# Task 2

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# Loading Data set into the DataFrame

Loading  $sign\_mnist.csv$  data into dataframe. The name of the DataFrame is 'df'.

	Impo	orting r	necess	ary libra	aries														
In [1]:	from from from from from	m skle m skle m skle m skle m skle m skle	earn.t earn.m earn.l earn.m earn.p	ree im etrics inear_ odel_s reproc	import [ impor model electi	ecision t accu import on imp	onTree( uracy_s SGDC] ort tr ort Star	Classin score, lassif: rain_te	fier confus ier est_spi	sion_ma	atrix,	classific	ation_rep	port					
In [2]:	Load df	7/	e data:	as pd set into		aFrame													
In [2]: Out[2]:	Load df : df.h	ort pa ding th = pd.r head()	e data:	as pd set into sv('si	gn_mni	st.cs\	/ <b>'</b> )	pixel6	pixel7	pixel8	pixel9	pixel775	pixel776	pixel777	pixel778	pixel779	pixel780	pixel781	pixel782
	Load df : df.h	ort pa ding th = pd.r head()	e data:	as pd set into sv('si	gn_mni	st.cs\	/ <b>'</b> )	pixel6 143	pixel7	pixel8	pixel9	AND REAL PROPERTY.		pixel777 207	pixel778	pixel779 206	pixel780 206	pixel781 206	pixel782 204
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	Load df : df.l	ding th  = pd.r head() label	e data:	as pd set into sv('si pixel2 118	gn_mni pixel3 127	pixel4	pixel5	143	146	150	153	207	207 149	207	207	206	206	206	204
	Load  df = df.H	ort pa ding th = pd.r head() label   3 6	e datas e datas read_c pixel1 107 155	as pd set into sv('si pixel2 118 157	gn_mni pixel3 127 156	pixel4 134 156	pixel5 139 156	143 157	146 156	150 158	153 158	207	207 149 201	207 128 200	207 87	206 94	206 163	206 175	A 100 CO

# Selecting Dependent and Independent Variables

Since in the data set, label is the output column, it becomes the dependent column. Rest other columns are the Independent columns. So assigning y to label and x to other columns.

```
Checking number of columns and rows

In [3]: print(df.shape)
(10000, 785)

Assigning Independent variables to x and dependent variable to y

In [4]: x = df.iloc[:, 1:]
y = df.iloc[:, 0]

Demensions of Independent and Dependent variables

In [5]: print(x.shape)
print(y.shape)
(10000, 784)
(10000,)
```

Principle Component Analysis (PCA) is used to reduce the dimensions of the independent variable (x), since we don't know how many number of components to reduce simply following the variance - covariance rule of PCA algorithm which is ranging between 0.95 to 0.99, this automatically reduces to the best dimensions possible.

```
Principle Component Analysis (PCA) is used to reduce the demensions of the independent variable (x), since we dont know how many number of components to reduce simply following the variance - covaraince rule of PCA algorithm which is ranging between 0.95 to 0.99, this automatically reduces to the best demensions possible.

In [6]: pca = PCA(n_components=0.95)
    pca.fit(x)
    x_pca = pca.transform(x)
    print(x_pca.shape)

(10000, 112)

Our columns has been reduced from 784 to 112 after applying PCA

Splitting the dataset into training 80% and test sets into 20%

In [7]: x_train, x_test, y_train, y_test = train_test_split(
    x_pca, y, test_size=0.2, random_state=42)

Standardization of independent variable x - mean to 0 and standard deviation to 1

In [8]: scaler = StandardScaler()
    x_train_scaled = scaler.fit_transform(x_train)
    x_test_scaled = scaler.fit_transform(x_test)
```

# SGDClassifier

Using sklearn.metrics we use accuracy\_score function to get the percentage accuracy of model, normally we use confusion matrix for classification algorithms since we already standardiized our data we are using accuracy as our metrics.

Stochastic gradient descent performance metrics:

Accuracy score for test set: 88.35 Accuracy score for train set: 94.875

# Decision Tree Classifier

Since our columns are 112 after dimensionality reduction, max\_depth is the depth of tree or the level of the tree = n/2 which is 112/2 = 51, max\_depth = 51

# Random Forest Classifier

Here,  $n_{estimators}$  is the number of different trees we want to create and train the model therefore  $n_{estimators} = 10$  means we want 10 trees and max\_depth = 51 is same as before which we used.

```
Random Forest Classifier
           Here, n estimators is the number of different trees we want to create and train the model therefore n estimators = 10 means we want 10 trees and max depth
           = 51 is same as before which we used.
In [14]: rfc = RandomForestClassifier(n_estimators=10, max_depth=51, random_state=42)
           rfc.fit(x_train_scaled, y_train)
          y_pred_rfc = rfc.predict(x_test_scaled)
y_train_pred_rfc = rfc.predict(x_train_scaled)
           print('Random Forest Classifier performance metrics :')
          print('Accuracy score for test set:', accuracy_score(y_test, y_pred_rfc)*100)
print('Accuracy score for train set:',
                 accuracy_score(y_train, y_train_pred_rfc)*100)
           Random Forest Classifier performance metrics :
           Accuracy score for test set: 99.65
Accuracy score for train set: 99.9875
           Finally, comparing our performance metrics of 3 different Classifiers
           Stochastic gradient descent has 88.35 %
           Decision tree classifier has 88.44 %
           Random Forest Classifier has 99.65 %
           Since, Random Forest Classifier has highest accuracy of 99.65 %. Out of the 3 Classifiers, we could say Random Forest Classifiers is the best.
 In [ ]:
```

Comparison of the classifiers

# Finally, comparing our performance metrics of 3 different Classifiers Stochastic gradient descent has 88.35 % Decision tree classifier has 88.44 % Random Forest Classifier has 99.65 % Since, Random Forest Classifier has highest accuracy of 99.65 %. Out of the 3 Classifiers, we could say Random Forest Classifiers is the best. In []:

# Task 3

Installing Required Modules and libraries

google\_play\_scraper was the library that was explicitly used.

```
Importing necessary libraries

In [319]: import pandas as pd import numpy as np from google_play_scraper import app, Sort, reviews import pprint 
print('Libraries Imported')

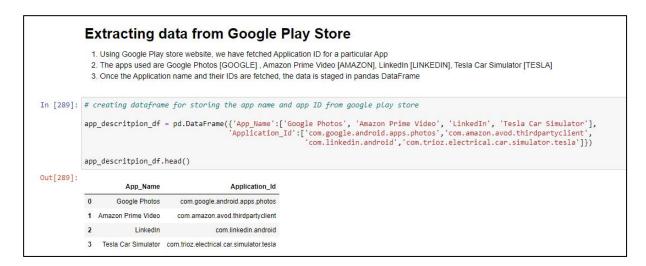
Libraries Imported
```

# Extracting data from Google Play Store

Using Google Play store website, we have fetched Application ID for a particular App

The apps used are Google Photos [GOOGLE], Amazon Prime Video [AMAZON], LinkedIn [LINKEDIN], Tesla Car Simulator [TESLA]

Once the Application name and their IDs are fetched, the data is staged in pandas DataFrame



# Scraping the Reviews from the data

- 1. Using reviews function of google\_play\_scraper module, we were able to scrap or extract the reviews of the application posted by several users.
- 2. Since our data is maintained in a dataframe, so by using Application\_id as the key column iin the dataframe, iteration is done to navigate through all the company apps and get the reviews for each apps.
- 3. Depending on which group the data belongs to, Segregation is done in 4 different lists.
- 4. In the Output of the code snippet, multiple reviews from all the companies are listed. These are getting populated one at a time in those 4 lists by using append method.
- 5. checking which app id is currently being read and assigning the list accordingly
- 6. Once the app id is decided then data is appended in the list

# Scraping Reviews for each company apps

- 1. Using reviews function of google\_play\_scraper module, we were able to scrap or extract the reviews of the application posted by several users.
- Since our data is maintained in a dataframe, so by using Application\_id as the key column iin the dataframe, iteration is done to navigate through all the company apps and get the reviews for each apps.
- 3. Depending on which group the data belongs to, Segregation is done in 4 different lists.
- 4. In the Output of the code snippet, multiple reviews from all the companies are listed. These are getting populated one at a time in those 4 lists by using append method.
- 5. checking which app id is currently being read and assigning the list accordingly
- 6. Once the app id is decided then data is appended in the list

```
In [320]: app_reviews = []
             for app_id in app_descritpion_df['Application_Id']:
                for score in list(range(1, 6)):
   for sort_order in [Sort.MOST_RELEVANT, Sort.NEWEST]:
                     app_review, _ = reviews(
                        app_id,
lang='en',
                        country='us'
                        sort=sort_order,
                        count= 200 if score == 3 else 100,
                        filter_score_with=score
                     for r in app_review:
                                                most_relevant' if sort_order == Sort.MOST_RELEVANT else 'newest'
                        r['sortOrder'] = 'mo
r['appId'] = app_id
                  # checking which app id is currently being read and assigning the list accordingly
                  #Once the app id is decided then data is appended in the list
for contents in range(len(app_review)):
                             if app_id == 'com.google.android.apps.photos':
    pprint.pprint("GOOGLE DATA LOAD BEGINS")
                                  pprint.pprint(app_review[contents]['content'])
google_list.append(app_review[contents]['content'])
                             elif app_id == 'com.amazon.avod.thirdpartyclient':
```

```
for contents in range(len(app_review)):
    if app_id == 'com.google.android.apps.photos':
        pprint.pprint("GOOGLE DATA LOAD BEGINS")
        pprint.pprint(app_review[contents]['content'])

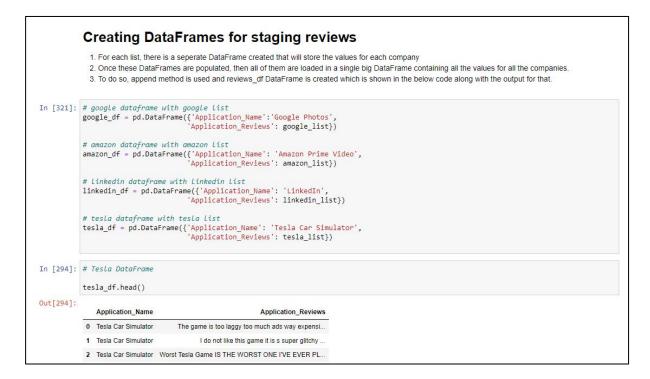
    elif app_id == 'com.amazon.avod.thirdpartyclient':
        pprint.pprint("ANAZON DATA LOAD BEGINS")
        pprint.pprint(app_review[contents]['content'])

    elif app_id == 'com.linkedin.android':
        pprint.pprint("LINKEDIN DATA LOAD BEGINS")
        pprint.pprint("TESLA DATA LOAD BEGINS")
        pprint.pprint("TESLA DATA LOAD BEGINS")
        pprint.pprint("TESLA DATA LOAD BEGINS")
        pprint.pprint("TESLA DATA LOAD BEGINS")
        pprint.pprint(app_review[contents]['content'])
    tesla_list.append(app_review[contents]['content'])
```

#### Output: List of reviews

# Creating Dataframe for Staging the reviews

- 1. For each list, there is a seperate DataFrame created that will store the values for each company
- 2. Once these DataFrames are populated, then all of them are loaded in a single big DataFrame containing all the values for all the companies.
- 3. To do so, append method is used and reviews\_df DataFrame is created which is shown in the below code along with the output for that.

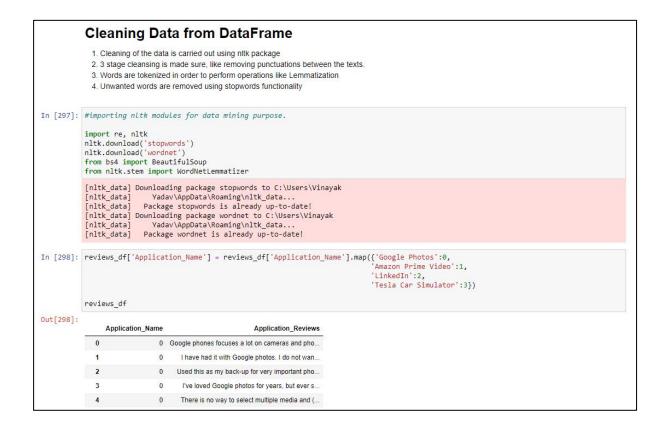


# Appending all the data into a single dataframe



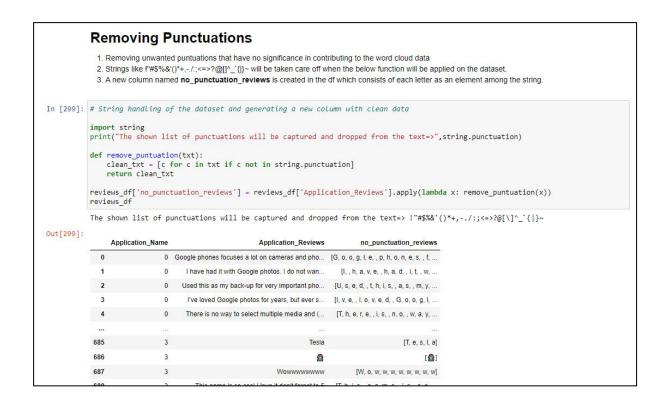
# Cleaning data from Dataframe

- 1. Cleaning of the data is carried out using nltk package
- 2. 3 stage cleansing is made sure, like removing punctuations between the texts.
- 3. Words are tokenized in order to perform operations like Lemmatization
- 4. Unwanted words are removed using stopwords functionality



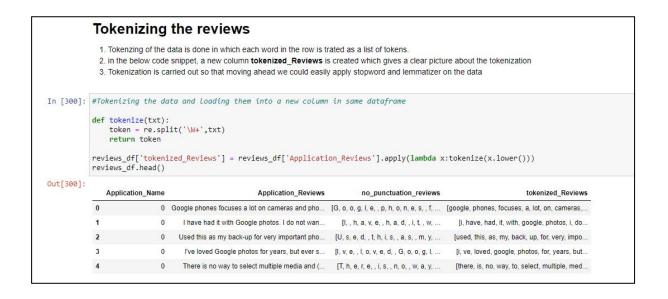
# Removing Punctuations

- 1. Removing unwanted puntuations that have no significance in contributing to the word cloud data
- 2. Strings like !"#\$%&'()\*+,-./:;<=>?@[]^\_`{|}~ will be taken care off when the below function will be applied on the dataset.
- 3. A new column named **no\_punctuation\_reviews** is created in the df which consists of each letter as an element among the string.



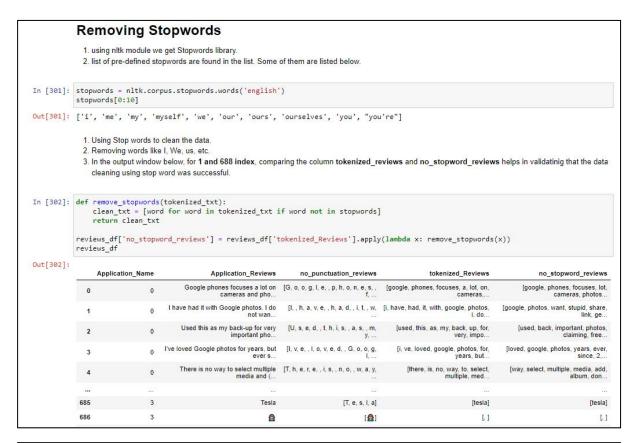
# Tokenizing

- 1. Tokenzing of the data is done in which each word in the row is trated as a list of tokens.
- in the below code snippet, a new column tokenized\_Reviews is created which gives a clear picture about the tokenization
- Tokenization is carried out so that moving ahead we could easily apply stopword and lemmatizer on the data



# Removing Stopwords

- 1. Using Stop words to clean the data.
- 2. Removing words like I, We, us, etc.
- In the output window below, for 1 and 688 index, comparing the column tokenized\_reviews and no\_stopword\_reviews helps in validatining that the data cleaning using stop word was successful



[way, select, multiple, media, add album, don	[there, is, no, way, to, select, multiple, med	[T, h, e, r, e, , i, s, , n, o, , w, a, y,	There is no way to select multiple media and (	0	4
92	223		1123	0420	***
[tesia	[tesla]	[T, e, s, l, a]	Tesla	3	685
[,	[.]	[2]	<b>A</b>	3	686
[wowwwwwwww	[wowwwwwwww]	[W, o, w, w, w, w, w, w, w, w]	Wowwwwwww	3	687
[game, cool, love, forget, 5	[this, game, is, so, cool, i, love, it, don, t	[T,h,i,s,,g,a,m,e,,i,s,,s,o,	This game is so cool I love it don't forget to 5	3	688
[good, game	[good, game]	[G, o, o, d, , g, a, m, e]	Good game	3	689

# Lemmatizing

- 1. Lemmatization technique is used to convert all the plurals to signulars
- 2. It is also used to find the synonyms and assign on synonym to all similar kind of words

- in the below output for index 1 in column no\_stopword\_reviews and lemmatized\_reviews we can see that 'memories' is changed to 'memory'.
- 4. There may be many such changes in the dataframe which cannot be displayed in here on a small display wndow

#### Lemmatization of the stopwords 1. Lemmatization technique is used to convert all the plurals to signulars 2. It is also used to find the synonyms and assign on synonym to all similar kind of words 3. in the below output for index 1 in column no stopword reviews and lemmatized reviews we can see that 'memories' is changed to 'memory'. 4. There may be many such changes in the dataframe which cannot be displayed in here on a small display wndow In [322]: def lemmatization(tokenized\_txt): lemmatized = WordNetLemmatizer() lemma = " ".join([lemmatized.lemmatize(word) for word in tokenized\_txt]) return lemma $reviews\_df['lemmatized\_reviews'] = reviews\_df['no\_stopword\_reviews']. apply(lambda \ x:lemmatization(x) \ ) \\ reviews\_df$ Out[322]: Application\_Name Application\_Reviews no\_punctuation\_reviews tokenized\_Reviews no\_stopword\_reviews lemmatized\_reviews Google phones focuses a lot [G, o, o, g, l, e, , p, h, o, n, e, google, phones, focuses, [google, phones, focuses, lot, on cameras and pho... s, f, ... a, lot, on, cameras,... cameras, photos... google phone focus lot camera photo one would ... 0 I have had it with Google $\begin{array}{c} \text{[I, , h, a, v, e, , h, a, d, , i, t, ,} \\ \text{photos. I do not wan...} \end{array}$ [i, have, had, it, with, google, photos, want, stupid, google, photos, i, do... share, link, ge... Used this as my back-up for [U, s, e, d, , t, h, i, s, , a, s, , uery important pho... [used, this, as, my, back, up, for, very, impo... fused, back, important. used back important photo claiming free unlimi... photos, claiming, free... I've loved Google photos for $\begin{array}{cc} [l,v,e,,l,o,v,e,d,,G,o,o,\\ & years,but \ ever \ s... \end{array}$ There is no way to select [T, h, e, r, e, , i, s, , n, o, , w, multiple media and (... a, y, ... [there, is, no, way, to, select, multiple, media, select, multiple, med... add, album, don... way select multiple medium add album done 1 1 .... I like it because it have a [I, , I, i, k, e, , i, t, , b, e, c, a, [i, like, it, because, it, have, u, ... a, battery, ] like battery 684 [like, battery, ] 685 3 Tesla [T, e, s, I, a] [tesla] [tesla] tesla 687 3 Wowwwwwww [W, o, w, w, w, w, w, w, w, w] [wowwwwwwww] [wwwwwwwww] $\label{eq:continuous} 3 \qquad \begin{array}{ll} \text{This game is so cool I love it} & [\mathsf{T},\mathsf{h},\mathsf{i},\mathsf{s},\mathsf{,g},\mathsf{a},\mathsf{m},\mathsf{e},\mathsf{,i},\mathsf{s},\mathsf{,}\\ \mathsf{don't}\,\mathsf{forget}\,\mathsf{to}\,\mathsf{5} & \mathsf{so,...} \end{array} \qquad \begin{array}{ll} [\mathsf{this},\mathsf{game},\mathsf{is},\mathsf{so},\mathsf{cool},\mathsf{i},\\ \mathsf{love},\mathsf{it},\mathsf{don},\mathsf{t}... \end{array}$ 688 [game, cool, love, forget, 5] game cool love forget 5 Good game [G, o, o, d, , g, a, m, e] [good, game] [good, game] 689 good game 4244 rows × 6 columns

# Data Munging

- 1. Since Stopwords and lemmatization can never work 100%, there are few data that will be left behind.
- Here in the below snippet, on the lemmatized column, we are trying to remove all those rows which have blank values
- 3. Blank values or empty spaces will create no contribution anywhere so it's better to remove such data

# Performing Data munging to further clean the data 1. Since Stopwords and lemmatization can never work 100%, there are few data that will be left behind. 2. Here in the below snippet, on the lemmatized column, we are trying to remove all those rows which have blank values 3. Blank values or empty spaces will create no contribution anywhere so it's better to remove such data In [323]: # taking a count of those records with blank data or space character in the record reviews\_df[(reviews\_df['lemmatized\_reviews']=='')|(reviews\_df['lemmatized\_reviews']==' ')].count() Out[323]: Application\_Name Application\_Reviews no\_punctuation\_reviews tokenized\_Reviews no\_stopword\_reviews lemmatized reviews dtype: int64 In [324]: # Converting all the spaces to numpy NaN value $reviews\_df['lemmatized\_reviews'].replace(['',' '],np.NaN,inplace=True) \\ reviews\_df.isnull().sum()$ Out[324]: Application\_Name Application\_Reviews no\_punctuation\_reviews tokenized\_Reviews no\_stopword\_reviews 0 lemmatized\_reviews dtype: int64 0 In [325]: # there were 46 rows with NaN value #dropping the Null values and checking the final dataset reviews\_df.dropna(inplace=True) reviews\_df.isnull().sum() Out[325]: Application\_Name Application\_Reviews no\_punctuation\_reviews tokenized Reviews 0 no\_stopword\_reviews lemmatized reviews 0 dtype: int64

# Word Cloud

# Word Cloud for Displaying Top 10 Words 1. Using all the above dataframes one at a time to craete a word cloud 2. Maximum words to be displayed in the word cloud 10 3. There are 4 different word clouds generated for 4 different company apps 4. Using wordcloud, matplottib, stopword packages together, all 4 word clouds are shown below In [331]: # Creating google word cloud #joining all the rows into 1 single row so that it forms a string to be read an calucate the top 10 words google\_text= ''.join(reviews for reviews in only\_google\_df.lemsatized\_reviews) print('Combined texts number of word counts for Google is {}'.format(len(google\_text))) from wordcloud import bloodcloud, 5TOPWORDS import matplotlib.pyplot as plt # adding some new words to the stopword (which we felt is of no significance) list and appending it with the pre-defined ones stopwords = ['one', 'want', 'way', 'pic', 'app', 'google', 'thing'] + list(STOPWORDS) # generating the word cloud wordcloud' wordcloud (stopwords =stopwords, max\_font\_size=100, max\_words=10, background\_color='thistle').generate(google\_text) plt.salis(off') plt.salis(off')

```
In [332]:

# Creating Amazon word cloud

# jaining all the rows into 1 single row so that it forms a string to be read an calucate the top 10 words amazon_text= ''.join(reviews for reviews in only_amazon_df.lemmatired_reviews)
print('Combined total number of word counts for Amazon is {}'.format(len(amazon_text)))

from wordcloud import Wordcloud, STOPWORDS import matpletlib.pyplet as plt

# adding some more words to the stopword (which we felt is of no significance) list and appending it with the pre-defined ones stopwords = ['app','pay','one', 'time'] + list(STOPWORDS)

# generating the word cloud
wordcloud = Wordcloud(stopwords =stopwords, max_font_size=100, max_words=10, background_color='moccasin').generate(amazon_text)
plt.lmshow(wordcloud, interpolation='bilinear')
plt.sis(si(fr'))
plt.sigure(figsize=[20,10])
plt.show()

Combined total number of word counts for Amazon is 123023

# great

# Combined total number of word counts for Amazon is 123023

# Great

# Combined total number of word counts for Amazon is 123023
```

```
In [336]: # Creating Linkedin word cloud
            #joining all the rows into 1 single row so that it forms a string to be read an calucate the top 10 words
linkedin_text= ''.join(reviews for reviews in only_linkedin_df.lemmatized_reviews)
print('Combined total number of word counts for LinekedIN is {}'.format(len(linkedin_text)))
             from wordcloud import WordCloud, STOPWORDS
             import matplotlib.pyplot as plt
            # adding some more words to the stopword (which we felt is of no significance) list and appending it with the pre-defined ones stopwords = ['app','time','use','way','new'] + list(STOPWORDS)
             # generating the word cloud
             wordcloud = WordCloud(stopwords = stopwords, max_font_size=100, max_words=10, background_color='turquoise').generate(linkedin_tex
             plt.imshow(wordcloud, interpolation='bilinear')
             plt.axis('off')
plt.figure(figsize=[20,10])
             plt.show()
             4
             Combined total number of word counts for LinekedIN is 139988
              people DOS Tnotification
              update
                great WOT
               good linkedin
             <Figure size 1440x720 with 0 Axes>
```

