Automatic Part-of-Speech Tagging

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- Reminder: Part-of-Speech (PoS) tagging is the process of classifying words into **lexical categories:**
  - We predict/guess the PoS category of a word.
  - The goal is to be correct inasmuch as possible.

Automatic Part-of-Speech Tagging

- How to make a part-of-speech tagger?
  - Using a single tag (the most frequent tag), e.g., tag everything as noun.
  - Rule-based methods: use *morphological* patterns, e.g., look into suffixes and prefixes, to determine the PoS of words.
  - Use a dictionary look-up.
  - Use statistical techniques.

Automatic Part-of-Speech Tagging

- In the remaining of this session we work with tagged sentences.

```
>>> from nltk.corpus import brown
>>> brown_tagged_sents = \
      brown.tagged_sents(categories='news', tagset='universal')
>>> brown_sents = brown.sents(categories='news')
```

The Default Tagger

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```
>>> tags = [tag for (word, tag) in \
      brown.tagged_words(categories='news')]
>>> nltk.FreqDist(tags).max()
'NN‘
>>> default_tagger = nltk.DefaultTagger('NN')
```

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```
>>> raw = 'I do not like green eggs'
>>> tokens = word_tokenize(raw)
>>> default_tagger.tag(tokens)
[('I', 'NN'), ('do', 'NN'), ('not', 'NN'), ('like', 'NN'), ('green', 'NN'), ('eggs', 'NN')]
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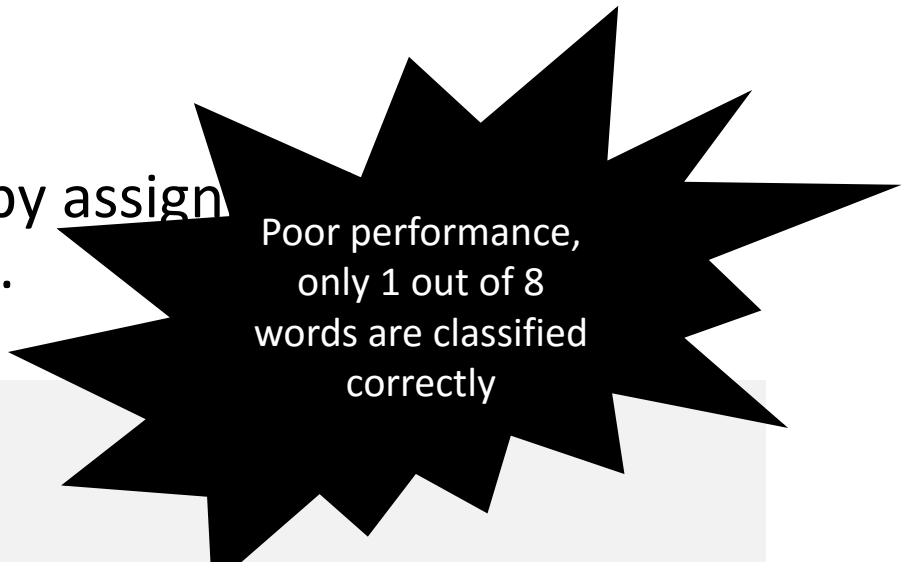


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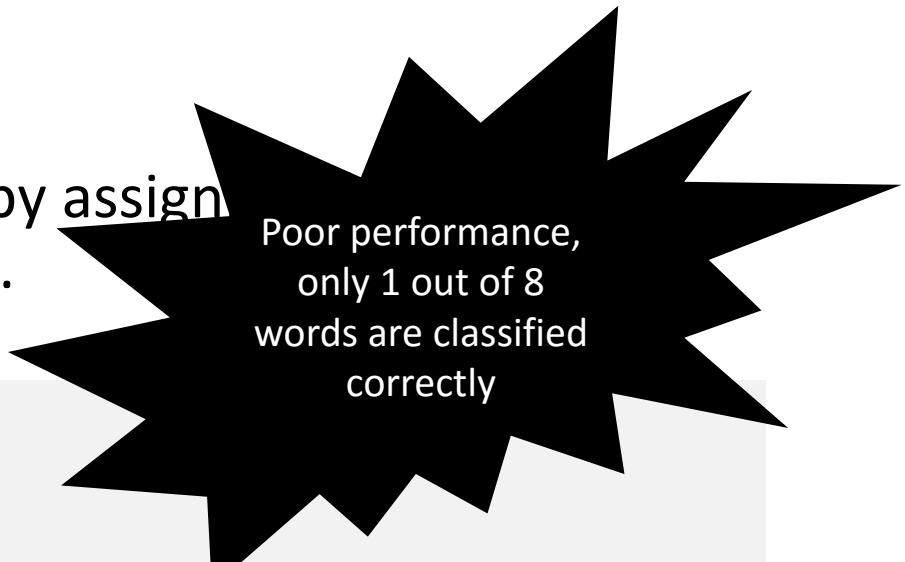


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```

```
>>> default_tagger.evaluate(brown_tagged_sents)
0.13089484257215028
```

The Regular Expression Tagger

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```
>>> patterns = [
      (r'.*ing$', 'VBG'), # gerunds
      (r'.*ed$', 'VBD'), # simple past
      (r'.*es$', 'VBZ'), # 3rd singular present
      (r'.*ould$', 'MD'), # modals
      (r'.*\'s$', 'NN$'), # possessive nouns
      (r'.*s$', 'NNS'), # plural nouns
      (r'^-?[0-9]+(.[0-9]+)?$', 'CD'), # cardinal numbers
      (r'.*', 'NN') # nouns (default)
]
```

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```
>>> regexp_tagger = nltk.RegexpTagger(patterns)
>>> regexp_tagger.tag(brown_sents[3])
[('``', 'NN'), ('Only', 'NN'), ('a', 'NN'), ('relative',
'NN'), ('handful', 'NN'), ('of', 'NN'), ('such', 'NN'),
('reports', 'NNS'), ('was', 'NNS'), ('received', 'VBD'),
("''", 'NN'), (',', 'NN'), ('the', 'NN'), ...]
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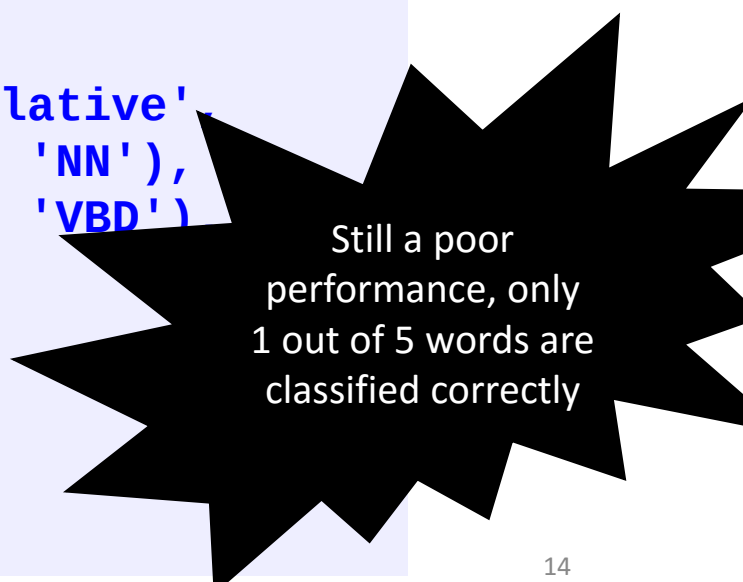

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>>> regexp_tagger.evaluate(brown_tagged_sents)

0.20326391789486245
```

The Unigram (Look-up) Tagger

- Find the hundred most frequent words and store their most likely tag.
- Use this information as the model for a "lookup tagger"
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>>> fd = nltk.FreqDist(brown.words(categories='news'))
>>> cfd = nltk.ConditionalFreqDist(\
      brown.tagged_words(categories='news', tagset='universal'))
>>> most_freq_words = [word[0] for word in fd.most_common(100)]
>>> likely_tags = dict((word, cfd[word].max()) for \
      word in most_freq_words)
>>> baseline_tagger = nltk.UnigramTagger(model=likely_tags)
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>>> baseline_tagger.evaluate(brown_tagged_sents)
0.45578495136941344
```

Much better performance

The Lookup Tagger (backoff)

- The output of the previous tagger is full of “None” tags:
  - Words that are not among the 100 most frequent words.
- In these cases we can assign words to a default tag:
  - First, use the lookup table
  - If a word is not found, then use the default tagger
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- The above process known as **backoff.**

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      backoff=nltk.DefaultTagger('NN'))
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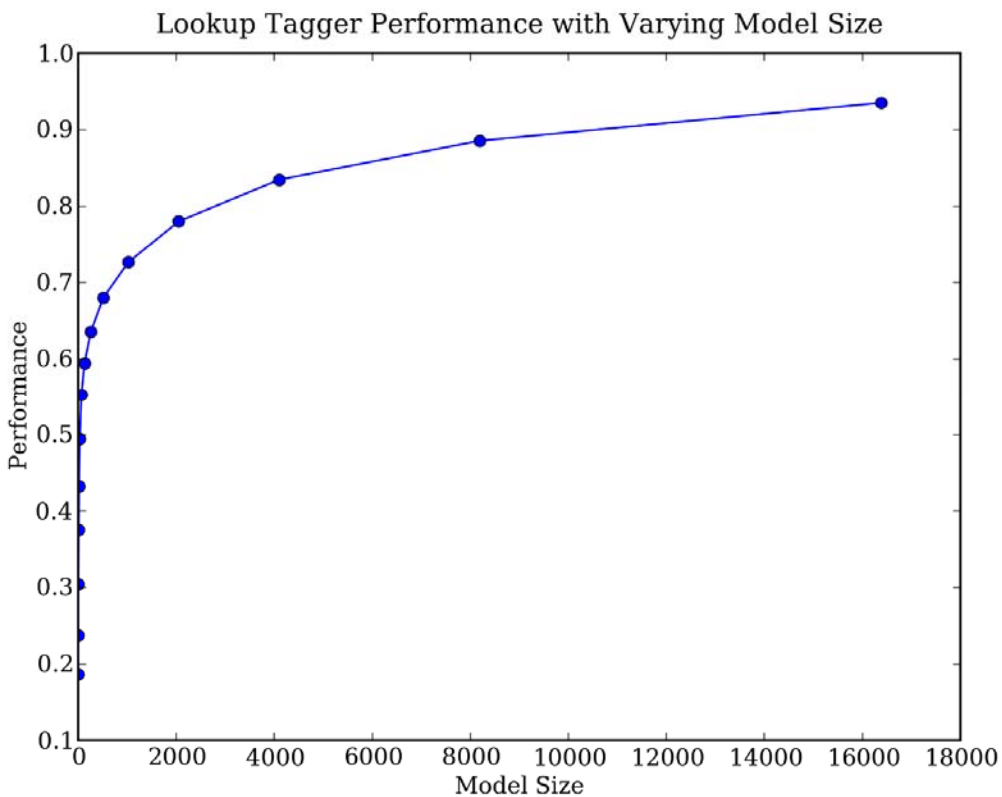
The Lookup Tagger



- Performance initially increases rapidly as the model size grows, eventually reaching a plateau, when large increases in model size yield little improvement in performance.

Evaluation

- In natural language processing, evaluation is a central theme.
- As you witnessed**,** we use **gold standard** test data for the evaluation:
  - **gold standard** test data: a corpus which has been manually annotated and it is accepted as a standard against which the guesses of an automatic system are assessed.
  - In pervious examples, the tagged sentences from the Brown corpus.
- **Separating the Training and Testing Data:** to avoid over fitting!
  - A tagger may simply memorized its training data and has no generalization ability, i.e. it may be useless for tagging new text.

N-Gram Tagging

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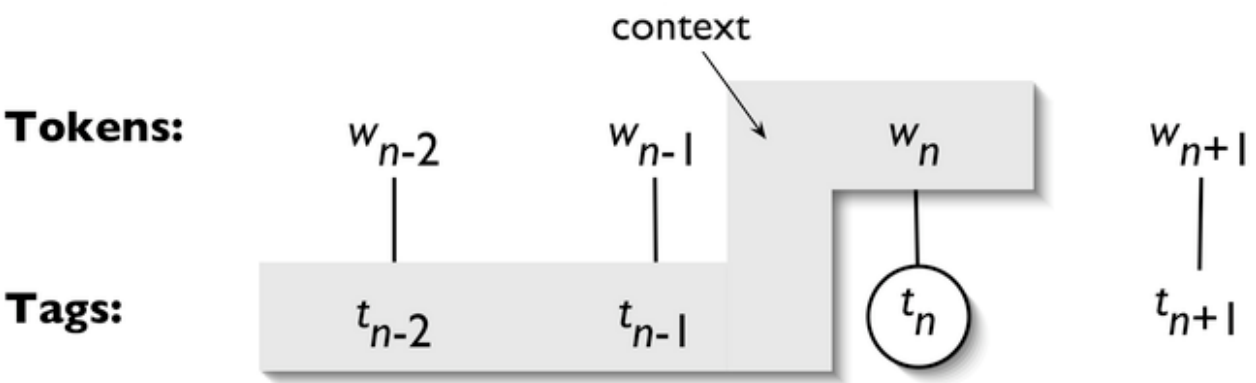
  - We tag a word like “book” always as known no matter the context is “to book” or “the book”.
- An **n-gram tagger** is a generalization of a unigram tagger.

N-Gram Tagging

- The context in an **n-gram tagger** is the current word together with the part-of-speech tags of the *n*-1 preceding tokens.



- The **`NgramTagger`** class uses a tagged training corpus to determine which part-of-speech tag is most likely for each context.

N-Gram Tagging: bigram tagging

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>>> from nltk.corpus import brown
>>> brown_tagged_sents = brown.tagged_sents(categories='news')
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>>> bigram_tagger = nltk.BigramTagger(train_sents)
>>> bigram_tagger.tag(brown_sents[2007])
[('Various', 'JJ'), ('of', 'IN'), ('the', 'AT'), ('apartments',
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This is due to the problem known as the *data sparsity*:

- As *n* gets larger, the specificity of the contexts increases, as does the chance that the data we wish to tag contains contexts that were not present in the training data.

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  - use the more accurate algorithms when possible, but when it is necessary use algorithms with wider coverage.

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- One way to address the trade-off between accuracy and coverage is to combine algorithms:
  - use the more accurate algorithms when possible, but when it is necessary use algorithms with wider coverage.
- In the PoS tagging scenario:
  - Try tagging a token with the bigram tagger.
  - If the bigram tagger fails to find a tag for the token, try the unigram tagger.
  - If the unigram tagger is also unable to find a tag, use a default tagger.

Combining Taggers

```
>>> t0 = nltk.DefaultTagger('NN')
>>> t1 = nltk.UnigramTagger(train_sents, backoff=t0)
>>> t2 = nltk.BigramTagger(train_sents, backoff=t1)
>>> t2.evaluate(test_sents)
0.844513...
```

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- The tagger with a smaller context backs off the tagger with the context of larger size.

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- Exercise: extend the above example by defining a **`TrigramTagger`**, which backs off to **`t2`**.

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- One useful method is to limit the the vocabulary of a tagger to the most frequent *n* words, and to replace every other word with a special word *UNK:*

Tagging Unknown (out-of-vocabulary) Words

- In the previous slide, the proposed regular-expression tagger or a default tagger are unable to make use of context.
- One useful method is to limit the the vocabulary of a tagger to the most frequent *n* words, and to replace every other word with a special word *UNK:*
  - During training, a unigram tagger will probably learn that *UNK* is often a noun.
  - However, the n-gram taggers will detect contexts in which it has some other tag, e.g. that a verb follows the preposition *to*.

Storing Taggers

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To save a model

```
>>> from pickle import dump
>>> output = open('t2.pkl', 'wb')
>>> dump(t2, output, -1)
>>> output.close()
```

To load a model

```
>>> from pickle import load
>>> input = open('t2.pkl', 'rb')
>>> tagger = load(input)
>>> input.close()
```

Performance Limitations

- What is the upper limit to the performance of an n-gram tagger?
  - How many cases of PoS ambiguity does a trigram tagger encounter?

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      ((x[1], y[1], z[0]), z[1])
      for sent in brown_tagged_sents
      for x, y, z in nltk.trigrams(sent))
>>> ambiguous_contexts = [c for c in cfd.conditions() if len(cfd[c]) > 1]
>>> float(sum(cfd[c].N() for c in ambiguous_contexts) )/ cfd.N()
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In 5% of cases there is more than one tag that could be legitimately assigned to the current word according to the training data!

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- Another way to investigate the performance of a tagger is to study its mistakes.
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- Another way to investigate the performance of a tagger is to study its errors.
  - Some tags may be harder than others to assign
  - It might be possible to treat them specially by pre or post-processing the data.
  - A convenient way to look at tagging errors is the **confusion matrix (**expected tags (the gold standard) against actual tags generated by a tagger).

Performance Limitations

- **Confusion matrix**

```
>>> test_tags = [tag for sent in brown.sents(categories='editorial')
                 for (word, tag) in tagger.tag(sent)]
>>> gold_tags = [tag for (word, tag) in
      brown.tagged_words(categories='editorial')]
>>> print(nltk.ConfusionMatrix(gold_tags, test_tags))
```

Some observations

1. Definition of the tagset is an important that influences the performance of a tagger.

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- Tagging process collapses distinctions:
  - e.g. lexical identity is usually lost when all personal pronouns are tagged PRP.
- Tagging process introduces new distinctions and removes ambiguities:
  - e.g. *deal* tagged as *VB* or *NN*.
- These collapsing distinctions and introducing new distinctions are valuable in classification tasks but also in the overall performance of a tagger.

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2. In n-gram tagging, a potential issue is the size of their n-gram table (language model):

- It is important to strike a balance between model size and tagger performance.

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1. Definition of the tagset is an important that influences the performance of a tagger.

2. In n-gram tagging, a potential issue is the size of their n-gram table (language model):
   - It is important to strike a balance between model size and tagger performance.

3. The information used in our implemented n-gram tagger is limited to the prior context:
   - words themselves might be a useful source of information!

Transformation-Based Tagging

- Brill tagger, is a kind of *transformation-based learning*, named after Eric Brill its inventor:
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- A Brill tagger successively transforms a bad tagging of a text into a better one.
- It is a supervised learning technique (similar to n-gram tagging):
  - i.e. annotated data is required.

Transformation-Based Tagging

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- Rules are in the general form of "replace T_1 with T_2 in the context *C.*"

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```
nltk.tag.brill.demo()
```

Further Reading

- Chapters 4 and 5 of (Jurafsky & Martin, 2008) contain more advanced material on n-grams and part-of-speech tagging.
- Look at HOWTO sections of NLTK website (http://nltk.org/howto).
  - http://www.nltk.org/howto/probability.html