Machine Learning
For Natural Language Processing

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Regular Expressions

- Meta Characters: Character matches
  - . : wildcard, match a single character
  - ^: start of a string
  - $: end of a string
  - []: matches one of the set of characters within []
  - []a-z: matches one of the range of characters a, b, …z
  - [^abc]: matches a character that is not a, b or c.
  - aIb: matches either a or b, where a and b are strings
  - (): scopeing of operators
  - \: escape character for special characters (\t, \n, \b)

Regular Expressions

- Meta Characters: Character Symbols
  - \b: matches word boundary
  - \d: any digit, equivalent to [0-9]
  - \D: any non-digit, equivalent to [^0-9]
  - \s: any whitespace, equivalent to [\t\n\r\f\v]
  - \S: any non whitespace, equivalent to [^\t\n\r\f\v]
  - \w: alpha-numeric character, equivalent to [a-zA-Z0-9_]
  - \W: non alpha-numeric character , equivalent to [^a-zA-Z0-9_]

Regular Expressions

- Meta Characters: Repetitions
    - *: matches zero or more occurrences
    - +: matches one or more occurrences
    - ?: matches zero or one occurrences
    - {n}: exactly n repetitions, n>=0
    - {n,}: at least n repetitions
    - {,n}: at most n repetitions
    - {m,n}: at least m and at most m repetitions

Regular Expressions

- Examples
  - *Dates*

  "5-2-2020, 15/2/2020, 2020/2/4 autre autre"

  r'(\d{1,4}[.\-/]\d{1,2}[.\-/]\d{1,4})'

  - *Emails*

  "ahmed@dgi.gov.ma, maryam@dgi.ma ahmadi3maryam@gmail.com other text here"

  r'[\w.-]+@[\w.-]+'

Character Encoding

Monsieur le directeur, j'ai le plaisir de vous informer d'un cas d'evasion fiscale concernant la société SOKA dirigé par Monsieur Ahmadi Ahmed. La société est domiciliée à l'adresse 31 Boulevard ANNASR, Rabat, Maroc. Son registre de commerce RC: 112233 et ICE: 445566778899. Veuillez agréer Monsieur, mes salutations distinguées.

السيد المدير ، يسرني أن أبلغكم بحالة التهرب الضريبي فيما يتعلق بشركة SOKA برئاسة السيد أحمدي أحمد. يقع مقر الشركة في 31 شارع النصر، الرباط ، المغرب. السجل التجاري RC: 112233 و ICE: 445566778899. تفضلوا سيدي بقبول أطيب تحياتي.

Arabic text encoding

- Windows-1256,
- UTF-8,
- CP720,
- ISO 8859-6.

Arabic text display Reshaper

- Unicode bidirectional algorithm, implemented with python-bidi.
- http://pydj.mpcabd.xyz/arabic-reshaper/
- https://camel.abudhabi.nyu.edu/madamira/

Tokenization

- Detect patterns in text
- Word Tokenization

['Monsieur', 'le', 'directeur', ',', "j'ai", 'le', 'plaisir', 'de', 'vous', 'informer', "d'un", 'cas', "d'evasion", 'fiscale', 'concernant', 'la', 'société', 'SOKA', 'dirigé', 'par', 'Monsieur', 'Ahmadi', 'Ahmed', '.', 'La', 'société', 'est', 'domiciliée', 'à', "l'adresse", '31', 'Boulevard', 'ANNASR', ',', 'Rabat', ',', 'Maroc', '.', 'Son', 'registre', 'de', 'commerce', 'RC', ':', '112233', 'et', 'ICE', ':', '445566778899', '.', 'Veuillez', 'agréer', 'Monsieur', ',', 'mes', 'salutations', 'distinguées', '.']

Issues
Punctuation, Numbers, Special characters, Equations, Formula, Languages, Normalization (often by stemming)

Tokenization

- Detect patterns in text
- Word Tokenization
- Sentence Tokenization

["Monsieur le directeur, j'ai le plaisir de vous informer d'un cas d'evasion fiscale concernant la société SOKA dirigé par Monsieur Ahmadi Ahmed.",
"La société est domiciliée à l'adresse 31 Boulevard ANNASR, Rabat, Maroc.",
"Son registre de commerce RC: 112233 et ICE: 445566778899.",
"Veuillez agréer Monsieur, mes salutations distinguées."]

Issues
Punctuation, Numbers, Special characters, Equations, Formula, Languages, Normalization (often by stemming)

POS tagging

Abbreviation	Meaning
CC	coordinating conjunction
CD	cardinal digit
DT	determiner
EX	existential there
FW	foreign word
IN	preposition/subordinating conjunction
JJ	adjective (large)
JJR	adjective, comparative (larger)
JJS	adjective, superlative (largest)
LS	list market
MD	modal (could, will)
NN	noun, singular (cat, tree)
NNS	noun plural (desks)
NNP	proper noun, singular (sarah)
NNPS	proper noun, plural (indians or americans)
PDT	predeterminer (all, both, half)
POS	possessive ending (parent\ 's)
PRP	personal pronoun (hers, herself, him,himself)
PRP$	possessive pronoun (her, his, mine, my, our)

Abbreviation	Meaning
RB	adverb (occasionally, swiftly)
RBR	adverb, comparative (greater)
RBS	adverb, superlative (biggest)
RP	particle (about)
TO	infinite marker (to)
UH	interjection (goodbye)
VB	verb (ask)
VBG	verb gerund (judging)
VBD	verb past tense (pleaded)
VBN	verb past participle (reunified)
VBP	verb, present tense not 3rd person singular(wrap)
VBZ	verb, present tense with 3rd person singular (bases)
WDT	wh-determiner (that, what)
WP	wh- pronoun (who)
WRB	wh- adverb (how)

[('Monsieur', 'NNP'), ('le', 'CC'), ('directeur,', 'JJ'), ("j'ai", 'NN'), ('le', 'NN'), ('plaisir', 'NN'), ('de', 'IN'), ('vous', 'JJ'), ('informer', 'NN'), ("d'un", 'NN'), ('cas', 'NN'), ("d'evasion", 'NN'), ('fiscale', 'NN'), ('concernant', 'NN'), ('la', 'NN'), ('société', 'FW'), ('SOKA', 'NNP'), ('dirigé', 'NN'), ('par', 'NN'), ('Monsieur', 'NNP'), ('Ahmadi', 'NNP'), ('Ahmed.', 'NNP'), ('La', 'NNP'), ('société', 'NN'), ('est', 'JJS'), ('domiciliée', 'NN'), ('à', 'NNP'), ("l'adresse", 'VBZ'), ('31', 'CD'), ('Boulevard', 'NNP'), ('ANNASR,', 'NNP'), ('Rabat,', 'NNP'), ('Maroc.', 'NNP'), ('Son', 'NNP'), ('registre', 'FW'), ('de', 'FW'), ('commerce', 'NN'), ('RC:', 'NNP'), ('112233', 'CD'), ('et', 'NN'), ('ICE:', 'NNP'), ('445566778899.', 'CD'), ('Veuillez', 'NNP'), ('agréer', 'NN'), ('Monsieur,', 'NNP'), ('mes', 'VBZ'), ('salutations', 'NNS'), ('distinguées.', 'NN')]

Chunking

Regular Expressions in POS taggers

Example: Search for
<NNP.?>*<CD.?>

RC:/NNP 112233/CD
ICE:/NNP 445566778899./CD

Name of symbol	Description
.	Any character except new line
*	Match 0 or more repetitions
?	Match 0 or 1 repetitions

[('Monsieur', 'NNP'), ('le', 'CC'), ('directeur,', 'JJ'), ("j'ai", 'NN'), ('le', 'NN'), ('plaisir', 'NN'), ('de', 'IN'), ('vous', 'JJ'), ('informer', 'NN'), ("d'un", 'NN'), ('cas', 'NN'), ("d'evasion", 'NN'), ('fiscale', 'NN'), ('concernant', 'NN'), ('la', 'NN'), ('société', 'FW'), ('SOKA', 'NNP'), ('dirigé', 'NN'), ('par', 'NN'), ('Monsieur', 'NNP'), ('Ahmadi', 'NNP'), ('Ahmed.', 'NNP'), ('La', 'NNP'), ('société', 'NN'), ('est', 'JJS'), ('domiciliée', 'NN'), ('à', 'NNP'), ("l'adresse", 'VBZ'), ('31', 'CD'), ('Boulevard', 'NNP'), ('ANNASR,', 'NNP'), ('Rabat,', 'NNP'), ('Maroc.', 'NNP'), ('Son', 'NNP'), ('registre', 'FW'), ('de', 'FW'), ('commerce', 'NN'), ('RC:', 'NNP'), ('112233', 'CD'), ('et', 'NN'), ('ICE:', 'NNP'), ('445566778899.', 'CD'), ('Veuillez', 'NNP'), ('agréer', 'NN'), ('Monsieur,', 'NNP'), ('mes', 'VBZ'), ('salutations', 'NNS'), ('distinguées.', 'NN')]

Stemming and Lemmatization

- Used for text cleaning: map a group of words to the same root form
- Removing the suffixes or prefixes
- Stemming
  - Apply a set of rules to extract the stem (is fast)
  - The stem might not be an actual language word
- Lemmatization
  - The lemma is an actual language word
  - Based on WordNet corpus (is slow)

plaisir ===> plais
de ===> de
vous ===> vous
informer ===> inform

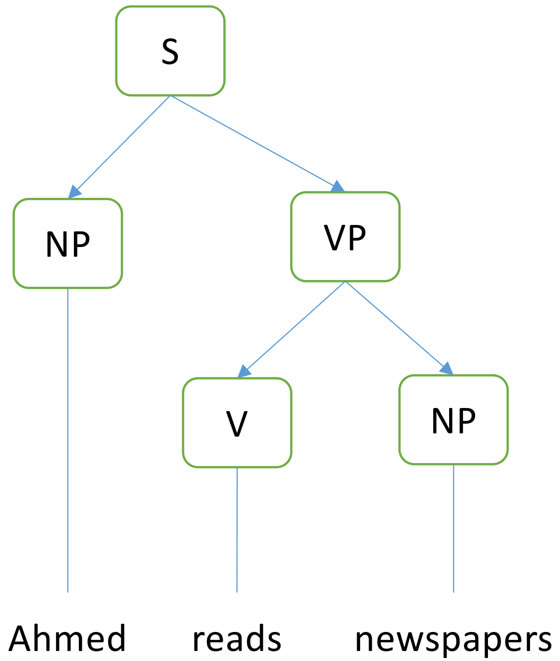
Parsing

- Parsing: Extract meaning from a sequence of words
- Lexicon : vocabulary of all possible words
- Grammar: how the words have to be linked together

Goal: NP VP
VP: Verb
VP: Verb NP
VP: Verb NP PP
PP: Preposition NP
NP: Noun
NP: Article NP
NP: Adjective Noun
NP: NP PP

"Ahmed reads newspapers"

Noun Verb Noun



Parsing

- **English**
  - **Treebank:** Large grammar tree learned form wall street Journal database
- **Arabic**
  - Penn Arabic Treebank (ATB): from newswires
- **Complexity**
  - "Une idée verte dors furieusement »

Named Entity Recognition

- Locating and classifying named entities in texts
- Recognize places, people, dates, values, organizations, etc.

3 class: Location, Person, Organization
4 class: Location, Person, Organization, Misc
7 class: Location, Person, Organization, Money, Percent, Date, Time

- Language dependent
  - English -> use NLTK
  - French -> train your model
  - Arabic -> train your model
  - https://nlp.stanford.edu/software/CRF-NER.shtml

Word representation

- One hot vector (Manning 10:45)
  - No inherent relationships between words
    - No similatity
    - Example motel and hotel (13:00)

Topic Segmentation

- TF-IDF
  - Measures how relevant a term is in a document
  - Map words to vectors
  - Map documents to vectors
  - Ignore the order of words

- A : "a new car, used car, car review"
- B : "a friend in need is a friend indeed"

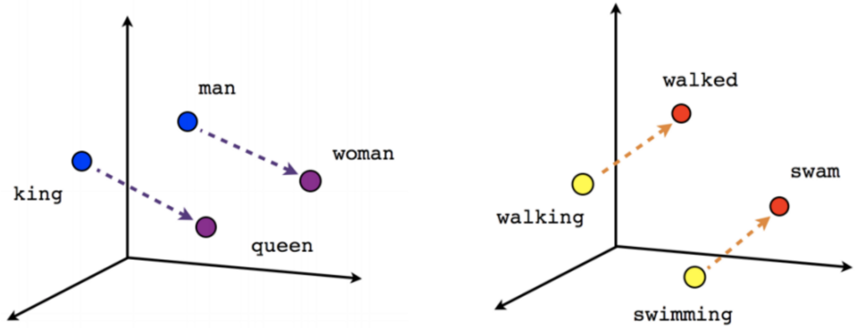
word	TF		IDF	TF * IDF	
	A	B		A	B
a	1 / 7	2 / 8	Log (2 / 2) = 0	0	0
new	1 / 7	0	Log (2 / 1) = 0.3	0.04	0
car	3 / 7	0	Log (2 / 1) = 0.3	0.13	0
used	1 / 7	0	Log (2 / 1) = 0.3	0.04	0
review	1 / 7	0	Log (2 / 1) = 0.3	0.04	0
friend	0	2 / 8	Log (2 / 1) = 0.3	0	0.08
in	0	1 / 8	Log (2 / 1) = 0.3	0	0.04
need	0	1 / 8	Log (2 / 1) = 0.3	0	0.04
is	0	1 / 8	Log (2 / 1) = 0.3	0	0.04
indeed	0	1 / 8	Log (2 / 1) = 0.3	0	0.04

Topic Segmentation

- Word Embedding (Word2Vec)
  - Map words to vectors
  - Take into account word's context and position
  - Cosine Similarity

$$sim(A,B) = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|}$$

Word Embedding



Male-Female

Verb tense

Edit Distance

- Levenshtein Distance
  - Measure of similarity between two strings
  - minimum number of edit operations
    - deletions,
    - insertions,
    - substitutions

		m	o	n	k	e	y
	0	1	2	3	4	5	6
m	1	0	1	2	3	4	5
o	2	1	0	1	2	3	4
n	3	2	1	0	1	2	3
e	4	3	2	1	1	1	2
y	5	4	3	2	2	2	1

Tools

- [NLTK]
  - Documentation https://www.nltk.org/
  - import nltk
  - nltk.download()
- [Google API]
  - https://cloud.google.com/natural-language/