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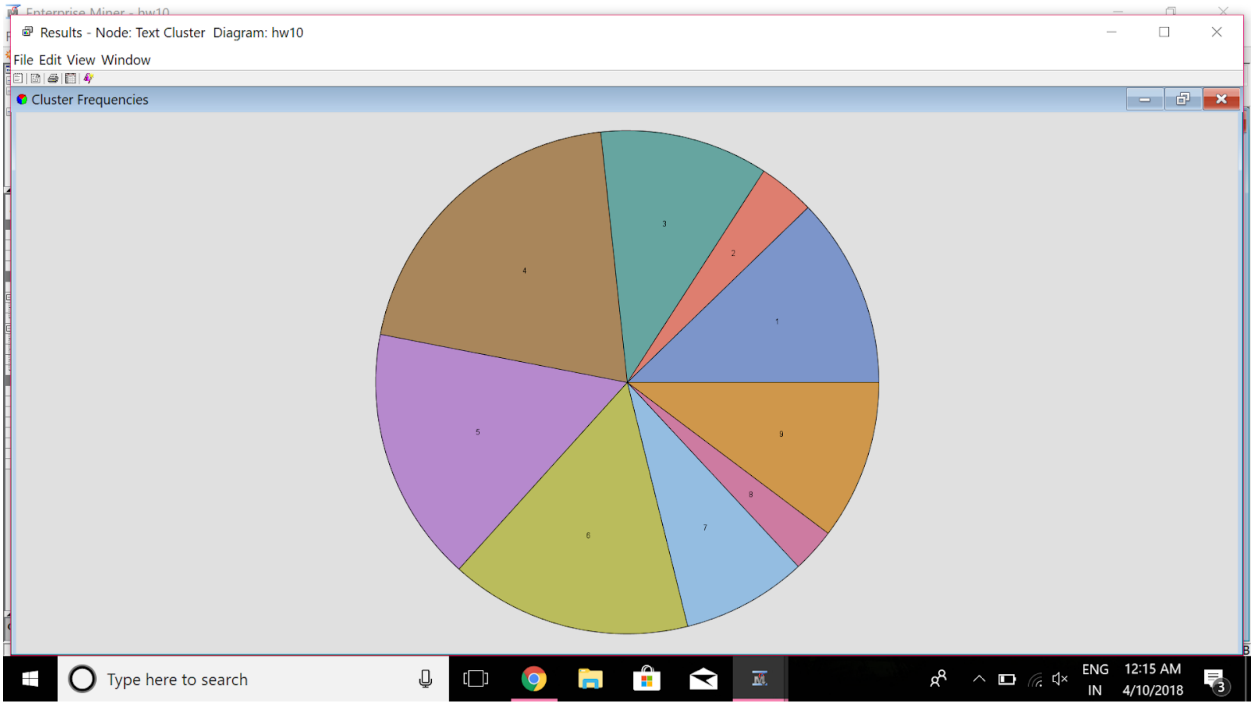
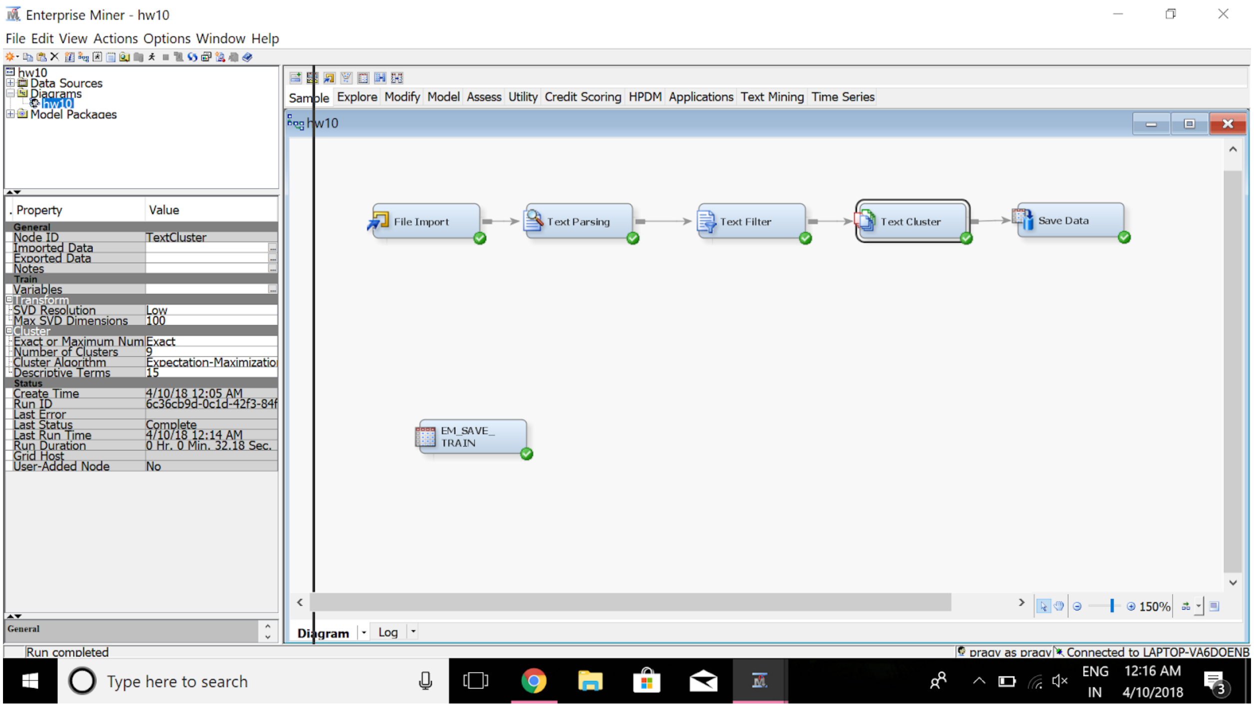
I have tried the assignment in both SAS and Python.

SAS





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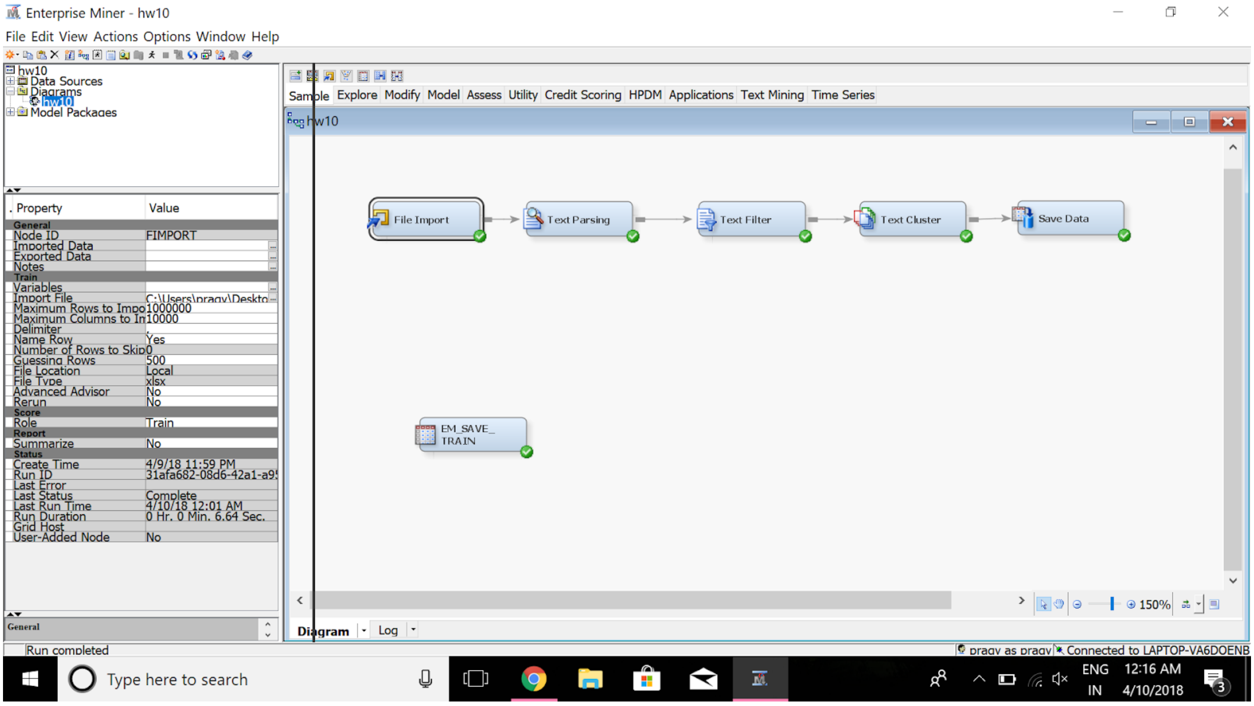

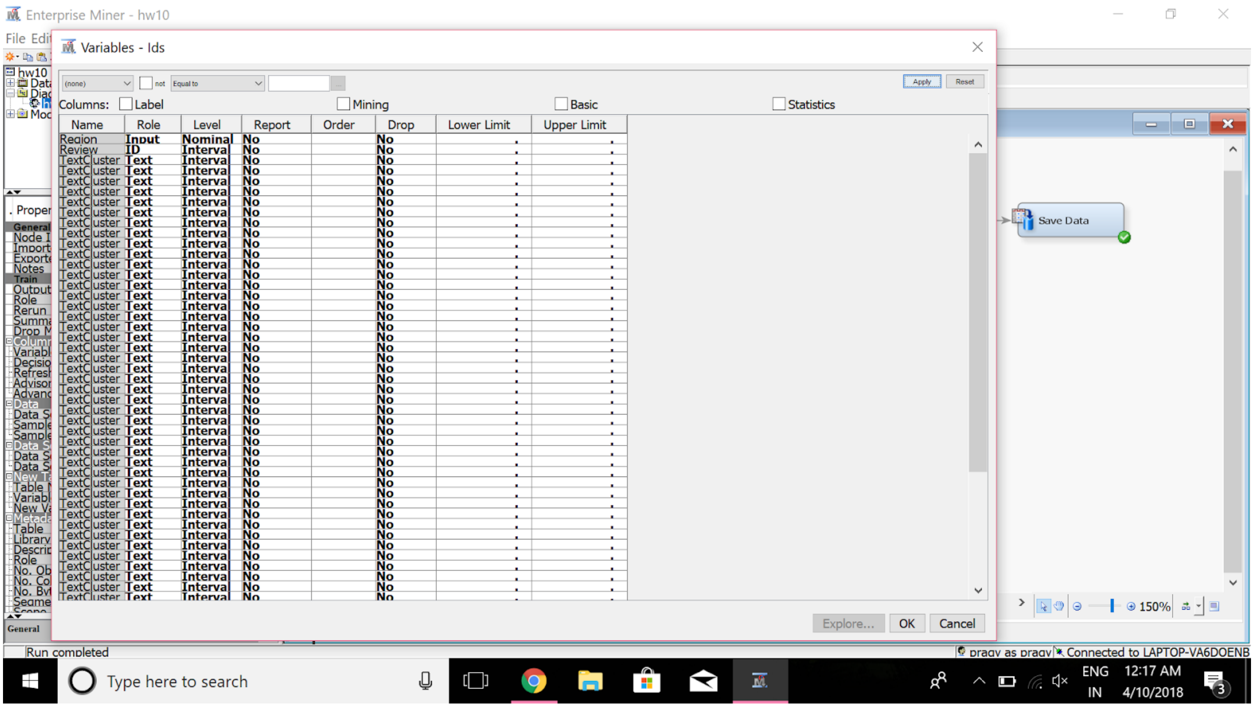

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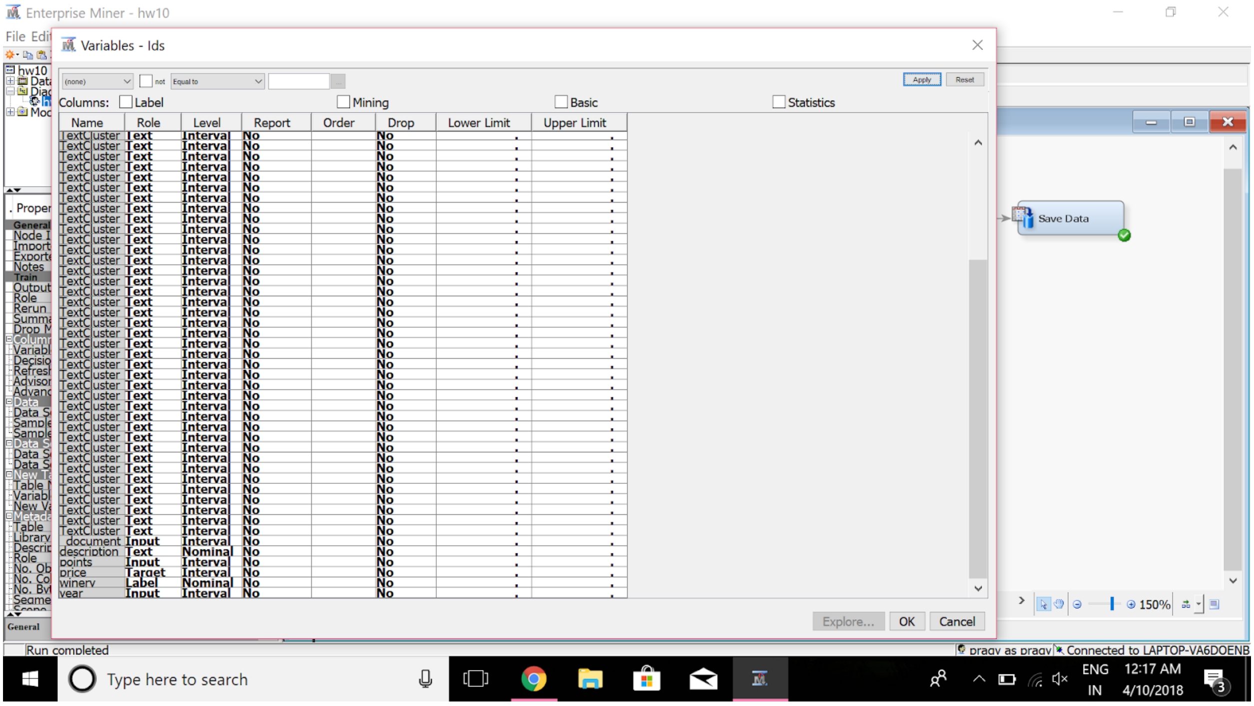

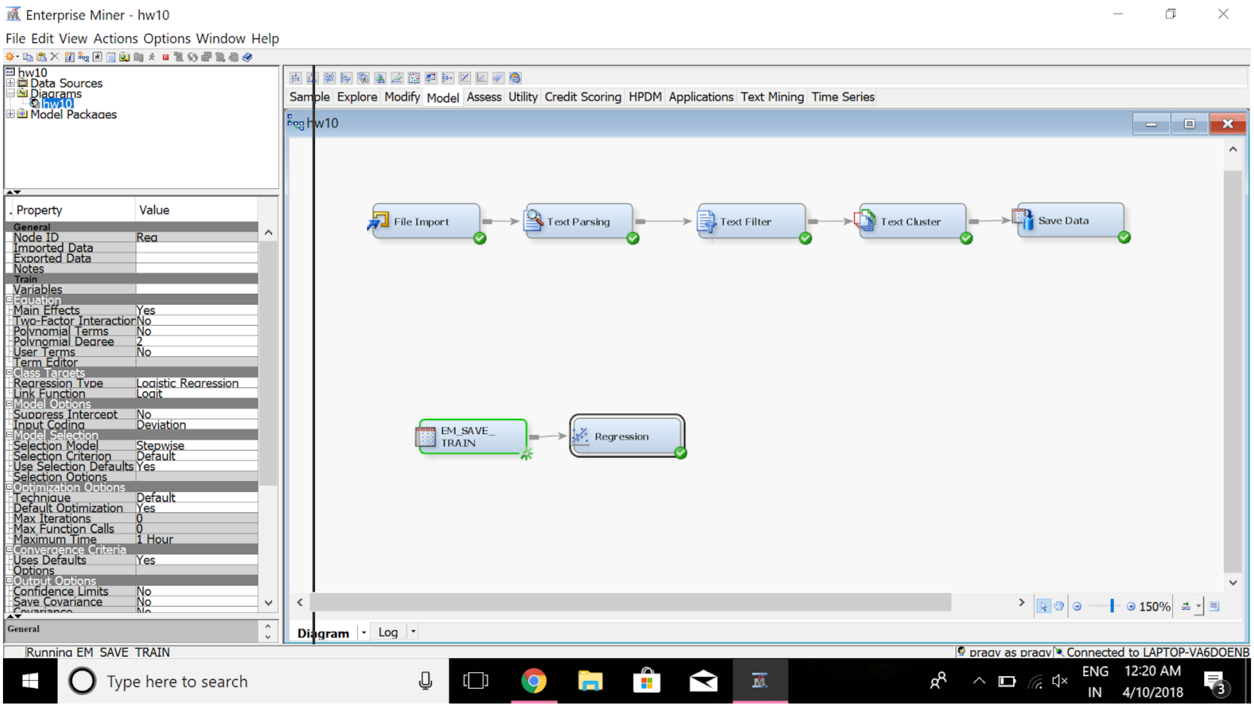

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Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	39	5201467	133371	117.20	<.0001
Error	5609	6382649	1137.929910		
Corrected Total	5648	11584116			

Model Fit Statistics

R-Square	0.4490	Adj R-Sq	0.4452
AIC	39791.6788	BIC	39794.3113
SBC	40057.2481	C(p)	35.6781

Type 3 Analysis of Effects

Effect	DF	Sum of Squares	F Value	Pr > F
Region	16	592151.692	32.52	<.0001
TextCluster_SVD11	1	22472.5282	19.75	<.0001
TextCluster_SVD12	1	155321.325	136.49	<.0001
TextCluster_SVD13	1	29869.2704	26.25	<.0001
TextCluster_SVD14	1	7260.7682	6.38	0.0116
TextCluster_SVD15	1	8669.3107	7.62	0.0058
TextCluster_SVD16	1	12248.8335	10.76	0.0010
TextCluster_SVD19	1	5243.6527	4.61	0.0319
TextCluster_SVD2	1	29937.3103	26.31	<.0001
TextCluster_SVD20	1	22753.0170	20.00	<.0001
TextCluster_SVD21	1	55064.6377	48.39	<.0001
TextCluster_SVD23	1	23934.4866	21.03	<.0001
TextCluster_SVD24	1	21108.9920	18.55	<.0001
TextCluster_SVD30	1	41099.7896	36.12	<.0001
TextCluster_SVD32	1	20443.0418	17.97	<.0001
TextCluster_SVD39	1	6250.1802	5.49	0.0191
TextCluster_SVD4	1	80277.8117	70.55	<.0001
TextCluster_SVD41	1	4878.4134	4.29	0.0384
TextCluster_SVD45	1	5186.3524	4.56	0.0328
TextCluster_SVD5	1	85720.1918	75.33	<.0001
TextCluster_SVD6	1	4649.4178	4.09	0.0433
TextCluster_SVD8	1	33321.7904	29.28	<.0001
TextCluster_SVD9	1	18171.1986	15.97	<.0001
points	1	1433536.61	1259.78	<.0001

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	t Value	Pr > |t|
Intercept		1	-490.8	15.1580	-32.38	<.0001
Region	California Other	1	-5.1178	3.4856	-1.47	0.1421
Region	Central Coast	1	-0.9603	3.2287	-0.30	0.7662
Region	Central Valley	1	-8.8512	4.3218	-2.05	0.0406

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Region	Clear Lake	1	10.3801	31.9057	0.33	0.7449
Region	High Valley	1	-2.7591	18.5902	-0.15	0.8820
Region	Lake County	1	-3.9944	6.1981	-0.64	0.5193
Region	Mendocino	1	-7.2383	6.5186	-1.11	0.2669
Region	Mendocino County	1	-12.1969	6.7002	-1.82	0.0688
Region	Mendocino Ridge	1	9.7025	18.5918	0.52	0.6018
Region	Mendocino/Lake Counties	0	0	.	.	.
Region	Napa	1	21.9288	3.0958	7.08	<.0001
Region	Napa-Sonoma	1	12.2873	5.9743	2.06	0.0398
Region	North Coast	1	-9.2420	4.5830	-2.02	0.0438
Region	Red Hills Lake County	1	-7.5242	6.0122	-1.25	0.2108
Region	Redwood Valley	1	-12.7751	18.5626	-0.69	0.4913
Region	Sierra Foothills	1	-5.7533	5.0568	-1.14	0.2553
Region	Sonoma	1	0.6190	3.1954	0.19	0.8464
TextCluster_SVD11		1	14.8329	3.3378	4.44	<.0001
TextCluster_SVD12		1	40.9614	3.5060	11.68	<.0001
TextCluster_SVD13		1	18.0297	3.5191	5.12	<.0001
TextCluster_SVD14		1	9.0717	3.5913	2.53	0.0116
TextCluster_SVD15		1	9.9472	3.6038	2.76	0.0058
TextCluster_SVD16		1	-12.0296	3.6666	-3.28	0.0010
TextCluster_SVD19		1	7.9600	3.7081	2.15	0.0319
TextCluster_SVD2		1	-10.7025	2.0866	-5.13	<.0001
TextCluster_SVD20		1	16.6686	3.7277	4.47	<.0001
TextCluster_SVD21		1	26.4049	3.7958	6.96	<.0001
TextCluster_SVD23		1	17.6138	3.8406	4.59	<.0001
TextCluster_SVD24		1	16.1919	3.7594	4.31	<.0001
TextCluster_SVD30		1	23.3678	3.8883	6.01	<.0001
TextCluster_SVD32		1	-17.8783	4.2180	-4.24	<.0001
TextCluster_SVD39		1	9.9056	4.2266	2.34	0.0191
TextCluster_SVD4		1	-23.6416	2.8147	-8.40	<.0001
TextCluster_SVD41		1	-8.6404	4.1730	-2.07	0.0384
TextCluster_SVD45		1	9.0801	4.2532	2.13	0.0328
TextCluster_SVD5		1	25.7882	2.9712	8.68	<.0001
TextCluster_SVD6		1	-6.3382	3.1356	-2.02	0.0433
TextCluster_SVD8		1	18.6213	3.4412	5.41	<.0001
TextCluster_SVD9		1	13.4913	3.3761	4.00	<.0001
points		1	6.0189	0.1696	35.49	<.0001

PYTHON

```
import pandas as pd
import string
import nltk
from nltk import pos_tag
from nltk.tokenize import word_tokenize
from nltk.stem.snowball import SnowballStemmer
from nltk.stem import WordNetLemmatizer
from nltk.corpus import wordnet as wn
from nltk.corpus import stopwords
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.decomposition import LatentDirichletAllocation

#
```

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```
# nltk.download('punkt')
# nltk.download('averaged_perceptron_tagger')
# nltk.download('stopwords')
# nltk.download('wordnet')


# my_analyzer replaces both the preprocessor and tokenizer
# it also replaces stop word removal and ngram constructions

def my_analyzer(s):
    # Synonym List
    syns = {'veh': 'vehicle', 'car': 'vehicle', 'chev': 'cheverolet', \
            'chevy': 'cheverolet', 'air bag': 'airbag', \
            'seat belt': 'seatbelt', "n't": 'not', 'to30': 'to 30', \
            'wont': 'would not', 'cant': 'can not', 'cannot': 'can not', \
            'couldnt': 'could not', 'shouldnt': 'should not', \
            'wouldnt': 'would not', }

    # Preprocess String s
    s = s.lower()
    s = s.replace(',', '. ')
    # Tokenize
    tokens = word_tokenize(s)
    tokens = [word.replace(',', '') for word in tokens]
    tokens = [word for word in tokens if ('*' not in word) and \
              ("''" != word) and ("``" != word) and \
              (word != 'description') and (word != 'dtype') \
              and (word != 'object') and (word != "'s")]

    # Map synonyms
    for i in range(len(tokens)):
        if tokens[i] in syns:
            tokens[i] = syns[tokens[i]]

    # Remove stop words
    punctuation = list(string.punctuation) + ['..', '...']
    pronouns = ['i', 'he', 'she', 'it', 'him', 'they', 'we', 'us', 'them']
    stop = stopwords.words('english') + punctuation + pronouns
    filtered_terms = [word for word in tokens if (word not in stop) and \
                      (len(word) > 1) and (not word.replace('.', '', 1).isnumeric()) \
                      and (not word.replace("'", '', 2).isnumeric())]

    # Lemmatization & Stemming - Stemming with WordNet POS
    # Since lemmatization requires POS need to set POS
    tagged_words = pos_tag(filtered_terms, lang='eng')
    # Stemming with for terms without WordNet POS
    stemmer = SnowballStemmer("english")
    wn_tags = {'N': wn.NOUN, 'J': wn.ADJ, 'V': wn.VERB, 'R': wn.ADV}
    wnl = WordNetLemmatizer()
    stemmed_tokens = []
    for tagged_token in tagged_words:
        term = tagged_token[0]
        pos = tagged_token[1]
        pos = pos[0]
        try:
            pos = wn_tags[pos]
            stemmed_tokens.append(wnl.lemmatize(term, pos=pos))
```

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```
        except:
            stemmed_tokens.append(stemmer.stem(term))
    return stemmed_tokens


# Further Customization of Stopping and Stemming using NLTK
def my_preprocessor(s):
    # Vectorizer sends one string at a time
    s = s.lower()
    s = s.replace(',', '. ')
    print("preprocessor")
    return (s)


def my_tokenizer(s):
    # Tokenize
    print("Tokenizer")
    tokens = word_tokenize(s)
    tokens = [word.replace(',', '') for word in tokens]
    tokens = [word for word in tokens if word.find('*') != True and \
             word != "''" and word != "``" and word != 'description' \
             and word != 'dtype']
    return tokens


# Increase Pandas column width to let pandas read large text columns
pd.set_option('max_colwidth', 32000)
# Read GMC Ignition Recall Comments from NTHSA Data
#file_path = '/Users/Home/Desktop/python/Excel/'
df = pd.read_excel("wine.xlsx")

# Setup simple constants
n_docs     = len(df['description'])
n_samples  = n_docs
m_features = None
s_words    = 'english'
ngram = (1,2)

# Setup reviews in list 'discussions'
discussions = []
for i in range(n_samples):
    discussions.append(("%s" %df['description'].iloc[i]))

# Create Word Frequency by Review Matrix using Custom Analyzer
cv = CountVectorizer(max_df=0.95, min_df=2, max_features=m_features,\
                     analyzer=my_analyzer, ngram_range=ngram)
tf = cv.fit_transform(discussions)

print("\nVectorizer Parameters\n", cv, "\n")


# LDA For Term Frequency x Doc Matrix
n_topics        = 15
max_iter        =  5
learning_offset = 20.
learning_method = 'online'
# In sklearn, LDA is synonymous with SVD (according to their doc)
```

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```
lda = LatentDirichletAllocation(n_components=n_topics, max_iter=max_iter,\
                                learning_method=learning_method, \
                                learning_offset=learning_offset, \
                                random_state=12345)
lda.fit_transform(tf)
print('{:.<22s}{:>6d}'.format("Number of Reviews", tf.shape[0]))
print('{:.<22s}{:>6d}'.format("Number of Terms",     tf.shape[1]))
print("\nTopics Identified using LDA")
tf_features = cv.get_feature_names()
max_words = 15
for topic_idx, topic in enumerate(lda.components_):
        message  = "Topic #%d: " %topic_idx
        message += " ".join([tf_features[i]
                             for i in topic.argsort()[:-max_words - 1:-1]])
        print(message)
        print()

# LDA for TF-IDF x Doc Matrix
# First Create Term-Frequency/Inverse Doc Frequency by Review Matrix
# This requires constructing Term Freq. x Doc. matrix first
tf_idf = TfidfTransformer()
print("\nTF-IDF Parameters\n", tf_idf.get_params(),"\n")
tf_idf = tf_idf.fit_transform(tf)
# Or you can construct the TF/IDF matrix from the data
tfidf_vect = TfidfVectorizer(max_df=0.95, min_df=2, max_features=m_features,\
                             analyzer=my_analyzer, ngram_range=ngram)
tf_idf = tfidf_vect.fit_transform(discussions)
print("\nTF_IDF Vectorizer Parameters\n", tfidf_vect, "\n")

lda = LatentDirichletAllocation(n_components=n_topics, max_iter=max_iter,\
                                learning_method=learning_method, \
                                learning_offset=learning_offset, \
                                random_state=12345)
lda.fit_transform(tf_idf)
print('{:.<22s}{:>6d}'.format("Number of Reviews", tf.shape[0]))
print('{:.<22s}{:>6d}'.format("Number of Terms",     tf.shape[1]))
print("\nTopics Identified using LDA with TF_IDF")
tf_features = cv.get_feature_names()
max_words = 15
for topic_idx, topic in enumerate(lda.components_):
        message = "Topic #%d: " % topic_idx
        message += " ".join([tf_features[i]
                             for i in topic.argsort()[:-max_words - 1:-1]])
        print(message)
        print()
```

```
Vectorizer Parameters
 CountVectorizer(analyzer=<function my_analyzer at 0x100561e18>, binary=False,
        decode_error='strict', dtype=<class 'numpy.int64'>,
        encoding='utf-8', input='content', lowercase=True, max_df=0.95,
        max_features=None, min_df=2, ngram_range=(1, 2), preprocessor=None,
        stop_words=None, strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)

Number of Reviews..... 13135
Number of Terms.......  6263
```

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Topics Identified using LDA
Topic #0: nose caramel palate vanilla rather bottle blueberry roast reserve peak aroma element bake atlas one-dimensional

Topic #1: interesting chewy tangy luxurious several raisins site seamlessly problem saddle burst marry eucalyptus super two

Topic #2: flavor blackberry cherry wine oak dry tannin soft drink finish black currant ripe fruit cabernet

Topic #3: green get thin ageability graphite sip pepper sweetly note star minty bouquet decent fruit glass

Topic #4: slightly may form within expect richly slight level textured layered herbal alcohol cool lushness wine

Topic #5: mountain wine fruit mark need vineyard time beyond come big tannin anoth together powerful satisfy

Topic #6: new mineral want vintage real cab french oak opulent sour great value price wine acidic

Topic #7: cocoa appeal power concentration bitter old density sizable tightly couple never blackcurrant herbaceous world wound

Topic #8: blackberry flavor cabernet currant year wine tannin dry oak rich black drink ripe cab show

Topic #9: solid sweetness case paso linger vanilla production core produce roble focus spice backbone intensely forest

Topic #10: black wine valley palate show dark fruit tannin vineyard cedar nose red cherry olive napa

Topic #11: fine bottle complexity year develop frame oakville great sonoma three reward pie beautiful next additional

Topic #12: especially opulence fleshy velvet firmly iron record consider track create special fist glove fat gracefully

Topic #13: like taste flavor sweet cherry blackberry wine alcohol soft seem fruit raisin almost hot little

Topic #14: wine cabernet merlot blend verdot tannin petit finish red black juicy franc oak sauvignon soft

TF-IDF Parameters
```
{'norm': 'l2', 'smooth_idf': True, 'sublinear_tf': False, 'use_idf': True}
```

TF_IDF Vectorizer Parameters
```
TfidfVectorizer(analyzer=<function my_analyzer at 0x100561e18>, binary=False,
     decode_error='strict', dtype=<class 'numpy.int64'>,
     encoding='utf-8', input='content', lowercase=True, max_df=0.95,
     max_features=None, min_df=2, ngram_range=(1, 2), norm='l2',
     preprocessor=None, smooth_idf=True, stop_words=None,
     strip_accents=None, sublinear_tf=False,
     token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, use_idf=True,
     vocabulary=None)
```

Number of Reviews..... 13135
Number of Terms....... 6263

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Topics Identified using LDA with TF_IDF
Topic #0: muscular small-production breadth asian red-cherry mixed longtime mountain-grown penetrate crowd-pleasing meatiness michael lip-smacking beaulieu float

Topic #1: richer orange section zest rosé alongsid toughly brushy roundness olallieberry cloves elongate slow program verging

Topic #2: flavor blackberry wine cherry dry currant cabernet oak tannin drink ripe year sweet rich cab

Topic #3: bean join farm sultry distinctive black-olive western crack affordably fruit-driven plushness neighbor suggestive restrained boisterous

Topic #4: rusticity dustiness astringently unevenly thread multiple cabernet-like tannin-acid concord handsome ginger stubborn cloud 2023–2033 punchy

Topic #5: porty barely harsh eucalyptus acceptable compost cough dot vegetal heavily likable delight heavy-handed echo tiny-production

Topic #6: tad flat showcasing damp cake bay memorable spent abundance disjoint shin grapy greet philippe tread

Topic #7: george beckstoffer vibrancy impart umami rhubarb iii stemmy midway six-plus stretch risk ahead red-fruit quaff

Topic #8: today opposite lightness luxuriously terribly gooey seduces separate exploration belies medium-length 2009–2015 praiseworthy loud backbon

Topic #9: pairing own pliant ferment oak-like oregano zin reviewer william sea state foley mustiness slide condense

Topic #10: light-bodied graceful somehow quiet recall black-plum capture abundant softens aging darkly unfurl la stewy urge

Topic #11: lend gamy conveys sport high-elevation nick goldschmidt weedy drinker land tightness akin indicate intertwine vanilla-tinged

Topic #12: sweaty refresh pillowy unctuous brother funky celebration chile status deserves withstand similarly positive sister daou

Topic #13: cardamom overshadow black-fruit associate nickel tamp son baldacci masculine company disturb phelps whatev tingle vision

Topic #14: wine black tannin finish fruit palate flavor cabernet red cherry oak cedar soft dry blackberry

Process finished with exit code 0