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NLP Lab 9 : Building Bigram Tagger

EXERCISE - 1

```
In [1]: import nltk
In [2]: | from nltk.tokenize import sent_tokenize,word_tokenize
        import nltk
In [5]:
         nltk.download('averaged_perceptron_tagger')
         [nltk_data] Downloading package averaged_perceptron_tagger to
         [nltk data]
                         C:\Users\1MSCDSA13\AppData\Roaming\nltk_data...
         [nltk data]
                       Package averaged perceptron tagger is already up-to-
         [nltk data]
                           date!
Out[5]: True
In [7]: import nltk
         nltk.download('punkt')
         [nltk_data] Downloading package punkt to
         [nltk data]
                         C:\Users\1MSCDSA13\AppData\Roaming\nltk data...
                       Unzipping tokenizers\punkt.zip.
         [nltk data]
Out[7]: True
In [8]: | text = word_tokenize("And now for something completely different")
         nltk.pos_tag(text)
Out[8]: [('And', 'CC'),
          ('now', 'RB'),
          ('for', 'IN'),
          ('something', 'NN'),
('completely', 'RB'),
          ('different', 'JJ')]
         EXERCISE - 2
```

In [9]: | from nltk.corpus import brown

```
In [10]: | nltk.download('brown')
              [nltk data] Downloading package brown to
              [nltk_data]
                                      C:\Users\1MSCDSA13\AppData\Roaming\nltk_data...
              [nltk data]
                                   Unzipping corpora\brown.zip.
Out[10]: True
In [11]: | tagsen = brown.tagged_sents()
              tagsen
Out[11]: [[('The', 'AT'), ('Fulton', 'NP-TL'), ('County', 'NN-TL'), ('Grand', 'JJ-TL'), ('Jury', 'NN-TL'), ('said', 'VBD'), ('Friday', 'NR'), ('an', 'AT'), ('investiga
              tion', 'NN'), ('of', 'IN'), ("Atlanta's", 'NP$'), ('recent', 'JJ'), ('primary', 'NN'), ('election', 'NN'), ('produced', 'VBD'), ('``', '``'), ('no', 'AT'), ('e vidence', 'NN'), ("''", "''"), ('that', 'CS'), ('any', 'DTI'), ('irregularitie s', 'NNS'), ('took', 'VBD'), ('place', 'NN'), ('.', '.')], [('The', 'AT'), ('ju
              ry', 'NN'), ('further', 'RBR'), ('said', 'VBD'), ('in', 'IN'), ('term-end', 'N
              N'), ('presentments', 'NNS'), ('that', 'CS'), ('the', 'AT'), ('City', 'NN-TL'),
              ('Executive', 'JJ-TL'), ('Committee', 'NN-TL'), (',', ','), ('which', 'WDT'),
              ('had', 'HVD'), ('over-all', 'JJ'), ('charge', 'NN'), ('of', 'IN'), ('the', 'A T'), ('election', 'NN'), (',', ','), ('``', '``'), ('deserves', 'VBZ'), ('the', 'AT'), ('praise', 'NN'), ('and', 'CC'), ('thanks', 'NNS'), ('of', 'IN'), ('th
              e', 'AT'), ('City', 'NN-TL'), ('of', 'IN-TL'), ('Atlanta', 'NP-TL'), ("''"
              "''"), ('for', 'IN'), ('the', 'AT'), ('manner', 'NN'), ('in', 'IN'), ('which',
              'WDT'), ('the', 'AT'), ('election', 'NN'), ('was', 'BEDZ'), ('conducted', 'VB
              N'), ('.', '.')], ...]
```

Prepare data sets

```
In [12]: len(tagsen)
```

Out[12]: 57340

```
In [13]:
           br_train = tagsen[0:50000]
           br_test = tagsen[50000:]
           br_test[0]
Out[13]: [('I', 'PPSS'),
            ('was', 'BEDZ'),
            ('loaded', 'VBN'),
            ('with', 'IN'),
            ('suds', 'NNS'),
('when', 'WRB'),
            ('I', 'PPSS'),
            ('ran', 'VBD'),
            ('away', 'RB'),
            (',',','),
('and', 'CC'),
            ('I', 'PPSS'),
            ("haven't", 'HV*'),
            ('had', 'HVN'),
            ('a', 'AT'),
            ('chance', 'NN'),
            ('to', 'TO'),
            ('wash', 'VB'),
            ('it', 'PPO'),
('off', 'RP'),
('.', '.')]
```

Build a bigram tagger

```
In [14]: t0 = nltk.DefaultTagger('NN')
t1 = nltk.UnigramTagger(br_train, backoff=t0)
t2 = nltk.BigramTagger(br_train, backoff=t1)
```

Evaluate

```
In [15]: t2.evaluate(br_test)
```

Out[15]: 0.9111006662708622

Explore

```
In [16]: # 1.
  total_train = [len(l) for l in br_train]
  sum(total_train)
```

Out[16]: 1039920

```
In [17]: | total_test = [len(l) for l in br_test]
          sum(total_test)
Out[17]: 121272
In [18]: # 2.
          t1.evaluate(br_test)
Out[18]: 0.8897849462365591
In [19]: | t2.evaluate(br_test)
Out[19]: 0.9111006662708622
In [20]: # 3.
          br_train[0]
Out[20]: [('The', 'AT'),
           ('Fulton', 'NP-TL'),
           ('County', 'NN-TL'), ('Grand', 'JJ-TL'), ('Jury', 'NN-TL'),
           ('said', 'VBD'),
           ('Friday', 'NR'),
           ('an', 'AT'),
           ('investigation', 'NN'),
           ('of', 'IN'),
           ("Atlanta's", 'NP$'),
           ('recent', 'JJ'),
('primary', 'NN'),
           ('election', 'NN'),
           ('produced', 'VBD'),
           ('``', '``'),
           ('no', 'AT'),
           ('evidence', 'NN'),
           ("''", "''"),
           ('that', 'CS'),
           ('any', 'DTI'),
           ('irregularities', 'NNS'),
           ('took', 'VBD'),
           ('place', 'NN'),
           ('.', '.')]
In [21]: br_train
          [1277]
Out[21]: [1277]
In [22]: | br_train[1277] [11]
Out[22]: ('cold', 'JJ')
In [23]: # 4.
          br_train_flat = [(word, tag) for sent in br_train for (word, tag) in sent]
```

```
In [24]: | br train flat[:40]
Out[24]: [('The', 'AT'),
           ('Fulton', 'NP-TL'), ('County', 'NN-TL'),
           ('Grand', 'JJ-TL'),
('Jury', 'NN-TL'),
           ('said', 'VBD'),
           ('Friday', 'NR'),
           ('an', 'AT'),
           ('investigation', 'NN'),
           ('of', 'IN'),
           ("Atlanta's", 'NP$'),
           ('recent', 'JJ'),
           ('primary', 'NN'),
           ('election', 'NN'),
('produced', 'VBD'),
           ('``', '``'),
           ('no', 'AT'),
           ('evidence', 'NN'),
           ("''", "''"),
           ('that', 'CS'),
           ('any', 'DTI'),
           ('irregularities', 'NNS'),
           ('took', 'VBD'),
           ('place', 'NN'),
           ('.', '.'),
           ('The', 'AT'),
           ('jury', 'NN'),
           ('further', 'RBR'),
           ('said', 'VBD'),
           ('in', 'IN'),
           ('term-end', 'NN'),
           ('presentments', 'NNS'),
           ('that', 'CS'),
           ('the', 'AT'),
           ('City', 'NN-TL'),
           ('Executive', 'JJ-TL'),
           ('Committee', 'NN-TL'),
           (',', ','),
           ('which', 'WDT'),
           ('had', 'HVD')]
In [25]: | br_train_flat[13]
Out[25]: ('election', 'NN')
In [26]: # 5. a)
          fd = nltk.FreqDist(br train flat)
          cfd = nltk.ConditionalFreqDist(br_train_flat)
```

```
In [27]: | cfd['cold'].most_common()
Out[27]: [('JJ', 110), ('NN', 8), ('RB', 2)]
In [28]:
          # 5. b)
          br_train_2grams = list(nltk.ngrams(br_train_flat, 2))
          br_train_cold = [a[1] for (a,b) in br_train_2grams if b[0] == 'cold']
          fdist = nltk.FreqDist(br_train_cold)
          [tag for (tag, _) in fdist.most_common()]
Out[28]: ['AT',
           'IN',
           'CC',
           'QL',
           'BEDZ',
           'JJ',
           ٔ را را
           'DT',
           'PP$',
           'RP',
           'NN',
           'VBN',
           'VBD',
           'CS',
           'BEZ',
           'DOZ',
           'RB',
           'PPSS',
           'BE',
           'VB',
           'VBZ',
           'NP$',
           'BEDZ*',
           '--',
           'DTI',
           'WRB',
           'BED']
```

```
In [29]:
         # 5. c)
          br_pre = [(w2+"/"+t2, t1) for ((w1,t1),(w2,t2)) in br_train_2grams]
          br_pre_cfd = nltk.ConditionalFreqDist(br_pre)
          br_pre
          ('had/HVD', 'WDT'),
          ('over-all/JJ', 'HVD'),
          ('charge/NN', 'JJ'),
          ('of/IN', 'NN'),
          ('the/AT', 'IN'),
          ('election/NN', 'AT'),
          (',/,', 'NN'),
          ('``/``', ','),
          ('deserves/VBZ', '``'),
          ('the/AT', 'VBZ'),
           ('praise/NN', 'AT'),
          ('and/CC', 'NN'),
          ('thanks/NNS', 'CC'),
          ('of/IN', 'NNS'),
          ('the/AT', 'IN'),
          ('City/NN-TL', 'AT'),
          ('of/IN-TL', 'NN-TL'),
          ('Atlanta/NP-TL', 'IN-TL'),
          ("''/'", 'NP-TL'),
          ('for/IN', "''"),
In [30]: | # 5. d)
         br_pre_cfd['cold/NN'].most_common()
Out[30]: [('AT', 4), ('JJ', 2), (',', 1), ('DT', 1)]
```

```
In [31]: br_pre_cfd['cold/JJ'].most_common()
Out[31]: [('AT', 38),
           ('IN', 14),
           ('CC', 8),
           ('QL', 7),
           ('BEDZ', 7),
           ('JJ', 4),
           ('DT', 3),
           (',', 3),
           ('PP$', 3),
           ('``', 2),
           ('NN', 2),
           ('VBN', 2),
           ('VBD', 2),
           ('CS', 1),
           ('BEZ', 1),
           ('DOZ', 1),
           ('RB', 1),
           ('PPSS', 1),
           ('BE', 1),
           ('VB', 1),
           ('VBZ', 1),
           ('NP$', 1),
           ('BEDZ*', 1),
           ('--', 1),
           ('RP', 1),
           ('DTI', 1),
           ('WRB', 1),
           ('BED', 1)]
In [32]:
         # 6.
          bigram tagger = nltk.BigramTagger(br train)
In [33]: # 6. a)
          text1 = word tokenize('I was very cold.')
         bigram_tagger.tag(text1)
Out[33]: [('I', 'PPSS'), ('was', 'BEDZ'), ('very', 'QL'), ('cold', 'JJ'), ('.', '.')]
In [34]:
         # 6. b)
          text2 = word_tokenize('I had a cold.')
         bigram_tagger.tag(text2)
Out[34]: [('I', 'PPSS'), ('had', 'HVD'), ('a', 'AT'), ('cold', 'JJ'), ('.', '.')]
```

```
In [35]: # 6. c)
         text3 = word_tokenize('I had a severe cold.')
         bigram_tagger.tag(text3)
Out[35]: [('I', 'PPSS'),
          ('had', 'HVD'),
          ('a', 'AT'),
          ('severe', 'JJ'),
          ('cold', 'JJ'),
          ('.', '.')]
In [36]:
         # 6. d)
         text4 = word_tokenize('January was a cold month.')
         bigram_tagger.tag(text4)
Out[36]: [('January', None),
          ('was', None),
          ('a', None),
          ('cold', None),
          ('month', None),
          ('.', None)]
In [44]:
         #7
         sentences = [
             "I was very cold",
             "I had a cold",
             "I had a severe cold",
             "January was a cold month"
         1
         for sentence in sentences:
             words = nltk.word tokenize(sentence)
             pos tags = nltk.pos tag(words)
             print(pos_tags)
         [('I', 'PRP'), ('was', 'VBD'), ('very', 'RB'), ('cold', 'JJ')]
         [('I', 'PRP'), ('had', 'VBD'), ('a', 'DT'), ('cold', 'JJ')]
         [('I', 'PRP'), ('had', 'VBD'), ('a', 'DT'), ('severe', 'JJ'), ('cold', 'NN')]
         [('January', 'NNP'), ('was', 'VBD'), ('a', 'DT'), ('cold', 'JJ'), ('month', 'N
         N')]
In [37]: # 8. a)
         text5 = word_tokenize('I failed to do so.')
         bigram_tagger.tag(text5)
Out[37]: [('I', 'PPSS'),
          ('failed', 'VBD'),
          ('to', 'TO'),
          ('do', 'DO'),
          ('so', 'RB'),
          ('.', '.')]
```

```
In [38]: # 8. b)
           text6 = word_tokenize('I was happy,but so was my enemy.')
           bigram_tagger.tag(text6)
Out[38]: [('I', 'PPSS'),
            ('was', 'BEDZ'),
            ('happy', 'JJ'),
            (',', ','),
('but', 'CC'),
            ('so', 'RB'),
('was', 'BEDZ'),
            ('my', 'PP$'),
            ('enemy', 'NN'),
            ('.', '.')]
In [39]: # 8. c)
           text7 = word tokenize('So, how was the exam?')
           bigram_tagger.tag(text7)
Out[39]: [('So', 'RB'),
           (',',','),
('how', 'WRB'),
('was', 'BEDZ'),
('the', 'AT'),
            ('exam', None),
            ('?', None)]
In [40]:
           # 8. d)
           text8 = word tokenize('The students came in early so they can get good seats.')
           bigram_tagger.tag(text8)
Out[40]: [('The', 'AT'),
            ('students', 'NNS'),
            ('came', 'VBD'),
            ('in', 'IN'),
            ('early', 'JJ'),
            ('so', 'CS'),
            ('they', 'PPSS'),
            ('can', 'MD'),
('get', 'VB'),
            ('good', 'JJ'),
            ('seats', 'NNS'),
            ('.', '.')]
```

```
In [41]: # 8. e)
         text9 = word tokenize('She failed the exam, so she must take it again.')
         bigram_tagger.tag(text9)
Out[41]: [('She', 'PPS'),
          ('failed', 'VBD'),
          ('the', 'AT'),
          ('exam', None),
          (',', None),
          ('so', None),
          ('she', None),
          ('must', None),
          ('take', None),
          ('it', None),
          ('again', None),
          ('.', None)]
In [42]: # 8. f)
         text10 = word tokenize('That was so incredible.')
         bigram_tagger.tag(text10)
Out[42]: [('That', 'DT'),
          ('was', 'BEDZ'),
          ('so', 'QL'),
          ('incredible', 'JJ'),
          ('.', '.')]
In [43]: # 8. g)
         text11 = word tokenize('Wow, so incredible.')
         bigram tagger.tag(text11)
Out[43]: [('Wow', None), (',', None), ('so', None), ('incredible', None), ('.', None)]
In [45]:
         # 9.
         text11 = word tokenize('so')
         bigram tagger.tag(text11)
Out[45]: [('so', 'RB')]
```

#10

The bigram tagger is a part-of-speech (POS) tagger that assigns a POS tag to each word in a text based on the preceding word. It is a simple and efficient algorithm that uses a bigram language model to predict the most likely POS tag for each word based on the probability of observing that tag given the previous tag.

Strengths:

The bigram tagger is fast and computationally efficient compared to other more complex POS taggers. It can process large amounts of text quickly and accurately.

It can handle unknown words by assigning them the most common POS tag in the training corpus.

The bigram model can capture some context and syntactic dependencies between adjacent words, leading to improved accuracy in some cases.

Limitations:

The bigram tagger relies heavily on the previous word to assign POS tags, so it may miss more complex dependencies or contextual cues that are further away. It can't capture long-range dependencies or structural information that spans more than two adjacent words.

It can't handle words that have multiple POS tags or ambiguous meanings, leading to incorrect tagging.

The accuracy of the bigram tagger heavily depends on the quality and size of the training corpus. A small or biased corpus can lead to poor tagging performance.

In conclusion, the bigram tagger is a useful and efficient POS tagging tool for certain applications, especially in cases where a large training corpus is available and where simple contextual cues are sufficient for accurate tagging. However, it has clear limitations in handling more complex language structures, ambiguous words, and long-range dependencies.

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