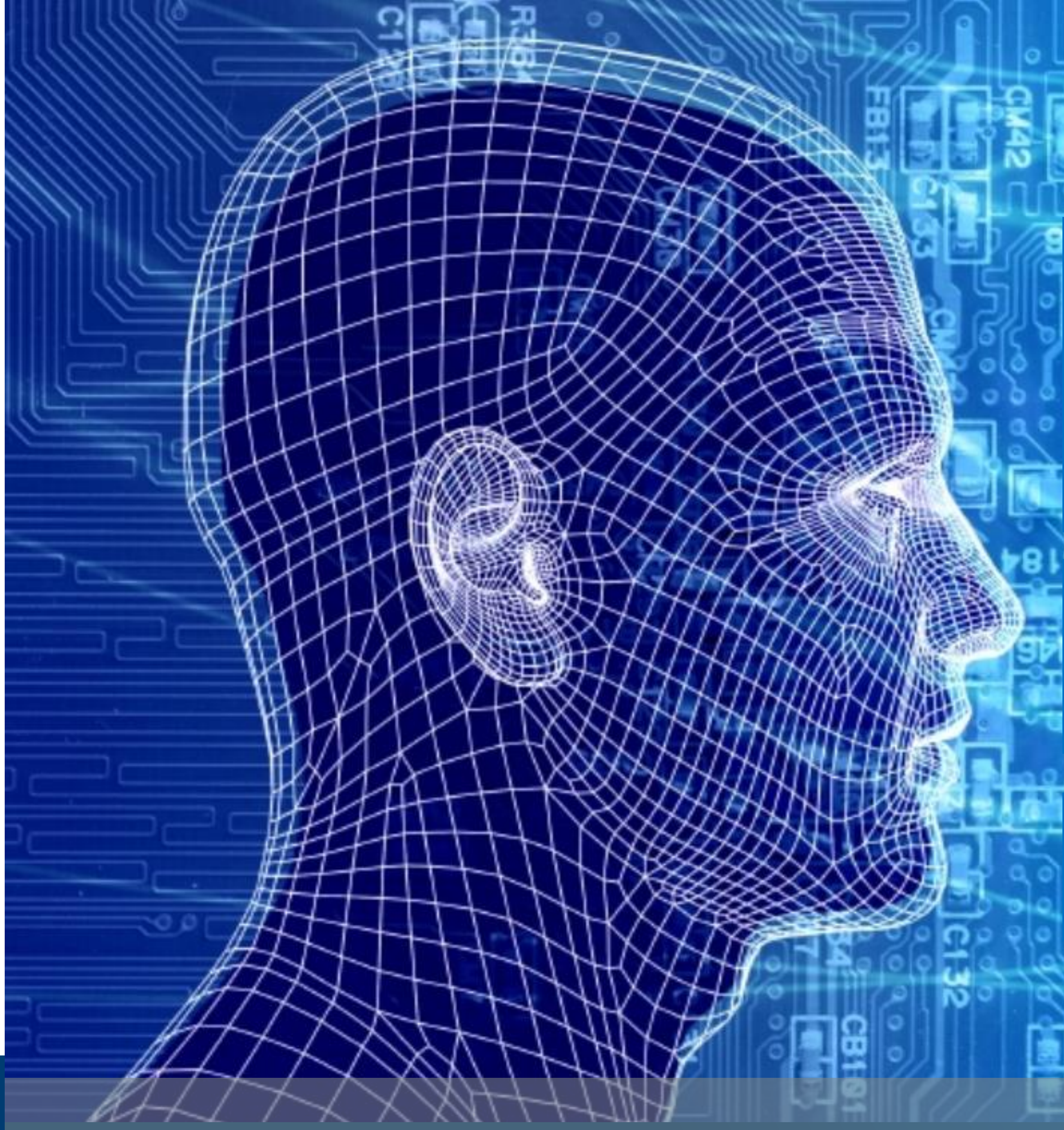


Natural Language Processing with PyTorch

Yashesh A. Shroff, PhD

Ravi Ilango

March 3-26, 2021

AICamp NLP Bootcamp

Contact:

yshroff@gmail.com, @yashroff (twitter)

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
    - POS, Word embedding
  - Lab (30mins)

Session 2:

- Module 3 Lecture (20mins): Key packages & libraries in NLP; dive into SpaCy
- Lab (20mins): SpaCy
- Lab: PyTorch

Session 3 & 4: Focus on use cases

- Module 4: Using RNN, LSTM with PyTorch
- Using Seq2Seq model for machine translation
- Lab: Seq2Seq model using PyTorch
- Text Classification
  - Lab: LSTM based text classifier
  - Lab: TFIDF and Logistic Regression based 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

- Module 5: 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

Session 6:

Learning Objective

- Question / Answering through developing a chatbot

•Session Outline

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

<Capstone Project Assignment>

Session 7:

Learning Objective

- MLOps using a text classification model

•Session Outline

- Scheduler Overview
- Implementation walk-through

Session 8:

Capstone Project Presentations

- End to end including MLOps

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`

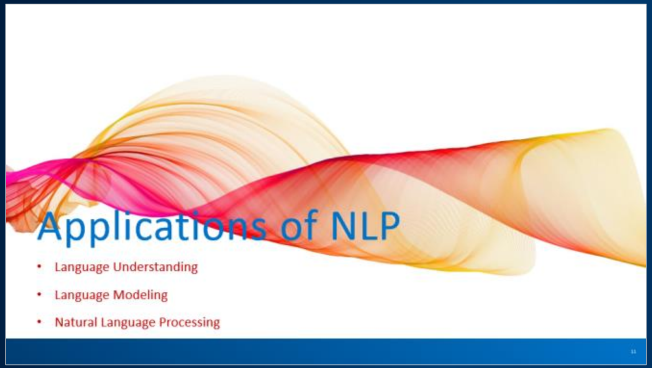
Use conda or pipenv to install the requirements dependencies in a virtual environment.

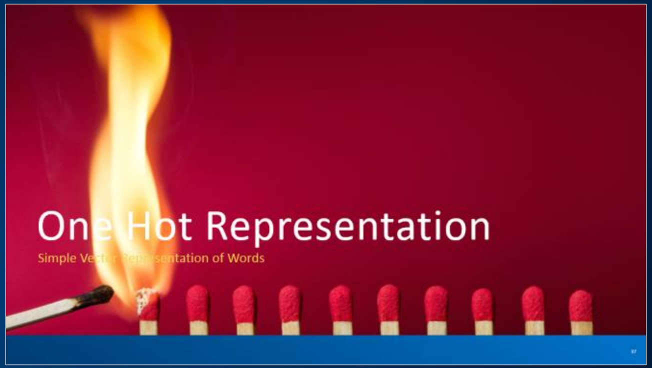
```
import numpy as np
import matplotlib.pyplot as plt

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")
```

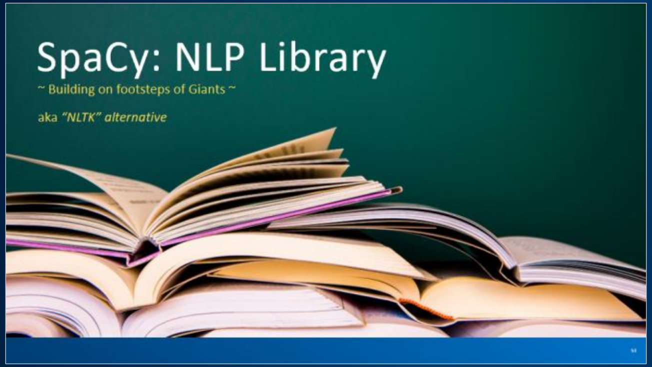
* Where Pretrained Language Model doesn't exist in SpaCy (more compact distro)

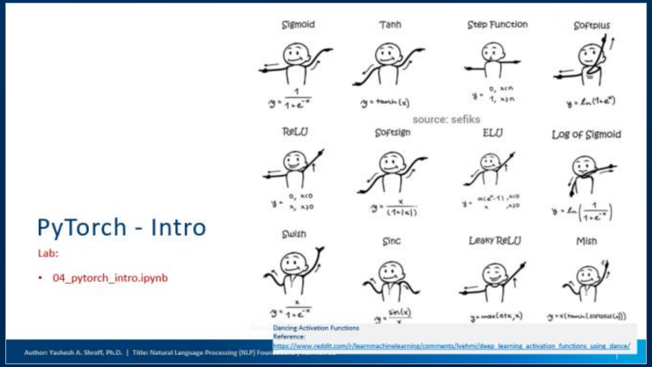
Part 1: Foundations of NLP

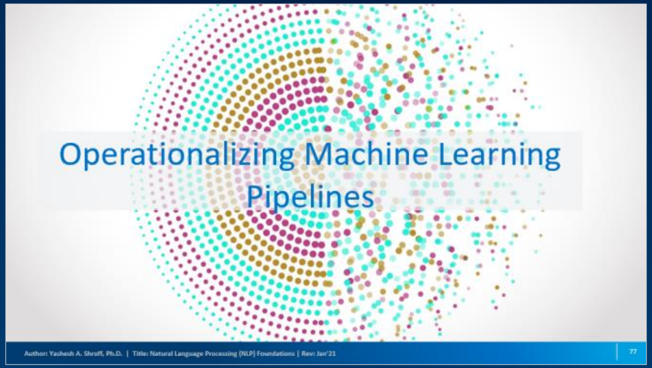




Part 2: Practicum







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

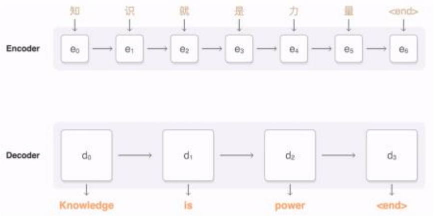
Voicebots: Voiq Sales & Marketing

Text and auto-generation: Gmail

Sentiment analysis: Social media (finance, reviews)

Information extraction: Unstructured (news, finance)

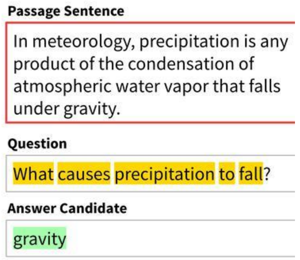
NLP Tasks



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

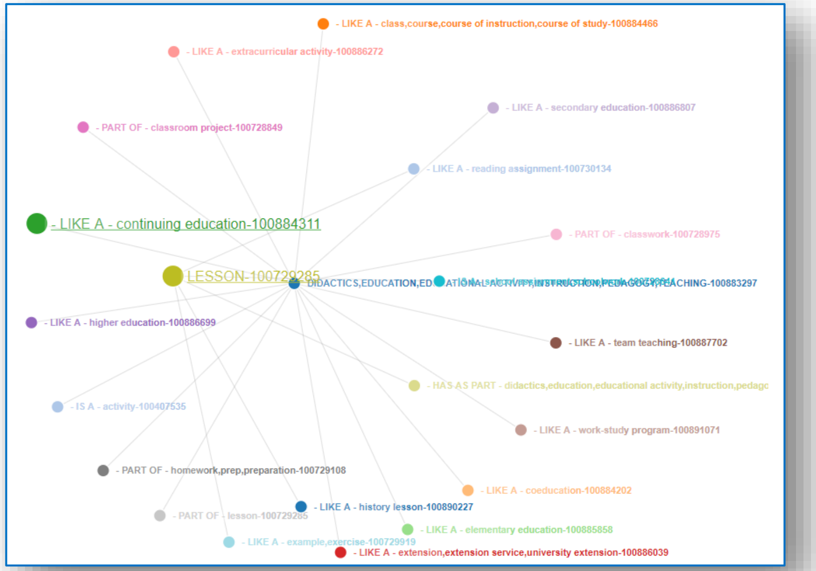
- word2vec: Mikolov et. al. (Google)
- GloVe: Pennington et al., Stanford CS. EMNLP 2014
- ElMo:
- ELMo (Embeddings from Language Models)
  - Memory augmented deep learning
- Survey paper (https://arxiv.org/abs/1708.02709)
  - Blog (https://medium.com/dair-ai/deep-learning-for-nlp-an-overview-of-recent-trends-d0d8f40a776d)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

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

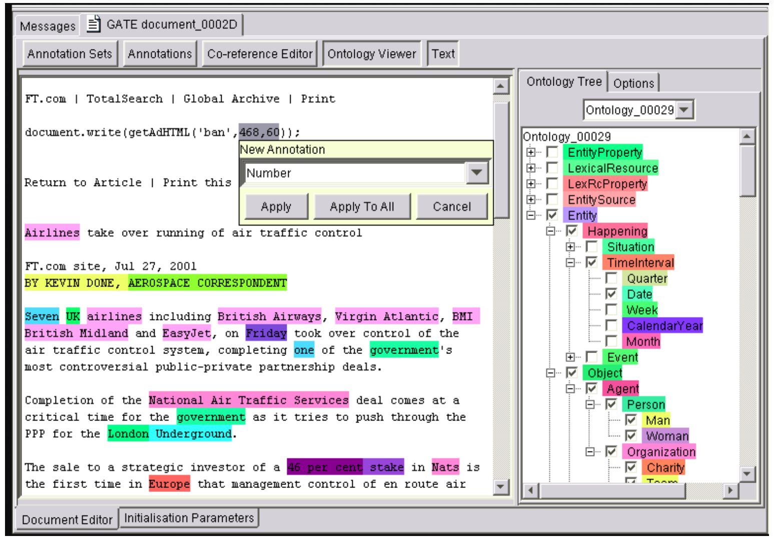
Heuristics based approach to NLP

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

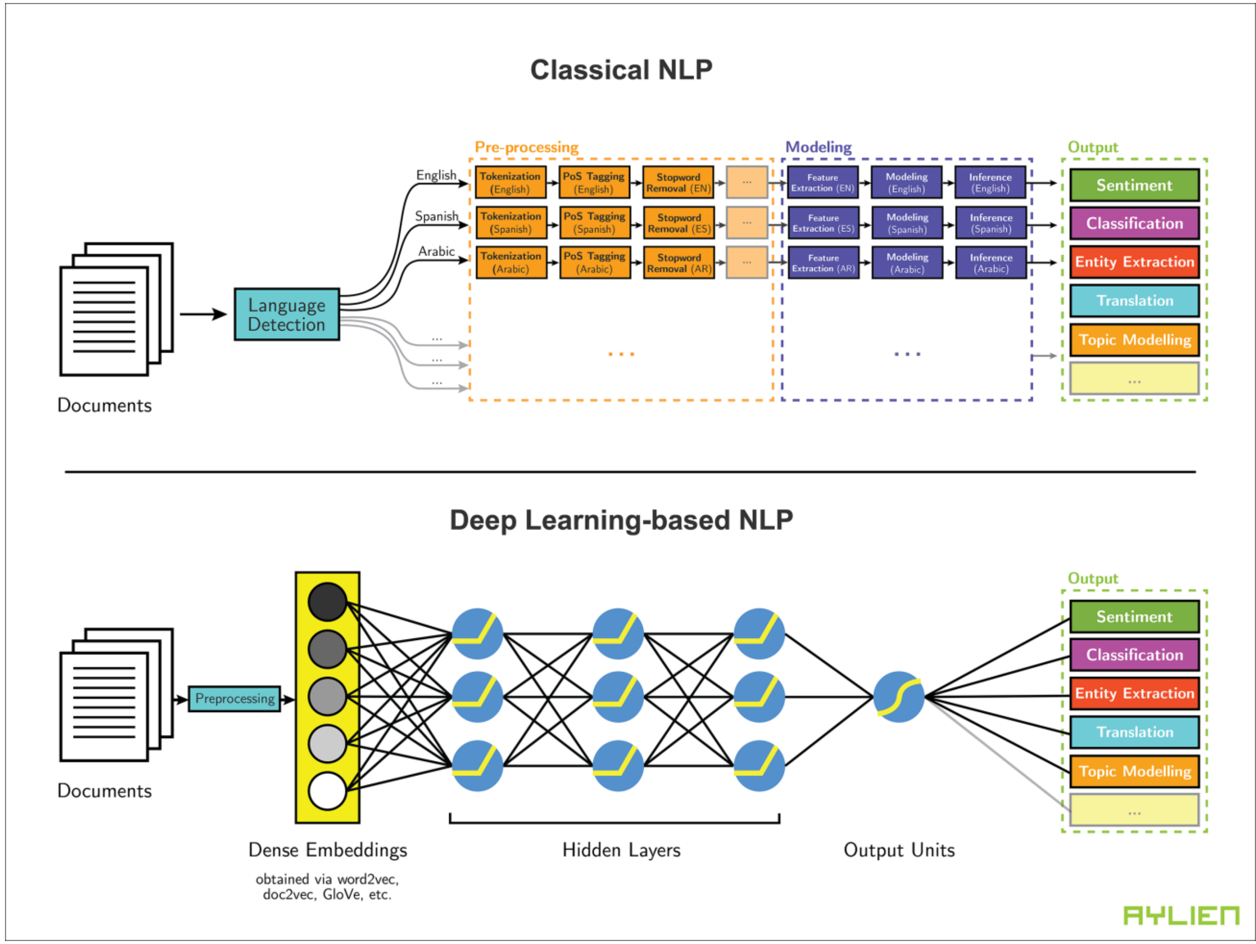


- Regex: ^([a-zA-Z0-9_\-\.]+)@([a-zA-Z0-9_\-\.]+)\.([a-zA-Z]{2,5})$
  - Key sub-strings, such as product ID
- Context-Free Grammar (formal): GATE / JAPE



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

Classical vs. DL NLP

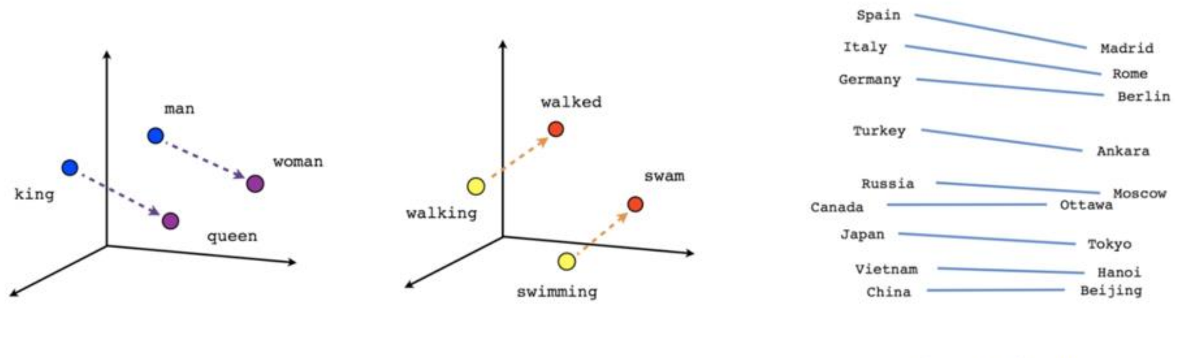


Classical:

- 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

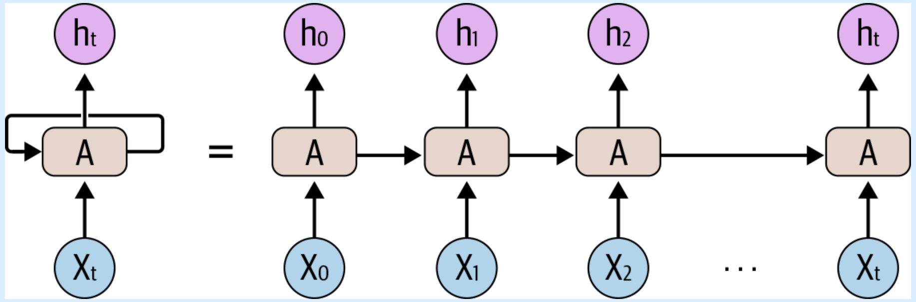
Algorithm	Description
Naïve Bayes	Assumes feature independence (naïve) Ex. Frequency of specific words for classification
Support Vector Machines	Leans optimal (linear or non-linear) decision boundaries between classes (sports vs political articles)
Hidden Markov Models	Models unobserved hidden states 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

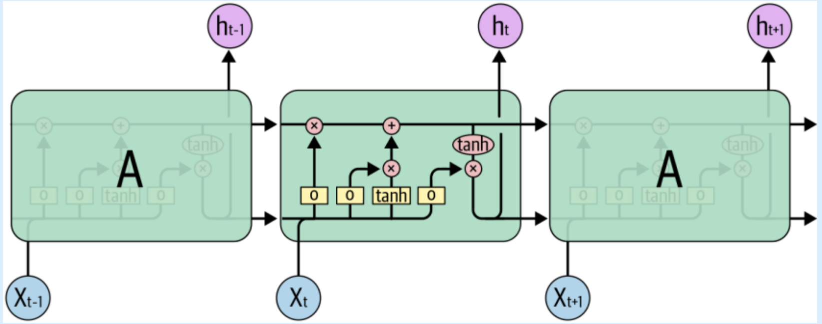
Recurrent Neural Networks

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



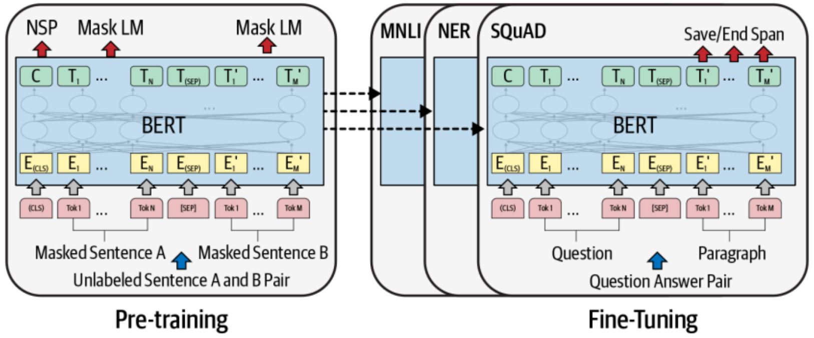
Long-Short Term Memory

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



Transformers

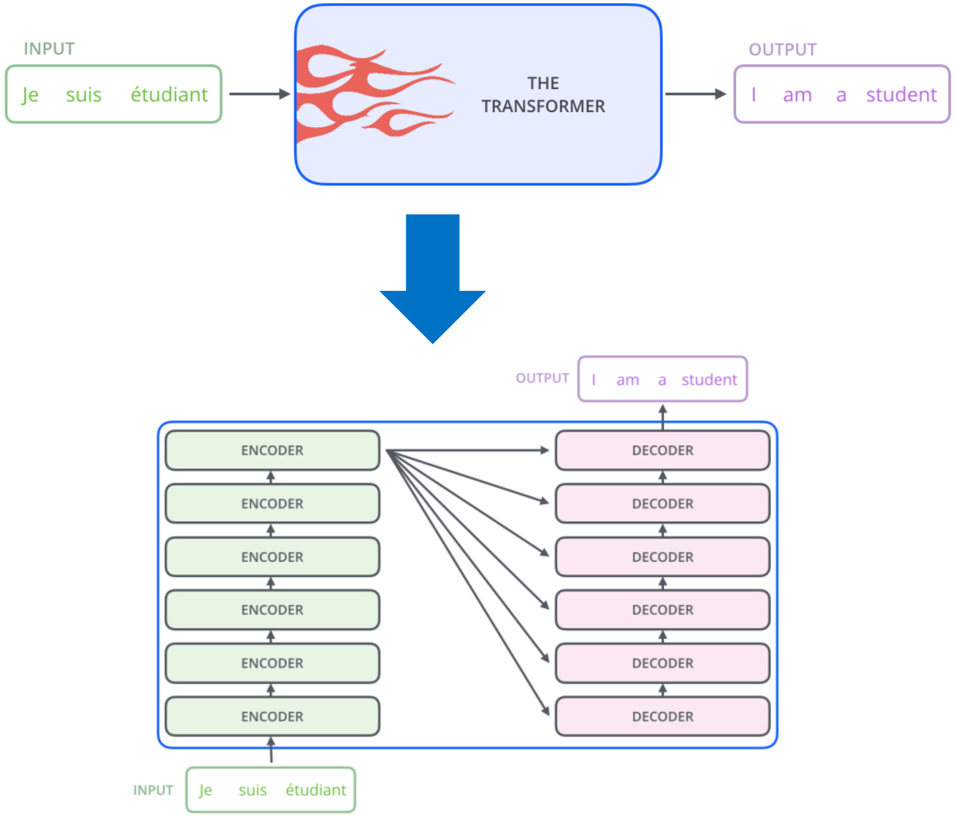
- Language modeling with context 'around' a word
- Transfer learning applies to downstream tasks

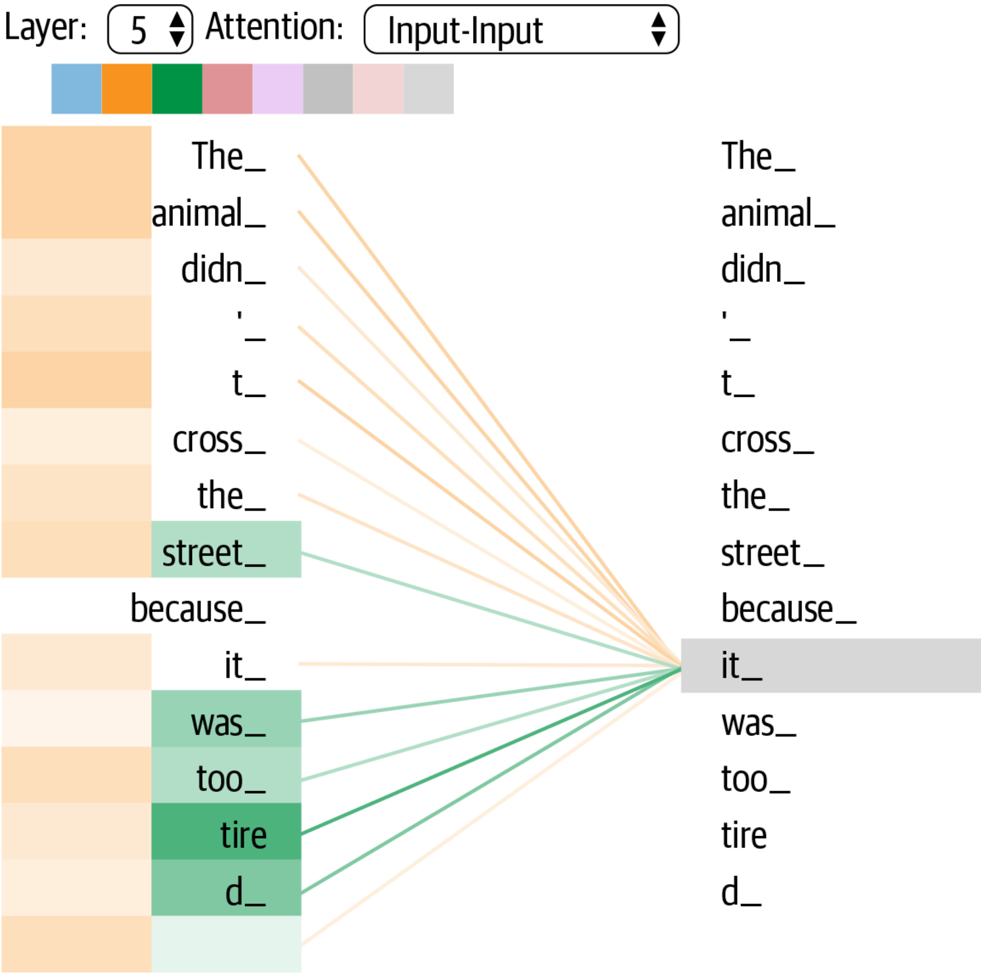


Christopher Colah: Understanding LSTM Networks
Jacob, et. Al "BERT Pre-Training Paper"

Transformer (motivation)

Self-Attention Mechanism



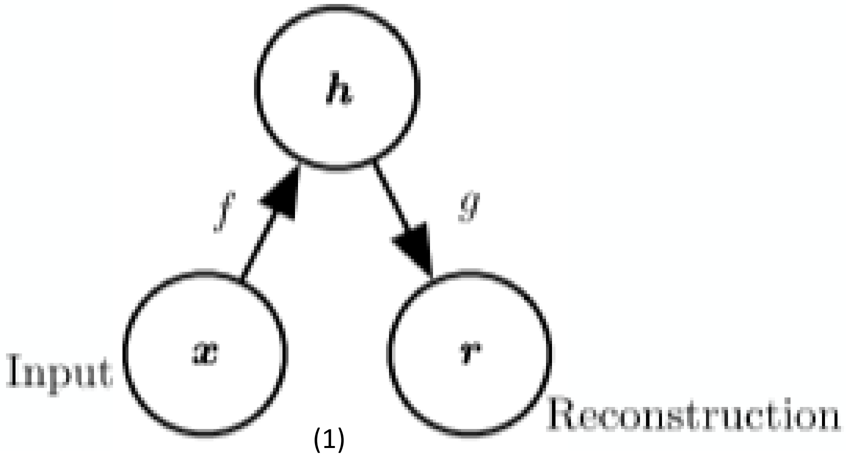


Jay Alammar: [The Illustrated Transformer]

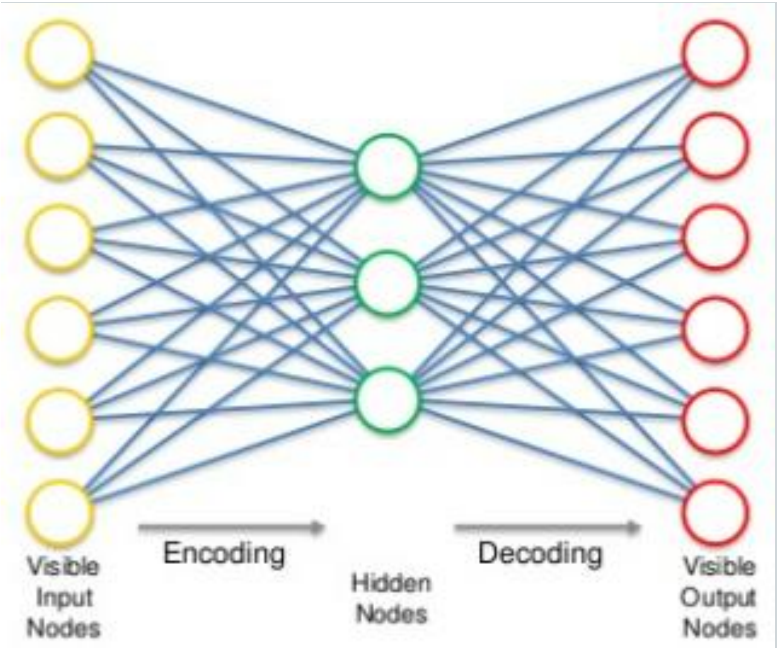
Autoencoder

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

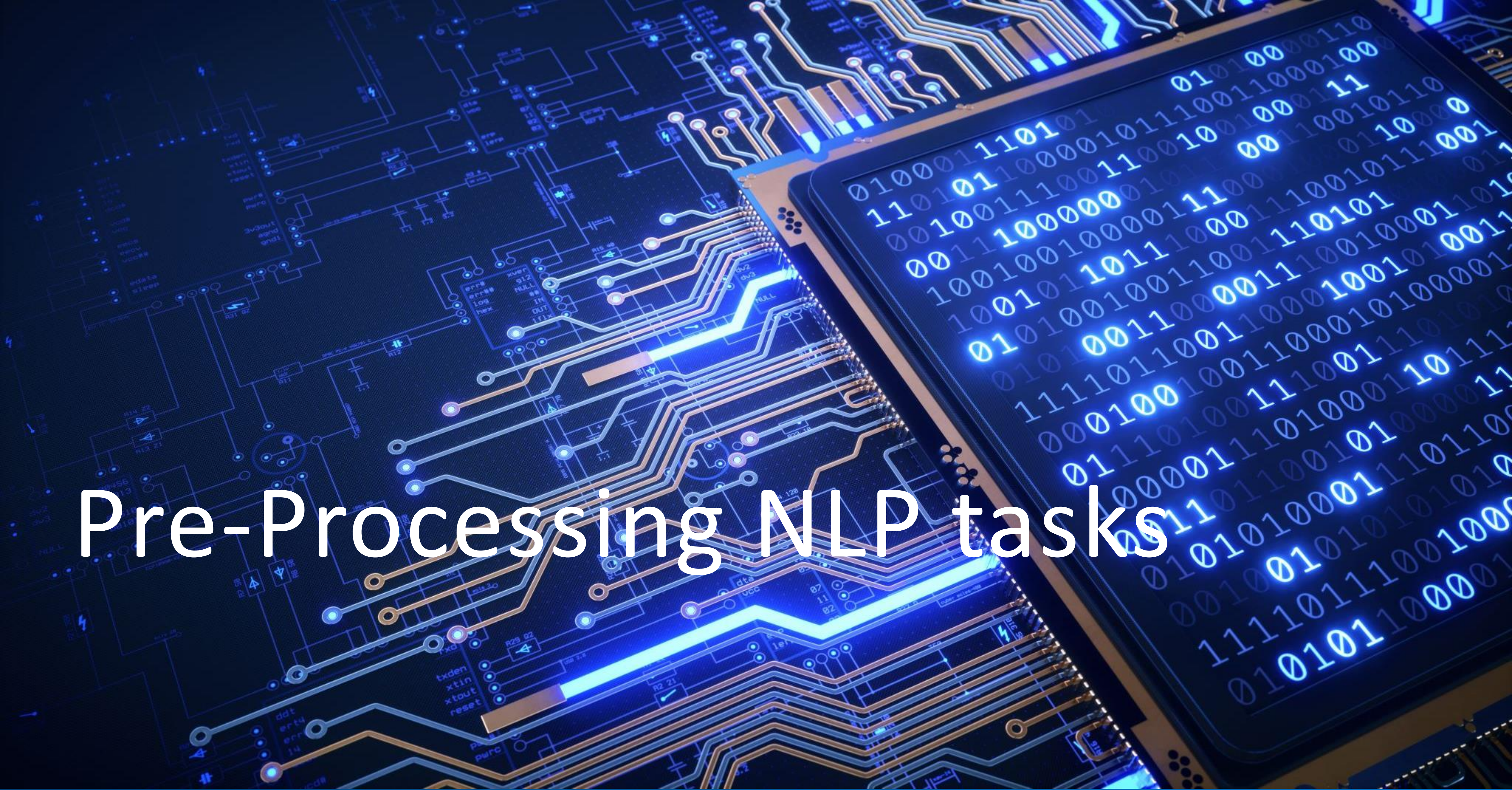


(1)



(2)

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



Pre-Processing NLP tasks

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)
```

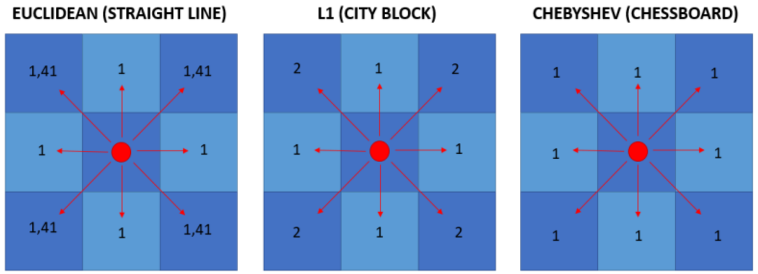
Lab

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

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

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

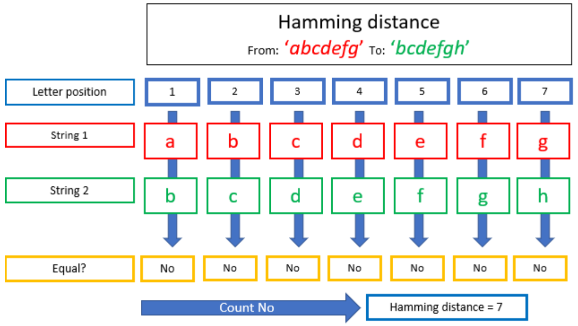
$$dist(A, B) = |x_A - x_B| + |y_A - y_B|$$

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

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

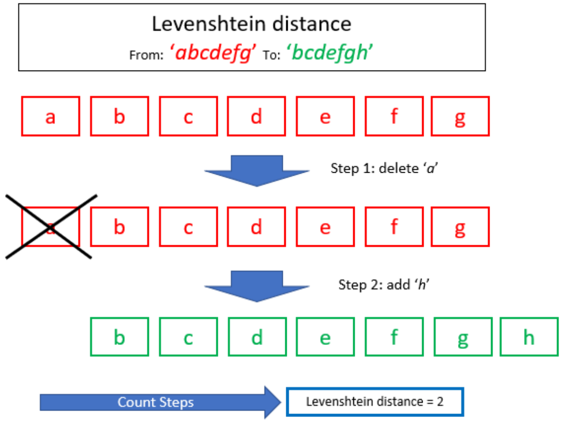
Ref: https://towardsdatascience.com/3-distances-that-every-data-scientist-should-know-59d864e5030a

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

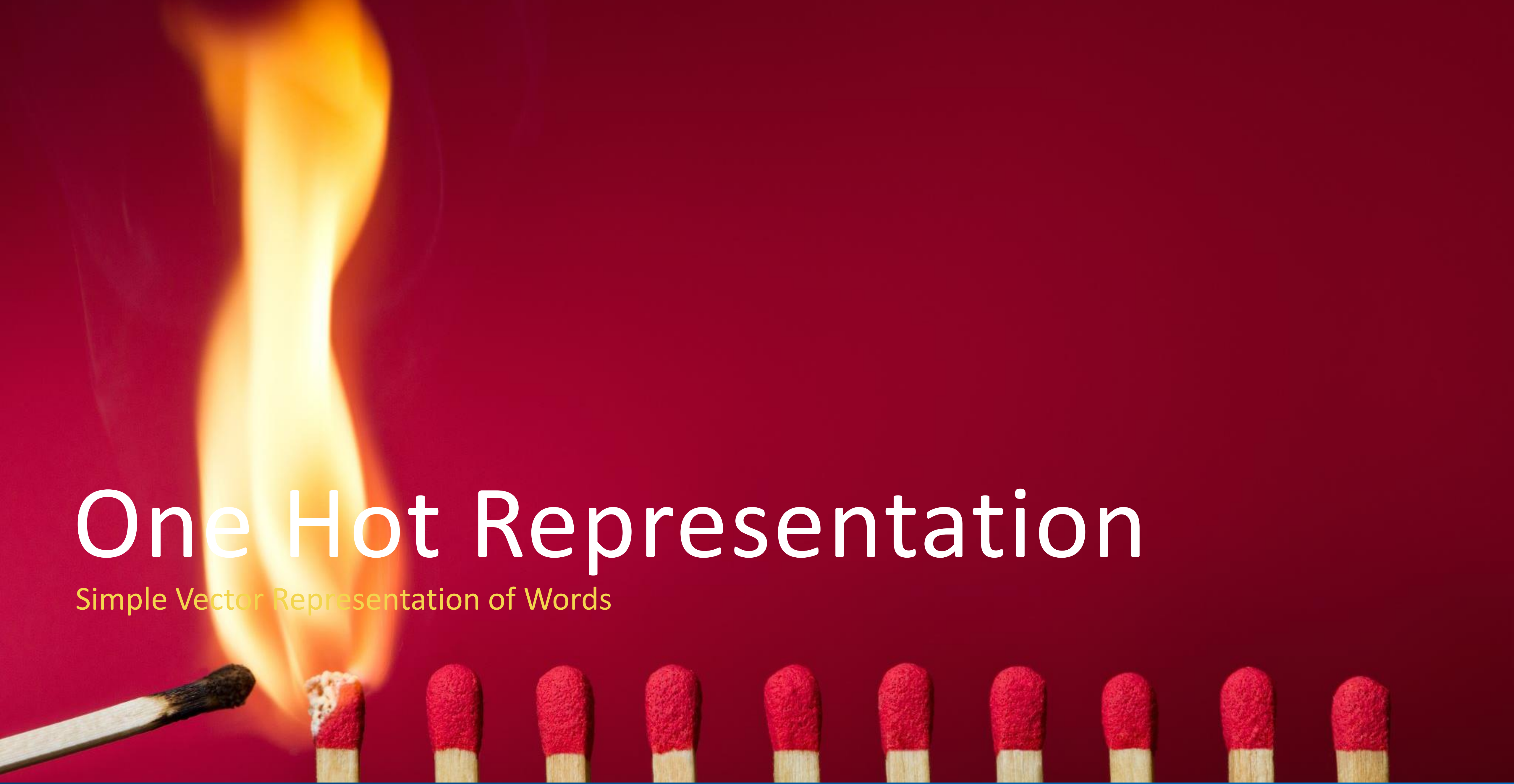
Represent — Represent word in numeric encoding

Collect — Collect into a Tensor to represent a document

One Hot Encoding

Frequency

Prediction



One Hot Representation

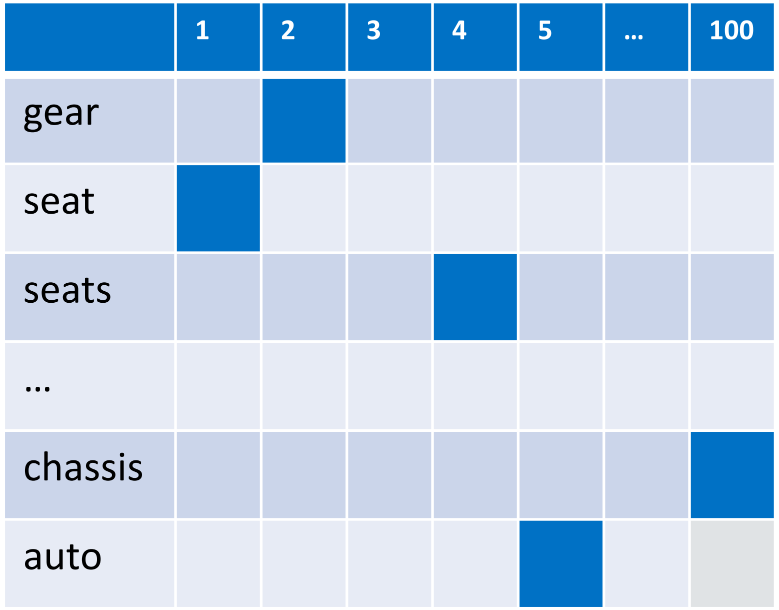
Simple Vector Representation of Words

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



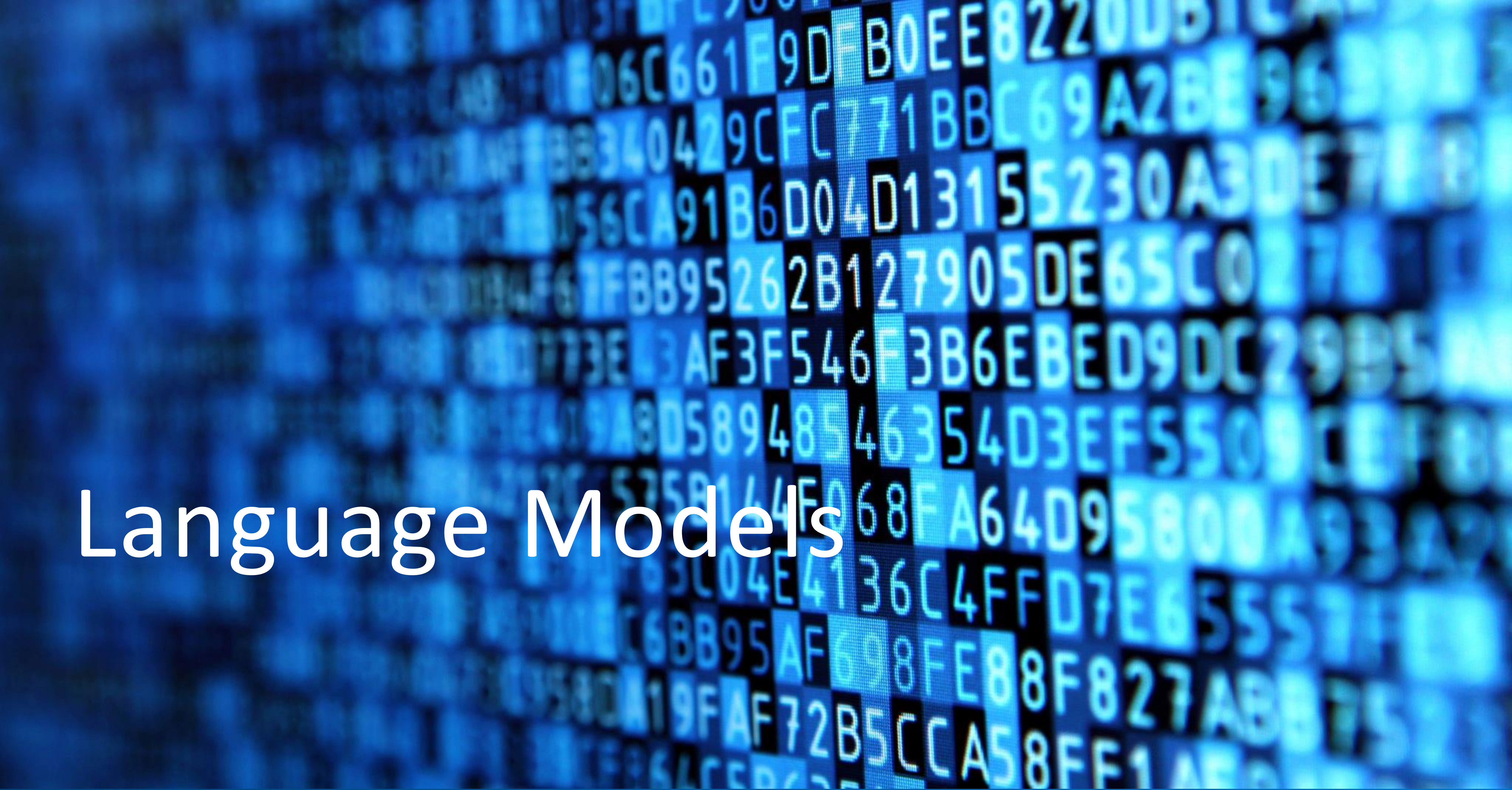
Challenges with this approach:

- 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

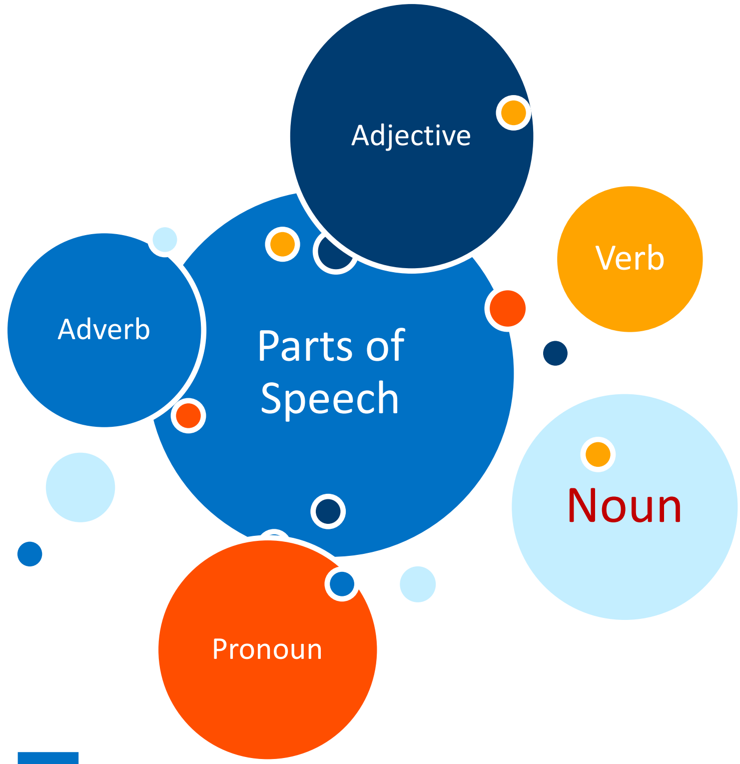
Google Colab:

- `02_inefficient.ipynb`



Language Models

Parts of Speech Tagging



Rule based
- ~1k+ constraints

Transformation

Stochastic
- Training corpus
- Probability of certain tag occurring

One tag for each part of speech

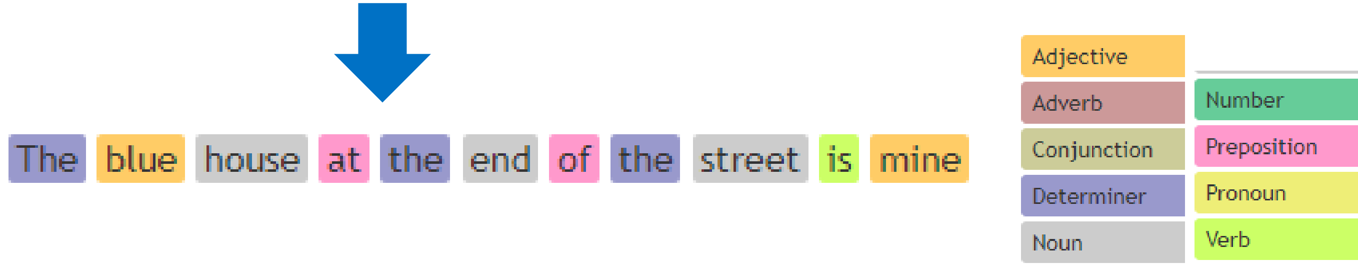
- Choose a courser tagset (~6 is useful)
- Finely grained tagsets exist (ex. Upenn Tree Bank II)

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

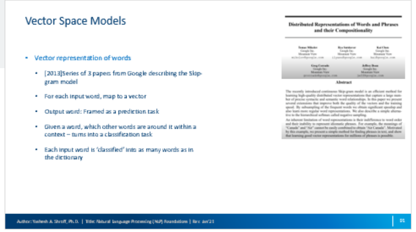
- Count Vector
- TF-IDF
- Co-occurrence Vector

- 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	

$$TF = \frac{\#\ times\ term\ T\ appears\ in\ the\ document}{\#\ of\ terms\ in\ the\ document, m}$$

$$IDF = \left(\frac{Number\ of\ documents, N}{Numer\ of\ documents\ in\ which\ term\ T\ appears, n}\right) = \log\left(\frac{N}{n}\right)$$

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	4	2	1	2	1
is	4	0	1	2	2	1
not	2	1	0	1	0	0
lazy	1	2	1	0	0	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

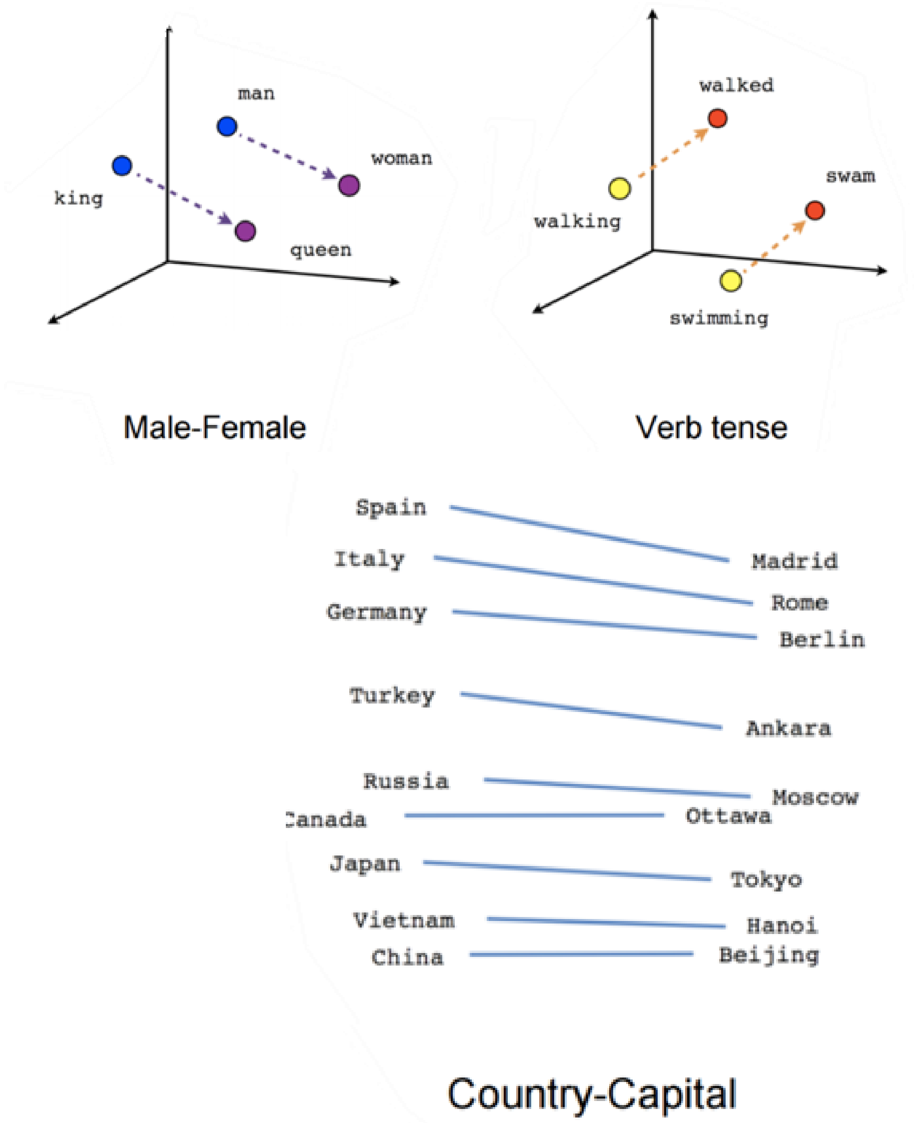
- Uses SVD decomposition and PCA to reduce dimensionality

- 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

- 20min: CBOW & Skip-Gram

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

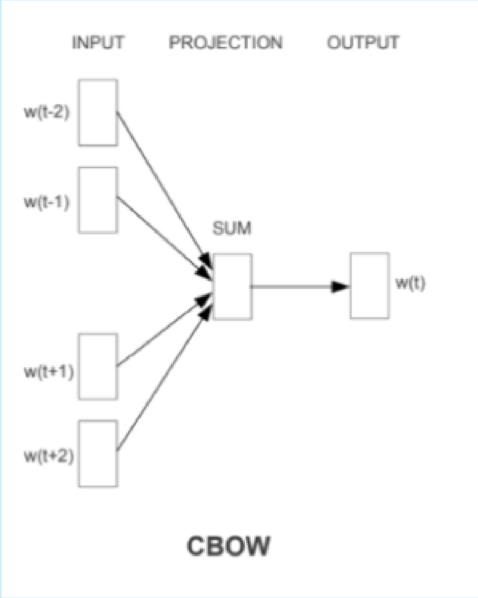
Word Vectors

Moving beyond OHE

Word Embedding

Prediction based **Word2Vec**

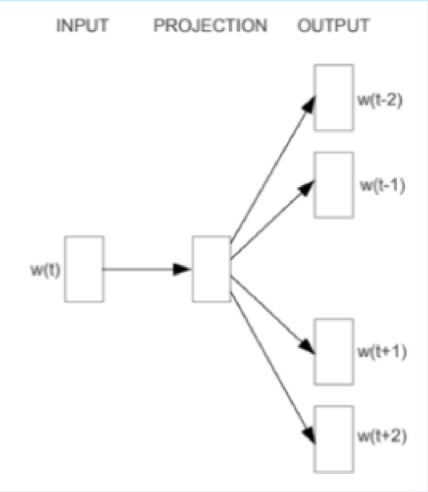
CBOW



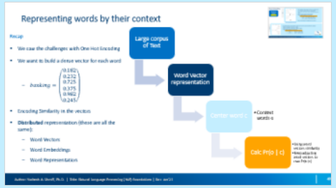
https://arxiv.org/pdf/1301.3781.pdf

- 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

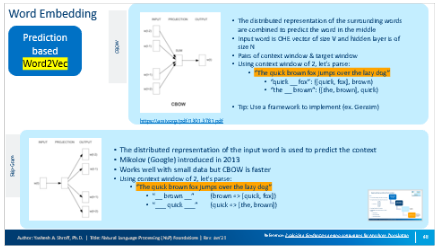


- The distributed representation of the input word is used to predict the context
- Mikolov (Google) introduced in 2013
- Works well with small data but CBOW is faster
- Using context window of 2, let's parse:
  - "The quick brown fox jumps over the lazy dog"
    - "__ brown __" (brown => [quick, fox])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



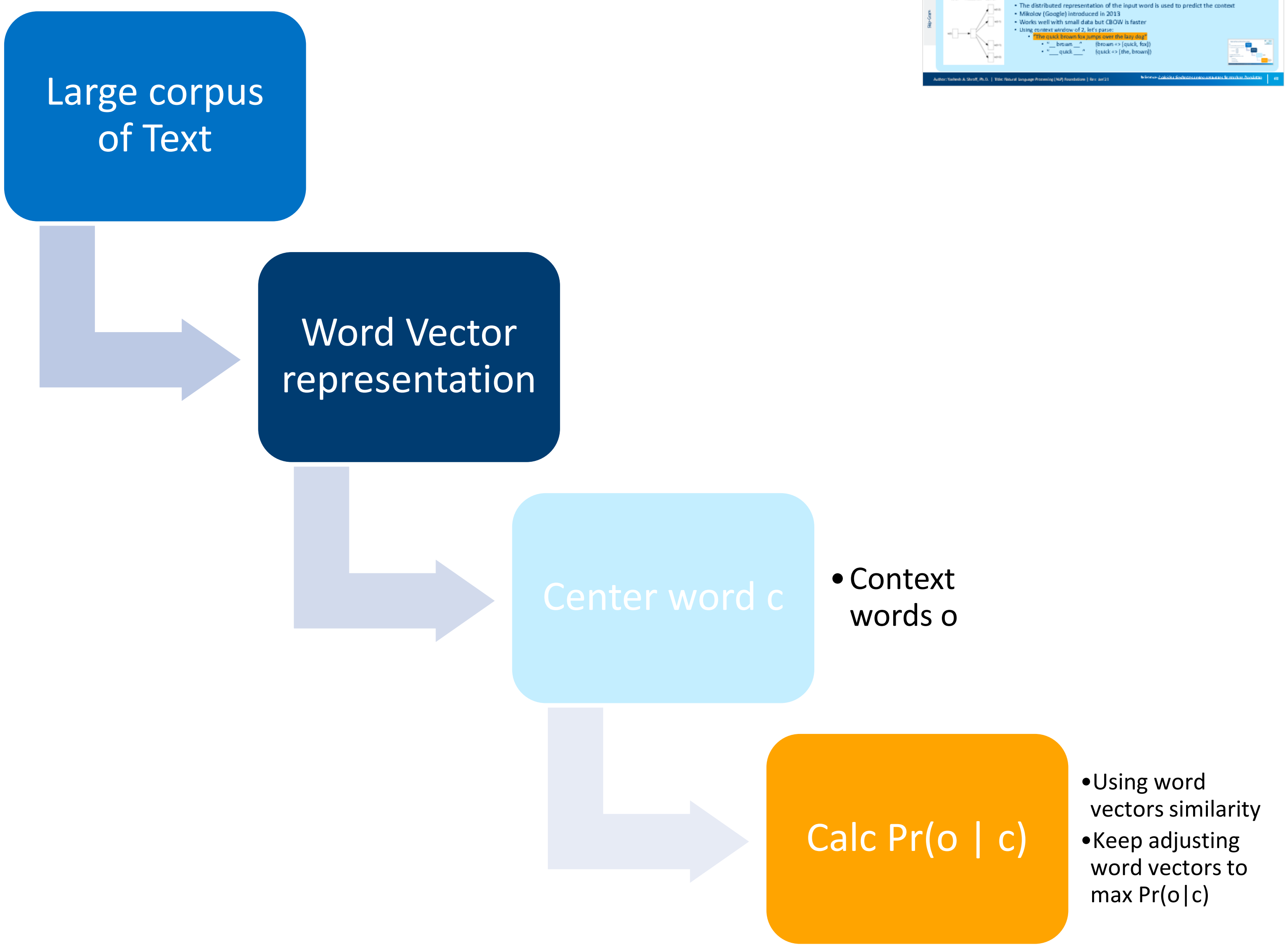
Reference: *Exploiting Similarities among Languages for Machine Translation*

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



Skip-Gram Objective Function

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

***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

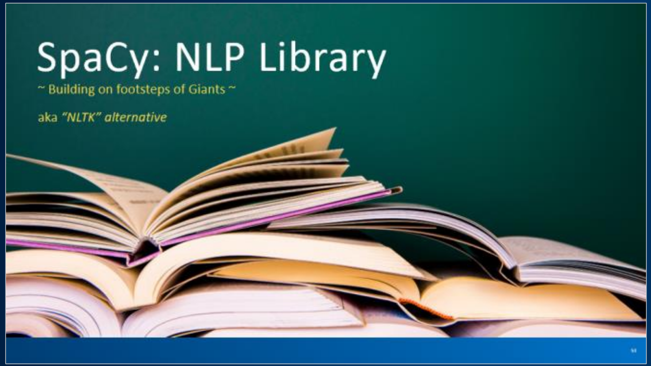
context — center word — context

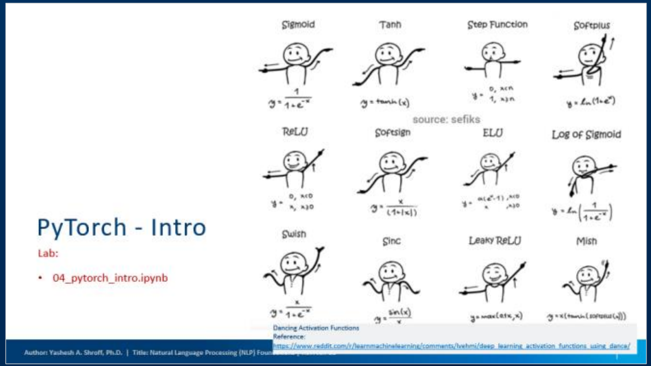
… deposits into local currency have occurred during banking crises

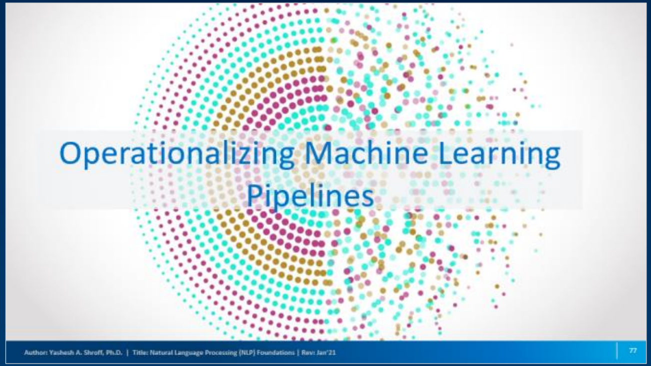
… deposits into local currency have occurred during banking crises

- 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

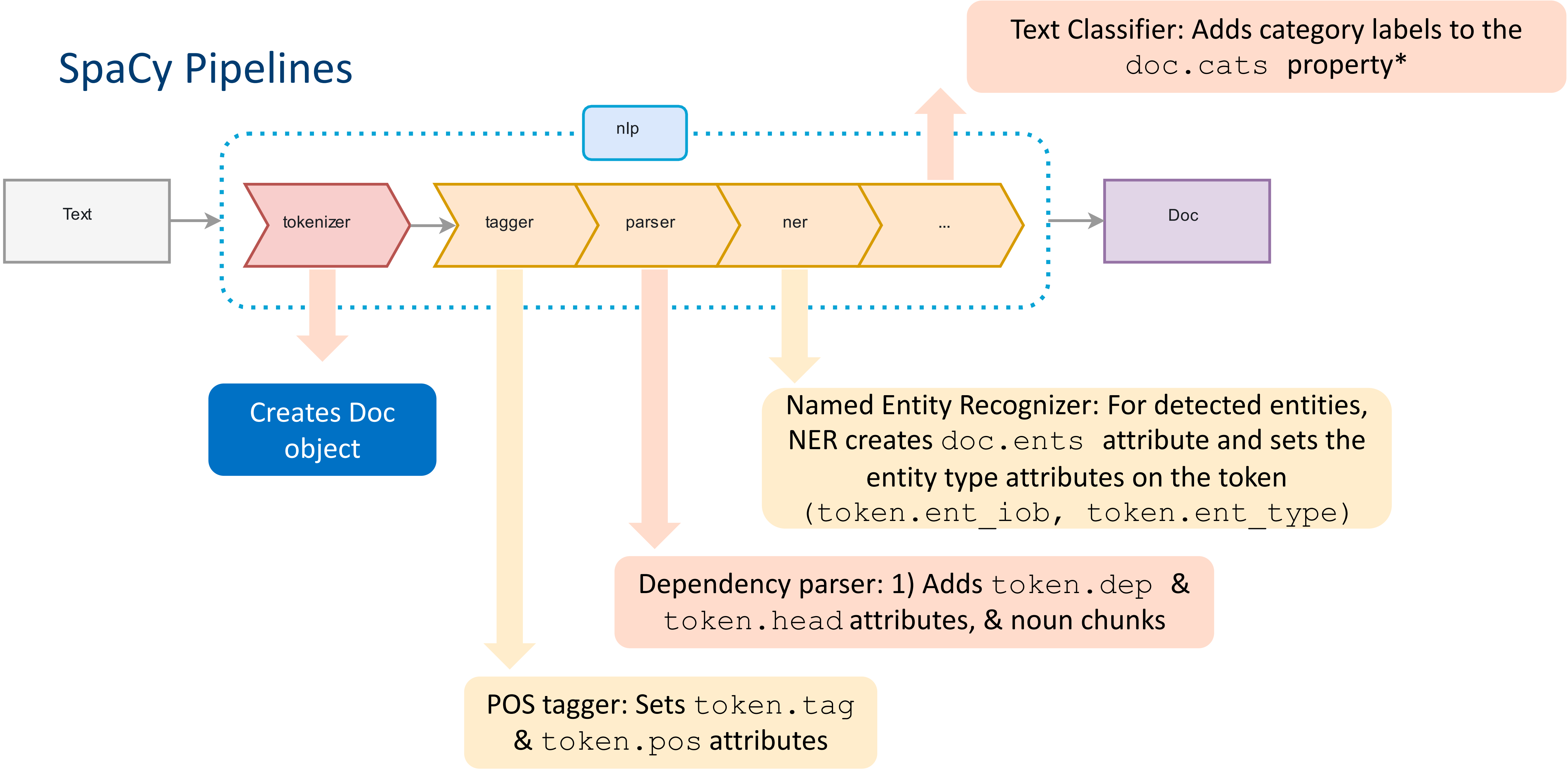
```
python -m spacy download 'en_core_web_sm'
```

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

```python
# 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']
```

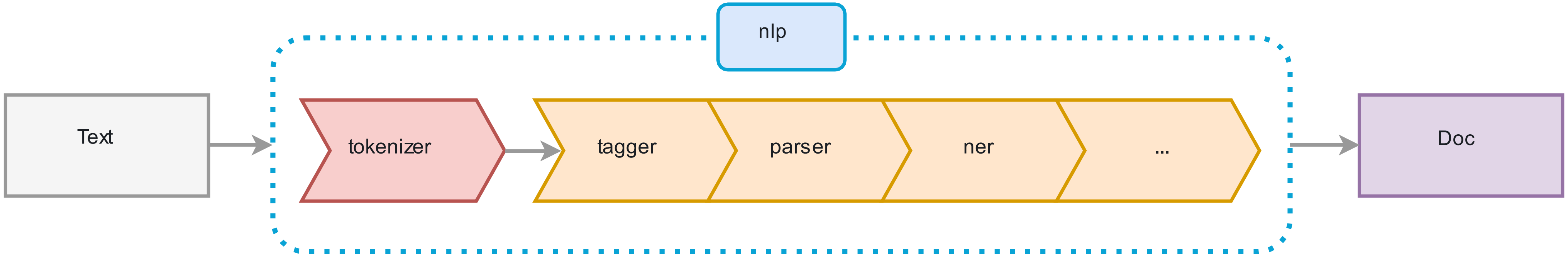
Functions applied to the Doc & set attributes

```
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

```python
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”)

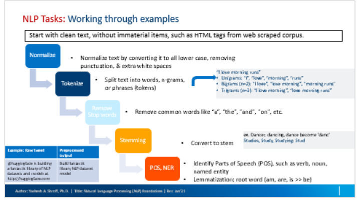
Universal Parts of Speech Tagging

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	

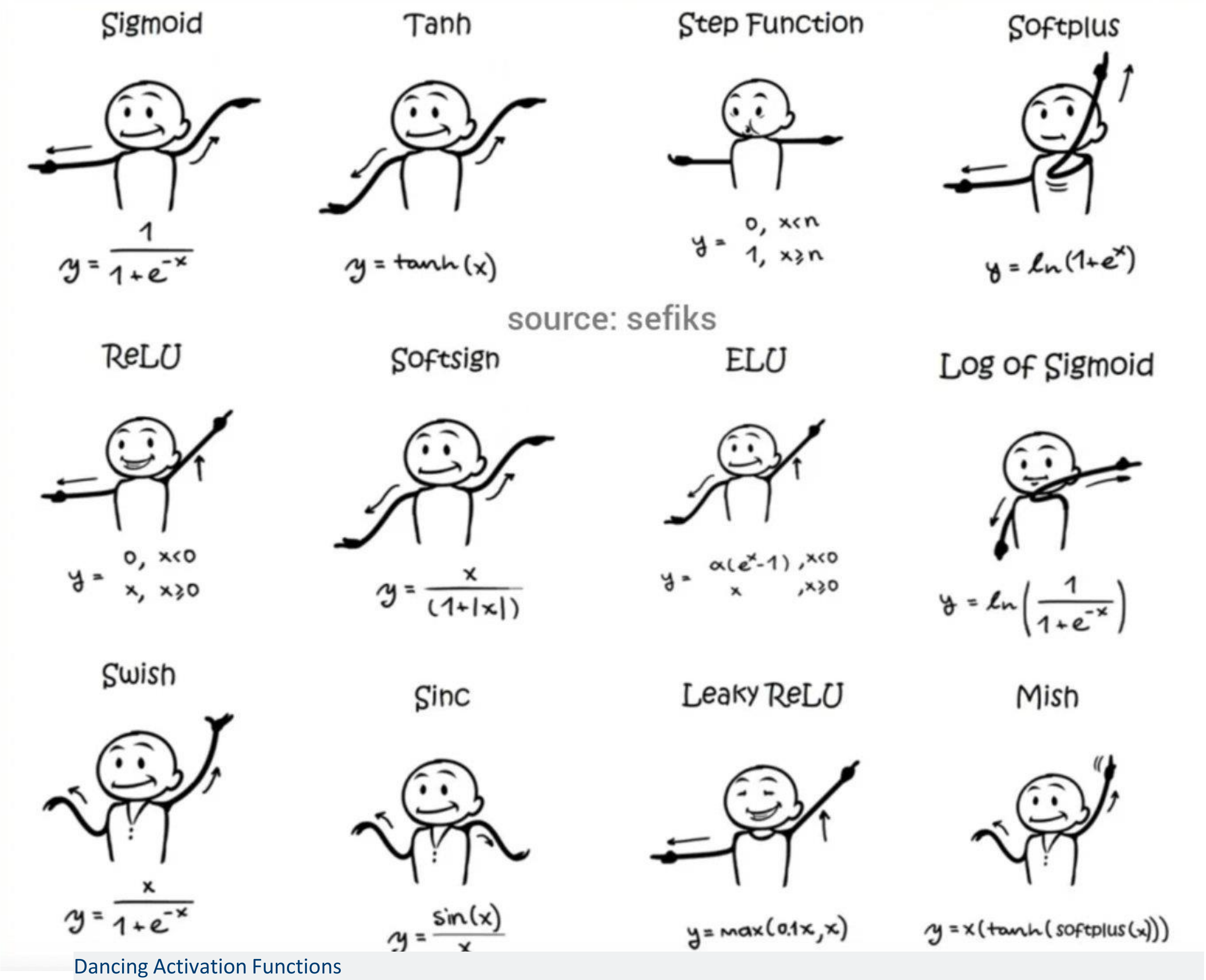
Objective:

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

SpaCy

Lab:

- 03_SpaCy.ipynb



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

PyTorch - Intro

Lab:

- 04_pytorch_intro.ipynb

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.

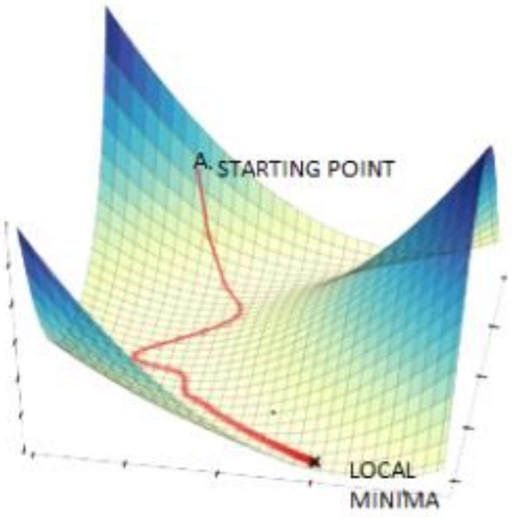
torchvision: Image data and image transformation library used for computer vision. Used for MNIST, COCO, CIFAR, and others.

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

$$\frac{d}{dw}\left[(xw-y)^2\right]$$
$$= 2\,(xw-y)\cdot\frac{d}{dw}[xw-y]$$
$$= 2\,(xw-y)\left(x\cdot\frac{d}{dw}[w]+\frac{d}{dw}[-y]\right)$$
$$= 2\,(xw-y)\,(x\cdot 1+0)$$
$$= 2x\,(xw-y)$$

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

Find w that minimizes the loss

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

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

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

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

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

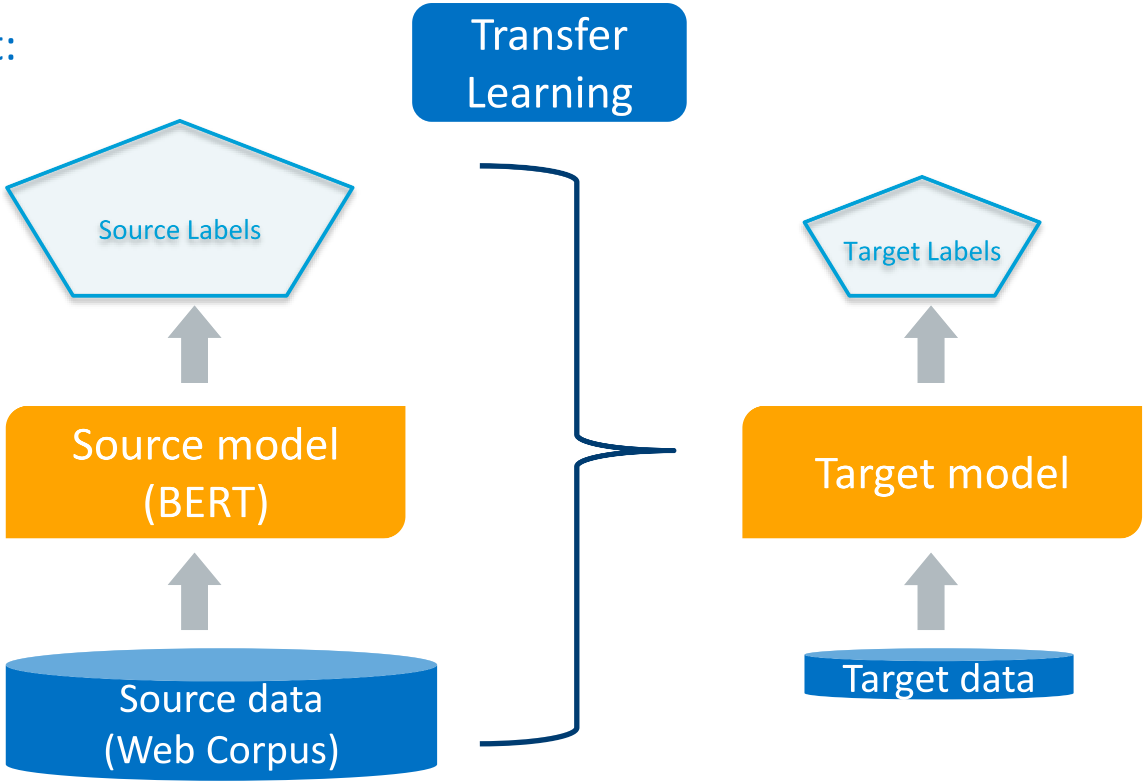
* https://torchtext.readthedocs.io/en/latest/data.html

Model Pre-training

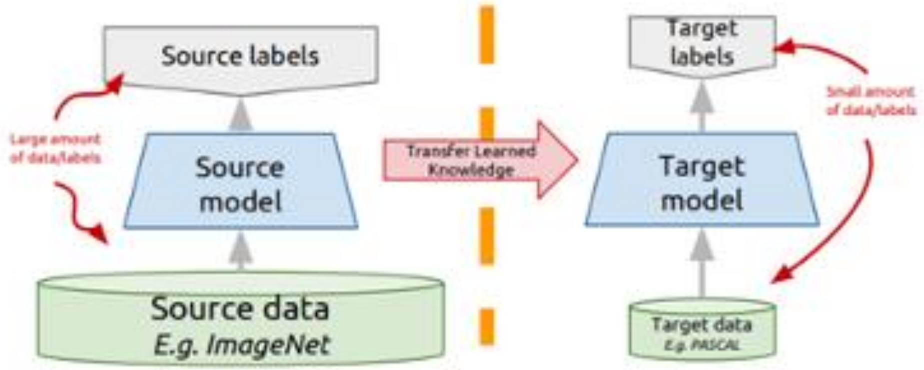
From ULMFiT to Transformers

Transfer Learning

The basic concept:



Transfer learning concept



Conventional approach:

- Training a deep learning model from scratch using your data
- Challenge: high compute, high data requirements)

Transfer learning approach:

- Start with a network trained on a different domain and source task
- Adapt it for your domain and target task (smaller compute and data requirements)
  - Can also apply for the same domain but different task or
    - For example: Imagenet dataset trained computer vision model applied to transfer learning for detecting species of butterflies or types of leaves
  - Different domain and same task
    - For example: Image segmentation in self driving for detecting pedestrians applied to image segmentation task in healthcare for detecting tumor

Transfer Learning: History & State of the Art

Pre-2018:

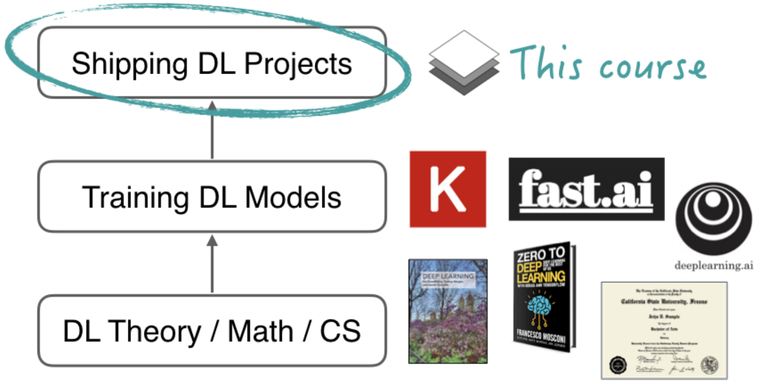
2018: Jeremy Howard released ULMFiT – an approach to solve NLP problems, took away 90% of the developer pain in running new models

- AWD-LSTM neural network pre-trained on Wikitext-103

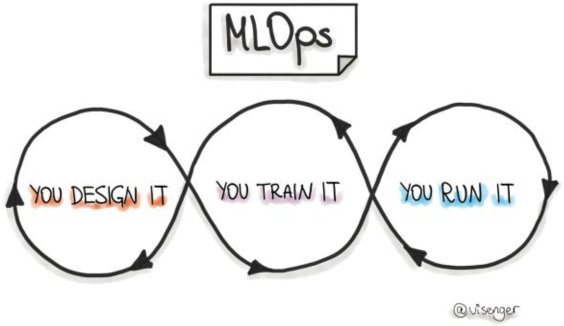
Post 2018: Attention is all you Need became popular, proposing the 'Transformer' architecture. Huggingface has a "Transformer" library that was used as the architecture for BERT, Transformer-XL, XLNet and (facebook) RoBERTa and XLM and OpenAI (GPT, GPT-2)

Operationalizing Machine Learning Pipelines

Resources for ML in Production

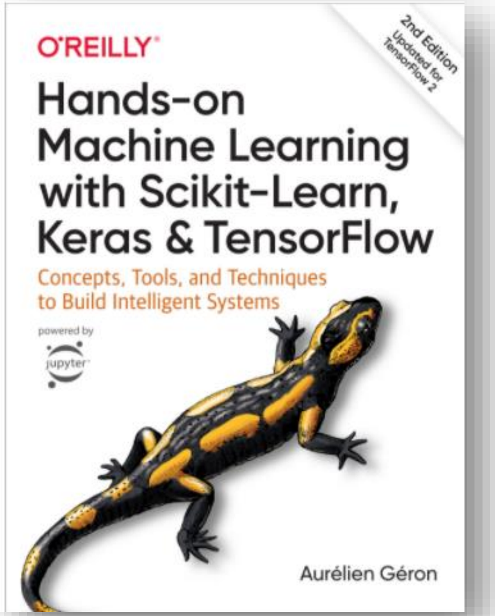


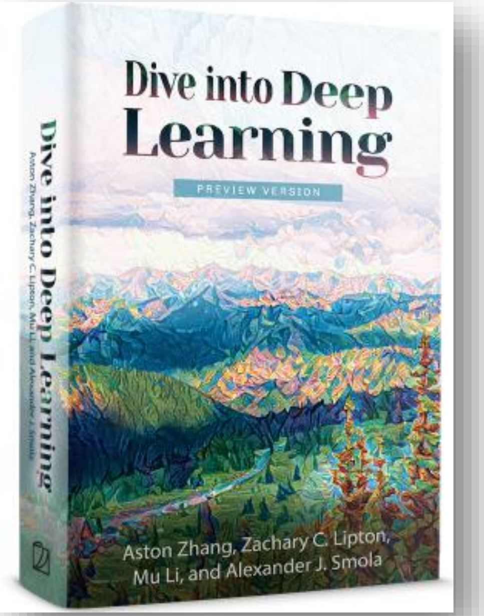
1. **Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, 2nd Edition**
2. **Dive into Deep Learning (https://d2l.ai/:** *Aston Zhang, Zack C. Lipton, Mu Li, and Alex J. Smola*
3. **Full Stack Deep Learning (https://course.fullstackdeeplearning.com/)**
4. **Designing Data-Intensive Applications (***Martin Kleppmann***)**
5. **Building Machine Learning Pipelines (***Hannes Hapke and Catherine Nelson***)**
6. **Building Machine Learning Powered Applications (***Emmanuel Ameisen***)**
7. **Introducing MLOps: How to Scale Machine Learning in the Enterprise (***Clément Stenac, Léo Dreyfus-Schmidt, Kenji Lefèvre, Nicolas Omont, and Mark Treveil***)**
8. **Awesome MLOps (https://github.com/visenger/awesome-mlops)**
9. **Awesome production machine learning (https://github.com/EthicalML/awesome-production-machine-learning)**
10. **Kubeflow for Machine Learning (***Trevor Grant, Holden Karau, Boris Lublinsky, Richard Liu, Ilan Filonenko***)**

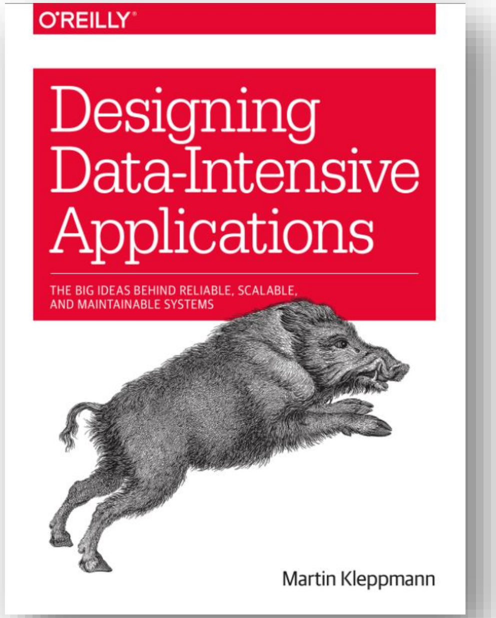


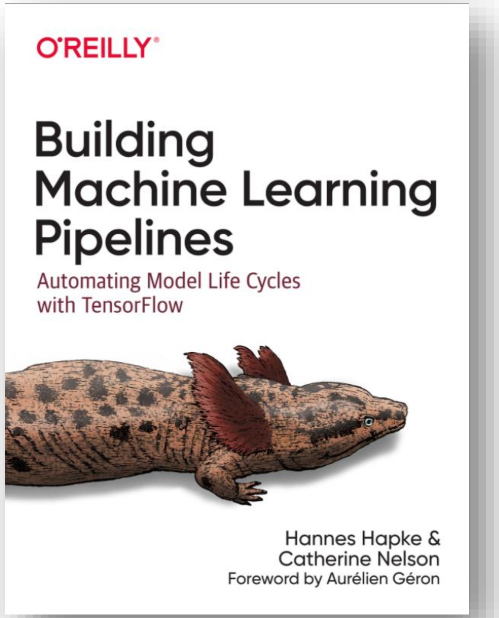
Explaining predictions & models	Privacy preserving ML	Model & data versioning
Model Training Orchestration	Model Serving and Monitoring	Neural Architecture Search
Reproducible Notebooks	Visualisation frameworks	Industry-strength NLP
Data pipelines & ETL	Data Labelling	Data storage
Functions as a service	Computation distribution	Model serialisation
Optimized calculation frameworks	Data Stream Processing	Outlier and Anomaly Detection
Feature engineering	Feature Stores	Adversarial Robustness
Commercial Platforms		

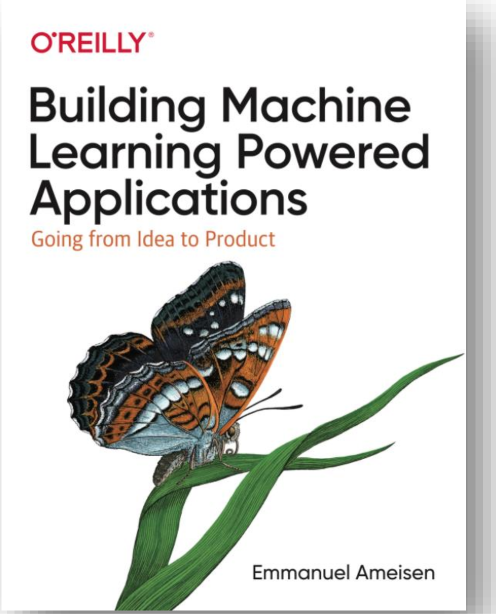
Credit: https://elvissaravia.substack.com/p/my-recommendations-to-learn-machine

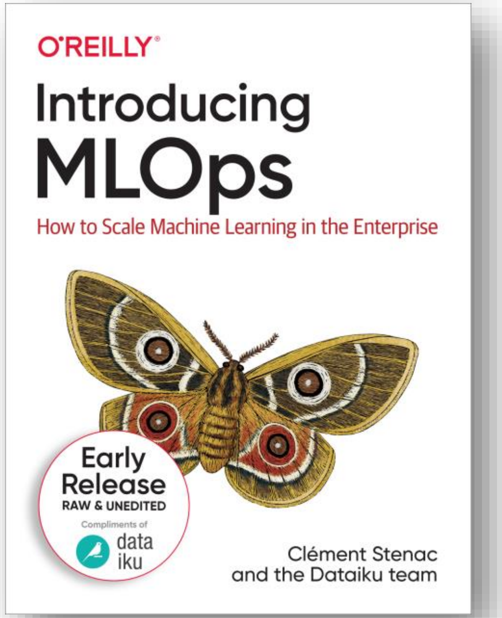

O'REILLY
2nd Edition
Updated for TensorFlow 2
Hands-on Machine Learning with Scikit-Learn, Keras & TensorFlow
Concepts, Tools, and Techniques to Build Intelligent Systems
powered by
jupyter
Aurélien Géron

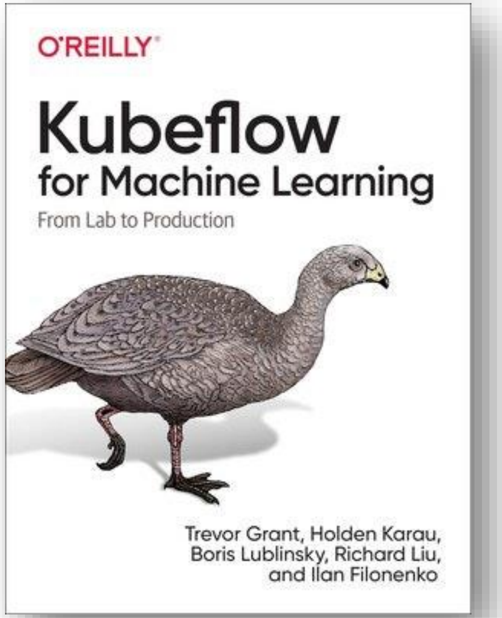

Dive into Deep Learning
PREVIEW VERSION
Aston Zhang, Zachary C. Lipton, Mu Li, and Alexander J. Smola
Dive into Deep Learning


O'REILLY
Designing Data-Intensive Applications
THE BIG IDEAS BEHIND RELIABLE, SCALABLE, AND MAINTAINABLE SYSTEMS
Martin Kleppmann


O'REILLY
Building Machine Learning Pipelines
Automating Model Life Cycles with TensorFlow
Hannes Hapke & Catherine Nelson
Foreword by Aurélien Géron

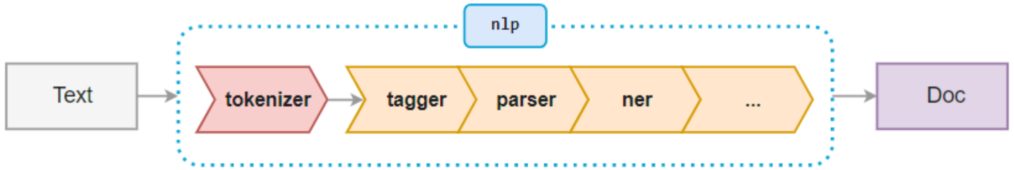

O'REILLY
Building Machine Learning Powered Applications
Going from Idea to Product
Emmanuel Ameisen


O'REILLY
Introducing MLOps
How to Scale Machine Learning in the Enterprise
Early Release
RAW & UNEDITED
Compliments of
data iku
Clément Stenac and the Dataiku team


O'REILLY
Kubeflow for Machine Learning
From Lab to Production
Trevor Grant, Holden Karau, Boris Lublinsky, Richard Liu, and Ilan Filonenko

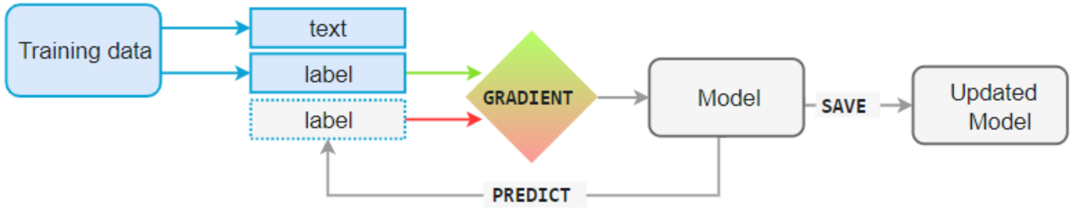
Language Processing Pipelines

- SpaCy's `nlp` class first tokenizes the text
- Default pipeline: tagger, parser, NER
- Can add custom components at any point in the pipeline
- Finally, produce a `Doc` object



Training Models

- SpaCy's `nlp` class first tokenizes the text
- Default pipeline: tagger, parser, NER
- Can add custom components at any point in the pipeline
- Finally, produce a `Doc` object



Is there a way to automate the flow?

Reference: spacy.io

Wrapping Up

One more thing…

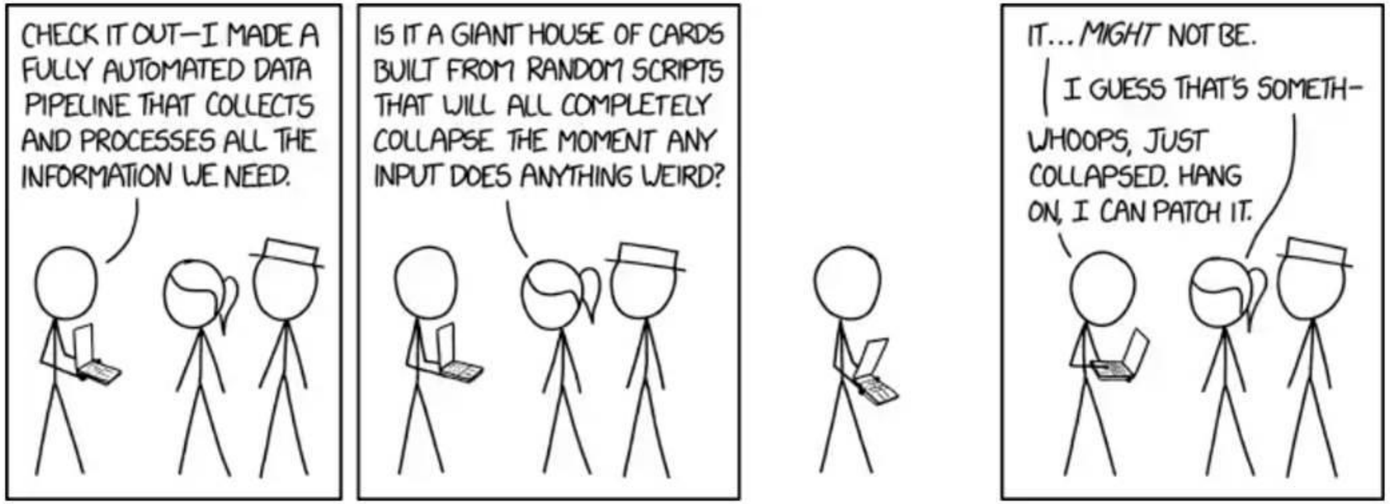


Image source: [xkcd: Data Pipeline](https://xkcd.com/2054/)

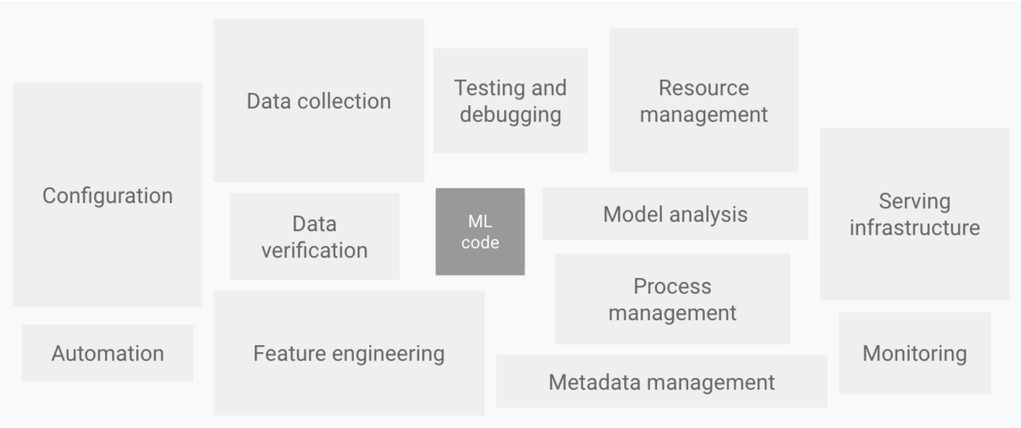
Creating NLP pipelines

Problem statement:

- Building a deep learning model is a small part of an end-to-end cycle of deploying an app
- Building an NLP pipeline is critical in managing model versions, dataset versions, and ensuring resiliency of the infrastructure

Directed Acyclic Graph, or DAG, to the rescue

- DAG is a data pipeline, an ETL process, or a workflow
- Each node or task of DAG includes an operator: Python, Bash, etc.
- When to use:
  - Going beyond cron jobs
  - Usually when business logic demands it



Source: https://cloud.google.com/solutions/machine-learning/mlops-continuous-delivery-and-automation-pipelines-in-machine-learning

Airflow installation

Setup:

```
pip3 install apache-airflow

# Set home env
export AIRFLOW_HOME=$(pwd)

# Initialize dB
airflow initdb
```

```
# Client
airflow scheduler

# in a different terminal, run:
airflow webserver
```

Simple DAG Script

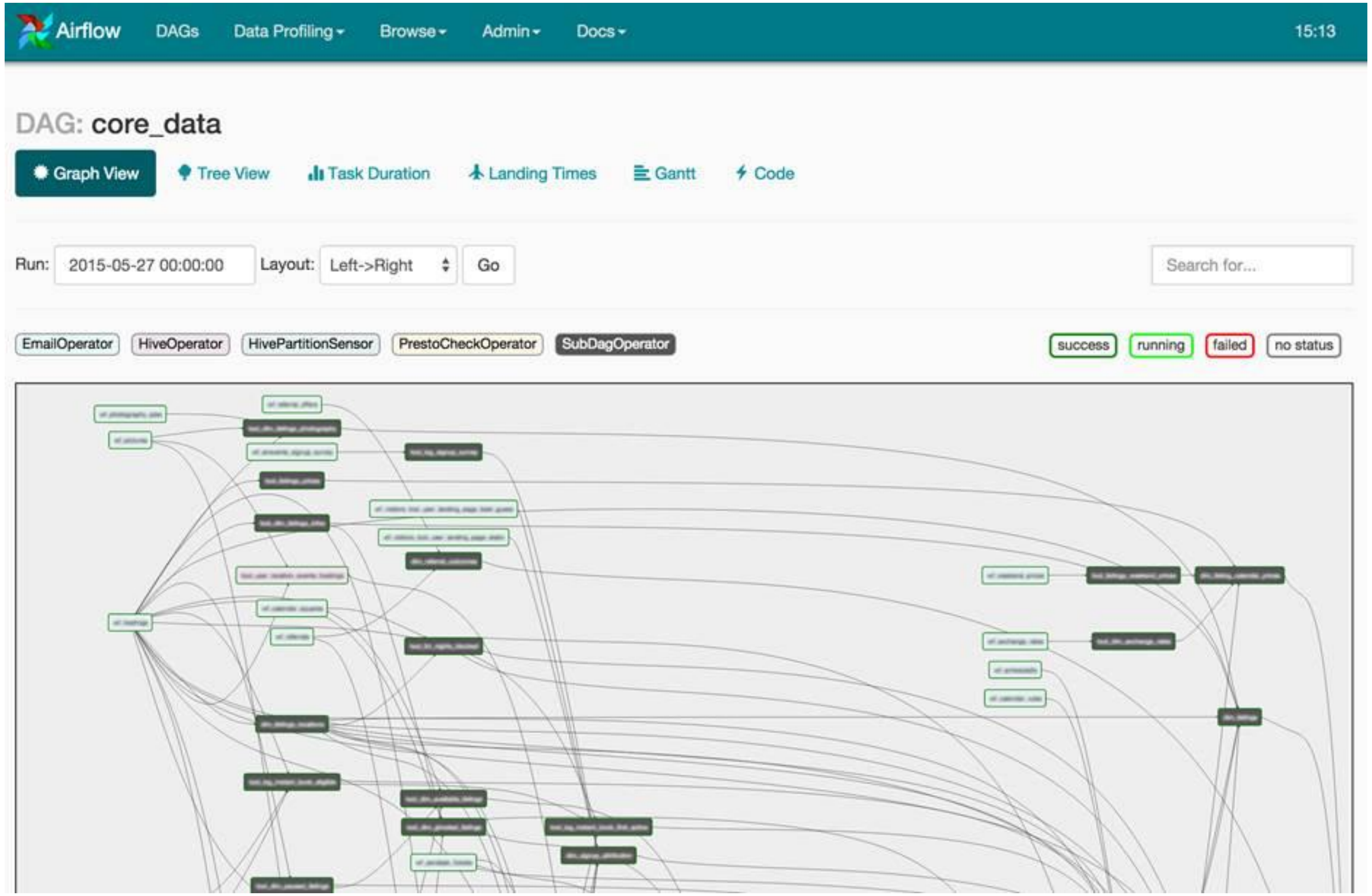
```
# Python standard modules
from datetime import datetime, timedelta
# Airflow modules
from airflow import DAG
from airflow.operators.bash_operator import BashOperator
default_args = {
      'owner': 'airflow’,
      'depends_on_past': False,
      # Start on 27th of June, 2020
      'start_date': datetime(2020, 6, 27),
      'email': ['airflow@example.com’],
      'email_on_failure': False,
      'email_on_retry': False,
      # In case of errors, do one retry
      'retries': 1,
      # Do the retry with 30 seconds delay after the error
      'retry_delay': timedelta(seconds=30),
      # Run once every 15 minutes
      'schedule_interval': '*/15 * * * *’
}
```

```
# After defining the parameters, tell the DAG what to actually do
and # the dependencies for each task
with DAG(
      dag_id='simple_bash_dag’,
      default_args=default_args,
      schedule_interval=None,
      tags=['my_dags’],
) as dag:
      #Here we define our first task
      t1 = BashOperator(
      bash_command="touch ~/my_bash_file.txt",
      task_id="create_file")
      #Here we define our second task
      t2 = BashOperator(bash_command="mv ~/my_bash_file.txt
      ~/my_bash_file_changed.txt",
      task_id="change_file_name")
      # Configure T2 to be dependent on T1’s execution t1 >> t2
```

Ref: https://towardsdatascience.com/data-pipeline-orchestration-on-steroids-getting-started-with-apache-airflow-part-1-22b503036ee

How it looks in practice

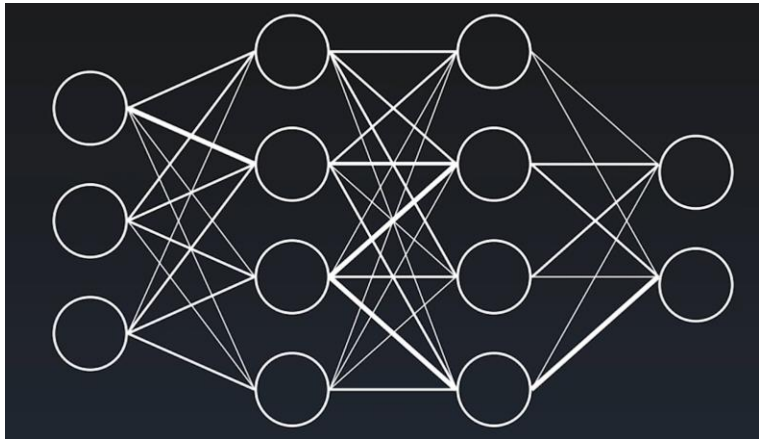
- Data warehousing: Organize & clean input text
- A/B testing (trying out different models)
- Business Policy & governance compliance
- AWS – Managed Workflow for Apache Airflow

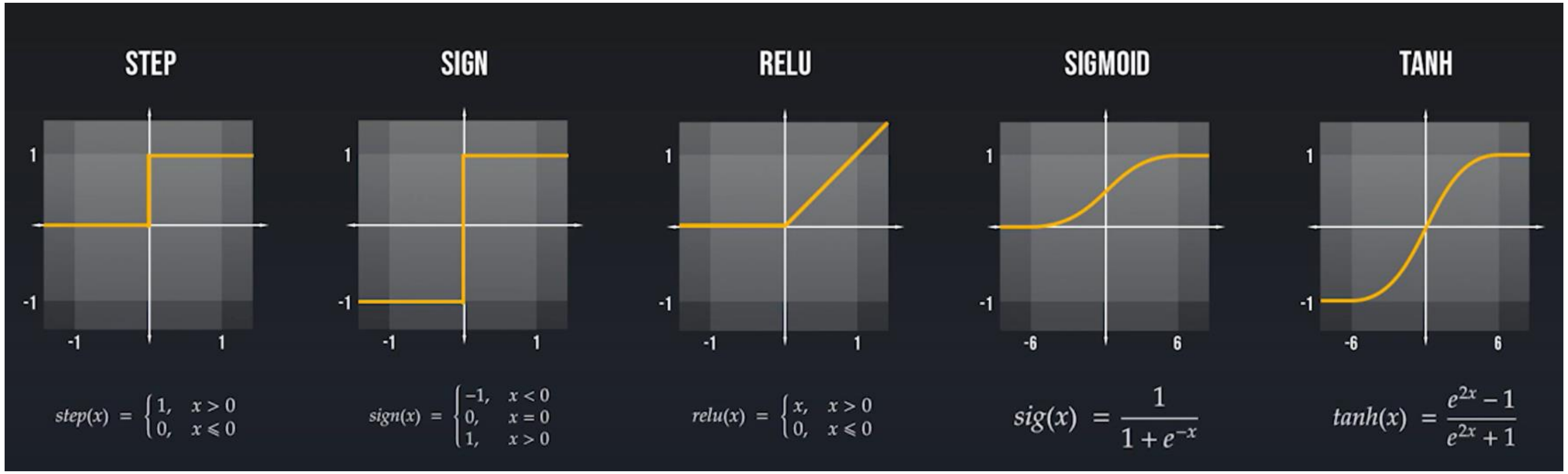


Goto:
https://airflow.apache.org/docs/stable/tutorial.html
https://aws.amazon.com/blogs/aws/introducing-amazon-managed-workflows-for-apache-airflow-mwaa/

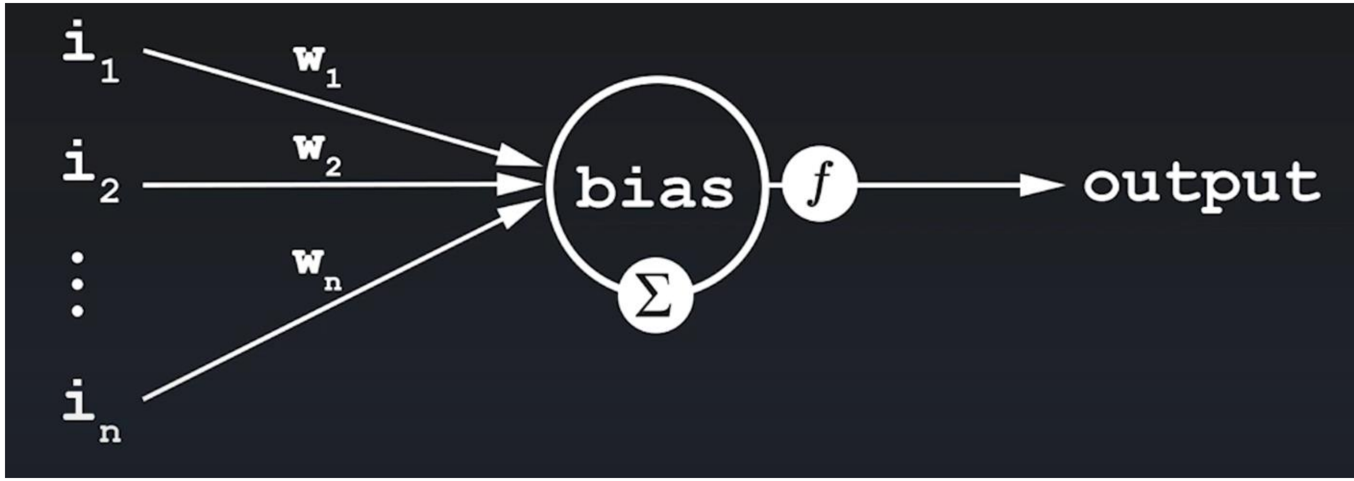
Neural Network from Scratch

Activation Function



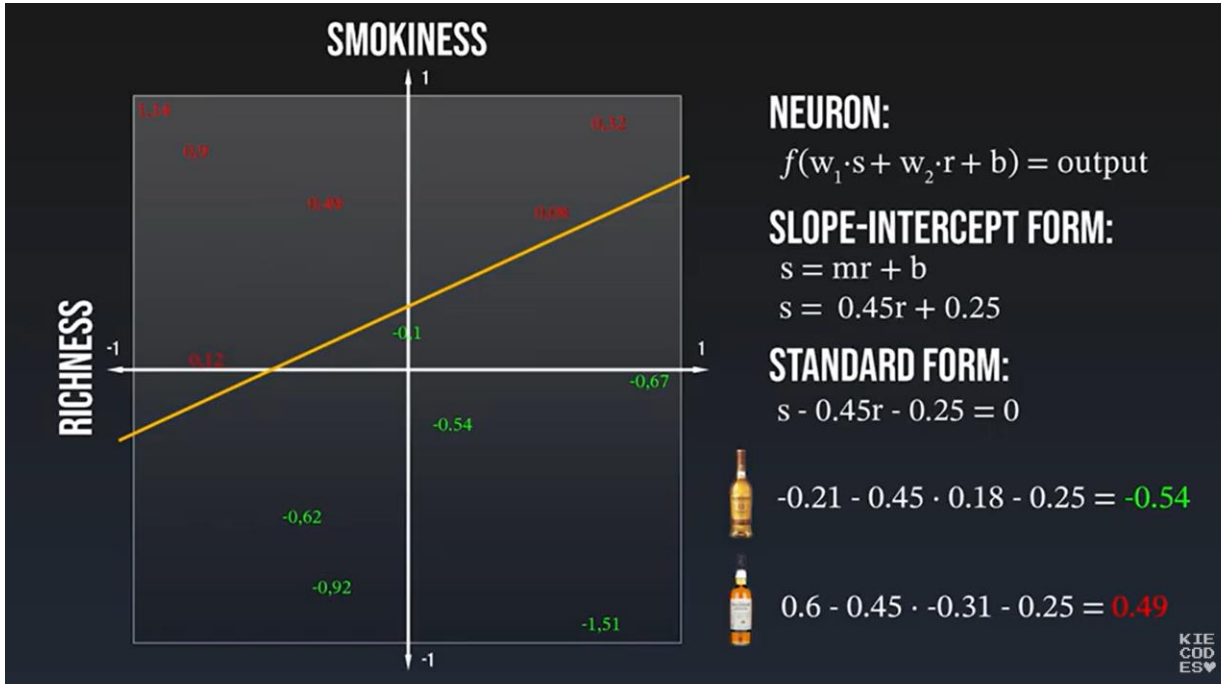


Modeled after Neurons (cell-body, dendrites, axons)



$$f(i_1 \cdot w_1 + i_2 \cdot w_2 + \ldots + i_n \cdot w_n + b) = \text{output}$$

Linear regression with Neurons



The activation function keeps the output within a certain range

Sometimes we don’t want to pass the strength fo the decision rather just the decision itself

Previous slide had a choice of function used: problem, structure of the net and the training algo used

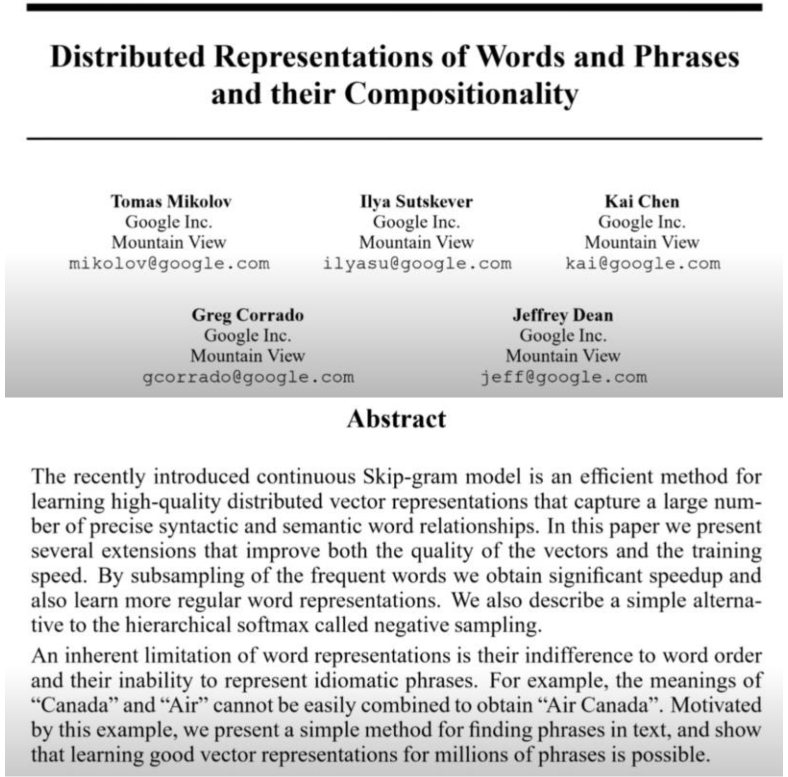
Step function returns 1 for all positive inputs & 0 for rest

F(standard form) => step function

Backup

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

Tomas Mikolov Google Inc. Mountain View mikolov@google.com

Ilya Sutskever Google Inc. Mountain View ilyasu@google.com

Kai Chen Google Inc. Mountain View kai@google.com

Greg Corrado Google Inc. Mountain View gcorrado@google.com

Jeffrey Dean Google Inc. Mountain View jeff@google.com

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.

References

Models

- FastText: https://fasttext.cc/
- CBOW and Skip-gram comparison: https://fasttext.cc/docs/en/unsupervised-tutorial.html
- NLTK vs SpaCy: https://www.activestate.com/blog/natural-language-processing-nltk-vs-spacy/
- Geek4Geeks Python Word Embeddings: https://www.geeksforgeeks.org/python-word-embedding-using-word2vec/
- Multi-lingual text analysis: https://aylien.com/blog/leveraging-deep-learning-for-multilingual
- Hero NLP libraries: https://elitedatascience.com/python-nlp-libraries
- Huggingface Universal Sentence Embeddings: https://medium.com/huggingface/universal-word-sentence-embeddings-ce48ddc8fc3a
- Goldberg, Yoav. "Neural Network Methods for Natural Language Processing." Synthesis Lectures on Human Language Technologies 10.1 (2017): 1–309.

Word Embeddings

- Language modeling technique used for mapping words to vectors of real numbers. It represents words or phrases in vector space with several dimensions. Word embeddings can be generated using various methods like neural networks, co-occurrence matrix, probabilistic models, etc.

Word2Vec

- Consists of models for generating word embedding. These models are shallow two-layer neural networks having one input layer, one hidden layer and one output layer. Word2Vec utilizes two architectures :
  - **CBOW (Continuous Bag of Words)** model predicts the current word given context words within specific window. The input layer contains the context words, and the output layer contains the current word. The hidden layer contains the number of dimensions in which we want to represent current word present at the output layer.
  - **Skip Gram** predicts the surrounding context words within specific window given current word. The input layer contains the current word, and the output layer contains the context words. The hidden layer contains the number of dimensions in which we want to represent current word present at the input layer.

Ref: https://www.geeksforgeeks.org/python-word-embedding-using-word2vec/

Backup

Difference between Autoencoders & word2vec

	Autoencoder	Word2Vec
Dense Representation	An auto-encoder's job is to represent a (sparse) input dataset in a compressed form that retains the most relevant information such that it may be reconstructed at the output with minimal loss from the compressed representation. In order to do this, the input data is subjected to an information bottleneck so that the encoder is able to learn the most efficient 'latent representation' of the input rather than just memorizing the input. This is similar in spirit to matrix factorization.	Converts a sparse unique indexing of the vocabulary (i.e. in the input text, each word in the vocabulary is represented as unique index in a dictionary) to a continuous, dense, and distributed representation that can be considered to be a compressed 'latent representation' of words in the vocabulary. This can also be considered to be similar in spirit to matrix factorization, but the goal is to encode the context around the word rather than the word itself.
Type of Network	Originally proposed, the encoder and decoders are simple, fully connected, feed forward neural nets, but nothing prevents replacement of the networks by CNNs, RNNs and other deep net architectures	Originally proposed for simple, shallow, fully connected feed forward networks since the goal was to allow for fast training from large amounts of data, but similar to auto encoders, nothing prevents replacement of the network by deep net, RNNs or other architectures.
Learning Problem	Is a self-supervised learning problem because there are no explicit labels. The input dataset also serves as the output label since the goal is reconstruction.	is an unsupervised problem (corpus of unlabelled text) posed as a binary classification problem because the goal is predict the source context words given the target word (skip-gram) or predict the target word given the source context (CBOW).
Input Dataset	Can be applied to any sort of input dataset where learning a dense representation is useful.	Specifically used only for words in natural language, but nothing prevents using the method from using the technique for other sparse representations where learning the context is important/useful.
Loss Function	learn by back-propagating the reconstruction loss from decoder to encoder.	learn by back-propagating the gradient from the soft-max classifier to the dense word vectors such that the cross entropy loss of the classifier is minimized

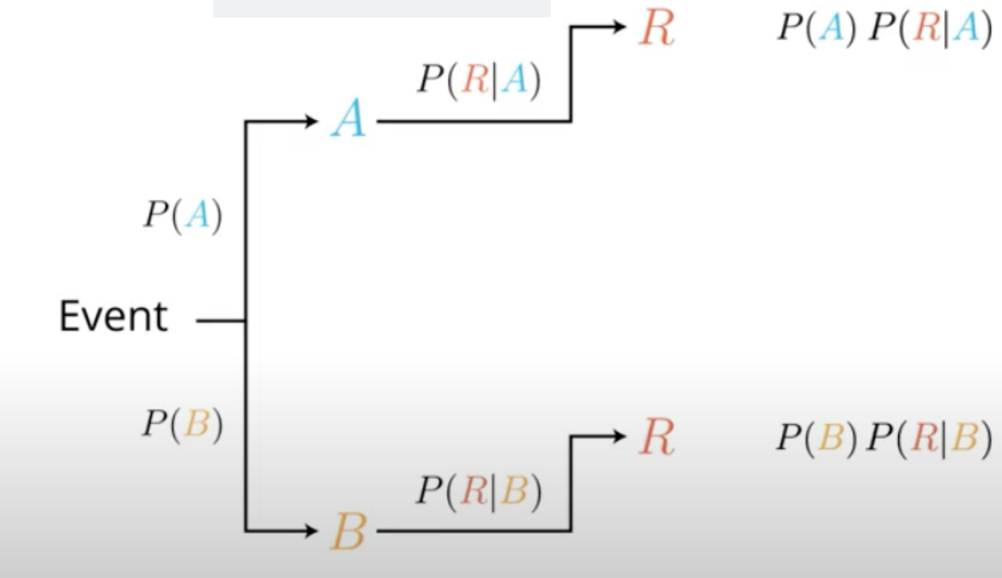
Word2Vec Code Implementation

https://fasttext.cc/docs/en/unsupervised-tutorial.html

- CBOW and Skip Gram implementations
- Get the data:
  - wget https://dumps.wikimedia.org/enwiki/latest/enwiki-latest-pages-articles.xml.bz2
- Trains 1GB of Wiki data; not feasible for our purpose
- See Ravi’s training for Word2Vec overview

Bayes Theorem

Prior



Posterior

$$P(A|R) = \frac{P(A)P(R|A)}{P(A)P(R|A) + P(B)P(R|B)}$$

$$P(B|R) = \frac{P(B)P(R|B)}{P(A)P(R|A) + P(B)P(R|B)}$$

Since these two probabilities do not add to one, we just divide them both by their sum so that the new probabilities now do add to one.

1. Naïve assumption: assume that our probabilities are independent.
   - P(A&B) = P(A)*P(B)
2. Conditional probability – the basis for our theorem
   - P(A|B)*P(B) = P(B|A)*P(A) => P(A|B) α P(B|A)*P(A)

Machine Learning: Supervised Learning Loss Methods

Loss Function	Application	Pros	Cons	Notes
OLS: Squared Loss	Regression	Differentiable everywhere	Sensitive to outliers/noise	Estimates mean label; most popular regression loss function
Absolute Loss	Regression	Less sensitive to noise than OLS	Not differentiable at 0	Estimates the mean label
Huber Loss (Smooth Absolute Loss)	Regression	Behaves like squared loss when loss is small and absolute loss when large		
Log-Cosh Loss	Regression	Similar to Huber Loss, but twice differentiable everywhere		
Hinge Loss	Classification		Standard SVM is only differentiable everywhere at p=2	Standard SVM (p=1) (Differentiable) Squared Hingeless SVM (p=2)
Log-Loss	Classification	Outputs are well-tuned; popular		As z->Inf, log-loss & hinge loss become increasingly parallel
Exponential Loss	Classification		Loss increases exponentially – extremely aggressive	Exponential loss & hinge loss are both upper-bounds of zero-one loss
Zero-One Loss	Classification		Non-continuous, which means it's not really practical to optimize	Loss is zero when the prediction is correct, and one when the prediction is incorrect

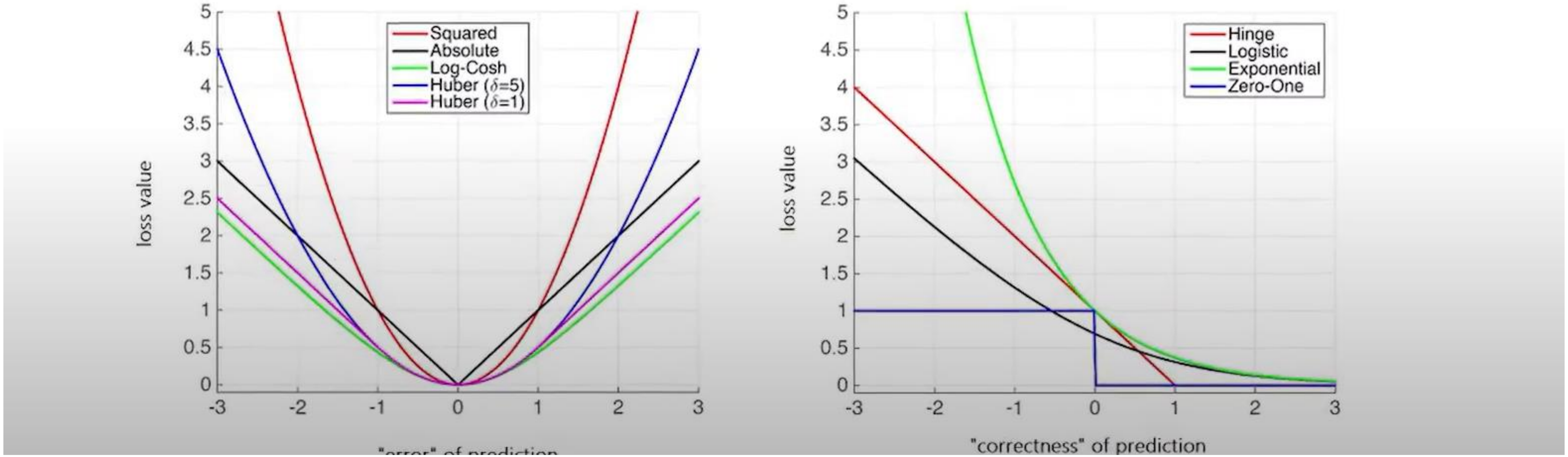
Ref: Econoscent – Visual guide to XGBoost (https://youtu.be/TyvYZ26alZs)

NLP Libraries

Library	Details
NLTK	**This is the library that everyone starts with.** A lot of text pre-processing capabilities are available such as tokenization, stemming, POS tagging, etc.
TextBlob	This was built on top of NLTK, is **easy to use**, and includes some additional functionality such as sentiment analysis and spell check.
Gensim	This library was built **specifically for topic modeling** and includes multiple techniques including LDA and LSI. It can also calculate document similarity.
SpaCy	This is the newest of the bunch and is known for its **fast performance** since it was written in Cython. It can do a lot of things that NLTK can do.

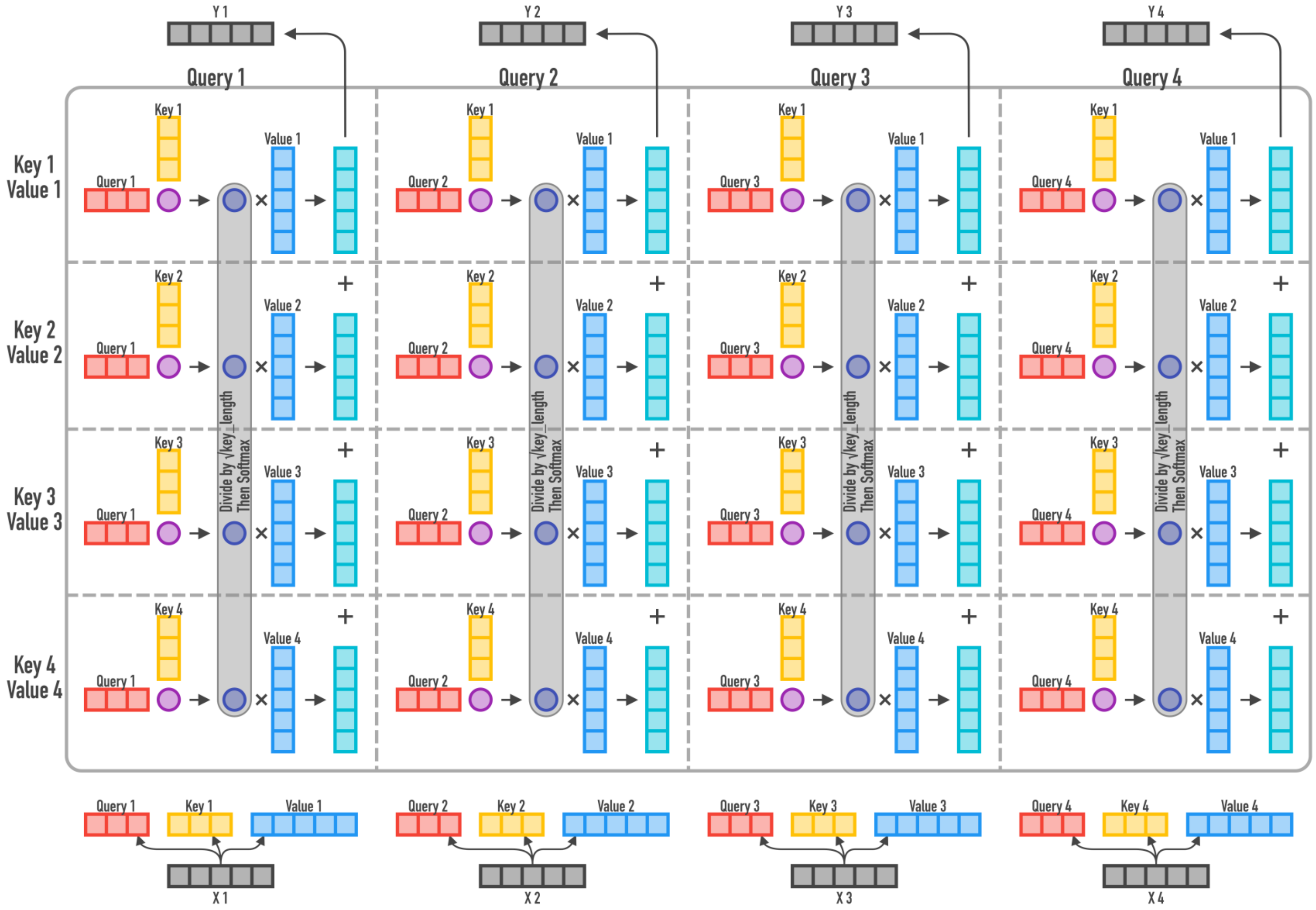
Credit - PyOhio Lecture:
https://youtu.be/xvqsFTUsOmc?t=6495

Machine Learning: Supervised Loss Functions



Ref: Econoscent – Visual guide to XGBoost (https://youtu.be/TyvYZ26alZs)

Attention is All you Need



https://twitter.com/javier_a2/status/1352706777192792065?s=20

Neural Language Models

https://drive.google.com/file/d/149m3wRavTp4DQZ6RJTej8KP8gv4jnkPW/edit

Input Text Into Neural Network (somehow) -> NN maps all this context onto a vector -> this vector represents the next word -> get a big word embedding matrix which basically contains a vector for every possible word the model knows how to output.

Then, all we need to do is compute the similarity by doing a dot product between the context vector and each of these word vectors and we'll get a likelihood of predicting the next word. Next, we train this model by maximum likelihood in the 'obvious way'.

We often don't deal with words directly, we deal with sub-words or characters...All the skill is in building the encoder.

The first try was with convolutional models. Interpret a phrase the same way, regardless fo the order. Each word gets the same context vector.