## is450 Cheat Sheet

# Cheatography

## by cheatingcvrlo via cheatography.com/183658/cs/38238/

### preprocessing pipeline

```
def corpus2docs(corpus):
       fids = corpus.fi leids()
       docs1 = []
       for fid in fids:
               doc raw = corpus.ra w(fid)
              doc = nltk.w ord _to ken ize (do c_raw)
               doc s1.a pp end (doc)
       docs2 = [[w.lo wer() for w in doc] for doc in docs1]
       docs3 = [[w for w in doc if re.sea rch ('^ [a-z]+\$', w)] for doc in docs2]
       docs4 = [[w for w in doc if w not in stop_list] for doc in docs3]
       docs5 = [[stem mer.st em(w) for w in doc] for doc in docs4]
       return docs5
def docs2v ecs (docs, dictio nary):
       # docs is a list of documents returned by corpus 2docs.
       # dictionary is a gensim.co rpo ra.D ic tionary object.
       vecs1 = [dicti ona ry.d oc 2bo w(doc) for doc in docs]
       tfidf = gensim.mo del s.T fid fMo del (vecs1)
       vecs2 = [tfidf [vec] for vec in vecs1]
```

return vecs2

POS tags	
N (noun)	dog, cat, chair
V (verb)	read, write, get
ADJ (adjective)	pretty, smart, blue
ADV (adverb)	gently, carefully, extremely
P (preposition)	in, on, by, with, about
PRO (pronoun)	I, me, mine, it, they
CON (conju- nction)	and, or, but, while, because
INT (interjection)	ooh, wow, yeah
DET (deter- miner)	all, his, they
AUX (auxiliary verb)	have done, might do
PAR (particle)	look <b>up</b> , get <b>on</b>
NUM (numeral)	one, two, three

LDA



LDA	
gibbs sampling	1. random word-to-topic assignment
	2. re-assign each word to a topic, one by one, assuming all other assignments are correct
hyperp- arameters	high \$alpha\$> documents feature a mixture of most topics
	high \$eta\$> topics feature a mixture of most words
evaluation	coherence (PMI), human eval

Sentiment-Topic Model (Plate Notation)

Discourse Markers			
causal	because		
consequence	as a result		
conditional	if		
temporal	when		
additive	and		
elaboration	[exemplification, re- wording]		
contrastive/con- cessive	but		
Preparation for NLTK classifier			
#doc_tuple = (doc_representation, label)			

```
> ({'police':1, 'lawye r':1, 'court
e')
#train_set = [doc_tuple1, doc_tuple2, ...]
```

Context-free grammar

Grammar = {		
obj ects: [		
Wor ds/ tokens:		
terminals,		
Right <b>pos</b> ve:		
tags,		
syntactic		
tags,		
sèntence		
];		
Rules: [		
X: node name, #eg		
" VP" (verb phrase)		
Y: sequence of		
objects that make up X #eg		
(V+NP)		
]		
1		

#### topis topis topics topics

Cluster Purity

 $P_i = \max_j P_{ij}$   $P_{ij} = \frac{\#docs(class = j, cluster = i)}{\#docs(cluster = i)}$ 

verall purity

 $\sum_{i=1}^{K} \left[ \frac{\# docs(cluster = i)}{\# docs} \cdot P_i \right] \qquad K = \# clusters$ 

#### Morphemes

stems, affixes (prefix/suffix). Useful for POS tagging and text normalization

Semantics	
synonyms	diff words, same meaning
polyseme	same word, diff meaning
hypernym/- hyponym	category >>> specific
meronym/m- etonym	part >>> whole

		_
Entropy		

 $e_i = -\sum_{j=1}^L P_{ij} \log_2 P_{ij}$ 

Pointwise Mutual Information

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 $PMI(w_i, w_j) = \log \frac{p(w_i, w_j)}{p(w_i) p(w_j)}$ 

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