Here we look at Medical Transcriptions dataset from Kaggle <a href="https://www.kaggle.com/tboyle10/medicaltranscriptions">https://www.kaggle.com/tboyle10/medicaltranscriptions</a>

This data was scraped from mtsamples.com

Inspiration Can you correctly classify the medical specialties based on the transcription text?

Let us import all the necessary libraries

```
import spacy
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import string
import re
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.decomposition import PCA
from sklearn.linear model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.manifold import TSNE
from nltk.tokenize import word_tokenize
from nltk.tokenize import sent_tokenize
from nltk.stem import WordNetLemmatizer
from imblearn.over_sampling import SMOTE
```

A method to get unique words(vocabulary) and sentence count in a list of text

```
def get_sentence_word_count(text_list):
   sent_count = 0
   word_count = 0
   vocab = \{\}
   for text in text_list:
        sentences=sent_tokenize(str(text).lower())
        sent_count = sent_count + len(sentences)
        for sentence in sentences:
            words=word_tokenize(sentence)
            for word in words:
                if(word in vocab.keys()):
                    vocab[word] = vocab[word] +1
                else:
                    vocab[word] =1
   word count = len(vocab.keys())
   return sent_count,word_count
```

Lets do some exploratory analysis of data

```
clinical_text_df = pd.read_csv('mtsamples.csv')
print(clinical_text_df.columns)
clinical_text_df.head(5)
```

	Unnamed: 0	description	medical_specialty	sample_name	transcription	keywords
0	0	A 23-year-old white female presents with comp	Allergy / Immunology	Allergic Rhinitis	SUBJECTIVE:, This 23-year- old white female pr	allergy / immunology, allergic rhinitis, aller
1	1	Consult for laparoscopic gastric bypass.	Bariatrics	Laparoscopic Gastric Bypass Consult - 2	PAST MEDICAL HISTORY:, He has difficulty climb	bariatrics, laparoscopic gastric bypass, weigh
2	2	Consult for laparoscopic gastric bypass.	Bariatrics	Laparoscopic Gastric Bypass Consult - 1	HISTORY OF PRESENT ILLNESS: , I have seen ABC	bariatrics, laparoscopic gastric bypass, heart
3	3	2-D M-Mode. Doppler.	Cardiovascular / Pulmonary	2-D Echocardiogram - 1	2-D M-MODE: , ,1. Left atrial enlargement wit	cardiovascular / pulmonary, 2-d m-mode, dopple
4	4	2-D Echocardiogram	Cardiovascular / Pulmonary	2-D Echocardiogram - 2	The left ventricular cavity     size and wall	cardiovascular / pulmonary, 2-d, doppler, echo

```
clinical_text_df = clinical_text_df[clinical_text_df['transcription'].notna()]
sent_count,word_count= get_sentence_word_count(clinical_text_df['transcription'].tolist())
print("Number of sentences in transcriptions column: "+ str(sent_count))
print("Number of unique words in transcriptions column: "+str(word_count))

data_categories = clinical_text_df.groupby(clinical_text_df['medical_specialty'])
i = 1
print('==========0riginal Categories =============')
for catName,dataCategory in data_categories:
    print('Cat:'+str(i)+' '+catName + ' : '+ str(len(dataCategory)) )
```

```
i = i+1
print('==========')
```

```
Number of sentences in transcriptions column: 140214
Number of unique words in transcriptions column: 35822
=======0riginal Categories ===========
Cat:1 Allergy / Immunology: 7
Cat:2 Autopsy: 8
Cat:3 Bariatrics: 18
Cat:4 Cardiovascular / Pulmonary: 371
Cat:5 Chiropractic: 14
Cat:6 Consult - History and Phy.: 516
Cat:7 Cosmetic / Plastic Surgery: 27
Cat:8 Dentistry: 27
Cat:9 Dermatology: 29
Cat:10 Diets and Nutritions: 10
Cat:11 Discharge Summary: 108
Cat:12 ENT - Otolaryngology: 96
Cat:13 Emergency Room Reports: 75
Cat:14 Endocrinology: 19
Cat:15 Gastroenterology: 224
Cat:16 General Medicine: 259
Cat:17 Hematology - Oncology: 90
Cat:18 Hospice - Palliative Care: 6
Cat:19 IME-OME-Work Comp etc.: 16
Cat:20 Lab Medicine - Pathology: 8
Cat:21 Letters: 23
Cat:22 Nephrology: 81
Cat:23 Neurology: 223
Cat:24 Neurosurgery: 94
Cat:25 Obstetrics / Gynecology: 155
Cat:26 Office Notes: 50
Cat:27 Ophthalmology: 83
Cat:28 Orthopedic: 355
Cat:29 Pain Management: 61
Cat:30 Pediatrics - Neonatal: 70
```

```
Cat:31 Physical Medicine - Rehab: 21
    Cat:32 Podiatry: 47
    Cat:33 Psychiatry / Psychology: 53
    Cat:34 Radiology: 273
    Cat:35 Rheumatology: 10
    Cat:36 SOAP / Chart / Progress Notes : 166
    Cat:37 Sleep Medicine: 20
    Cat:38 Speech - Language: 9
    Cat:39 Surgery: 1088
    Cat:40 Urology: 156
    _____
filtered data categories = data categories.filter(lambda x:x.shape[0] > 50)
final data categories = filtered data categories.groupby(filtered data categories['medical specialty'])
i=1
print('======Reduced Categories =========')
for catName,dataCategory in final_data_categories:
   print('Cat:'+str(i)+' '+catName + ' : '+ str(len(dataCategory)) )
   i = i+1
print('======= Reduced Categories =========')
Cat:1 Cardiovascular / Pulmonary: 371
    Cat:2 Consult - History and Phy.: 516
    Cat: 3 Discharge Summary: 108
    Cat:4 ENT - Otolaryngology: 96
    Cat:5 Emergency Room Reports: 75
    Cat:6 Gastroenterology: 224
    Cat:7 General Medicine: 259
    Cat:8 Hematology - Oncology: 90
    Cat:9 Nephrology: 81
    Cat:10 Neurology: 223
    Cat:11 Neurosurgery: 94
    Cat:12 Obstetrics / Gynecology: 155
    Cat:13 Ophthalmology: 83
    Cat:14 Orthopedic: 355
    Cat:15 Pain Management: 61
```

```
Cat:16 Pediatrics - Neonatal: 70
   Cat:17 Psychiatry / Psychology: 53
   Cat:18 Radiology: 273
   Cat:19 SOAP / Chart / Progress Notes : 166
   Cat:20 Surgery: 1088
   Cat:21 Urology: 156
   ======= Reduced Categories ==========
print('=======Reduced Categories Transcription example============')
i=1
for catName, dataCategory in final data categories:
  print('Cat:'+str(i)+' '+catName + ' : '+ str(len(dataCategory)) )
  dataList = dataCategory['transcription'].tolist()
  print('==========')
  print('Sample Transcription:'+str(dataList[10]))
  print('=========:')
  i = i+1
print('======== Reduced Categories Transcription example==========')
   =======Reduced Categories Transcription example=============
   Cat:1 Cardiovascular / Pulmonary: 371
   _____
   Sample Transcription: PREOPERATIVE DIAGNOSIS: , Need for intravenous access., POSTOPERATIVE DIAGNOSIS: , Need for int
   ______
   Cat:2 Consult - History and Phy.: 516
   _____
   Sample Transcription: CHIEF COMPLAINT:, Well-child check., HISTORY OF PRESENT ILLNESS:, This is a 12-month-old fema
   _____
   Cat: 3 Discharge Summary: 108
   _____
   Sample Transcription: ADMITTING DIAGNOSES, 1. Prematurity., 2. Appropriate for gestational age., 3. Maternal group B st
   _____
   Cat:4 ENT - Otolaryngology: 96
   ______
   Sample Transcription: POSTOPERATIVE DIAGNOSIS:, Chronic adenotonsillitis., PROCEDURE PERFORMED:, Tonsillectomy and
   _____
   Cat:5 Emergency Room Reports: 75
```

Cat:6 Gastroenterology: 224

\_\_\_\_\_

Sample Transcription: PREOPERATIVE DIAGNOSIS: , Gastrostomy (gastrocutaneous fistula)., POSTOPERATIVE DIAGNOSIS: , Gastrostomy (gastrocutaneous fistula).

Cat:7 General Medicine: 259

\_\_\_\_\_

Sample Transcription:REASON FOR ADMISSION: , Sepsis., HISTORY OF PRESENT ILLNESS: ,The patient is a pleasant but de

Cat:8 Hematology - Oncology: 90

\_\_\_\_\_

Sample Transcription: HISTORY OF PRESENT ILLNESS: , This is a 19-year-old known male with sickle cell anemia. He co

Cat:9 Nephrology: 81

\_\_\_\_\_\_

Sample Transcription: REASON FOR CONSULTATION:, Renal failure evaluation for possible dialysis therapy., HISTORY OF

Cat:10 Neurology: 223

\_\_\_\_\_

Sample Transcription: PREOPERATIVE DIAGNOSIS:, Headaches, question of temporal arteritis., POSTOPERATIVE DIAGNOSIS:,

Cat:11 Neurosurgery: 94

\_\_\_\_\_\_

Sample Transcription: PREOPERATIVE DIAGNOSIS:, Squamous cell carcinoma of right temporal bone/middle ear space., POS

Cat:12 Obstetrics / Gynecology: 155

\_\_\_\_\_

Sample Transcription:FINDINGS:,By dates the patient is 8 weeks, 2 days.,There is a gestational sac within the endom

Cat:13 Ophthalmology: 83

\_\_\_\_\_

Sample Transcription: PROCEDURE IN DETAIL:, After appropriate operative consent was obtained, the patient was broug

\_\_\_\_\_

Cat:14 Orthopedic: 355

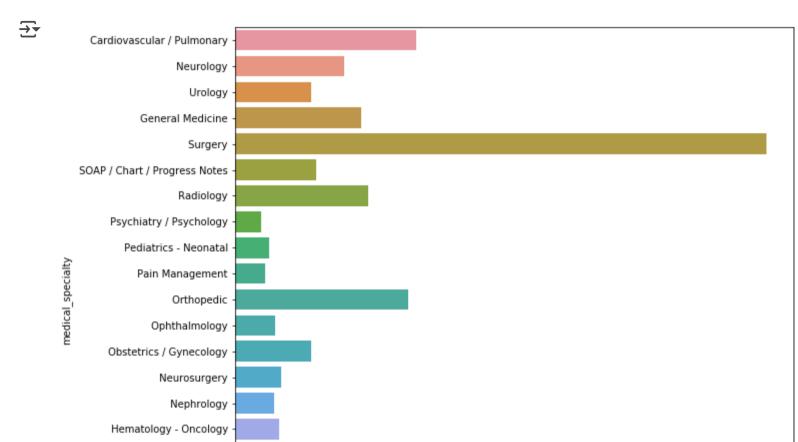
\_\_\_\_\_

Sample Transcription: PROCEDURES: , Total knee replacement., PROCEDURE DESCRIPTION:, The patient was bought to the o

800

600 count 1000

```
plt.figure(figsize=(10,10))
sns.countplot(y='medical_specialty', data = filtered_data_categories )
plt.show()
```



Ó

200

400

Gastroenterology

ENT - Otolaryngology

Discharge Summary

Emergency Room Reports

Consult - History and Phy.

We are interested only in the 'transcription' and 'medical\_specialty' columns in the dataset

```
data = filtered_data_categories[['transcription', 'medical_specialty']]
data = data.drop(data[data['transcription'].isna()].index)
data.shape
→ (4597, 2)
print('Sample Transcription 1:'+data.iloc[5]['transcription']+'\n')
print('Sample Transcription 2:'+data.iloc[125]['transcription']+'\n')
print('Sample Transcription 3:'+data.iloc[1000]['transcription'])
    Sample Transcription 1:CC:, Confusion and slurred speech., HX , (primarily obtained from boyfriend): This 31 y/o RHF (
    Sample Transcription 2:ADMITTING DIAGNOSES:,1. Hematuria.,2. Benign prostatic hyperplasia.,3. Osteoarthritis.,DISCHAF
    Sample Transcription 3:PREOPERATIVE DIAGNOSES: , Phimosis and adhesions., POSTOPERATIVE DIAGNOSES: , Phimosis and adhe
Lets define soome methods for cleaning the data
def clean text(text ):
   text = text.translate(str.maketrans('', '', string.punctuation))
   text1 = ''.join([w for w in text if not w.isdigit()])
   REPLACE BY SPACE RE = re.compile('[/(){}\[\]\])
   #BAD SYMBOLS_RE = re.compile('[^0-9a-z #+_]')
    text2 = text1.lower()
   text2 = REPLACE BY SPACE RE.sub('', text2) # replace REPLACE BY SPACE RE symbols by space in text
   #text2 = BAD_SYMBOLS_RE.sub('', text2)
    return text2
def lemmatize_text(text):
```

```
wordlist=[]
lemmatizer = WordNetLemmatizer()
sentences=sent_tokenize(text)

intial_sentences= sentences[0:1]
final_sentences = sentences[len(sentences)-2: len(sentences)-1]

for sentence in intial_sentences:
    words=word_tokenize(sentence)
    for word in words:
        wordlist.append(lemmatizer.lemmatize(word))

for sentence in final_sentences:
    words=word_tokenize(sentence)
    for word in words:
        wordlist.append(lemmatizer.lemmatize(word))
return ' '.join(wordlist)
```

## Lets clean the data

```
data['transcription'] = data['transcription'].apply(lemmatize_text)
data['transcription'] = data['transcription'].apply(clean_text)

print('Sample Transcription 1:'+data.iloc[5]['transcription']+'\n')
print('Sample Transcription 2:'+data.iloc[125]['transcription']+'\n')
print('Sample Transcription 3:'+data.iloc[1000]['transcription'])
```

Sample Transcription 1:cc confusion and slurred speech hx primarily obtained from boyfriend this yo rhf experienced a Sample Transcription 2:admitting diagnosis hematuria he is to follow up with dr g of urology in the next week by phore Sample Transcription 3:preoperative diagnosis phimosis and adhesion postoperative diagnosis phimosis and adhesion pro-

Lets us peform feature extraction using TfidfVectorizer to generate tf-idf features. For more on tf-idf check here:

https://en.wikipedia.org/wiki/Tf%E2%80%93idf In information retrieval, tf-idf or TFIDF, short for term frequency-inverse document frequency, is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus.[1] It is often used as a weighting factor in searches of information retrieval, text mining, and user modeling. The tf-idf value increases proportionally to the number of times a word appears in the document and is offset by the number of documents in the corpus that contain the word, which helps to adjust for the fact that some words appear more frequently in general.

```
vectorizer = TfidfVectorizer(analyzer='word', stop_words='english',ngram_range=(1,3), max_df=0.75, use_idf=True, smooth_
tfIdfMat = vectorizer.fit_transform(data['transcription'].tolist() )
feature_names = sorted(vectorizer.get_feature_names())
print(feature_names)

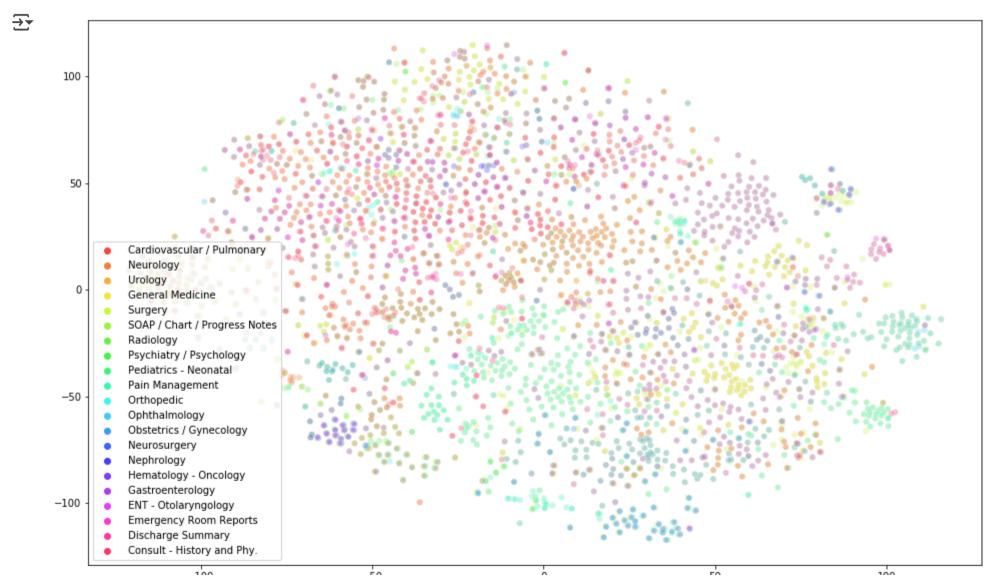
    ['abc', 'abcd', 'abdomen', 'abdomen pelvis', 'abdominal', 'abdominal pain', 'abnormal', 'abnormality', 'abscess', 'accompanies')
```

Lets visualize the tf-idf features using t-sne plot. For more on t-sne check here: <a href="https://en.wikipedia.org/wiki/T-">https://en.wikipedia.org/wiki/T-</a>

distributed\_stochastic\_neighbor\_embedding T-distributed Stochastic Neighbor Embedding (t-SNE) is a machine learning algorithm for visualization developed by Laurens van der Maaten and Geoffrey Hinton.[1] It is a nonlinear dimensionality reduction technique well-suited for embedding high-dimensional data for visualization in a low-dimensional space of two or three dimensions. Specifically, it models each high-dimensional object by a two- or three-dimensional point in such a way that similar objects are modeled by nearby points and dissimilar objects are modeled by distant points with high probability.

```
import gc
gc.collect()
tfIdfMatrix = tfIdfMat.todense()
labels = data['medical_specialty'].tolist()
tsne_results = TSNE(n_components=2,init='random',random_state=0, perplexity=40).fit_transform(tfIdfMatrix)
plt.figure(figsize=(16,10))
palette = sns.hls_palette(21, l=.6, s=.9)
sns.scatterplot(
    x=tsne_results[:,0], y=tsne_results[:,1],
    hue=labels,
```

```
palette= palette,
    legend="full",
    alpha=0.3
)
plt.show()
```



Let us do PCA to reduce dimensionality of features. <a href="https://en.wikipedia.org/wiki/Principal\_component\_analysis">https://en.wikipedia.org/wiki/Principal\_component\_analysis</a> PCA is defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by some scalar projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on

```
gc.collect()
pca = PCA(n_components=0.95)
tfIdfMat_reduced = pca.fit_transform(tfIdfMat.toarray())
labels = data['medical_specialty'].tolist()
category_list = data.medical_specialty.unique()
X_train, X_test, y_train, y_test = train_test_split(tfIdfMat_reduced, labels, stratify=labels,random_state=1)

print('Train_Set_Size:'+str(X_train.shape))
print('Test_Set_Size:'+str(X_test.shape))

Train_Set_Size:(3447, 614)
Test_Set_Size:(1150, 614)
```

Let us use Logisitic Regression to learn on training data and predict on test data <a href="https://scikit-learn.org/stable/modules/generated/sklearn.linear\_model.LogisticRegression.html">https://scikit-learn.org/stable/modules/generated/sklearn.linear\_model.LogisticRegression.html</a>

```
clf = LogisticRegression(penalty= 'elasticnet', solver= 'saga', l1_ratio=0.5, random_state=1).fit(X_train, y_train)
y_test_pred= clf.predict(X_test)
```

Let us visualize the confusion matrix and the classification results

```
labels = category_list
cm = confusion_matrix(y_test, y_test_pred, labels)
```

```
C:\Users\Rithesh\anaconda3\lib\site-packages\sklearn\utils\validation.py:71: FutureWarning: Pass labels=[' Cardiovasc' Surgery' ' SOAP / Chart / Progress Notes' ' Radiology'
' Psychiatry / Psychology' ' Pediatrics - Neonatal' ' Pain Management'
' Orthopedic' ' Ophthalmology' ' Obstetrics / Gynecology' ' Neurosurgery'
' Nephrology' ' Hematology - Oncology' ' Gastroenterology'
' ENT - Otolaryngology' ' Emergency Room Reports' ' Discharge Summary'
' Consult - History and Phy.'] as keyword args. From version 0.25 passing these as positional arguments will result FutureWarning)
```

```
fig = plt.figure(figsize=(20,20))
ax= fig.add_subplot(1,1,1)
sns.heatmap(cm, annot=True, cmap="Greens",ax = ax,fmt='g'); #annot=True to annotate cells

# labels, title and ticks
ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels');
ax.set_title('Confusion Matrix');
ax.xaxis.set_ticklabels(labels); ax.yaxis.set_ticklabels(labels);
plt.setp(ax.get_yticklabels(), rotation=30, horizontalalignment='right')
plt.show()
```



												Confu	usion M	atrix									
	, puln	nonary -	29	1	0	4	33	2	7	0	0	0	0	0	0	0	0	0	0	0	0	0	17
	Cardiovascular   Puln	rology -	0	15	0	0	6	1	16	0	0	0	2	0	0	0	0	0	0	0	0	0	16
		- Kpolon	0	0	5	0	20	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	12
	General Me	dicine -	3	0	0	7	3	7	0	0	0	0	1	0	0	0	0	0	0	0	1	3	40
	Genera.	<sup>nldely</sup> -	19	2	7	0	196	1	0	0	0	0	23	2	6	0	0	0	14	0	0	0	2
			3	1	0	5	1	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19
S	OAP   Chart   Progress	iology -	13	11	1	0	4	0	25	0	0	0	6	0	2	0	0	0	0	0	0	0	6
			0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	12
	<sub>Psychiatry I</sub> Psych Pediatrics - Ne	onatal -	1	0	0	0	3	0	2	0	0	0	0	0	0	0	0	0	0	0	0	2	9
	pediatrics Pain Manag	ement -	0	0	0	0	10	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	1
True labels	Pain Ma.	opedic -	0	1	0	0	43	1	10	0	0	1	23	0	0	0	0	0	0	0	0	1	9
	Ophrhain		0	0	0	0	10	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	3
	Object	cology -	0	0	0	0	26	2	1	0	0	0	0	0	5	0	0	0	0	0	0	0	5
	Obstetnics   Gyne Neuros	<sup>nldely</sup> -	1	0	0	0	20	0	0	0	0	0	2	0	0	1	0	0	0	0	0	0	0
	Nebu	rology -	0	0	0	0	4	1	5	0	0	0	0	0	0	0	2	0	0	0	0	1	7
	atology on	cology -	0	0	1	0	7	1	1	0	0	0	0	0	1	0	0	0	0	0	0	1	10
	, kolody																						

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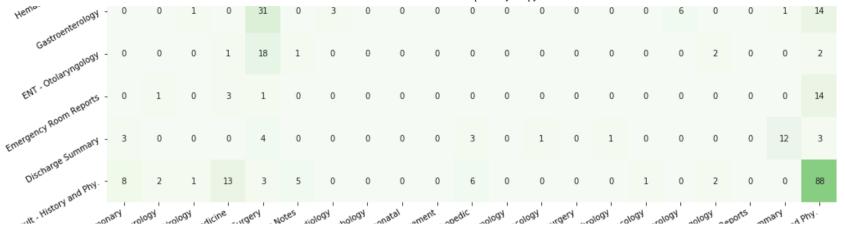
- 150

- 125

- 100

- 75

- 50



print(classification\_report(y\_test,y\_test\_pred,labels=category\_list))

<b>→</b>		precision	recall	f1-score	support
	Cardiovascular / Pulmonary	0.40	0.39	0.40	93
	Neurology	0.40	0.41	0.41	56
	Urology	0.22	0.13	0.16	39
	General Medicine	0.20	0.15	0.17	65
	Surgery	0.47	0.65	0.55	272
	SOAP / Chart / Progress Notes	0.32	0.29	0.30	42
	Radiology	0.35	0.32	0.34	68
	Psychiatry / Psychology	0.00	0.00	0.00	13
	Pediatrics - Neonatal	0.00	0.00	0.00	17
	Pain Management	0.46	0.40	0.43	15
	Orthopedic	0.40	0.36	0.38	89
	Ophthalmology	0.47	0.33	0.39	21
	Office Notes	0.00	0.00	0.00	12
	Obstetrics / Gynecology	0.39	0.31	0.34	39
	Neurosurgery	0.00	0.00	0.00	24
	Nephrology	0.33	0.15	0.21	20
	Hematology - Oncology	0.00	0.00	0.00	22
	Gastroenterology	0.48	0.23	0.31	56
	ENT – Otolaryngology	0.56	0.21	0.30	24
	Emergency Room Reports	0.00	0.00	0.00	19
	Discharge Summary	0.41	0.52	0.46	27
	Consult – History and Phy.	0.32	0.59	0.41	129

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accuracy			0.39	1162
macro avg	0.28	0.25	0.25	1162
weighted avg	0.36	0.39	0.36	1162

C:\Users\Rithesh\anaconda3\lib\site-packages\sklearn\metrics\\_classification.py:1221: UndefinedMetricWarning: Precis:
 \_warn\_prf(average, modifier, msg\_start, len(result))

Let us apply some domain knowledge and see if we can improve the results

```
filtered data categories['medical specialty'] =filtered data categories['medical specialty'].apply(lambda x:str.strip(x)
mask = filtered data categories['medical specialty'] == 'Surgery'
filtered data categories = filtered data categories [~mask]
final data categories = filtered data categories.groupby(filtered data categories['medical specialty'])
mask = filtered data categories['medical specialty'] == 'SOAP / Chart / Progress Notes'
filtered_data_categories = filtered_data_categories[~mask]
mask = filtered_data_categories['medical_specialty'] == 'Office Notes'
filtered data categories = filtered data categories [~mask]
mask = filtered data categories['medical specialty'] == 'Consult - History and Phy.'
filtered_data_categories = filtered_data_categories[~mask]
mask = filtered data categories['medical specialty'] == 'Emergency Room Reports'
filtered data categories = filtered data categories [~mask]
mask = filtered_data_categories['medical_specialty'] == 'Discharge Summary'
filtered_data_categories = filtered_data_categories[~mask]
111
mask = filtered_data_categories['medical_specialty'] == 'Pediatrics - Neonatal'
filtered data categories = filtered data categories[~mask]
111
mask = filtered_data_categories['medical_specialty'] == 'Pain Management'
filtered_data_categories = filtered_data_categories[~mask]
mask = filtered_data_categories['medical_specialty'] == 'General Medicine'
filtered data categories = filtered data categories[~mask]
mask = filtered data categories['medical specialty'] == 'Neurosurgery'
```

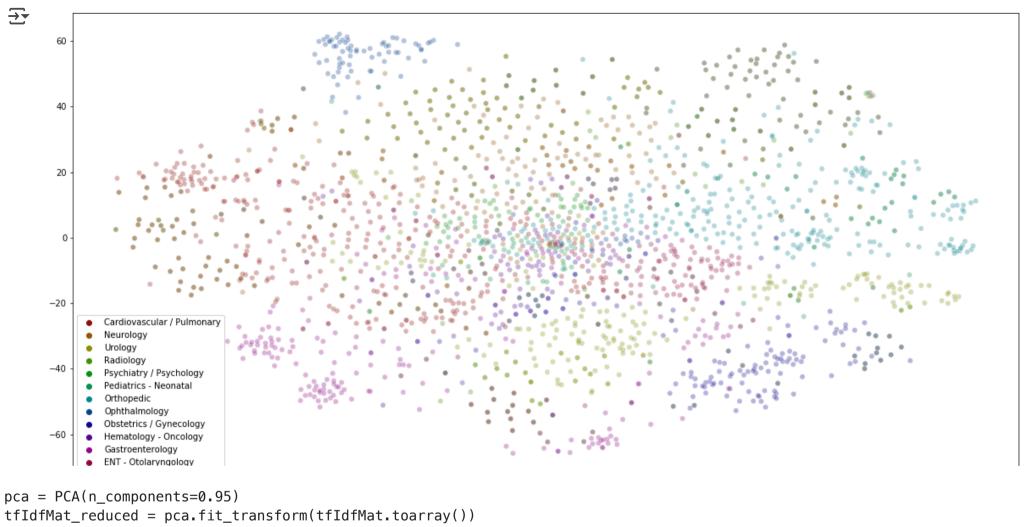
filtered\_data\_categories.loc[mask, 'medical\_specialty'] = 'Neurology'

```
mask = filtered data categories['medical specialty'] == 'Nephrology'
filtered data categories.loc[mask, 'medical specialty'] = 'Urology'
i=1
print('=======Reduced Categories========')
for catName,dataCategory in final data categories:
   print('Cat:'+str(i)+' '+catName + ' : '+ str(len(dataCategory)) )
   i = i+1
print('=======Reduced Categories=======')
data = filtered_data_categories[['transcription', 'medical_specialty']]
data = data.drop(data[data['transcription'].isna()].index)
data.shape
=======Reduced Categories============
    Cat:1 Cardiovascular / Pulmonary: 371
    Cat: 2 ENT - Otolaryngology: 96
    Cat:3 Gastroenterology: 224
    Cat:4 Hematology - Oncology: 90
    Cat:5 Neurology: 317
    Cat:6 Obstetrics / Gynecology: 155
    Cat:7 Ophthalmology: 83
    Cat:8 Orthopedic: 355
    Cat: 9 Pediatrics - Neonatal: 70
    Cat:10 Psychiatry / Psychology: 53
    Cat:11 Radiology: 273
    Cat:12 Urology: 237
    ======Reduced Categories========
    (2324, 2)
```

Let us use sciscpacy models to detect medical entities in our text scispaCy is a Python package containing spaCy models for processing biomedical, scientific or clinical text. For more on scispacy check here: <a href="https://allenai.github.io/scispacy/">https://allenai.github.io/scispacy/</a>

```
nlp = spacy.load("en ner bionlp13cg md")
def process_Text( text):
    wordlist=[]
    doc = nlp(text)
    for ent in doc.ents:
       wordlist.append(ent.text)
    return ' '.join(wordlist)
data['transcription'] = data['transcription'].apply(process Text)
data['transcription'] = data['transcription'].apply(lemmatize text)
data['transcription'] = data['transcription'].apply(clean text)
print('Sample Transcription 1:'+data.iloc[5]['transcription']+'\n')
print('Sample Transcription 2:'+data.iloc[125]['transcription']+'\n')
print('Sample Transcription 3:'+data.iloc[1000]['transcription'])
    Sample Transcription 1:boyfriend bed her right facial right child bp name on only motor rue pronator extremity flex
    Sample Transcription 2:performed ureteral stent right renal pelvis urine right upper pole patient right kidney pat:
    Sample Transcription 3:uterine bleeding uterine bleeding vaginal hysterectomy anesthesia endotracheal endotracheal a
vectorizer = TfidfVectorizer(analyzer='word', stop_words='english',ngram_range=(1,3), max_df=0.75,min_df=5, use_idf=True
tfIdfMat = vectorizer.fit transform(data['transcription'].tolist() )
feature_names = sorted(vectorizer.get_feature_names())
print(feature_names)
→ ['abc', 'abcd', 'abdomen', 'abdomen abdomen', 'abdomen bowel', 'abdomen patient', 'abdominal', 'abdominal cavity', '¿
```

```
import gc
gc.collect()
tfIdfMatrix = tfIdfMat.todense()
labels = data['medical_specialty'].tolist()
tsne_results = TSNE(n_components=2,init='random',random_state=0, perplexity=40).fit_transform(tfIdfMatrix)
plt.figure(figsize=(20,10))
palette = sns.hls_palette(12, l=.3, s=.9)
sns.scatterplot(
    x=tsne_results[:,0], y=tsne_results[:,1],
    hue=labels,
    palette= palette,
    legend="full",
    alpha=0.3
)
plt.show()
```



```
pca = PCA(n_components=0.95)

tfIdfMat_reduced = pca.fit_transform(tfIdfMat.toarray())

labels = data['medical_specialty'].tolist()

category_list = data.medical_specialty.unique()
```

Let us create train and test sets. Let us use logistic regression for developing a classification model and then visualize the results

```
X_train, X_test, y_train, y_test = train_test_split(tfIdfMat_reduced, labels, stratify=labels,random_state=1)
print('Train_Set_Size:'+str(X_train.shape))
print('Test_Set_Size:'+str(X_test.shape))
```

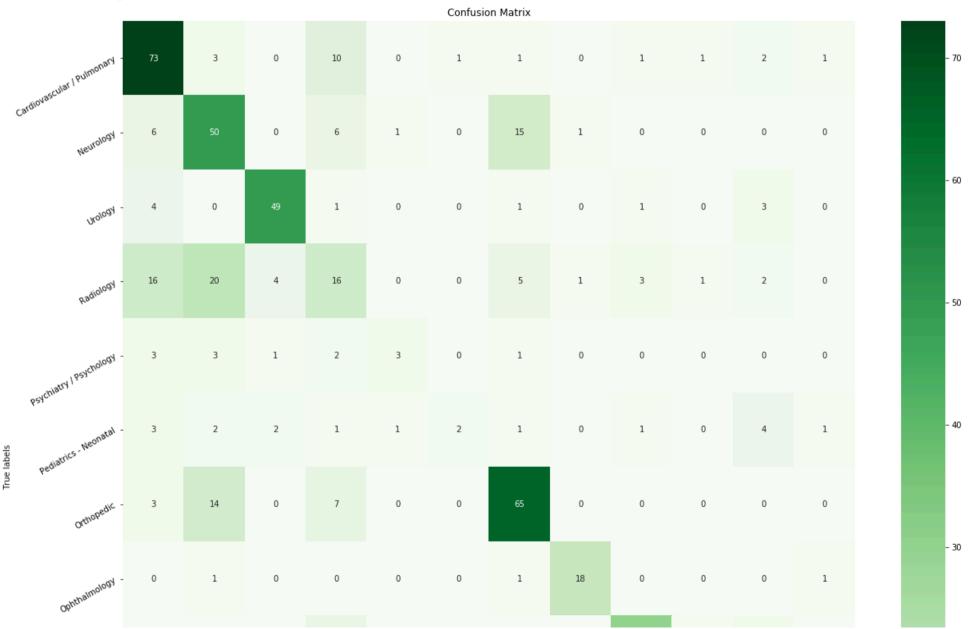
```
→ Train Set Size: (1743, 582)
    Test Set Size: (581, 582)
#clf = MLPClassifier(random_state=1, max_iter=300).fit(X_train, y_train)
clf = LogisticRegression(penalty= 'elasticnet', solver= 'saga', l1_ratio=0.5, random_state=1).fit(X_train, y_train)
v test pred= clf.predict(X test)
labels = category list
cm = confusion_matrix(y_test, y_test_pred, labels)
fig = plt.figure(figsize=(20,20))
ax= fig.add subplot(1,1,1)
sns.heatmap(cm, annot=True, cmap="Greens",ax = ax,fmt='g'); #annot=True to annotate cells
# labels, title and ticks
ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels');
ax.set title('Confusion Matrix');
ax.xaxis.set ticklabels(labels); ax.yaxis.set ticklabels(labels);
plt.setp(ax.get yticklabels(), rotation=30, horizontalalignment='right')
plt.setp(ax.get_xticklabels(), rotation=30, horizontalalignment='right')
plt.show()
print(classification report(y test,y test pred, labels=category list))
```



C:\Users\Rithesh\anaconda3\lib\site-packages\sklearn\utils\validation.py:71: FutureWarning: Pass labels=['Cardiovas
'Psychiatry / Psychology' 'Pediatrics - Neonatal' 'Orthopedic'

'Ophthalmology' 'Obstetrics / Gynecology' 'Hematology - Oncology'

'Gastroenterology' 'ENT — Otolaryngology'] as keyword args. From version 0.25 passing these as positional argument FutureWarning)



Obstetnics   Gynecology	0	0	0	5	0	0	0	0	30	1	3	0	- 20
Obster		1	0	2	0	0	2	0	1	5	4	0	
Hematov.		0	2	4	0	0	3	0	1	2	42	0	- 10
Cholaryngology -	1	1	0	2	0	1	0	0	0	0	0	19	
Cardiovascular   Pul	monary ,	Nentology	nology,	psychiatry   Psy	pediatrics -	Neonatal	ophthal Ophthal	obstetnics   Gyn	ecology Hematology - O	ncology Gastroen	ENT - Otolary	ngalagy	- 0
•						Predic	ted labels						

			Predicte	d labels
	precision	recall	f1-score	support
Cardiovascular / Pulmonary	0.62	0.78	0.69	93
Neurology	0.53	0.63	0.57	79
Urology	0.84	0.83	0.84	59
Radiology	0.29	0.24	0.26	68
Psychiatry / Psychology	0.60	0.23	0.33	13
Pediatrics - Neonatal	0.50	0.11	0.18	18
Orthopedic	0.68	0.73	0.71	89
Ophthalmology	0.90	0.86	0.88	21
Obstetrics / Gynecology	0.79	0.77	0.78	39
Hematology - Oncology	0.50	0.23	0.31	22
Gastroenterology	0.70	0.75	0.72	56
ENT - Otolaryngology	0.86	0.79	0.83	24
			0 61	E01

Since some classes are in minority we can use SMOTE(Synthetic Minority Over-sampling Technique) to generate more sample form minority class to solve the data imbalance problem. For more on SMOTE check here: <a href="https://arxiv.org/pdf/1106.1813.pdf">https://arxiv.org/pdf/1106.1813.pdf</a>. Let us generate new dataset using SMOTE and then perform classification on them

```
smote over sample = SMOTE(sampling strategy='minority')
labels = data['medical specialty'].tolist()
X, y = smote over sample.fit resample(tfIdfMat reduced, labels)
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,random_state=1)
print('Train Set Size:'+str(X train.shape))
print('Test Set Size:'+str(X test.shape))
→ Train Set Size: (1981, 582)
    Test Set Size: (661, 582)
clf = LogisticRegression(penalty= 'elasticnet', solver= 'saga', l1 ratio=0.5, random state=1).fit(X trail
v test pred= clf.predict(X test)
Let us visualize the data
labels = category list
cm = confusion matrix(y test, y test pred, labels)
fig = plt.figure(figsize=(20,20))
ax= fig.add subplot(1,1,1)
sns.heatmap(cm, annot=True, cmap="Greens",ax = ax,fmt='g'); #annot=True to annotate cells
# labels, title and ticks
ax.set xlabel('Predicted labels');ax.set ylabel('True labels');
ax.set_title('Confusion Matrix');
ax.xaxis.set_ticklabels(labels); ax.yaxis.set_ticklabels(labels);
plt.setp(ax.get_yticklabels(), rotation=30, horizontalalignment='right')
plt.setp(ax.get_xticklabels(), rotation=30, horizontalalignment='right')
```

plt.show()
print(classification\_report(y\_test,y\_test\_pred,labels=category\_list))



C:\Users\Rithesh\anaconda3\lib\site-packages\sklearn\utils\validation.py:71: FutureWarning: Pass labels=['Cardiovas
'Psychiatry / Psychology' 'Pediatrics - Neonatal' 'Orthopedic'

'Ophthalmology' 'Obstetrics / Gynecology' 'Hematology - Oncology'

'Gastroenterology' 'ENT — Otolaryngology'] as keyword args. From version 0.25 passing these as positional argument FutureWarning)

