1.Feature_Extraction

May 5, 2018

0.1 Feature extraction: to vectorize given words

- we are converting each word to a vectorized form which is a binary vector (containing only 0s and 1s)
- Each feature/column is a binary question. e.g. is first letter capitalized or not ? (Yes = 1 / No = 0)
- We are considering mainly suffix , prefix , prev and next context , some english rules of words as features
- At the end we will store this feature dataframe to a csv file, for future use: as this code takes time

```
In [1]: # importing necessary packages
        import pandas as pd
        import numpy as np
        import time
0.1.1 Loading training data
In [2]: df = pd.read_csv('./Data_for_postagging/postrain', sep = " ")
        df.head()
        df.shape
Out[2]: (211727, 3)
In [3]: # final dataframe : it ll be our data matrix
        final= pd.DataFrame(index = range(211730) , columns = ['word', 'tag', 'capitalize',
                                                                 'digit_first',
                                                                 's_dig__e_alpha', 'p_anti',
                                                                'p_pre', 'p_un',
                                                                'p_dis', 'p_inter', 'p_mis',
                                                                'p_non', 'p_over_under',
```

'p_in_im', 'p_en_em', 's_able',

's_ed_ing','s_tion_ion','s_est',

's_en','s_ly','s_er','s_\'s_s\''

's_al_ial',

'prev_word'])

's_less', 's_e_es',

```
#prev_word represents that prev word is a, an or the
         final
         #df = pd.DataFrame(index=range(numRows), columns=range(numCols))
         #final['word'][2] = 1
         final.shape
         final.head()
Out[3]:
           word
                  tag capitalize digit_first s_dig__e_alpha p_anti p_pre p_un p_dis
         0
            {\tt NaN}
                  NaN
                               NaN
                                                                       NaN
                                                                              NaN
                                                                                   {\tt NaN}
                                                                                           NaN
                                             NaN
                                                               NaN
         1
            NaN
                  NaN
                               NaN
                                             NaN
                                                               NaN
                                                                       NaN
                                                                              {\tt NaN}
                                                                                    NaN
                                                                                           NaN
         2
            NaN
                               NaN
                                             NaN
                                                                       NaN
                                                                                    NaN
                                                                                           NaN
                  NaN
                                                               NaN
                                                                              NaN
         3
            {\tt NaN}
                  NaN
                               NaN
                                             NaN
                                                               NaN
                                                                       NaN
                                                                              {\tt NaN}
                                                                                    {\tt NaN}
                                                                                           NaN
            NaN
                  NaN
                               NaN
                                             NaN
                                                               NaN
                                                                       NaN
                                                                              {\tt NaN}
                                                                                    NaN
                                                                                           NaN
           p_inter
                                s_ed_ing s_tion_ion s_est s_less s_e_es s_en s_ly s_er
                         . . .
         0
                NaN
                                      NaN
                                                   NaN
                                                          NaN
                                                                  NaN
                                                                           NaN
                                                                                {\tt NaN}
                                                                                      NaN
                                                                                            NaN
                         . . .
                                      NaN
                                                   NaN
         1
                NaN
                                                          NaN
                                                                  NaN
                                                                           {\tt NaN}
                                                                                {\tt NaN}
                                                                                      NaN
                                                                                            NaN
                         . . .
         2
                NaN
                                      NaN
                                                   NaN
                                                          NaN
                                                                  NaN
                                                                          {\tt NaN}
                                                                                NaN
                                                                                      NaN
                                                                                            NaN
                        . . .
         3
                NaN
                                      NaN
                                                   {\tt NaN}
                                                          NaN
                                                                  NaN
                                                                          NaN
                                                                                NaN
                                                                                      NaN
                                                                                            NaN
         4
                NaN
                                      NaN
                                                   NaN
                                                          NaN
                                                                  NaN
                                                                          NaN NaN
                                                                                      {\tt NaN}
                                                                                            NaN
                         . . .
           s_'s_s' prev_word
         0
                NaN
                            NaN
         1
                NaN
                            NaN
         2
                NaN
                            NaN
         3
                NaN
                            NaN
         4
                NaN
                            NaN
         [5 rows x 27 columns]
0.1.2 Extracting feautures
In [ ]: for i in df.index.values:
              j += 1
             # if(j > 10):
                   break
              if df.word[i][0].isupper():
                  final['capitalize'][i] = 1
              else:
                  final['capitalize'][i] = 0
```

if df.word[i][0].isdigit():

```
final['digit_first'][i] = 1
else:
    final['digit_first'][i] = 0
if df.word[i][0].isdigit() and df.word[i][-1].isalpha():
    final['s_dig__e_alpha'][i] = 1
else:
    final['s_dig__e_alpha'][i] = 0
if df.word[i].startswith('anti'):
    final['p_anti'][i] = 1
else:
    final['p_anti'][i] = 0
if df.word[i].startswith('pre'):
    final['p_pre'][i] = 1
else:
    final['p_pre'][i] = 0
if df.word[i].startswith('un'):
    final['p_un'][i] = 1
else:
    final['p_un'][i] = 0
if df.word[i].startswith('dis'):
    final['p_dis'][i] = 1
else:
    final['p_dis'][i] = 1
if df.word[i].startswith('inter'):
    final['p_inter'][i] = 1
else:
    final['p_inter'][i] = 0
if df.word[i].startswith('mis'):
    final['p_mis'][i] = 1
else:
    final['p mis'][i] = 0
if df.word[i].startswith('non'):
    final['p_non'][i] = 1
else:
    final['p_non'][i] = 0
if df.word[i].startswith('over') or df.word[i].startswith('under'):
    final['p_over_under'][i] = 1
else:
    final['p_over_under'][i] = 1
if df.word[i].startswith('in') or df.word[i].startswith('im'):
    final['p_in_im'][i] = 1
else:
```

```
final['p_in_im'][i] = 0
if df.word[i].startswith('en') or df.word[i].startswith('em'):
    final['p_en_em'][i] = 1
else:
    final['p_en_em'][i] = 0
if df.word[i].endswith('able'):
    final['s_able'][i] = 1
else:
    final['s_able'][i] = 0
if df.word[i].endswith('al') or df.word[i].endswith('ial'):
    final['s_al_ial'][i] = 1
else:
    final['s_al_ial'][i] = 0
if df.word[i].endswith('ed') or df.word[i].endswith('ing'):
    final['s_ed_ing'][i] = 1
else:
    final['s_ed_ing'][i] = 0
if df.word[i].endswith('tion') or df.word[i].endswith('ion'):
    final['s_tion_ion'][i] = 1
else:
    final['s_tion_ion'][i] = 0
if df.word[i].endswith('est'):
    final['s_est'][i] = 1
else:
    final['s_est'][i] = 0
if df.word[i].endswith('less'):
    final['s_{less'}][i] = 1
else:
    final['s_less'][i] = 0
if df.word[i].endswith('e') or df.word[i].endswith('es'):
    final['s_e_es'][i] = 1
else :
    final['s e es'][i] = 0
if df.word[i].endswith('en'):
    final['s_en'][i] = 1
else:
    final['s_en'][i] = 0
if df.word[i].endswith('ly'):
    final['s_ly'][i]=1
else:
    final['s_ly'][i]=0
if df.word[i].endswith('er'):
    final['s_er'][i] = 1
else:
```

```
if df.word[i].endswith('\'s') or df.word[i].endswith('s\''):
                final['s_\'s_s\''][i] = 1
            else:
                final['s_{'s_s}''][i] = 0
            if i >= 1:
                if df.word[i-1] == 'a' or df.word[i-1] == 'an' or df.word[i-1] == 'the':
                    final['prev_word'][i] = 1
                else:
                    final['prev_word'][i] = 0
            else:
                final['prev_word'][i] = 0
            final['word'][i] = df.word[i]
            final['tag'][i] = df['pos_tag'][i]
            #if(j % 20000 == 0):
               print(j)
        # append tks 2 mins for first 20000 and then time increases exponentially
        # fixed size array tks 10 mins for every 20k rows
        # NEVER EVER use append (means arraylist) when u knw array size in advance
        # performance of array is way way better than arraylist
0.1.3 Storing featurized dataframe to disk: for future use
In [4]: # storing the featurized df to disk into csv format
        final.to_csv('./final_df_by_arr.csv',sep = ',' , index = False , encoding = 'utf-8')
        # reading from disk
        checkdf = pd.read_csv('./final_df.csv' , sep = ',' )
        print(checkdf.shape)
        checkdf.head()
(211727, 27)
Out [4]:
                 word tag capitalize digit_first s_dig__e_alpha p_anti p_pre
        0 Confidence
                        NN
                                      1
                                                   0
                                                                   0
                                                                            0
                                                                                   0
        1
                   in
                        ΙN
                                      0
                                                   0
                                                                   0
                                                                            0
                                                                                   0
        2
                        DT
                                      0
                                                   0
                                                                   0
                                                                            0
                                                                                   0
                  the
        3
                pound
                        NN
                                      0
                                                   0
                                                                   0
                                                                            0
                                                                                   0
        4
                   is VBZ
                                      0
                                                   0
                                                                                   0
           p_un p_dis p_inter
                                             s_ed_ing s_tion_ion s_est s_less
                                    . . .
              0
                     0
                                                                0
                                                                       0
                                    . . .
```

 $final['s_er'][i] = 0$

1	0	0		ο.		0	0	0	0
2	0	0		0 .		0	0	0	0
3	0	0		0 .		0	0	0	0
4	0	0		0 .		0	0	0	0
	s_e_es	s_en	s_ly	s_er	s_'s_s'	prev_word			
0	1	0	0	0	0	0			
1	0	0	0	0	0	0			
2	1	0	0	0	0	0			
3	0	0	0	0	0	1			
4	0	0	0	0	0	0			

[5 rows x 27 columns]

In []: checkdf['tag'].value_counts()

2.Softmax_Training

May 5, 2018

0.1 Training softmax model on train data: For standalone probabilities

- This notebook will add some more features we have considered later: such as length and adding prev and next context means: feature of prev word and next word ll be appended to current word feature
- Then we ll at last run softmax model for multiclass classfication and train it on training dataset

```
In [1]: # importing necessary packages
    import pandas as pd
    import numpy as np
```

0.1.1 loading featurized data matrix that we have already stored in disk (final_df.csv)

Out[2]:	word	tag	capitalize	digit_first	s_dige_alpha	p_anti	p_pre	`
0	Confidence	NN	1	0	0	0	0	
1	in	IN	0	0	0	0	0	
2	the	DT	0	0	0	0	0	
3	pound	NN	0	0	0	0	0	
4	is	VBZ	0	0	0	0	0	

	p_un	p_dis	p_inter	 s_ed_ing	s_tion_ion	s_est	s_less	\
0	0	0	0	 0	0	0	0	
1	0	0	0	 0	0	0	0	
2	0	0	0	 0	0	0	0	
3	0	0	0	 0	0	0	0	
4	0	0	0	 0	0	0	0	

	s_e_es	s_en	s_ly	s_er	s_'s_s'	prev_word
0	1	0	0	0	0	0
1	0	0	0	0	0	0
2	1	0	0	0	0	0
3	0	0	0	0	0	1
4	0	0	0	0	0	0

[5 rows x 27 columns]

0.1.2 Adding some more features: length, hyphen, all capital etc.

```
In [3]: length = []
        for s in df['word']:
             length.append(len(s))
        length_2 = np.asarray(length).reshape(-1,1)
        df['length'] = length_2
        df.head()
Out[3]:
                         tag capitalize digit_first s_dig__e_alpha p_anti p_pre
           Confidence
                          NN
                                        1
                                                                                 0
                                                                                        0
                                                                                 0
        1
                    in
                          IN
                                        0
                                                      0
                                                                        0
                                                                                        0
        2
                   the
                          DT
                                        0
                                                      0
                                                                        0
                                                                                 0
                                                                                        0
        3
                          NN
                                        0
                                                      0
                                                                        0
                                                                                 0
                                                                                        0
                 pound
        4
                    is
                        VBZ
                                        0
                                                      0
                                                                        0
                                                                                 0
                                                                                        0
                                            s_tion_ion s_est s_less s_e_es s_en
            p_un p_dis p_inter
                                     . . .
        0
               0
                      0
                                0
                                                              0
                                                                       0
                                     . . .
                                                      0
                                                                                1
        1
               0
                      0
                                0
                                                      0
                                                              0
                                                                       0
                                                                               0
                                                                                      0
                                     . . .
        2
                                                      0
                                                              0
                                                                       0
               0
                      0
                                0
                                     . . .
                                                                               1
                                                                                      0
        3
               0
                      0
                                0
                                                      0
                                                              0
                                                                       0
                                                                               0
                                                                                      0
                                     . . .
        4
               0
                      0
                                0
                                                      0
                                                              0
                                                                       0
                                                                               0
                                                                                      0
                                  prev_word
                 s_er s_'s_s'
            s_ly
        0
               0
                     0
                               0
                                           0
                                                   10
        1
               0
                                           0
                                                    2
                     0
                               0
        2
               0
                     0
                                           0
                                                    3
                               0
                                                    5
        3
               0
                     0
                               0
                                           1
               0
                                           0
                                                    2
         [5 rows x 28 columns]
In [48]: hyphen = []
         all_cap = []
         sp char = []
         cap_dot = []
         number = []
         st_alpha_dot = []
         e_day = []
         for i in df['word']:
              if('-' in i):
                  hyphen.append(1)
              else:
                  hyphen.append(0)
              if(i.isupper()):
                  all_cap.append(1)
              else:
                  all_cap.append(0)
```

```
if(('$' in i or ',' in i or '%' in i or '!' in i or '\'' in i or '"' in i) \
                and len(i) == 1):
                 sp_char.append(1)
             else:
                 sp_char.append(0)
             if(i[0].isupper() and i.endswith('.')):
                 cap_dot.append(1)
             else:
                 cap_dot.append(0)
             if(i[0].isdigit() and i[-1].isdigit() and ('.' in i or ',' in i)):
                 number.append(1)
             else:
                 number.append(0)
             if(i[0].isalpha() and '.' in i):
                 st_alpha_dot.append(1)
             else:
                 st_alpha_dot.append(0)
             if(i.endswith('day')):
                 e_day.append(1)
             else:
                 e_day.append(0)
         #print('\'')
In [50]: df['hyphen'] = hyphen
         df['all cap'] = all cap
         df['sp_char'] = sp_char
         df['cap_dot'] = cap_dot
         df['number'] = number
         df['st_alpha_dot'] = st_alpha_dot
         df['e_day'] = e_day
0.1.3 converting dataframe to Data Matrix 'X' and target column vector 'y'
In [51]: data = np.array(df)
         x = data[:,2:]
         x.shape
         y = df['tag']
         y.shape
         x.shape
Out[51]: (211727, 33)
0.1.4 Adding/Appending prev and next context: appending feature vect
In [52]: no_cols = x.shape[1] * 5
         features = np.zeros((211730,no cols))
```

```
b = no_cols / 5
      b = int(b)
In [53]: # taking prev and next words as feature vectors: appending the stored
       # feature vectors of the same
      for i in range(x.shape[0]):
          if(i==0):
             features[i][b * 2: b* 3] = x[i]
             features[i][b* 3:b* 4] = x[i+1]
             features[i][b* 4:b* 5] = x[i+2]
          elif(i == 1):
             features[i][b* 1:b* 2] = x[i-1]
             features[i][b* 3:b* 4] = x[i+1]
             features[i][b* 2:b* 3] = x[i]
             features[i][b* 4:b* 5] = x[i+2]
          elif(i == x.shape[0]-1):
             features[i][0:b* 1] = x[i-2]
             features[i][b* 1:b* 2] = x[i-1]
             features[i][b* 2:b* 3] = x[i]
          elif(i == x.shape[0]-2):
             features[i][b* 3:b* 4] = x[i+1]
             features[i][0:b* 1] = x[i-2]
             features[i][b* 1:b* 2] = x[i-1]
             features[i][b* 2:b* 3] = x[i]
          else:
             features[i][0:b* 1] = x[i-2]
             features[i][b* 1:b* 2] = x[i-1]
             features[i][b* 2:b* 3] = x[i]
             features[i][b* 3:b* 4] = x[i+1]
             features[i][b* 4:b* 5] = x[i+2]
In [54]: features[features.shape[0]]
0., 0., 1., 0., 0., 0., 0., 6., 0., 0., 0., 0., 0., 0., 0., 0.,
            0., 0., 0., 0., 0., 0., 3., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
            0., 0., 0., 0., 0., 2., 0., 0., 0., 0., 0., 0., 1., 0., 0.,
            0., 0., 0., 0., 0., 6., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0.,
            0., 0., 0., 0., 4., 0., 0., 0., 0., 0., 0., 0.])
```

```
In [56]: feature_vect = features[:-3]
         feature_vect.shape
Out [56]: (211727, 165)
0.1.5 Importing packages for running softmax model
In [61]: from sklearn import cross_validation
         from sklearn.model_selection import train_test_split
         from sklearn.cross_validation import cross_val_score
         import pickle
         from sklearn.naive_bayes import MultinomialNB
         from sklearn.metrics import accuracy_score
         from sklearn.metrics import confusion_matrix
         from sklearn.linear_model import LogisticRegression
0.1.6 Using label encoder to transform target label column to numerical encoding
In [62]: from sklearn import preprocessing
         le = preprocessing.LabelEncoder()
         le.fit(y)
         Y = le.transform(y)
0.1.7 Storing this mapping of tags to numerical numbers: we ll use this later in viterbi algo-
     rithm
In [63]: pair = dict()
         for i in range(Y.shape[0]):
             pair[y[i]] = Y[i]
         pickle.dump(pair, open('pair_unigrams.pkl', 'wb'))
0.1.8 Training softmax model
In [64]: softmax_2 = LogisticRegression( multi_class = 'multinomial', solver = 'sag')
         softmax_2.fit(feature_vect,Y)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\sag.py:326: ConvergenceWarning
  "the coef_ did not converge", ConvergenceWarning)
Out[64]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, max_iter=100, multi_class='multinomial',
```

tol=0.0001, verbose=0, warm_start=False)

n_jobs=1, penalty='12', random_state=None, solver='sag',

0.1.9 Storing Trained softmax model

```
In [65]: pickle.dump(softmax_2, open('softmax.pkl', 'wb'))
```

3.Softmax_C^2_classes

May 5, 2018

0.1 Training softmax model on train data: For 'C^2' number of classes

• This notebook is doing the same work as previous one (2.softmax_training) with one difference that in this well train softmax model on c^2 number of classes

```
In []: # importing necessary packages
    import pandas as pd
    import numpy as np
```

0.1.1 loading feateurzied data matrix from disk

0.1.2 adding more features

```
In [ ]: length = []
        for s in df['word']:
            length.append(len(s))
        length_2 = np.asarray(length).reshape(-1,1)
        df['length'] = length_2
        df.head()
In [ ]: hyphen = []
        all cap = []
        sp_char = []
        cap_dot = []
        number = []
        st_alpha_dot = []
        e_{day} = []
        for i in df['word']:
            if('-' in i):
                hyphen.append(1)
            else:
                hyphen.append(0)
            if(i.isupper()):
                all_cap.append(1)
            else:
```

```
all_cap.append(0)
            if(('$' in i or ',' in i or '%' in i or '!' in i or '\'' in i or '"' in i) \
               and len(i) == 1):
                sp_char.append(1)
            else:
                sp_char.append(0)
            if(i[0].isupper() and i.endswith('.')):
                cap_dot.append(1)
            else:
                cap_dot.append(0)
            if(i[0].isdigit() and i[-1].isdigit() and ('.' in i or ',' in i)):
                number.append(1)
            else:
                number.append(0)
            if(i[0].isalpha() and '.' in i):
                st_alpha_dot.append(1)
            else:
                st_alpha_dot.append(0)
            if(i.endswith('day')):
                e_day.append(1)
            else:
                e_day.append(0)
        #print('\'')
In [ ]: df['hyphen'] = hyphen
        df['all_cap'] = all_cap
        df['sp_char'] = sp_char
        df['cap_dot'] = cap_dot
        df['number'] = number
        df['st_alpha_dot'] = st_alpha_dot
        df['e_day'] = e_day
In [ ]: tags = df.tag.unique()
        len(tags)
0.1.3 creating c<sup>2</sup> number of classes : possible classes from train data
In [ ]: bigram = []
        for i in df.index.values:
            if( i == 0):
                s = 'DT'
                tag = " ".join([s, df.tag[i]])
                bigram.append(tag)
            else:
                tag = " ".join([df.tag[i-1], df.tag[i]])
                bigram.append(tag)
In [ ]: tags = np.asarray(bigram)
```

```
In [ ]: df['tags'] = bigram
In [ ]: df.head()
0.1.4 Data Matrix X and target coln y
In [ ]: data = np.array(df)
        x = data[:,2:-1]
        x.shape
        y = df['tags']
        y.shape
        x.shape
0.1.5 Adding context in feautres (prev and next)
In []: no_{cols} = x.shape[1] * 5
        features = np.zeros((211730,no_cols))
        b = no_{cols} / 5
        b = int(b)
In [ ]: # taking prev and next words as feature vectors : appending
        # the stored feature vectors of the same
        for i in range(x.shape[0]):
            if(i==0):
                features[i][b * 2: b* 3] = x[i]
                features[i][b* 3:b* 4] = x[i+1]
                features[i][b* 4:b* 5] = x[i+2]
            elif(i == 1):
                features[i][b* 1:b* 2] = x[i-1]
                features[i][b* 3:b* 4] = x[i+1]
                features[i][b* 2:b* 3] = x[i]
                features[i][b* 4:b* 5] = x[i+2]
            elif(i == x.shape[0]-1):
                features[i][0:b* 1] = x[i-2]
                features[i][b* 1:b* 2] = x[i-1]
                features[i][b* 2:b* 3] = x[i]
            elif(i == x.shape[0]-2):
                features[i][b* 3:b* 4] = x[i+1]
                features[i][0:b* 1] = x[i-2]
                features[i][b* 1:b* 2] = x[i-1]
                features[i][b* 2:b* 3] = x[i]
            else:
```

```
features[i][0:b* 1] = x[i-2]
                features[i][b* 1:b* 2] = x[i-1]
                features[i][b* 2:b* 3] = x[i]
                features[i][b* 3:b* 4] = x[i+1]
                features[i][b* 4:b* 5] = x[i+2]
In [ ]: features[features.shape[0]]
In [ ]: feature_vect = features[:-3]
        feature_vect.shape
In [ ]: counts = dict(df['tags'].value_counts())
In [ ]: for i in counts:
            if(counts[i] < 8):</pre>
                print(i)
0.1.6 importing packages for running softmax on c<sup>2</sup> no of classes
In [ ]: from sklearn import cross_validation
        from sklearn.model_selection import train_test_split
        from sklearn.naive_bayes import MultinomialNB
        from sklearn.metrics import accuracy_score
        from sklearn.metrics import confusion_matrix
        from sklearn.linear_model import LogisticRegression
        import pickle
In [ ]: from sklearn import preprocessing
        le = preprocessing.LabelEncoder()
        le.fit(y)
        Y = le.transform(y)
In [ ]: np.unique(Y).shape
In [ ]: softmax_2 = LogisticRegression( multi_class = 'multinomial', solver = 'sag')
        softmax 2.fit(feature vect,Y)
0.1.7 storing trained softmax model
In [ ]: pickle.dump(softmax_2, open('softmax_dual.pkl', 'wb'))
0.1.8 storing c^2 no of classes mapping: we ll use this in viterbi algorithm
In [ ]: pair = dict()
        for i in range(Y.shape[0]):
            pair[y[i]] = Y[i]
In [ ]: len(pair)
In [ ]: pickle.dump(pair, open('pair_bigrams.pkl', 'wb'))
In [ ]: softmax_2.predict_proba(feature_vect[3].reshape(1,-1))
In [ ]: pair
```

4. Viterbi_Algorithm

May 5, 2018

0.1 Applying viterbi Algorithm: to consider tag sequence information: DP approach

• in this notebook well apply viterbialgorithm on test data, and conclude with accuracy on test data

```
In []: # importing necessary pacakges
    import pandas as pd
    import numpy as np
    import pickle
```

0.1.1 loading test featurized data matrix to work on

0.1.2 adding some more feautres

```
In [ ]: length = []
        for s in df['word']:
            length.append(len(s))
        length_2 = np.asarray(length).reshape(-1,1)
        df['length'] = length_2
In [ ]: hyphen = []
        all_cap = []
        sp_char = []
        cap_dot = []
        number = []
        st_alpha_dot = []
        e_{day} = []
        for i in df['word']:
            if('-' in i):
                hyphen.append(1)
            else:
                hyphen.append(0)
            if(i.isupper()):
                all_cap.append(1)
```

```
all_cap.append(0)
            if(('$' in i or ',' in i or '%' in i or '!' in i or '\'' in i or '"' in i) \
               and len(i) == 1):
                sp_char.append(1)
            else:
                sp_char.append(0)
            if(i[0].isupper() and i.endswith('.')):
                cap_dot.append(1)
            else:
                cap_dot.append(0)
            if(i[0].isdigit() and i[-1].isdigit() and ('.' in i or ',' in i)):
                number.append(1)
            else:
                number.append(0)
            if(i[0].isalpha() and '.' in i):
                st_alpha_dot.append(1)
            else:
                st_alpha_dot.append(0)
            if(i.endswith('day')):
                e_day.append(1)
            else:
                e_day.append(0)
        #print('\'')
In [ ]: df['hyphen'] = hyphen
        df['all_cap'] = all_cap
        df['sp_char'] = sp_char
        df['cap_dot'] = cap_dot
        df['number'] = number
        df['st_alpha_dot'] = st_alpha_dot
        df['e_day'] = e_day
In [ ]: tags = df.tag.unique()
        len(tags)
0.1.3 creating a datamatrix 'X' and target label coln vector 'y'
In [ ]: data = np.array(df)
        x = data[:,2:]
        x.shape
        y = df['tag']
        y.shape
0.1.4 adding prev and next context as features
In []: no_{cols} = x.shape[1] * 5
        features = np.zeros((47380,no_cols))
```

else:

```
b = int(b)
In []: # taking prev and next words as feature vectors: appending the stored feature vectors
        for i in range(x.shape[0]):
            if(i==0):
                features[i][b * 2: b* 3] = x[i]
                features[i][b* 3:b* 4] = x[i+1]
                features[i][b* 4:b* 5] = x[i+2]
            elif(i == 1):
                features[i][b* 1:b* 2] = x[i-1]
                features[i][b* 3:b* 4] = x[i+1]
                features[i][b* 2:b* 3] = x[i]
                features[i][b* 4:b* 5] = x[i+2]
            elif(i == x.shape[0]-1):
                features[i][0:b* 1] = x[i-2]
                features[i][b* 1:b* 2] = x[i-1]
                features[i][b* 2:b* 3] = x[i]
            elif(i == x.shape[0]-2):
                features[i][b* 3:b* 4] = x[i+1]
                features[i][0:b* 1] = x[i-2]
                features[i][b* 1:b* 2] = x[i-1]
                features[i][b* 2:b* 3] = x[i]
            else:
                features[i][0:b* 1] = x[i-2]
                features[i][b* 1:b* 2] = x[i-1]
                features[i][b* 2:b* 3] = x[i]
                features[i][b* 3:b* 4] = x[i+1]
                features[i][b* 4:b* 5] = x[i+2]
In [ ]: feature_vect = features[:-3]
        feature_vect.shape
0.1.5 label encoding
In [ ]: from sklearn import preprocessing
        le = preprocessing.LabelEncoder()
        le.fit(y)
        Y = le.transform(y)
```

 $b = no_cols / 5$

0.1.6 Loading trained softmax model for both c and c^2 no of classes, and also loading mapping of class label to numerical encoding

```
In []: uni_pairs = pickle.load(open('./pair_unigrams.pkl', 'rb'))
    bi_pairs = pickle.load(open('./pair_bigrams.pkl', 'rb'))
    soft_uni = pickle.load(open('./softmax.pkl', 'rb'))
    soft_bi = pickle.load(open('./softmax_dual.pkl', 'rb'))
```

0.1.7 creating list of sentences on which we ll apply viterbi algo: dynamic programming approach

0.2 Viterbi Alogrithm Implementation

```
In []: feat_vect_cnt = 0
    total_pred_cnt = 0
    total_actual_cnt = 0

for sent in list_sent:

    table = np.zeros((44,len(sent)))
    tindex = np.zeros((44,len(sent)), dtype=int)

# taking standalone probs of first word of a sent
    x = soft_uni.predict_proba(feature_vect[feat_vect_cnt].reshape(1,-1))

#intialization : storing standalone probs of w1 in column 1
for i in range(x.shape[1]):
        table[i][0] = x[0][i]

tindex[:,0:1] = -1
#print(table[:,0:1].shape)
```

```
# viterbi algorithm : dp logic
word = 1
            # starting with 2nd coln : word2
while(word < len(sent)):</pre>
    for tag in range (0,44):
        t1name = res[tag]
        prob2 = soft_bi.predict_proba(feature_vect[word + feat_vect_cnt].reshape(1
        mulmax = 0
        index = -1
        #print(prob2[0])
        for t2 in range(0,44):
                                   # loop for first tag
            tag_pair = " ".join([res[t2],t1name])
                #print(tag_pair)
                                                 # if pair is thr then use prob els
            if(tag_pair in bi_pairs):
                sec_term = prob2[0][bi_pairs[tag_pair]]
                #print(" a " ,sec_term)
                f_term = table[t2][word-1]
                #print(f_term)
                                                # pr(ti/w1)
                mul_term = f_term * sec_term
                if(mul_term > mulmax):
                    mulmax = mul term
                    index = t2
        table[tag][word] = mulmax
                                        # storing max prob out of 44 pssble probs
        tindex[tag][word] = index  # storing index in tindex
    word += 1
print('start of sent : ',total_actual_cnt)
# storing tag sequences tht maximizes the probability in reverse order
j = tindex.shape[1] - 1
#np.max(table[:, -1:])
k = np.argmax(table[:, -1:])
tag_index = []
tag_index.append(k)
while j > 0:
    k = tindex[k][j]
    j -= 1
    tag_index.append(k)
# actual ordering
actual = []
for i in reversed(tag_index):
    actual.append(res[i])
total_actual_cnt += len(actual)
```

```
# calculating accuracy
c = 0
j = feat_vect_cnt
for i in range(len(actual)):
    if df.tag[j] == actual[i]:
        c += 1
        j += 1
total_pred_cnt += c

# increasing feature_vector count to starting of the next sent
feat_vect_cnt += len(sent)

#print(c/len(actual))

accuracy = (total_pred_cnt/total_actual_cnt)*100
print("accuracy: " , accuracy)
```

Accuracy: 67.4441184541022