CSCI6409 Process of Data Science

Assignment 3

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Question 1

Installing Dependencies

In [4]:

```
# importing the relevant modules
import pandas as pd
import numpy as np
from datetime import date
import datetime
import json
import nltk
nltk.download('punkt')
nltk.download('stopwords')
import warnings
warnings.filterwarnings('ignore')
import pickle
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     /users/grad/devesh/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     /users/grad/devesh/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Importing data

In [5]:

```
# Data source
data = pd.read_json('sample1.jsonl', lines=True)
```

In [6]:

```
data['vote'].isna().sum()
```

Out[6]:

804511

In [7]:

```
data['image'].isna().sum()
```

Out[7]:

997767

We see a lot of missing values in 'vote' and 'image' columns. It would be ideal to drop them during data preprocessing.

In [8]:

```
data.shape
```

Out[8]:

(1000000, 12)

Identifying data quality issues and pre-processing data according to data quality plan

As part of data pre-processing, we imported the raw data from the JSON file using Pandas package. Once the data gets imported we perform sanity checks and observe the data to make it ready for analysis.

As part of pre-processing, we perform the following operations -

i) **Removed Nan values.** Ex - Column - 'image' and 'vote', contain a lot of Nan values.

ii) **Reset index**

iii) **Extracted text from the columns which were in non-string format.** Ex - Column 'style' is in JSON format of key-value pair. To extract useful information, we extract the value and kept it in a seprate column called 'styleUpdate'.

In [9]:

```
#Extracting value column from style
data['styleUpdate'] =data['style'].astype('str').replace("'}","", regex=True).replace("{'Format:': '","",regex = True)


#Dropping image and vote column
data = data.drop(['image', 'vote'], axis = 1)
data
```

Out[9]:

	overall	verified	reviewTime	reviewerID	asin	style	reviewerName	reviewText	summary	unixReviewTime	styleUpc
0	3	False	05 18, 2002	AJ8AQG2X9JJ2Y	0001712799	{'Format:': ' School & Library Binding'}	Donald Gillies	Dr. Seuss has some really brilliant books. Th...	A below-average Dr. Seuss Book	1021680000	Scho Libı Binc
1	5	True	12 11, 2014	A12Q7B7NT716RV	0001712799	{'Format:': ' Hardcover'}	True Value Girl	Love it	Five Stars	1418256000	Hardcc
2	4	False	01 6, 2006	A1DK5AZMXS1QA3	0002006448	{'Format:': ' Hardcover'}	Newton Ooi	Hand-woven carpets are one of the few products...	Tourism as history	1136505600	Hardcc
3	4	False	12 8, 2014	A1JMSX54DO3LOP	0002005263	{'Format:': ' Kindle Edition'}	Bookzilla	Compelling, twisting mystery involving several...	Compelling, twisting mystery	1417996800	Kir Edi
4	2	True	03 3, 2014	A2IP27AZB3D1SM	0002005263	{'Format:': ' Kindle Edition'}	J. A. Drummond	I have read many of the Hillerman books and en...	Tony missed the mark	1393804800	Kir Edi
...	...	...	...	...	...	...	...	...	...	...	
999995	3	True	12 1, 2017	A1PLIAXAWGGEZO	B01HH2OZVS	{'Format:': ' Kindle Edition'}	Linda Cope	What I liked most was the personal stories of ...	What I liked most was the personal stories of ...	1512086400	Kir Edi
999996	3	False	12 22, 2016	A1Q3MLS48AUBKO	B01HHC2MD6	{'Format:': ' Kindle Edition'}	weaselbit	The story is alright. The writing style is a b...	The story is alright. The writing style is a ...	1482364800	Kir Edi
999997	5	False	07 2, 2016	A34MRZFAZPPESL	B01HHC2MD6	{'Format:': ' Kindle Edition'}	skygypsy	I really loved this little book. The author's...	A Lovely Little Feel-Good Story	1467417600	Kir Edi
999998	5	True	01 26, 2017	ARFHS6IU8WI0	B01HIIHU7W	{'Format:': ' Kindle Edition'}	DonnaL	I have read everything Keith Blackmore has wri...	Love Keith Blackmore's books!	1485388800	Kir Edi
999999	5	True	07 4, 2016	A22FAHV2R6BUVR	B01HJBPTUI	{'Format:': ' Kindle Edition'}	Amy's Bookshelf Reviews	Another amazing book by Ernst. Sequels are not...	Masterful	1467590400	Kir Edi

1000000 rows × 11 columns

In [10]:

```
data = data.dropna()
data.shape
```

Out[10]:

(981723, 11)

In [11]:

```
#Reset index
df = data.reset_index()
```

Downsampling - We have taken 10000 rows to run our model. We tried to run our model with more number of rows, however the performance of the model was pretty similar with larger dataset. Also, there were instances when we the kernel died when we took larger dataset.

In [12]:

```
df = df.sample(n = 10000, random_state=42)
```

In [13]:

```
df.shape
```

Out[13]:

(10000, 12)

Calculating properties of textual data

Since the a lot of fields in the dataset are textual fields, we will be calculating following properties of the textual data

i) Text length (i.e., the number of characters).

ii) The number of words.

iii) Presence of non-alphanumeric characters.

In [14]:

```
#Calculating length of Text column
df['reviewTextLength'] = df['reviewerName'].str.len()
df['summaryLength'] = df['summary'].str.len()
df['styleUpdateLength'] = df['styleUpdate'].str.len()
```

In [15]:

```
#Calculating number of words
df['reviewTextCount'] = df['reviewText'].str.count(' ') + 1
df['summaryCount'] = df['summary'].str.count(' ') + 1
df['styleUpdateCount'] = df['styleUpdate'].str.count(' ') + 1
```

In [16]:

```
#Calculating whether column contains non-alphanumeric characters
df['reviewTextAlphaNum'] = df['reviewerName'].str.isalnum()
df['summaryAlphaNum'] = df['summary'].str.isalnum()
df['styleUpdateAlphaNum'] = df['styleUpdate'].str.isalnum()
```

Data Quality Report

To calculate data quality report for both categorical and continous features, we select only those columns which contain ,the properties of the textual data

In [17]:

```
#Fetching only relevant properties in a separate dataset for performing analysis and generating data quality reports
df_DQR = df[["overall", "verified", "reviewTime", "reviewerID", "asin", "reviewTextLength", "summaryLength",
          "reviewTextCount", "summaryCount", "reviewTextAlphaNum", "summaryAlphaNum",
           "styleUpdateLength", "styleUpdateCount", "styleUpdateAlphaNum"]]
```

Continuous features report

Continous features report includes the following -

1. Minimum
2. 1st quartile
3. Mean
4. 2nd quartile - Median
5. 3rd quartile
6. Maximum
7. Standard deviation
8. Total num of instances
9. % missing values
10. Cardinality - Number of unqiue values for a given feature

In [18]:

```
#Defining function to generate data quality report for continuous features in the dataset
def build_continuous_features_report(data_df):

    stats = {
        "Count": len,
        "Miss %": lambda churn_df: churn_df.isna().sum() / len(churn_df) * 100,
        "Card.": lambda churn_df: churn_df.nunique(),
        "Min": lambda churn_df: churn_df.min(),
        "1st Qrt.": lambda churn_df: churn_df.quantile(0.25),
        "Mean": lambda churn_df: churn_df.mean(),
        "Median": lambda churn_df: churn_df.median(),
        "3rd Qrt": lambda churn_df: churn_df.quantile(0.75),
        "Max": lambda churn_df: churn_df.max(),
        "Std. Dev.": lambda churn_df: churn_df.std(),
    }
    contin_feat_names = data_df.select_dtypes("number").columns
    continuous_data_df = data_df[contin_feat_names]

    report_df = pd.DataFrame(index=contin_feat_names, columns=stats.keys())

    for stat_name, fn in stats.items():
        # NOTE: ignore warnings for empty features
        with warnings.catch_warnings():
            warnings.simplefilter("ignore", category=RuntimeWarning)
            report_df[stat_name] = fn(continuous_data_df)

    return report_df
```

In [19]:

```
build_continuous_features_report(df_DQR)
```

Out[19]:

	Count	Miss %	Card.	Min	1st Qrt.	Mean	Median	3rd Qrt	Max	Std. Dev.
overall	10000	0.0	5	1	4.0	4.3620	5.0	5.0	5	1.002026
reviewTextLength	10000	0.0	55	1	7.0	11.2385	11.0	15.0	104	5.421177
summaryLength	10000	0.0	132	1	10.0	26.0436	19.0	34.0	192	20.419784
reviewTextCount	10000	0.0	702	1	21.0	98.1421	43.0	108.0	2666	154.244481
summaryCount	10000	0.0	30	1	2.0	4.6655	3.0	6.0	34	3.795636
styleUpdateLength	10000	0.0	19	4	10.0	13.2803	15.0	15.0	32	2.955741
styleUpdateCount	10000	0.0	4	2	2.0	2.6508	3.0	3.0	5	0.543221

Categorical features report

Categorical features report includes:

1. Mode - most repeated value (value with highest frequency)
2. 2nd mode - 2nd most repeated value
3. Frequency of mode

4. Proportion of mode in the dataset
5. Frequency of 2nd mode
6. Proportion of 2nd mode in the dataset
7. % missing values
8. Cardinality - number of unique values for a given feature

In [20]:

```
#Defining function to generate data quality report for categorical features in the dataset
def build_categorical_features_report(data_df):

    def _mode(data_df):
        return data_df.apply(lambda ft: ft.mode().to_list()).T

    def _mode_freq(data_df):
        return data_df.apply(lambda ft: ft.value_counts()[ft.mode()].sum())

    def _second_mode(data_df):
        return data_df.apply(lambda ft: ft[~ft.isin(ft.mode())].mode().to_list()).T

    def _second_mode_freq(data_df):
        return data_df.apply(
            lambda ft: ft[~ft.isin(ft.mode())]
            .value_counts()[ft[~ft.isin(ft.mode())].mode()]
            .sum()
        )

    stats = {
        "Count": len,
        "Miss %": lambda data_df: data_df.isna().sum() / len(data_df) * 100,
        "Card.": lambda data_df: data_df.nunique(),
        "Mode": _mode,
        "Mode Freq": _mode_freq,
        "Mode %": lambda data_df: _mode_freq(data_df) / len(data_df) * 100,
        "2nd Mode": _second_mode,
        "2nd Mode Freq": _second_mode_freq,
        "2nd Mode %": lambda data_df: _second_mode_freq(data_df) / len(data_df) * 100,
    }

    feature_names = data_df.select_dtypes(exclude="number").columns
    print(feature_names)
    continuous_data_df = data_df[feature_names]
    report_df = pd.DataFrame(index=feature_names, columns=stats.keys())


    for stat_name, fn in stats.items():
        # NOTE: ignore warnings for empty features
        with warnings.catch_warnings():
            warnings.simplefilter("ignore", category=RuntimeWarning)
            report_df[stat_name] = fn(continuous_data_df)

    return report_df
```

Removing boolean variables in the dataset to calculate categorical data quality report

In [21]:

```
df_removed = df_DQR.drop(["verified"],axis = 1).drop(["reviewTextAlphaNum"], axis =1).drop(["summaryAlphaNum"] ,axis =1).drop(["styleUpdateAlphaNum"] ,axis =1)
```

In [22]:

```
build_categorical_features_report(df_removed)
```

Index(['reviewTime', 'reviewerID', 'asin'], dtype='object')

Out[22]:

	Count	Miss %	Card.	Mode	Mode Freq	Mode %	2nd Mode	2nd Mode Freq	2nd Mode %
reviewTime	10000	0.0	3226	[07 18, 2017]	18	0.18	[07 22, 2014]	16	0.16
reviewerID	10000	0.0	9817	[A2F6N60Z96CAJI]	4	0.04	[A15RKFWXR5W3PP, A1K4S4MWXI9E9M, A1UH21GLZTYYR...	30	0.30
asin	10000	0.0	9250	[0297859382, B000X1MX7E]	22	0.22	[0099911701]	9	0.09

Miss		Mode	Mode		2nd Mode	2nd Mode

Top 50 words in each textual column

To calculate top 50 words in each textual column, we execute the following steps -

i) Remove all the stop words

ii) Stack all the words in one given column

iii) Calculate number of occurences for each word and select the top 50 words with highest occurences

In [23]:

```
df_clean = df[["reviewerName", "reviewText", "summary", "styleUpdate"]].dropna().replace('[^a-zA-Z0-9 ]', '', regex=True) #removing special characters
```

In [24]:

```
from nltk.corpus import stopwords
stop = stopwords.words('english')
```

Reviewer Name

In [25]:

```
#reviewerName
df_clean['reviewerName_withoutStopWords'] = df_clean.reviewerName.apply(lambda x: ' '.join([word for word in x.split() if word not in (stop)]))

df_clean.reviewerName_withoutStopWords.str.split(expand=True).stack().value_counts().to_frame().head(50)
```

Out[25]:

	0
Customer	876
Amazon	518
Kindle	375
J	203
M	200
A	188
L	170
C	159
S	129
D	127
B	125
R	113
K	97
E	93
G	91
W	75
John	70
T	67
H	67
Book	63
Linda	62
P	59
David	57
Smith	57
Michael	56
Reader	50
The	46
Mary	45

	0
Mary	45
Barbara	42
James	42
Robert	42
Carol	40
N	40
Susan	38
F	37
Karen	34
Richard	33
Jennifer	31
Reviews	31
Ann	31
Books	31
William	28
Sandra	27
Lynn	27
Michelle	27
Lee	27
Bill	27
Johnson	27
Judy	26
Thomas	25

Reviewer Text

In [26]:

```
#reviewerText
df_clean['reviewText_withoutStopWords'] = df_clean.reviewText.dropna().apply(lambda x: ' '.join([word for word in x.split() if word not in (stop)]))
```

In [27]:

```
df_clean["reviewText_withoutStopWords"].str.split(expand=True).stack().value_counts().to_frame().head(50)
```

Out[27]:

	0
I	19794
book	11526
read	5110
The	4981
story	4386
one	3825
This	3118
like	2684
love	2379
books	2278
It	2274
characters	2223
would	2173
good	2167
really	1926
series	1881
time	1872
great	1839
reading	1793

	0
reading	1793
much	1703
well	1662
get	1631
life	1610
first	1604
way	1495
author	1411
also	1352
many	1328
even	1303
know	1230
could	1225
people	1162
A	1158
see	1120
little	1111
think	1088
loved	1078
dont	1030
make	1018
end	1010
Im	998
written	985
find	984
He	981
enjoyed	952
new	952
want	938
two	936
But	930
character	927

Summary

In [28]:

```
#summary
df_clean['summary_withoutStopWords'] = df_clean.summary.dropna().apply(lambda x: ' '.join([word for word in x.split() if word not in (stop)]))
df_clean.summary_withoutStopWords.str.split(expand=True).stack().value_counts().to_frame().head(50)
```

Out[28]:

	0
Stars	1303
Five	939
book	931
A	723
read	660
I	586
Great	574
The	349
good	348
Good	342
story	326
great	281

	0
Four	236
Book	216
love	214
Read	204
series	198
This	192
Not	161
Love	150
Very	145
Excellent	134
one	132
like	128
Another	125
books	110
Loved	107
best	104
One	101
An	101
fun	94
reading	90
It	90
loved	87
Three	86
Wonderful	84
What	80
really	76
Fun	75
much	74
Interesting	70
written	65
new	65
Story	63
Amazing	62
better	61
stars	61
time	60
novel	60
mystery	59

Style

In [29]:

```
#styleUpdate
df_clean['styleUpdate_withoutStopWords'] = df_clean.styleUpdate.dropna().apply(lambda x: ' '.join([word for word in x.split() if word not in (stop)]))
df_clean.styleUpdate_withoutStopWords.str.split(expand=True).stack().value_counts().to_frame().head(50)
```

Out[29]:

	0
Edition	5686
Kindle	5685
Paperback	2698
Hardcover	1384
Mass	321
Market	321

	0
book	50
Board	50
Audio	43
CD	41
Audiobook	20
Audible	20
Spiralbound	16
Leather	15
Imitation	9
Bound	9
Pamphlet	8
Cards	8
Calendar	8
Misc	7
Supplies	6
Hardcoverspiral	6
Binding	6
Plastic	6
Comb	6
Perfect	6
DVD	6
Flexibound	5
Cassette	5
MP3	4
Library	3
Staple	3
Book	3
Bonded	3
Vinyl	3
Map	3
Diary	3
AudioVideo	3
Video	2
Amazon	2
Unknown	2
Card	2
Ringbound	2
Style	1
Player	1
Bookmark	1
Color	1
Preloaded	1
CDROM	1
9th	1

Proportion of each format within the style column

In [30]:

```
df_clean['styleUpdate_withoutStopWords'].value_counts().sort_values()
```

Out[30]:

```
Bookmark                        1
Preloaded Digital Audio Player  1
Misc                            1
CDROM                           1
```

CDROM 1
Style Name 9th Edition 1
Roughcut 1
Textbook Binding 1
Bluray 1
Pocket Book 1
Color Paperback 1
School Library Binding 1
Stationery 1
Card Book 2
Amazon Video 2
Ringbound 2
Unknown Binding 2
Library Binding 2
Staple Bound 3
Diary 3
Leather Bound 3
Kindle Edition AudioVideo 3
Vinyl Bound 3
Bonded Leather 3
Map 3
MP3 CD 4
Flexibound 5
Audio Cassette 5
DVD 6
Hardcoverspiral 6
Plastic Comb 6
Perfect Paperback 6
Misc Supplies 6
Pamphlet 8
Cards 8
Calendar 8
Imitation Leather 9
Spiralbound 16
Audible Audiobook 20
Audio CD 37
Board book 50
Mass Market Paperback 321
Hardcover 1384
Paperback 2370
Kindle Edition 5682
Name: styleUpdate_withoutStopWords, dtype: int64

Based on the above results,

i) Format with highest occurence - **Kindle Edition**

ii) Format with lowest occurence - **Size XLarge, Paperback Bunko, Print Demand , Color Foam Gliders 995, Diskette**

Patterns within the data

After closely analysing the data, we can observe a pattern of reviews for various formats.

Pattern I - The number of review ratings are in the exact same descending order as the rating itself.

In [31]:

```
#1.4.4 - Overall Score
df['overall'].value_counts()
```

Out[31]:

5 6180
4 2258
3 871
2 384
1 307
Name: overall, dtype: int64

Pattern II - Distribution of reviews for highest reviewed format - 'Kindle Edition'

The distribution is same as that of the overall distribution. More people have given positive reviews than negative reviews. More than 50% of reviews are coming from 4 and 5 rating.

In [32]:

```
df_kindle = df[df['styleUpdate'].str.contains('Kindle Edition')]
```

```
df_kindle['overall'].value_counts()
```

Out[32]:

```
5    3443
4    1380
3     497
2     199
1     166
Name: overall, dtype: int64
```

Pattern III - Distribution of review text length.

Based on the count of the review text, it can be observed that highest number of reviews have total length as just 2 words.

In [33]:

```
df["reviewTextCount"].value_counts()
```

Out[33]:

```
2       291
21      218
23      205
22      200
20      173
       ...
1775      1
803       1
843       1
859       1
787       1
Name: reviewTextCount, Length: 702, dtype: int64
```

In [34]:

```
df.head(20)
```

Out[34]:

	index	overall	verified	reviewTime	reviewerID	asin	style	reviewerName	reviewText	summary	...	styleUpdate
278056	281077	2	True	09 12, 2014	A4K6YWO1XO8E2	0553099957	{'Format:': ' Kindle Edition'}	Rick	Mildly amusing but tiresome and repetitive in ...	Mildly amusing but tiresome and repetitive in ...	...	Kindle Edition
948792	965612	5	False	03 4, 2014	A2CAWO3IRUS9C7	1609078063	{'Format:': ' Paperback'}	Stephanie Buckner	In this day and age, with modern media telling...	Discover True Beauty!	...	Paperback
638299	643206	5	True	11 1, 2015	A2YJMETJWHZKLT	1518661564	{'Format:': ' Kindle Edition'}	Mary L	Spoilers****** Such a great story! Kian is a k...	Kian and Jo.....rdan	...	Kindle Edition
21471	22572	5	True	01 26, 2013	A3TCBK4JXM2GJ0	0060254939	{'Format:': ' Hardcover'}	Counselor Chris	I have this book in my office, since my childr...	A Classic!	...	Hardcover
893151	909004	5	True	09 19, 2017	A3FMGCROI5BDGT	0316395072	{'Format:': ' Hardcover'}	Jacqueline LaMonica	This book was wonderful! If you love books an...	Wonderful!	...	Hardcover
879836	895425	5	False	09 3, 2010	AMYTL79JMGQ6D	0778327884	{'Format:': ' Paperback'}	Mary Ann	This book seems to be one of a series with whi...	Better late than never	...	Paperback
585275	590111	5	True	11 25, 2014	A3IP8SKF2GBNCW	1495204499	{'Format:': ' Kindle Edition'}	Lyn morris	See Volume 3 comments. This first volume grab...	I love it when an author captures his/her read...	...	Kindle Edition
635067	639970	5	False	10 15, 2015	A3LAGHXGTU9D1M	1517006120	{'Format:': ' Kindle Edition'}	Kindle Customer	Enjoyed this first book and am really looking ...	Love this author	...	Kindle Edition
									I had never			

	index	overall	verified	reviewTime	reviewerID	asin	style	reviewerName	reviewText	summary	...	styleUpdate
283237	286281	5	True	04 18, 2011	AULBG1CBNU4J1	0553588087	{'Format:': ' Mass Market Paperback'}	BARBARA F. AMES	I had never anything by Lisa Andersen but...	TOUGH TO PUT DOWN!	...	Mass Market Paperback
296338	299559	4	True	02 13, 2014	A5TJYQOA447SZ	0615816126	{'Format:': ' Kindle Edition'}	Patrica Rickaby	Gritty real crime stories told by the author i...	Real Crime	...	Kindle Edition
445830	450143	5	True	07 26, 2017	A1MEADWMSIP6JB	0997667729	{'Format:': ' Kindle Edition'}	Mary Lou Sansone	This book and the 2 previous ones in this seri...	Great series.	...	Kindle Edition
333911	337430	5	True	05 11, 2006	A2U0W6B8IVRVXI	0756609976	{'Format:': ' Hardcover'}	Laura Johnson	My 3+ year old daughter and I checked this out...	The Book that made my Daughter want to become ...	...	Hardcover
828500	843504	5	True	04 28, 2015	A483CZ67W5XNY	0060142839	{'Format:': ' Hardcover'}	lilbitz	Beautifully illustrated!	Five Stars	...	Hardcover
498988	503600	1	False	01 3, 2015	A1ZCQVMOFYYJCV	1442476907	{'Format:': ' Audible Audiobook'}	kim bock	Although Philippa Gregory is from Africa most ...	South Africa prohibited by Audible.com to buy ...	...	Audible Audiobook
268344	271311	2	True	03 9, 2015	A1S0DW7Z40VH19	0528011499	{'Format:': ' Spiral-bound'}	Amazon Customer	For detail route planning - especially for dri...	Not enough detail for off highway route planning.	...	Spiral-bound
177459	179905	5	True	02 21, 2015	A3EGXTWYTX75XW	0345543246	{'Format:': ' Kindle Edition'}	Maureen Pellati	Grisham's books hook you from the first page -...	Five Stars	...	Kindle Edition
261160	264063	5	True	06 1, 2016	A1O4PLZ297NJO7	0471291072	{'Format:': ' Hardcover'}	Charmiann	Started reading and has a lot of great stories...	Unexplained Mysteries odf World War II	...	Hardcover
462344	466720	4	False	07 28, 2013	A3RWHGR0T4XCFX	1400165946	{'Format:': ' Paperback'}	Richard Reese (author of Understanding Sustain...	Once upon a time, long, long ago, musicians St...	A long strange trip	...	Paperback
754273	759876	5	True	08 28, 2013	A1A9R07NGH85UG	1939865603	{'Format:': ' Kindle Edition'}	Amazon Customer	I have all the Force family books. I like the ...	can't wait for the next book.	...	Kindle Edition
330273	333760	5	True	07 14, 2014	A2NI2Y212NUW0J	0744554020	{'Format:': ' Hardcover'}	Mr. Chris Stoffel	What a precious story to share with all ages a...	The dvd is just as precious and recommended as...	...	Hardcover

20 rows × 21 columns

Question 2

Merging 'reviewText' and 'summary' column into one

In [35]:

```
df['reviewTextSumaaryMerge'] = df['reviewText'] + " " + df['summary']
```

In [36]:

```
df.shape
```

Out[36]:

(10000, 22)

Removing non-alphanumeric characters in the merged column - **'reviewTextSumaaryMerge'**

In [37]:

```
#Removing non-alphabetic characters
```

```
df_clean['reviewTextSumaaryMerge'] = df['reviewTextSumaaryMerge'].replace('[^a-zA-Z ]', '', regex=True)
```

In [38]:

```
df_clean.shape
```

Out[38]:

(10000, 9)

In [39]:

```
df_clean.head()
```

Out[39]:

	reviewerName	reviewText	summary	styleUpdate	reviewerName_withoutStopWords	reviewText_withoutStopWords	summary_withoutStopWords
278056	Rick	Mildly amusing but tiresome and repetitive in ...	Mildly amusing but tiresome and repetitive in ...	Kindle Edition	Rick	Mildly amusing tiresome repetitive places Im t...	Mildly amusing tiresome repetitive places
948792	Stephanie Buckner	In this day and age with modern media telling ...	Discover True Beauty	Paperback	Stephanie Buckner	In day age modern media telling us beautiful e...	Discover True Beaut
638299	Mary L	Spoilers Such a great story Kian is a killer A...	Kian and Jordan	Kindle Edition	Mary L	Spoilers Such great story Kian killer And made...	Kian Jordan
21471	Counselor Chris	I have this book in my office since my childre...	A Classic	Hardcover	Counselor Chris	I book office since children adults What said ...	A Classi
893151	Jacqueline LaMonica	This book was wonderful If you love books and...	Wonderful	Hardcover	Jacqueline LaMonica	This book wonderful If love books bookstores d...	Wonderfu

Removing stop words and any nan characters in the merged column - **'reviewTextSumaaryMerge'**

In [40]:

```
#Removing stop words and Nan
df_clean['reviewTextSummaryMerge_withoutStopWords'] = df_clean.reviewTextSumaaryMerge.dropna().apply(lambda x: ' '.join([word for word in x.
split() if word not in (stop)]))
```

Here we will tokenize the cleaned column containing the data

In [41]:

```
import nltk
sentences = []
for i in df_clean.reviewTextSummaryMerge_withoutStopWords.tolist():
    sentences.append(nltk.sent_tokenize(i))
```

Lemmatization

Lemmatization is a process of reducing a word into its canonical or base form as mentioned in a dictionary. The process of lemmatization groups all the forms/ tenses of a word into its base form. Unlike stemming, the root word here is an actual word.

In [42]:

```
from nltk.stem import WordNetLemmatizer
import re
```

```
lemmatizer = WordNetLemmatizer()

corpus = []
```

Lemmatization vs Stemming [2]

The main difference between stemming and lemmsatization is that, the latter has a higher accuracy and is perferred in context analysis. When the context of the textual data analysis is important, lemmatization gives better resutls as it reduces all the words to their meaningful root word unlike stemming where it reduces it to the common root word, which may or may not have a meaning.

Since the context here is important, lemmatization sounds like a preferred choice over stemming.

Once the lemmatization has been performed, we concatenate all the sentences to the corpus dataset that can be leveraged by vectorizers to compute bag of words and TF-IDF

In [43]:

```
# Lemmatization
for i in range(len(sentences)):
    sent = str(sentences[i])
    sent = sent.lower()
    sent= sent.split()
    sent = ' '.join(sent)
    corpus.append(sent)
```

Bag of Words

We will extract a bag of words from the above dataset. A BoW is simply an unordered collection of words and their frequencies (counts)

In [44]:

```
len(corpus)
```

Out[44]:

10000

In [45]:

```
# # Creating bag of words model
from sklearn.feature_extraction.text import CountVectorizer

vectorizer = CountVectorizer(stop_words='english')
X = vectorizer.fit_transform(corpus)
wordBag = pd.DataFrame(X.A, columns=vectorizer.get_feature_names())

wordBag
```

Out[45]:

	aa	aana	aargh	aaron	ab	aback	abadaba	abagail	abandon	abandonados	...	zucchini	zuccoto	zulfiqar	zuni	zuri	zurich	zusak	zusaks
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
9996	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
9997	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
9998	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
9999	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0

10000 rows × 46156 columns

The above output shows the bag of words created from each sentence.

TF-IDF - Term Frequency and Inverse Term Frequency [1]

TF-IDF stands for Term Frequency-Inverse Document Frequency. Instead of giving more weight to words that occur more frequently, it gives a higher weight to words that occur less frequently (across the entire corpus)

In a specific use cases, TF-IDF gives high results as it gives more weightage to less-frequently used words.

In [46]:

```
# # Creating the TF-IDF model
from sklearn.feature_extraction.text import TfidfVectorizer

vectorizer = TfidfVectorizer(stop_words='english', max_df=1.0, min_df=1, use_idf=False)
X = vectorizer.fit_transform(corpus)
TFIDF = pd.DataFrame(np.round(X.A,3), columns=vectorizer.get_feature_names())
TFIDF
```

Out[46]:

	aa	aana	aargh	aaron	ab	aback	abadaba	abagail	abandon	abandonados	...	zucchini	zuccoto	zulfiqar	zuni	zuri	zurich	zusak	zusal
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
9995	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
9996	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
9997	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
9998	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
9999	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0

10000 rows × 46156 columns

In [47]:

```
TFIDF.shape
```

Out[47]:

(10000, 46156)

Question 3

Building a model

We have decided to use Multinomial Naivev Bayes for text classification. It is a naive bayes algorithm that assumes a multinomial distribution and is advantageous when the dataset is not too large. Since we are using 10000 samples for our modelling, we found multinomial Naive Bayes model to be appropriate.

In [48]:

```
# target feature
y = df[['overall']]
y.head()
```

Out[48]:

	overall
278056	2
948792	5
638299	5
21471	5
893151	5

overall

In [49]:

```
y.shape
```

Out[49]:

(10000, 1)

Feature selection

We performed feature selection in the preprocessing step. We combined the review summary and text columns into one column called 'reviewTextSumaaryMerge'. After stop word removal, we have used this column to get the tfidf vector and eventually feed it into the model.

In [50]:

```
from sklearn.model_selection import train_test_split
```

In [51]:

```
# splitting the data into training, testing and validation sets in the ratio of 60:20:20
X_train, X_test, y_train, y_test  = train_test_split(TFIDF, y, test_size = 0.2, random_state =
42)
print('X_train shape:', X_train.shape)
print('y_train shape:', y_train.shape)
print('X_test shape:', X_test.shape)
print('y_test shape:', y_test.shape)
```

X_train shape: (8000, 46156)
y_train shape: (8000, 1)
X_test shape: (2000, 46156)
y_test shape: (2000, 1)

In [52]:

```
X_train, X_val, y_train, y_val  = train_test_split(X_train, y_train, test_size = 0.25, random_state =
42)
print('X_val shape:', X_val.shape)
print('y_val shape:', y_val.shape)
```

X_val shape: (2000, 46156)
y_val shape: (2000, 1)

In [53]:

```
y_train = y_train.values.ravel()
y_train
```

Out[53]:

array([5, 5, 5, ..., 5, 5, 5])

In [54]:

```
from nltk.stem.snowball import SnowballStemmer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.metrics import classification_report

stemmer = SnowballStemmer("english", ignore_stopwords=True)
# create a class to vectorize stemmed text by frequency counts
class StemmedCountVectorizer(CountVectorizer):
    # function to create an analyzer function
    def build_analyzer(self):
        # initialize CountVectorizer and call build_analyzer on it
        analyzer = super(StemmedCountVectorizer, self).build_analyzer()
        # return a function that stems each token of input and counts
        return lambda doc: ([stemmer.stem(w) for w in analyzer(doc)])

stemmed_count_vect = StemmedCountVectorizer(stop_words='english')
```

In [55]:

```
from sklearn.naive_bayes import MultinomialNB

# initialize the MNB model
nb_clf= MultinomialNB()

# use the training data to train the MNB model
nb_clf.fit(X_train, y_train)
```

Out[55]:

MultinomialNB()

In [56]:

```
# Model prediction
y_pred_train = nb_clf.predict(X_train)
y_pred_val = nb_clf.predict(X_val)
y_pred_test = nb_clf.predict(X_test)
```

Evaluation Metrics

For evaluation we are creating a classification report with the help of 'classification_report' module from skleanr.metrics. The report displays precision, recall and f1-score for all the target feature levels. It also returns accuracy, macro average and weighted average. Below are the classification reports for train, validation and test set.

In [57]:

```
print(classification_report(y_train, y_pred_train))
```

```
              precision    recall  f1-score   support

           1       0.00      0.00      0.00       190
           2       0.00      0.00      0.00       223
           3       0.00      0.00      0.00       482
           4       1.00      0.00      0.00      1372
           5       0.62      1.00      0.77      3733

    accuracy                           0.62      6000
   macro avg       0.32      0.20      0.15      6000
weighted avg       0.62      0.62      0.48      6000
```

In [58]:

```
print(classification_report(y_val, y_pred_val))
```

```
              precision    recall  f1-score   support

           1       0.00      0.00      0.00        58
           2       0.00      0.00      0.00        78
           3       0.00      0.00      0.00       205
           4       0.00      0.00      0.00       436
           5       0.61      1.00      0.76      1223

    accuracy                           0.61      2000
   macro avg       0.12      0.20      0.15      2000
weighted avg       0.37      0.61      0.46      2000
```

In [59]:

```
print(classification_report(y_test, y_pred_test))
```

```
              precision    recall  f1-score   support

           1       0.00      0.00      0.00        59
           2       0.00      0.00      0.00        83
           3       0.00      0.00      0.00       184
           4       0.00      0.00      0.00       450
           5       0.61      1.00      0.76      1224

    accuracy                           0.61      2000
```

macro avg	0.12	0.20	0.15	2000
weighted avg	0.37	0.61	0.46	2000

In [60]:

```
from sklearn import metrics
print('\nTraining Accuracy score:', metrics.accuracy_score(y_train, y_pred_train))
print('Validation Accuracy score:', metrics.accuracy_score(y_val, y_pred_val))
print('Testing Accuracy score:', metrics.accuracy_score(y_test, y_pred_test))
```

Training Accuracy score: 0.6226666666666667
Validation Accuracy score: 0.6115
Testing Accuracy score: 0.612

ROC AUC score

Another metric used for multiclass classification is ROC AUC score (Area Under the Receiver Operating Characteristic Curve). It quantifies the model's ability to distinguish between each class. The metric is only used with classifiers that can generate class membership probabilities.

3

In [61]:

```
from sklearn.metrics import roc_auc_score

# Generate class membership probabilities
y_pred_probs_tr =  nb_clf.predict_proba(X_train)
y_pred_probs_va =  nb_clf.predict_proba(X_val)
y_pred_probs_te = nb_clf.predict_proba(X_test)


print('\nTraining ROC AUC score', roc_auc_score(y_train, y_pred_probs_tr, average="weighted", multi_class="ovr"))
print('Validation ROC AUC score', roc_auc_score(y_val, y_pred_probs_va, average="weighted", multi_class="ovr"))
print('Testing ROC AUC score', roc_auc_score(y_test, y_pred_probs_te, average="weighted", multi_class="ovr"))
```

Training ROC AUC score 0.7384915956988167
Validation ROC AUC score 0.6113107830451028
Testing ROC AUC score 0.634800555593488

The above numbers show that ROC AUC score for train set is the highest, where as it is the lowest for validation set.

In [62]:

```
# converting y_train back to dataframe
y_train = pd.DataFrame(y_train, columns=['overall'])
y_train.head()
```

Out[62]:

	overall
0	5
1	5
2	5
3	5
4	5

Hyperparameter tuning

Hyperparameter optimization or tuning is the problem of choosing a set of optimal hyperparameters for a learning algorithm. Multinomial Naive Bayes has parameters - alpha, fit_prior and class_prior. We can fiddle with the alpha parameter to get different results. 4

In [67]:

```
from sklearn.experimental import enable_halving_search_cv
from sklearn.model_selection import HalvingRandomSearchCV
parameters = {'alpha': (0.0001, 0.001, 0.01, 0.1, 1.0)}
halving_random = HalvingRandomSearchCV(estimator=nb_clf, param_distributions=parameters, factor=3, n_jobs=-3, random_state=0)
halving_random.fit(X_train, y_train)
halving_random.best_estimator
```

```
halving_random.best_estimator_
# halving_random.best_params_
```

Out[67]:

MultinomialNB(alpha=0.1)

We have used HalvingRandomSearchCV instead of GridSearcCV or RandomizedSearchCV for hyperparameter tuning, because it is much faster and returns very similar results in much less time. Furthermore, the kernel was crashing repeatedly when we tried to execute GridSearchCV and RandomizedSearchCV.

Nevertheless, the above results show that the model performs the best when the value of the parameter 'alpha' is 0.1 for multinomial Naive Bayes

Avoiding Overfitting

To avoid overfitting in text classification, we can perform stemming and lemmatization of the data. In our case, we have performed lemmatization. Lemmatization (and stemming) are ways to shrink the size of the vocabulary space.

For eg: By turning the words 'reading', 'reader' and 'reads' all into the stem or lemma 'read', the sparsity of the dataset can be drastically reduced. This really helps avoid overfitting because overly sparse data can lead to overfitting.

Stop word removal is also a step we performed that helps in avoiding overfitting. Stop words do not carry meaning of their own, but only in the context of a sentence. Having stop words can make the model more prone to overfitting. Therefore, preprocessing here plays a very important role to ensure that that the model does not overfit.

5

Learning Curve

In [79]:

```
from sklearn.model_selection import learning_curve
train_sizes = [1, 100, 300, 500, 1000]
train_sizes, train_scores, validation_scores = learning_curve(
MultinomialNB(),
X=X_train, y=y_train, train_sizes=train_sizes, cv=5, scoring='accuracy' ,n_jobs=-1, verbose=1)
# train_scores_mean = train_scores.mean(axis = 1)
train_scores_mean = np.mean(train_scores, axis=1)
# validation_scores_mean = validation_scores.mean(axis = 1)
validation_scores_mean = np.mean(validation_scores, axis = 1)
```

```
[learning_curve] Training set sizes: [   1  100  300  500 1000]
```

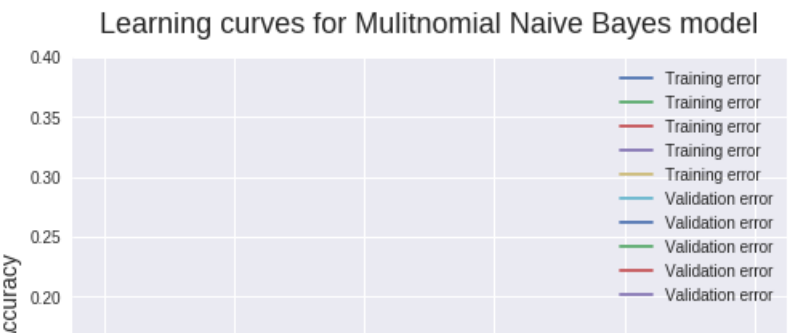
```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 40 concurrent workers.
[Parallel(n_jobs=-1)]: Done  25 out of  25 | elapsed:    5.6s finished
```

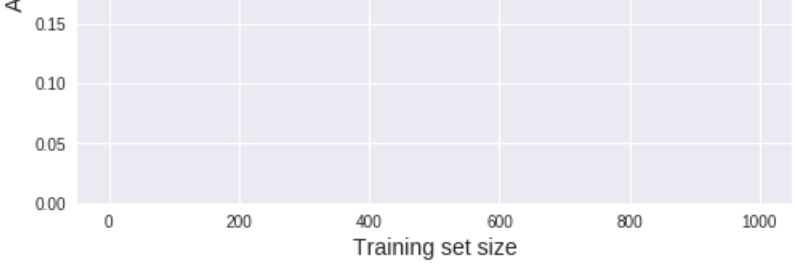
In [78]:

```
import matplotlib.pyplot as plt
plt.style.use('seaborn')
plt.plot(train_sizes, train_scores_mean, label = 'Training error')
plt.plot(train_sizes, validation_scores_mean, label = 'Validation error')
plt.ylabel('Accuracy', fontsize = 14)
plt.xlabel('Training set size', fontsize = 14)
plt.title('Learning curves for Mulitnomial Naive Bayes model', fontsize = 18, y = 1.03)
plt.legend()
plt.ylim(0,0.4)
```

Out[78]:

(0, 0.4)





Question 4

Part of speech tagging

Part of Speech (POS) tagging is the process of assigning Part of Speech tags to the words in a sentence. POS is performed at the token level.

In [81]:

```
from nltk import pos_tag # function that tags words by their part of speech (POS)
import nltk
nltk.download('averaged_perceptron_tagger')
```

```
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /users/grad/devesh/nltk_data...
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
```

Out[81]:

True

6

In [82]:

```
tagged_reviewtext_summary = df_clean['reviewTextSummaryMerge_withoutStopWords'].str.split().map(pos_tag)
tagged_reviewtext_summary.head()
```

Out[82]:

```
278056    [(Mildly, RB), (amusing, VBG), (tiresome, JJ),...
948792    [(In, IN), (day, NN), (age, NN), (modern, JJ),...
638299    [(Spoilers, NNS), (Such, JJ), (great, JJ), (st...
21471     [(I, PRP), (book, NN), (office, NN), (since, I...
893151    [(This, DT), (book, NN), (wonderful, JJ), (If,...
Name: reviewTextSummaryMerge_withoutStopWords, dtype: object
```

In [83]:

```
tagged_reviewtext_summary = list(tagged_reviewtext_summary)
```

Extracting the nouns only by filtering tags starting with 'NN'.

In [85]:

```
new_list = []
for i in tagged_reviewtext_summary:
    temp = [j[0] for j in i if j[1].startswith("NN")]
    new_list.append(temp)

print(new_list[:20])
```

```
[['places', 'Im', 'times', 'slippages', 'failure', 'history', 'relics', 'characters', 'chapters', 'interest', 'quality', 'rededication', 'writing', 'Doomsday', 'Book', 'Mildly', 'places'], ['day', 'age', 'media', 'trap', 'My', 'teeth', 'My', 'hair', 'thin', 'Should', 'cover', 'gray', 'Ugh', 'beauty', 'Satan', 'set', 'trap', 'women', 'convince', 'bodies', 'value', 'Heavenly', 'Father', 'prisons', 'words', 'views', 'behaviors', 'book', 'compilation', 'authors', 'everything', 'Time', 'Out', 'Women', 'speakers', 'children', 'LaNae', 'Valentine', 'Lisa', 'Tensmeyer', 'Hansen', 'perspectives', 'woman', 'pause', 'dialogue', 'Every', 'soul', 'God', 'see', 'book', 'wealth', 'inspiration', 'Discover', 'True', 'Beauty'], ['Spoilers', 'story', 'Kian', 'killer', 'hero', 'life', 'life', 'Fast', 'Jordan', 'Her', 'life', 'Choiceslet', 'everyone', 'Bamits', 'Jos', 'thats', 'Lots', 'lots', 'thing', 'part', 'stars', 'Jordan'], ['book', 'office', 'children', 'adults', 'way', 'Maurice', 'Sendak', 'mothers', 'Wild', 'Things', 'misbehaving', 'sent', 'bed', 'Max', 'returns', 'waiting', 'lives', 'heart'], ['book', 'books', 'bookstores', 'book', 'book', 'order', 'enter', 'bookstores', 'Great', 'Wonderful'], ['book', 'series', 'fiction', 'characters', 'lives', 'prevail', 'situations', 'breakfast', 'scene', 'cinnamon', 'rolls', 'Chapter', 'price', 'admission', 'volume', 'problem', 'predecessors', 'predictableValentine', 'OK', 'place', 'visitwith', 'carousel', 'park', 'Better'], ['Volume', 'comments', 'volume', 'author', 'captures', 'reader', 'get', 'Wehr', 'author', 'captures'], ['Enjoyed', 'book', 'Zane', 'aspects', 'book', 'disturb', 'read', 'Just', 'Linc', 'pants', 'days', 'Love', 'author'], ['anything', 'Lisa',
```

Andersen', 'review', 'newspaper', 'title', 'look', 'books', 'reel', 'hook', 'surprise', 'Great', 'character', 'delineation', 'folks', 'A', 'writer', 'Highly', 'TOUGH', 'TO', 'PUT', 'DOWN'], ['Gritty', 'crime', 'stories', 'author', 'conversation', 'style', 'feelings', 'cop', 'actions', 'cops', 'victims', 'interactions', 'Crime'], ['book', 'ones', 'series', 'book', 'way', 'author', 'Love', 'suspense', 'everything', 'Dont', 'Great', 'series'], ['year', 'daughter', 'times', 'day', 'passionate', 'itWhen', 'copy', 'Valentines', 'daySince', 'book', 'daughter', 'doctor', 'body', 'books', 'Ive', 'body', 'DK', 'books', 'kids', 'photographs', 'text', 'books', 'information', 'way', 'grow', 'years', 'book', 'Book', 'Daughter', 'become', 'Doctor'], ['Stars'], ['Philippa', 'Gregory', 'Africa', 'audio', 'books', 'reason', 'cannot', 'South', 'Africa', 'Too', 'South', 'Africa', 'Audiblecom', 'download', 'Philippa', 'Gregorys', 'books'], ['detail', 'route', 'planning', 'Interstate', 'Highways', 'scale', 'maps', 'Ill', 'book', 'store', 'detail', 'state', 'state', 'maps', 'Im', 'highway', 'route', 'planning'], ['Grishams', 'books', 'page', 'Stars'], ['reading', 'lot', 'stories', 'Mysteries', 'World', 'War', 'II'], ['time', 'musicians', 'Stephen', 'Stills', 'Judy', 'Collins', 'romance', 'Judy', 'heart', 'Stephen', 'Suite', 'Judy', 'Blue', 'Eyes', 'line', 'head', 'spin', 'Dont', 'sounds', 'idea', 'beings', 'Brian', 'Fagans', 'book', 'CroMagnon', 'segment', 'family', 'history', 'news', 'studies', 'DNA', 'Europeans', 'genes', 'invading', 'farmers', 'Fertile', 'Crescent', 'exterminate', 'genes', 'immigrants', 'DNAIt', 'staggers', 'imagination', 'contemplate', 'beauty', 'vitality', 'Ice', 'Age', 'Europe', 'heartbreaking', 'illuminating', 'memories', 'book', 'connection', 'ancient', 'paintings', 'artists', 'ancestors', 'images', 'family', 'My', 'people', 'lands', 'mammoths', 'bison', 'herds', 'streams', 'sense', 'homecoming', 'job', 'world', 'Ice', 'Age', 'swings', 'glaciers', 'glaciers', 'climate', 'hunters', 'game', 'times', 'hunters', 'meat', 'meat', 'events', 'temperatures', 'degrees', 'Fahrenheit', 'degrees', 'Celsius', 'colder', 'intervals', 'climate', 'course', 'lifetime', 'Siberia', 'forest', 'Sahara', 'grasslands', 'time', 'France', 'EnglandThe', 'news', 'tribes', 'Europe', 'farmers', 'corn', 'Mexico', 'innovation', 'bit', 'shadows', 'generations', 'Fagan', 'transition', 'agriculture', 'innovation', 'technology', 'hominids', 'ancestors', 'Asia', 'Neanderthals', 'stage', 'Neanderthals', 'Europe', 'years', 'temperate', 'forests', 'Neanderthals', 'luckless', 'dullards', 'cleverness', 'spans', 'time', 'dance', 'planet', 'destroy', 'boresCroMagnon', 'refers', 'clans', 'Europe', 'species', 'Africa', 'years', 'years', 'Europe', 'years', 'continent', 'CroMagnons', 'caves', 'peepholes', 'Neanderthals', 'years', 'reasonsThe', 'trademark', 'weapon', 'CroMagnons', 'spear', 'stone', 'antler', 'land', 'variety', 'prey', 'deer', 'reindeer', 'Thus', 'meat', 'nursery', 'spearchuckers', 'countryside', 'eras', 'summers', 'plant', 'foods', 'meat', 'core', 'source', 'Homo', 'sapiens', 'hunters', 'day', 'AfricaLater', 'bow', 'arrow', 'Bows', 'years', 'evidence', 'bow', 'BC', 'bow', 'critters', 'distance', 'Nets', 'traps', 'spears', 'Rabbits', 'birds', 'rodents', 'meat', 'hunters', 'consumption', 'plant', 'foods', 'years', 'Younger', 'Dryas', 'period', 'weather', 'years', 'droughts', 'East', 'humans', 'grass', 'seeds', 'history', 'combination', 'family', 'planning', 'climate', 'change', 'bullet', 'train', 'catastropheWithin', 'generations', 'people', 'East', 'Turkey', 'farming', 'wetter', 'conditions', 'Younger', 'Dryas', 'economies', 'wildfire', 'Anatolia', 'Europe', 'years', 'evolution', 'Ice', 'Age', 'Europe', 'Time', 'glaciers', 'toll', 'meager', 'evidence', 'timeline', 'holes', 'theories', 'research', 'Fagans', 'book', 'visit', 'WikipediaAnnoyingly', 'number', 'ideas', 'evidence', 'speculation', 'example', 'Neanderthals', 'language', 'brains', 'circuits', 'innovation', 'ecocideFagan', 'Homo', 'squad', 'praise', 'species', 'Effective', 'technology', 'acute', 'selfawareness', 'intimate', 'relationship', 'environment', 'CroMagnon', 'personality', 'regions', 'Europe', 'conditionsIm', 'glad', 'book', 'lot', 'era', 'civilization', 'period', 'warm', 'food', 'production', 'system', 'climate', 'problems', 'hotter', 'Fagan', 'roller', 'coaster', 'climate', 'history', 'hammers', 'brains', 'fact', 'Mama', 'Nature', 'praise', 'intelligence', 'innovation', 'cloud', 'stinky', 'funk', 'Where', 'line', 'innovation', 'self destruction', 'Are', 'Is', 'questions', 'rug', 'treasureRichard', 'Adrian', 'ReeseAuthor', 'Bust', 'A', 'trip'], ['family', 'books', 'women', 'men', 'book', 'Great', 'reads', 'book'], ['story', 'share', 'dvd', 'dvd']]

In [86]:

```
# converting all the upper case letters into lower case
new_list_lower = []
for i in range(len(new_list)):
    sent_ = str(new_list[i])
    sent_ = sent_.lower()
    sent_= sent_.split()
    sent_ = ' '.join(sent_)
    new_list_lower.append(sent_)
```

Word Bag

In [87]:

```
from sklearn.feature_extraction.text import CountVectorizer

vectorizer1 = CountVectorizer(stop_words='english')
X1 = vectorizer1.fit_transform(new_list_lower)
wordBag1 = pd.DataFrame(X1.A, columns=vectorizer1.get_feature_names())

wordBag1
```

Out[87]:

	aa	aana	aargh	aaron	ab	abadaba	abagail	abandon	abandonados	abandoned	...	zucchini	zuccoto	zulfiqar	zuni	zuri	zurich	zusak	z
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	
9996	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	
9997	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	
9998	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	
9999	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	

10000 rows × 31772 columns

TD-IDF: Term frequency-inverse document frequency

Creating tdidf model for data only containing nouns.

In [88]:

```
#  Creating the TF-IDF model
from sklearn.feature_extraction.text import TfidfVectorizer

vectorizer2 = TfidfVectorizer(stop_words='english', max_df=1.0, min_df=1, use_idf=False)
X2 = vectorizer2.fit_transform(new_list_lower)
TFIDF_2 = pd.DataFrame(np.round(X2.A,3), columns=vectorizer2.get_feature_names())
TFIDF_2
```

Out[88]:

	aa	aana	aargh	aaron	ab	abadaba	abagail	abandon	abandonados	abandoned	...	zucchini	zuccoto	zulfiqar	zuni	zuri	zurich	zusak
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9996	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9997	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9998	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9999	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0

10000 rows × 31772 columns

Building a model

Repeating Question 3 after extracting nouns only to obtain a bag-of-words tf-idf weighted vector representation.

In [89]:

```
# target feature
y.head()
```

Out[89]:

	overall
278056	2
948792	5
638299	5
21471	5
893151	5

In [90]:

```
# splitting the data into training, testing and validation sets in the ratio of 60:20:20
X_train1, X_test1, y_train1, y_test1  = train_test_split(TFIDF_2, y, test_size = 0.2, random_state =
42)
print('X_train shape:', X_train1.shape)
print('y_train shape:', y_train1.shape)
print('X_test shape:', X_test1.shape)
print('y_test shape:', y_test1.shape)
```

```
X_train shape: (8000, 31772)
y_train shape: (8000, 1)
X_test shape: (2000, 31772)
y_test shape: (2000, 1)
```

In [91]:

```
X_train1, X_val1, y_train1, y_val1  = train_test_split(X_train1, y_train1, test_size = 0.25, random_state =
42)
print('X_val shape:', X_val1.shape)
print('y_val shape:', y_val1.shape)
```

```
X_val shape: (2000, 31772)
y_val shape: (2000, 1)
```

In [92]:

```
from sklearn.naive_bayes import MultinomialNB

# initialize the MNB model
nb_clf_1= MultinomialNB()

# use the training data to train the MNB model
nb_clf_1.fit(X_train1, y_train1)
```

Out[92]:

```
MultinomialNB()
```

In [93]:

```
# Fitting the model
y_pred_train_ = nb_clf_1.predict(X_train1)
y_pred_val_ = nb_clf_1.predict(X_val1)
y_pred_test_ = nb_clf_1.predict(X_test1)
```

Evaluation metrics

Using the same evaluation metrics that were used in the earlier model.

In [94]:

```
# Classification report
print(classification_report(y_train1, y_pred_train_))
```

```
              precision    recall  f1-score   support

           1       0.00      0.00      0.00       190
           2       0.00      0.00      0.00       223
           3       0.00      0.00      0.00       482
           4       1.00      0.00      0.01      1372
           5       0.62      1.00      0.77      3733

    accuracy                           0.62      6000
   macro avg       0.32      0.20      0.15      6000
weighted avg       0.62      0.62      0.48      6000
```

In [95]:

```
print(classification_report(y_val1, y_pred_val_))
```

```
              precision    recall  f1-score   support

           1       0.00      0.00      0.00        58
           2       0.00      0.00      0.00        78
           3       0.00      0.00      0.00       205
           4       0.00      0.00      0.00       436
           5       0.61      1.00      0.76      1223

    accuracy                           0.61      2000
   macro avg       0.12      0.20      0.15      2000
weighted avg       0.37      0.61      0.46      2000
```

In [96]:

```
print(classification_report(y_test1, y_pred_test_))
```

```
              precision    recall  f1-score   support
```

```
           1       0.00      0.00      0.00        59
           2       0.00      0.00      0.00        83
           3       0.00      0.00      0.00       184
           4       0.00      0.00      0.00       450
           5       0.61      1.00      0.76      1224

    accuracy                           0.61      2000
   macro avg       0.12      0.20      0.15      2000
weighted avg       0.37      0.61      0.46      2000
```

In [97]:

```
from sklearn import metrics
print('\nTraining Accuracy score:', metrics.accuracy_score(y_train1, y_pred_train_))
print('Validation Accuracy score:', metrics.accuracy_score(y_val1, y_pred_val_))
print('Testing Accuracy score:', metrics.accuracy_score(y_test1, y_pred_test_))
```

```
Training Accuracy score: 0.6228333333333333
Validation Accuracy score: 0.6115
Testing Accuracy score: 0.612
```

ROC AUC score

In [98]:

```
from sklearn.metrics import roc_auc_score

# Generate class membership probabilities
y_pred_probs_tr_ =  nb_clf_1.predict_proba(X_train1)
y_pred_probs_va_ =  nb_clf_1.predict_proba(X_val1)
y_pred_probs_te_ = nb_clf_1.predict_proba(X_test1)


print('\nTraining ROC AUC score', roc_auc_score(y_train1, y_pred_probs_tr_, average="weighted", multi_class="ovr"))
print('Validation ROC AUC score', roc_auc_score(y_val1, y_pred_probs_va_, average="weighted", multi_class="ovr"))
print('Testing ROC AUC score', roc_auc_score(y_test1, y_pred_probs_te_, average="weighted", multi_class="ovr"))
```

```
Training ROC AUC score 0.7630139148890116
Validation ROC AUC score 0.5849414293697982
Testing ROC AUC score 0.6100637370427366
```

The above ROC AUC scores show that performance on training set has improved after only nouns were extracted from the raw data. Whereas, performance on testing data has degraded as compared to the previous model.

Hyperparamter tuning

In [99]:

```
from sklearn.experimental import enable_halving_search_cv
from sklearn.model_selection import HalvingRandomSearchCV
parameters = {'alpha': (0.0001, 0.001, 0.01, 0.1, 1.0)}
halving_random_ = HalvingRandomSearchCV(estimator=nb_clf_1, param_distributions=parameters, factor=3, n_jobs=-1, random_state=0)
halving_random_.fit(X_train1, y_train1)
halving_random_.best_estimator_
halving_random_.best_params_
```

Out[99]:

```
{'alpha': 0.1}
```

Similar process was followed for hyperparameter tuning as we used HalvingRandomSearchCV again for quicker results. Like previous time, result shows that the model performs the best when the value of the parameter 'alpha' is 0.1 for multinomial Naive Bayes

Statistical Significance Test

7

In [146]:

```
from sklearn.naive_bayes import MultinomialNB
```

```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedStratifiedKFold
from numpy import mean
from numpy import std

labels = np.array(y)


# train_features, test_features, train_labels, test_labels = train_test_split(TFIDF_2, labels, test_size = 0.25, random_state = 42)

cv1 = RepeatedStratifiedKFold(n_splits=5, n_repeats=3, random_state=1)
scores1 = cross_val_score(nb_clf, TFIDF, y, scoring='accuracy', cv=cv1, n_jobs=-1)
print('First Model Mean Accuracy: %.3f (%.3f)' % (mean(scores1), std(scores1)))


# important_indices = [df_update_list.index('brightness'), df_update_list.index('scan'), df_update_list.index('bright_t31')]
# train_important = train_features[["brightness", "scan", "confidence"]]
# test_important = test_features[["brightness", "scan", "confidence"]]

cv2 = RepeatedStratifiedKFold(n_splits=5, n_repeats=3, random_state=1)
scores2 = cross_val_score(nb_clf_1, TFIDF_2, y, scoring='accuracy', cv=cv2, n_jobs=-1)
print('Second Model Mean Accuracy: %.3f (%.3f)' % (mean(scores2), std(scores2)))


# score1 = rf.fit(train_important, train_labels).score(test_important, test_labels)
# score2 = lr.fit(train_important, train_labels).score(test_important, test_labels)
```

```
First Model Mean Accuracy: 0.618 (0.000)
Second Model Mean Accuracy: 0.618 (0.000)
```

Since we have used the same model (Multinomial Naive Bayes) for both the scenarios, i.e before POS and after POS, the mean accuracy in both the instances is the same. This implies that part of speech tagging did not really have an impact on model's preformance.

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In [ ]: