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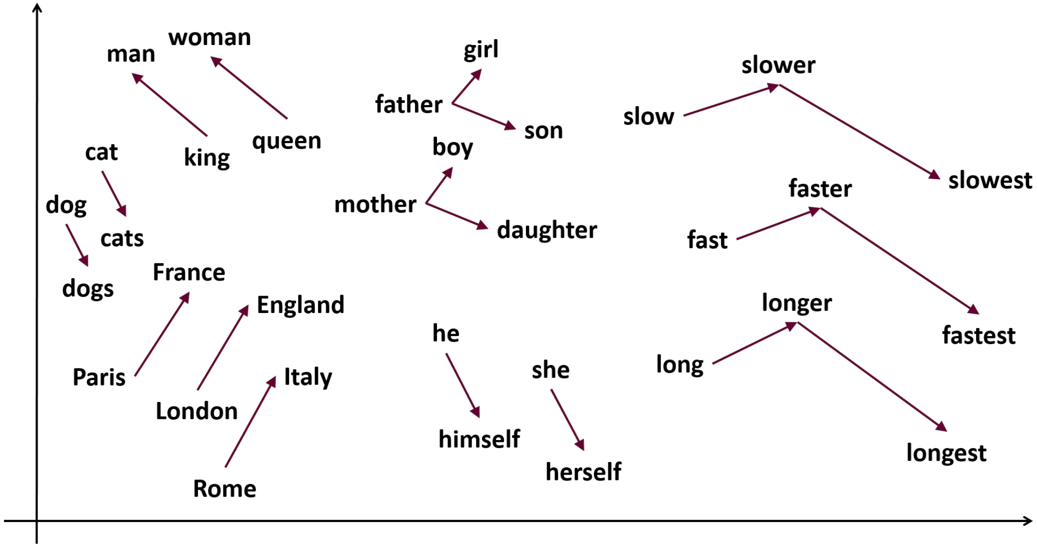
Semantic analysis using word embeddings and language models

Fotis Jannidis and Leonard Konle

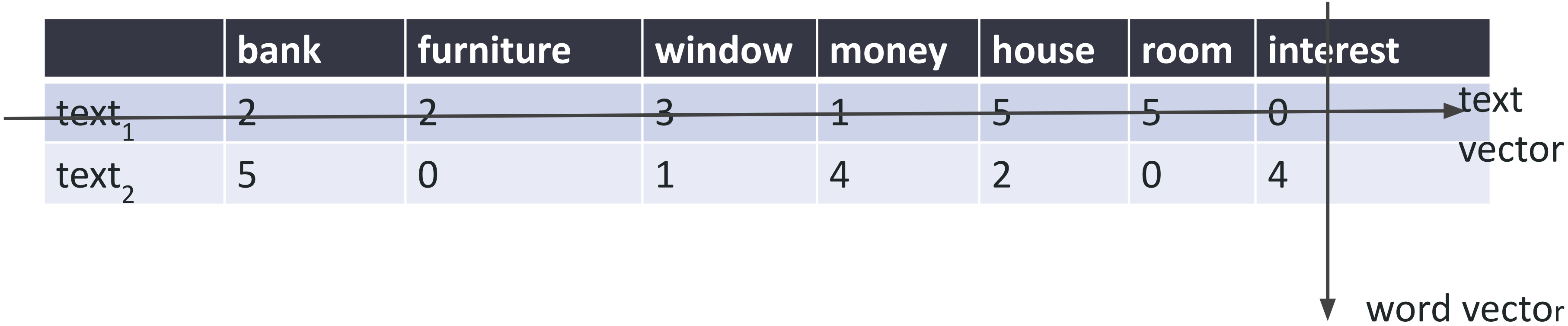
Block 1: Distributional Semantics and Word Embeddings

- Intro to Distributional Semantics
- Word2Vec and FastText
- Similarity Measurement



text and word representations

- Text similarity
  - + easy to evaluate
  - + many useful applications
  - - meaning of a text only captured as a relation to other texts
- In this context texts are usually modeled as a bag of words (bow) in a document-term matrix:



	bank	furniture	window	money	house	room	interest
text_1	2	2	3	1	5	5	0
text_2	5	0	1	4	2	0	4

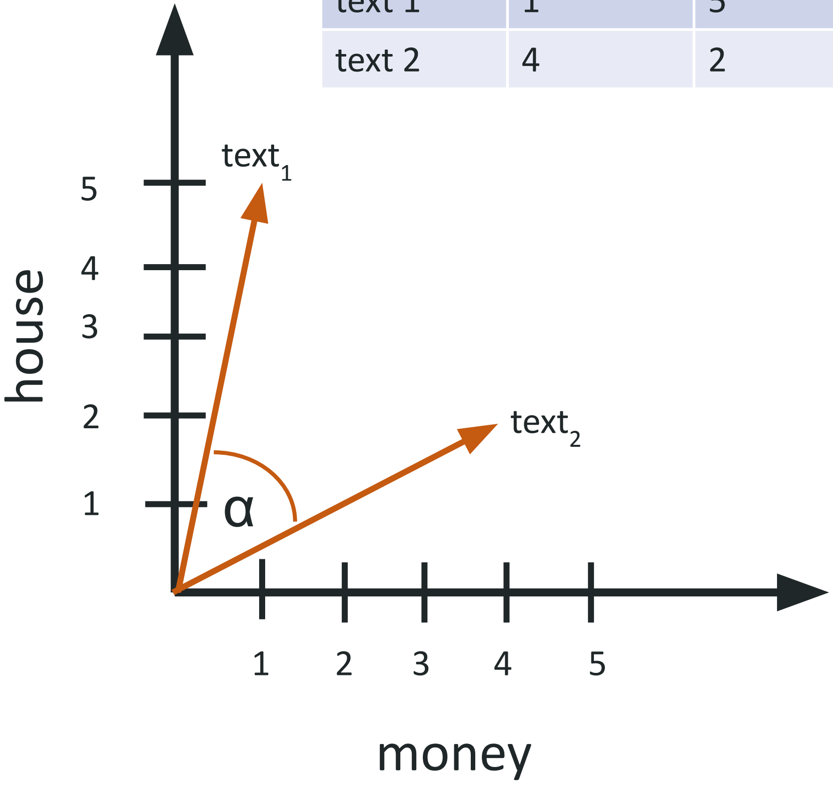
text vector

word vector

Text similarity

- Using the bow representation text can be viewed as a point in vector space (more exact: as a vector from the origin to the point)
- Text similarity can be modeled as the distance between the points
- Best measure for distance is the cosine of the angle α between the vectors

	money	house
text 1	1	5
text 2	4	2



Word meaning and context

“Before their lives violently intersected, two men who were shot to death and the man the police believe killed them had all fought the same scourge” New York Times 21.3.22

Basic intuition

- The meaning of a word can be understood by looking at the words which come up together with the word.

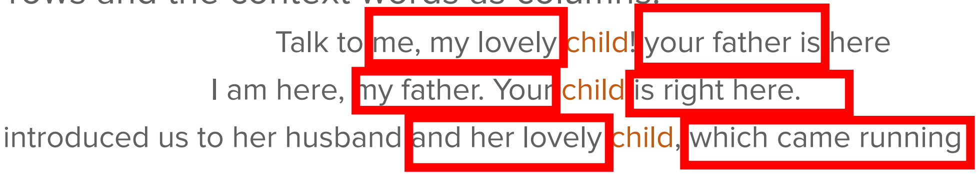
„You shall know a word by the company it keeps” (Firth 1957)

„examine the syntagmatic environments in which a word occurs, and you shall know more about the kind of word you are dealing with.” (Geeraerts 2009)

- Central concept ‘collocation’: ‘a lexical relation between two or more words which have a tendency to co-occur within a few words of each other in running text’ (Stubbs 2002: 24)
- „In corpus linguistics, a **collocation** is a sequence of words or terms that co-occur more often than would be expected by chance.” (engl. Wikipedia 14.11.2017)

Word similarity

- A vector over a whole text is not a very good representation, loss of specifitity
- Instead a context for a focus word is defined, for example 3 words to the left and 3 words to the right. On this basis we can create a new matrix, a word-context matrix, with the focus words as rows and the context words as columns:



Talk to me, my lovely child! your father is here

I am here, my father. Your child is right here.

introduced us to her husband and her lovely child, which came running

This creates a word – cooccurrence matrix:

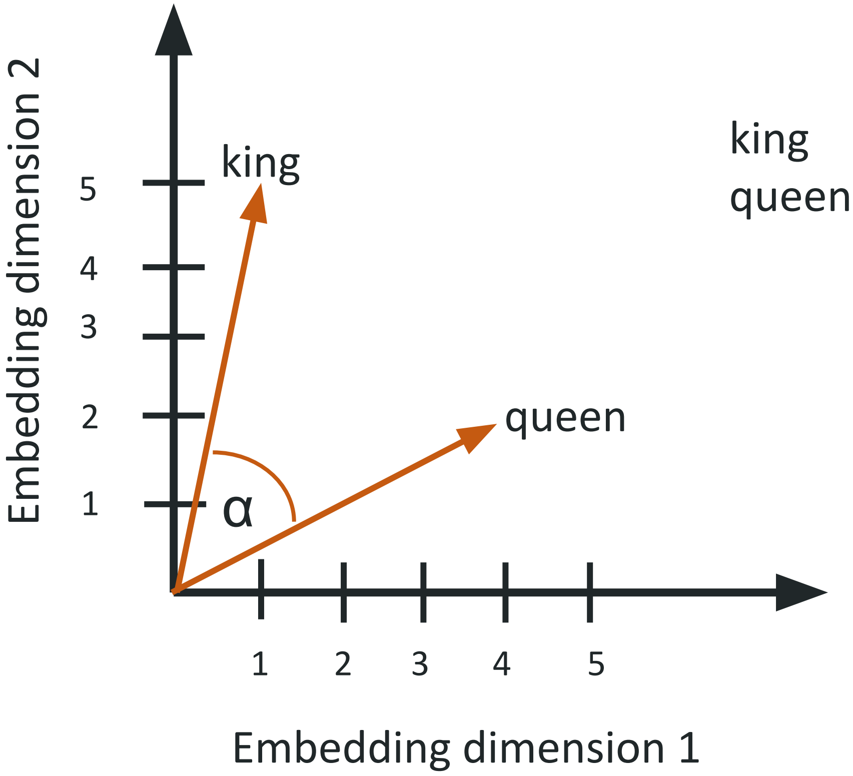
	And	Father	My	lovely	Is	Me	My	your
child	1	2	2	2	1	1	1	2

Depending on the size of the context this results still in a very large and very sparse matrix

word2vec

- Word2vec (Mikolov et al. 2013) unsupervised machine learning using a shallow neural net and a huge amount of unlabeled training data
- word2vec produces a dense vector representation of words, usually just 100-300 numbers
- in contrast to a word-context matrix we have no idea about the meaning of the numbers
- The word meaning and the relationships between words are encoded spatially

Word Embedding



2-dimensional vector

king	= [1, 5]
queen	= [4, 2]

Usually word embeddings have 100-300 dimensions (=numbers)

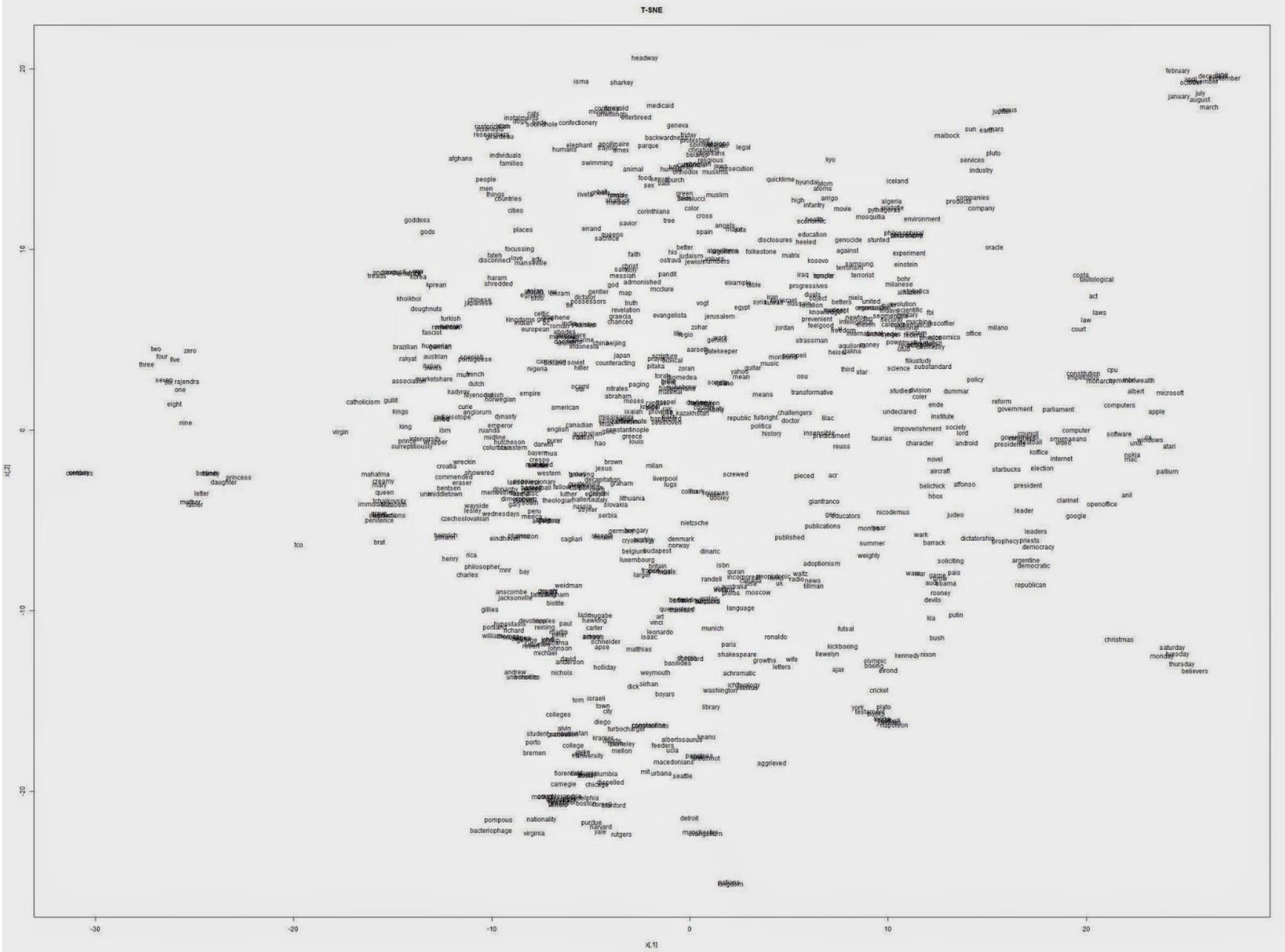
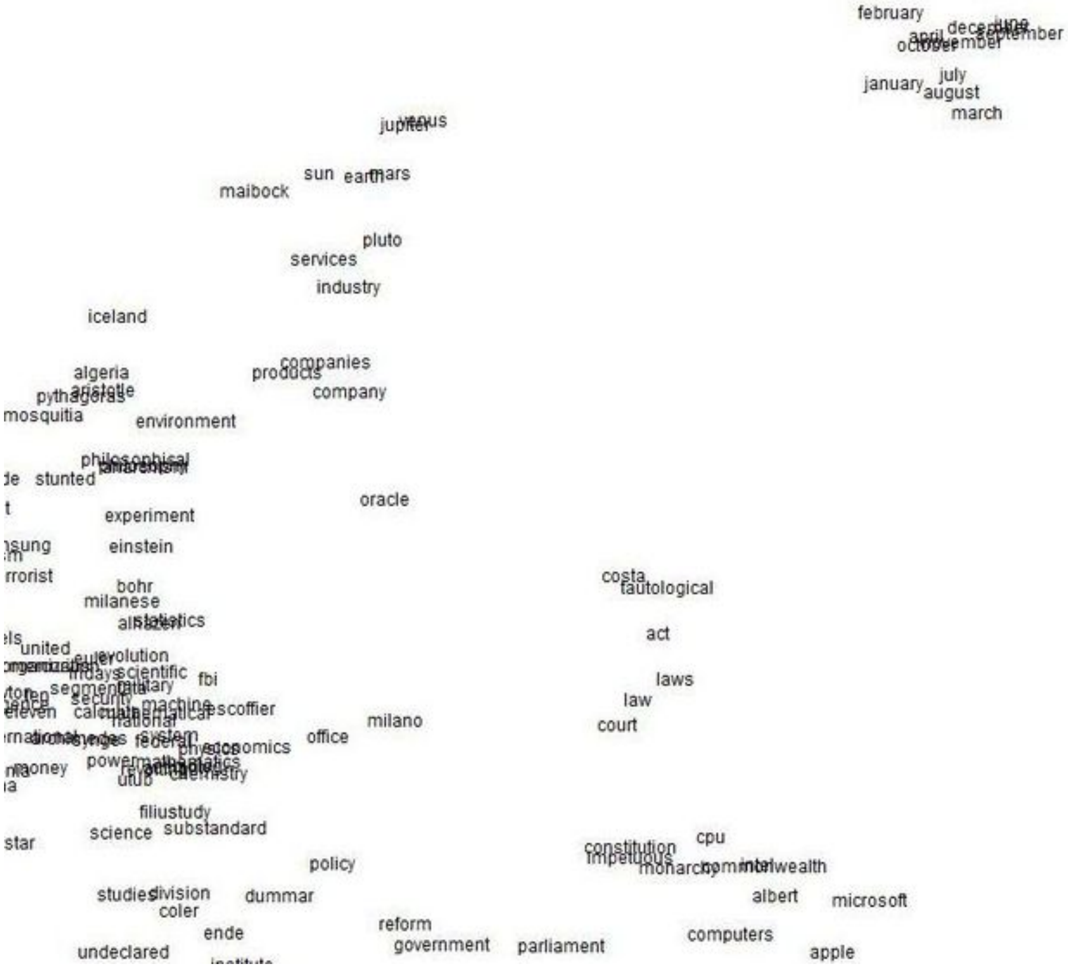


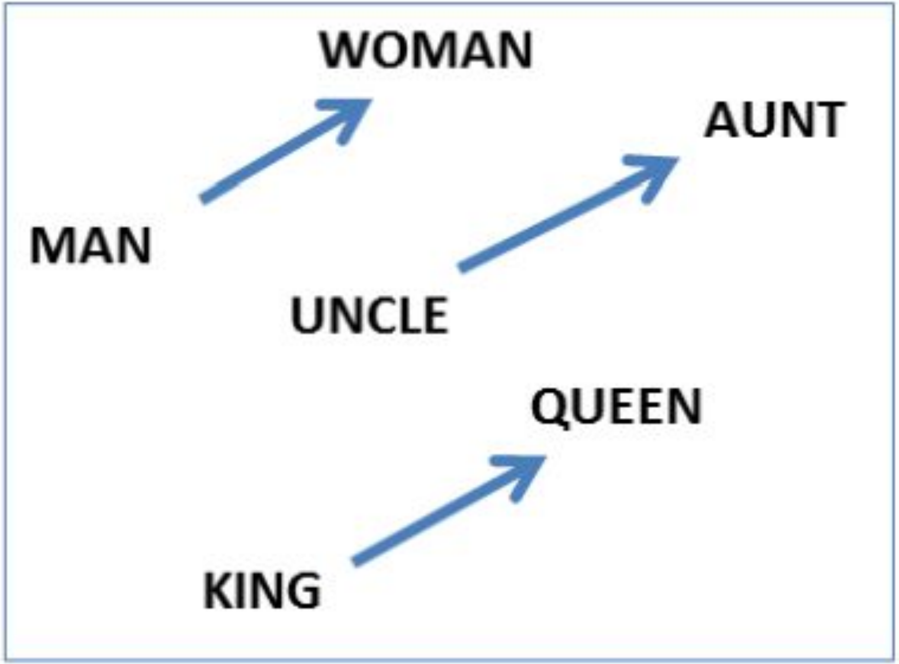
Image: http://learningaboutdata.blogspot.fr/2014/06/plotting-word-embedding-using-tsne-with.html



Spatial proximity indicates semantic similarity

Directions in vector space represent language information

Gender



Plural

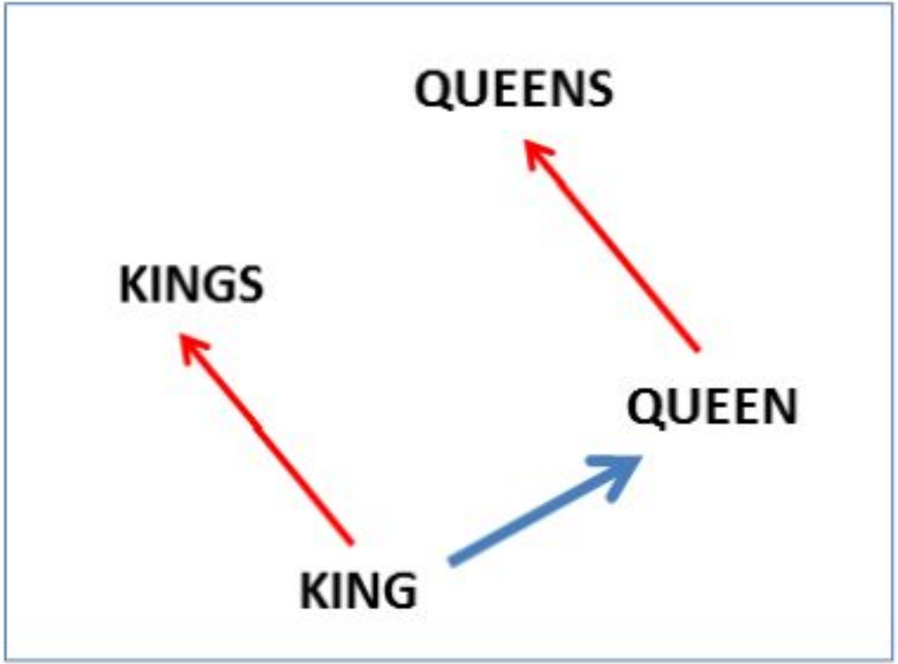
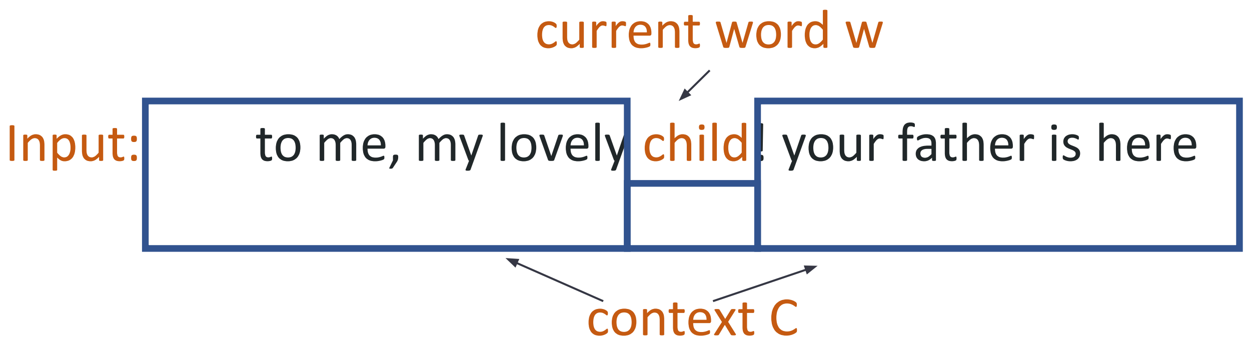


Image: Mikolov, Yih, Zweig 2013

Creating word embeddings with word2vec



current word w

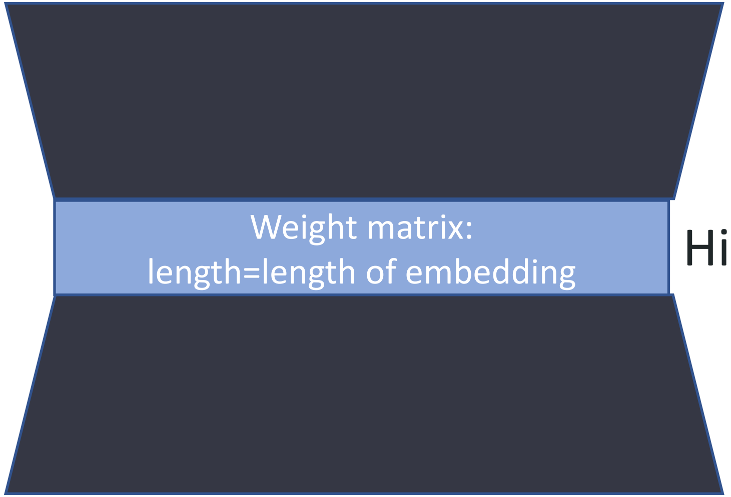
Input: to me, my lovely child! your father is here

context C

- Input is read sequentially. Each word becomes the current word and then its context is retrieved:
  w=child: C = {father, is, here, lovely, me, my, to, your}

Recurrent neural network with one hidden layer

Input: word sequences
(words in contexts)



Weight matrix:
length=length of embedding

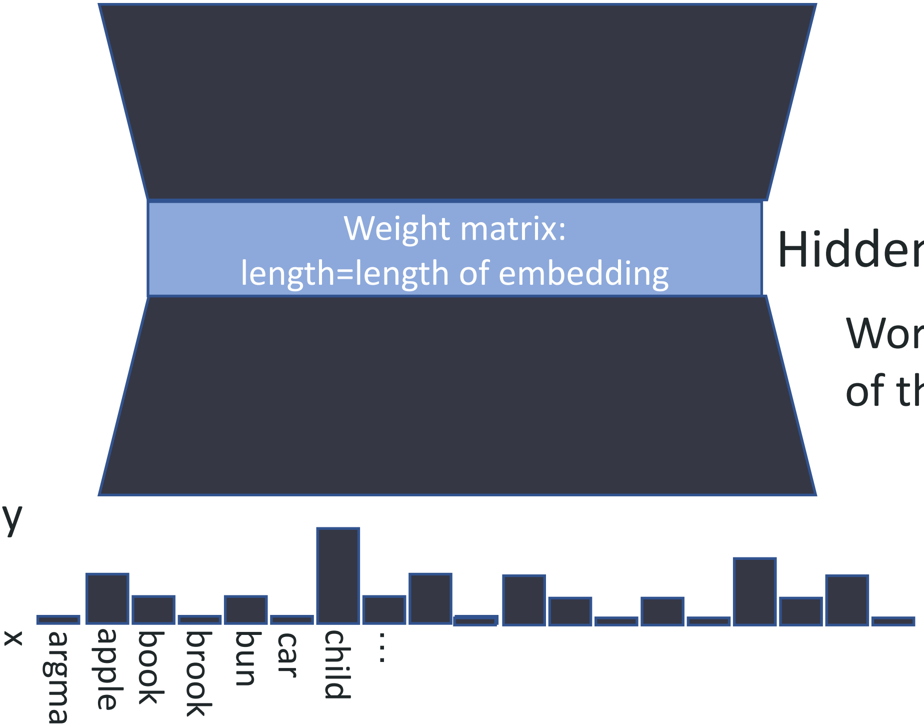
Hidden layer

Word vectors are the weights
of the hidden layer

Output: 1) prediction of context words C given current word w (CBOW)
2) prediction of current word w given the context C (skipgram)

Recurrent neural network with one hidden layer

Input: word sequences
(words in contexts)



Weight matrix:
length=length of embedding

Hidden layer

Word vectors are the weights of the hidden layer

CBOW: p(w|C)
Output is a probability distribution over the whole vocabulary

Output

word embeddings - milestones

- word2vec (Mikolov et al. 2013)
- Glove (Pennington et al. 2014)
- Fasttext (Bojanowski et al. 2016)
  - Pretrained models for 157 languages (Grave et al. 2018)
- Elmo (Peters et al. 2018)
- Bert (Devlin et al. 2018)

Glove

- Created by using a word – word cooccurrence matrix
- Based not on the probability of the words but the ratio of the probabilities
- Code available on Github
- Pretrained vectors: English (Wikipedia ++)

Fasttext

- each character n-gram is associated with a vector
- each word is represented as a bag of character n-grams, n>2 and n<7
    - words being represented as the sum of character n-gram representations
- W = ‘where’ and n= 3:
  <wh, whe, her, ere, re> <where>
- Adds subword information, for example morphological information, to the model
- Allows a reasonable representation of out-of-vocabulary words based on n-grams
- Code is available
- Since 2018 word embeddings for 157 languages available, based on Wikipedia and Common Crawl

Demo 1

https://colab.research.google.com/drive/1jgSXhQuzLIPyM8ncKd56JlfnLV0OoQEX?usp=sharing

Block 2: Demonstration

- Word Similarity Scores
- PLM for Sequence Classification (Sentiment)
- PLM for Sentence Similarity

Demonstration Notebooks will be shared and work with ELTeC Corpora cloned to Google Collaboratory without further requirements.

Distributional Semantics and Word Embeddings

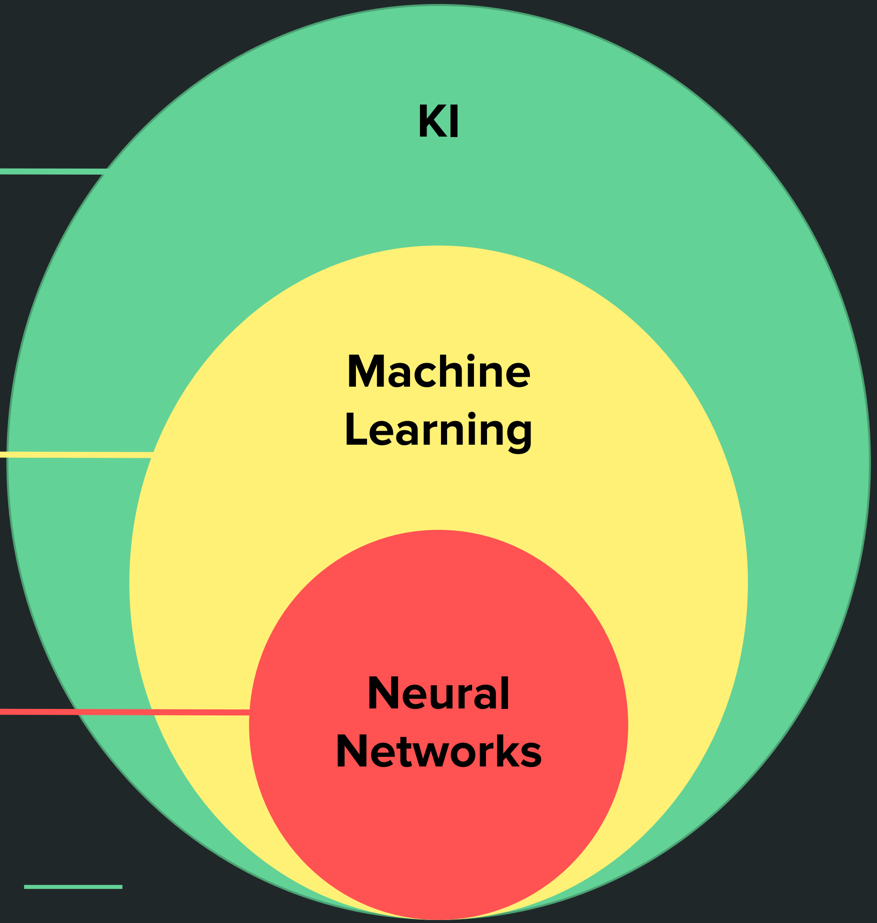
Pretrained Language Models

Machine Learning, Deep Learning & KI

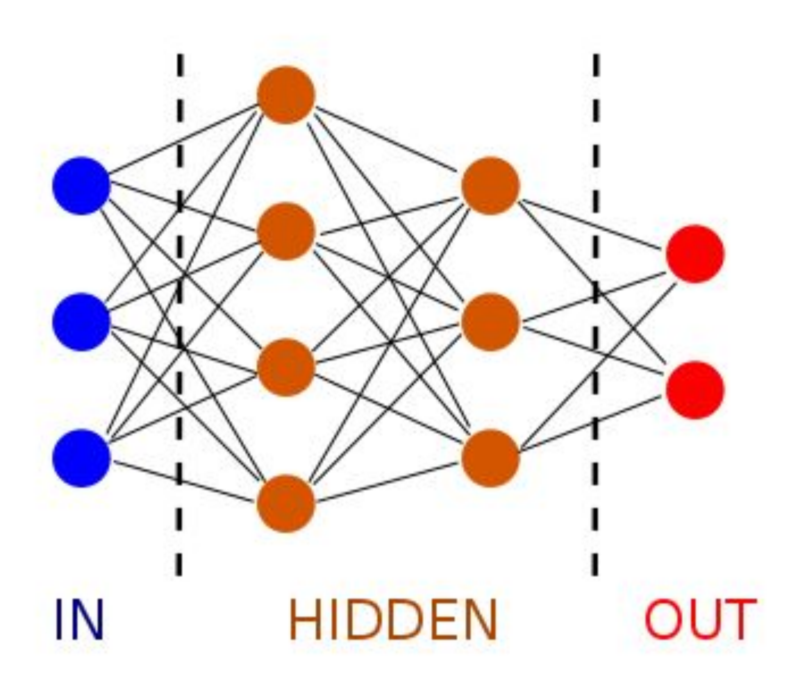
Simulation of human decision structures by algorithms in order to solve problems as autonomously as possible.

Implicit replication of these structures by adaptation of algorithms using examples

Distribution of the learning process to a net structure



Neural Networks



Fully-Connected Feedforward Network

Neural Nets - Neurons

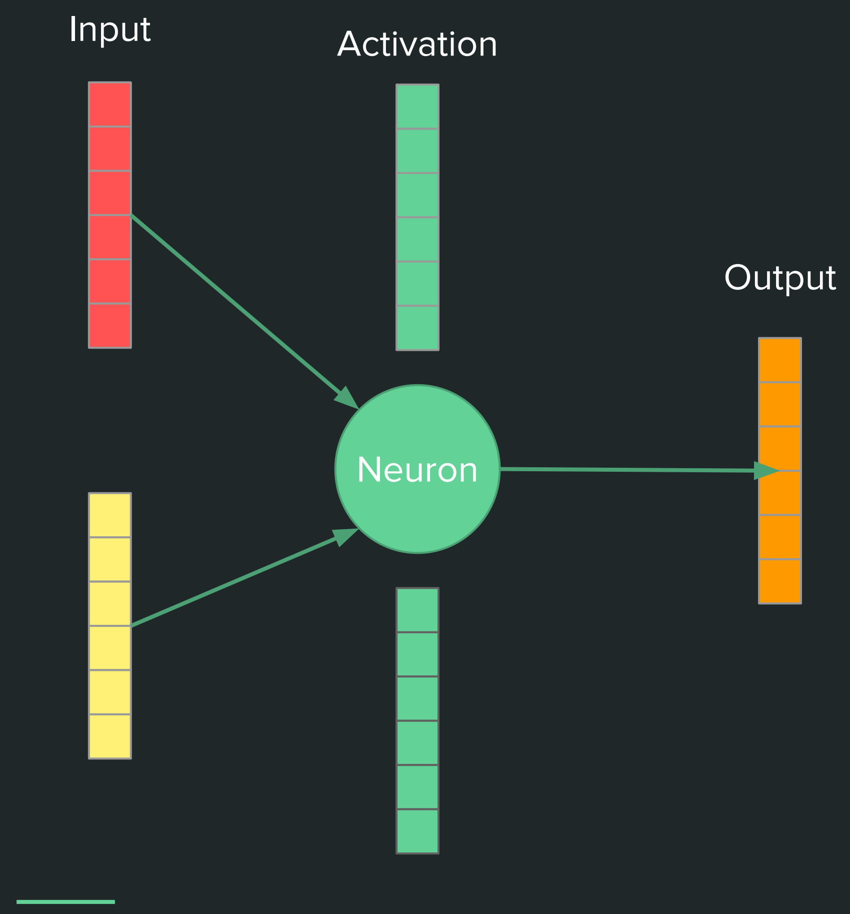
The output of a neuron is determined by its activation function:

$$y = wx + b$$

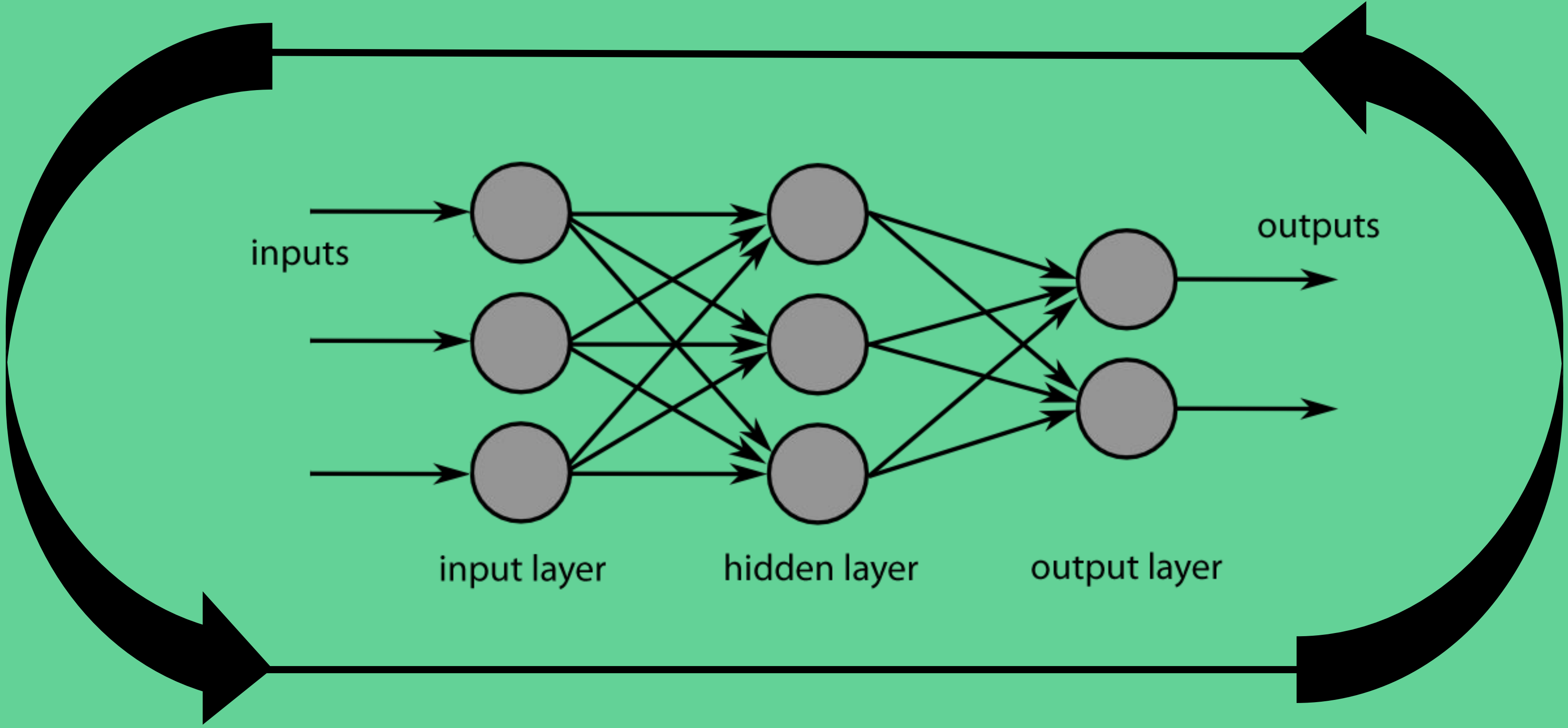
x: Input

w: weights

b: bias



back propagation



forward pass

Neural Networks - Key Terms

- **Neuron**: Smallest unit in networks
- **Layer**: A set of parallel neurons
- **Task**: Problem to be solved
- **Batch**: Number of examples before a backpropagation
- **Epoch**: One loop over all examples
- **Loss**: Distance between optimal result and output of the network

BERT

Bidirectional **E**ncoder **R**epresentations from **T**ransformers

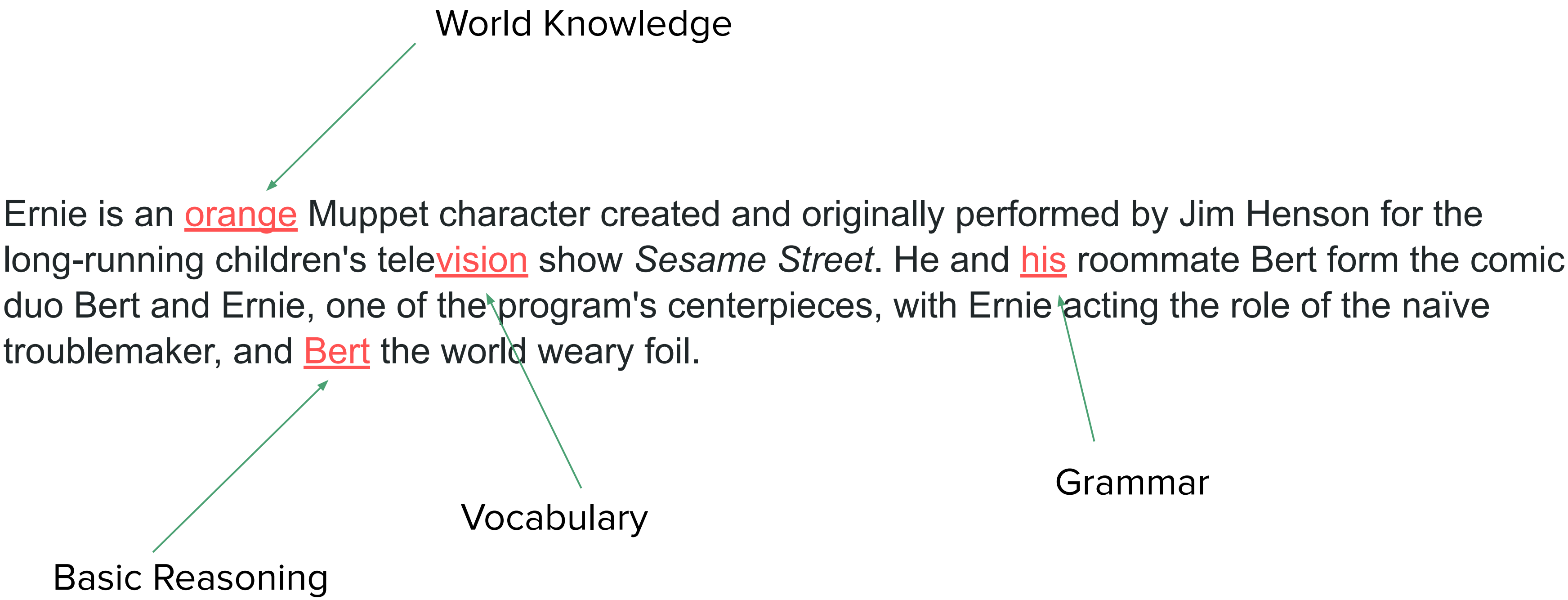
BERT - Task

- BERTs Task is Masked Language Modeling (MLM)
- Basically a cloze test

Ernie is an orange Muppet character created and originally performed by Jim Henson for the long-running children's television show *Sesame Street*. He and his roommate Bert form the comic duo Bert and Ernie, one of the program's centerpieces, with Ernie acting the role of the naïve troublemaker, and Bert the world weary foil.

Ernie is an ______ Muppet character created and originally performed by Jim Henson for the long-running children's tele____ show *Sesame Street*. He and ___ roommate Bert form the comic duo Bert and Ernie, one of the program's centerpieces, with Ernie acting the role of the naïve troublemaker, and ____ the world weary foil.

BERT - Task



World Knowledge

Ernie is an orange Muppet character created and originally performed by Jim Henson for the long-running children's television show *Sesame Street*. He and his roommate Bert form the comic duo Bert and Ernie, one of the program's centerpieces, with Ernie acting the role of the naïve troublemaker, and Bert the world weary foil.

Grammar

Vocabulary

Basic Reasoning

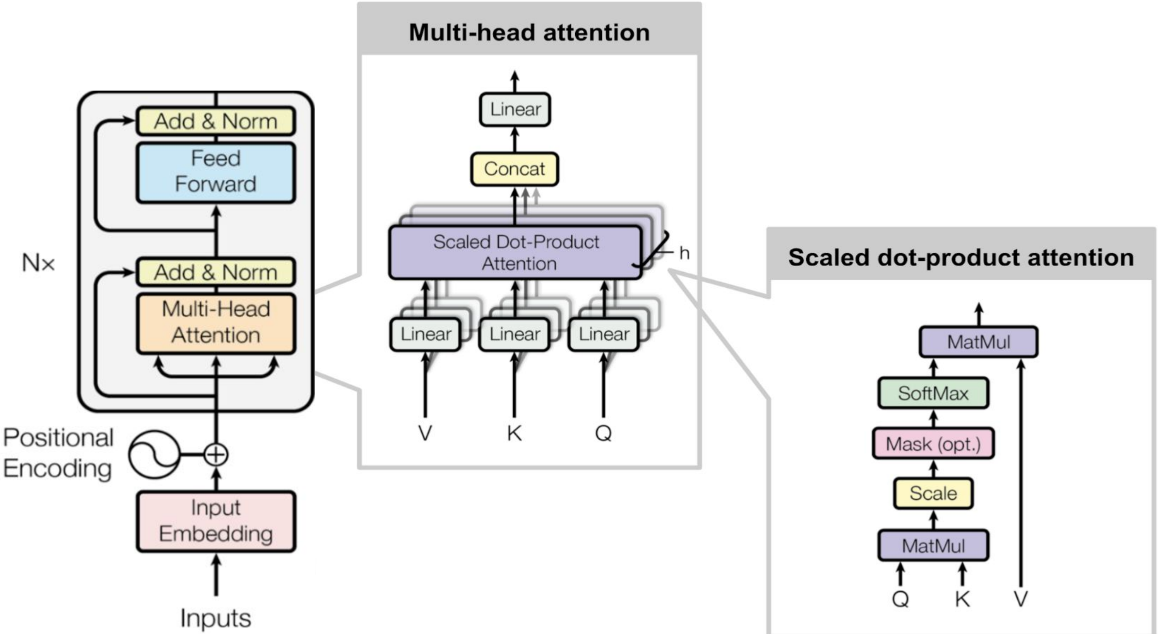
Demo: https://huggingface.co/distilbert-base-uncased?text=Ernie+is+an+%5BMASK%5D+Muppet+character+created+and+orriginally+performed+by+Jim+Henderson+for+the+long-running+children%27s+television+show+Sesame+Street.

BERT - Tokenization

ernie,is,an,orange,mu,##ppet,character,created,and,originally,performed,by,jim,hen,##son,for,the,long,-,running,children,',s,television,show,ses,##ame,street,.,he,and,his,room,##mate,bert,form,the,comic,duo,bert,and,ernie,,,one,of,the,program,',s,center,##piece,##s,,,with,ernie,acting,the,role,of,the,nai,##ve,trouble,##maker,,,and,bert,the,world,wear,##y,foi,##l,.

- No classic word tokenization
- Instead tokenization based on 30.000 word pieces
  - Reduces cloze filling complexity
  - Idea: Which choice of words allows the representation of a corpus as the shortest possible chain
- If a word is not in the list of word pieces, it’s composed out of multiple word pieces

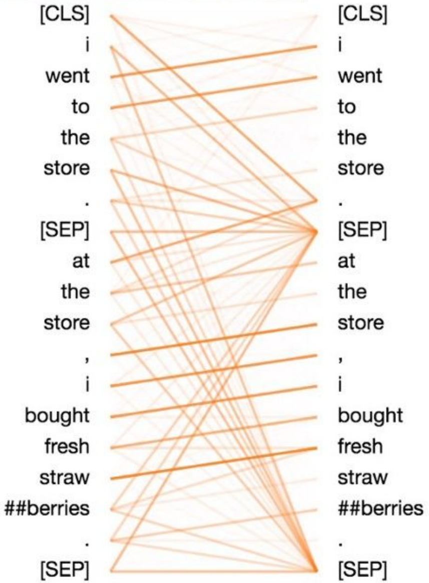
BERT - Network



The Transformer Layer

BERT - Network

- Each word is related to itself and all other words in an input.
- This is done 12 times per layer
- 12 layers in sequence[1]
- Resulting in 11M Parameters ~ 1.3GB



Attention Mechanism

[1] Bert$_{\text{Base}}$ Model

BERT - Trainingdata

- Huge amounts of:
  - Webtext
  - Forums
  - Wikis
  - Online Newspaper
  - Books
- Original Bert:
  - Google Book Corpus: 11.000 books (5GB)
  - English Wikipedia: 6.000.000 Articles (40GB)
- Best German Bert:
  - 163 GB (mostly german common crawl)

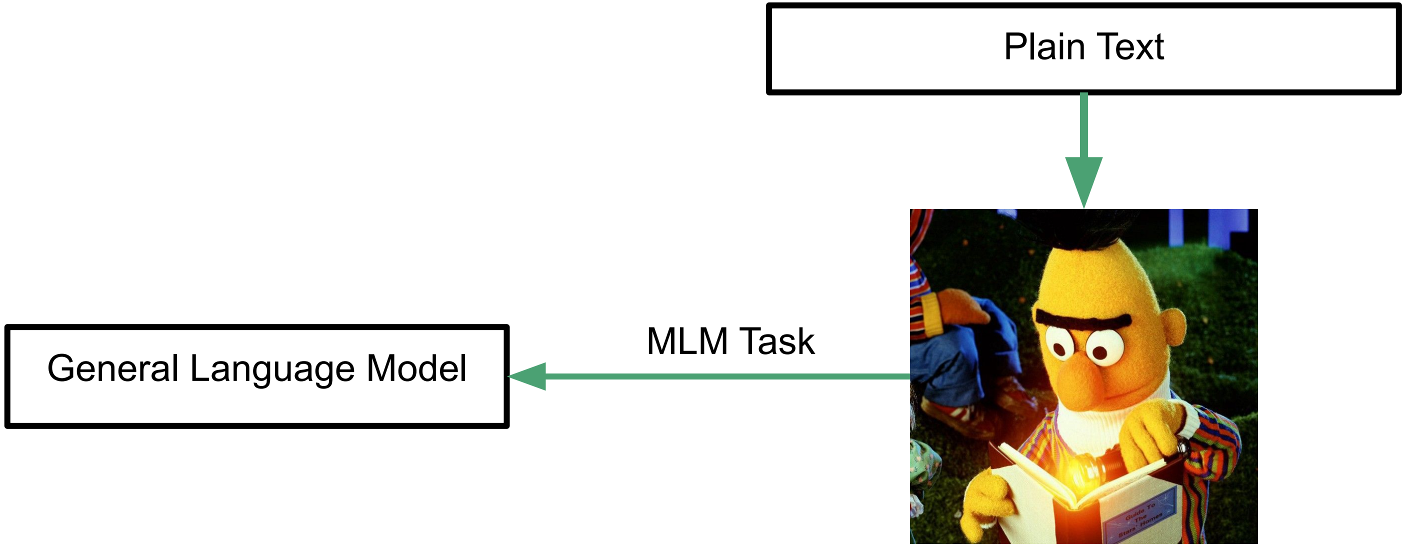
Cost of training one Bert Model: ~6000€ (4 days)

Why is BERT useful?

- No one really needs a neural cloze test solver, but:
    - Similar to word2vec we can use its inner representation for
        - Words (not worth it)
        - Sentences
        - Paragraphs
    - Make use of world knowledge, grammar, vocabulary to train
        - Document Classification
        - NER
        - Sentiment
        - ...

BERT can be seen as a compressed representation of all texts it's been trained on.

BERT Fine-Tuning



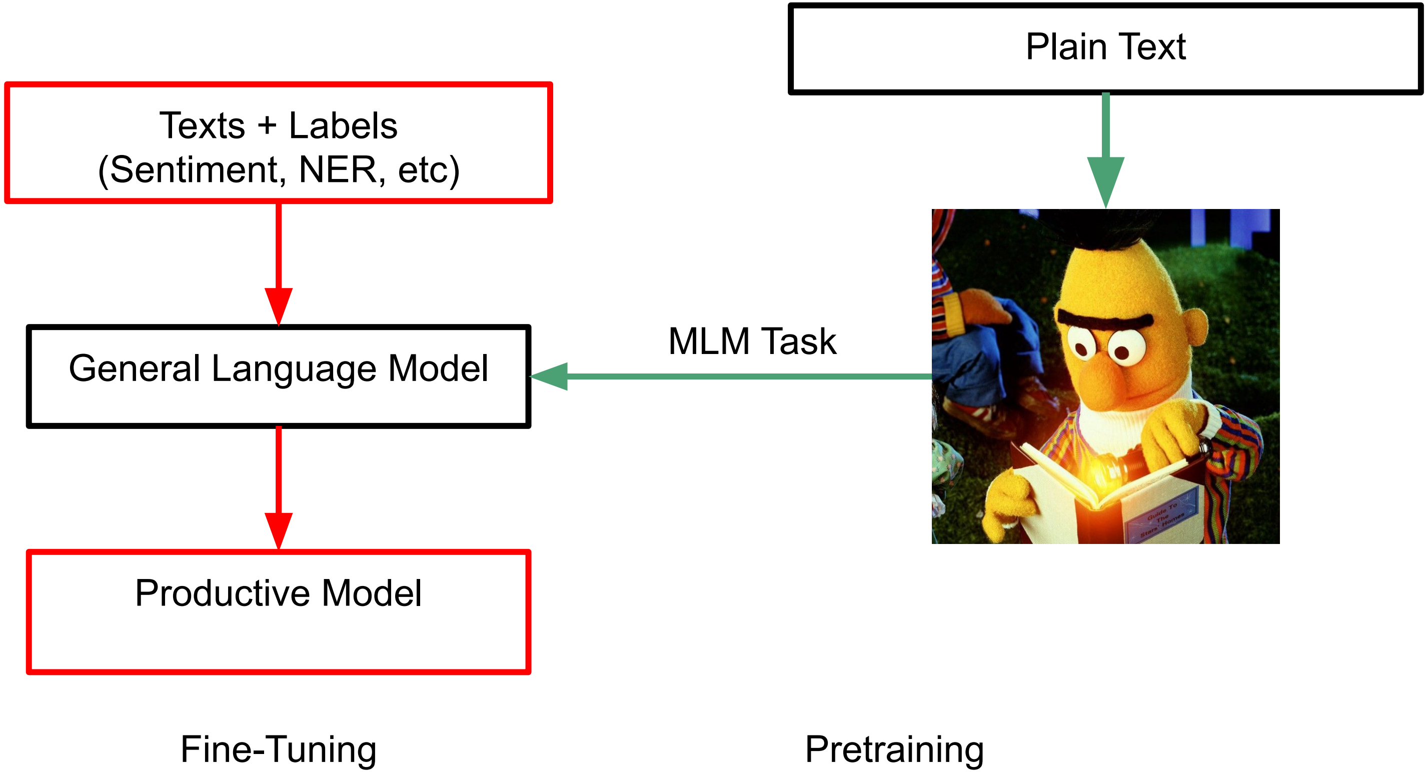
Plain Text

MLM Task

General Language Model

Pretraining

BERT Fine-Tuning



Plain Text

Texts + Labels (Sentiment, NER, etc)

MLM Task

General Language Model

Productive Model

Fine-Tuning

Pretraining

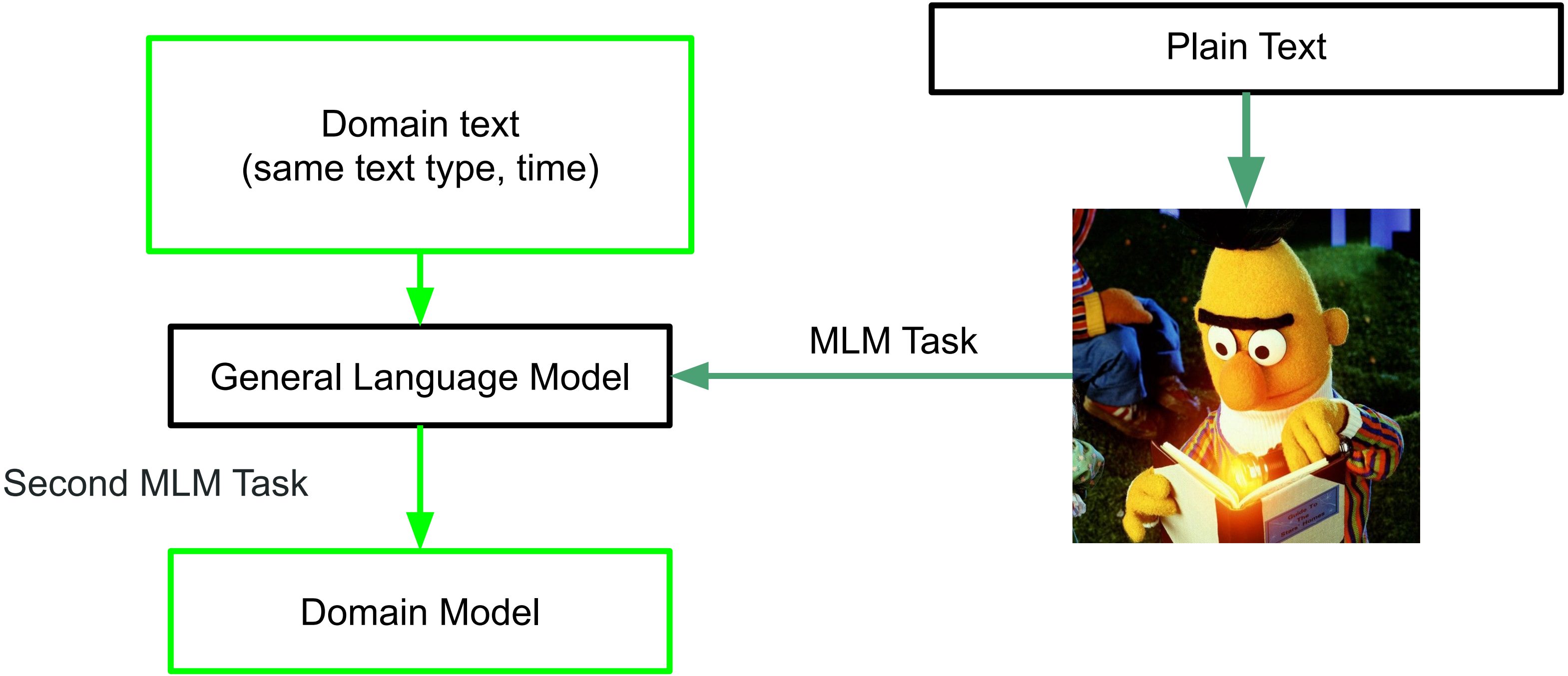
The Domain Problem

- Bert learns from modern webtext, newspapers etc.
- Typically DH deals with literary text and or texts older than webtext
    - Results in a difference between pretraining and application in:
        - Vocabulary
        - Orthography
        - Style
        - Semantic
        - Required World Knowledge

BUT: Pretrained Language Models still achieve best results even in forgein domains.

AND: We can alter Models to fit our needs (Domain Adaptation)

BERT domain adaptation



Domain text
(same text type, time)

General Language Model

Second MLM Task

Domain Model

Plain Text

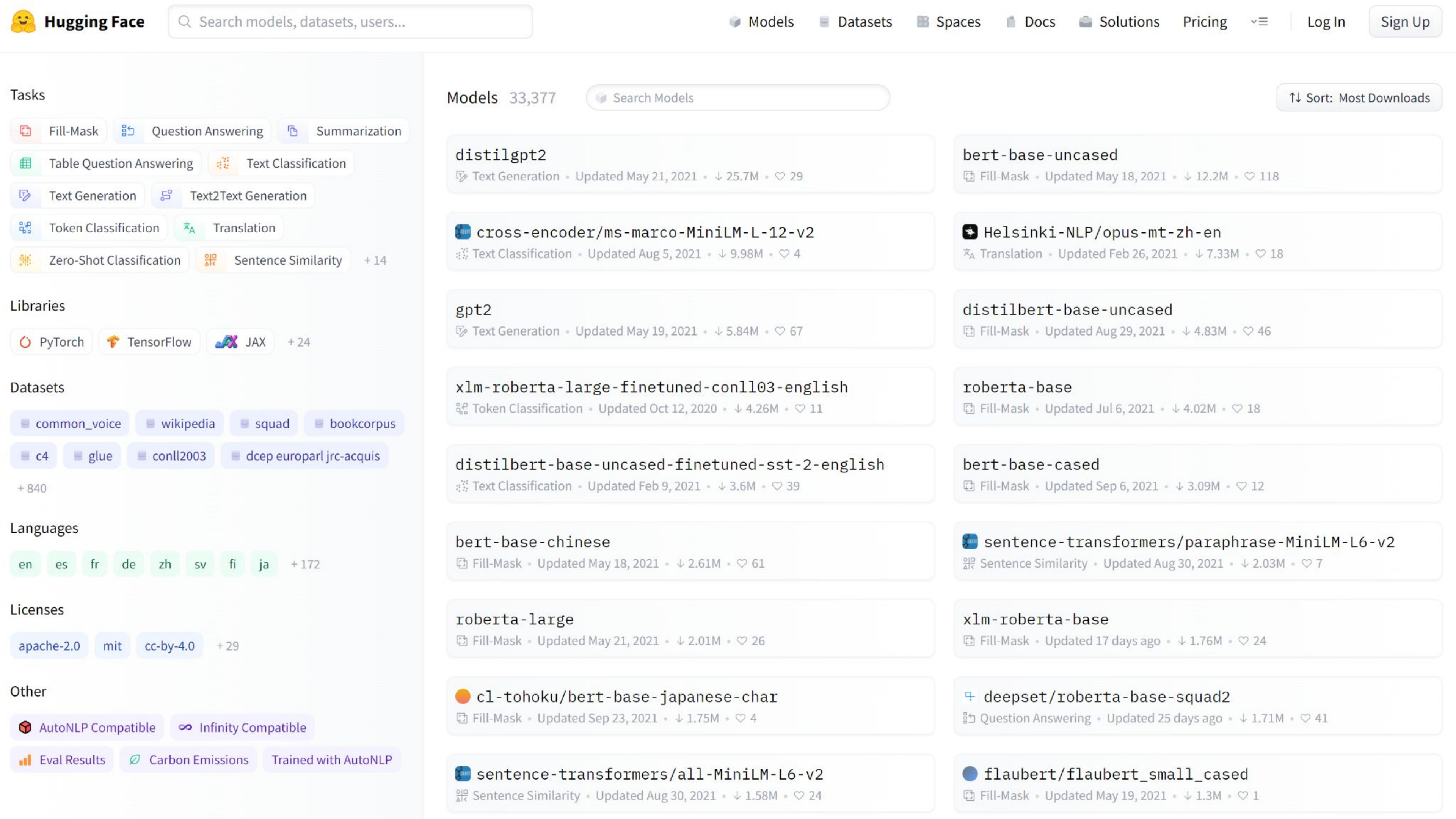
MLM Task

Domain Adaptation

Pretraining

HuggingFace

- Python Packages
    - transformers: Train, Fine-Tune, Usage of Language Models
    - tokenizers: Train and apply Word Piece Tokenizer
- Modelhub
    - Free Repository for general and fine-tuned Language Models
- Datasets
    - Free Repository with standardized Training Datasets (MLM and FineTuning)



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Libraries

PyTorch · TensorFlow · JAX · + 24

Datasets

common_voice · wikipedia · squad · bookcorpus · c4 · glue · conll2003 · dcep europarl jrc-acquis · + 840

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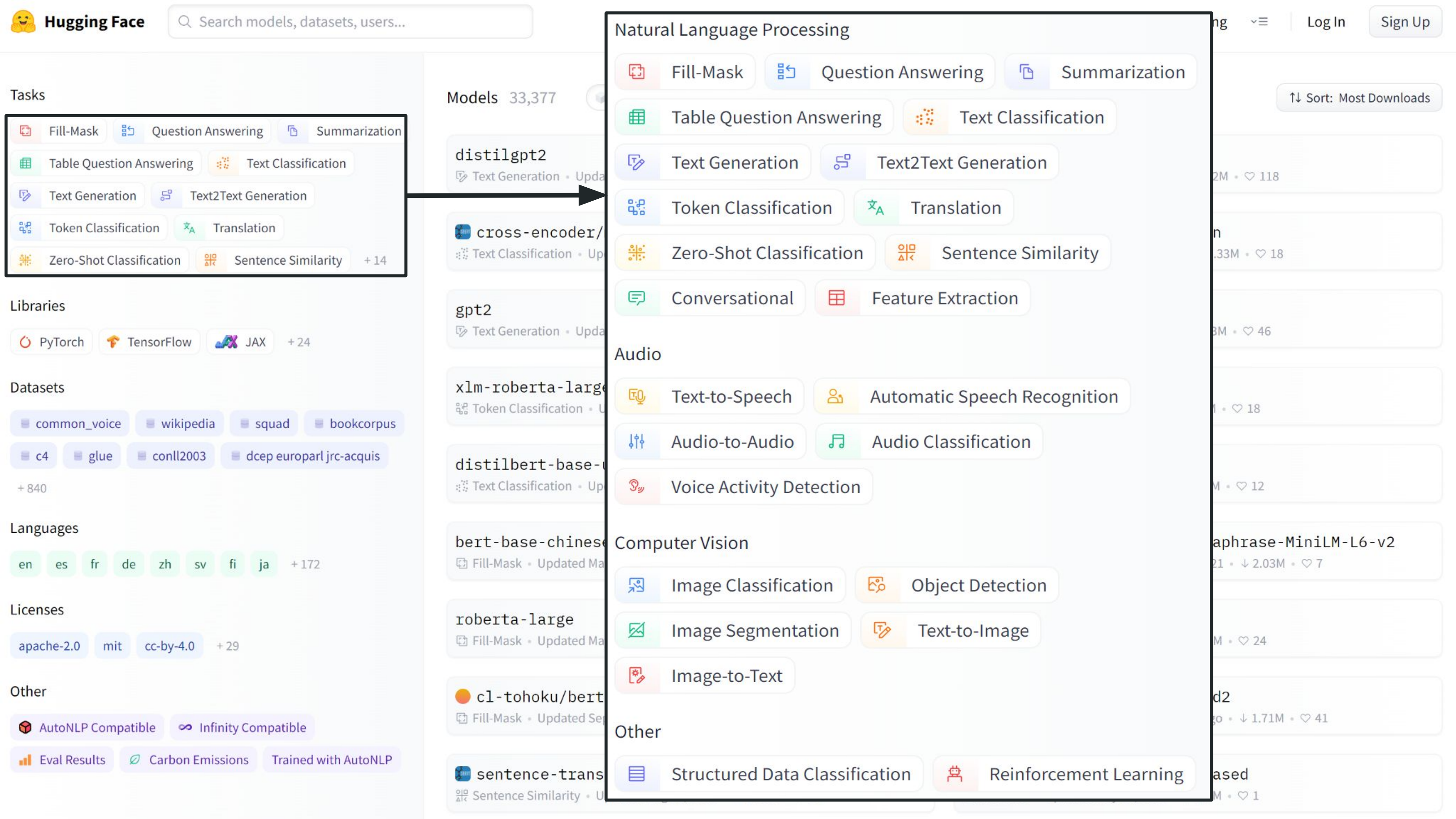
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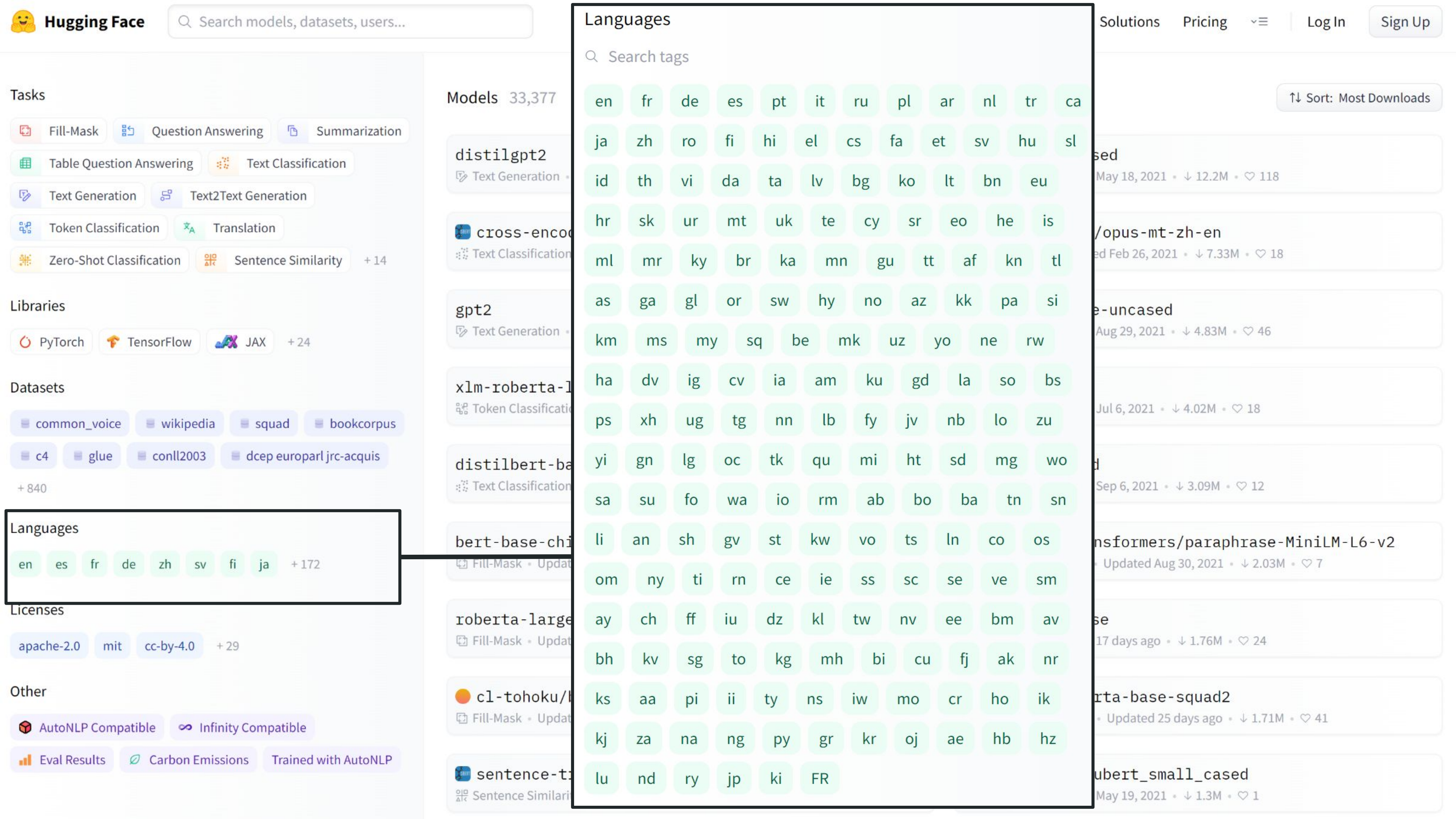
Other
Structured Data Classification
Reinforcement Learning



Hugging Face

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ay ch ff iu dz kl tw nv ee bm av
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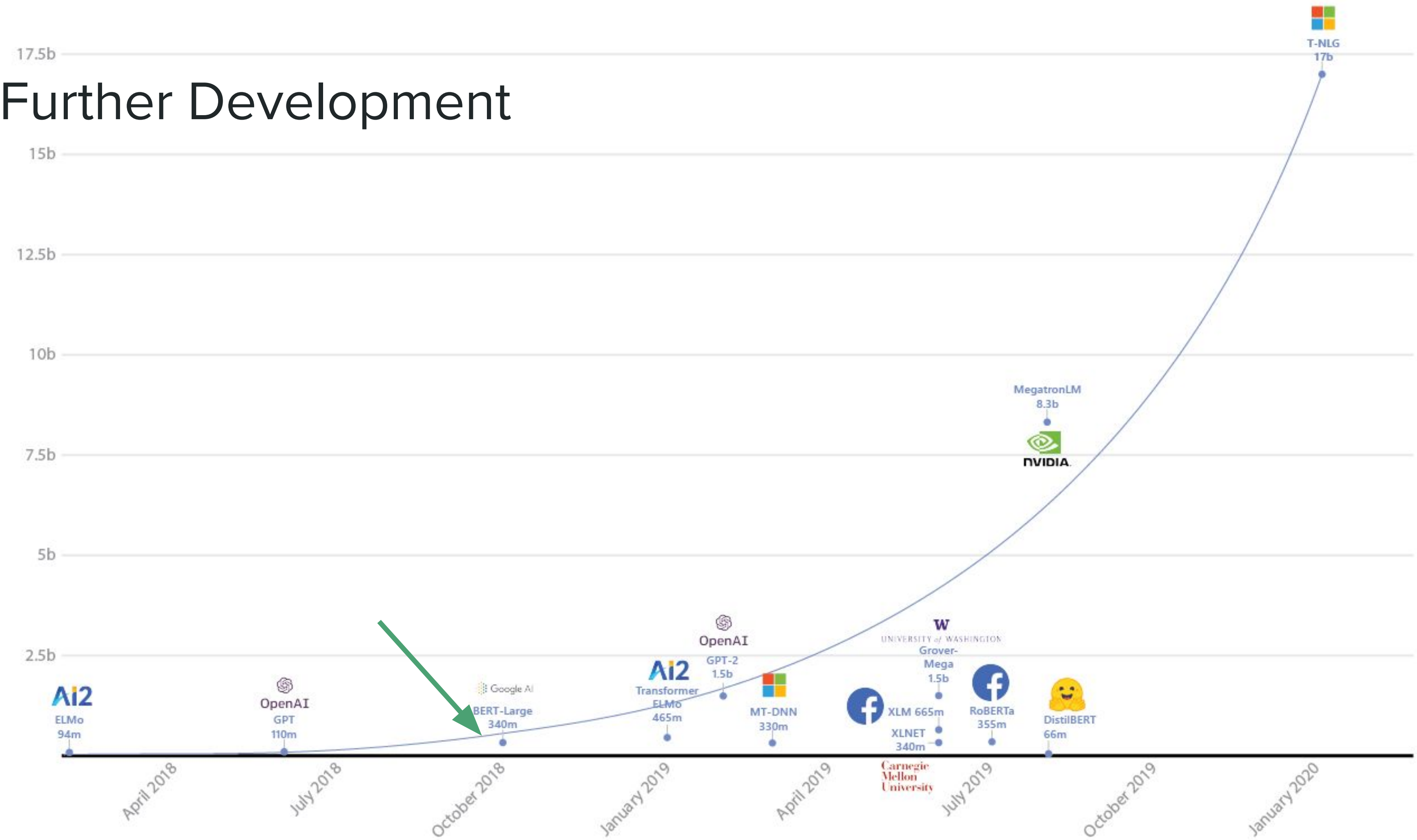
- https://huggingface.co/csebuetnlp/mT5_multilingual_XLSum
  - Multilingual Text Summarization
- https://huggingface.co/nlptown/bert-base-multilingual-uncased-sentiment
  - Text Sentiment Analysis (en, fr, de, es, nl)
- https://huggingface.co/sentence-transformers/paraphrase-xlm-r-multilingual-v1

Further Development



Demo Task 1 - Sentiment Analysis

Task: Classify the Sentiment of a Sequence

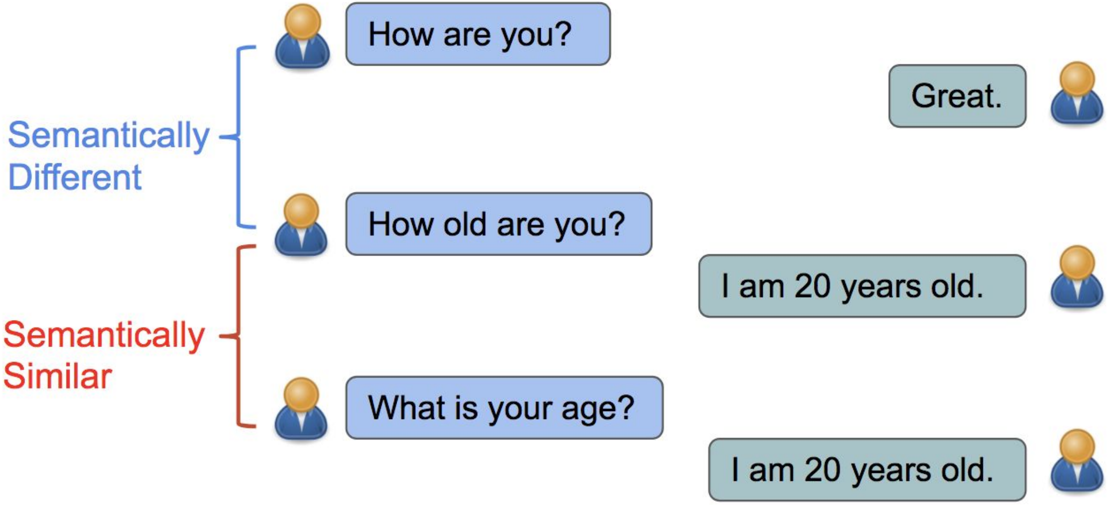
Classes: 1,2,3,4,5| 1: very negative, 5: very positive

Data: Movie Reviews

Demo Task 2 - Sentence Similarity

Task: Compute the (general, relative) similarity between sentences

Data: Human ratings of semantic similarity



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Demo 2

https://colab.research.google.com/drive/1AvVUMtp7yq9iloE5pINTmwOQ8AYiIJt-?usp=sharing