IR Lab2 Last

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```
[1]: import pandas as pd
     import numpy as np
     import re
     import nltk
     from nltk.corpus import stopwords
     from nltk.tokenize import word_tokenize
     from autocorrect import Speller
     from spellchecker import SpellChecker
     import time
     from datetime import datetime
     import spacy
     from textblob import TextBlob
     from nltk.corpus import words
     from nltk.metrics.distance import jaccard_distance
     from nltk.util import ngrams
     from nltk.metrics.distance import edit_distance
     from nltk.stem import PorterStemmer
     from textblob import Word
     from nltk.stem import WordNetLemmatizer
     import wordcloud
     from wordcloud import WordCloud, STOPWORDS
     import plotly.express as px
     import matplotlib.pyplot as plt
     import matplotlib.pyplot as plt
     import squarify
     import seaborn as sns
     start_program = datetime.now()
```

#Part1.2

0.1 NLTK

Features

Text Analytics and NLP
Compare Text Analytics, NLP and Text Mining
 Text Analysis Operations using NLTK
 Tokenization
 Stopwords
 Lexicon Normalization such as Stemming and Lemmatization
 POS Tagging
Sentiment Analysis
Text Classification
Performing Sentiment Analysis using Text Classification

0.2 TextBlob 1.2.1

Features

Noun phrase extraction
Part-of-speech tagging
Sentiment analysis
Classification (Naive Bayes, Decision Tree)
Language translation and detection powered by Google Translate
Tokenization (splitting text into words and sentences)
Word and phrase frequencies
Parsing
n-grams
Word inflection (pluralization and singularization) and lemmatization
Spelling correction
Add new models or languages through extensions
WordNet integration

0.3 cpaCy 1.2.1

Features

Non-destructive tokenization
Named entity recognition
Support for 50+ languages
pretrained statistical models and word vectors
State-of-the-art speed
Easy deep learning integration
Part-of-speech tagging
Labelled dependency parsing
Syntax-driven sentence segmentation
Built in visualizers for syntax and NER
Convenient string-to-hash mapping
Export to numpy data arrays
Efficient binary serialization
Easy model packaging and deployment
Robust, rigorously evaluated accuracy

```
[]:
[]:
[2]: # #Execute time
     ttw = pd.read_csv('ttw2_finalSpell.csv')
     ttw.dropna(inplace=True)
[3]: # #Execute time
     start time = datetime.now()
     stop_words = set(stopwords.words('english'))
     ttw2 = ttw.copy()
     ttw.dropna(inplace=True)
     ttw2['tweet'] = ttw2['tweet'].str.lower()
     ttw2['tweet'] = ttw2['tweet'].str.replace('[^\w\s]','')
     ttw2['tweet'] = ttw2['tweet'].str.replace('[^a-z ]','')
     ttw2['tweet'] = ttw2['tweet'].apply(lambda x: " ".join(x for x in x.split() if_
     →x not in stop_words))
     print('Time elapsed in (hh:mm:ss.ms): "{}"'.format(datetime.now() - start_time))
     ttw2.head(20)
```

Time elapsed in (hh:mm:ss.ms): "0:00:00.225842"

```
[3]:
            label
         id
                                                                   tweet
          1
                 0
                    user father dysfunctional selfish drags kids d...
     1
          2
                    user user thanks credit cant use cause dont of ...
     2
          3
                 0
                                                        birthday majesty
     3
          4
                 0
                                            model love u take u time ur
     4
          5
                 0
                                                     factsguide society
     5
          6
                    huge fan fare big talking leave chaos pay disp...
     6
          7
                     user camping tomorrow user user user user...
     7
          8
                 0
                                next school year year exams cant think
     8
          9
                 0
                                                               love land
     9
         10
                 0
                                                   user user welcome im
     10
         11
                  0
                         consumer price index mom climbed previous may
     11
         12
                  0
     12
         13
                                                    get see daddy today
     13
         14
                             user calls middle school build wall chant
     14
         15
                                                                 comment
     15
         16
                  0
                                                    ouchjunior angrygot
     16
         17
                 0
                                                          thankful paper
     17
         18
                  0
                            smiles around via ig user user make people
     18
         19
                                    know essential oils made chemicals
     19
         20
```

```
[]:
[4]: ttw3 = ttw2.copy()
     ttw3.dropna(inplace=True)
[5]: #TOKENIZATION WITH NLTK
     #Execute time
     start_time = datetime.now()
     #print(ttw3['tweet'][3351])
     for i in range(len(ttw3['tweet'][:10])):
         word_data = ttw3['tweet'][i]
         nltk_tokens = nltk.word_tokenize(word_data)
         print(nltk_tokens)
     print('Time elapsed in (hh:mm:ss.ms): "{}"'.format(datetime.now() - start time))
    ['user', 'father', 'dysfunctional', 'selfish', 'drags', 'kids', 'dysfunction']
    ['user', 'user', 'thanks', 'credit', 'cant', 'use', 'cause', 'dont', 'offer',
    'wheelchair', 'vans', 'px']
    ['birthday', 'majesty']
    ['model', 'love', 'u', 'take', 'u', 'time', 'ur']
    ['factsguide', 'society']
    ['huge', 'fan', 'fare', 'big', 'talking', 'leave', 'chaos', 'pay', 'disputes',
    'get']
    ['user', 'camping', 'tomorrow', 'user', 'user', 'user', 'user', 'user', 'user',
    'user', 'danny']
    ['next', 'school', 'year', 'year', 'exams', 'cant', 'think']
    ['love', 'land']
    ['user', 'user', 'welcome', 'im']
    Time elapsed in (hh:mm:ss.ms): "0:00:00.021990"
[6]: #TOKENIZATION WITH TEXTBLOB
     #Execute time
     start_time = datetime.now()
     #ttw3.dropna(inplace=True)
     for i in range(len(ttw3['tweet'][:10])):
         text = ttw3['tweet'][i]
         blob_object = TextBlob(text)
         print(blob_object.words)
     print('Time elapsed in (hh:mm:ss.ms): "{}"'.format(datetime.now() - start_time))
    ['user', 'father', 'dysfunctional', 'selfish', 'drags', 'kids', 'dysfunction']
    ['user', 'user', 'thanks', 'credit', 'cant', 'use', 'cause', 'dont', 'offer',
    'wheelchair', 'vans', 'px']
    ['birthday', 'majesty']
    ['model', 'love', 'u', 'take', 'u', 'time', 'ur']
    ['factsguide', 'society']
```

```
['huge', 'fan', 'fare', 'big', 'talking', 'leave', 'chaos', 'pay', 'disputes',
    'get']
    ['user', 'camping', 'tomorrow', 'user', 'user', 'user', 'user', 'user', 'user', 'user',
    'user', 'danny']
    ['next', 'school', 'year', 'year', 'exams', 'cant', 'think']
    ['love', 'land']
    ['user', 'user', 'welcome', 'im']
    Time elapsed in (hh:mm:ss.ms): "0:00:00.009995"
[7]: #TOKENIZATION WITH spaCy
     #Execute time
     start_time = datetime.now()
     for i in range(len(ttw3['tweet'][:5])):
         nlp = spacy.blank('en')
         doc = nlp(ttw3['tweet'][i])
         print(doc)
     #ur or en?????????????????????
     print('Time elapsed in (hh:mm:ss.ms): "{}"'.format(datetime.now() - start_time))
    user father dysfunctional selfish drags kids dysfunction
    user user thanks credit cant use cause dont offer wheelchair vans px
    birthday majesty
    model love u take u time ur
    factsguide society
    Time elapsed in (hh:mm:ss.ms): "0:00:01.530282"
[8]: #SPELLING WITH NLTK
     correct_spellings = words.words()
     #Execute time
     start_time = datetime.now()
     entries=ttw2['tweet'][:5]
     for entry in entries:
         temp = [(jaccard_distance(set(ngrams(entry, 2)), set(ngrams(w, 2))),w) for__
     →w in correct_spellings if w[0] == entry[0]]
         print(sorted(temp, key = lambda val:val[0])[0][1])
     print('Time elapsed in (hh:mm:ss.ms): "{}"'.format(datetime.now() - start_time))
    undersatisfaction
    unsepulchered
    birthday
    modelmaker
    facticide
```

```
Time elapsed in (hh:mm:ss.ms): "0:00:02.039506"
```

```
[9]: #SPELLING WITH TEXTBLOB
      #Execute time
      start_time = datetime.now()
      for i in range(len(ttw2['tweet'][:5])):
          text = TextBlob(ttw2['tweet'][i])
          text = text.correct()
          print(text)
      print('Time elapsed in (hh:mm:ss.ms): "{}"'.format(datetime.now() - start_time))
     user father dysfunctional selfish drags kiss dysfunction
     user user thanks credit can use cause dont offer wheelchair van pp
     birthday majesty
     model love u take u time or
     factsguide society
     Time elapsed in (hh:mm:ss.ms): "0:00:03.506966"
[10]: # #SPELLING WITH spaCy
                                         ############# library trouble
      # import contextualSpellCheck
      # #Execute time
      # start_time = datetime.now()
      # for i in range(len(ttw2['tweet'][:5])):
            nlp = spacy.load('en_core_web_sm')
            contextualSpellCheck.add_to_pipe(nlp)
            doc = nlp(ttw2['tweet'][i])
            print(doc._.performed_spellCheck) #Should be True
            print(doc.\_.outcome\_spellCheck) #Income was $9.4 million compared to the
      →prior year of $2.7 million.
      # print('Time elapsed in (hh:mm:ss.ms): "{}"'.format(datetime.now() -
       ⇒start time))
 []:
[11]: #LEMMATIZATION with NLTK
      # #Execute time
      start_time = datetime.now()
      lemmatizer = WordNetLemmatizer()
```

```
for i in range(len(ttw3['tweet'][:5])):
          print('Before: ', ttw3['tweet'][i].split())
          words = [lemmatizer.lemmatize(word) for word in ttw3['tweet'][i].split()]
          print('After: ',words)
      print('Time elapsed in (hh:mm:ss.ms): "{}"'.format(datetime.now() - start_time))
     Before:
               ['user', 'father', 'dysfunctional', 'selfish', 'drags', 'kids',
     'dysfunction']
     After:
              ['user', 'father', 'dysfunctional', 'selfish', 'drag', 'kid',
     'dysfunction']
               ['user', 'user', 'thanks', 'credit', 'cant', 'use', 'cause', 'dont',
     Before:
     'offer', 'wheelchair', 'vans', 'px']
            ['user', 'user', 'thanks', 'credit', 'cant', 'use', 'cause', 'dont',
     'offer', 'wheelchair', 'van', 'px']
     Before: ['birthday', 'majesty']
              ['birthday', 'majesty']
     After:
     Before: ['model', 'love', 'u', 'take', 'u', 'time', 'ur']
             ['model', 'love', 'u', 'take', 'u', 'time', 'ur']
     After:
              ['factsguide', 'society']
     Before:
     After:
              ['factsguide', 'society']
     Time elapsed in (hh:mm:ss.ms): "0:00:02.205064"
[12]: #LEMMATIZATION WITH TEXTBLOB
      # #Execute time
      start_time = datetime.now()
      for i in range(len(ttw3['tweet'][:5])):
          print('Before: ', ttw3['tweet'][i].split())
          words = [Word(word).lemmatize() for word in ttw3['tweet'][i].split()]
          print('After: ',words)
      print('Time elapsed in (hh:mm:ss.ms): "{}"'.format(datetime.now() - start_time))
               ['user', 'father', 'dysfunctional', 'selfish', 'drags', 'kids',
     Before:
     'dysfunction']
              ['user', 'father', 'dysfunctional', 'selfish', 'drag', 'kid',
     After:
     'dysfunction']
               ['user', 'user', 'thanks', 'credit', 'cant', 'use', 'cause', 'dont',
     Before:
     'offer', 'wheelchair', 'vans', 'px']
              ['user', 'user', 'thanks', 'credit', 'cant', 'use', 'cause', 'dont',
     After:
     'offer', 'wheelchair', 'van', 'px']
     Before: ['birthday', 'majesty']
     After:
              ['birthday', 'majesty']
     Before: ['model', 'love', 'u', 'take', 'u', 'time', 'ur']
              ['model', 'love', 'u', 'take', 'u', 'time', 'ur']
     After:
```

```
['factsguide', 'society']
     Before:
              ['factsguide', 'society']
     After:
     Time elapsed in (hh:mm:ss.ms): "0:00:00.005997"
[13]: #LEMMATIZATION WITH spaCy
      # #Execute time
      start time = datetime.now()
      nlp = spacy.load("en_core_web_sm")
      for i in range(len(ttw3['tweet'][:5])):
          text = ttw3['tweet'][i]
          print('Before: ', text.split())
          doc = nlp(text)
          temp = [word.lemma_ for word in doc]
          print('After: ', temp)
      print('Time elapsed in (hh:mm:ss.ms): "{}"'.format(datetime.now() - start_time))
     Before: ['user', 'father', 'dysfunctional', 'selfish', 'drags', 'kids',
     'dysfunction']
     After: ['user', 'father', 'dysfunctional', 'selfish', 'drag', 'kid',
     'dysfunction']
     Before: ['user', 'user', 'thanks', 'credit', 'cant', 'use', 'cause', 'dont',
     'offer', 'wheelchair', 'vans', 'px']
     After: ['user', 'user', 'thank', 'credit', 'can', 'not', 'use', 'cause', 'do',
     'not', 'offer', 'wheelchair', 'van', 'px']
     Before: ['birthday', 'majesty']
     After: ['birthday', 'majesty']
     Before: ['model', 'love', 'u', 'take', 'u', 'time', 'ur']
     After: ['model', 'love', 'u', 'take', 'u', 'time', 'ur']
     Before: ['factsguide', 'society']
     After: ['factsguide', 'society']
     Time elapsed in (hh:mm:ss.ms): "0:00:01.482067"
 []:
[14]: #STEMMING WITH NLTK
      # #Execute time
      start_time = datetime.now()
      ps = PorterStemmer()
      for i in range(len(ttw3['tweet'][:5])):
          text = ttw3['tweet'][i]
          print('Before: ', text.split())
```

```
temp = [ps.stem(w) for w in text.split()]
          print('After: ', temp)
     print('Time elapsed in (hh:mm:ss.ms): "{}"'.format(datetime.now() - start_time))
     Before: ['user', 'father', 'dysfunctional', 'selfish', 'drags', 'kids',
     'dysfunction']
     After: ['user', 'father', 'dysfunct', 'selfish', 'drag', 'kid', 'dysfunct']
     Before: ['user', 'user', 'thanks', 'credit', 'cant', 'use', 'cause', 'dont',
     'offer', 'wheelchair', 'vans', 'px']
     After: ['user', 'user', 'thank', 'credit', 'cant', 'use', 'caus', 'dont',
     'offer', 'wheelchair', 'van', 'px']
     Before: ['birthday', 'majesty']
     After: ['birthday', 'majesti']
     Before: ['model', 'love', 'u', 'take', 'u', 'time', 'ur']
     After: ['model', 'love', 'u', 'take', 'u', 'time', 'ur']
     Before: ['factsguide', 'society']
     After: ['factsguid', 'societi']
     Time elapsed in (hh:mm:ss.ms): "0:00:00.004000"
[15]: #STEMMING WITH TEXTBLOB
      #No stemming in TextBlob
[16]: #STEMMING WITH spaCy
      #Also no stemming in spaCy
 []:
[17]: #ACRONYM OR ABBREVIATIONS WITH NLTK
      #No ACRONYM OR ABBREVIATIONS WITH NLTK
[18]: #ACRONYM OR ABBREVIATIONS WITH TEXTBLOB
      import scispacy
      from scispacy.abbreviation import AbbreviationDetector
      # #Execute time
      start_time = datetime.now()
      nlp = spacy.load("en_core_web_sm")
      abbreviation_pipe = AbbreviationDetector(nlp)
      nlp.add_pipe(abbreviation_pipe)
      for i in range(len(ttw3['tweet'][:5])):
          text = ttw3['tweet'][i]
          print('Before: ', text)
```

```
text = "StackOverflow (SO) is a question and answer site for professional...
       →and enthusiast programmers. SO rocks!"
          doc = nlp(text)
          altered tok = [tok.text for tok in doc]
          for abrv in doc._.abbreviations:
              altered tok[abrv.start] = str(abrv..long form)
          print('After: ', altered_tok)
     print('Time elapsed in (hh:mm:ss.ms): "{}"'.format(datetime.now() - start_time))
     Before: user father dysfunctional selfish drags kids dysfunction
     After: ['StackOverflow', '(', 'StackOverflow', ')', 'is', 'a', 'question',
     'and', 'answer', 'site', 'for', 'professional', 'and', 'enthusiast',
     'programmers', '.', 'StackOverflow', 'rocks', '!']
     Before: user user thanks credit cant use cause dont offer wheelchair vans px
     After: ['StackOverflow', '(', 'StackOverflow', ')', 'is', 'a', 'question',
     'and', 'answer', 'site', 'for', 'professional', 'and', 'enthusiast',
     'programmers', '.', 'StackOverflow', 'rocks', '!']
     Before: birthday majesty
     After: ['StackOverflow', '(', 'StackOverflow', ')', 'is', 'a', 'question',
     'and', 'answer', 'site', 'for', 'professional', 'and', 'enthusiast',
     'programmers', '.', 'StackOverflow', 'rocks', '!']
     Before: model love u take u time ur
     After: ['StackOverflow', '(', 'StackOverflow', ')', 'is', 'a', 'question',
     'and', 'answer', 'site', 'for', 'professional', 'and', 'enthusiast',
     'programmers', '.', 'StackOverflow', 'rocks', '!']
     Before: factsguide society
     After: ['StackOverflow', '(', 'StackOverflow', ')', 'is', 'a', 'question',
     'and', 'answer', 'site', 'for', 'professional', 'and', 'enthusiast',
     'programmers', '.', 'StackOverflow', 'rocks', '!']
     Time elapsed in (hh:mm:ss.ms): "0:00:00.927470"
[19]: # NO ACRONYM OR ABBREVIATIONS WITH spaCy
[20]: #SYNONYMS WITH NLTK
      from nltk.corpus import wordnet
      synonyms = []
      for syn in wordnet.synsets("user"):
          for 1 in syn.lemmas():
             synonyms.append(l.name())
      print(synonyms)
```

[]:

```
print(wordnet.synsets('user'))
      print(wordnet.synsets('user')[0].lemmas()[0].name())
      # for syn in wordnet.synsets(str(x)):
            for l in syn.lemmas():
      #
                synonyms.append(l.name())
     ['user', 'exploiter', 'user', 'drug_user', 'substance_abuser', 'user']
     [Synset('user.n.01'), Synset('exploiter.n.01'), Synset('drug_user.n.01')]
     user
[21]: #NO SYNONYMS WITH TEXTBLOB
[22]: #NO SYNONYMS WITH spaCy
 []:
      #NO WSD WAS FOUND WITH ALL LIBRARIES
[23]:
 []:
[24]: #NER WITH NLTK
      import nltk
      from nltk.tokenize import word_tokenize
      from nltk.tag import pos_tag
      ex = 'European authorities fined Google a record $5.1 billion on Wednesday for ⊔
       \hookrightarrowabusing its power in the mobile phone market and ordered the company to
       →alter its practices'
      def preprocess(sent):
          sent = nltk.word_tokenize(sent)
          sent = nltk.pos_tag(sent)
          return sent
      sent = preprocess(ex)
      print(sent)
      pattern = 'NP: {<DT>?<JJ>*<NN>}'
      cp = nltk.RegexpParser(pattern)
      cs = cp.parse(sent)
      from nltk.chunk import conlltags2tree, tree2conlltags
      from pprint import pprint
      iob_tagged = tree2conlltags(cs)
```

```
#pprint(iob_tagged)
      ne_tree = nltk.ne_chunk(pos_tag(word_tokenize(ex)))
      print(ne_tree)
     [('European', 'JJ'), ('authorities', 'NNS'), ('fined', 'VBD'), ('Google',
     'NNP'), ('a', 'DT'), ('record', 'NN'), ('$', '$'), ('5.1', 'CD'), ('billion',
     'CD'), ('on', 'IN'), ('Wednesday', 'NNP'), ('for', 'IN'), ('abusing', 'VBG'),
     ('its', 'PRP$'), ('power', 'NN'), ('in', 'IN'), ('the', 'DT'), ('mobile', 'JJ'),
     ('phone', 'NN'), ('market', 'NN'), ('and', 'CC'), ('ordered', 'VBD'), ('the',
     'DT'), ('company', 'NN'), ('to', 'TO'), ('alter', 'VB'), ('its', 'PRP$'),
     ('practices', 'NNS')]
     (S
       (GPE European/JJ)
       authorities/NNS
       fined/VBD
       (PERSON Google/NNP)
       a/DT
       record/NN
       $/$
       5.1/CD
       billion/CD
       on/IN
       Wednesday/NNP
       for/IN
       abusing/VBG
       its/PRP$
       power/NN
       in/IN
       the/DT
       mobile/JJ
       phone/NN
       market/NN
       and/CC
       ordered/VBD
       the/DT
       company/NN
       to/TO
       alter/VB
       its/PRP$
       practices/NNS)
[25]:
      # NO NER WITH TEXTBLOB
[26]: #NER WITH spaCy
      import spacy
```

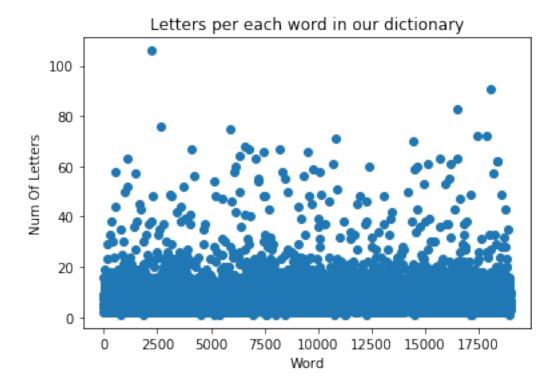
```
from spacy import displacy
      from collections import Counter
      import en_core_web_sm
      nlp = en_core_web_sm.load()
      doc = nlp('European authorities fined Google a record $5.1 billion on Wednesday⊔
       \hookrightarrowfor abusing its power in the mobile phone market and ordered the company to_{\sqcup}
       →alter its practices')
      pprint([(X.text, X.label_) for X in doc.ents])
     [('European', 'NORP'),
      ('Google', 'ORG'),
      ('$5.1 billion', 'MONEY'),
      ('Wednesday', 'DATE')]
 []:
[27]: ttw = pd.read_csv('ttw2_finalSpell.csv')
      ttw.dropna(inplace=True)
[28]: #PART 4.1
      #first cleaning of data from lab1
      #take and return dataframe
      def first_cleaning(ttw):
          start time = datetime.now()
          print(len(ttw))
          stop_words = set(stopwords.words('english'))
          ttw2 = ttw.copy()
          ttw2['tweet'] = ttw2['tweet'].str.lower()
          ttw2['tweet'] = ttw2['tweet'].str.replace(r'(\s)#\w+',' ')
          ttw2['tweet'] = ttw2['tweet'].str.replace('[^\w\s]','')
          ttw2['tweet'] = ttw2['tweet'].str.replace('[^a-z ]','')
          ttw2['tweet'] = ttw2['tweet'].apply(lambda x: " ".join(x for x in x.split()_
       →if x not in stop_words))
          ttw2.dropna(inplace=True)
          print(len(ttw))
          print('Time after first cleaning in (hh:mm:ss.ms): "{}"'.format(datetime.
       →now() - start_time))
          return ttw2
      #TOKENIZATION WITH NLTK
```

```
#function that take dataframe and return our first dictionary as list data\sqcup
\rightarrowstructure
def myDictFunc(ttw):
    dic = set()
    start time = datetime.now()
    for i in ttw['tweet']:
        nltk_tokens = nltk.word_tokenize(i)
        for x in nltk_tokens:
            dic.add(x)
    print('Time after dict creation in (hh:mm:ss.ms): "{}"'.format(datetime.
→now() - start_time))
    return list(dic)
#4.2
#A graph to know ratio between num of letters per each word
#We use it to see the difference of words lengh beefore and after stemming and _{
m L}
\rightarrow lemmatization
def firstGraph(dic):
    start_time = datetime.now()
    NumOf Let = []
    NumOfWord = []
    for t in dic:
        NumOf_Let.append(len(t))
        NumOfWord.append(dic.index(t))
    plt.scatter(NumOfWord, NumOf_Let)
    plt.style.use('default')
    plt.xlabel('Word')
    plt.ylabel('Num Of Letters')
    plt.title('Letters per each word in our dictionary')
    print('Time after first graph execute in (hh:mm:ss.ms): "{}"'.
 →format(datetime.now() - start_time))
#Wordcloud
#With this graph we can see amounth of the words
#We use it to see the difference of words amounth before and after stemming and _{
m L}
\rightarrow lemmatization
```

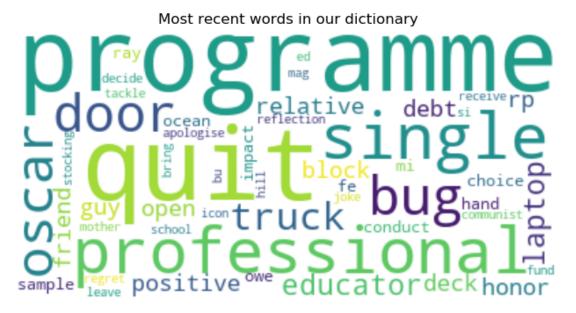
```
def wordcloudGraph(dic):
   start_time = datetime.now()
# Create and generate a word cloud image:
   wordcloud = WordCloud(max_words=50, background_color="white",_
# Display the generated image:
   plt.figure(figsize = (8, 8), facecolor = None)
   plt.imshow(wordcloud, interpolation='bilinear')
   plt.title('Most recent words in our dictionary')
   plt.axis("off")
   plt.show()
   print('Time after wordcloud graph execute in (hh:mm:ss.ms): "{}"'.
 →format(datetime.now() - start_time))
#LEMMATIZATION WITH TEXTBLOB
def myLemmatize(dic):
   start_time = datetime.now()
   dic = [Word(word).lemmatize() for word in dic]
   print('Time after lemmatization in (hh:mm:ss.ms): "{}"'.format(datetime.
 →now() - start_time))
   return dic
#STEMMING WITH NLTK
def myStemm(dic):
   start_time = datetime.now()
   ps = PorterStemmer()
   emp = [ps.stem(w) for w in dic]
   print('Time after stemming in (hh:mm:ss.ms): "{}"'.format(datetime.now() -
→start_time))
   return emp
#3.6
#spellchecker
#spell function for fast spelling operations on our dictionary
def mySpeller(dic):
   start_time = datetime.now()
   spell = Speller(lang='en')
   words_after_speller = [spell(word) for word in dic]
```

```
print('Time after spelling dictionary in (hh:mm:ss.ms): "{}"'.
       →format(datetime.now() - start_time))
          return words_after_speller
[29]: ttw_after_first_cleaning = first_cleaning(ttw)
     31825
     31825
     Time after first cleaning in (hh:mm:ss.ms): "0:00:00.262848"
 []:
[30]: #First try
      #4.1
      first_time = datetime.now()
      my_dict = myDictFunc(ttw_after_first_cleaning)
      firstGraph(my_dict)
      wordcloudGraph(my_dict)
      dic_after_lemma = myLemmatize(my_dict)
      firstGraph(dic after lemma)
      wordcloudGraph(dic_after_lemma)
      dic_after_stemm = myStemm(dic_after_lemma)
      firstGraph(dic_after_stemm)
      wordcloudGraph(dic_after_stemm)
      dic_after_spelling = mySpeller(dic_after_stemm)
      firstGraph(dic_after_spelling)
      wordcloudGraph(dic_after_spelling)
      firstDict = set(dic_after_spelling)
      first_time_final = datetime.now() - first_time
      print('Lenght of second dictionary is: ', len(firstDict))
      print('First try execute time: ', first_time_final)
```

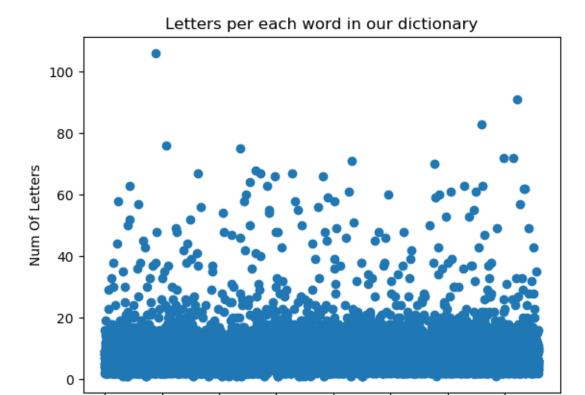
Time after dict creation in (hh:mm:ss.ms): "0:00:04.109559"



Time after first graph execute in (hh:mm:ss.ms): "0:00:05.134574"



Time after wordcloud graph execute in (hh:mm:ss.ms): "0:00:00.704048" Time after lemmatization in (hh:mm:ss.ms): "0:00:00.200875"



Word

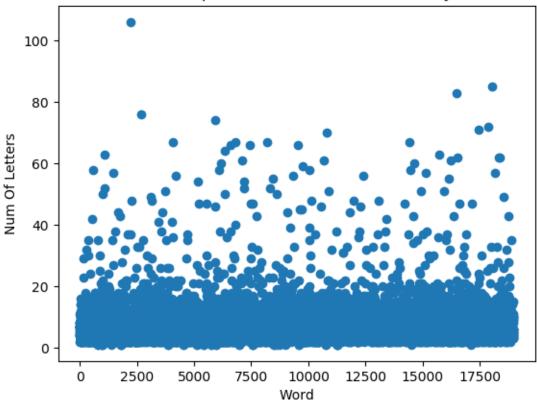
12500 15000

Time after first graph execute in (hh:mm:ss.ms): "0:00:04.579305"



Time after wordcloud graph execute in (hh:mm:ss.ms): "0:00:00.582106" Time after stemming in (hh:mm:ss.ms): "0:00:00.538694"



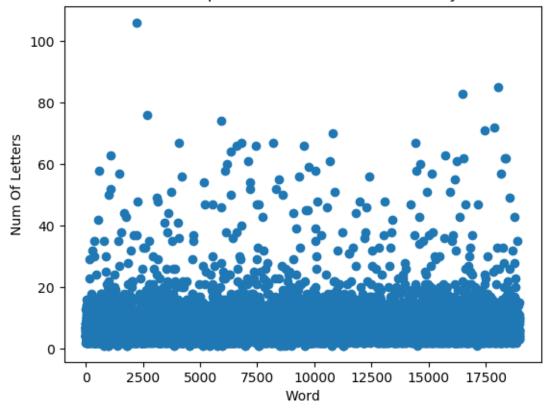


Time after first graph execute in (hh:mm:ss.ms): "0:00:03.505665"



Time after wordcloud graph execute in (hh:mm:ss.ms): "0:00:00.652863" Time after spelling dictionary in (hh:mm:ss.ms): "0:26:51.070701"

Letters per each word in our dictionary



Time after first graph execute in (hh:mm:ss.ms): "0:00:03.226488"



Time after wordcloud graph execute in (hh:mm:ss.ms): "0:00:00.562874"

Lenght of second dictionary is: 13258 First try execute time: 0:27:14.870750

[]:

```
[31]: #Second try
second_time = datetime.now()

my_dict2 = myDictFunc(ttw_after_first_cleaning)

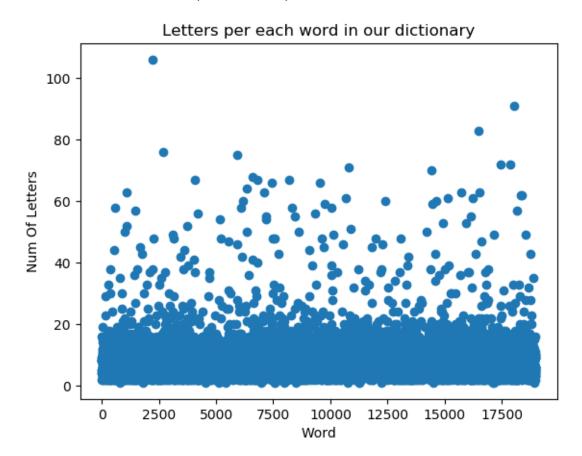
firstGraph(my_dict2)
wordcloudGraph(my_dict2)

dic_after_lemma2 = myLemmatize(my_dict2)
firstGraph(dic_after_lemma2)
wordcloudGraph(dic_after_lemma2)

dic_after_spelling2 = mySpeller(dic_after_lemma2)
firstGraph(dic_after_spelling2)
wordcloudGraph(dic_after_spelling2)
wordcloudGraph(dic_after_spelling2)
```

```
dic_after_stemm2 = myStemm(dic_after_spelling2)
firstGraph(dic_after_stemm2)
wordcloudGraph(dic_after_stemm2)
secondDict = set(dic_after_stemm2)
second_time_final = datetime.now() - second_time
print('Lenght of second dictionary is: ', len(secondDict))
print('Second try execute time: ', second_time_final)
```

Time after dict creation in (hh:mm:ss.ms): "0:00:03.808224"

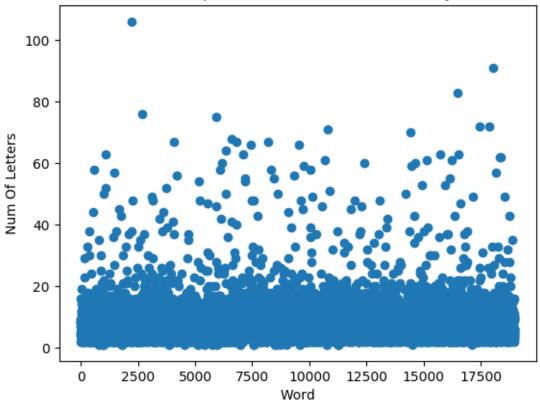


Time after first graph execute in (hh:mm:ss.ms): "0:00:04.615745"

Most recent words in our dictionary Oglicare Oglicary Owe friend of stocking Oscar but block debt trucking Oscar but block open guy doors but but trucking open guy doors but but but trucking open guy doors but trucki

Time after wordcloud graph execute in (hh:mm:ss.ms): "0:00:00.637302" Time after lemmatization in (hh:mm:ss.ms): "0:00:00.163295"

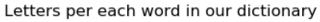


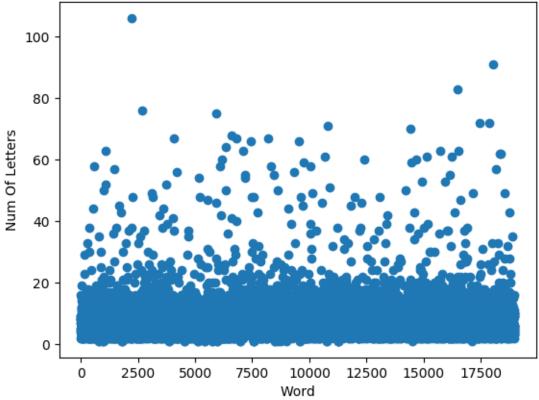


Time after first graph execute in (hh:mm:ss.ms): "0:00:04.273853"



Time after wordcloud graph execute in (hh:mm:ss.ms): "0:00:00.536438" Time after spelling dictionary in (hh:mm:ss.ms): "0:25:19.430013"





Time after first graph execute in (hh:mm:ss.ms): "0:00:04.281733"

Most recent words in our dictionary

professional treaty Cattendant classic

pactorial treaty Cattendant classic

let Cattendant classic

pack let Self

cruise person mummy truck le

let dadwoman

relative

bug by let programme brother

bug by let programme brother

ton Cry

dinerd

core Cry

dinerd

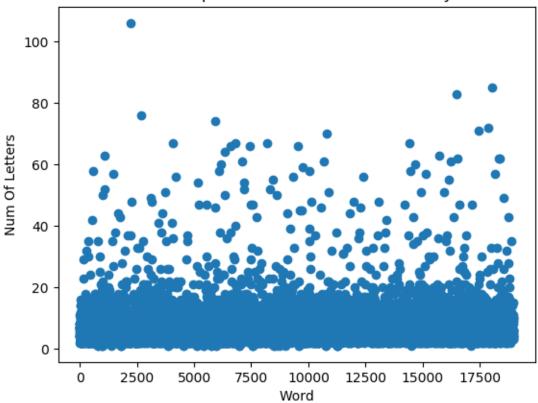
core cry

dinerd

life

Time after wordcloud graph execute in (hh:mm:ss.ms): "0:00:00.587710" Time after stemming in (hh:mm:ss.ms): "0:00:00.536953"





Time after first graph execute in (hh:mm:ss.ms): "0:00:03.354593"

Most recent words in our dictionary



Time after wordcloud graph execute in (hh:mm:ss.ms): "0:00:00.596261" Lenght of second dictionary is: 14252 Second try execute time: 0:25:42.823125

```
[]:
[]:
[]:
[32]: #Third try

third_time = datetime.now()

my_dict3 = myDictFunc(ttw_after_first_cleaning)

firstGraph(my_dict3)
 wordcloudGraph(my_dict3)

dic_after_spelling3 = mySpeller(my_dict3)
 firstGraph(dic_after_spelling3)
 wordcloudGraph(dic_after_spelling3)

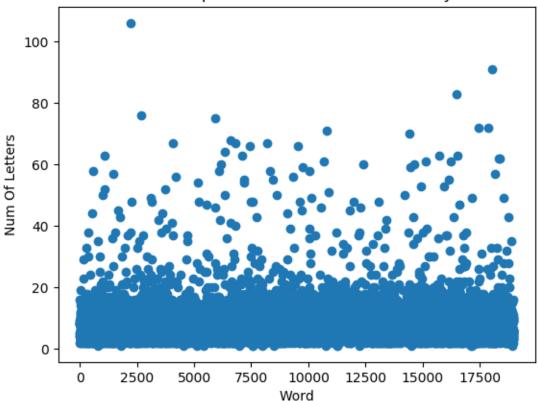
dic_after_lemma3 = myLemmatize(dic_after_spelling3)
 firstGraph(dic_after_lemma3)
 wordcloudGraph(dic_after_lemma3)
```

```
dic_after_stemm3 = myStemm(dic_after_lemma3)
firstGraph(dic_after_stemm3)
wordcloudGraph(dic_after_stemm3)

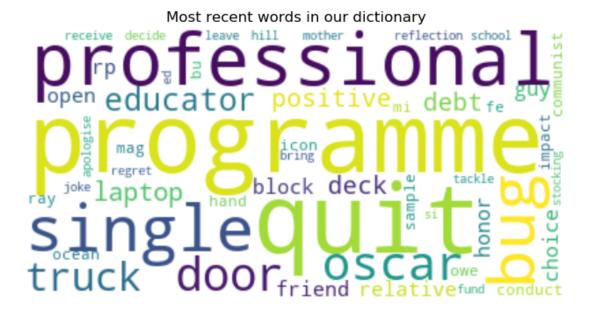
thirdDict = set(dic_after_stemm3)
third_time_final = datetime.now() - third_time
print('Lenght of third dictionary is: ', len(thirdDict))
print('Third try execute time: ', third_time_final)
```

Time after dict creation in (hh:mm:ss.ms): "0:00:03.799074"

Letters per each word in our dictionary

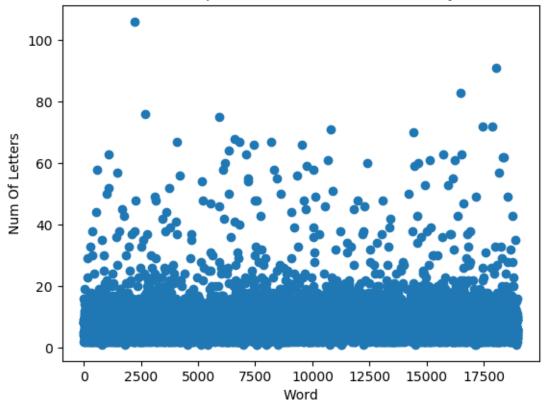


Time after first graph execute in (hh:mm:ss.ms): "0:00:04.567764"

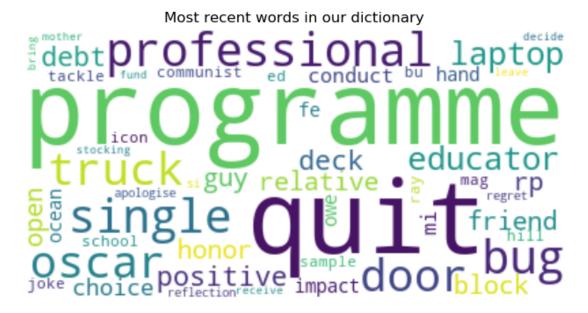


Time after wordcloud graph execute in (hh:mm:ss.ms): "0:00:00.641876" Time after spelling dictionary in (hh:mm:ss.ms): "0:25:21.312909"

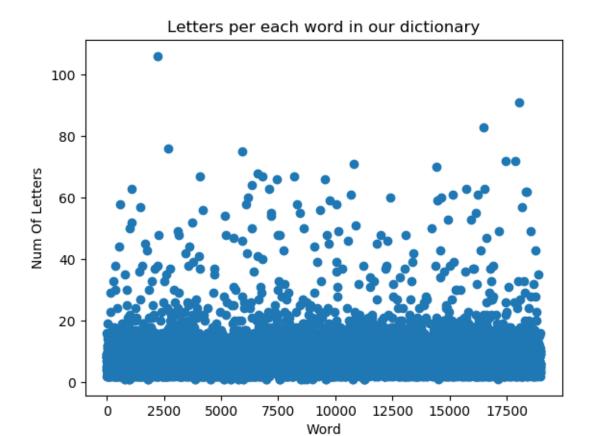




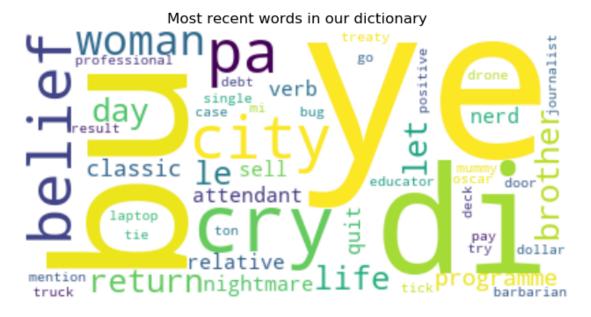
Time after first graph execute in (hh:mm:ss.ms): "0:00:04.921216"



Time after wordcloud graph execute in (hh:mm:ss.ms): "0:00:00.687136" Time after lemmatization in (hh:mm:ss.ms): "0:00:00.259334"

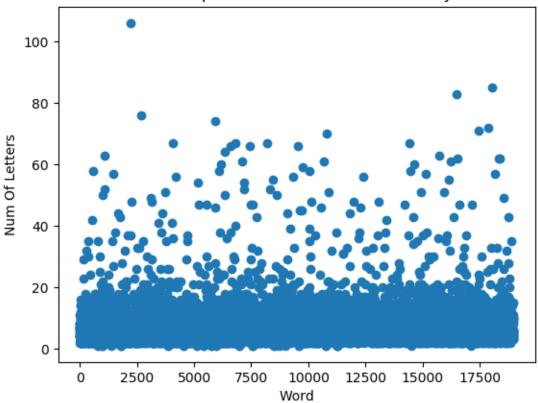


Time after first graph execute in (hh:mm:ss.ms): "0:00:04.571223"

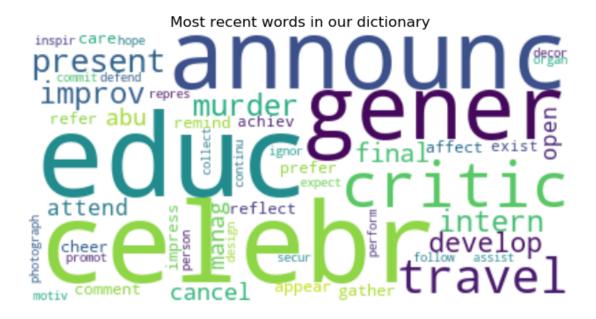


Time after wordcloud graph execute in (hh:mm:ss.ms): "0:00:00.549450" Time after stemming in (hh:mm:ss.ms): "0:00:00.591743"

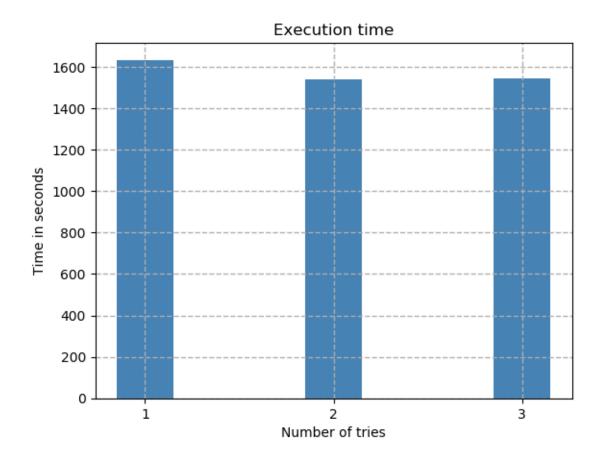




Time after first graph execute in (hh:mm:ss.ms): "0:00:03.524551"

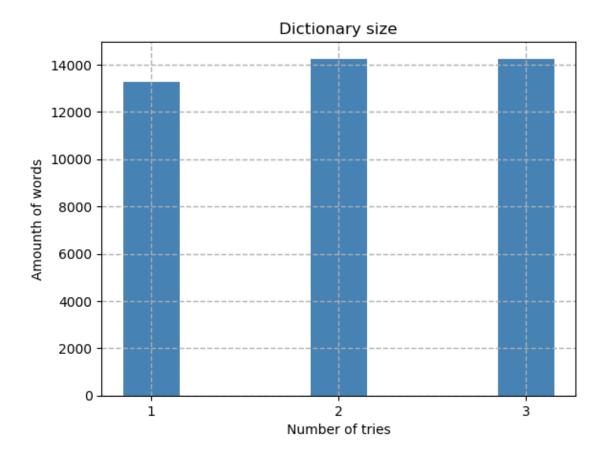


```
Time after wordcloud graph execute in (hh:mm:ss.ms): "0:00:00.601909" Lenght of third dictionary is: 14289 Third try execute time: 0:25:46.043796
```



```
[34]: #Summary part 3.2

12 = [len(firstDict),len(secondDict),len(secondDict)]
x = np.arange(len(1))
plt.bar(x+1,12,width = 0.3, color = 'steelblue')
plt.grid( linestyle='--', linewidth=1)
plt.xlabel('Number of tries')
plt.ylabel('Amounth of words')
plt.xticks([1,2,3])
plt.title('Dictionary size')
plt.yticks()
plt.style.use('default')
plt.show()
```



Under those graphs we can see that our first try take more time to execute code but on the second graph we can see that first try cause less words in our dictionary, when two other tries give us more and the same number of words. So we take first algoritm to obtain the most suitable dictionary.

```
[35]: print('Time after whole checkings are done in (hh:mm:ss.ms): "{}"'.

→format(datetime.now() - start_program))
```

Time after whole checkings are done in (hh:mm:ss.ms): "1:18:58.311754"

[]:

1 Part 2

```
[36]: import pandas as pd
import os
import collections
import time
from datetime import datetime
import pickle
```

1.0.1 ->data

```
[37]: df = ttw_after_first_cleaning
# wordList= ["user", "run", "love", "google", "absabs", " ", "#", "@", "best", "."]
wordList = firstDict

print("data load")
```

data load

1.1 Matrix Build

```
[38]: class matrix:
          def __init__(self,df,wordList,id_len=100):
              self.df=df
              self.wordList=wordList
              self.id_len=id_len
              # Convert the dictionary into DataFrame
              self.new_df = pd.DataFrame( [[bool(False)]*len(wordList)]*id_len )
              self.new_df.columns = wordList
              ID=0
              for tweet in df["tweet"][:id_len]:
                  tokens = tweet.split()
                  for token in tokens:
                      if token in wordList:
                          self.new_df[token][ID]=bool(True)
                  ID += 1
              #2.1.1
              print("")
              print("#2.1.1")
              self.new_df.to_csv('out.csv', index=False)
              print("file out.csv saved ")
              self.new_df.T.to_csv('out_T.csv', index=True)
              print("file out_T.csv saved ")
              #2.1.2
              print("")
              print("#2.1.2")
```

```
print("File out.csv size : ",os.path.getsize('out.csv'),"Byte")
    print("File out_T.csv size : ",os.path.getsize('out_T.csv'),"Byte")
    #2.1.3
    print("")
    print("#2.1.3")
    #print(self.new_df.value_counts())
      for word in self.new_df:
          print(self.new_df[word].value_counts())
    print("")
    print("")
    print(self.new_df.head(100))
def And(self, words_list=[]):
    works like set operator "intersection"
    :param words_list: list of words to find
    :return: appearences of words_list sorted by intersection-operrator
    set_dict={}
    for word in words_list:
        if word not in self.new_df:
            return "No match"
        tempData=(self.new_df[word].loc[self.new_df[word]==True]).index
        set_dict[word] = set(tempData.values)
    result=None
    for word in set_dict:
        if result == None:
            result = set_dict[word]
        else:
            result = (set(result)).intersection(set(set_dict[word]))
        new_result=[]
        for index in result:
```

```
new_result.append(index + 1)
    return new_result
def Or(self, words_list):
    works like set operator "union"
    :param words_list: list of words to find
    :return: appearences of words_list sorted by union-operrator
    set_dict={}
    for word in words_list:
        if word not in self.new_df:
            return "No match"
        tempData=(self.new_df[word].loc[self.new_df[word]==True]).index
        set_dict[word] = set(tempData.values)
        #set_dict[word]=[set(self.new_df[word])]
    result=None
    for word in set_dict:
        if result == None:
            result = set_dict[word]
        else:
            result = (set(result)).union(set(set_dict[word]))
        new_result=[]
        for index in result:
            new_result.append(index + 1)
    return new_result
def Not(self, words_list):
    works like set operator "difference"
    :param words_list: list of words to find
    :return: appearences of words_list sorted by difference-operrator
    11 11 11
    set_dict={}
    for word in words_list:
```

```
if word not in self.new_df:
    return "No match"
tempData=(self.new_df[word].loc[self.new_df[word]==True]).index
set_dict[word]=set(tempData.values)

result=None

for word in set_dict:
    if result == None:
        result = set_dict[word]

else:
    result = (set(result)).difference(set(set_dict[word]))

new_result=[]

for index in result:
    new_result.append(index + 1)

return new_result
```

1.2 Reverse indexes

```
#
               amount_per_tweet=0
# #
                print("ID ===> ",ID)
# #
                print("tweet ===> ", tweet)
              if(type(tweet) != float):
                   tokens = tweet.split()
#
              #print(type(tokens))
              for token in set(tokens):
#
                   if token in wordList:
#
                       # set_dict[word]=set(tempData.values)
#
#
#
                       # len(test)
#
#
                       # data = df.loc[df.cell == id]
#
                       # rows = df.index
#
#
                       tempData=(self.new_df[token].loc[self.
\rightarrow new_df[token] == True]).index
#
                       #list of tweets wich contains word
#
                       tempData=list(np.asarray(tempData) + 1)
                       # print("tempData => ",tempData)
#
                       # amount of tweets wich contains word
                       amount_per_file=len(tempData)
#
#
                       # print("amount_per_file => ",amount_per_file)
# #
                    print(type({(np.where(np.array(tokens)==token)[0]).tolist}))
# #
                    print((np.where(np.array(tokens)==token)[0]).tolist)
          print("ver 1 Done")
#
```

```
#
         ############################ ver 2
         #for tweet in df["tweet"][:id len]:
         #print(df["tweet"][:id_len])
         #print((df["tweet"][:id_len]).values)
#
         df=df[df["tweet"].notnull()]
         split_test=(df["tweet"][:id_len]).values
          print(split_test)
# #
          print("_____")
# #
          print(type((df["tweet"][:id_len]).values))
# #
         print("_____")
          print("_____")
          print(np.array_split(split_test,1))
          print("_____")
         print("_____")
# #
          print("_____")
# #
# #
          print(type(np.array_split(split_test,1)))
         #print(' '.join(list((np.array_split(split_test,1))[0])))
#
         new_word_list=set((' '.join(list((np.array_split(split_test,1))[0]))).
\rightarrow split())
         #TEST=set(np.split((df["tweet"][:id_len]).values))
         # print(new word list)
#
         #print(TEST)
         print("ver 2 Done")
       self.ver_3_dict={}
       for token in wordList:
              tempData=(self.new_df[token].loc[self.new_df[token]==True]).
→index
              #list of tweets wich contains word
              tempData=list(np.asarray(tempData) + 1)
              #print("tempData => ",tempData)
```

```
# amount of tweets wich contains word
            amount_per_file=len(tempData)
                # print("amount_per_file => ",amount_per_file)
            self.ver_3_dict[token]=[len(tempData),dict.fromkeys(tempData,__
→0)]
            for place_list in self.ver_3_dict[token][1].keys():
                 df["tweet"][place_list-1]
               #print(df["tweet"][place_list-1])
               index_list=[m.start() for m in re.finditer(token, __
self.ver_3_dict[token][1][place_list] =
#[0, 5, 10, 15]
               #if token == "user":
                   #print(place_list)
                   #print((df["tweet"][place_list-1]).count(token))
      #print(self.ver_3_dict)
     print(self.ver_3_dict["user"][1])
     print("ver 3 Done")
     print("#2.1.1")
     afile = open('out.pkl', 'wb')
     pickle.dump(self.ver_3_dict, afile)
     afile.close()
```

```
print("File out.pkl saved")
    #print(self.ver_3_dict)
    print("#2.1.2")
    print("File out.pkl size : ",os.path.getsize('out.pkl'),"Byte")
    print("#2.1.3")
    print("Has only useful information")
def And(self, words_list=[]):
    works like set operator "intersection"
    :param words_list: list of words to find
    :return: appearences of words_list sorted by intersection-operrator
    set_dict={}
    for word in words_list:
        if word not in self.ver_3_dict.keys():
            return "No match"
        set_dict[word] = set(self.ver_3_dict[word][1].keys())
    result=None
    for word in set_dict:
        if result == None:
            result = set_dict[word]
        else:
            result = (set(result)).intersection(set(set_dict[word]))
        new_result=[]
        for index in result:
            new_result.append(index)
    return new_result
def And_2(self, words_list=[]):
    works like set operator "intersection"
    :param words_list: list of words to find
    :return: appearences of words_list sorted by intersection-operrator
```

```
n n n
set_dict={}
word_count_dict={}
for word in set(words_list):
    word_count_dict[word] = words_list.count(word)
    if word not in self.ver_3_dict.keys():
        return "No match"
    #for
      print(self.ver_3_dict[word][1].keys())
    set_dict[word] = []
    for key in self.ver_3_dict[word][1].keys():
        #if key+1 > self.ver_3_dict[word][1][key][0]:
        if word_count_dict[word] < self.ver_3_dict[word][1][key][0]+1:</pre>
            set_dict[word].append(key)
result=None
dif_word_count={}
for word in set_dict:
    if result == None:
        result = set_dict[word]
    else:
        result = (set(result)).intersection(set(set_dict[word]))
    new_result=[]
    for index in result:
        new_result.append(index)
return new_result
```

```
def Or(self, words_list=[]):
    works like set operator "intersection"
    :param words_list: list of words to find
    :return: appearences of words_list sorted by intersection-operrator
    HHHH
    set_dict={}
    for word in words_list:
        if word not in self.ver_3_dict.keys():
            return "No match"
        set_dict[word] = set(self.ver_3_dict[word][1].keys())
    result=None
    for word in set_dict:
        if result == None:
            result = set_dict[word]
        else:
            result = (set(result)).union(set(set_dict[word]))
        new_result=[]
        for index in result:
            new_result.append(index)
    return new_result
def Or_2(self, words_list=[]):
    works like set operator "intersection"
    :param words_list: list of words to find
    :return: appearences of words_list sorted by intersection-operrator
    set_dict={}
    word_count_dict={}
    for word in set(words_list):
        word_count_dict[word]=words_list.count(word)
```

```
if word not in self.ver_3_dict.keys():
            return "No match"
        set_dict[word] = set(self.ver_3_dict[word][1].keys())
          for key in self.ver_3_dict[word][1].keys():
              if\ word\_count\_dict[word] < self.ver\_3\_dict[word][1][key][0]+1:
                  set_dict[word].append(key)
    result=None
    dif_word_count={}
    for word in set_dict:
        if result == None:
            result = set_dict[word]
        else:
            result = (set(result)).union(set(set_dict[word]))
        new_result=[]
        for index in result:
            new_result.append(index)
    return new_result
def Not(self, words_list=[]):
    works like set operator "intersection"
    :param words_list: list of words to find
    :return: appearences of words_list sorted by intersection-operrator
    n n n
    set_dict={}
    word_count_dict={}
    for word in set(words_list):
        word_count_dict[word] = words_list.count(word)
        if word not in self.ver_3_dict.keys():
            set_dict[word] = []
        else:
            set_dict[word] = set(self.ver_3_dict[word][1].keys())
```

```
if words_list.count(word) > 1:
                set_dict[word] = []
    result=None
    for word in set_dict:
        if result == None:
            result = set_dict[word]
        else:
            result = (set(result)).difference(set(set_dict[word]))
        new_result=[]
        for index in result:
            new_result.append(index)
    return new_result
def Not_2(self, words_list=[]):
    works like set operator "intersection"
    :param words_list: list of words to find
    :return: appearences of words_list sorted by intersection-operrator
    11 11 11
    set_dict={}
    word_count_dict={}
    for word in set(words_list):
        word_count_dict[word]=words_list.count(word)
        if word not in self.ver_3_dict.keys():
            set_dict[word] = []
        else:
            set_dict[word] = set(self.ver_3_dict[word][1].keys())
            if words_list.count(word) > 1:
                set_dict[word] = []
    result=None
    dif_word_count={}
    for word in set_dict:
        if result == None:
            result = set_dict[word]
```

```
else:
    result = (set(result)).difference(set(set_dict[word]))

new_result=[]

for index in result:
    new_result.append(index)

return new_result
```

1.3 Prints

```
[40]: def to_integer(dt_time):
    #print(dt_time.days)
    #print(type(dt_time))
    print(dt_time.days)
    return 100000*dt_time.days + 1000*dt_time.seconds + dt_time.microseconds
```

```
[42]: print("")
    print("Matrix : len 100")
    print("")

start_time = datetime.now()
    M1=matrix(df,wordList,id_len=100)
    time_dict["M1"]["Create"]=to_integer(datetime.now() - start_time)
    size_dict["1"]["out.csv"]=os.path.getsize('out.csv')
    size_dict["1"]["out_T.csv"]=os.path.getsize('out_T.csv')

print("")
    print("Reverse indexes : len 100")
    print("")

start_time = datetime.now()
```

```
R1=Reverse_indexes(df,wordList,100)
time_dict["R1"]["Create"]=to_integer(datetime.now() - start_time)
size_dict["1"]["out.pkl"]=os.path.getsize('out.pkl')
```

Matrix : len 100

#2.1.1

file out.csv saved
file out_T.csv saved

#2.1.2

File out.csv size : 8068445 Byte File out_T.csv size : 8081894 Byte

#2.1.3

	chance	ry	burs	t init		sh	manipulationlawless		awless	shitload	sonic	\
0	Fal	se Fal		e Fal	se	False			False	False	False	
1	Fal	lse Fal		e Fal	se	False			False	False	False	
2	Fal	lse Fal		e Fal	se	False	Fa		False	False	False	
3	Fal	False Fa		e Fal	se	False	F		False	False	False	
4	False Fa		Fals	e Fal	se	False	False		False	False	False	
	•••		•••				•••	•••	•••			
95	Fal	False Fal		e Fal	se	False			False	False	False	
96	Fal	False Fal		e Fal	se	False			False	False	False	
97	Fal	alse Fal		e Fal	se	False		False		False	False	
98	Fal	lse Fal		e Fal	se	False		False		False	False	
99	Fal	se Fals				False	False		False	False False		
	rida	a	ро	journ		lov	reborn	kill	vomit	camiilab	eck \	
0	False	Fal	se	False		False	False	False	False	Fa	lse	
1	False	Fal	se	False		False	False	False	False	False		
2	False	Fal	se	False		False	False	False	False	Fa	lse	
3	False	Fal	se	False	•••	False	False	False	False	Fa	lse	
4	False	False		False		False	False	False	False	Fa	alse	
	•••			•••		•••			•••			
95	False	Fal	se	False		False	False	False	False	Fa	lse	
96	False	Fal	se	False	•••	False	False	False	False	e False		
97	False	Fal	se	False	•••	False	False	False	False	Fa	False	
98	False	False		False	•••	False	False	False	False	Fa	lse	
99	False Fals		se :	False		False	False	False	False	Fa	lse	
	c 1			63 . 1				٠.				

fandom abe flightless uptake feelinggoodal O False False False False

```
False False
                                      False
                                                     False
     1
                              False
          False False
     2
                              False
                                      False
                                                     False
     3
          False False
                              False
                                      False
                                                     False
     4
                             False
                                      False
          False False
                                                     False
     . .
     95
          False False
                             False
                                      False
                                                     False
     96
          False False
                             False
                                      False
                                                     False
     97
          False False
                             False
                                      False
                                                     False
          False False
                             False
                                      False
                                                     False
     98
     99
          False False
                             False
                                      False
                                                     False
     [100 rows x 13258 columns]
     Reverse indexes : len 100
     {1: [1, [0]], 2: [2, [0, 5]], 7: [8, [0, 22, 27, 32, 37, 42, 47, 52]], 10: [2,
     [0, 5]], 14: [1, [0]], 19: [2, [21, 26]], 24: [2, [0, 5]], 25: [6, [0, 5, 10,
     15, 20, 25]], 27: [1, [0]], 29: [1, [18]], 32: [4, [0, 5, 10, 15]], 33: [1,
     [0]], 38: [1, [0]], 44: [1, [20]], 52: [1, [4]], 53: [1, [24]], 54: [1, [0]],
     57: [1, [0]], 59: [1, [0]], 62: [1, [45]], 65: [1, [0]], 66: [1, [0]], 71: [1,
     [0]], 74: [1, [0]], 77: [5, [0, 14, 22, 27, 32]], 78: [2, [0, 40]], 79: [2, [0,
     5]], 81: [2, [0, 5]], 82: [3, [0, 30, 43]], 90: [2, [22, 27]], 91: [2, [0, 29]],
     93: [1, [44]], 95: [1, [57]], 96: [1, [0]]}
     ver 3 Done
     #2.1.1
     File out.pkl saved
     #2.1.2
     File out.pkl size: 465305 Byte
     #2.1.3
     Has only useful information
[43]: print("")
      print("Matrix : len 1000")
      print("")
      start_time = datetime.now()
      M2=matrix(df,wordList,id_len=1000)
      time_dict["M2"]["Create"]=to_integer(datetime.now() - start_time)
      size_dict["2"]["out.csv"]=os.path.getsize('out.csv')
      size_dict["2"]["out_T.csv"]=os.path.getsize('out_T.csv')
      print("")
      print("Reverse indexes : len 1000")
      print("")
```

```
start_time = datetime.now()
R2=Reverse_indexes(df,wordList,1000)
time_dict["R2"]["Create"]=to_integer(datetime.now() - start_time)
size_dict["2"]["out.pkl"]=os.path.getsize('out.pkl')
```

Matrix : len 1000

#2.1.1

file out.csv saved
file out_T.csv saved

#2.1.2

File out.csv size : 79658683 Byte File out_T.csv size : 79674832 Byte

#2.1.3

	chance	ry	burst		init		sh	manipulationlawless		shitload	soni	c \			
0	Fal	False Fal		False Fa		se	False			False	False	Fals	е		
1	False F		False		False		False			False	False	Fals	е		
2	False		False		False		False			False	False	Fals	е		
3	False		False		e Fal		False			False	False	Fals	е		
4	Fal	False I		False		se	False			False	False	Fals	е		
										•••	•••				
95	Fal	False 1		False		se	False		False		False	Fals	е		
96	Fal	False Fa		False		se	False			False	False	Fals	е		
97	Fal	se Fal		False		se Fal		se	False		False		False	Fals	е
98	Fal	se	e Fals		Fal	se	False		False		False	Fals	е		
99	Fal	False		se	e Fals		False		False		False	Fals	е		
	rida	6	apo	jo	urn	•••	lov	reborn	kill	vomit	camiilab	eck	\		
0	False	Fa:	lse	False		•••	False	False	False	False	False				
1	False	Fa:	lse	False		•••	False	False	False	False	e False				
2	False	Fa:	alse F		lse	•••	False	False	False	False	e False				
3	False	Fa.	alse Fa		lse		False	False	False	False	Fa	lse			
4	False	Fa:	Talse Fa		lse		False	False	False	False	Fa	alse			
	•••	•••		•••		•••	•••			•••					
95	False	Fa:	lse	Fa	lse	•••	False	False	False	False	Fa	lse			
96	False	Fa.	lse	Fa	lse	•••	False	False	False	False	Fa	lse			
97	False	lse False Fa		Fa	lse		False	False	False	False	False				
98	False	Fa:	lse	Fa	lse		False	False	False	False	Fa	lse			
99	False	Fa:	lse	Fa	lse		False	False	False	False	Fa	lse			

fandom abe flightless uptake feelinggoodal

```
0
     False
             False
                                    False
                                                      False
                           False
1
     False
             False
                           False
                                    False
                                                      False
2
     False
             False
                           False
                                    False
                                                      False
3
             False
                           False
                                    False
     False
                                                      False
4
     False
             False
                           False
                                    False
                                                      False
. .
        •••
95
     False
             False
                                                      False
                           False
                                    False
96
     False
             False
                           False
                                    False
                                                      False
97
     False
             False
                                    False
                                                      False
                           False
98
     False
             False
                           False
                                    False
                                                      False
99
     False
             False
                           False
                                    False
                                                      False
```

[100 rows x 13258 columns]

Reverse indexes : len 1000

{1: [1, [0]], 2: [2, [0, 5]], 7: [8, [0, 22, 27, 32, 37, 42, 47, 52]], 10: [2, [0, 5]], 14: [1, [0]], 19: [2, [21, 26]], 24: [2, [0, 5]], 25: [6, [0, 5, 10, 15, 20, 25]], 27: [1, [0]], 29: [1, [18]], 32: [4, [0, 5, 10, 15]], 33: [1, [0]], 38: [1, [0]], 44: [1, [20]], 52: [1, [4]], 53: [1, [24]], 54: [1, [0]], 57: [1, [0]], 59: [1, [0]], 62: [1, [45]], 65: [1, [0]], 66: [1, [0]], 71: [1, [0]], 74: [1, [0]], 77: [5, [0, 14, 22, 27, 32]], 78: [2, [0, 40]], 79: [2, [0, 5]], 81: [2, [0, 5]], 82: [3, [0, 30, 43]], 90: [2, [22, 27]], 91: [2, [0, 29]], 93: [1, [44]], 95: [1, [57]], 96: [1, [0]], 103: [4, [0, 5, 10, 15]], 108: [1, [13]], 109: [1, [12]], 110: [1, [0]], 112: [1, [0]], 114: [1, [12]], 115: [6, [0, 5, 29, 34, 39, 44]], 123: [2, [0, 5]], 130: [1, [0]], 138: [1, [0]], 141: [1, [0]], 142: [1, [19]], 144: [1, [0]], 148: [3, [6, 11, 28]], 149: [2, [0, 37]], 155: [3, [0, 5, 10]], 162: [3, [28, 33, 38]], 166: [1, [21]], 167: [1, [0]], 168: [3, [0, 5, 27]], 172: [1, [0]], 173: [2, [0, 5]], 174: [2, [0, 9]], 178: [1, [6]], 180: [4, [0, 15, 39, 87]], 186: [2, [62, 67]], 188: [1, [27]], 199: [2, [0, 5]], 203: [1, [0]], 206: [3, [0, 5, 10]], 207: [1, [0]], 211: [1, [0]], 214: [1, [10]], 216: [1, [0]], 217: [1, [0]], 220: [2, [65, 91]], 221: [1, [11]], 224: [1, [14]], 225: [2, [0, 27]], 237: [4, [6, 11, 16, 21]], 238: [2, [30, 35]], 245: [1, [0]], 247: [3, [0, 5, 10]], 251: [1, [0]], 253: [3, [26, 31, 36]], 258: [2, [0, 5]], 264: [1, [0]], 267: [1, [18]], 269: [1, [0]], 273: [3, [28, 33, 38]], 280: [1, [0]], 282: [1, [0]], 285: [1, [0]], 286: [1, [54]], 292: [2, [17, 29]], 293: [2, [19, 36]], 297: [1, [0]], 299: [2, [66, 71]], 301: [2, [0, 36]], 302: [2, [0, 30]], 306: [1, [0]], 307: [1, [43]], 312: [1, [0]], 316: [3, [0, 10, 33]], 320: [1, [34]], 322: [1, [0]], 326: [1, [0]], 329: [5, [0, 5, 10, 15, 20]], 333: [1, [0]], 336: [2, [9, 57]], 339: [1, [0]], 342: [4, [0, 5, 16, 21]], 344: [1, [26]], 347: [1, [0]], 349: [2, [0, 5]], 351: [1, [23]], 354: [1, [0]], 356: [2, [0, 31]], 358: [1, [0]], 364: [1, [0]], 371: [1, [33]], 375: [1, [0]], 378: [1, [14]], 379: [1, [0]], 387: [1, [0]], 388: [1, [0]], 389: [2, [0, 5]], 395: [1, [0]], 396: [1, [0]], 397: [1, [0]], 399: [2, [38, 47]], 401: [1, [0]], 403: [1, [0]], 406: [1, [0]], 408: [2, [5, 15]], 409: [1, [57]], 412: [1, [0]], 418: [1, [23]], 419: [3, [41, 46, 51]], 421: [1, [0]], 423: [4, [0, 31, 36, 41]], 433: [1, [0]], 434: [1, [0]], 441: [1, [0]], 443: [1, [0]], 445:

```
[4, [0, 5, 10, 15]], 456: [1, [0]], 458: [3, [0, 5, 10]], 459: [2, [22, 35]],
460: [1, [5]], 464: [1, [0]], 466: [1, [17]], 470: [1, [0]], 473: [1, [52]],
479: [1, [27]], 481: [2, [0, 55]], 482: [1, [12]], 490: [1, [0]], 494: [1, [0]],
500: [2, [0, 5]], 503: [1, [0]], 504: [1, [43]], 507: [1, [0]], 509: [1, [0]],
510: [1, [0]], 511: [1, [0]], 516: [1, [0]], 517: [1, [0]], 518: [2, [0, 15]],
522: [2, [0, 5]], 528: [1, [0]], 532: [1, [0]], 535: [1, [0]], 536: [1, [0]],
537: [1, [0]], 539: [1, [0]], 540: [1, [0]], 541: [3, [23, 28, 33]], 542: [1,
[0]], 545: [1, [0]], 549: [1, [7]], 557: [1, [0]], 558: [2, [23, 28]], 559: [1,
[0]], 564: [1, [29]], 566: [1, [25]], 567: [3, [0, 5, 10]], 568: [1, [0]], 570:
[2, [0, 13]], 571: [3, [0, 5, 10]], 574: [3, [0, 55, 60]], 575: [2, [0, 16]],
576: [1, [0]], 580: [1, [0]], 583: [1, [0]], 585: [1, [21]], 586: [1, [18]],
587: [1, [35]], 588: [1, [0]], 590: [1, [17]], 592: [1, [0]], 596: [1, [14]],
597: [2, [19, 24]], 598: [2, [0, 5]], 599: [1, [0]], 600: [1, [57]], 602: [1,
[4]], 605: [3, [0, 60, 65]], 611: [1, [0]], 617: [2, [0, 5]], 618: [3, [35, 40,
45]], 619: [1, [46]], 620: [1, [0]], 621: [2, [0, 10]], 624: [1, [0]], 629: [1,
[0]], 631: [3, [0, 5, 10]], 632: [1, [0]], 637: [1, [40]], 642: [2, [18, 31]],
643: [1, [0]], 651: [4, [0, 5, 10, 24]], 652: [1, [4]], 653: [2, [0, 11]], 661:
[1, [18]], 662: [1, [0]], 664: [1, [0]], 665: [1, [3]], 670: [1, [0]], 675: [1,
[0]], 678: [1, [0]], 680: [2, [38, 43]], 690: [1, [0]], 691: [1, [0]], 692: [1,
[0]], 695: [2, [38, 50]], 696: [1, [24]], 701: [1, [0]], 702: [2, [0, 5]], 703:
[1, [0]], 706: [1, [5]], 708: [2, [0, 38]], 711: [1, [52]], 712: [4, [0, 16, 21,
26]], 717: [1, [0]], 718: [1, [0]], 719: [1, [0]], 724: [1, [0]], 725: [2, [0,
44]], 733: [2, [0, 5]], 734: [1, [0]], 735: [2, [0, 24]], 738: [1, [43]], 742:
[1, [21]], 747: [1, [0]], 753: [1, [0]], 759: [2, [0, 43]], 760: [3, [36, 45,
54]], 765: [6, [0, 5, 10, 46, 51, 56]], 768: [1, [0]], 769: [1, [0]], 771: [2,
[0, 5]], 775: [5, [0, 5, 10, 15, 20]], 776: [2, [0, 5]], 777: [1, [0]], 779: [3,
[0, 34, 39]], 781: [2, [0, 17]], 782: [1, [0]], 786: [1, [0]], 787: [1, [0]],
788: [1, [0]], 789: [1, [7]], 791: [3, [0, 55, 60]], 792: [1, [0]], 793: [1,
[0]], 794: [1, [0]], 796: [1, [0]], 805: [1, [16]], 810: [1, [0]], 812: [1,
[6]], 816: [1, [0]], 818: [3, [0, 5, 10]], 820: [1, [41]], 822: [2, [0, 5]],
823: [1, [16]], 826: [1, [8]], 827: [3, [0, 5, 59]], 832: [1, [45]], 833: [2,
[0, 5]], 836: [1, [0]], 839: [3, [37, 42, 47]], 842: [1, [0]], 843: [1, [4]],
844: [1, [0]], 849: [3, [0, 5, 10]], 850: [8, [0, 5, 10, 15, 20, 25, 30, 35]],
857: [2, [18, 23]], 858: [2, [30, 35]], 859: [1, [0]], 865: [1, [0]], 868: [1,
[10]], 869: [1, [24]], 870: [1, [0]], 871: [1, [0]], 874: [2, [0, 34]], 876: [1,
[0]], 877: [2, [0, 40]], 878: [1, [0]], 880: [2, [6, 17]], 881: [4, [0, 10, 20,
25]], 882: [1, [0]], 890: [3, [0, 22, 27]], 891: [2, [0, 39]], 905: [1, [0]],
913: [1, [0]], 916: [2, [0, 5]], 923: [1, [18]], 927: [2, [0, 18]], 930: [1,
[0]], 932: [1, [0]], 936: [3, [0, 5, 10]], 937: [2, [0, 5]], 940: [2, [4, 20]],
943: [2, [0, 40]], 950: [1, [0]], 952: [1, [0]], 955: [2, [0, 50]], 959: [1,
[0]], 968: [1, [0]], 969: [2, [0, 5]], 970: [1, [0]], 973: [1, [36]], 975: [1,
[0]], 976: [4, [4, 9, 14, 19]], 977: [3, [0, 5, 10]], 979: [3, [48, 53, 58]],
980: [1, [0]], 985: [2, [0, 17]], 987: [1, [0]], 989: [1, [0]], 994: [1, [20]],
998: [1, [0]], 1000: [1, [0]]}
ver 3 Done
#2.1.1
File out.pkl saved
#2.1.2
```

```
File out.pkl size : 661573 Byte #2.1.3
Has only useful information
```

1.4 Find

```
[44]: start_time = datetime.now()
      print("M1.And(user)",M1.And(["user"]))
      time_dict["M1"]["find"]=to_integer(datetime.now() - start_time)
      start_time = datetime.now()
      print("M2.And(user)", M2.And(["user"]))
      time_dict["M2"]["find"]=to_integer(datetime.now() - start_time)
      start_time = datetime.now()
      print("R1.And(user)",R1.And(["user"]))
      time_dict["R1"]["find"]=to_integer(datetime.now() - start_time)
      start_time = datetime.now()
      print("R2.And(user)",R2.And(["user"]))
      time_dict["R2"]["find"]=to_integer(datetime.now() - start_time)
      start_time = datetime.now()
      print("R1.And_2(user)",R1.And_2(["user"]))
      time_dict["R1"]["find_2"]=to_integer(datetime.now() - start_time)
      start_time = datetime.now()
      print("R2.And_2(user)",R2.And_2(["user"]))
      time_dict["R2"]["find_2"]=to_integer(datetime.now() - start_time)
```

```
M1.And(user) [1, 2, 7, 10, 14, 19, 24, 25, 27, 29, 32, 33, 38, 44, 52, 53, 54, 57, 59, 62, 65, 66, 71, 74, 77, 78, 79, 81, 82, 90, 91, 93, 95, 96]

M2.And(user) [1, 2, 7, 10, 14, 19, 24, 25, 27, 29, 32, 33, 38, 44, 52, 53, 54, 57, 59, 62, 65, 66, 71, 74, 77, 78, 79, 81, 82, 90, 91, 93, 95, 96, 103, 108, 109, 110, 112, 114, 115, 123, 130, 138, 141, 142, 144, 148, 149, 155, 162, 166, 167, 168, 172, 173, 174, 178, 180, 186, 188, 199, 203, 206, 207, 211, 214, 216, 217, 220, 221, 224, 225, 237, 238, 245, 247, 251, 253, 258, 264, 267, 269, 273, 280, 282, 285, 286, 292, 293, 297, 299, 301, 302, 306, 307, 312, 316, 320, 322, 326, 329, 333, 336, 339, 342, 344, 347, 349, 351, 354, 356, 358, 364, 371, 375,
```

```
378, 379, 387, 388, 389, 395, 396, 397, 399, 401, 403, 406, 408, 409, 412, 418,
419, 421, 423, 433, 434, 441, 443, 445, 456, 458, 459, 460, 464, 466, 470, 473,
479, 481, 482, 490, 494, 500, 503, 504, 507, 509, 510, 511, 516, 517, 518, 522,
528, 532, 535, 536, 537, 539, 540, 541, 542, 545, 549, 557, 558, 559, 564, 566,
567, 568, 570, 571, 574, 575, 576, 580, 583, 585, 586, 587, 588, 590, 592, 596,
597, 598, 599, 600, 602, 605, 611, 617, 618, 619, 620, 621, 624, 629, 631, 632,
637, 642, 643, 651, 652, 653, 661, 662, 664, 665, 670, 675, 678, 680, 690, 691,
692, 695, 696, 701, 702, 703, 706, 708, 711, 712, 717, 718, 719, 724, 725, 733,
734, 735, 738, 742, 747, 753, 759, 760, 765, 768, 769, 771, 775, 776, 777, 779,
781, 782, 786, 787, 788, 789, 791, 792, 793, 794, 796, 805, 810, 812, 816, 818,
820, 822, 823, 826, 827, 832, 833, 836, 839, 842, 843, 844, 849, 850, 857, 858,
859, 865, 868, 869, 870, 871, 874, 876, 877, 878, 880, 881, 882, 890, 891, 905,
913, 916, 923, 927, 930, 932, 936, 937, 940, 943, 950, 952, 955, 959, 968, 969,
970, 973, 975, 976, 977, 979, 980, 985, 987, 989, 994, 998, 1000]
R1.And(user) [1, 2, 7, 10, 14, 19, 24, 25, 27, 29, 32, 33, 38, 44, 52, 53, 54,
57, 59, 62, 65, 66, 71, 74, 77, 78, 79, 81, 82, 90, 91, 93, 95, 96]
R2.And(user) [1, 2, 7, 10, 14, 19, 24, 25, 27, 29, 32, 33, 38, 44, 52, 53, 54,
57, 59, 62, 65, 66, 71, 74, 77, 78, 79, 81, 82, 90, 91, 93, 95, 96, 103, 108,
109, 110, 112, 114, 115, 123, 130, 138, 141, 142, 144, 148, 149, 155, 162, 166,
167, 168, 172, 173, 174, 178, 180, 186, 188, 199, 203, 206, 207, 211, 214, 216,
217, 220, 221, 224, 225, 237, 238, 245, 247, 251, 253, 258, 264, 267, 269, 273,
280, 282, 285, 286, 292, 293, 297, 299, 301, 302, 306, 307, 312, 316, 320, 322,
326, 329, 333, 336, 339, 342, 344, 347, 349, 351, 354, 356, 358, 364, 371, 375,
378, 379, 387, 388, 389, 395, 396, 397, 399, 401, 403, 406, 408, 409, 412, 418,
419, 421, 423, 433, 434, 441, 443, 445, 456, 458, 459, 460, 464, 466, 470, 473,
479, 481, 482, 490, 494, 500, 503, 504, 507, 509, 510, 511, 516, 517, 518, 522,
528, 532, 535, 536, 537, 539, 540, 541, 542, 545, 549, 557, 558, 559, 564, 566,
567, 568, 570, 571, 574, 575, 576, 580, 583, 585, 586, 587, 588, 590, 592, 596,
597, 598, 599, 600, 602, 605, 611, 617, 618, 619, 620, 621, 624, 629, 631, 632,
637, 642, 643, 651, 652, 653, 661, 662, 664, 665, 670, 675, 678, 680, 690, 691,
692, 695, 696, 701, 702, 703, 706, 708, 711, 712, 717, 718, 719, 724, 725, 733,
734, 735, 738, 742, 747, 753, 759, 760, 765, 768, 769, 771, 775, 776, 777, 779,
781, 782, 786, 787, 788, 789, 791, 792, 793, 794, 796, 805, 810, 812, 816, 818,
820, 822, 823, 826, 827, 832, 833, 836, 839, 842, 843, 844, 849, 850, 857, 858,
859, 865, 868, 869, 870, 871, 874, 876, 877, 878, 880, 881, 882, 890, 891, 905,
913, 916, 923, 927, 930, 932, 936, 937, 940, 943, 950, 952, 955, 959, 968, 969,
970, 973, 975, 976, 977, 979, 980, 985, 987, 989, 994, 998, 1000]
R1.And_2(user) [1, 2, 7, 10, 14, 19, 24, 25, 27, 29, 32, 33, 38, 44, 52, 53, 54,
57, 59, 62, 65, 66, 71, 74, 77, 78, 79, 81, 82, 90, 91, 93, 95, 96]
R2.And_2(user) [1, 2, 7, 10, 14, 19, 24, 25, 27, 29, 32, 33, 38, 44, 52, 53, 54,
57, 59, 62, 65, 66, 71, 74, 77, 78, 79, 81, 82, 90, 91, 93, 95, 96, 103, 108,
109, 110, 112, 114, 115, 123, 130, 138, 141, 142, 144, 148, 149, 155, 162, 166,
167, 168, 172, 173, 174, 178, 180, 186, 188, 199, 203, 206, 207, 211, 214, 216,
217, 220, 221, 224, 225, 237, 238, 245, 247, 251, 253, 258, 264, 267, 269, 273,
```

```
280, 282, 285, 286, 292, 293, 297, 299, 301, 302, 306, 307, 312, 316, 320, 322,
     326, 329, 333, 336, 339, 342, 344, 347, 349, 351, 354, 356, 358, 364, 371, 375,
     378, 379, 387, 388, 389, 395, 396, 397, 399, 401, 403, 406, 408, 409, 412, 418,
     419, 421, 423, 433, 434, 441, 443, 445, 456, 458, 459, 460, 464, 466, 470, 473,
     479, 481, 482, 490, 494, 500, 503, 504, 507, 509, 510, 511, 516, 517, 518, 522,
     528, 532, 535, 536, 537, 539, 540, 541, 542, 545, 549, 557, 558, 559, 564, 566,
     567, 568, 570, 571, 574, 575, 576, 580, 583, 585, 586, 587, 588, 590, 592, 596,
     597, 598, 599, 600, 602, 605, 611, 617, 618, 619, 620, 621, 624, 629, 631, 632,
     637, 642, 643, 651, 652, 653, 661, 662, 664, 665, 670, 675, 678, 680, 690, 691,
     692, 695, 696, 701, 702, 703, 706, 708, 711, 712, 717, 718, 719, 724, 725, 733,
     734, 735, 738, 742, 747, 753, 759, 760, 765, 768, 769, 771, 775, 776, 777, 779,
     781, 782, 786, 787, 788, 789, 791, 792, 793, 794, 796, 805, 810, 812, 816, 818,
     820, 822, 823, 826, 827, 832, 833, 836, 839, 842, 843, 844, 849, 850, 857, 858,
     859, 865, 868, 869, 870, 871, 874, 876, 877, 878, 880, 881, 882, 890, 891, 905,
     913, 916, 923, 927, 930, 932, 936, 937, 940, 943, 950, 952, 955, 959, 968, 969,
     970, 973, 975, 976, 977, 979, 980, 985, 987, 989, 994, 998, 1000]
[45]: start time = datetime.now()
      print("M1.And(school)",M1.And(["school"]))
      #time_dict["M1"]["And"]=datetime.now() - start_time
      start_time = datetime.now()
      print("M2.And(school)", M2.And(["school"]))
      #time_dict["M2"]["And"]=datetime.now() - start_time
      start_time = datetime.now()
      print("R1.And(school)",R1.And(["school"]))
      #time_dict["R1"]["And"]=datetime.now() - start_time
      start_time = datetime.now()
      print("R2.And(school)",R2.And(["school"]))
      #time dict["R2"]["And"]=datetime.now() - start time
      start_time = datetime.now()
      print("R1.And_2(school)",R1.And_2(["school"]))
      #time_dict["R1"]["And"]=datetime.now() - start_time
      start time = datetime.now()
      print("R2.And_2(school)",R2.And_2(["school"]))
      #time_dict["R2"]["And"]=datetime.now() - start_time
     M1.And(school) [14, 8]
     M2.And(school) [488, 528, 14, 8]
     R1.And(school) [8, 14]
     R2.And(school) [8, 488, 14, 528]
     R1.And_2(school) [8, 14]
     R2.And_2(school) [8, 14, 488, 528]
```

1.5 AND

```
[46]: start time = datetime.now()
      print("M1.And(user school)",M1.And(["user","school"]))
      time_dict["M1"]["And"]=to_integer(datetime.now() - start_time)
      start_time = datetime.now()
      print("M2.And(user school)",M2.And(["user","school"]))
      time_dict["M2"]["And"]=to_integer(datetime.now() - start_time)
      start_time = datetime.now()
      print("R1.And(user school)",R1.And(["user","school"]))
      time_dict["R1"]["And"]=to_integer(datetime.now() - start_time)
      start_time = datetime.now()
      print("R2.And(user school)",R2.And(["user","school"]))
      time_dict["R2"]["And"]=to_integer(datetime.now() - start_time)
      start_time = datetime.now()
      print("R1.And_2(user school)",R1.And_2(["user","school"]))
      time_dict["R1"]["And_2"]=to_integer(datetime.now() - start_time)
      start_time = datetime.now()
      print("R2.And_2(user school)",R2.And_2(["user","school"]))
      time_dict["R2"]["And_2"]=to_integer(datetime.now() - start_time)
     M1.And(user school) [14]
     M2.And(user school) [14, 528]
     R1.And(user school) [14]
     R2.And(user school) [528, 14]
     R1.And_2(user school) [14]
     R2.And_2(user school) [528, 14]
     1.6 OR
[47]: start_time = datetime.now()
      print("M1.Or(love school)",M1.Or(["love","school"]))
      time_dict["M1"]["Or"]=to_integer(datetime.now() - start_time)
      start_time = datetime.now()
```

print("M2.Or(love school)",M2.Or(["love","school"]))

time_dict["M2"]["Or"]=to_integer(datetime.now() - start_time)

```
start_time = datetime.now()
      print("R1.Or(love school)",R1.Or(["love","school"]))
      time_dict["R1"]["Or"]=to_integer(datetime.now() - start_time)
      start_time = datetime.now()
      print("R2.Or(love school)",R2.Or(["love","school"]))
      time_dict["R2"]["Or"]=to_integer(datetime.now() - start_time)
      start_time = datetime.now()
      print("R1.Or_2(love school)",R1.Or_2(["love","school"]))
      time_dict["R1"]["Or_2"]=to_integer(datetime.now() - start_time)
      start_time = datetime.now()
      print("R2.Or_2(love school)",R2.Or_2(["love","school"]))
      time_dict["R2"]["Or_2"]=to_integer(datetime.now() - start_time)
     M1.Or(love school) [97, 4, 8, 9, 14, 47, 52, 55, 27]
     M2.Or(love school) [4, 8, 9, 268, 269, 14, 911, 528, 277, 27, 797, 798, 926,
     163, 806, 811, 684, 47, 52, 55, 697, 825, 699, 828, 957, 447, 835, 453, 326,
     585, 330, 332, 974, 337, 470, 473, 219, 222, 97, 741, 358, 488, 369, 118, 377,
     891, 508]
     R1.Or(love school) [97, 4, 8, 9, 14, 47, 52, 55, 27]
     R2.Or(love school) [4, 8, 9, 268, 269, 14, 911, 528, 277, 27, 797, 798, 926,
     163, 806, 811, 684, 47, 52, 55, 697, 825, 699, 828, 957, 447, 835, 453, 326,
     585, 330, 332, 974, 337, 470, 473, 219, 222, 97, 741, 358, 488, 369, 118, 377,
     891, 508]
     R1.Or_2(love school) [97, 4, 8, 9, 14, 47, 52, 55, 27]
     R2.Or_2(love school) [4, 8, 9, 268, 269, 14, 911, 528, 277, 27, 797, 798, 926,
     163, 806, 811, 684, 47, 52, 55, 697, 825, 699, 828, 957, 447, 835, 453, 326,
     585, 330, 332, 974, 337, 470, 473, 219, 222, 97, 741, 358, 488, 369, 118, 377,
     891, 508]
[48]: print(time_dict)
     {'M1': {'Create': 845417, 'find': 0, 'And': 15625, 'Or': 1998}, 'M2': {'Create':
     254744, 'find': 0, 'And': 0, 'Or': 2998}, 'R1': {'Create': 480812, 'find': 0,
     'And': 0, 'Or': 0, 'find_2': 0, 'And_2': 0, 'Or_2': 0}, 'R2': {'Create':
     1007024, 'find': 0, 'And': 0, 'Or': 0, 'find_2': 0, 'And_2': 0, 'Or_2': 0}}
[49]: print(size dict)
```

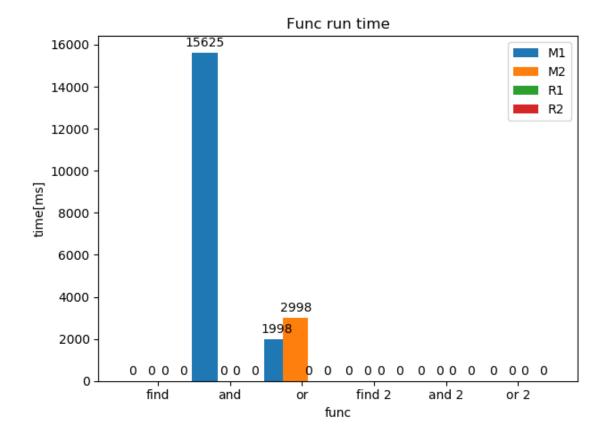
1.7 Plot for function run time

```
[51]: import matplotlib import matplotlib.pyplot as plt import numpy as np
```

```
[52]: time_arr_all=[]
      for kclass in time_dict.keys():
          time_arr=[]
          for key in (time_dict[kclass].keys()):
              if key !="Create":
                  time_arr.append(time_dict[kclass][key])
          time_arr_all.append(time_arr)
      print(time arr all)
      labels = ['find', 'and', 'or', ]
      labels1 = ['find', 'and', 'or', 'find 2', 'and 2', 'or 2']
      time_arr_all[0].append(0)
      time_arr_all[0].append(0)
      time_arr_all[0].append(0)
      time_arr_all[1].append(0)
      time_arr_all[1].append(0)
      time_arr_all[1].append(0)
      M_1 = time_arr_all[0]
      M_2 = time_arr_all[1]
      R_1 = time_arr_all[2]
      R_2 = time_arr_all[3]
      x1 = np.arange(len(labels1)) # the label locations
      width = 0.35 # the width of the bars
```

```
fig, ax = plt.subplots()
rects1 = ax.bar(x1 - width/1, M_1, width, label='M1')
rects2 = ax.bar(x1 - width/4, M_2, width, label='M2')
rects3 = ax.bar(x1 + width/4, R_1, width, label='R1')
rects4 = ax.bar(x1 + width/1, R_2, width, label='R2')
# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('time[ms]')
ax.set_xlabel('func')
ax.set_title('Func run time')
ax.set_xticks(x1)
ax.set_xticklabels(labels1)
ax.legend()
def autolabel(rects):
    """Attach a text label above each bar in *rects*, displaying its height."""
    for rect in rects:
        height = rect.get_height()
        ax.annotate('{}'.format(height),
                    xy=(rect.get_x() + rect.get_width() / 2, height),
                    xytext=(0, 3), # 3 points vertical offset
                    textcoords="offset points",
                    ha='center', va='bottom')
autolabel(rects1)
autolabel(rects2)
autolabel(rects3)
autolabel(rects4)
fig.tight_layout()
plt.show()
```

[[0, 15625, 1998], [0, 0, 2998], [0, 0, 0, 0, 0, 0], [0, 0, 0, 0, 0]]

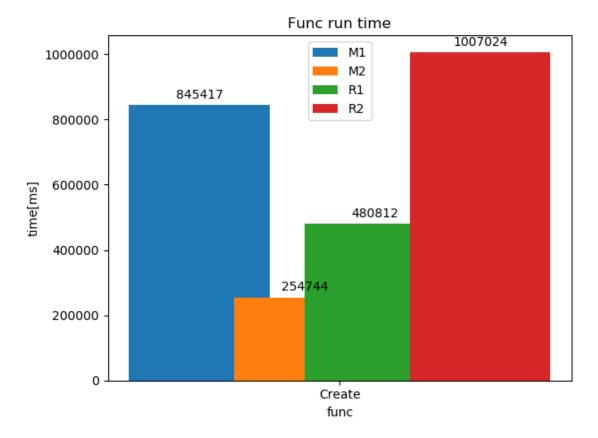


1.7.1 Conclusion

* func 2 only Reverse indexes opperators #### 1) we get pretty good time for Matrix and Reverse indexes #### 2) Reverse indexes works faster becouse of it's structur

2 Plot for creation run time

```
labels = ["Create"]
labels1 = ["Create"]
M_1 = time_arr_all[0]
M_2 = time_arr_all[1]
R_1 = time_arr_all[2]
R_2 = time_arr_all[3]
x1 = np.arange(len(labels1)) # the label locations
width = 0.35 # the width of the bars
fig, ax = plt.subplots()
rects1 = ax.bar(x1 - width/1, M_1, width, label='M1')
rects2 = ax.bar(x1 - width/4, M_2, width, label='M2')
rects3 = ax.bar(x1 + width/4, R_1, width, label='R1')
rects4 = ax.bar(x1 + width/1, R_2, width, label='R2')
# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('time[ms]')
ax.set xlabel('func')
ax.set_title('Func run time')
ax.set xticks(x1)
ax.set_xticklabels(labels1)
ax.legend()
def autolabel(rects):
    """Attach a text label above each bar in *rects*, displaying its height."""
    for rect in rects:
        height = rect.get_height()
        ax.annotate('{}'.format(height),
                    xy=(rect.get_x() + rect.get_width() / 2, height),
                    xytext=(0, 3), # 3 points vertical offset
                    textcoords="offset points",
                    ha='center', va='bottom')
autolabel(rects1)
autolabel(rects2)
autolabel(rects3)
autolabel(rects4)
fig.tight_layout()
plt.show()
```



2.0.1 Conclusion

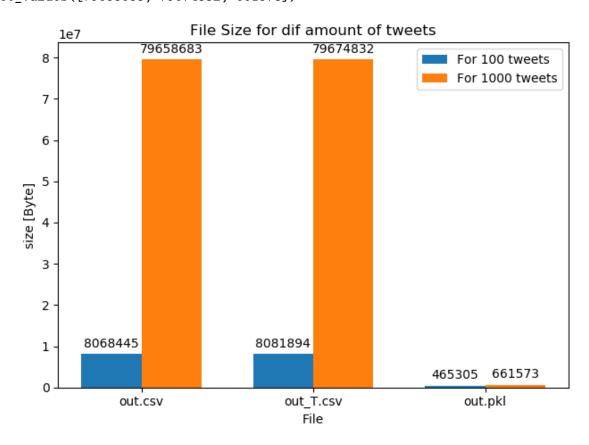
1) Reverse indexes works faster becouse it's struct stor only true values and it also use part of matrix struct ### 2) for real test we need to separate between Matrix and Reverse indexes #### * sorry it takes long time to recompile the code

3 Plot for size of files

return Max

```
[56]: labels1 = ["out.csv","out_T.csv","out.pkl"]
      T_1=size_dict["1"].values()
      T_2=size_dict["2"].values()
      print(T_1)
      print(T_2)
      x1 = np.arange(len(labels1)) # the label locations
      #y1 = np.arange(range(0,MaxSize(size dict),MaxSize(size dict)/10))
      width = 0.35 # the width of the bars
      fig, ax = plt.subplots()
      rects1 = ax.bar(x1 - width/2, T_1, width, label="For 100 tweets")
      rects2 = ax.bar(x1 + width/2, T_2, width, label="For 1000 tweets")
      # Add some text for labels, title and custom x-axis tick labels, etc.
      ax.set_ylabel('size [Byte]')
      ax.set_xlabel('File')
      ax.set_title('File Size for dif amount of tweets')
      #ax.set_yticks(y1)
      ax.set_xticks(x1)
      ax.set_xticklabels(labels1)
      ax.legend()
      def autolabel(rects):
          """Attach a text label above each bar in *rects*, displaying its height."""
          for rect in rects:
              height = rect.get_height()
              ax.annotate('{}'.format(height),
                          xy=(rect.get_x() + rect.get_width() / 2, height),
                          xytext=(0, 3), # 3 points vertical offset
                          textcoords="offset points",
                          ha='center', va='bottom')
      autolabel(rects1)
      autolabel(rects2)
      fig.tight_layout()
      plt.show()
```

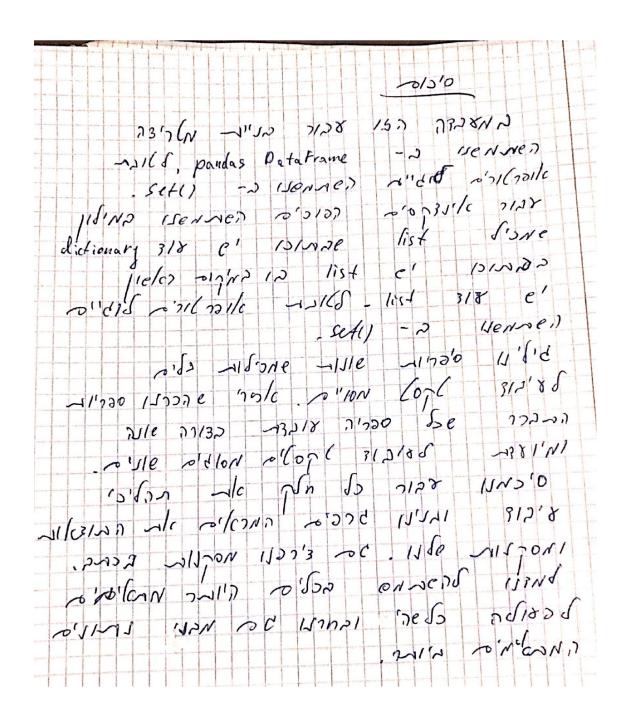
dict_values([8068445, 8081894, 465305]) dict_values([79658683, 79674832, 661573])



3.0.1 Conclusion

1) Reverse indexes have best results becouse of it's struct and maybe also file format $\#\#\#\ 2$) size(DataFrame)==size(DataFrame_T)

[58]:



Сканировано с CamScanner

[]:[