Week 1: Introduction and overview

Text Analytics and Natural Language Processing
Instructor: Benjamin Batorsky

NOTE: Please download week_1_intro_student.ipynb from Canvas now!

About me

Associate Director, Data Science

PhD, Policy Analysis

MIT MANAGEMENT SLOAN SCHOOL

Food Supply Chain Analytics and Sensing Group

Global pilots of risk-based food safety testing technology

Teaching Fellows

Stuart Neilson

MA, Economics

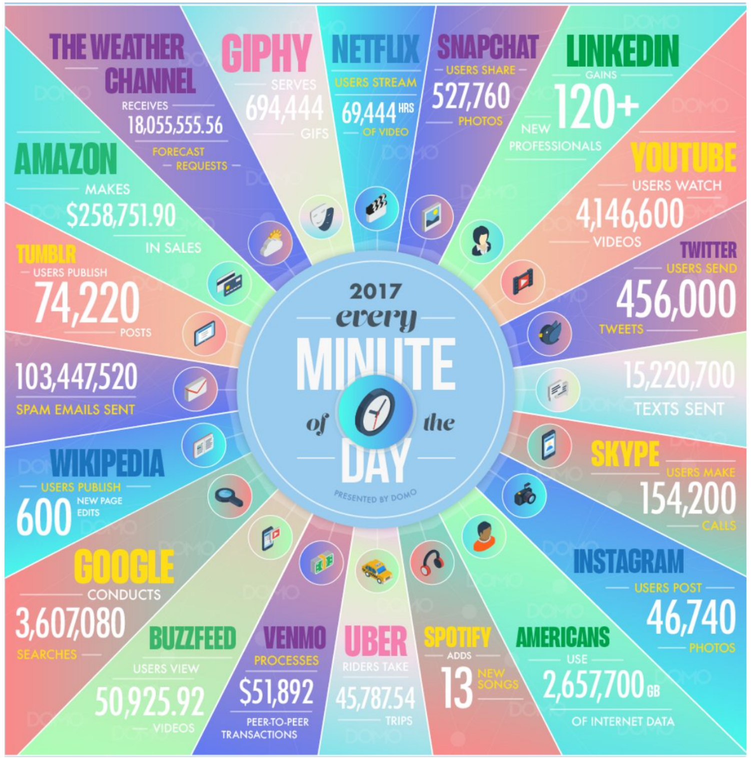
Current work is in the banking industry, building models to predict losses from loan defaults

Megan Fantes

MS, Computer Science

Focus in Data Science and Machine Learning for Big Data

Explosion of data...unstructured data, that is



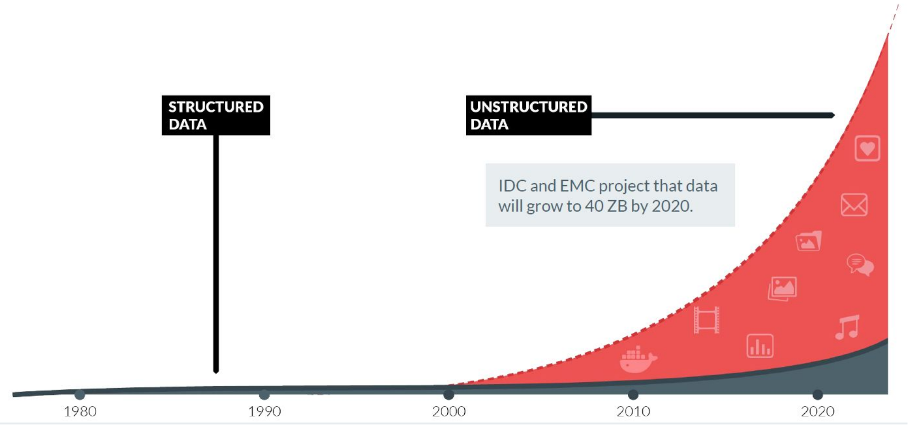
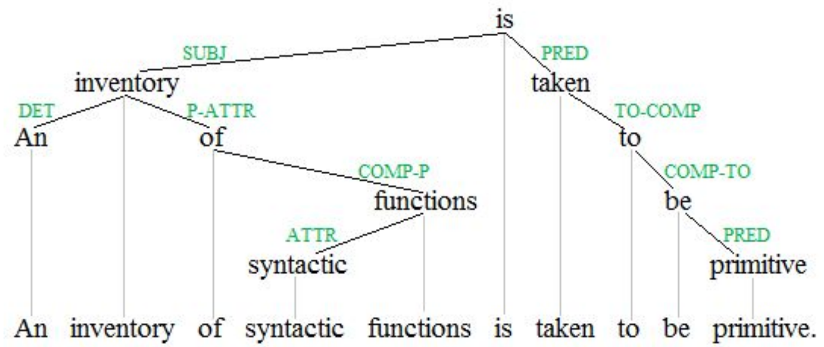


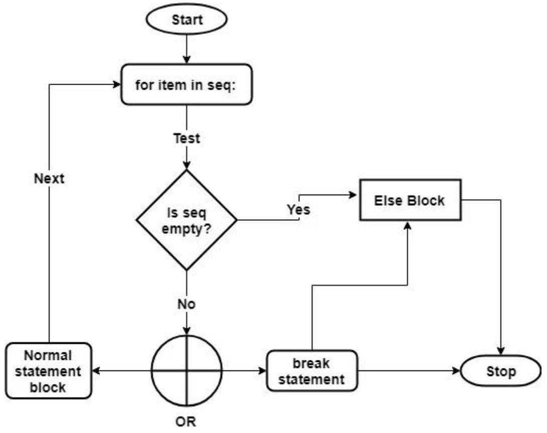
Chart:https://www.datanami.com/2017/02/01/solving-storage-just-beginning-minio-ceo-periasamy/
Data: IDC Structured Versus Unstructured Data: The Balance of Power Continues to Shift, March 2014

What is Natural Language?

"A language that has developed naturally in use (as contrasted with an artificial language or computer code)." (Oxford Dictionary definition)



https://en.wikipedia.org/wiki/Dependency_grammar



https://www.techbeamers.com/python-for-loop/

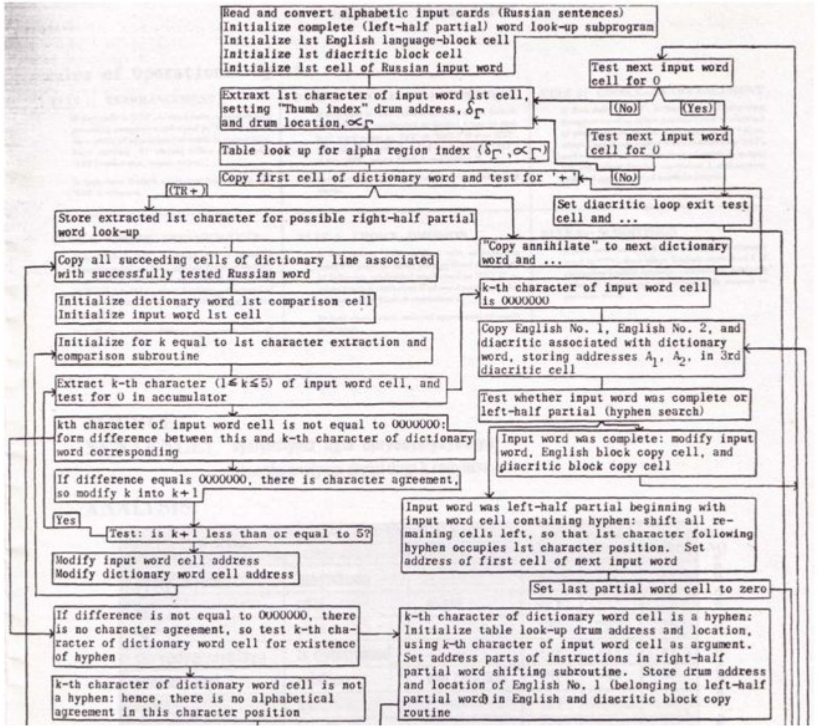
Natural language vs programming language

Natural language

Programming language

How do we process language into text?

1950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Initialize complete (left-half partial) word look-up subprogram
Initialize 1st English language-block cell
Initialize 1st diacritic block cell
Initialize 1st cell of Russian input word
Test next input word cell for 0
(No)
(Yes)
Extraxt 1st character of input word 1st cell, setting "Thumb index" drum address, δΓ and drum location, ∝Γ
Test next input word cell for 0
Table look up for alpha region index (δΓ, ∝Γ)
(No)
Copy first cell of dictionary word and test for '+'
(TR+)
Set diacritic loop exit test cell and ...
Store extracted 1st character for possible right-half partial word look-up
"Copy annihilate" to next dictionary word and ...
Copy all succeeding cells of dictionary line associated with successfully tested Russian word
k-th character of input word cell is 0000000
Initialize dictionary word 1st comparison cell
Initialize input word 1st cell
Copy English No. 1, English No. 2, and diacritic associated with dictionary word, storing addresses A1, A2, in 3rd diacritic cell
Initialize for k equal to 1st character extraction and comparison subroutine
Extract k-th character (1≤k≤5) of input word cell, and test for 0 in accumulator
Test whether input word was complete or left-half partial (hyphen search)
kth character of input word cell is not equal to 0000000: form difference between this and k-th character of dictionary word corresponding
Input word was complete: modify input word, English block copy cell, and diacritic block copy cell
If difference equals 0000000, there is character agreement, so modify k into k+1
Input word was left-half partial beginning with input word cell containing hyphen: shift all remaining cells left, so that 1st character following hyphen occupies 1st character position. Set address of first cell of next input word
Yes
Test: is k+1 less than or equal to 5?
Modify input word cell address
Modify dictionary word cell address
Set last partial word cell to zero
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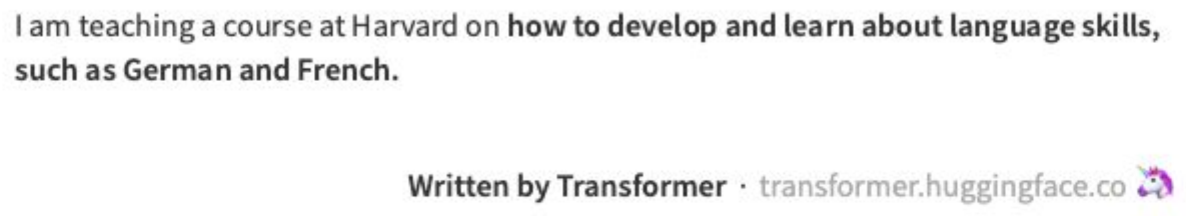
k-th character of dictionary word cell is not a hyphen: hence, there is no alphabetical agreement in this character position

2013

https://jalammar.github.io/visualizing-neural-machine-translation-mechanics-of-seq2seq-models-with-attention/

Now we can do things like this

Write with Transformer from HuggingFace:
https://transformer.huggingface.co/doc/distil-gpt2

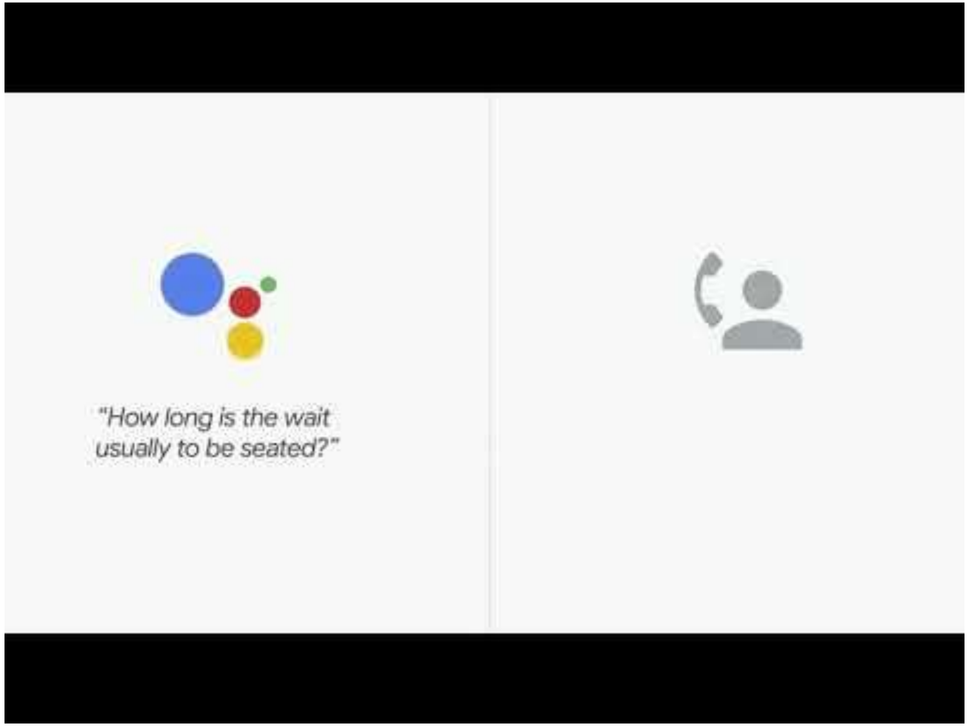


I am teaching a course at Harvard on **how to develop and learn about language skills, such as German and French.**

Written by Transformer · transformer.huggingface.co

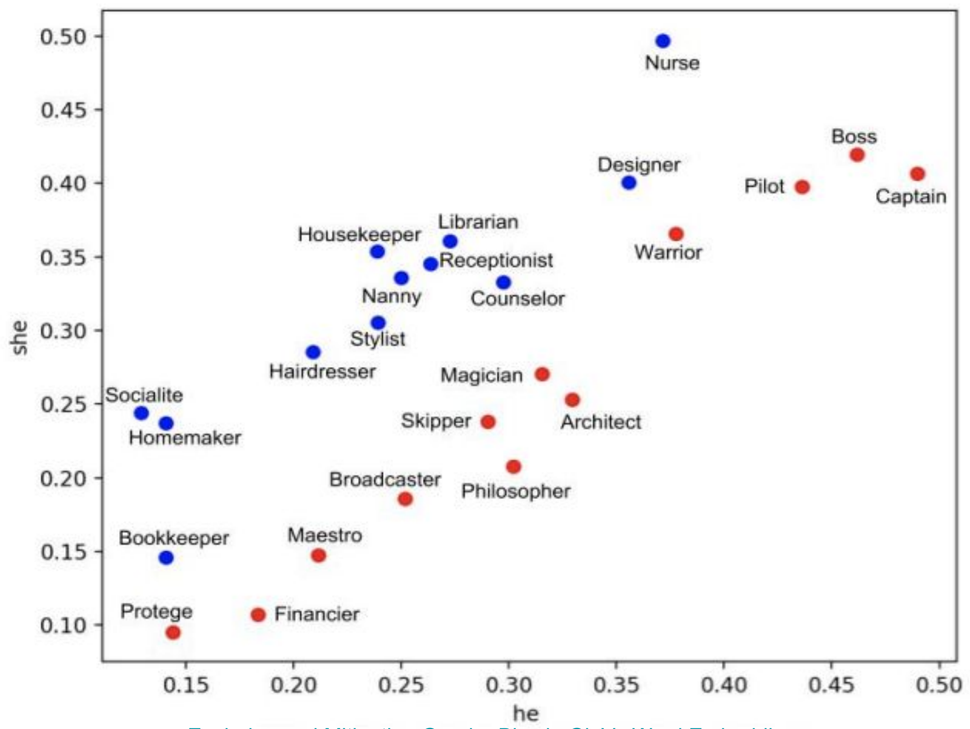
And this:

Google Assistant making a reservation



Though also, this:

Word vector similarity between gender words and occupations



[Exploring and Mitigating Gender Bias in GloVe Word Embeddings]

Other interesting uses?

What are some uses you’ve seen or worked with?

Course overview

Focus by week

1. Introduction and overview of Natural Language Processing
   Assignment #0
2. From text to vectors
   Assignment #1
3. Vectors in context: Recurrent models and word embeddings
   Assignment #2
4. Attention and Transformers
   Assignment #3
5. Scoping an NLP project
   Midterm
6. Supervised and unsupervised applications
   Project outline (assignment #4) due
7. Issues and applications in NLP

Final project due by Monday Aug 10 by 6:30pm ET

Grading:

- 5% Participation in forum discussions of readings
- 30% Assignments (4 in total)
- 25% Online midterm exam
- 40% Final project (includes project outline)

Assignments/midterm due by the start of class Monday

Prerequisites

- Python Syntax
  - Functions, objects, flow control
- Pandas/NumPy
  - DataFrames, arrays, indexing, common functions/attributes
- Matrix/vector algebra
- Statistics
  - Basic descriptive stats
  - Some idea about hypothesis testing
- Machine learning
  - General understanding of supervised/unsupervised, vocabulary

Python

Free course (a lot of other sources available as well)
https://www.udacity.com/course/introduction-to-python--ud1110

Pandas/NumPy/Stats

Python Data Science Handbook

Matrix algebra

https://www.khanacademy.org/math/algebra-home/alg-matrices

My teaching philosophy

- Ideally: This is a conversation, we're exploring these topics together
  - Reality: We have a syllabus, and we're going to do our best to get through it
- I want everyone to succeed, to learn and be engaged
  - I do my best to make sure all requirements are reasonable and clear
  - You let me know when you feel I'm not meeting these standards
- I am heavily in the implementation/application world
  - We will explore theory, but likely not go deep into the maths
    - Optional materials will give you opportunity to dive into that
  - I'm primarily aiming to give you a base of tools/code you can use in your projects and research

Assignments

- Assignments mostly involving writing code to implement a method or arrive at an answer
- Avoid copy-pasting code from the internet
  - If you use a snippet, cite your source
- If you use github repositories, make sure they are private

Assignment 0 due at the end of the week!

Assignment 1 on Canvas NOW!

DUE: Week 2, Monday 6/29, 6:30pm

Example assignment:

- Write a function that tokenizes a given dataset
- Analyze the dataset using this function
- Calculate some metrics based on this dataset

Midterm

- Focused on the first half of the course (theory+application)
- Delivered online, timed
  - Open CLASS notes
  - Feel free to use library documentation, but AVOID searching for answers (time limit!)
- Three parts
  - Multiple choice
  - Short answer
  - Application

Final projects

- Application of techniques and strategies learned as part of the course
- May work on the project individually or as a group (no more than 3)
  - If a group, all individuals must be involved
  - Scope is expected to be expanded if it's a group deliverable

Start thinking about it NOW!

Project OUTLINE (assignment 4) due (**latest!**):

Week 6, Monday, 7/27, 6:30pm ET

Project due: Monday AFTER week 7, 8/10

Some neat data resources

https://github.com/awesomedata/awesome-public-datasets#naturallanguage, Kaggle, Google data search

Project must contain the following components:

- A clear research question or problem to address
- A description of the dataset and justification of why it is appropriate to solve the problem
- Exploratory analyses of the dataset
- A description of the methodology to be applied and justification of its use
- Runnable code for applying the methodology and analyzing results
- Deployment strategy
  - (optional, if appropriate)
- Results and conclusions

Tips for project outline (assignment 4)

- Include all the sections the final project will have (see previous slide)
- Include all people involved (up to 3)
- Submit to Canvas (will add to general documents module)
- Get it done early so we can give feedback early!
    - Not TOO early: probably want to wait until week 3 (model focus)

Requirements

- First half of course: Theory + Application
  - 50/50 lecture slides/application notebooks
- Second half of course: Mainly application
  - 30/70 lecture slides/application notebooks
- Required for following application notebooks
  - Access to github page
  - Online
    - Google account for using https://colab.research.google.com/
  - Local machine
    - Python 3.7
    - Libraries: Scikit-learn, pandas, transformers, SpaCy

Discussions on Piazza

- Role of Piazza (as I see it)
    - Share resources/commentary
    - Discuss topics
    - Ask questions/troubleshooting
- Also: A way to stay engaged, even if you can’t attend live!

Participation counts!

Teaching Fellow Sessions

- TFs will dig into topics discussed in class, answer questions, etc
- Useful to get additional discussion, clarity
- Good place to bring questions that can’t be covered in Piazz
- Poll currently on Canvas
    - Thursday session (Megan)
    - Saturday session (Stuart)

Note about the current situation

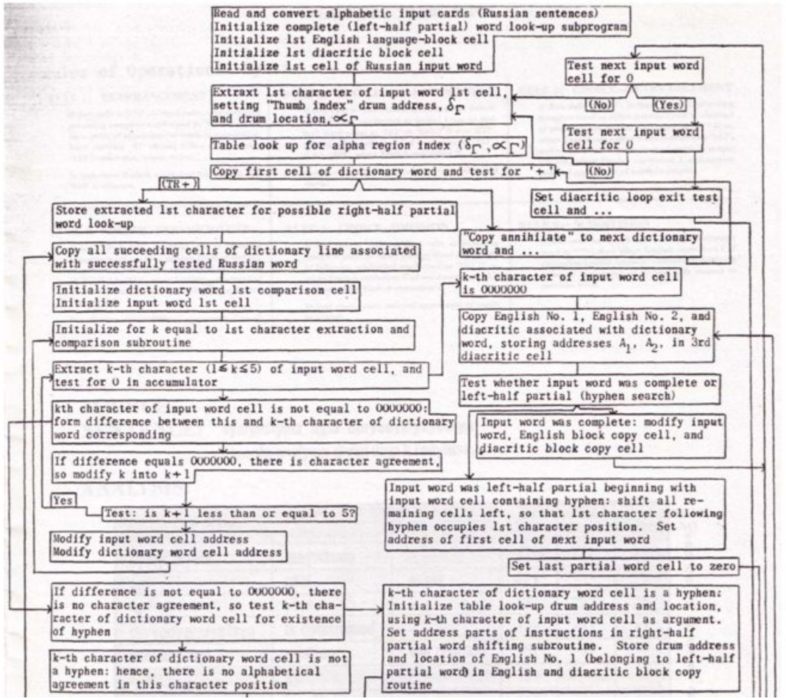
- Get in touch as soon as you can if there’s any issues with meeting course requirements
- Our main aim is to ensure success: You all in the course, us in delivering useful material and feedback
- It’s a tough time: But we’ve got this!

History of NLP: 1940s-1950s

- Focus on machine translation
  - Actually a VERY difficult task
  - Why?

History of NLP: 1940s-1950s

- Focus on machine translation
  - Actually a VERY difficult task
- Approach mainly dictionary-based
- Mostly focus on syntax vs semantics
  - Syntax: Structure
  - Semantics: Meaning
  - “Cows flow supremely”, syntactically correct, semantically meaningless
  - Syntax-driven processing
    - Store information about relationships between different parts of sentence
    - Cows flow, the flow is supreme
  - Semantic-driven processing
    - Incorporate information outside of the language itself, like a cow is an animal
- No application-ready solutions by the end of this era
  - But started the conversation/thinking



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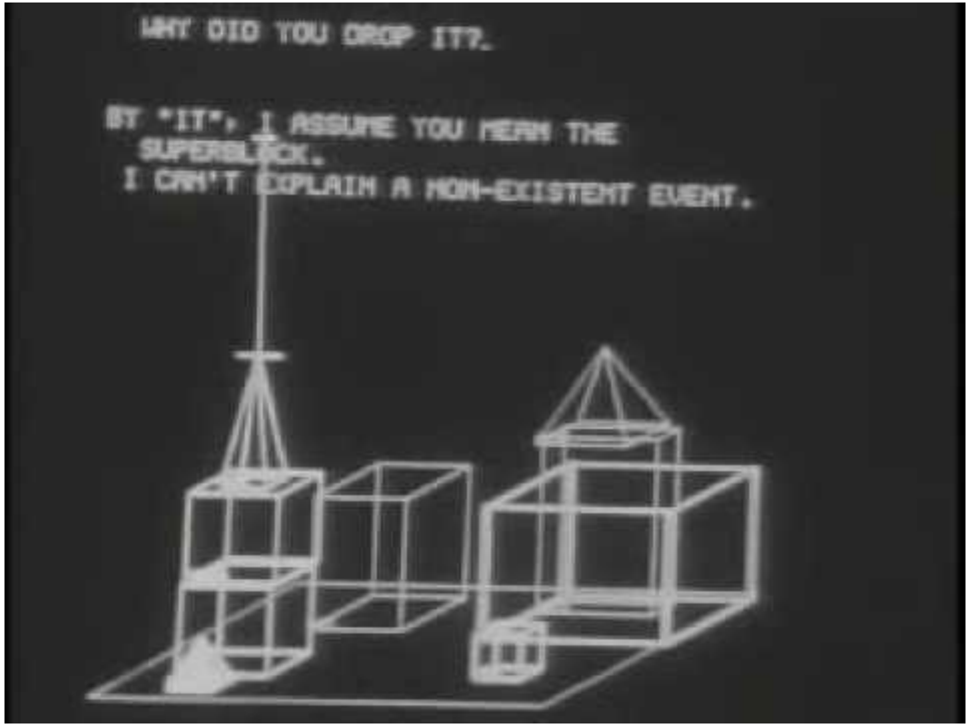
1960s-1970s: Shift to semantic-driven processing

- Semantic-driven processing
  - Focus on meaning/relationships
  - Incorporate information outside of the language itself
- SHRLDU
  - Map query to stored relationship map of the machine state
- Focus on pulling in different data sources
  - Lots of focus on tools for data integration
- Still not enough
  - Uninteresting results on actual dealing with natural language
  - User-machine exchanges difficult to handle “naturally”

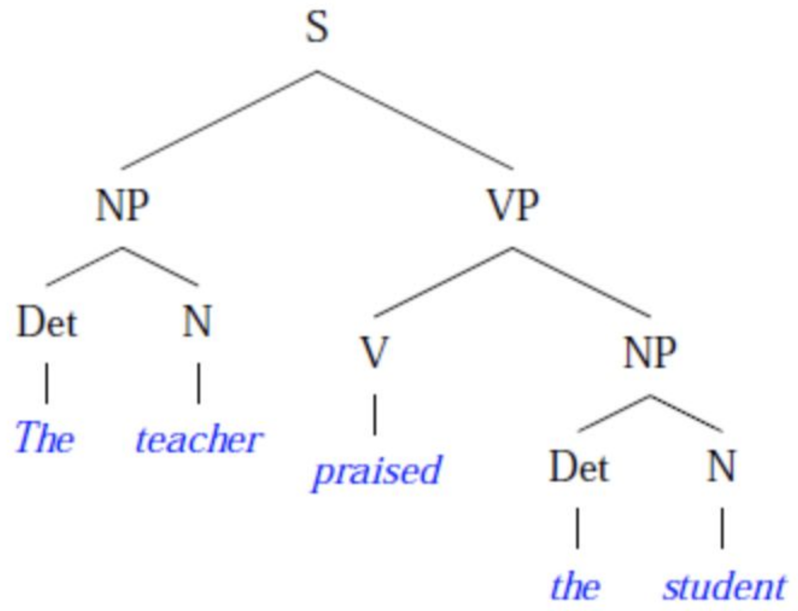


WHY DID YOU DROP IT?.

BY "IT", I ASSUME YOU MEAN THE SUPERBLOCK.
I CAN'T EXPLAIN A NON-EXISTENT EVENT.

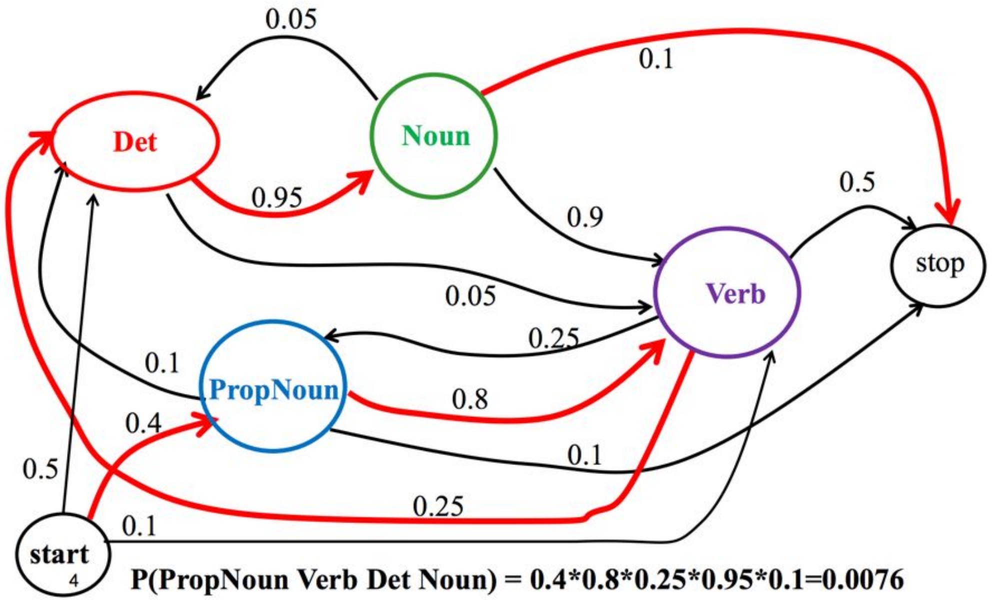
1970s-1980s: Joining of linguistics and AI

- Linguistics (Study of language)
  - Noam Chomsky’s ideas of “generative grammar”
  - Focus on categorization/computability
- AI
  - Increasing focus on representations of meanings/intention
- Joining together, building of community
  - New conferences
  - New standardized tasks to measure performance



1990s-2000s: Shift towards statistical NLP

- Increasing attention on probabilistic models of language
    - Visual of parsing trees with probabilities, Markov Models
    - Probabilities of certain words appearing, the precursor to modern language models
- Also newly available data sources for developing/testing
    - WordNet (https://wordnet.princeton.edu/)
        - Inventory of English words and their relationships
    - Penn TreeBank (https://catalog.ldc.upenn.edu/LDC99T42)
        - Text parsed for part of speech, dependencies, etc
    - Ontonotes (https://catalog.ldc.upenn.edu/LDC2013T19)
        - Text labelled with entities (e.g. places and persons)
    - The internet!



To the notebooks!

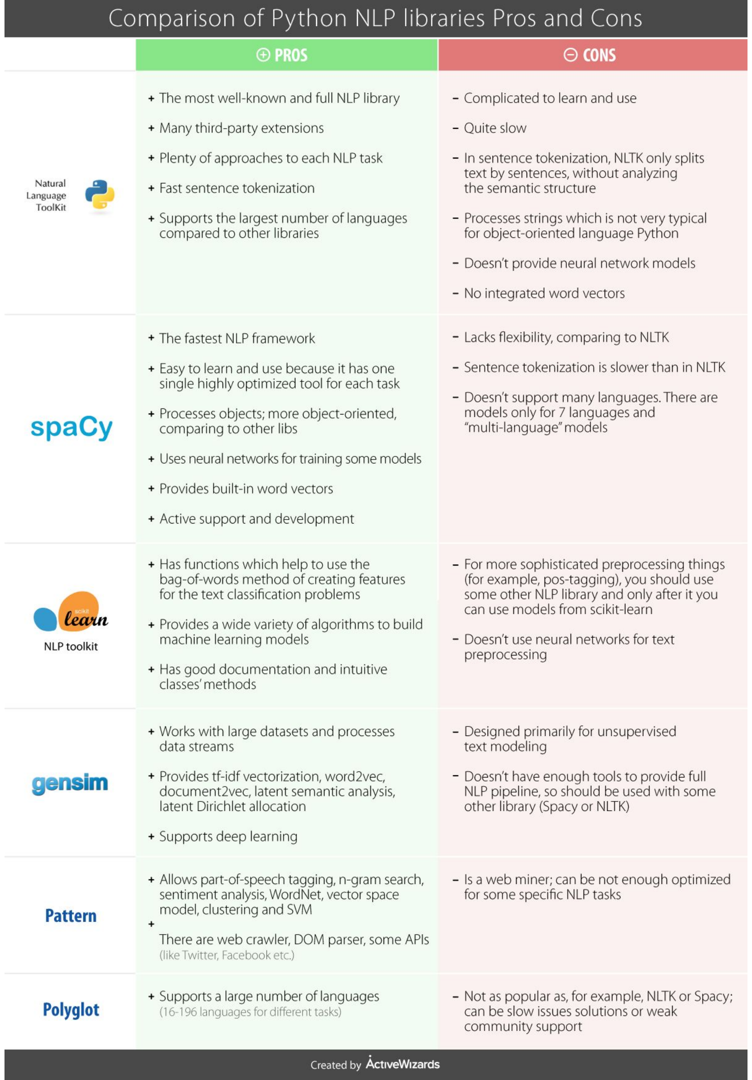
Download the week_1_intro_student.ipynb file from Module 1

Go to: https://colab.research.google.com/

Select the option to upload a notebook into Collab

You’re done!

NLP libraries



Comparison of Python NLP libraries Pros and Cons

	⊕ PROS	⊖ CONS
Natural Language ToolKit	+ The most well-known and full NLP library + Many third-party extensions + Plenty of approaches to each NLP task + Fast sentence tokenization + Supports the largest number of languages compared to other libraries	- Complicated to learn and use - Quite slow - In sentence tokenization, NLTK only splits text by sentences, without analyzing the semantic structure - Processes strings which is not very typical for object-oriented language Python - Doesn't provide neural network models - No integrated word vectors
spaCy	+ The fastest NLP framework + Easy to learn and use because it has one single highly optimized tool for each task + Processes objects; more object-oriented, comparing to other libs + Uses neural networks for training some models + Provides built-in word vectors + Active support and development	- Lacks flexibility, comparing to NLTK - Sentence tokenization is slower than in NLTK - Doesn't support many languages. There are models only for 7 languages and "multi-language" models
scikit learn NLP toolkit	+ Has functions which help to use the bag-of-words method of creating features for the text classification problems + Provides a wide variety of algorithms to build machine learning models + Has good documentation and intuitive classes' methods	- For more sophisticated preprocessing things (for example, pos-tagging), you should use some other NLP library and only after it you can use models from scikit-learn - Doesn't use neural networks for text preprocessing
gensim	+ Works with large datasets and processes data streams + Provides tf-idf vectorization, word2vec, document2vec, latent semantic analysis, latent Dirichlet allocation + Supports deep learning	- Designed primarily for unsupervised text modeling - Doesn't have enough tools to provide full NLP pipeline, so should be used with some other library (Spacy or NLTK)
Pattern	+ Allows part-of-speech tagging, n-gram search, sentiment analysis, WordNet, vector space model, clustering and SVM + There are web crawler, DOM parser, some APIs (like Twitter, Facebook etc.)	- Is a web miner; can be not enough optimized for some specific NLP tasks
Polyglot	+ Supports a large number of languages (16-196 languages for different tasks)	- Not as popular as, for example, NLTK or Spacy; can be slow issues solutions or weak community support

Created by ActiveWizards

[Comparison of Top 6 Python NLP Libraries - ActiveWizards — your AI partner]

Stanza (formerly StanfordNLP)

- https://github.com/stanfordnlp/stanza/
- Similar “pipeline” structure to spaCy
  - stanza.download('en')
  - nlp = stanza.Pipeline('en')
- Large amount of languages models (POS/NER)
  - https://stanfordnlp.github.io/stanza/available_models.html
- Spacy-Stanza
  - https://spacy.io/universe/project/spacy-stanza
  - Most of the same attributes available
- If looking for a language that’s not available consider Stanza or http://ufal.mff.cuni.cz/udpipe

Tokenization

- Definition: “A useful semantic unit”
- What is a “useful semantic unit”?

“I am learning Natural Language Processing (NLP)”

What are the useful units of meaning here?

Tokenization

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I, am, learning

Natural Language Processing

NLP

Tokenization

- Definition: “A useful semantic unit”
- What is a “useful semantic unit”?

“I am learning Natural Language Processing (NLP)”

What are the useful units of meaning here?

I, am, learning (split on whitespace)

Natural Language Processing (entity)

NLP (entity as acronym)

(NLP) (special treatment of text in parentheses?

N-grams

- N-gram: Continuous sequence of N tokens
  - Tokens != words (see previous slides)
- Important considerations
  - “not”, “good” vs “not good”
  - Named-entities (e.g. Cities, people)
  - Exploring co-occurrence

count(natural language) / count (language)

count(english language) / count (language)

“I am learning Natural Language Processing (NLP)”

<split on whitespace>

Unigrams

I, am, learning, Natural, Language, Processing, (NLP)

Bigrams

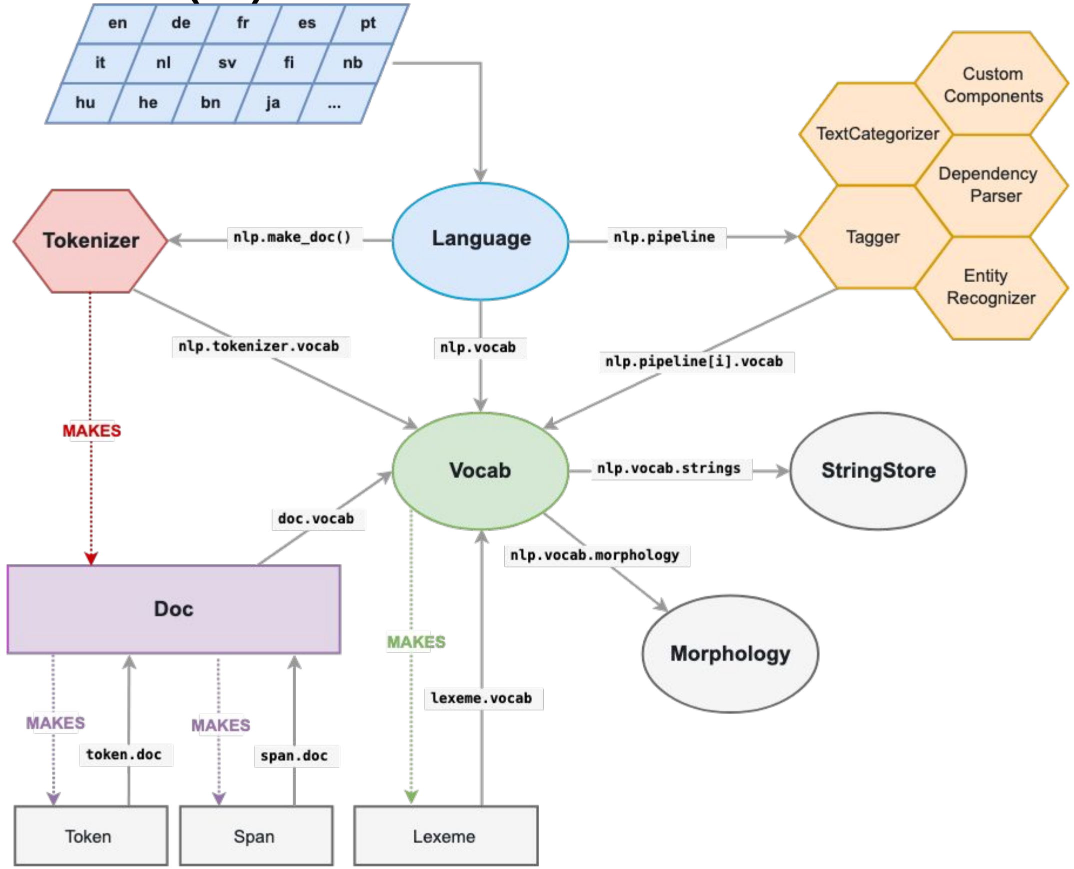
I am, am learning, learning Natural...

7-grams

I am learning Natural Language Processing (NLP)

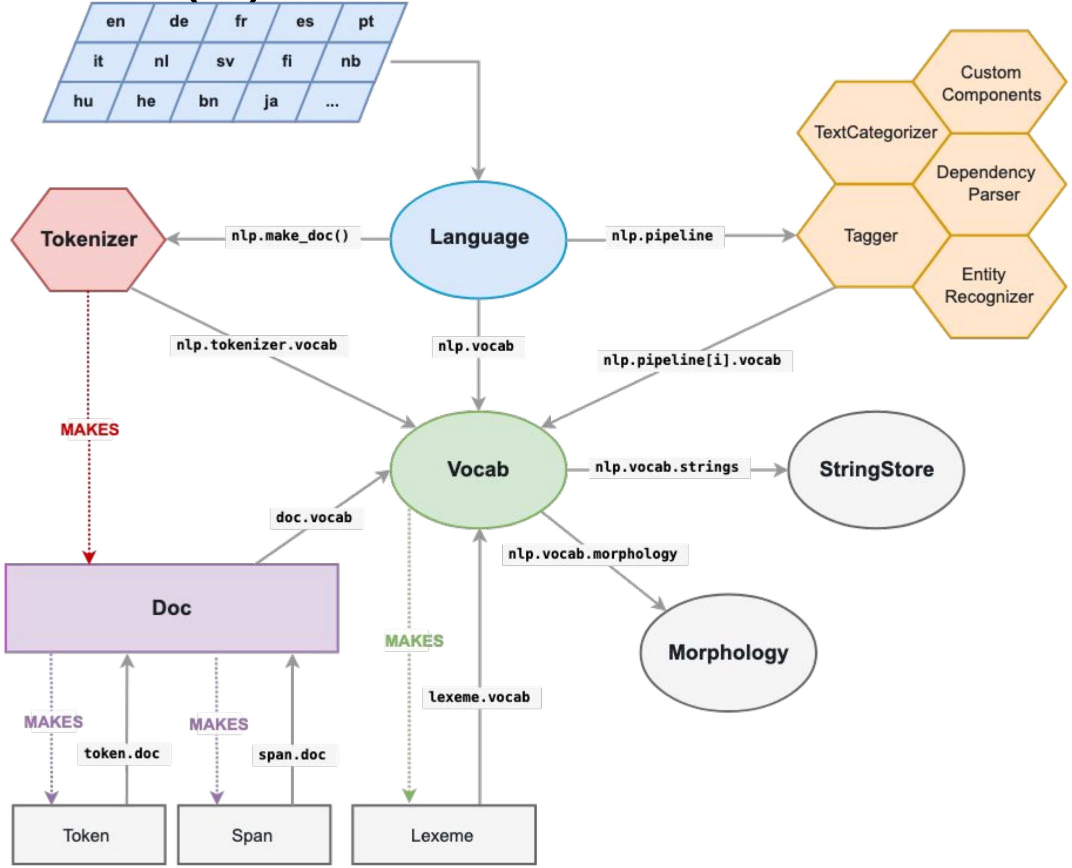
SpaCy's Language models (1)

- Language model: Tokenization/processing pipeline
- Base: Tokenizer + Vocab
  - Tokenizer
    - Processing of text
  - Vocab
    - Contains all "lexemes"
- Document -> Span -> Token
  - .text = raw text
  - Document/Span
  - Token
    - .shape_
      - We = Xx
      - we = xx
    - .is_alpha (boolean)
    - .is_stop (boolean)



SpaCy’s Language models (2)

- Can load “trained” language models
- Additional pipeline components
  - Entity recognition
  - Part of speech tagging
  - Dependency parsing
  - Categorization
  - Anything else (custom attributes)
- Products of these
  - Document/Span
    - .ents (named entities)
    - .sents
    - .noun_chunks
  - Token
    - .dep_ (e.g. nsubj)
    - .lemma_ (dictionary form)
    - .pos_ (part of speech)



What is the point of NLP?

What is the main challenge of working with text data?

How is it different from structured data (e.g. stock ticker, height/weight)?

What are we looking for when we’re trying to find these “useful semantic units”?

What is the point of NLP?

What is the main challenge of working with text data?

How is it different from structured data (e.g. stock ticker, height/weight)?

What are we looking for when we’re trying to find these “useful semantic units”?

Main goal: Create an informative representation of text

Stemming vs Lemmatization

Goal: Reduce related words to a common “base form”

Stemming

Set of heuristics to transform suffixes. Most of the word stays intact.

“He does natural language processing”

↓

“He doe natural language process”

Implemented in: NLTK, PyStemmer

Lemmatization

Transforms word to their “lemma”, or dictionary form. This may change the word entirely.

“He is doing natural language processing”

↓

“He be do natural language process”

Implemented in: NLTK, spaCy

Stop words

- Extremely common words that have little information
  - “the”, “at”, “from”, “to”, “in”
- No single list of these
  - Consequences to choosing overly strict/broad

In June 2020, I took a course at Harvard Extension School in Cambridge.

Stop words

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  - “the”, “at”, “from”, “to”, “in”
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<Remove stop words (SpaCy)>

June 2020 took course Harvard Extension School Cambridge

Issues with stop words

Scikit-learn

Example: “hasn’t” is removed using “hasnt”

https://github.com/scikit-learn/scikit-learn/blob/fd237278e895b42abe8d8d09105cbb82dc2cbba7/sklearn/feature_extraction/_stop_words.py

SpaCy

Example: “hasn’t” is removed using “has” and contraction “n’t”

https://github.com/explosion/spaCy/blob/master/spacy/lang/en/stop_words.py

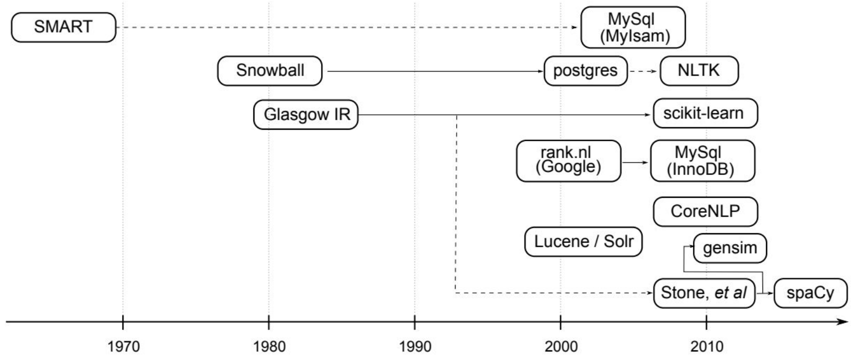

Figure 1: Family tree of popular stop word lists.

https://www.aclweb.org/anthology/W18-2502.pdf

Named-Entities

- Named-entity: A real-world named object (e.g. person, place, organization)
    - New York City is different than just an assembly of three words “new”, “york” and “city”
- To identify these
    - Dictionaries
    - Pattern-matching
    - Models

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In June 2020 [DATE], I took a course at Harvard Extension School [ORG] in Cambridge [LOC].

Be a tokenizer

Growth in the availability of text data and computational power along with the development of powerful new techniques has led to a revolution in the field of Natural Language Processing (NLP) in the past few years. This course will provide an application-focused overview of the field from tokenization to state-of-the-art models such as Recurrent Neural Networks and Transformers. The first half of the course will introduce students to the theoretical background along with Python code for implementation.

What are the “named entities” here?

What are the stop words?

What is the role of non-alpha characters?

What is the role of capitalization?

Be a tokenizer

Cos i was out shopping wif darren jus now n i called him 2 ask wat present he wan lor. Then he started guessing who i was wif n he finally guessed darren lor.

What are the “named entities” here?

What are the stop words?

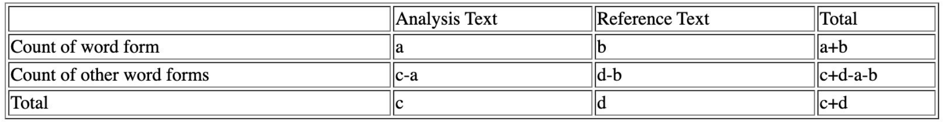
What is the role of non-alpha characters?

What is the role of capitalization?

Exercise: Create a tokenization pipeline

Log-likelihood ratio with word counts

- Enables comparison of word-level counts between two documents/corpora
- Test of hypothesis: Frequency of word is equivalent between analysis and reference
  - Expected count = number of words in document i * the pooled frequency across both documents
- Provides a test of significance for differences in frequency
- Accessible via simple word counts!



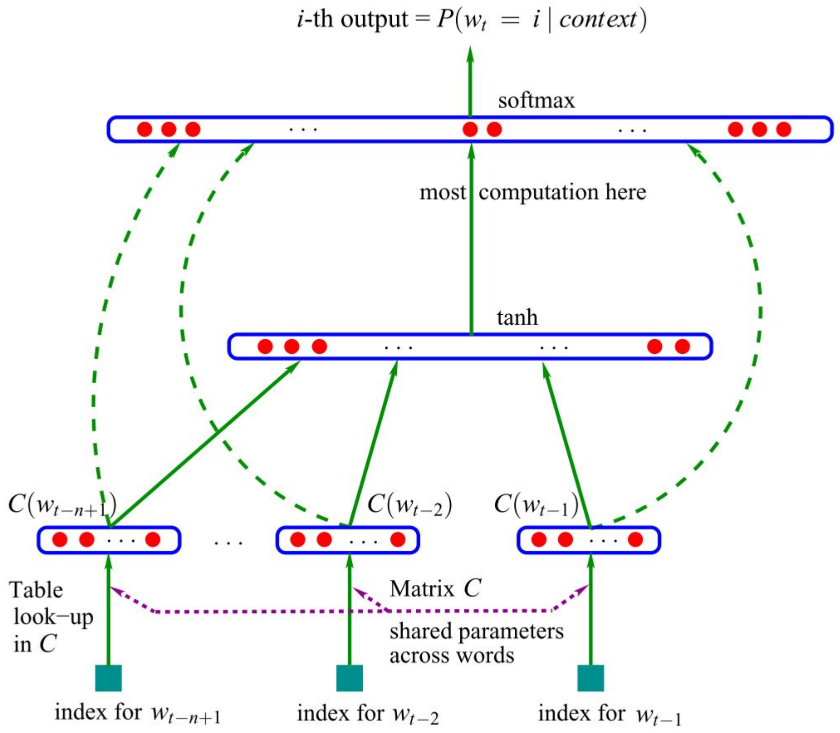
	Analysis Text	Reference Text	Total
Count of word form	a	b	a+b
Count of other word forms	c-a	d-b	c+d-a-b
Total	c	d	c+d

$$E1 = c*(a+b)/(c+d)$$
$$E2 = d*(a+b)/(c+d)$$
$$G^2 = 2*((a*\ln(a/E1)) + (b*\ln(b/E2)))$$

https://wordhoard.northwestern.edu/userman/analysis-comparewords.html

2000s: Advent of Neural Models for NLP

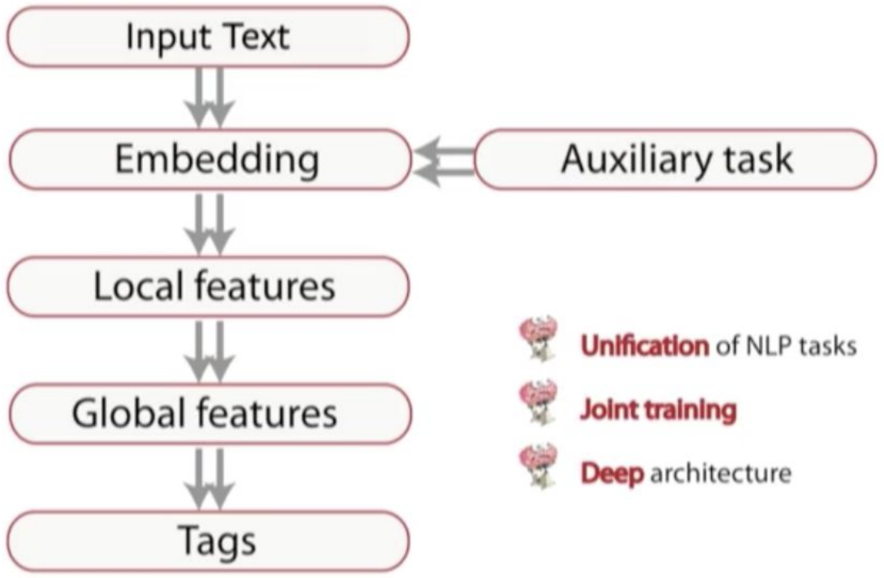
- Focused on language modelling task
  - Given context words, predict next word
  - “Do you want to go out for <mask>”
  - “I ate so much I am so <mask>”
  - “I’m so tired, I think I’ll take a <mask>”
- Apply Neural Net architectures to language modelling task
  - Neural Net: Model that connects inputs to outputs through sets of computations
- Bengio et. al. (2001) A Neural Probabilistic Language Model
  - Context words fed into a matrix that “represents” the information
  - These representations then fed into a computation layer
  - Output: Prediction of the target word
    - “Full”: 70% likely, “tired” 20% likely, etc



A Neural Probabilistic Language Model
(https://papers.nips.cc/paper/1839-a-neural-probabilistic-language-model.pdf)

2008: Multi-task learning

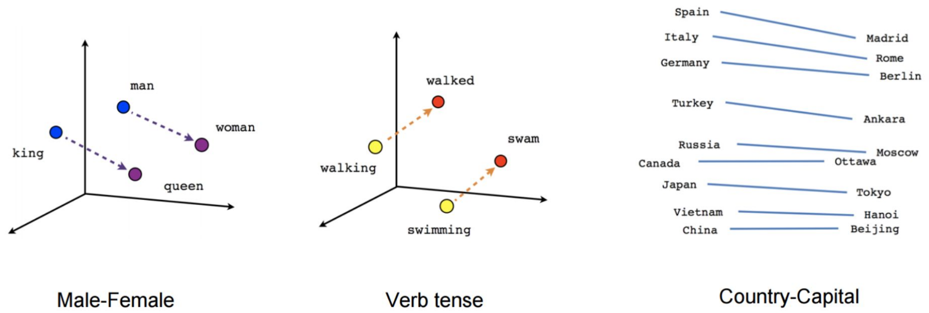
- Multi-task learning: One model, multiple related tasks
  - Trains representations (e.g. lookup tables) jointly so that it performs well on both
- Collobert and Weston (2008)
  - Word lookup table trained jointly from two different tasks
  - Basically the precursor to the idea of word embeddings



https://www.facebook.com/722677142/posts/10155393881507143/

2013: Word embeddings

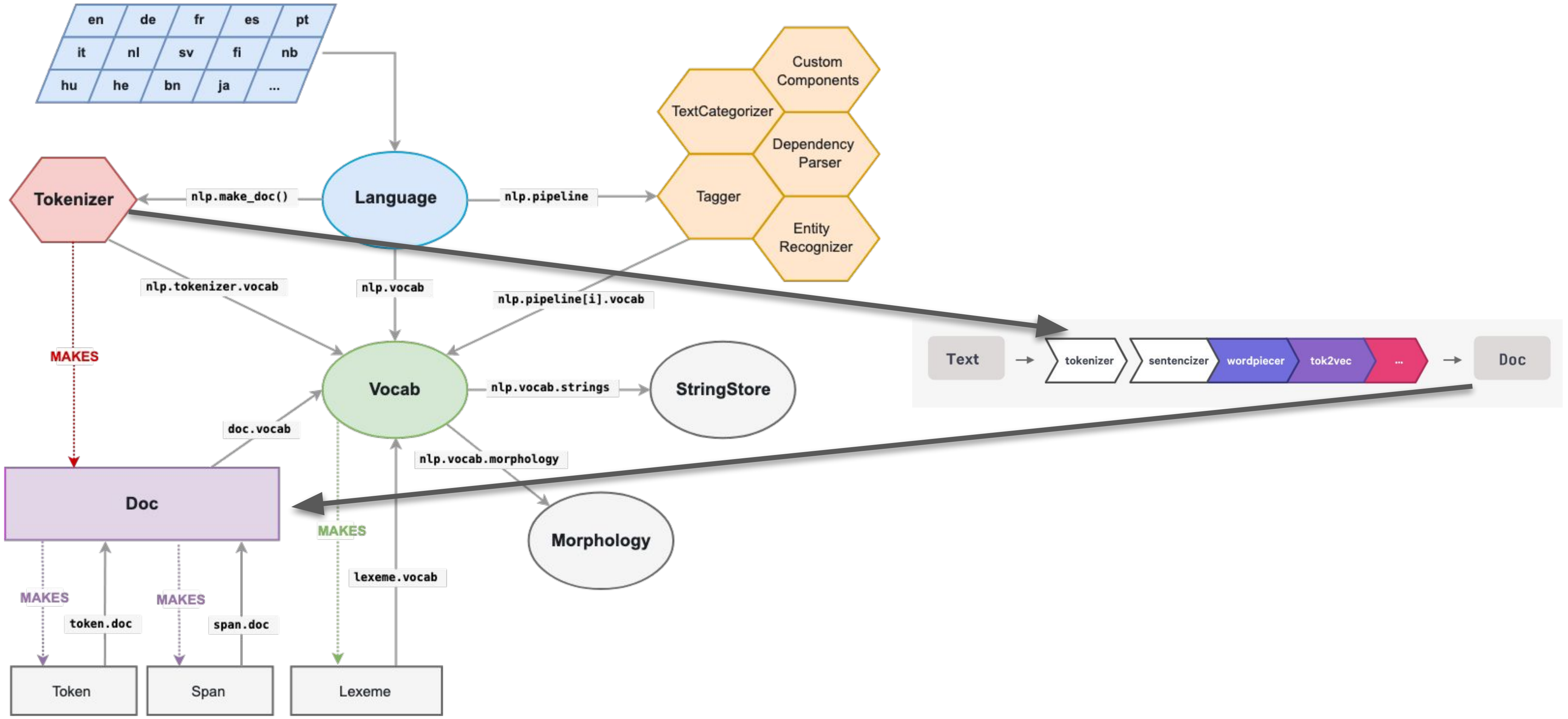
- Mikolov paper
  - Efficient computation of embedding technique used in the 2000s
  - Word2Vec implementation
- Huge amount of adaptation/modifications
  - GloVe: Co-occurance based
  - Sub-word/character-level
  - Use of different corpora for training
  - Out-of-vocabulary handling
  - Training implementation in open-source libraries (e.g. gensim)
- Major revolution: It's fairly easy to make more informed representations of words
- Caveat: Widespread use raises issues of bias
  - Extensive research finds training on most large datasets introduces gender/racial bias
  - Not an issue with the method particularly, more with irresponsible use



[1301.3781] Efficient Estimation of Word Representations in Vector Space

To the notebooks!

SpaCy + Transformers



Assignment 1 overview

- Using what we’ve learned this week on a real-world dataset
- IMDB movie reviews dataset, split into positive/negative
  - From paper: https://www.aclweb.org/anthology/P11-1015.pdf
  - Full dataset: http://ai.stanford.edu/~amaas/data/sentiment/
- Construct tokenization function
- Create word counts
- Find “discriminative words”
- Apply a dictionary-based approach to sentiment analysis
- Compare to spaCy’s English model “polarity” score