Natural Language Processing with PyTorch

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REV. May 2021

Workshop Notes & Lab References

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Session Outline

- **Session 1:**
  - Module 1 (30mins, Lecture): Foundations
    - Fundamentals and application of Language Modeling Tools
    - Classical vs DL NLP
    - NLP Pipeline
  - Lab (30mins): NLTK from scratch
    - Setting up your environment
    - NLTK (tokenization)
  - Module 2 (30mins):
    - Use NLP pipeline to process documents
    - Text Pre-Processing (POS, Stemming)
  - Lab (30mins)

Session 2:

- Module 3: Lecture (30mins): Word embeddings
  - Lab (20min): Key packages & libraries in NLP
  - Lab (20mins): TF-IDF lab
- Module 4: Lecture & Lab (60mins): Getting to know SpaCy

Session 3:

- Module 5: Lecture & Lab (40mins): PyTorch
- Lecture & Lab (60mins): Using RNN with PyTorch
  - Using Seq2Seq model for machine translation
  - Lab: Seq2Seq model using PyTorch

Session 4: Focus on use cases

- Module 6: Lecture & Lab (60mins) MLOps using scheduler (AirFlow) – on AWS (credentials to be provided)
- Module 7: Using LSTM with PyTorch
- Text Classification
  - Lab: LSTM based text classifier

Learning Objective

- Foundations: Fundamentals and application of Language Modeling Tools
- Overview of Natural Language Processing Techniques & Transfer Learning
- Use NLP pipeline to process documents, Word Vectors
- Introduction to key packages and libraries
- Introduction to spaCy and PyTorch

Session Outline

Session 5:
•Learning Objective
- Deep dive into Transformer architecture

•Session Outline
- Introduction to Transformers
  - Paper review (Attention is All you Need)
  - Transfer Learning Fundamentals
  - Pre-trained models, such as BERT, XLNet from Huggingface
- Lab(s): Solve NLP problems using PyTorch, pre-trained models
- **Capstone Project Assignment**

Session 6:
Learning Objective
- Question / Answering through developing a chatbot

•Session Outline
- Theory
- Stanford **Question Answering** Dataset (SQuAD)
- Lab: Develop a chatbot

Session 7:
Learning Objective
- MLOps using a text classification model

•Session Outline
- Scheduler Overview
- Implementation walk-through

Session 8:
Lecture & Lab: Review key concepts / models / libraries
Capstone Project Presentations

A word about the training (setting expectations for the next 4 weeks)

What we cover:

- Deep Learning based Neural Machine Translation approach with some theoretical background and heavy labs usage
- Covers modern (last 2-4 years) development in NLP
- Gives a practitioner’s perspective on how to build your NLP pipeline

What we do not cover much beyond foundational context:

- Statistical and probabilistic approach (minimal)
- Early Neural Machine Translation approaches (marginal)

"You shall know a word by the company it keeps"

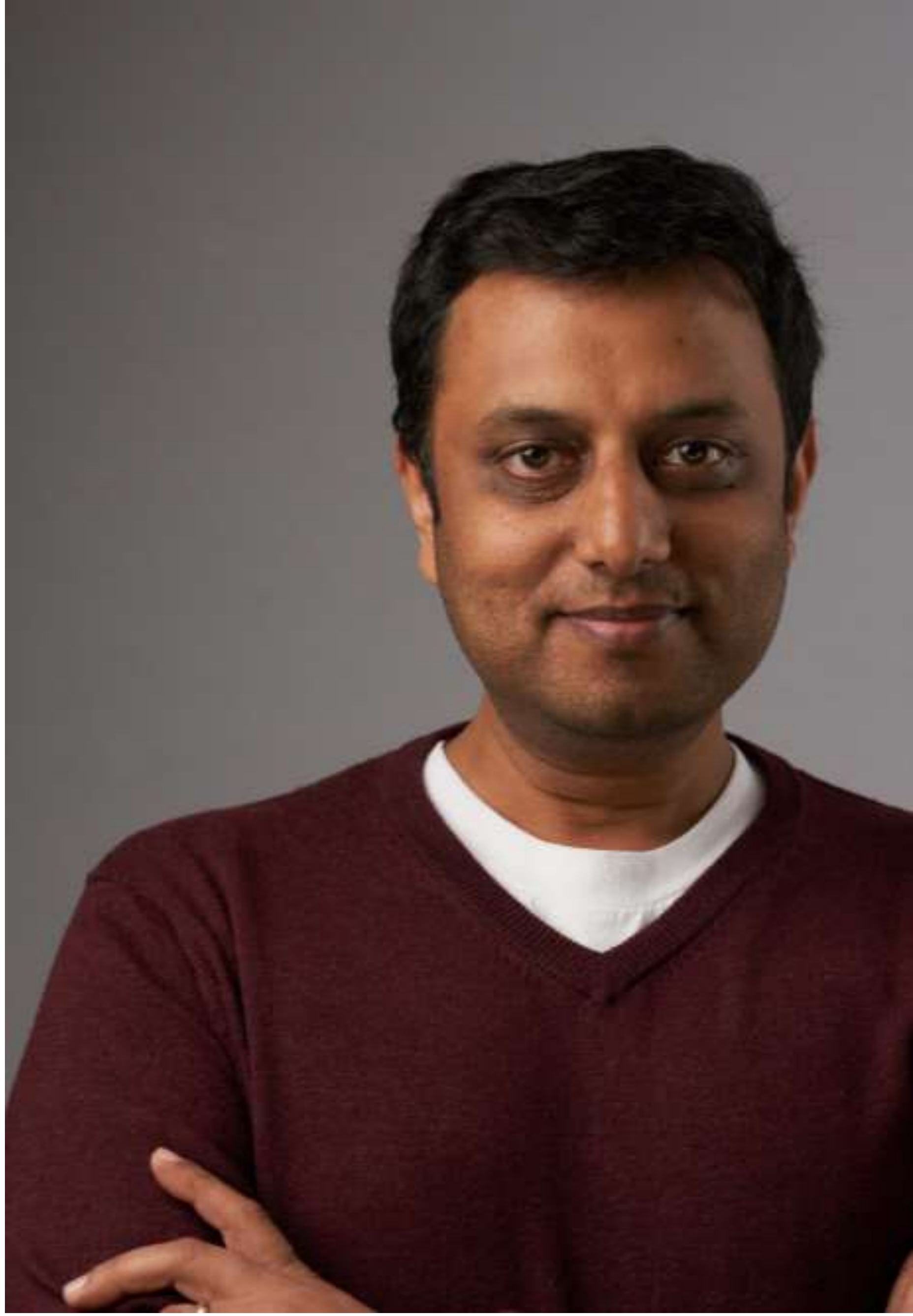
J.R. Firth, 1957

Context is important if you want to understand the meaning of a word

Yashesh A. Shroff

Bit about me:

- Working at Intel as a Strategic Planner, responsible for driving ecosystem growth for AI, media, and graphics on discrete GPU platforms for the Data Center
- Prior roles in IOT, Mobile Client, and Intel manufacturing
- Academic background:
  - ~15 published papers, 5 patents
  - PhD from UC Berkeley (EECS)
  - MBA from Columbia Graduate School of Business (Corp Strategy)
  - Intensely passionate about programming & product development
- Contact:
  - Twitter: @yashroff, yshroff@gmail.com, https://linkedin/yashroff



Setting up your Environment

Most of the lab work will be in the Python Jupyter notebooks in the workshop Github repo:

- Jupyter (https://jupyter.org/install)
- PyTorch (https://pytorch.org/get-started/locally/#start-locally)
- spaCy (https://spacy.io/usage)
- Hugging face transformer (https://huggingface.co/transformers/installation.html)

Training GitHub Repo

Install git on your laptop:

- https://git-scm.com/book/en/v2/Getting-Started-Installing-Git

And run the following command:

```
• git clone https://github.com/yasheshshroff/NLPworkshop.git
```

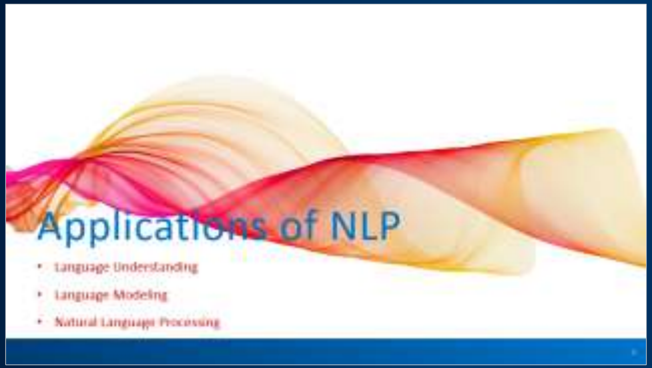
Use conda or pipenv to install the requirements dependencies in a virtual environment.

```
import numpy as np
import matplotlib.pyplot as plt

conda create -n pynlp python=3.6
source activate pynlp
conda install ipython
conda install -c conda-forge jupyterlab
conda install pytorch torchvision -c pytorch
pip install transformers
```

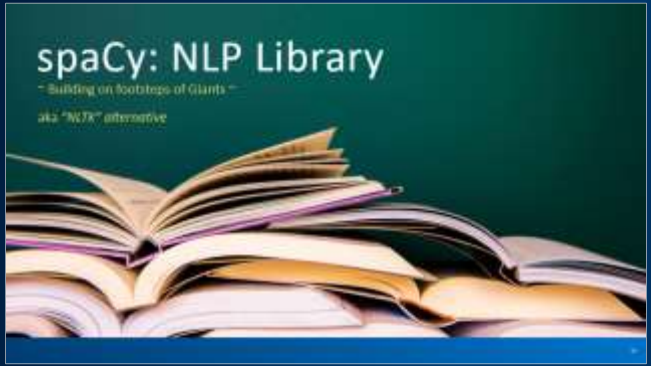
```
# Install spacy and download pretrained language model
$ pip install -U spacy
$ pip install -U spacy-lookups-data # Lang Lemmatization*
$ python -m spacy download en_core_web_sm

In Python:
import spacy
nlp = spacy.load("en_core_web_sm")
```

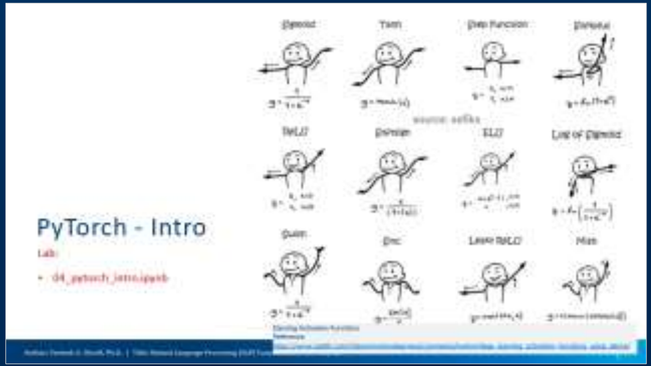
* Where Pretrained Language Model doesn't exist in spaCy (more compact distro)

Part 1: Foundations of NLP



Part 2: Practicum





Applications of NLP

- Language Understanding
- Language Modeling
- Natural Language Processing

Common Applications of Natural Language Processing

Machine Translation
Translating from one language to another

Speech Recognition

Question Answering
Understanding what the user wants

Text Summarization
Concise version of long text

Chatbots

Text2Speech, Speech2Text
Translation of text into spoken words and vice-versa

Voicebots

Text and auto-generation

Sentiment analysis

Information extraction

Common Applications of Natural Language Processing

Machine Translation: Google Translate

Speech Recognition: Siri, Alexa, Cortana

Question Answering: Google Assistant

Text Summarization: Legal, Healthcare

Chatbots: Helpdesk

Text2Speech, Speech2Text

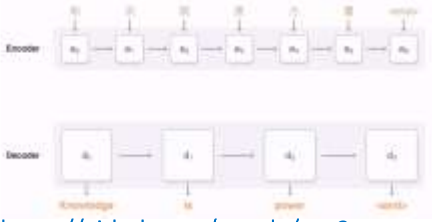
Voicebots: Voiq Sales & Marketing

Text and auto-generation: Gmail

Sentiment analysis: Social media (finance, reviews)

Information extraction: Unstructured (news, finance)

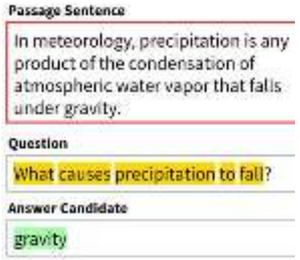
NLP Tasks



https://github.com/google/seq2seq

Machine Translation

- Benchmarks:
  - https://paperswithcode.com/task/machine-translation
- Legal document translation
- Unsupervised Machine Translation
- Low-Resource Neural Machine Translation
- Transliteration



Question Answering

- Benchmarks:
  - https://paperswithcode.com/task/question-answering
- Knowledge-base answering
- Open-domain question answering
- Answer selection
- Community question answering

Text Classification Algorithms: A survey

Text Classification

- Benchmarks:
  - https://paperswithcode.com/task/text-classification
- Topic models
- Document classification
- Sentence classification
- Emotion Classification

Sentiment Analysis

- Benchmarks:
  - https://paperswithcode.com/task/question-answering
- Twitter sentiment analysis
- Aspect-Based sentiment analysis
- Multimodal sentiment analysis

& More…

Text Generation	NER
Text summarization	Natural Language Inference
Information Retrieval	Dependency Parsing
Dialog	Emotion Recognition
Semantic Textual Similarity	Reading comprehension

741 benchmarks • 306 tasks • 100 datasets • 8368 papers with code

Approaches to Natural Language Processing

From Heuristics to Deep Learning

A brief history of Machine Translation

Pre-2012: Statistical Machine Translation

- Language modeling, Probabilistic approach
- Con: Requires "high-resource" languages

Neural Machine Translation

- word2vec
- GloVe
- ELMo
- Transformer

Underlying common approaches

- Model, Training data, Training process

NMT: Key Papers

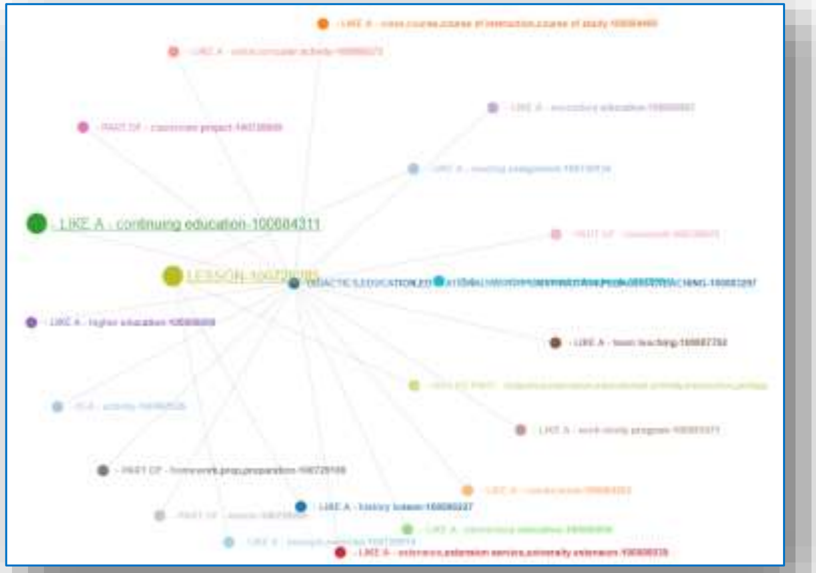
- word2vec: Mikolov et. al. (Google)
- GloVe: Pennington et al., Stanford CS. EMNLP 2014
- ElMo:
- ELMo (Embeddings from Language Models)
  - Memory augmented deep learning
- Survey paper (https://arxiv.org/abs/1708.02709)
  - Blog (https://medium.com/dair-ai/deep-learning-for-nlp-an-overview-of-recent-trends-d0d8f40a776d)
- Vaswani et al., Google Brain. December 2017.
  - *The Illustrated Transformer* blog post
  - *The Annotated Transformer* blog post

Ref: https://eigenfoo.xyz/transformers-in-nlp/

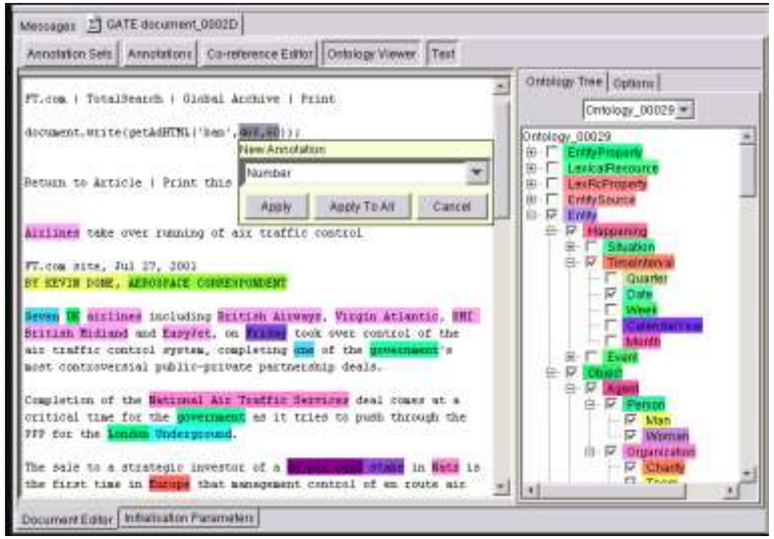
Heuristics based approach to NLP

Rules based AI systems requiring domain expertise. Applied as:

- Dictionary & thesaurus-based sentiment analysis with counts)
- Knowledge-based relationship between words and concepts
  - Wordnet – mapping of terms for similarity



- Regex: ^([a-zA-Z0-9_\-\.]+)@([a-zA-Z0-9_\-\.]+)\.([a-zA-Z]{2,5})$
  - Key sub-strings, such as product ID
- Context-Free Grammar (formal): GATE / JAPE



Reference: https://www.visual-thesaurus.com/wordnet.php?link=100883297

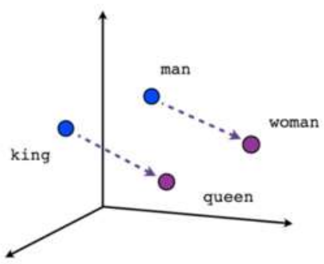
Classical vs. DL NLP

Classical:

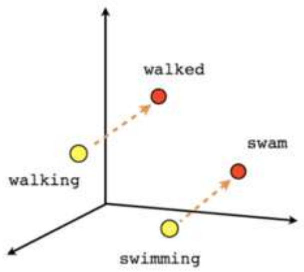
- Task customization for NLP Applications

DL Based NLP

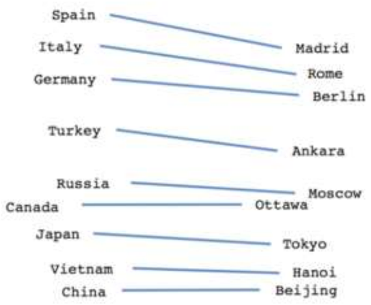
- Compressed representation
- Word Embeddings



Male-Female

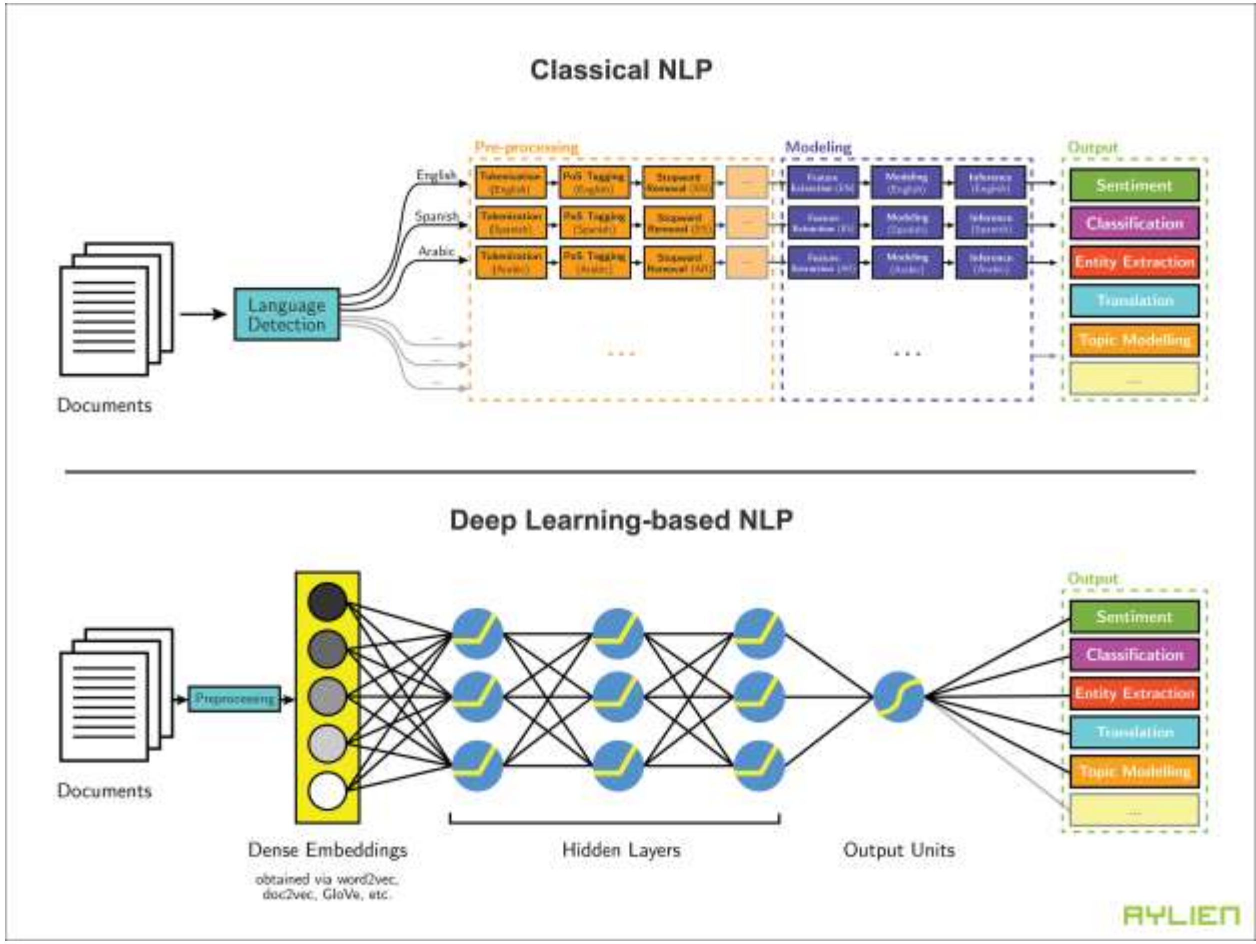


Verb tense



Country-Capital

Reference: https://arxiv.org/abs/1301.3781
(Efficient Estimation of Word Representations in Vector Space)



Reference: https://aylien.com/blog/leveraging-deep-learning-for-multilingual

Machine Learning based NLP

Supervised

- Text classification
- Regression

Unsupervised

- Document topic modeling

Feature Extraction → Feature Representation → Evaluation

Popular Machine Learning Algos for NLP

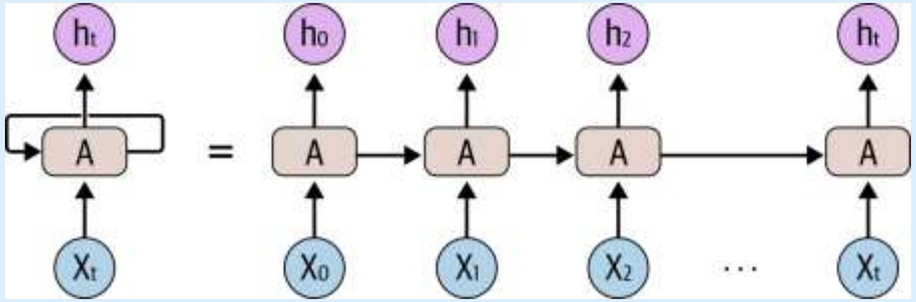
Algorithm	Description
Naïve Bayes	Assumes feature independence (naïve) Ex. Frequency of specific words for classification
Support Vector Machines	Leans optimal (linear or non-linear) decision boundaries between classes (sports vs political articles)
Hidden Markov Models	Models unobserved hidden states that generate observed data, for example, for parts-of-speech tagging*
Conditional Random Fields	Sequential, context-based information management, works better than HMM in a closed domain [1, 2]

* POS is covered next as a topic

Deep Learning in NLP

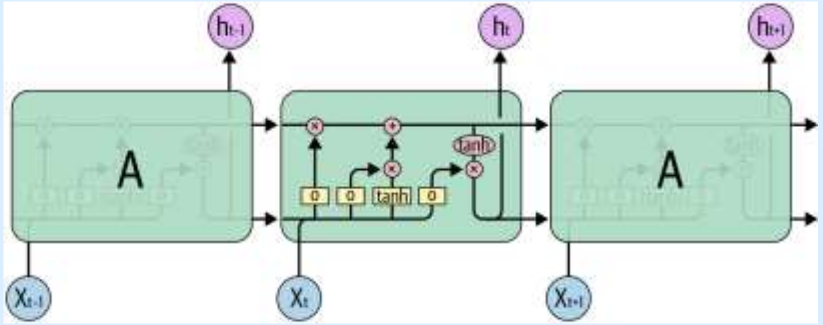
Recurrent Neural Networks

- Progressively reads input and generates output
- Capability to ‘remember’ short texts



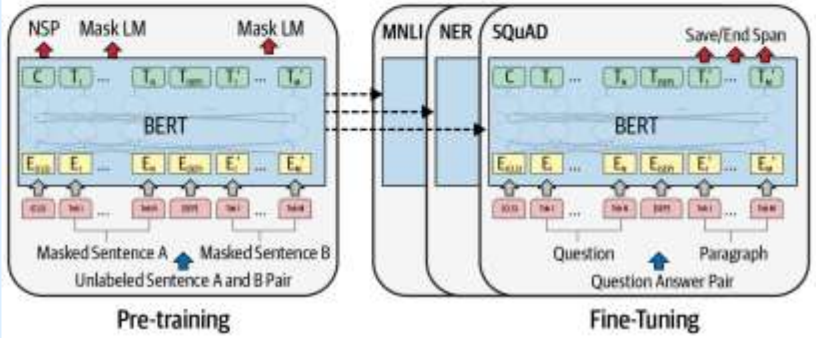
Long-Short Term Memory

- Improves upon RNN with longer text memory
- Ability to let go of certain context



Transformers

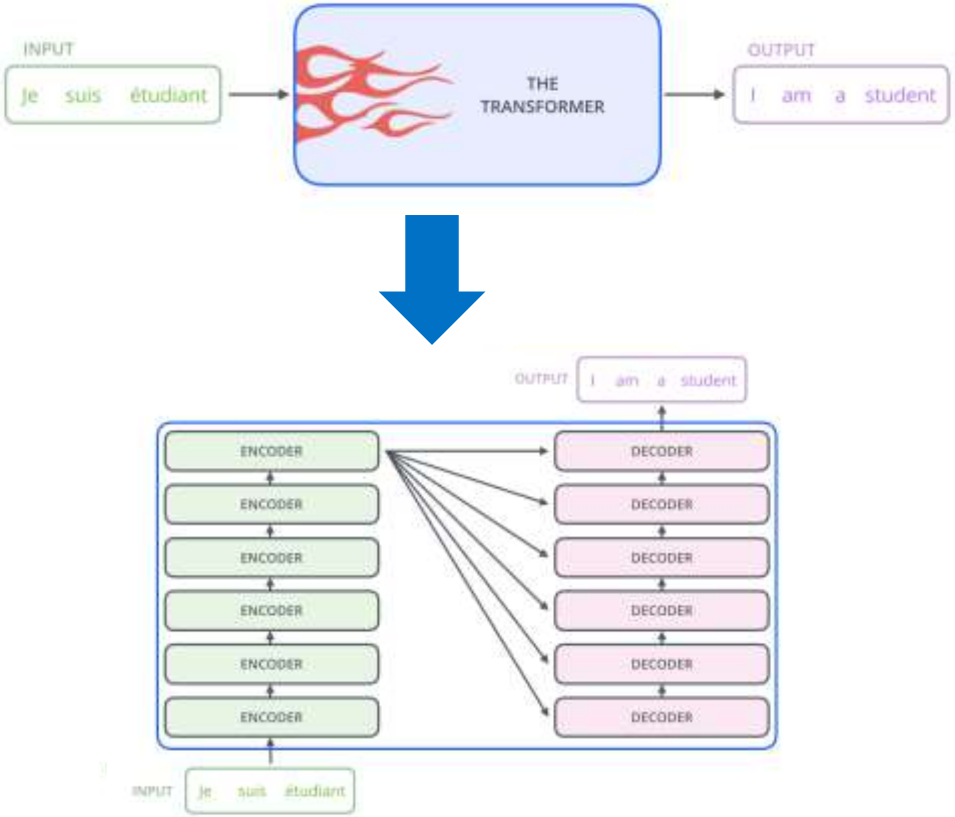
- Language modeling with context ‘around’ a word
- Transfer learning applies to downstream tasks

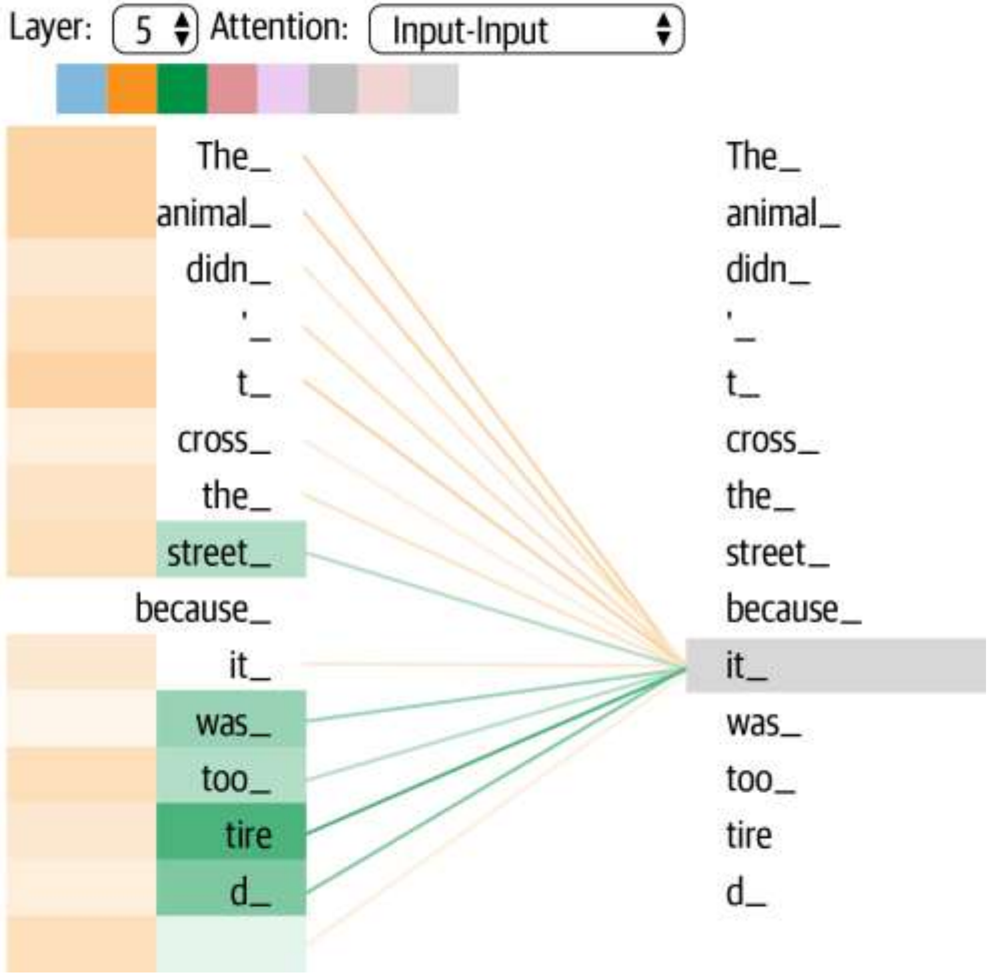


Christopher Colah: [Understanding LSTM Networks]
Jacob, et. Al “[BERT Pre-Training Paper]”

Transformer (motivation)

Self-Attention Mechanism



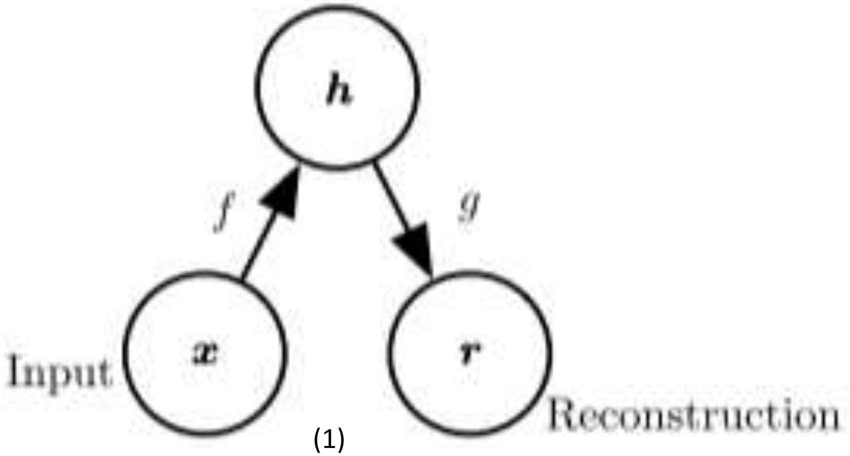


Jay Alammar: [The Illustrated Transformer]

Autoencoder

Learning Compressed Vector Representation

- Unsupervised learning
- Mapping a function of input to the output
- Reconstruct back to the output
- Example: Vector representation of text
  - Post training: collect the vector representation as a dense vector of the input text



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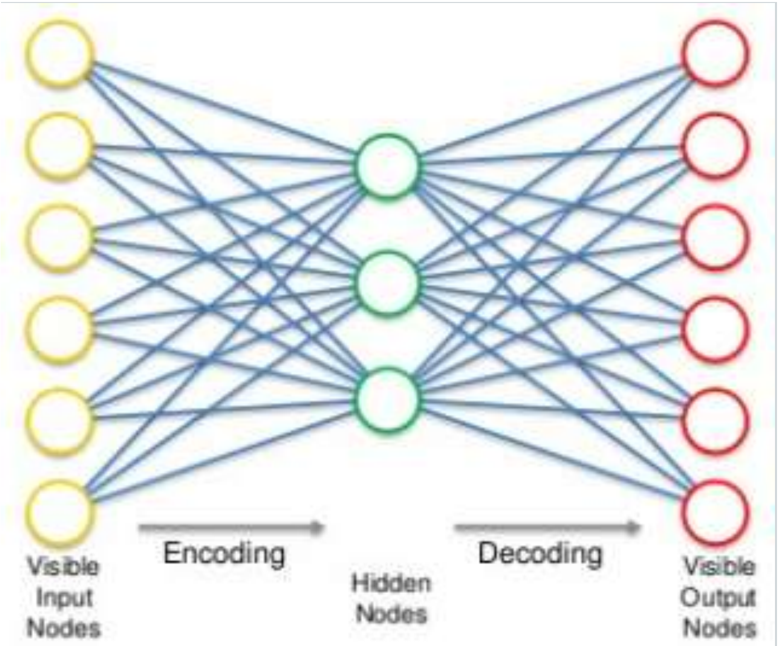
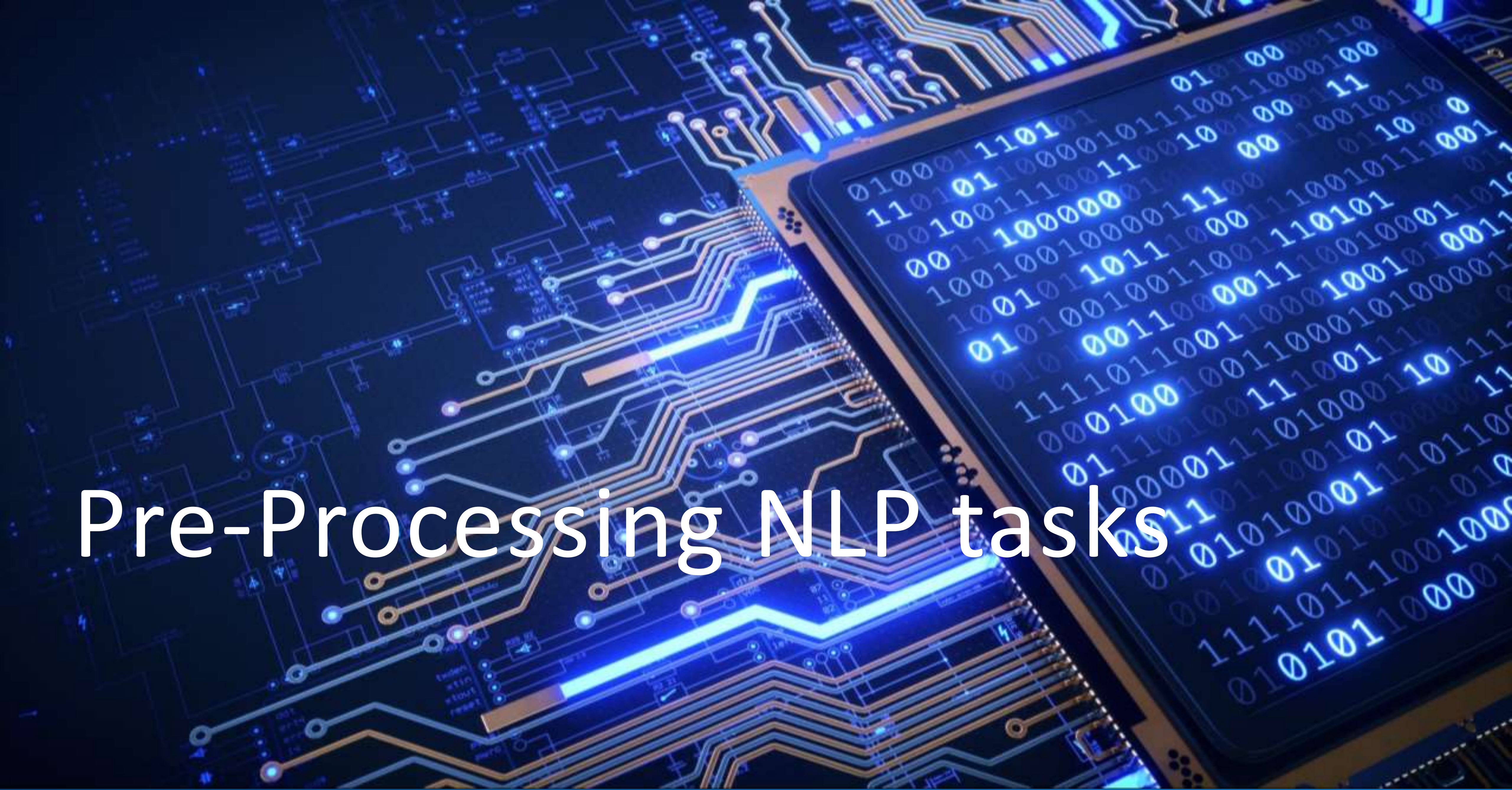


(2)

Ref:
1) Ian Goodfellow, "[The Deep Learning Book]"
2) Kirill Eremenko, [Auto Encoder]

Pre-Processing NLP tasks



Back at 12:15pm (Pacific)

NLP Preprocessing Tasks

Tokenization

- Splitting text into meaningful units (words, symbols)

POS tagging

- Words->Tokens (verbs, nouns, prepositions)

Dependency Parsing

- Labeling relationship between tokens

Chunking

- Combine related tokens ("San Francisco")

Lemmatization

- Convert to base form of words (slept -> sleep)

Stemming

- Reduce word to its stem (dance -> danc)

Named Entity Recognition

- Assigning labels to known objects: Person, Org, Date

Entity Linking

- Disambiguating entities across texts

NLP Tasks: Working through examples

Start with clean text, without immaterial items, such as HTML tags from web scraped corpus.

Normalize

- Normalize text by converting it to all lower case, removing punctuation, & extra white spaces

Tokenize

- Split text into words, n-grams, or phrases (tokens)

"I love morning runs"
- Unigrams: "I", "love", "morning", "runs"
- Bigrams (n=2): "I love", "love morning", "morning runs"
- Trigrams (n=3): "I love morning", "love morning runs"

Remove Stop words

- Remove common words like "a", "the", "and", "on", etc.

Stemming

- Convert to stem

ex. Dancer, dancing, dance become 'danc'
Studies, Study, Studying: Stud

POS, NER

- Identify Parts of Speech (POS), such as verb, noun, named entity
- Lemmatization: root word (am, are, is >> be)

Example: Raw tweet	Preprocessed output
@huggingface is building a fantastic library of NLP datasets and models at http://huggingface.com	Build fantastic library NLP dataset model

Top NLP Packages

NLTK

- Preprocessing: Tokenizing, POS-tagging, Lemmatizing, Stemming
- Cons: Slow, not optimized

Gensim

- Specialized, optimized library for topic-modeling and document similarity

spaCy

- ”Industry-ready” NLP modules.
- Optimized algorithms for tokenization, POS tagging
- Text parsing, similarity calculation with word vectors

Huggingface – Transformers / Datasets (Day 2)

Starting from scratch

Normalization: convert every letter to a common case so each word is represented by a unique token

```
text = text.lower()
text = re.sub(r"[^a-zA-Z0-9]", " ", text)
```

Token: Implies symbol, splitting each sentence into words

```
text = text.split()
```

```
from nltk.tokenize import word_tokenize
words = word_tokenize(text)
```

NLTK: Split text into sentences

```
from nltk.tokenize import sent_tokenize
sentences = sent_tokenize(text)
```

Stop-word removal

Stop-word removal

```
from nltk.corpus import stopwords
print(stopwords.words("english")
words = [w for w in words if not in stopwords.words("english")
```

Parts of speech tagging

```
from nltk import pos_tag
sentence = word_tokenize("Start practicing with small code.")
pos_text = pos_tag(sentence)
```

Name Entity Recognition (NER) to label names (used for indexing and searching for news articles)

```
from nltk import ne_chunk
ne_chunk(pos_text)
```

Normalizing word variations

1. Stemming: reducing words to their stem or root

```
from nltk.stem.porter import PorterStemmer
stemmed = [PorterStemmer().stem(w) for w in words]
print(stopwords.words("english")
words = [w for w in words if not in stopwords.words("english")
```

2. Lemmization

```
from nltk.stem.wordnet import WordNetLemmatizer
lemmed = [WordNetLemmatizer().lemmatize(w) for w in words]
lemmed = [WordNetLemmatizer().lemmatize(w, pos='v') for w in lemmed]
```

Name Entity Recognition (NER) to label names (used for indexing and searching for news articles)

```
from nltk import ne_chunk
ne_chunk(pos_text)
```

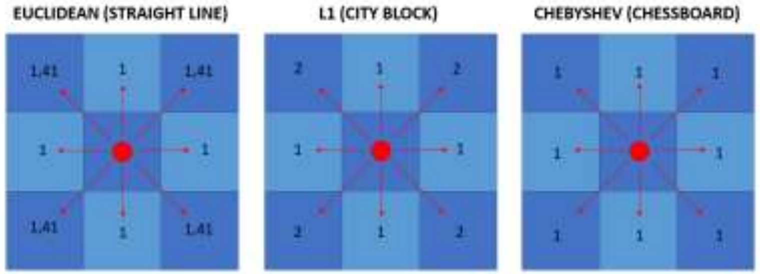
Lab

Google Colab:

1. `01_NLP_basics.ipynb`

Distance Similarity

Measuring distances: Euclidean, L1, & L-Infinity



- Euclidean Distance:
  - Computing the diagonal between the two points
  - Pythagoras theorem

$$dist(A, B) = \sqrt[2]{(x_A - x_B)^2 + (y_A - y_B)^2}$$

$$dist(A, B) = |x_A - x_B| + |y_A - y_B|$$

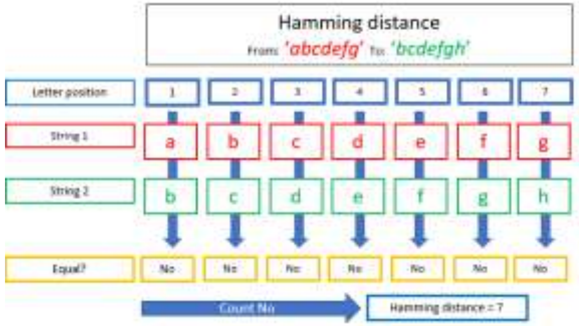
- L1 Distance
  - Also known as "Cityblock distance"
  - Measures distance only along straight lines

$$dist(A, B) = \max((|x_A - x_B|, |y_A - y_B|))$$

- Chebyshev Distance
  - Also known as L-Infinity or Chessboard distance
  - Can go one step in any direction

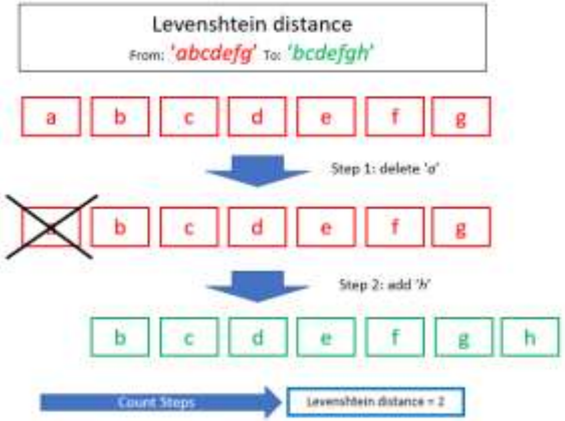
Ref: https://towardsdatascience.com/3-distances-that-every-data-scientist-should-know-59d864e5030a

Distance between texts



Hamming Distance

- Compares every letter of two strings based on position



Levenshtein Distance

- Given by the number of ops required to convert one string to another
  - Inserting, Deleting, Substituting characters

Cosine Distance

- Applies to vector representation of documents
  - Uses a word count vectorizer

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|}$$

	1	2	3
i	1	1	1
love	1	1	0
going	1	1	1
to	1	1	1
the	1	0	0
movies	1	0	0
work	0	1	1
why	0	0	1
is	0	0	1
it	0	0	1
always	0	0	1
raining	0	0	1
when	0	0	1
am	0	0	1

```
In [3]: from sklearn.metrics import pairwise

In [4]: vector_1 = [1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0]
        vector_2 = [1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0]
        vector_3 = [1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1]

In [5]: matrix = [vector_1, vector_2, vector_3]

In [6]: pairwise.cosine_similarity(matrix)

Out[6]: array([[1.        , 0.81649658, 0.36927447],
               [0.81649658, 1.        , 0.45226702],
               [0.36927447, 0.45226702, 1.        ]])
```


Ref: https://towardsdatascience.com/3-text-distances-that-every-data-scientist-should-know-7fcdf850e510

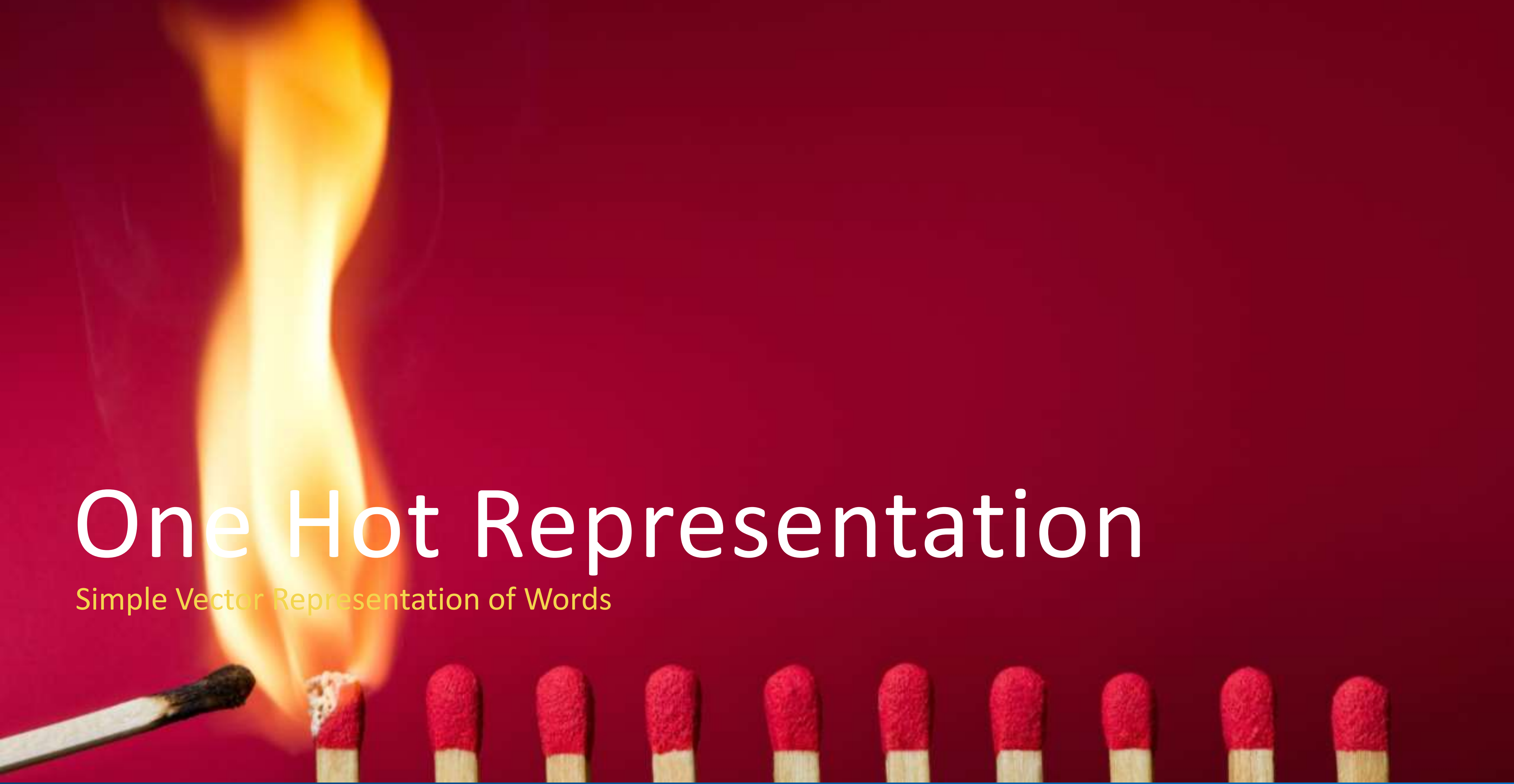
Sentiment Analysis

Text Classification

Text Classification with Neural Networks

Tokenize	Tokenize the document into words
Represent	Represent word in numeric encoding
Collect	Collect into a Tensor to represent a document

- One Hot Encoding
- Frequency
- Prediction



One Hot Representation

Simple Vector Representation of Words

One Hot Representation: Vector Representation of Words

Fundamental Idea

- Assume we have a toy 100-word vocabulary
- Associate to each word an index value between 1 to 100
- Each word is represented as a 100-dimension array-like representation
- All dimensions are zero, except for one corresponding to the word

Vocabulary
seat: 1
gear: 2
car: 3
seats: 4
auto: 5
engine: 6
belt: 7
…
chassis: 100

	1	2	3	4	5	…	100
gear							
seat							
seats							
…							
chassis							
auto							

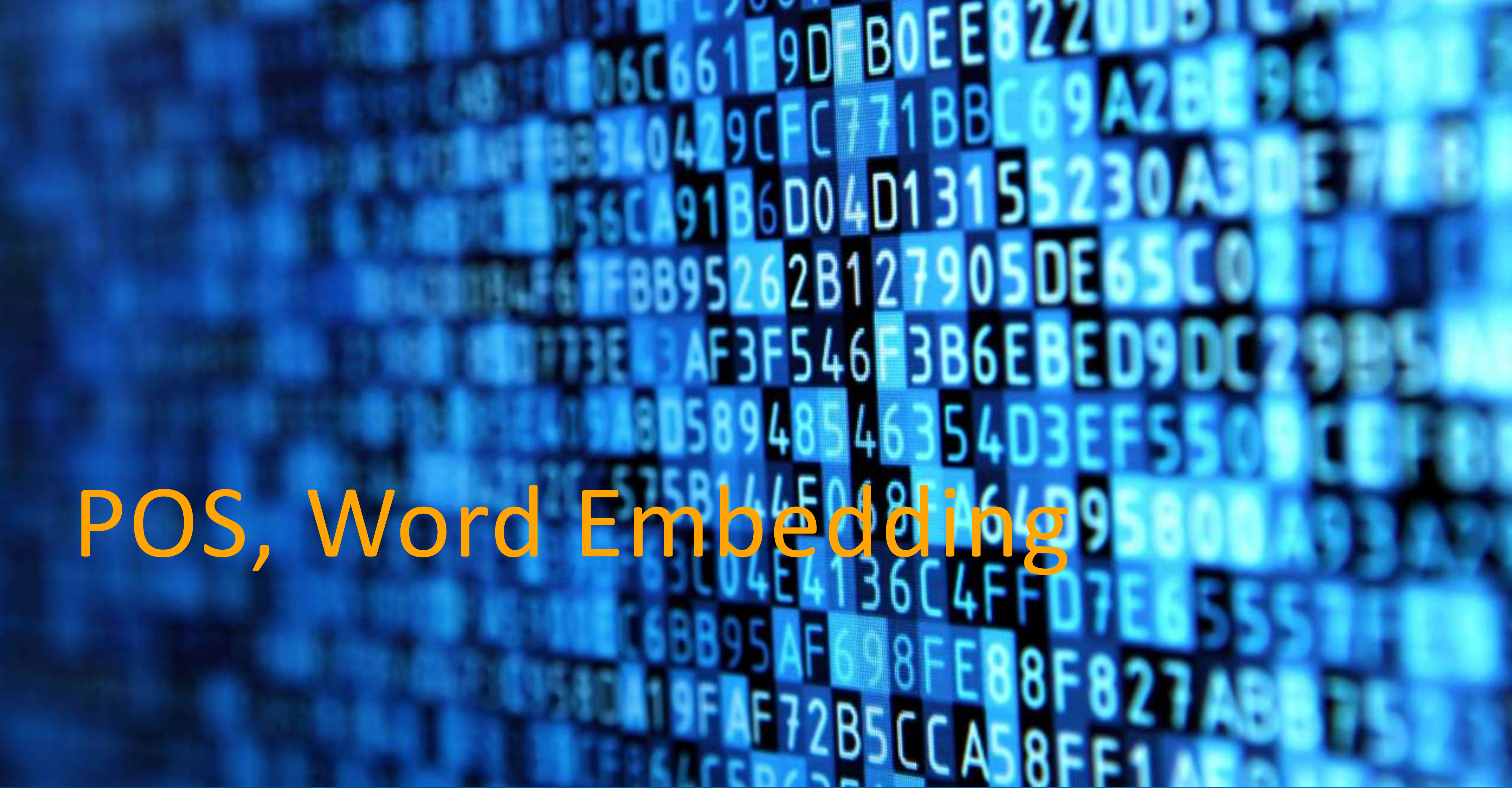
Challenges with this approach:

- Curse of dimensionality: Memory capacity issues
  - The size of the matrix is proportionate to vocab size (there are roughly 1 million words in the English language)
- Lack of **meaning** representation or word **similarity**
  - Hard to extract meaning. All words are equally apart
    - “seat” and “seats” vs “car” and “auto” (former resolved with stemming and lemmatization)

Lab

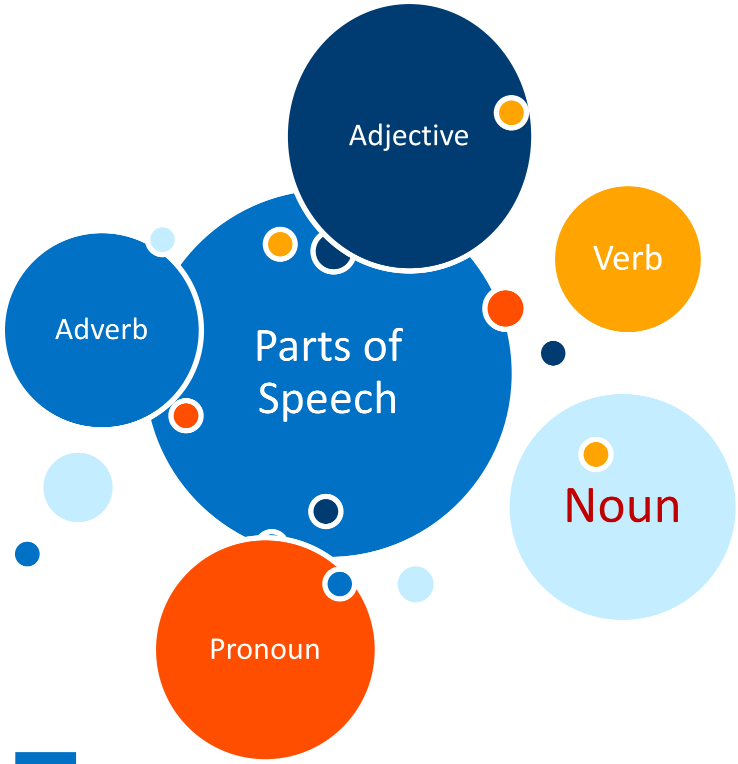
Google Colab:

- `02_inefficient.ipynb`



POS, Word Embedding

Parts of Speech Tagging



Rule based
- ~1k+ constraints

Transformation

Stochastic
- Training corpus
- Probability of certain tag occurring

One tag for each part of speech

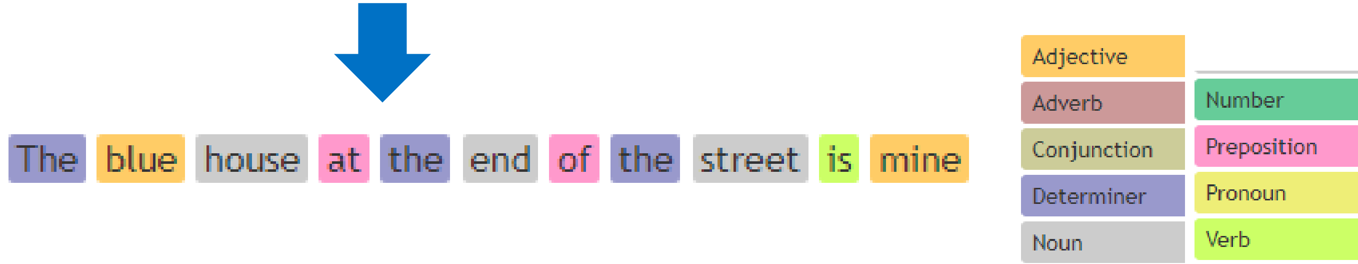
- Choose a courser tagset (~6 is useful)
- Finely grained tagsets exist (ex. Upenn Tree Bank II)

Sentence: "Flies like a flower"

- flies: Noun or Verb?
- like: preposition, adverb, conjunction, noun or verb?
- a: article, noun, or preposition
- flower: noun or verb?

https://parts-of-speech.info/

"The blue house at the end of the street is mine."



Word Embeddings

Techniques to convert text data to vectors

Frequency based

- Count Vector
- TF-IDF
- Co-occurrence Vector

- Count based feature engineering strategies (bag of words models)
- Effective for extracting features
- Not structured
    - Misses semantics, structure, sequence & nearby word context
- 3 main methods covered in this lecture. There are more…

Prediction based Word2Vec

- CBOW
- Skip-Gram

- Capture meaning of the word
- Semantic relationship with other adjacent words
    - Deep Learning based model computes distributed & dense vector representation of words
- Lower dimensionality than bag of words model approach
- **Alternative:** GloVe

Word Embedding

Frequency based

Count Vector

Doc 1	"The athletes were playing"
Doc 2	"Ronaldo was playing well"

	The	Athlete	was	playing	Ronaldo	well
Doc 1	1	1	1	1	0	0
Doc 2	0	0	1	1	1	1

- Real-world corpus can be millions of documents & 100s M unique words resulting in a very sparse matrix.
- Pick top 10k words as an alternative.

TF-IDF vectorization

Document 1: "This is about cars"
Document 2: "This is about kids"

Term	Count		TF-IDF
	Doc1	Doc2	Doc 1 example
This	2	1	2/8*log(2/2) = 0
is	3	2	3/8*log(2/2) = 0
about	1	2	1/8*log(2/2) = 0
Kids	0	4	
cars	2	0	2/8*log(2/1) = 0.075
Terms	8	9	

$$\left.\begin{array}{l} TF = \dfrac{\#\ times\ term\ T\ appears\ in\ the\ document}{\#\ of\ terms\ in\ the\ document, m} \\[2ex] IDF = \left(\dfrac{Number\ of\ documents, N}{Numer\ of\ documents\ in\ which\ term\ T\ appears, n}\right) = \log\left(\dfrac{N}{n}\right) \end{array}\right\} \text{Calculate } TF\ x\ IDF$$

- Term frequency across corpus accounted, but penalizes common words
- Words appearing only in a subset of document are weighed favorably

Co-Occurrence Vector

"He is not lazy. He is intelligent. He is smart"

	He	is	not	lazy	intelligent	smart
He	0	[illegible]	2	1	2	1
is	4	0	1	2	2	1
not	2	1	0	1	0	0
lazy	1	2	1	0	[illegible]	0
intelligent	2	2	0	0	0	0
smart	1	1	0	0	0	0

He	is	not	lazy	He	is	intelligent	He	is	smart
He	is	not	lazy	He	is	intelligent	He	is	smart
He	is	not	lazy	He	is	intelligent	He	is	smart
He	is	not	lazy	He	is	intelligent	He	is	smart

$$\underset{m\ x\ n}{\overset{\hat{X}}{\begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix}}} \approx \underbrace{\underset{m\ x\ r}{\overset{U}{\begin{pmatrix} u_{11} & \cdots & u_{1r} \\ \vdots & \ddots & \vdots \\ u_{m1} & \cdots & u_{mr} \end{pmatrix}}} \underset{r\ x\ r}{\overset{S}{\begin{pmatrix} s & 0 & \cdots \\ 0 & \ddots & \\ & & s_{rr} \end{pmatrix}}}}_{\text{Word-vector representation}} \underbrace{\underset{r\ x\ n}{\overset{V^T}{\begin{pmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{r1} & \cdots & v_{rn} \end{pmatrix}}}}_{\text{Context}}$$

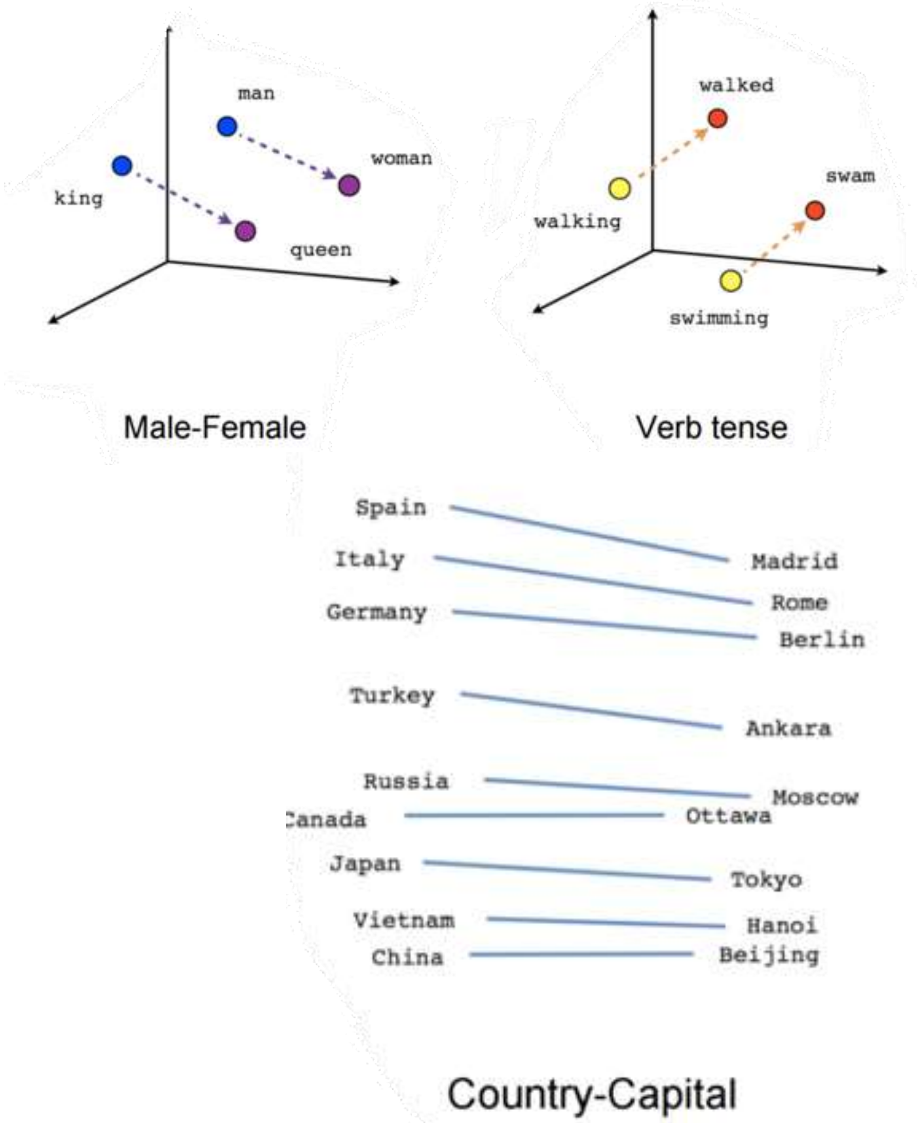
m: # of terms
n : m minus stop words
- Uses SVD decomposition and PCA to reduce dimensionality

- Similar words tend to occur together: "Airbus is a plane", "Boeing is a plane"
- Calculates the # of times words appear together in a context window

Prediction based Word Embedding

Key Idea: Words share context

- Embedding of a word in the corpus (numeric representation) is a function of its related words – words that share the same context
- Examples: “word” => (embeddings)
  - “car” => (“road”, “traffic”, “accident”)
  - “language” => (“words”, “vocabulary”, “meaning”)
  - “San Francisco” => (“New York”, “London”, “Paris”)



Reference: https://arxiv.org/abs/1301.3781
(Efficient Estimation of Word Representations in Vector Space)

Learning Outcomes for Session 2

Diving into Word2Vec

- 15min: CBOW & Skip-Gram
- 15min: Word2Vec lab with Gensim

spaCy library

- 30min: What it is, why it's important, key features, and when it's useful
- 30min: Hands-On: spaCy foundations, diving deep, and pipelines

PyTorch

- 10min: Intro - exercises
- 20min: Backpropagation – Autograd

Word Vectors

Moving beyond OHE

Vector Space Models

- Vector representation of words
  - [2013]Series of 3 papers from Google describing the Skip-gram model
  - For each input word, map to a vector
  - Output word: Framed as a prediction task
  - Given a word, which other words are around it within a context – turns into a classification task
  - Each input word is 'classified' into as many words as in the dictionary

Distributed Representations of Words and Phrases and their Compositionality

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Abstract

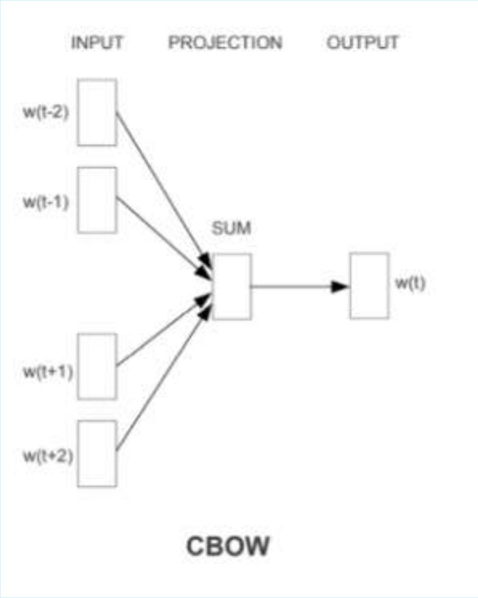
The recently introduced continuous Skip-gram model is an efficient method for learning high-quality distributed vector representations that capture a large number of precise syntactic and semantic word relationships. In this paper we present several extensions that improve both the quality of the vectors and the training speed. By subsampling of the frequent words we obtain significant speedup and also learn more regular word representations. We also describe a simple alternative to the hierarchical softmax called negative sampling.

An inherent limitation of word representations is their indifference to word order and their inability to represent idiomatic phrases. For example, the meanings of "Canada" and "Air" cannot be easily combined to obtain "Air Canada". Motivated by this example, we present a simple method for finding phrases in text, and show that learning good vector representations for millions of phrases is possible.

Word Embedding

Prediction based
Word2Vec

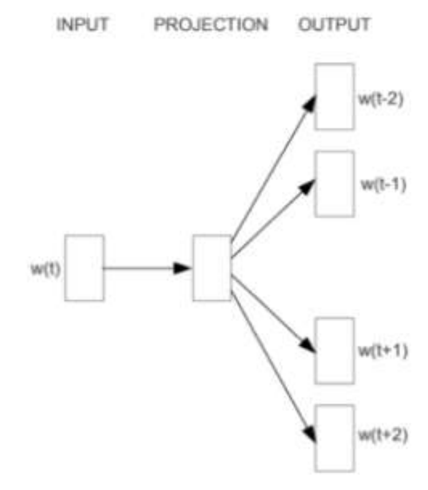
CBOW



https://arxiv.org/pdf/1301.3781.pdf

- The distributed representation of the surrounding words are combined to predict the word in the middle
- Input word is OHE vector of size V and hidden layer is of size N
- Pairs of context window & target window
- Using context window of 2, let's parse:
  - "The quick brown fox jumps over the lazy dog"
    - "quick __ fox": ([quick, fox], brown)
    - "the __ brown": ([the, brown], quick)
- Tip: Use a framework to implement (ex. Gensim)

Skip-Gram



- The distributed representation of the input word is used to predict the context
- Mikolov (Google) introduced in 2013
- Works well with small data but CBOW is faster
- Using context window of 2, let's parse:
  - "The quick brown fox jumps over the lazy dog"
    - "__ brown __" (brown => [quick, fox])
    - "___ quick ___" (quick => [the, brown])

Representing words by their context

Recap

- We saw the challenges with One Hot Encoding
- We want to build a dense vector for each word
  - $banking = \begin{pmatrix} 0.182 \\ 0.232 \\ 0.725 \\ 0.375 \\ 0.982 \\ 0.245 \end{pmatrix}$
- Encoding Similarity in the vectors
- **Distributed** representation (these are all the same):
  - Word Vectors
  - Word Embeddings
  - Word Representation

Large corpus of Text

Word Vector representation

Center word c

- Context words o

Calc Pr(o | c)

- Using word vectors similarity
- Keep adjusting word vectors to max Pr(o|c)

Skip-Gram Objective Function

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c, j\neq 0}\log P(w_{t+j}|w_j)$$

c **is the size of the training context**

Processing windows for Word2Vec Computing

$-3 \leq j \leq 3$

$P_r(w_{t+j}|w_t)$

… deposits into local currency have occurred during banking crises

context

center word

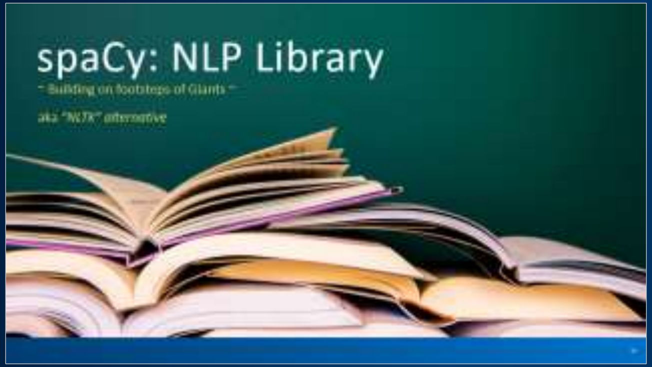
context

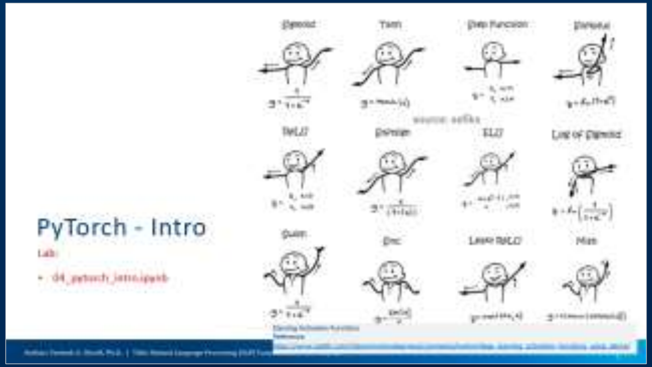
… deposits into local currency have occurred during banking crises

… deposits into local currency have occurred during banking crises

- Word2Vec Papers:
  - Efficient Estimation of Word Representations in Vector Space: https://arxiv.org/abs/1301.3781

Part 2: Practicum





spaCy: NLP Library

~ Building on footsteps of Giants ~

aka *“NLTK” alternative*

What is spaCy & Why Use it?

spaCy is *fast, accurate, with integrated word vectors.*

- Batteries included: Use the built-in tokenizer. Can add special tokens
- Pipeline approach: Part-of-speech tagging, and parsing requires a model

But what about Huggingface Transformers?

- We will cover Transformers in a later session – both are valuable, depending on your use case. spaCy 3.0 now has Transformer support, while Huggingface has more support for data pre-processing

What about NLTK?

- A very useful library for everything, but it misses the ‘glue’ that spaCy and Huggingface provide. Taking NLTK into production is more of a challenge, but it’s a very good first step to *learn* about the pre-processing steps

- Support for **70+ languages**
- **58 trained pipelines** for 18 languages
- Multi-task learning with pretrained **transformers** like BERT
- Pretrained **word vectors**
- State-of-the-art speed
- Production-ready **training system**
- Linguistically-motivated **tokenization**
- Components for **named entity** recognition, part-of-speech tagging, dependency parsing, sentence segmentation, **text classification**, lemmatization, morphological analysis, entity linking and more
- Easily extensible with **custom components** and attributes
- Support for custom models in **PyTorch**, **TensorFlow** and other frameworks
- Built in **visualizers** for syntax and NER
- Easy **model packaging**, deployment and workflow management
- Robust, rigorously evaluated accuracy

Getting started with spaCy

```
python -m spacy download 'en_core_web_sm'
```

```
import spacy
nlp = spacy.load('en_core_web_sm')
```

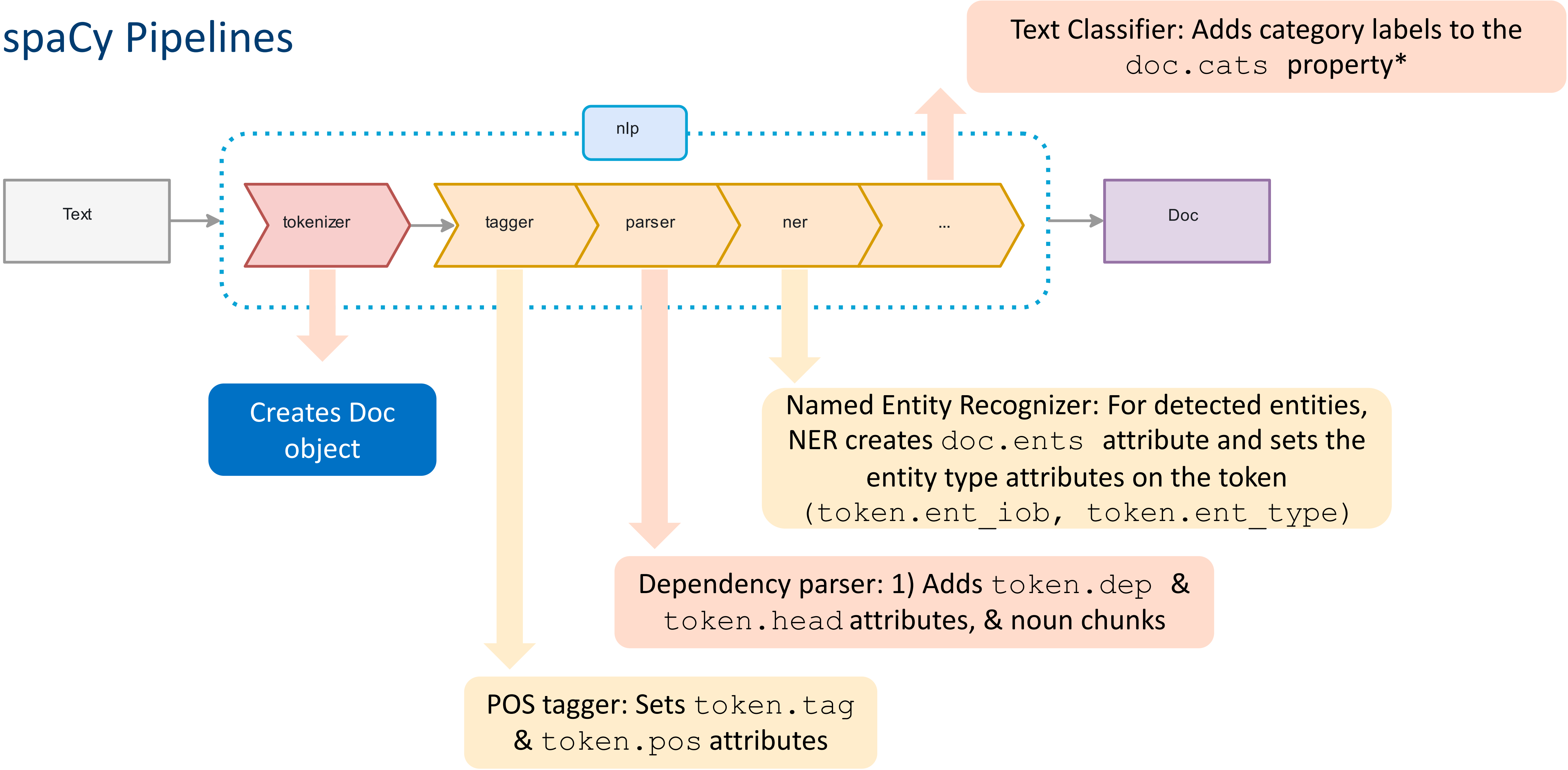
```
# Process whole documents
text = ("When Sebastian Thrun started working on self-driving cars at "
        "Google in 2007, few people outside of the company took him "
        "seriously. “I can tell you very senior CEOs of major American "
        "car companies would shake my hand and turn away because I wasn’t "
        "worth talking to,” said Thrun, in an interview with Recode earlier "
        "this week.")
doc = nlp(text)

# Analyze syntax
print("Noun phrases:", [chunk.text for chunk in doc.noun_chunks])
print("Verbs:", [token.lemma_ for token in doc if token.pos_ == "VERB"])

# Find named entities, phrases and concepts
for entity in doc.ents:
    print(entity.text, entity.label_)
```

spaCy: https://spacy.io/

spaCy Pipelines



*Not part of any pre-trained models

Spacy Models

meta.json

```
{
  "lang": "en",
  "name": "core_web_sm",
  "pipeline": ["tagger", "parser", "ner"]
}
```

Model	Size	Type
en_core_web_sm	11 MB	**Small:** Multi-task CNN trained on OntoNotes.
en_core_web_md	48 MB	**Medium:** Multi-task CNN trained on OntoNotes, with GloVe vectors trained on Common Crawl – 20k unique vectors for 685k keys
en_core_web_lg	746MB	**Large:** Multi-task CNN trained on OntoNotes, with GloVe vectors trained on Common Crawl - – 685k unique vectors & keys

```
nlp.pipe_names
```

```
['tok2vec', 'tagger', 'parser', 'ner', 'attribute_ruler', 'lemmatizer']
```

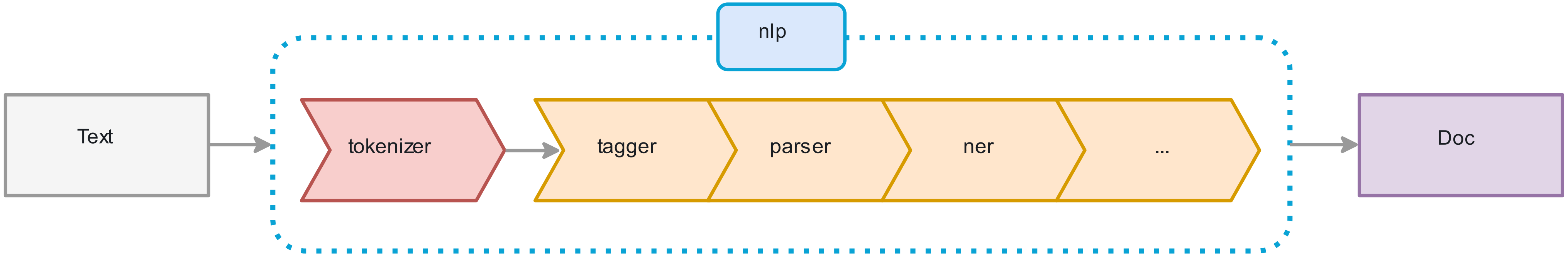
Functions applied to the Doc & set attributes

```
nlp.pipeline
```

```
[('tok2vec', <spacy.pipeline.tok2vec.Tok2Vec at 0x7f8329aaf810>),
 ('tagger', <spacy.pipeline.tagger.Tagger at 0x7f8329ab0bd0>),
 ('parser', <spacy.pipeline.dep_parser.DependencyParser at 0x7f832b2f5820>),
 ('ner', <spacy.pipeline.ner.EntityRecognizer at 0x7f8327284ac0>),
 ('attribute_ruler',
  <spacy.pipeline.attributeruler.AttributeRuler at 0x7f83294bca80>),
 ('lemmatizer',
  <spacy.lang.en.lemmatizer.EnglishLemmatizer at 0x7f832d2ed740>)]
```

spaCy Models: https://spacy.io/models/en

spaCy Custom Components



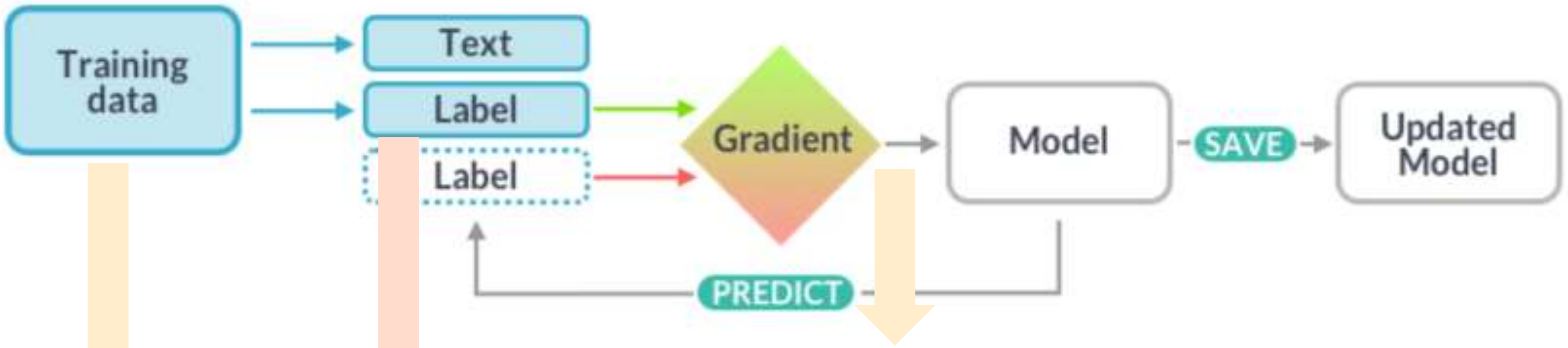
Custom components are executed when nlp(“text”) is called

```
nlp = spacy.load("en_core_web_sm")
def my_component(doc):
  print("Doc length:", len(doc))
  return doc

nlp.add_pipe(my_component, first=True)
print("Pipeline:", nlp.pipe_names)
# Output
# Pipeline: ['my_component', 'tagger', 'parser', 'ner']
```

- `nlp.add_pipe(component, last=True)`
- `nlp.add_pipe(component, first=True)`
- `nlp.add_pipe(component, before=“ner”)`
- `nlp.add_pipe(component, after=“tagger”)`

Training



Changing the weights

Input text and the label for prediction

Examples with annotations (labels)

Parts of the pipeline can be disabled during training

Training examples:

```
training_data = [
    ("iPhone X is coming", {"entities": [(0, 8, "GADGET")]}),
    ("I need a new phone! Any tips?", {"entities": []})
    ]
```

Universal Parts of Speech Tagging

spaCy Documentation:

- The individual mapping is specific to the training corpus and can be defined in the respective language data's `tag_map.py`.

Reference:

- https://spacy.io/api/annotation

Universal Part-of-speech Tags

spaCy maps all language-specific part-of-speech tags to a small, fixed set of word type tags following the Universal Dependencies scheme. The universal tags don't code for any morphological features and only cover the word type. They're available as the `Token.pos` and `Token.pos_` attributes.

POS	DESCRIPTION	EXAMPLES
ADJ	adjective	big, old, green, incomprehensible, first
ADP	adposition	in, to, during
ADV	adverb	very, tomorrow, down, where, there
AUX	auxiliary	is, has (done), will (do), should (do)
CONJ	conjunction	and, or, but
CCONJ	coordinating conjunction	and, or, but
DET	determiner	a, an, the
INTJ	interjection	psst, ouch, bravo, hello
NOUN	noun	girl, cat, tree, air, beauty
NUM	numeral	1, 2017, one, seventy-seven, IV, MMXIV
PART	particle	's, not,
PRON	pronoun	I, you, he, she, myself, themselves, somebody
PROPN	proper noun	Mary, John, London, NATO, HBO
PUNCT	punctuation	., (,), ?
SCONJ	subordinating conjunction	if, while, that
SYM	symbol	$, %, §, ©, +, −, ×, ÷, =, :), 😝
VERB	verb	run, runs, running, eat, ate, eating
X	other	sfpksdpsxmsa
SPACE	space	

Objective:

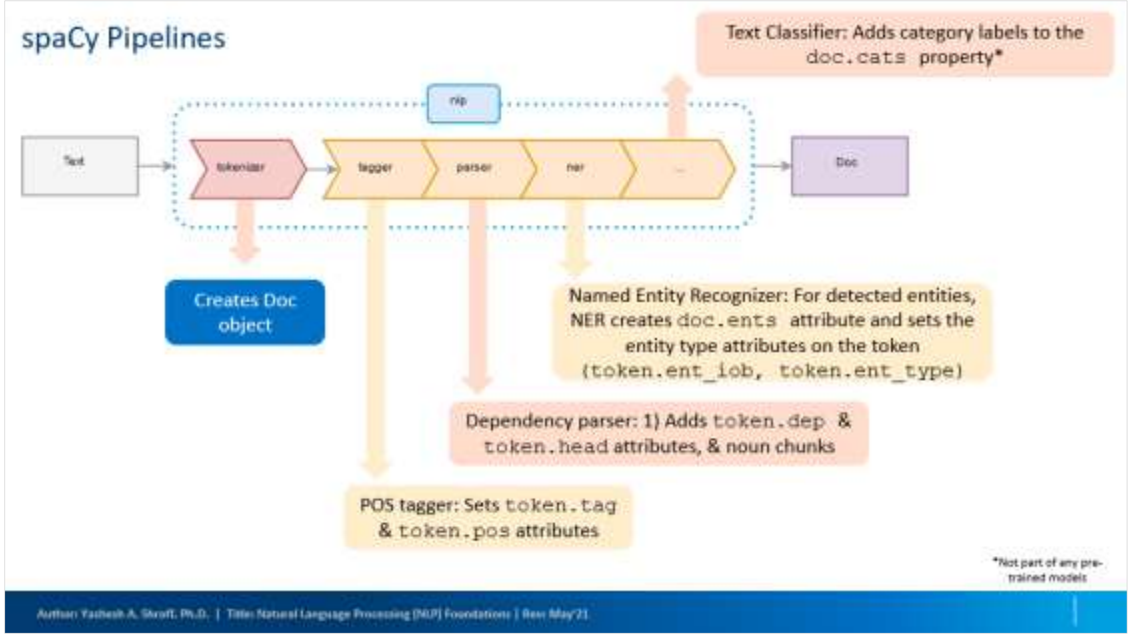
- Covered in lecture
    - Word–Embedding. Tokenization:
- NER: showing country
- POS
- Powered Regex with NER

spaCy

Lab:

- 03_spaCy.ipynb

Our Journey So Far



Pre-Processing

- (Tagging, Parts of Speech, Name Entity Recognition)

Vector Space Models

- Adding your own custom pipelines (Text Categorization example)

Word Embedding with Word2Vec

- Continuous Bag of Words
- Skip-Gram

Practicum with GloVe Word Embedding

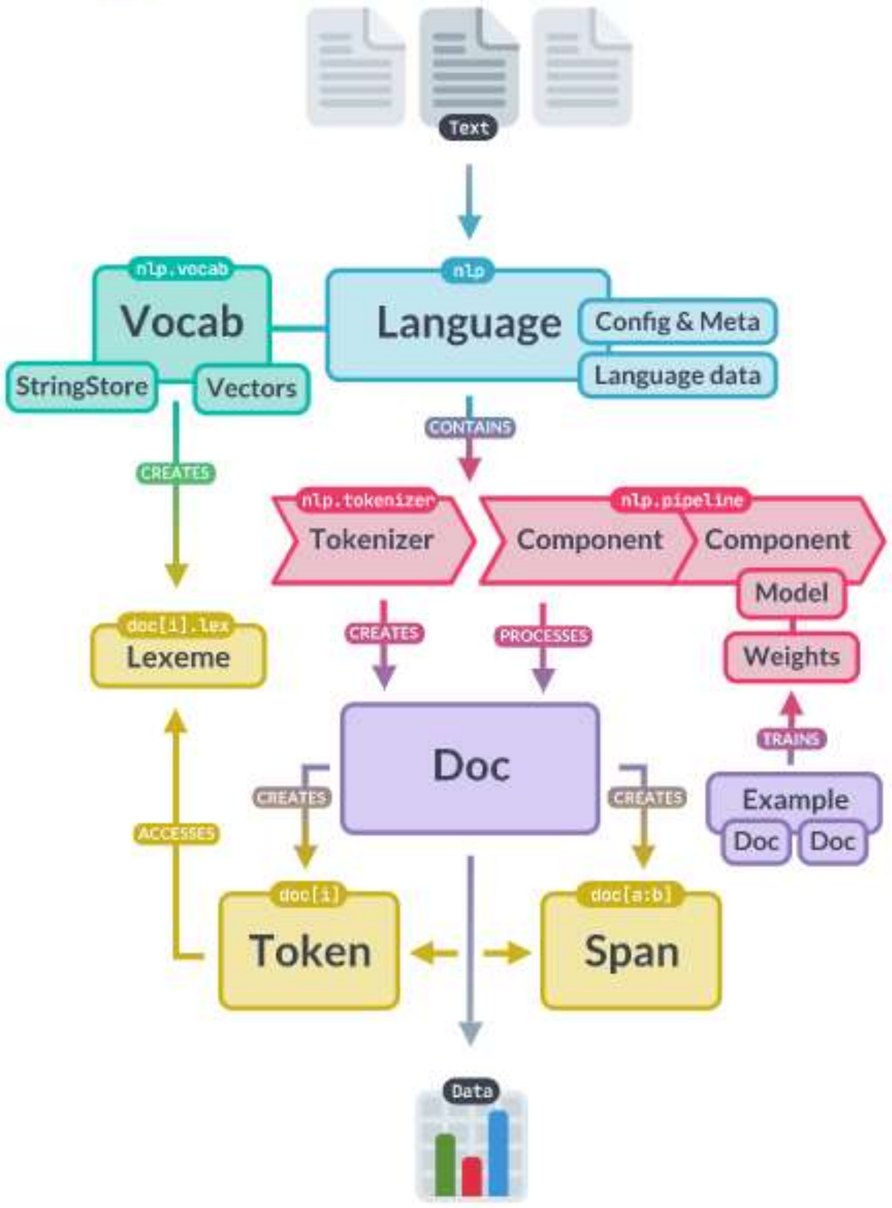
Where do you go from here with spaCy?

Keep practicing with sample text and code

Remember that spaCy is primarily about “Language” (NLP), “Vocab”, and “Doc” objects.

Pre-Processing:

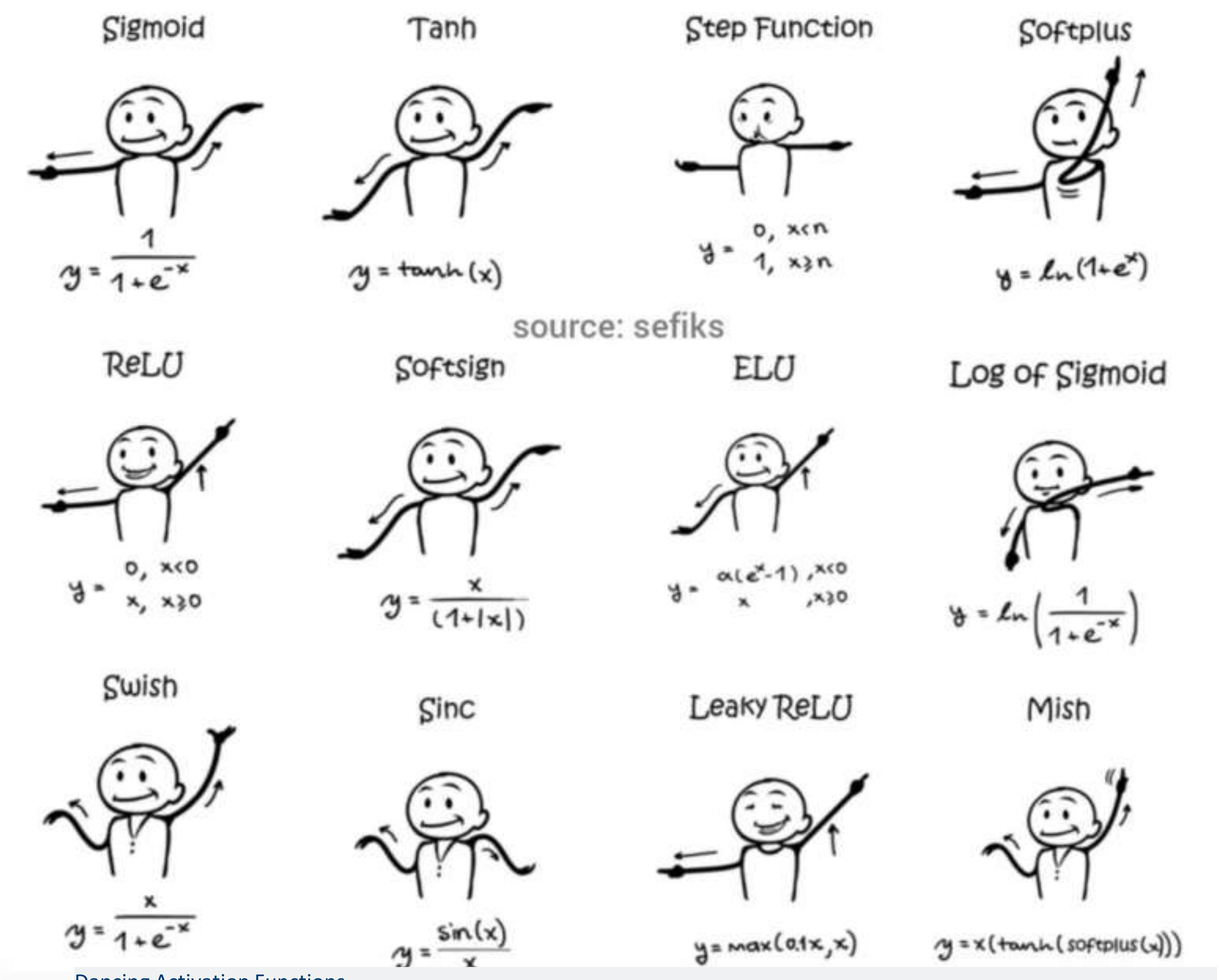
- This [tutorial](#) may be helpful



PyTorch - Intro

Lab:

- 04_pytorch_intro.ipynb



Dancing Activation Functions
Reference:
https://www.reddit.com/r/learnmachinelearning/comments/lvehmi/deep_learning_activation_functions_using_dance/

Deep Learning Frameworks

Top Frameworks

- PyTorch ⇐ Facebook
- Tensorflow/Keras ⇐ Google
- MXNet ⇐ Amazon
- Caffe ⇐ BAIR (now part of PyTorch)
- PaddlePaddle ⇐ Baidu

About PyTorch

- A deep learning framework originally built on Lua programming language and converted to Python
- Utilizes GPU as a replacement for Numpy (CPU)
- Imperative programming model (dynamic graph, generated at each step)
- Utilizes `tensor` as core data structure (similar to Numpy `ndarrays`)

Fundamentals of PyTorch

- Imperative Programming ➔ Computations are performed on the fly. This means code debugging is easier
- Graphs are not compiled ➔ Neural network is generated at runtime. TensorFlow uses a static graph representation
- Tensors and Numpy Arrays occupy the **same** memory space. Zero cost of conversion
- Building a Neural Net
  - Forward pass
    - Activations $z = w * x + b$
    - Affine transformations $a = sigmoid(z), a = \tanh(z)\,, a = ReLU(z), \ldots$
  - Loss calculation
    - $loss = MSE(y_{pred}, y_{actual}), MAE(\ldots)$
  - Back Prop

PyTorch Fundamentals

```
# 2D tensors
x = torch.tensor([[3.0, 8.0], [2.3, 1.4]])
print(m)

# 3D tensors
y = torch.tensor([[[3., 2.], [2., 1.]],
  [[2., 3.], [2., 0.]]])

print(x.shape)
print(y.shape)

# Indexing into the tensors
print(z[2])
print(z[1:3])

print(x[1][0]) # 2D
print(y[1][0][0]) # 3D
```

```
# Create a numpy array

x = np.array([[1, 2, 3], [3, 4, 5]])

Convert to torch tensor
y = torch.from_numpy(x)

# Convert torch to numpy
z = y.numpy()
```

```
t1 = torch.tensor([[1, 2, 3], [2, 3, 4]])
t2 = torch.tensor([[1, 2, 3], [2, 3, 4]])
print(t1 + t2) # normal addition works
print(torch.add(t1, t2)) # addition
print(torch.sub(t1, t2)) # subtraction
print(torch.mm(t1, t2)) # multiplication
print(t1/t2) # Division

a = torch.rand(3)
torch.sqrt(a)
tensor([nan, 1.02, 0.2, 0.33])
```

PyTorch Modules

Loading Dataset

- **torch.utils.data.Dataset**
- **torch.utils.data.DataLoader**

```
DataLoader(dataset, batch_size=1, shuffle=False, sampler=None,
           batch_sampler=None, num_workers=0, collate_fn=None,
           pin_memory=False, drop_last=False, timeout=0,
           worker_init_fn=None, *, prefetch_factor=2,
           persistent_workers=False)
```

Defining the Neural Network

- **torch.nn**
- **torch.optim** (update weight & biases)
- **torch.autograd** (backward pass to compute gradients)

torch.nn

- Containers
- Convolution Layers
- Pooling layers
- Padding Layers
- Non-linear Activations (weighted sum, nonlinearity)
- Non-linear Activations (other)
- Normalization Layers
- Recurrent Layers
- Transformer Layers
- Linear Layers
- Dropout Layers
- Sparse Layers
- Distance Functions
- Loss Functions
- Vision Layers
- DataParallel Layers (multi-GPU, distributed)
- Utilities
- Quantized Functions

Saving & Conversion

- **torch.save**
- **Convert to ONNX**

Other modules

- `torchtext`
- `torchvision`
- `torchaudio`
- `torchserve`

torchtext: Primarily for NLP tasks. Contains several modules for text preprocessing for sentiment analysis, Question Answering, and others.

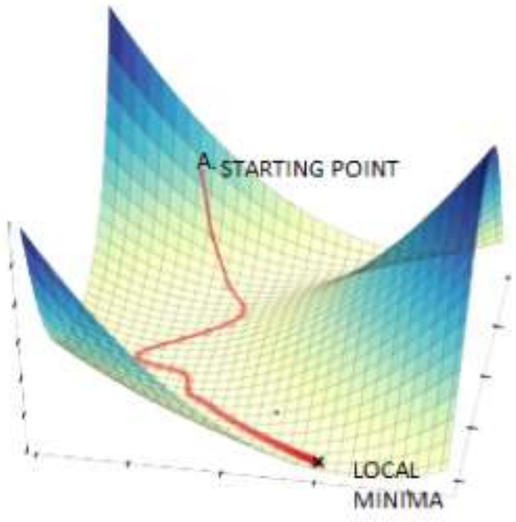
torchvision: Image data and image transformation library used for computer vision. Used for MNIST, COCO, CIFAR, and others.

torchaudio: Audio preprocessing and production deployment library with datasets of Cornell BirdCall Identification, UrbanSound8k, and others.

torchserve: Deploying model to production

https://pytorch.org/docs/stable/data.html
https://pytorch.org/docs/stable/nn.html

PyTorch Training using Autograd



- Cost or loss function between actual or predicted values: MSE, Absolute error, etc.
- Given a function, $f(x_1, x_2, x_3)$, gradient is given by:
  - $\nabla f(\mathrm{x}_1, \mathrm{x}_2, \mathrm{x}_3, \dots) = (\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \frac{\partial f}{\partial x_3}, \dots)$
- A gradient is a vector of partial derivatives. For a Neural Network with one neuron, this is:
  - $Gradient(\theta) = \nabla\theta(W_1, b_1) = \left(\frac{\partial\theta}{\partial W_1}, \frac{\partial\theta}{\partial b_1}\right)$
- With millions of neurons, this becomes:
  - $\nabla\theta\left(W_1, b_1, \dots W_{10,000}, b_{10,000}\right) = \left(\frac{\partial\theta}{\partial W_1}, \frac{\partial\theta}{\partial b_1}, \dots, \frac{\partial\theta}{\partial W_{10,000}}, \frac{\partial\theta}{\partial b_{10,000}}\right)$
  - PyTorch provides sophisticated methods for calculating & optimizing the loss function

Image credit: https://www.datasciencecentral.com/profiles/blogs/alternatives-to-the-gradient-descent-algorithm

Calculating Gradients

$$\frac{\partial y}{\partial x} = \frac{(f(x + \partial x) - f(x))}{\partial x}$$

Methods for calculating gradients

- Symbolic differentiation: conceptually simple, but hard to implement
- Numeric differentiation: Easy to implement but hard to scale
- Automatic differentiation: conceptually simple, but easy to implement

Autograd is the PyTorch package to calculate gradient for model parameters

Back propagation is implemented using a technique called reverse auto differentiation

- Weight parameters at time t+1 are calculated based on prior time-step weights minus the learning rate time the gradient at time *t.*
  - $W^{t+1} = W^t - \eta \times Gradient(\theta)^t$
  - This moves each parameter value in the direction of reducing gradient
- Every optimization algorithm implements weight update differently
  - PyTorch provides different options & you can write yours as well!

Symbolic differentiation of the loss Function

Find w that minimizes the loss

$$loss(w) = \frac{1}{N}\sum_{n=1}^{N}(\hat{y} - y)^2$$

$$\frac{\partial loss}{\partial w} = \frac{\partial (xw - y)^2}{\partial w}$$

$$\frac{\partial loss}{\partial w} = 2x * (wx - y)$$

$$w_{t+1} = w_t - \eta * 2x\,(xw - y)$$

$$\frac{\mathrm{d}}{\mathrm{d}w}\left[(xw-y)^2\right]$$

$$= 2\,(xw-y)\cdot\frac{\mathrm{d}}{\mathrm{d}w}[xw-y]$$

$$= 2\,(xw-y)\left(x\cdot\frac{\mathrm{d}}{\mathrm{d}w}[w]+\frac{\mathrm{d}}{\mathrm{d}w}[-y]\right)$$

$$= 2\,(xw-y)\,(x\cdot 1+0)$$

$$= 2x\,(xw-y)$$

https://www.derivative-calculator.net/

PyTorch:

$$\underset{w}{argmin}\; loss(w)$$

$$w_{t+1} = w_t - \eta\frac{\partial loss}{\partial w}$$

labs/04c_pytorch_symbolic_loss.ipynb

Reverse mode autodifferentiation

Forward pass to calculate the loss (y_pred – y_actual)

Reverse pass to update the parameter values (weights)

Implementing the symbolic differentiation

Symbolic Differentiation Lab: 04c_pytorch_symbolic_loss.ipynb

Attention

An attention unit takes all sub-regions and their context as input and outputs a weighted average of the regions, based on probabilities. Context is everything in this case

Context, C, comes from RNN and input regions Y come from the Conv NN.

Using `torchtext.<>` API

.data	.datasets	.vocab
• Fields • Iterators • Pipelines	• Sentiment analysis • Sequence tagging • Question classification	GLoVe CharNGram

* https://torchtext.readthedocs.io/en/latest/data.html