Text Processing / Mining / Search

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LIS Education And Data Science Integrated Network Group (LEADING) Bootcamp
Week 1: June 7, 2023

What We Will Cover

- Text Processing
  - Normalization
  - Regular Expressions (RegEx)
  - Stop words
  - Stemming
  - n-grams
- Text Mining ↑ incorporated into above
- Text Search
  - IR methods
  - Evaluating similarity

Goals of this Presentation

- Introduce aforementioned topics at a high level
- Practical:
  - Process data (text)
  - Be able to identify and extract relevant information
  - Small corpus, intent is to extrapolate
- Basic Information Retrieval concepts
  - Applicable both to text corpora and other kinds.

My Background/Specialization

- Computer Science PhD, research in web archiving
- In Information Science Dept. @ Drexel CCI
- Teaching:
  - INFO624: Information Retrieval
  - INFO600: Web Systems & Architecture
  - INFO202: Data Curation
- Authored multiple Python-based tools while a grad student
  - https://github.com/machawk1
- Coming from a Systems Development Background (cf. data science)
  - The tools to generate, consume the data

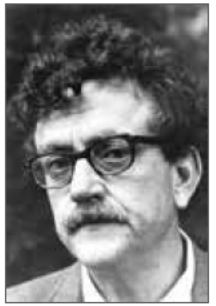
Sample Corpus (small collection of “Documents”)

- D_1 : The quick brown fox jumped over the lazy dog.
- D_2 : The sum of the square of the legs of a right triangle are equal to the square of the hypotenuse.
- D_3 : We are what we pretend to be, so we must be careful about what we pretend to be.

Preparation

- Tokenize
- Remove Stopwords
- Stem Words
- Construct N-grams

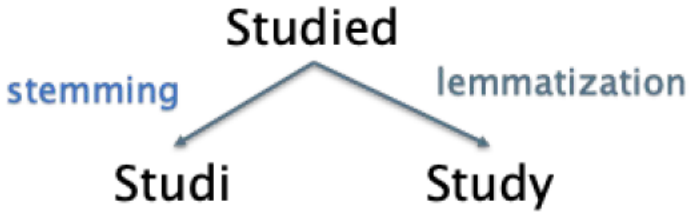
Tokenization



- Counting instances
  - D_3 : We are what we pretend to be, so we must be careful about what we pretend to be.
  - (1) We (2) are (3) what (4) we (5) pretend (6) to (7) be (8) so (9) must (10) careful (11) about
- Normalization
  - dog, dogs → dog
  - leading, leads, leader, leaders → lead
  - Simpler examples, e.g., Leading, leading, LEADING → leading
  - co-education? San Francisco? Hewlett-Packard

Tokenization

- Tokenization, normalization, and inverted index
- Normalization: casefolding, stemming, lemmatization
  - Leading, LEADING, leading → leading
  - C.A.T., cat, Cat → cat?
  - General Motors / general motors?
- Lemmatization: reducing to canonical/dictionary form
  - am, are, is → be
  - car , cars, car's, cars' → car
  - For example:
    - the boy's cars are different colors
    - The boy car be different color



Remove Stopwords

- The quick brown fox jumped over the lazy dog.
- The sum of the square of the legs of a right triangle are equal to the square of the hypotenuse.
- We are what we pretend to be, so we must be careful about what we pretend to be.

- Some bases/rationale for stopwords
  - Common / noisy / not semantically relevant

- To Be Or Not To Be (Hamlet)

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Stem Words

- Words “leading”, “leads”, “leaders”, “leader” all have same “root”
  - We want to coalesce for semantic/syntactic analysis
  - **Porter stemmer:** fast but not very precise
  - **Snowball (Porter2):** more aggressive but generally better than Porter
  - **Lancaster:** most aggressive, least readable result

Typical Porter rules

- sses → ss
- ies → i
- ational → ate
- tional → tion

Weight of word sensitive to rules (m>1) EMENT →

- replacement → replac
- cement → cement

Stem Words

% python3 (code to the right)
D0 stemmed terms: the quick brown fox jump over the lazi dog
.
D1 stemmed terms: the sum of the squar of the leg of a right triangl are equal to the squar of the hypotenus .
D2 stemmed terms: we are what we pretend to be , so we must be care about what we pretend to be .

```
import nltk
from nltk.stem.porter import *

d1 = "The quick brown fox jumped over the lazy dog."
d2 = "The sum of the square of the legs of a right triangle are equal to the square
of the hypotenuse."
d3 = "We are what we pretend to be, so we must be careful about what we pretend to
be."
docs = [d1, d2, d3]

porter_stemmer = PorterStemmer()

term_list = []
# Tokenize each document
for document in docs:
   term_list.append(nltk.word_tokenize(document))

stemmed_term_list = []
# Stem all tokens in each document
for i, term_list_for_doc in enumerate(term_list):
   stemmed_term_list.append([porter_stemmer.stem(word) for word in
term_list_for_doc])

# Print out stemmed term list per document
for i, doc in enumerate(docs):
   print(f'D{i} stemmed terms: {" ".join(stemmed_term_list[i])}')
```

colab

Construct N-grams

- Helps to identify multi-word semantics
- Bi-grams examples:
  - the quick; quick brown; brown fox; fox jumped; jumped over; over the; the lazy; lazy dog
- Tri-gram examples:
  - the quick brown; quick brown fox; brown fox jumped; fox jumped over; etc.
- Useful for identifying compound tokens
  - Drexel University
  - data science
  - The Queen of England

```
import nltk
from nltk.tokenize import word_tokenize

doc = "The quick brown fox jumped over the lazy dog."
tokens = nltk.word_tokenize(doc)
bigrm = nltk.bigrams(tokens)
print(*map(' '.join, bigrm), sep=', ')
```

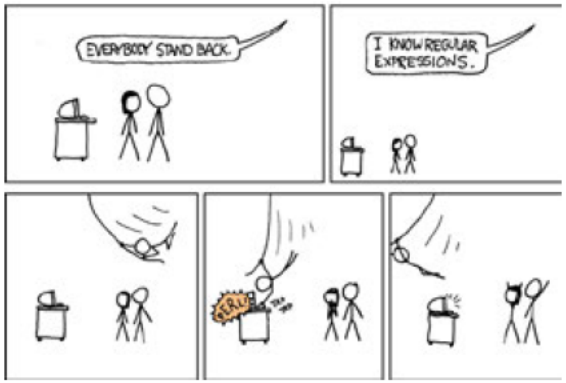
> The quick, quick brown, brown fox, fox jumped, jumped over, over the, the lazy, lazy dog, dog .

colab

Regular Expressions

- Test whether a string matches a pattern
- Useful for search/replace character string
- Commonly implemented: Perl, Python, text editors, UNIX command-line
- Powerful but confusing syntax

Regular Expressions



- Basic usage
  - Boolean: `analy(s|z)e` → matches analyze, analyse
  - Zero-or-one: `colou?r` → matches color, colour
  - Zero-or-more: `[a-z]*` → matches a, leading, dog, (empty string), etc. (but not LEADING)
  - One-or-more: `b[oO]+` → matches bo, bOooOOOoo, bOO
  - Matches *n* times: `b[o]{2}` → matches boo
  - Matches minimally *i* times: `a[r]{2,}gh` → matches arrgh, arrrrrrrrrrgh
  - Matches maximally *j* times: `b[o]{,4}` → matches boooo, boo, b
  - Matches between between *i* and *j* times (inclusive): `[bo]{1,3}` → bobobo, bo

How are RegEx useful?

- `re.findall('[a-z]+ of the [a-z]+', d2)`
  - Result: ['sum of the square', 'square of the hypotenuse']
- `re.findall('[a-z]{6,}', d2)`
  - Result: ['square', 'triangle', 'square', 'hypotenuse']
- Can also be compiled for reuse
  - `r = re.compile('\sthe\s[a-z]+')  # find all instance of ' the XXXX'`
  - `r.findall(d2)`
  - `Result: [' the square', ' the legs', ' the square', ' the hypotenuse']`

Shorthands
\s → whitespace
\d → digits
\w → word
...many other

D_2 : The sum of the square of the legs of a right triangle are equal to the square of the hypotenuse.

colab

Search: Evaluation

- Supposing we are searching for text in a collection, how do we measure what is a “good” result?
- An information retrieval standpoint
  - TF-IDF (term frequency - inverse document frequency)
  - Cosine Similarity
  - Precision & Recall

TF-IDF

- Term Frequency ($tf_{t,d}$): The number of times term *t* appears in document *d*
- A document with 10 occurrences of the term is *more relevant* than a document with 1 occurrence of the term.
  - But not 10 times more relevant.
  - We use logarithms to mitigate this effect.
- $tf = \frac{\text{term count}}{\text{\# of terms in document}}$

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TF-IDF

- Document Frequency (df)
  - Rare terms more informative than common terms (e.g., stopwords)
  - Give rare terms high weights

- $df = \frac{\text{\# documents with term in it}}{\text{\# of documents}}$

- Inverse $df = \frac{1}{df} = \frac{\text{\# documents}}{\text{\# documents w/ term}}$

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TF-IDF

- TF-IDF: weight of each term in a document to signify importance
- tf.idf = log(tf × idf)
- Ranking of a document for a query (which is most relevant):

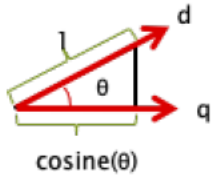
$$\text{Score}(q,d) = \sum_{t \in q \cap d} \text{tf.idf}_{t,d}$$

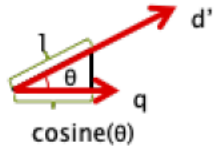
$$\text{tf.idf} = \frac{\text{term count}}{\text{\# of terms in document}} \times \frac{\text{\# documents}}{\text{\# documents w/ term}}$$

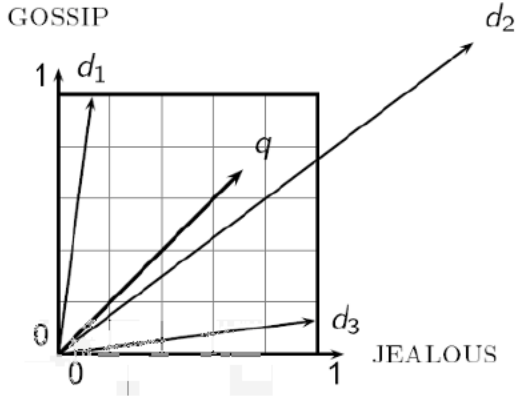
tf.idf = term frequency (tf) × inverse document frequency (idf)

Cosine Similarity

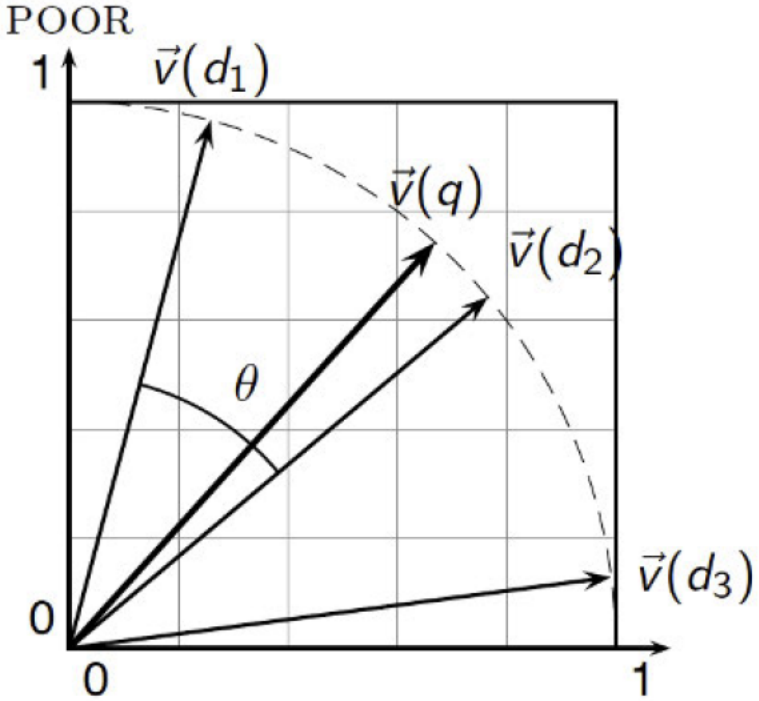
- Plot term vectors, vector length is affected by TF
  - e.g., document with just “be be be be be be”
- Distance between query and document is problematic
- Rather than vector magnitude, use angle between
  - Smaller angle → more similar documents
- To measure how close/similar they are:
  - The Euclidean distance between the two documents can be quite large
  - The angle between the two documents is 0, corresponding to maximal similarity. (Cosine = 1)
- Key idea: Rank documents according to angle with query.

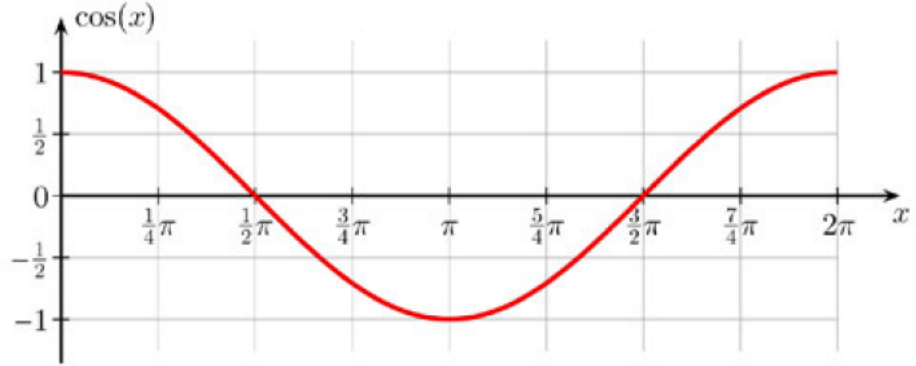






Cosine Similarity Illustrated





RICH

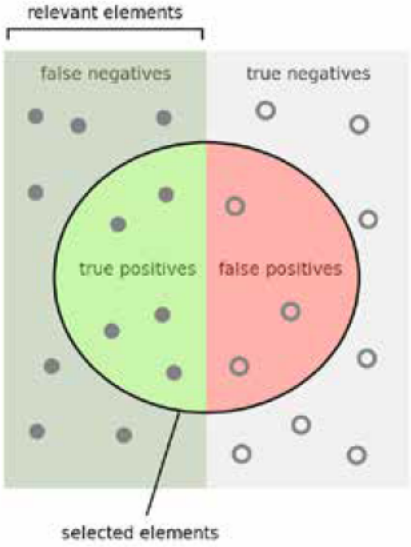
Vector Space Ranking

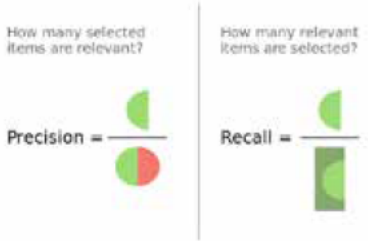
Using TF-IDF and Cosine Similarity together

- Represent the query as weighted tf-idf vector
- Represent each document as a weighted tf-idf vector
- Compute the cosine similarity score for the query vector and each document vector
- Rank documents with respect to the query by score
- Return top K (e.g., K=10) to the user

Precision & Recall

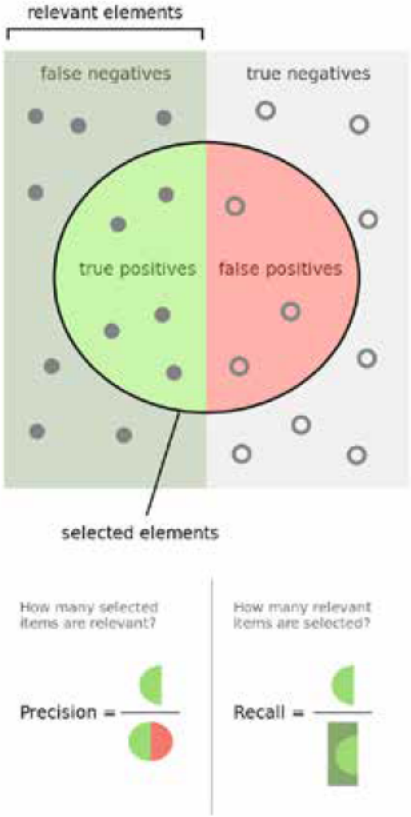
- **True Positive**: Things we got and should have gotten
- **False Positive**: Things we got and should not have gotten
- False Negative: Things we did not get and should have got
- True Negative: Things we did not get and should not have negative)





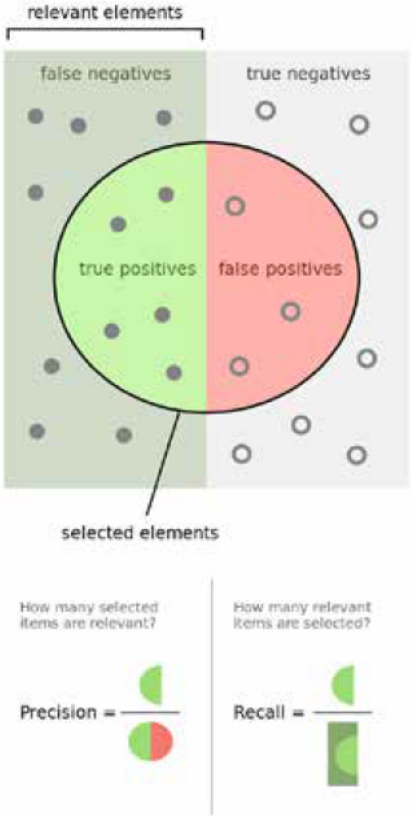
Precision & Recall

- Precision & Recall are a means of evaluating retrieval quality (each on a scale of 0.0 to 1.0)
  - What this entails may be domain-specific
  - Generally are inversely proportional
- **Precision**: # True positives over # results returned:
  - TP/(TP+FP)
- **Recall**: True positives over all positives
  - TP/(TP+FN)
- Neither metric is sufficient alone, can be gamed
  - High precision/ low recall: very few, but correct result (**P**: 1.0)
  - Low precision / high recall: return everything (**R**: 1.0)

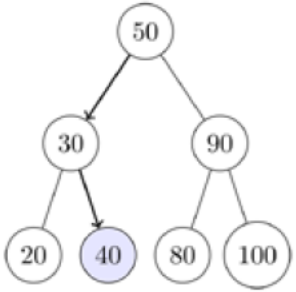


Precision & Recall

- Key is to find best balance between **Precision**/**Recall**
- F-Measure:
  - $$F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$
- Measures *accuracy* of the retrieval/classification method
- Range from 0.0 (e.g., recall=1.0) to 1.0 (balance **P**/**R**)

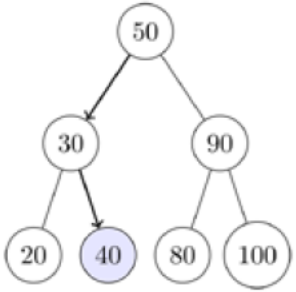


Time/Space Complexity



- Big-O notation
  - Search algorithms
  - Sorting algorithms
- Large data sets require efficient processing
- Sorting preferred, makes searching more efficient

Time/Space Complexity



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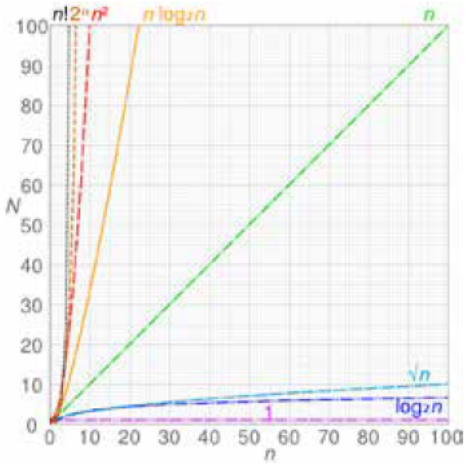
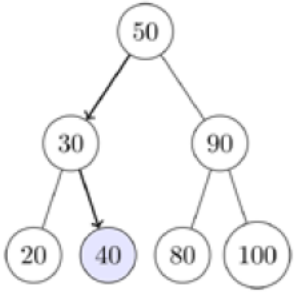


Finding an item in an ordered list

Time/Space Complexity



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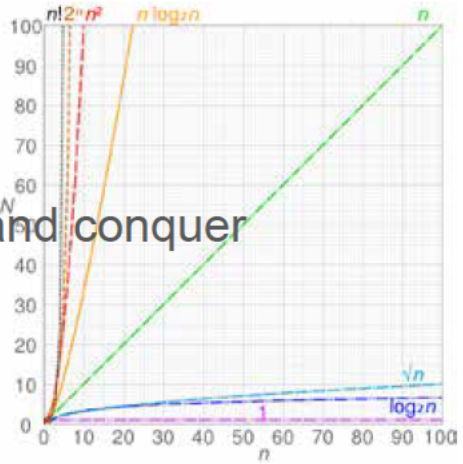
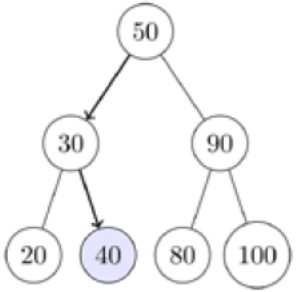


Finding an item a balanced tree structure

Time/Space Complexity



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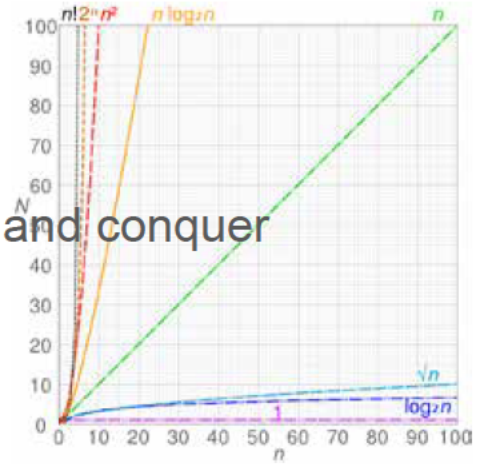
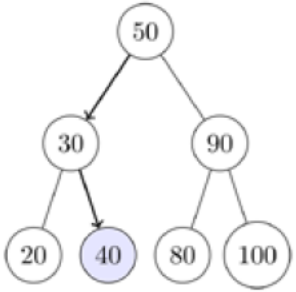
- **$O(n^k)$** → polynomial → Very inefficient, e.g., nested loops



Nested loops

Time/Space Complexity



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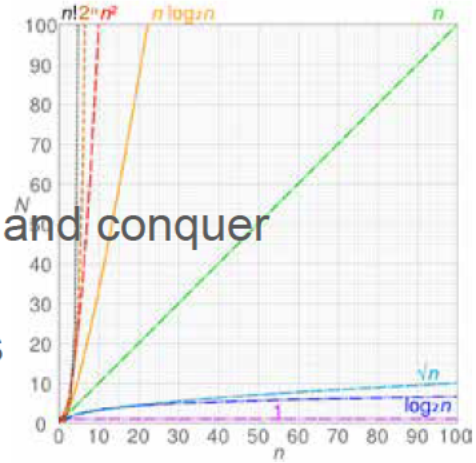
- **$O(n \log n)$** → n-log-n → More efficient than polynomial, less than linear

Various sorting algorithms: Heap, Merge, Quick



Parallelization

- Means of optimizing execution
- Multiprocessing
  - Execute tasks simultaneously using multiple processors.
  - `multiprocessing.Pool` and `multiprocessing.Process`
- Asynchronous vs. Synchronous execution
  - Sync: retains order, uses locking
  - Async: mixed order, but may finish quicker

Parallelization

- Identifying bottlenecks, programmatic dependencies
  - e.g., corpus metrics cannot be calculated until processing completed on all documents
- Works well for processes that can be chunked or sub-processes executed independently
  - e.g., classification, numerical calculation, relevant text extraction

In closing, topics covered

- Normalization
- Regular expressions
- Tokenization
- Stopwords
- Stemming
- N-grams
- TF-IDF
- Cosine Similarity
- Precision/Recall
- Complexity
- Parallelization