...	...	...
3292	3292	RET	C634Y	investigatedth transformingactivityofth ret pr...	7
3294	3294	RET	R886W	introduct inherit germ line activ mutat rearra...	7
3296	3296	RET	Y791F	ret proto-oncogen encod receptor tyrosin kinas...	7
3308	3308	RUNX1	R174*	famili platelet disord propens acut myeloid le...	7
3310	3310	RUNX1	Amplification	runx protein belong famili metazoan transcript...	7

952 rows × 5 columns

In [49]:
```
len(classes_list)# now wen have 8 different classes
```

Out[49]:
```
8
```

In [50]:
```
# now using the function above loop through all classes datasets
upsampled_classes_list=[]
for cla in classes_list:
    upsample_df=oversampling(training[training.target==7],cla)
    upsampled_classes_list.append(upsample_df)
```

In [51]:
```
# and we also include class 7 data
class_7df=training[training.target==7]
upsampled_classes_list.append(class_7df)
```

In [52]:
```
# combine majority and upsampled minority
upsampled=pd.concat(upsampled_classes_list)
# check new class counts
upsampled.target.value_counts(),len(upsampled_classes_list)
```

Out[52]:
```
(7    952
 6    952
 5    952
 4    952
 3    952
 2    952
 9    952
```

```
1    952
8    952
Name: target, dtype: int64,
9)
```

In [53]:
```
# declare target and inputs
target = upsampled.target
inputs= upsampled.drop(columns=['ID','target'], axis=1)
```

In [54]:
```
# target.to_csv("target.csv")
# inputs.to_csv("inputs.csv")
```

In [56]:
```
inputs.columns# check the columns
```

Out[56]:
```
Index(['Gene', 'Variation', 'cleaned_text'], dtype='object')
```

In [57]:
```
#train test split dataset
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(inputs, target, test_size=.2, random_state
=0)
```

Vectorizing Text Data

In [58]:
```
from sklearn.feature_extraction.text import CountVectorizer
```

In [59]:
```
def vectorizer(train,test):
    vectorizer=CountVectorizer()
    new_train=vectorizer.fit_transform(train)
    new_test=vectorizer.transform(test)
    return new_train,new_test
```

In [60]:
```
# Vectorize each column for x_train and x_test
gene_train,gene_test=vectorizer(x_train.Gene,x_test.Gene)
variation_train,variation_test=vectorizer(x_train.Variation,x_test.Variation)
cleaned_text_train,cleaned_text_test=vectorizer(x_train.cleaned_text,x_test.cleaned_text)
```

Naive Bayes

In [74]:
```
# Naive Bayes Classifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import mean_squared_error, accuracy_score, f1_score,make_scorer
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import GridSearchCV
f1 = make_scorer(f1_score , average='weighted')

def NB_GridSearch(X_train, y_train):
    grid_params = {'alpha':[0.1,0.2,0.3,0.4,0.5],
                   'fit_prior': [True, False],  }

    gs = GridSearchCV( MultinomialNB(), grid_params,scoring=f1, cv=10)
    gs.fit(X_train, y_train)
    print("Best Score: ", gs.best_score_)
    print("Best Alpha: ", gs.best_params_)

    return gs.best_params_.values()
```

In [78]:
```
def NaiveBayes(X_train,y_train,X_test,y_test,alpha,fit_prior):
    # fit the training dataset on the NB classifier
    Naive = MultinomialNB(alpha=0.1, fit_prior= True)
    Naive.fit(X_train,y_train)
    #prediction
    nb_train_pre=Naive.predict(X_train)
    nb_test_pre=Naive.predict(X_test)
    # Use accuracy_score function to get the accuracy
    print("Naive Bayes Train Accuracy Score :",accuracy_score(nb_train_pre, y_train))
    print("Naive Bayes Test Accuracy Score :",accuracy_score(nb_test_pre, y_test))
    # calculate f1 scores for test data and train data
    nb_f1_score_test=f1_score(y_test,nb_test_pre,average='weighted')
    nb_f1_score_train=f1_score(y_train,nb_train_pre,average='weighted')
    print("Train data f1 score:{}".format(nb_f1_score_train))
    print("Test data f1 score:{}".format(nb_f1_score_test ))
    print("confusion_matrix:{}".format(confusion_matrix(y_test, nb_test_pre)))
    print('==================================================================')
    return nb_train_pre,nb_test_pre
```

In [79]:
```
# to get best score and best alpha
alpha1,fit_prior1=NB_GridSearch(gene_train, y_train)
alpha2,fit_prior2=NB_GridSearch(variation_train, y_train)
```

```
alpha3,fit_prior3=NB_GridSearch(cleaned_text_train, y_train)
```

```
Best Score:  0.5970584437980415
Best Alpha:  {'alpha': 0.1, 'fit_prior': True}
Best Score:  0.7728241967182794
Best Alpha:  {'alpha': 0.1, 'fit_prior': True}
Best Score:  0.7511472104042424
Best Alpha:  {'alpha': 0.1, 'fit_prior': True}
```

In [80]:

```
# results
nb_train_pre1,nb_test_pre1=NaiveBayes(gene_train,y_train,gene_test,y_test,alpha1,fit_prior1)
nb_train_pre2,nb_test_pre2=NaiveBayes(variation_train,y_train,variation_test,y_test,alpha1,fit
_prior1)
nb_train_pre3,nb_test_pre3=NaiveBayes(cleaned_text_train,y_train,cleaned_text_test,y_test,alph
a1,fit_prior1)
```

```
Naive Bayes Train Accuracy Score : 0.6216807703530784
Naive Bayes Test Accuracy Score : 0.6003500583430572
Train data f1 score:0.6157672054520656
Test data f1 score:0.5930716695679839
confusion_matrix:[[ 93   2   7  28  36  12   8   2   4]
 [  3 115   5   1   8   7  27   9   2]
 [  7  10 118  13  31   0   1   9   0]
 [ 44   4   6 118  22   7   0   2   0]
 [ 12  12   3  11 101  17   7   6   4]
 [ 11   7   4   1  46  99  10  15   0]
 [  2  59  38   0  16   8  40  15   4]
 [  0  10   0   0   0   0   0 166  21]
 [  7   0   0   0   0   0   0  22 179]]
==================================================================
Naive Bayes Train Accuracy Score : 0.9772395681353954
Naive Bayes Test Accuracy Score : 0.8191365227537923
Train data f1 score:0.9774319139048305
Test data f1 score:0.8126132108732343
confusion_matrix:[[156   0   0   2  34   0   0   0   0]
 [  0 157   0   0  16   0   4   0   0]
 [  0   0 189   0   0   0   0   0   0]
 [  4   0   0 141  58   0   0   0   0]
 [  0   0   2   0 171   0   0   0   0]
 [  0   8   0   0  16 169   0   0   0]
 [  1  18   0   0 141   0  22   0   0]
 [  0   6   0   0   0   0   0 191   0]
 [  0   0   0   0   0   0   0   0 208]]
==================================================================
```

```
Naive Bayes Train Accuracy Score : 0.7993872191421068
Naive Bayes Test Accuracy Score : 0.7841306884480747
Train data f1 score:0.798351080032705
Test data f1 score:0.7846091468870092
confusion_matrix:[[135   1   2  18  24   8   3   1   0]
 [  2 153   0   1   1   0  19   1   0]
 [  2   1 146  19   8   0  13   0   0]
 [ 34   2   3 143  17   1   2   1   0]
 [ 10   8   3   5 117  10  14   3   3]
 [  5   8   2   2  19 147  10   0   0]
 [  1  38  12   0   1   0 129   1   0]
 [  0   0   0   0   0   0   0 176  21]
 [  0   0   0   0   0   0   0  10 198]]
==================================================================
```

Neural Network

In [65]:
```
# thanks to :https://realpython.com/python-keras-text-classification/
import keras
# from keras.models import Sequential
# from keras.layers import Dense, Dropout
# from keras.optimizers import RMSprop
from keras.optimizers import Adam, SGD
from keras.utils import to_categorical
```

In [70]:
```
def history_model(X_train, y_train,X_test, y_test):

    #Before we build our model, we need to know the input dimension of our feature vectors.
    input_dim = X_train.shape[1]
    # Add layers one by one in order
    model = Sequential()
    model.add(keras.layers.Dense(60, input_dim=input_dim, activation='relu', kernel_initialize
r='he_uniform'))
    model.add(keras.layers.Dense(10, activation='softmax'))
    opt = SGD(lr=0.01, momentum=0.9)
    #specify the optimizer and the loss function.
    model.compile(loss='categorical_crossentropy',
                  optimizer='adam',
                  metrics=['accuracy'])

    #Give an overview of the model and the number of parameters available for training:
    model.summary()
```

```
    model.summary()
    # # fit the model
    history = model.fit(X_train, y_train,epochs=50, verbose=2,
                        validation_data=(X_test, y_test),batch_size=70)
    return history, model
```

In [67]:
```
Y_train=to_categorical(y_train)
Y_test=to_categorical(y_test)
```

In [71]:
```
history1, model1=history_model(gene_train, Y_train,gene_test, Y_test)
history2, model2=history_model(variation_train, Y_train,variation_test, Y_test)
history3, model3=history_model(cleaned_text_train, Y_train,cleaned_text_test, Y_test)
```

```
Model: "sequential_6"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_11 (Dense)             (None, 60)                14520
_________________________________________________________________
dense_12 (Dense)             (None, 10)                610
=================================================================
Total params: 15,130
Trainable params: 15,130
Non-trainable params: 0
_________________________________________________________________
Train on 6854 samples, validate on 1714 samples
Epoch 1/50
 - 1s - loss: 2.2053 - accuracy: 0.2733 - val_loss: 2.0776 - val_accuracy: 0.4825
Epoch 2/50
 - 1s - loss: 1.8962 - accuracy: 0.5474 - val_loss: 1.6911 - val_accuracy: 0.5741
Epoch 3/50
 - 1s - loss: 1.4966 - accuracy: 0.5940 - val_loss: 1.3390 - val_accuracy: 0.5998
Epoch 4/50
 - 1s - loss: 1.2364 - accuracy: 0.6112 - val_loss: 1.1728 - val_accuracy: 0.5992
Epoch 5/50
 - 1s - loss: 1.1157 - accuracy: 0.6157 - val_loss: 1.0968 - val_accuracy: 0.5986
Epoch 6/50
 - 1s - loss: 1.0543 - accuracy: 0.6176 - val_loss: 1.0532 - val_accuracy: 0.6021
Epoch 7/50
 - 1s - loss: 1.0185 - accuracy: 0.6186 - val_loss: 1.0292 - val_accuracy: 0.6015
Epoch 8/50
 - 1s - loss: 0.9946 - accuracy: 0.6176 - val_loss: 1.0155 - val_accuracy: 0.5998
Epoch 9/50
```

```
 - 1s - loss: 0.9792 - accuracy: 0.6185 - val_loss: 1.0033 - val_accuracy: 0.6039
Epoch 10/50
 - 1s - loss: 0.9679 - accuracy: 0.6176 - val_loss: 0.9954 - val_accuracy: 0.6021
Epoch 11/50
 - 1s - loss: 0.9603 - accuracy: 0.6172 - val_loss: 0.9915 - val_accuracy: 0.5980
Epoch 12/50
 - 1s - loss: 0.9528 - accuracy: 0.6188 - val_loss: 0.9855 - val_accuracy: 0.5992
Epoch 13/50
 - 1s - loss: 0.9484 - accuracy: 0.6174 - val_loss: 0.9852 - val_accuracy: 0.5986
Epoch 14/50
 - 1s - loss: 0.9445 - accuracy: 0.6172 - val_loss: 0.9796 - val_accuracy: 0.6021
Epoch 15/50
 - 1s - loss: 0.9411 - accuracy: 0.6182 - val_loss: 0.9794 - val_accuracy: 0.5998
Epoch 16/50
 - 1s - loss: 0.9386 - accuracy: 0.6186 - val_loss: 0.9748 - val_accuracy: 0.6009
Epoch 17/50
 - 1s - loss: 0.9356 - accuracy: 0.6195 - val_loss: 0.9723 - val_accuracy: 0.6004
Epoch 18/50
 - 1s - loss: 0.9340 - accuracy: 0.6204 - val_loss: 0.9726 - val_accuracy: 0.5980
Epoch 19/50
 - 1s - loss: 0.9324 - accuracy: 0.6182 - val_loss: 0.9725 - val_accuracy: 0.6039
Epoch 20/50
 - 1s - loss: 0.9309 - accuracy: 0.6188 - val_loss: 0.9707 - val_accuracy: 0.6015
Epoch 21/50
 - 1s - loss: 0.9297 - accuracy: 0.6183 - val_loss: 0.9730 - val_accuracy: 0.5986
Epoch 22/50
 - 1s - loss: 0.9281 - accuracy: 0.6195 - val_loss: 0.9687 - val_accuracy: 0.6009
Epoch 23/50
 - 1s - loss: 0.9273 - accuracy: 0.6205 - val_loss: 0.9673 - val_accuracy: 0.6009
Epoch 24/50
 - 1s - loss: 0.9268 - accuracy: 0.6176 - val_loss: 0.9683 - val_accuracy: 0.5992
Epoch 25/50
 - 1s - loss: 0.9258 - accuracy: 0.6164 - val_loss: 0.9729 - val_accuracy: 0.5928
Epoch 26/50
 - 1s - loss: 0.9261 - accuracy: 0.6183 - val_loss: 0.9710 - val_accuracy: 0.6015
Epoch 27/50
 - 1s - loss: 0.9243 - accuracy: 0.6188 - val_loss: 0.9675 - val_accuracy: 0.6015
Epoch 28/50
 - 1s - loss: 0.9244 - accuracy: 0.6188 - val_loss: 0.9647 - val_accuracy: 0.6021
Epoch 29/50
 - 1s - loss: 0.9233 - accuracy: 0.6182 - val_loss: 0.9682 - val_accuracy: 0.6027
Epoch 30/50
 - 1s - loss: 0.9231 - accuracy: 0.6199 - val_loss: 0.9670 - val_accuracy: 0.5998
Epoch 31/50
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 - 1s - loss: 0.9234 - accuracy: 0.6183 - val_loss: 0.9696 - val_accuracy: 0.5998
Epoch 32/50
 - 1s - loss: 0.9219 - accuracy: 0.6208 - val_loss: 0.9678 - val_accuracy: 0.5974
Epoch 33/50
 - 1s - loss: 0.9227 - accuracy: 0.6188 - val_loss: 0.9667 - val_accuracy: 0.6039
Epoch 34/50
 - 1s - loss: 0.9220 - accuracy: 0.6185 - val_loss: 0.9653 - val_accuracy: 0.5963
Epoch 35/50
 - 1s - loss: 0.9218 - accuracy: 0.6193 - val_loss: 0.9659 - val_accuracy: 0.5992
Epoch 36/50
 - 1s - loss: 0.9206 - accuracy: 0.6167 - val_loss: 0.9660 - val_accuracy: 0.5992
Epoch 37/50
 - 1s - loss: 0.9210 - accuracy: 0.6176 - val_loss: 0.9666 - val_accuracy: 0.5980
Epoch 38/50
 - 1s - loss: 0.9208 - accuracy: 0.6186 - val_loss: 0.9669 - val_accuracy: 0.5980
Epoch 39/50
 - 1s - loss: 0.9203 - accuracy: 0.6185 - val_loss: 0.9668 - val_accuracy: 0.5992
Epoch 40/50
 - 1s - loss: 0.9203 - accuracy: 0.6195 - val_loss: 0.9670 - val_accuracy: 0.6004
Epoch 41/50
 - 0s - loss: 0.9198 - accuracy: 0.6186 - val_loss: 0.9687 - val_accuracy: 0.5974
Epoch 42/50
 - 0s - loss: 0.9186 - accuracy: 0.6172 - val_loss: 0.9701 - val_accuracy: 0.5957
Epoch 43/50
 - 1s - loss: 0.9194 - accuracy: 0.6170 - val_loss: 0.9687 - val_accuracy: 0.6009
Epoch 44/50
 - 0s - loss: 0.9191 - accuracy: 0.6189 - val_loss: 0.9701 - val_accuracy: 0.6009
Epoch 45/50
 - 1s - loss: 0.9190 - accuracy: 0.6170 - val_loss: 0.9711 - val_accuracy: 0.6015
Epoch 46/50
 - 1s - loss: 0.9190 - accuracy: 0.6169 - val_loss: 0.9667 - val_accuracy: 0.6033
Epoch 47/50
 - 1s - loss: 0.9184 - accuracy: 0.6191 - val_loss: 0.9686 - val_accuracy: 0.6015
Epoch 48/50
 - 1s - loss: 0.9194 - accuracy: 0.6202 - val_loss: 0.9686 - val_accuracy: 0.6009
Epoch 49/50
 - 1s - loss: 0.9186 - accuracy: 0.6161 - val_loss: 0.9658 - val_accuracy: 0.6009
Epoch 50/50
 - 1s - loss: 0.9190 - accuracy: 0.6191 - val_loss: 0.9659 - val_accuracy: 0.5974
Model: "sequential_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_13 (Dense)             (None, 60)                146880
```

```
dense_13 (Dense)             (None, 60)                140000
_________________________________________________________________
dense_14 (Dense)             (None, 10)                610
=================================================================
Total params: 147,490
Trainable params: 147,490
Non-trainable params: 0
_________________________________________________________________
Train on 6854 samples, validate on 1714 samples
Epoch 1/50
 - 1s - loss: 2.2117 - accuracy: 0.4056 - val_loss: 2.0611 - val_accuracy: 0.7089
Epoch 2/50
 - 1s - loss: 1.7969 - accuracy: 0.8297 - val_loss: 1.5322 - val_accuracy: 0.7795
Epoch 3/50
 - 1s - loss: 1.2291 - accuracy: 0.9472 - val_loss: 1.0709 - val_accuracy: 0.8891
Epoch 4/50
 - 1s - loss: 0.7919 - accuracy: 0.9745 - val_loss: 0.7719 - val_accuracy: 0.8938
Epoch 5/50
 - 1s - loss: 0.5054 - accuracy: 0.9746 - val_loss: 0.5878 - val_accuracy: 0.8996
Epoch 6/50
 - 1s - loss: 0.3286 - accuracy: 0.9756 - val_loss: 0.4797 - val_accuracy: 0.8973
Epoch 7/50
 - 1s - loss: 0.2233 - accuracy: 0.9755 - val_loss: 0.4153 - val_accuracy: 0.8985
Epoch 8/50
 - 1s - loss: 0.1626 - accuracy: 0.9772 - val_loss: 0.3779 - val_accuracy: 0.8961
Epoch 9/50
 - 1s - loss: 0.1269 - accuracy: 0.9755 - val_loss: 0.3549 - val_accuracy: 0.8996
Epoch 10/50
 - 1s - loss: 0.1047 - accuracy: 0.9762 - val_loss: 0.3403 - val_accuracy: 0.8938
Epoch 11/50
 - 1s - loss: 0.0905 - accuracy: 0.9765 - val_loss: 0.3314 - val_accuracy: 0.8961
Epoch 12/50
 - 1s - loss: 0.0814 - accuracy: 0.9759 - val_loss: 0.3257 - val_accuracy: 0.8973
Epoch 13/50
 - 1s - loss: 0.0745 - accuracy: 0.9768 - val_loss: 0.3201 - val_accuracy: 0.8961
Epoch 14/50
 - 1s - loss: 0.0700 - accuracy: 0.9752 - val_loss: 0.3201 - val_accuracy: 0.8973
Epoch 15/50
 - 1s - loss: 0.0662 - accuracy: 0.9765 - val_loss: 0.3127 - val_accuracy: 0.8961
Epoch 16/50
 - 1s - loss: 0.0634 - accuracy: 0.9767 - val_loss: 0.3134 - val_accuracy: 0.8973
Epoch 17/50
 - 1s - loss: 0.0613 - accuracy: 0.9764 - val_loss: 0.3110 - val_accuracy: 0.8973
Epoch 18/50
```

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 - 1s - loss: 0.0603 - accuracy: 0.9761 - val_loss: 0.3097 - val_accuracy: 0.8973
Epoch 19/50
 - 1s - loss: 0.0581 - accuracy: 0.9764 - val_loss: 0.3118 - val_accuracy: 0.8973
Epoch 20/50
 - 1s - loss: 0.0576 - accuracy: 0.9767 - val_loss: 0.3107 - val_accuracy: 0.8973
Epoch 21/50
 - 1s - loss: 0.0564 - accuracy: 0.9768 - val_loss: 0.3046 - val_accuracy: 0.8996
Epoch 22/50
 - 1s - loss: 0.0552 - accuracy: 0.9768 - val_loss: 0.3131 - val_accuracy: 0.8967
Epoch 23/50
 - 1s - loss: 0.0551 - accuracy: 0.9751 - val_loss: 0.3073 - val_accuracy: 0.8973
Epoch 24/50
 - 1s - loss: 0.0539 - accuracy: 0.9774 - val_loss: 0.3048 - val_accuracy: 0.8961
Epoch 25/50
 - 1s - loss: 0.0534 - accuracy: 0.9769 - val_loss: 0.3041 - val_accuracy: 0.8973
Epoch 26/50
 - 1s - loss: 0.0535 - accuracy: 0.9769 - val_loss: 0.3032 - val_accuracy: 0.8973
Epoch 27/50
 - 1s - loss: 0.0529 - accuracy: 0.9765 - val_loss: 0.3025 - val_accuracy: 0.8973
Epoch 28/50
 - 1s - loss: 0.0526 - accuracy: 0.9759 - val_loss: 0.3079 - val_accuracy: 0.8961
Epoch 29/50
 - 1s - loss: 0.0523 - accuracy: 0.9752 - val_loss: 0.3037 - val_accuracy: 0.8961
Epoch 30/50
 - 1s - loss: 0.0519 - accuracy: 0.9755 - val_loss: 0.3026 - val_accuracy: 0.8996
Epoch 31/50
 - 1s - loss: 0.0520 - accuracy: 0.9758 - val_loss: 0.3043 - val_accuracy: 0.8973
Epoch 32/50
 - 1s - loss: 0.0517 - accuracy: 0.9767 - val_loss: 0.3073 - val_accuracy: 0.8950
Epoch 33/50
 - 1s - loss: 0.0514 - accuracy: 0.9748 - val_loss: 0.3088 - val_accuracy: 0.8973
Epoch 34/50
 - 1s - loss: 0.0512 - accuracy: 0.9769 - val_loss: 0.2999 - val_accuracy: 0.8996
Epoch 35/50
 - 1s - loss: 0.0509 - accuracy: 0.9767 - val_loss: 0.2999 - val_accuracy: 0.8996
Epoch 36/50
 - 1s - loss: 0.0509 - accuracy: 0.9759 - val_loss: 0.3024 - val_accuracy: 0.8996
Epoch 37/50
 - 1s - loss: 0.0508 - accuracy: 0.9772 - val_loss: 0.3046 - val_accuracy: 0.8973
Epoch 38/50
 - 1s - loss: 0.0509 - accuracy: 0.9765 - val_loss: 0.3097 - val_accuracy: 0.8950
Epoch 39/50
 - 1s - loss: 0.0504 - accuracy: 0.9759 - val_loss: 0.3018 - val_accuracy: 0.8996
Epoch 40/50
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```
 - 1s - loss: 0.0506 - accuracy: 0.9755 - val_loss: 0.2980 - val_accuracy: 0.8996
Epoch 41/50
 - 1s - loss: 0.0501 - accuracy: 0.9767 - val_loss: 0.3014 - val_accuracy: 0.8996
Epoch 42/50
 - 1s - loss: 0.0502 - accuracy: 0.9762 - val_loss: 0.3017 - val_accuracy: 0.8938
Epoch 43/50
 - 1s - loss: 0.0500 - accuracy: 0.9755 - val_loss: 0.3043 - val_accuracy: 0.8961
Epoch 44/50
 - 1s - loss: 0.0497 - accuracy: 0.9769 - val_loss: 0.2981 - val_accuracy: 0.8996
Epoch 45/50
 - 1s - loss: 0.0504 - accuracy: 0.9753 - val_loss: 0.3022 - val_accuracy: 0.8961
Epoch 46/50
 - 1s - loss: 0.0496 - accuracy: 0.9772 - val_loss: 0.3020 - val_accuracy: 0.8973
Epoch 47/50
 - 1s - loss: 0.0504 - accuracy: 0.9742 - val_loss: 0.3066 - val_accuracy: 0.8973
Epoch 48/50
 - 1s - loss: 0.0499 - accuracy: 0.9772 - val_loss: 0.3020 - val_accuracy: 0.8961
Epoch 49/50
 - 1s - loss: 0.0501 - accuracy: 0.9758 - val_loss: 0.3011 - val_accuracy: 0.8973
Epoch 50/50
 - 1s - loss: 0.0498 - accuracy: 0.9767 - val_loss: 0.3061 - val_accuracy: 0.8973
Model: "sequential_8"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_15 (Dense)             (None, 60)                7647120
_________________________________________________________________
dense_16 (Dense)             (None, 10)                610
=================================================================
Total params: 7,647,730
Trainable params: 7,647,730
Non-trainable params: 0
_________________________________________________________________
Train on 6854 samples, validate on 1714 samples
Epoch 1/50
 - 27s - loss: 1.1684 - accuracy: 0.6570 - val_loss: 0.6470 - val_accuracy: 0.7993
Epoch 2/50
 - 27s - loss: 0.5375 - accuracy: 0.8216 - val_loss: 0.5605 - val_accuracy: 0.8186
Epoch 3/50
 - 26s - loss: 0.4335 - accuracy: 0.8496 - val_loss: 0.4699 - val_accuracy: 0.8518
Epoch 4/50
 - 25s - loss: 0.3750 - accuracy: 0.8653 - val_loss: 0.4928 - val_accuracy: 0.8471
Epoch 5/50
 - 25s - loss: 0.3608 - accuracy: 0.8677 - val_loss: 0.4879 - val_accuracy: 0.8431
```

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 - 25s - loss: 0.3608 - accuracy: 0.8677 - val_loss: 0.4679 - val_accuracy: 0.8451
Epoch 6/50
 - 26s - loss: 0.3518 - accuracy: 0.8726 - val_loss: 0.4457 - val_accuracy: 0.8495
Epoch 7/50
 - 30s - loss: 0.3348 - accuracy: 0.8793 - val_loss: 0.4756 - val_accuracy: 0.8559
Epoch 8/50
 - 38s - loss: 0.3156 - accuracy: 0.8761 - val_loss: 0.4620 - val_accuracy: 0.8553
Epoch 9/50
 - 51s - loss: 0.3096 - accuracy: 0.8802 - val_loss: 0.4638 - val_accuracy: 0.8448
Epoch 10/50
 - 32s - loss: 0.3121 - accuracy: 0.8821 - val_loss: 0.4943 - val_accuracy: 0.8384
Epoch 11/50
 - 30s - loss: 0.3038 - accuracy: 0.8808 - val_loss: 0.4697 - val_accuracy: 0.8524
Epoch 12/50
 - 27s - loss: 0.2952 - accuracy: 0.8837 - val_loss: 0.5020 - val_accuracy: 0.8489
Epoch 13/50
 - 28s - loss: 0.2845 - accuracy: 0.8865 - val_loss: 0.4479 - val_accuracy: 0.8565
Epoch 14/50
 - 27s - loss: 0.2838 - accuracy: 0.8879 - val_loss: 0.4757 - val_accuracy: 0.8635
Epoch 15/50
 - 49s - loss: 0.2903 - accuracy: 0.8869 - val_loss: 0.4753 - val_accuracy: 0.8541
Epoch 16/50
 - 28s - loss: 0.2719 - accuracy: 0.8913 - val_loss: 0.4635 - val_accuracy: 0.8606
Epoch 17/50
 - 31s - loss: 0.2729 - accuracy: 0.8901 - val_loss: 0.4451 - val_accuracy: 0.8670
Epoch 18/50
 - 28s - loss: 0.2737 - accuracy: 0.8884 - val_loss: 0.4392 - val_accuracy: 0.8594
Epoch 19/50
 - 33s - loss: 0.2650 - accuracy: 0.8923 - val_loss: 0.4662 - val_accuracy: 0.8652
Epoch 20/50
 - 31s - loss: 0.2721 - accuracy: 0.8906 - val_loss: 0.5097 - val_accuracy: 0.8466
Epoch 21/50
 - 31s - loss: 0.2710 - accuracy: 0.8887 - val_loss: 0.4537 - val_accuracy: 0.8617
Epoch 22/50
 - 30s - loss: 0.2610 - accuracy: 0.8910 - val_loss: 0.4620 - val_accuracy: 0.8419
Epoch 23/50
 - 27s - loss: 0.2666 - accuracy: 0.8910 - val_loss: 0.4564 - val_accuracy: 0.8565
Epoch 24/50
 - 28s - loss: 0.2566 - accuracy: 0.8947 - val_loss: 0.4734 - val_accuracy: 0.8652
Epoch 25/50
 - 27s - loss: 0.2569 - accuracy: 0.8926 - val_loss: 0.4762 - val_accuracy: 0.8536
Epoch 26/50
 - 27s - loss: 0.2626 - accuracy: 0.8944 - val_loss: 0.4713 - val_accuracy: 0.8705
Epoch 27/50
```

```
 - 27s - loss: 0.2604 - accuracy: 0.8929 - val_loss: 0.4359 - val_accuracy: 0.8629
Epoch 28/50
 - 28s - loss: 0.2614 - accuracy: 0.8919 - val_loss: 0.4347 - val_accuracy: 0.8681
Epoch 29/50
 - 27s - loss: 0.2577 - accuracy: 0.8923 - val_loss: 0.4543 - val_accuracy: 0.8594
Epoch 30/50
 - 28s - loss: 0.2540 - accuracy: 0.8947 - val_loss: 0.4673 - val_accuracy: 0.8588
Epoch 31/50
 - 29s - loss: 0.2593 - accuracy: 0.8938 - val_loss: 0.4529 - val_accuracy: 0.8547
Epoch 32/50
 - 28s - loss: 0.2523 - accuracy: 0.8954 - val_loss: 0.4746 - val_accuracy: 0.8536
Epoch 33/50
 - 28s - loss: 0.2544 - accuracy: 0.8958 - val_loss: 0.4812 - val_accuracy: 0.8606
Epoch 34/50
 - 26s - loss: 0.2511 - accuracy: 0.8933 - val_loss: 0.4650 - val_accuracy: 0.8629
Epoch 35/50
 - 28s - loss: 0.2434 - accuracy: 0.8974 - val_loss: 0.4677 - val_accuracy: 0.8693
Epoch 36/50
 - 27s - loss: 0.2493 - accuracy: 0.8945 - val_loss: 0.5142 - val_accuracy: 0.8588
Epoch 37/50
 - 27s - loss: 0.2489 - accuracy: 0.8961 - val_loss: 0.4614 - val_accuracy: 0.8606
Epoch 38/50
 - 27s - loss: 0.2511 - accuracy: 0.8950 - val_loss: 0.4824 - val_accuracy: 0.8699
Epoch 39/50
 - 28s - loss: 0.2532 - accuracy: 0.8929 - val_loss: 0.4608 - val_accuracy: 0.8611
Epoch 40/50
 - 27s - loss: 0.2498 - accuracy: 0.8952 - val_loss: 0.4679 - val_accuracy: 0.8746
Epoch 41/50
 - 26s - loss: 0.2507 - accuracy: 0.8957 - val_loss: 0.4813 - val_accuracy: 0.8641
Epoch 42/50
 - 29s - loss: 0.2522 - accuracy: 0.8936 - val_loss: 0.4689 - val_accuracy: 0.8699
Epoch 43/50
 - 28s - loss: 0.2441 - accuracy: 0.8987 - val_loss: 0.4864 - val_accuracy: 0.8699
Epoch 44/50
 - 26s - loss: 0.2391 - accuracy: 0.8974 - val_loss: 0.4942 - val_accuracy: 0.8623
Epoch 45/50
 - 26s - loss: 0.2410 - accuracy: 0.8986 - val_loss: 0.4780 - val_accuracy: 0.8763
Epoch 46/50
 - 27s - loss: 0.2442 - accuracy: 0.8942 - val_loss: 0.4952 - val_accuracy: 0.8571
Epoch 47/50
 - 27s - loss: 0.2392 - accuracy: 0.8977 - val_loss: 0.5171 - val_accuracy: 0.8600
Epoch 48/50
 - 26s - loss: 0.2377 - accuracy: 0.8990 - val_loss: 0.4981 - val_accuracy: 0.8676
Epoch 49/50
```

```
 - 27s - loss: 0.2392 - accuracy: 0.8961 - val_loss: 0.4993 - val_accuracy: 0.8763
Epoch 50/50
 - 27s - loss: 0.2401 - accuracy: 0.8993 - val_loss: 0.5078 - val_accuracy: 0.8611
```

In [75]:

```
def NN_results(history,model,x_train,x_test):
    #prediction
    nn_train_pre=model.predict_classes(x_train)
    nn_test_pre=model.predict_classes(x_test)
    #calculate f1 scores for test data and train data
    nn_f1_score_test=f1_score([int(i) for i in y_test],nn_test_pre,average='weighted')
    nn_f1_score_train=f1_score(y_train,nn_train_pre,average='weighted')
    print("Train data f1 score:{}".format(nn_f1_score_train))
    print("Test data f1 score:{}".format(nn_f1_score_test ))
    print(confusion_matrix(y_test, nn_test_pre))
    print('==================================================================')
    return nn_train_pre,nn_test_pre
```

In [76]:

```
# apply funtion above to obtian the results
nn_train_pre1,nn_test_pre1=NN_results(history1,model1,gene_train,gene_test)
nn_train_pre2,nn_test_pre2=NN_results(history2,model2,variation_train,variation_test)
nn_train_pre3,nn_test_pre3=NN_results(history3,model3,cleaned_text_train,cleaned_text_test)
```

```
Train data f1 score:0.6143893769581936
Test data f1 score:0.5884727438700839
[[ 82   7   7  39  30  13   8   2   4]
 [  4 115   5   1   7   7  27   9   2]
 [  7  10 118  13  31   0   1   9   0]
 [ 34   7   6 128  19   7   0   2   0]
 [ 11  12   3  13  97  20   7   6   4]
 [  6   7   4   6  46  99  10  15   0]
 [  2  62  38   0  13   8  40  15   4]
 [  0  10   0   0   0   0   0 166  21]
 [  7   0   0   0   0   0   0  22 179]]
==================================================================
Train data f1 score:0.9780175131194836
Test data f1 score:0.9038712574030837
[[156   0   0   2   0   0  34   0   0]
 [  0 157   0   0   1   0  19   0   0]
 [  0   0 189   0   0   0   0   0   0]
 [  4   0   0 141   1   0  57   0   0]
 [  0   0   2   0 160   0  11   0   0]
 [  0   8   0   0   0 169  16   0   0]
 [  0  15   0   0   0   0 167   0   0]
```

```
 [  0   6   0   0   0   0   0 191   0]
 [  0   0   0   0   0   0   0   0 208]]
==================================================================
Train data f1 score:0.9008979145717564
Test data f1 score:0.8606824067325949
[[149   2   4   9  18  10   0   0   0]
 [  1 163   0   0   5   0   8   0   0]
 [  2   0 173  11   3   0   0   0   0]
 [ 24   1  10 157   5   4   2   0   0]
 [ 14   1   2   9 135   5   4   0   3]
 [  5   2   0   0  20 165   1   0   0]
 [  5  31  11   0   4   1 129   0   1]
 [  0   0   0   0   0   0   0 197   0]
 [  0   0   0   0   0   0   0   0 208]]
==================================================================
```

Logistic regression

In [87]:

```
#import Logistic Regression
from sklearn.linear_model import LogisticRegression

def Logistic_Regression(X_train, y_train,X_test, y_test):
    log_re = LogisticRegression(max_iter=1000)
    log_re.fit(X_train, y_train)
    #calculate scores for test data and train data
    test_data_score = log_re.score(X_test, y_test)
    train_data_score = log_re.score(X_train, y_train)
    print("Train data score:{}".format(train_data_score ))
    print("Test data score:{}".format(test_data_score ))
    # predict values for test data and train data
    log_y_test_pre=log_re.predict(X_test)
    log_y_train_pre=log_re.predict(X_train)
    # calculate f1 scores for test data and train data
    log_f1_score_test=f1_score(y_test,log_y_test_pre,average="weighted")
    log_f1_score_train=f1_score(y_train,log_y_train_pre,average="weighted")

    print("Train data f1 score:{}".format(log_f1_score_train))
    print("Test data f1 score:{}".format(log_f1_score_test ))
    print('==================================================================')
    return log_y_train_pre,log_y_test_pre
```

In [88]:
```
log_y_train_pre1,log_y_test_pre1=Logistic_Regression(gene_train, y_train,gene_test, y_test)
log_y_train_pre2,log_y_test_pr2=Logistic_Regression(variation_train, y_train,variation_test, y
_test)
log_y_train_pre3,log_y_test_pre3=Logistic_Regression(cleaned_text_train, y_train,cleaned_text_
test, y_test)
```

```
Train data score:0.621388969944558
Test data score:0.603267211201867
Train data f1 score:0.615936855192663
Test data f1 score:0.5957018668273237
================================================================
Train data score:0.9768018675226146
Test data score:0.8961493582263711
Train data f1 score:0.9769987251836152
Test data f1 score:0.9029228363338574
================================================================
Train data score:0.9034140647796907
Test data score:0.8640606767794633
Train data f1 score:0.9039234128069726
Test data f1 score:0.8628257154404384
================================================================
```

Model Stacking

In [89]:
```
X_train = pd.DataFrame( {
    'nb_gene':nb_train_pre1,
    'nb_variation':nb_train_pre2,
    'nb_text':nb_train_pre3,
    'nn_gene':nn_train_pre1,
    'nn_variation':nn_train_pre2,
    'nn_text':nn_train_pre3,
    'log_gene':log_y_train_pre1,
    'log_variation':log_y_train_pre2,
    'log_text':log_y_train_pre3
   })

X_test = pd.DataFrame( {
    'nb_gene':nb_test_pre1,
    'nb_variation':nb_test_pre2,
    'nb_text':nb_test_pre3,
    'nn_gene':nn_test_pre1,
    'nn_variation':nn_test_pre2,
```

```
    'nn_text':nn_test_pre3,
    'log_gene':log_y_test_pre1,
    'log_variation':log_y_test_pr2,
    'log_text':log_y_test_pre3
        })
```

In [90]:
```
X_train.head()
```

Out[90]:

	nb_gene	nb_variation	nb_text	nn_gene	nn_variation	nn_text	log_gene	log_variation	log_text
0	5	1	5	5	1	5	5	1	5
1	7	7	7	7	7	7	7	7	7
2	9	9	9	9	9	9	9	9	9
3	3	3	3	3	3	3	3	3	3
4	7	2	2	7	2	2	7	2	2

In [91]:
```
X_test.head()
```

Out[91]:

	nb_gene	nb_variation	nb_text	nn_gene	nn_variation	nn_text	log_gene	log_variation	log_text
0	5	5	5	5	5	5	5	5	5
1	1	1	1	1	1	1	1	1	1
2	3	3	3	3	3	3	3	3	3
3	4	4	4	4	4	4	4	4	4
4	2	2	2	2	2	2	2	2	2

XGboost

In [92]:
```
from sklearn.model_selection import RandomizedSearchCV
import xgboost as xgb

# given prameters different values
RS={
             'n_estimators':list(range(260,290)),
                'max_depth':list(range(13,18)),
```

```
                 'max_features':[1,2,3],
               'min_samples_leaf':[13,14,15,16,17,18],
                'min_samples_split':[5,6,7,8,9,10]
               }
gbm=xgb.XGBClassifier(
                       n_jobs=-1,
                       random_state=0)
# randommized searchCV
rs=RandomizedSearchCV(gbm,RS,cv=5,scoring=f1,verbose=0)
```

In [93]:
```
# fit the train data
rs.fit(X_train,y_train)
```

Out[93]:
```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                           colsample_bylevel=1,
                                           colsample_bynode=1,
                                           colsample_bytree=1, gamma=0,
                                           learning_rate=0.1, max_delta_step=0,
                                           max_depth=3, min_child_weight=1,
                                           missing=None, n_estimators=100,
                                           n_jobs=-1, nthread=None,
                                           objective='binary:logistic',
                                           random_state=0, reg_alpha=0,
                                           reg_lambda=1, s...
                                         'max_features': [1, 2, 3],
                                         'min_samples_leaf': [13, 14, 15, 16, 17,
                                                              18],
                                         'min_samples_split': [5, 6, 7, 8, 9,
                                                               10],
                                         'n_estimators': [260, 261, 262, 263,
                                                          264, 265, 266, 267,
                                                          268, 269, 270, 271,
                                                          272, 273, 274, 275,
                                                          276, 277, 278, 279,
                                                          280, 281, 282, 283,
                                                          284, 285, 286, 287,
                                                          288, 289]},
                   pre_dispatch='2*n_jobs', random_state=None, refit=True,
                   return_train_score=False,
                   scoring=make_scorer(f1_score, average=weighted), verbose=0)
```

In [95]:
```
# obtian best parameters best score
rs.best_score_, rs.best_params
```

```
rs.best_score_,rs.best_params_
```

Out[95]:
```
(0.9948908366372446,
 {'n_estimators': 280,
  'min_samples_split': 5,
  'min_samples_leaf': 14,
  'max_features': 1,
  'max_depth': 13})
```

In [96]:
```
GBM = xgb.XGBClassifier(
                        n_estimators=280,
                        min_samples_split=5,
                        min_samples_leaf=14,
                        max_features= 1,
                        max_depth=13,
                        n_jobs=-1,
                        random_state=0)
# fit the model
GBM.fit(X_train, y_train)
```

Out[96]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=13, max_features=1,
              min_child_weight=1, min_samples_leaf=14, min_samples_split=5,
              missing=None, n_estimators=280, n_jobs=-1, nthread=None,
              objective='multi:softprob', random_state=0, reg_alpha=0,
              reg_lambda=1, scale_pos_weight=1, seed=None, silent=None,
              subsample=1, verbosity=1)
```

In [97]:
```
train_pre=GBM.predict(X_train)
test_pre=GBM.predict(X_test)
# obtian f1 score
f1_score_train=f1_score(list(y_train),train_pre,average="weighted")
f1_score_test=f1_score(list(y_test),test_pre,average="weighted")
# Score for train and test data
print("F1 Score of train data :" , f1_score_train)
print("F1 Score of test data :" ,f1_score_test)
```

```
F1 Score of train data : 0.9969347300484679
F1 Score of test data : 0.920427735492214
```

In [98]:
```
accuracy_train=accuracy_score(list(y_train),train_pre)
accuracy_test=accuracy_score(list(y_test),test_pre)
print("Accuracy of train data :" , accuracy_train)
print("Accuracy of test data :" ,accuracy_test)
```

```
Accuracy of train data : 0.996936095710534
Accuracy of test data : 0.9148191365227538
```

In [101]:
```
import itertools

def plot_confusion_matrix(cm, classes,

                        normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion Matrix, without normalization')

    print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

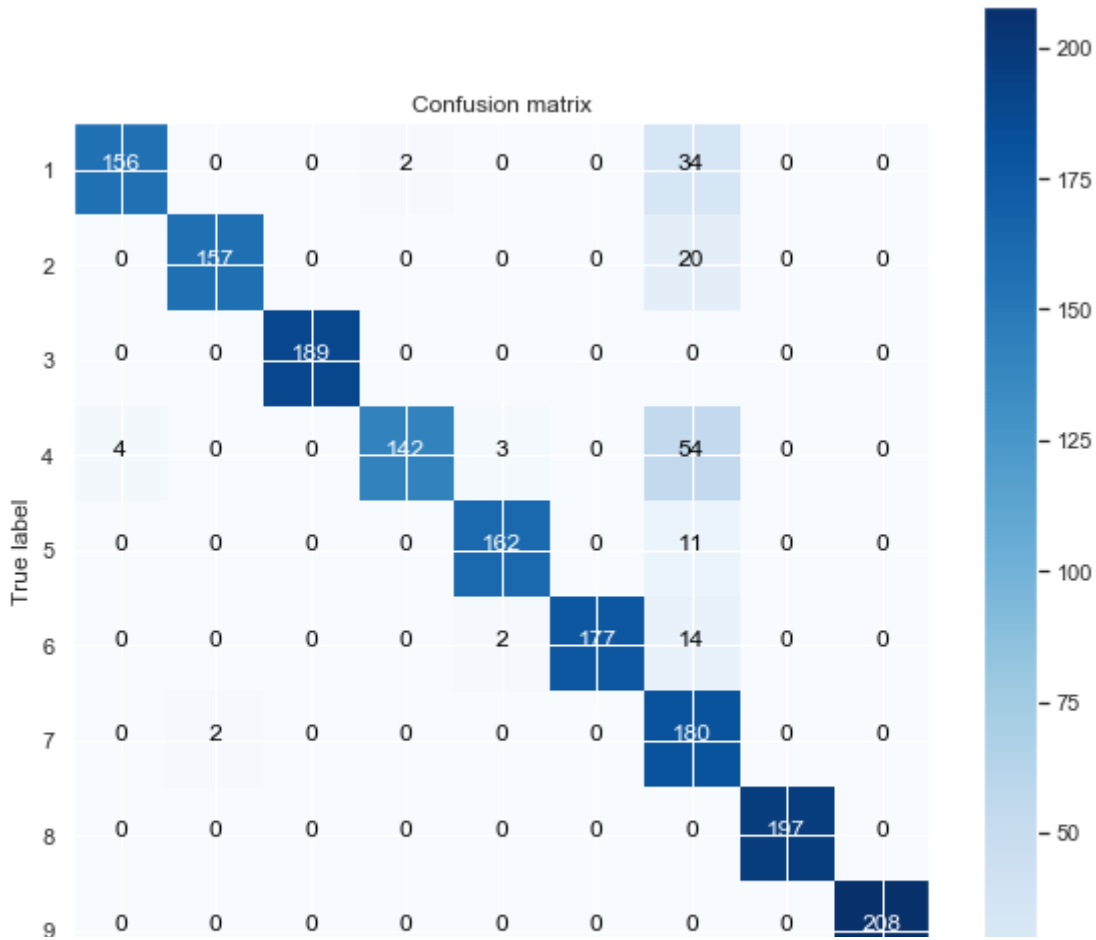
    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

In [102]:
```
classes=[1,2,3,4,5,6,7,8,9]
plt.figure(figsize=(8,8))
```

```
plot_confusion_matrix(confusion_matrix(y_test,test_pre), classes,
                      normalize=False,
                      title='Confusion matrix'
                     )
plt.show()
```

```
Confusion Matrix, without normalization
[[156   0   0   2   0   0  34   0   0]
 [  0 157   0   0   0   0  20   0   0]
 [  0   0 189   0   0   0   0   0   0]
 [  4   0   0 142   3   0  54   0   0]
 [  0   0   0   0 162   0  11   0   0]
 [  0   0   0   0   2 177  14   0   0]
 [  0   2   0   0   0   0 180   0   0]
 [  0   0   0   0   0   0   0 197   0]
 [  0   0   0   0   0   0   0   0 208]]
```



In [104]:
```
# Prediction vs Actual Values
y_test.value_counts().sort_index().plot(kind='bar',label='Actual Values',color='blue')
pd.Series(test_pre).value_counts().sort_index().plot(kind='bar',label='Predicted Values',color
='r',alpha=0.7)
plt.title('Actual Values VS Predictied Values')
plt.xlabel('Classes')
plt.ylabel("Counts")
plt.legend()
plt.show()
```