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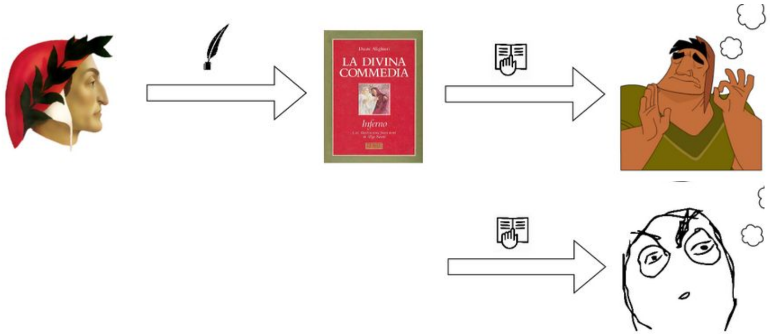
Outline

1) Task
2) Distributional Hypothesis
3) Deep Learning
4) Pre-Trained Language Models
5) NLP Tasks
   a) Sentiment Analysis
   b) Semantic Text Similarity
6) Proposal

The Task

Human Communication:

- is mainly non verbal
- … people have knowledge
- … people have biases
- … people have emotions
- … people have a mood



Task:

Demonstrate numerically that communication is inherently full of distortions and that information cannot be transmitted perfectly to others

The Distributional Hypothesis

What Drives Semantic Similarity?[1]

- **Accidental**
  - Abominate
  - Meander
  - Inadvertent
  - inhibit

- **FedEx**
  - car
  - UPS
  - rotate
  - Navy

- **Millennial**
  - octopus
  - fork
  - water
  - avocado

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- **Meaning**: closeness in terms of meaning
- **Word Knowledge**: concepts have similar properties, often occur together, or occur in similar context
- **Psychology**: two concepts fit together within an over-arching psychological schema or framework

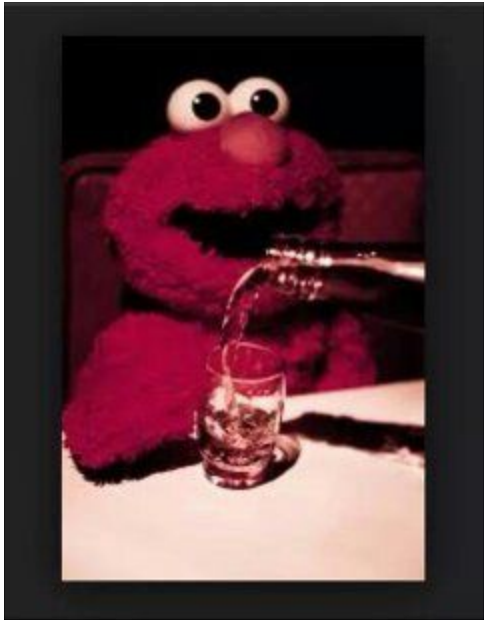
[1] Sean Simpson, EMNLP Lecture 21, 2018

Bardiwac

Does anyone knows what it is?

Here some clues…

1) he handed her a glass of bardiwac
2) beef dishes are made to complement the bardiwac
3) Malbec, one of the lesser-known bardiwac grapes, responds well to Australia's sunshine
4) I dined off bread and cheese and this excellent bardiwac



Correct answer!

Bardiwac is a wine!

Just kidding ….

Bardiwac is a fake word

The Distributional Hypothesis

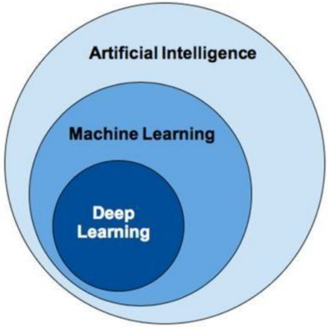
“Differences of meaning correlates with differences of distribution”

(Harris, 1970)

“You shall know a word by the company it keeps!”

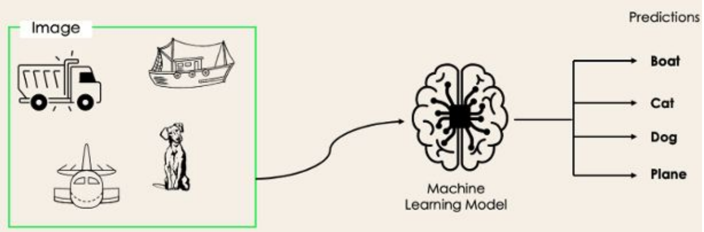
(Firth, 1957)

Deep Learning



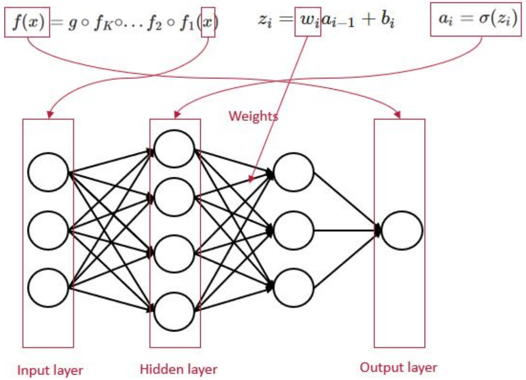
Deep Neural Networks

Machine Learning models are **function approximation algorithms**



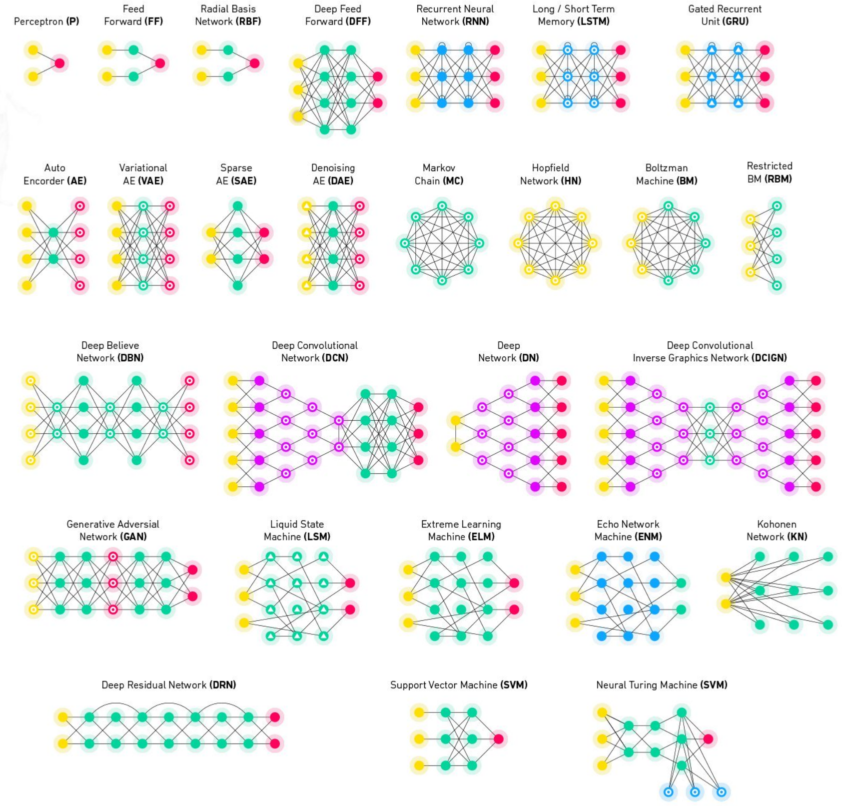
Deep Learning:

- based on neural networks
- capable of learn **extremely complex functions**
- **automatic feature extraction**
- effort moved from feature engineering to architecture engineering
- requires large amounts of data



https://playground.tensorflow.org

Tons of architectures!



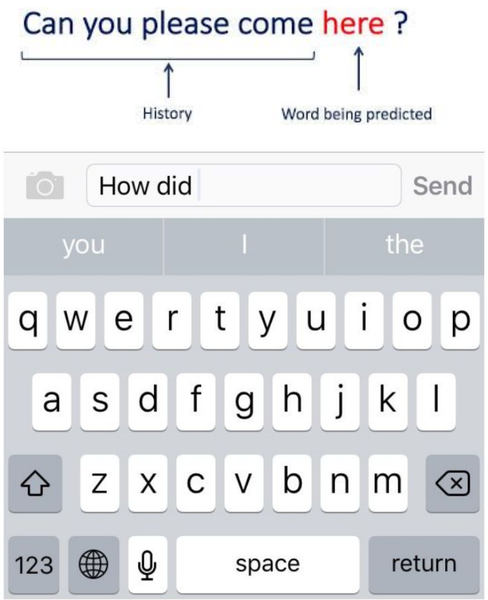
Pre-Trained Language Models

Language Models

- is a probabilistic statistical model that determines the probability of a given sequence of words occurring in a sentence based on the previous words.

- language modelling is usually a non-supervised process

- Language Models are the backbone of NLP:
  → they are a way of transforming qualitative information about text into quantitative information that machines can understand



Pre-Training and Fine-Tuning

Pre-Training:

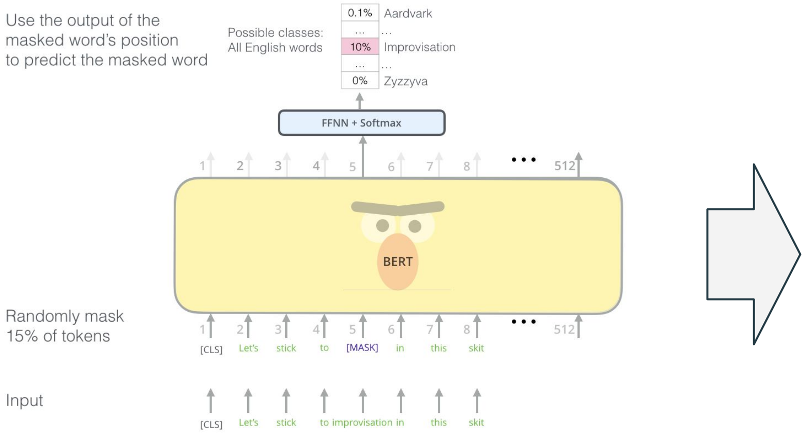
- allows the model to learn general knowledge
- sometimes specific tasks are chosen to this aim
- extremely expensive
- requires large amount of data

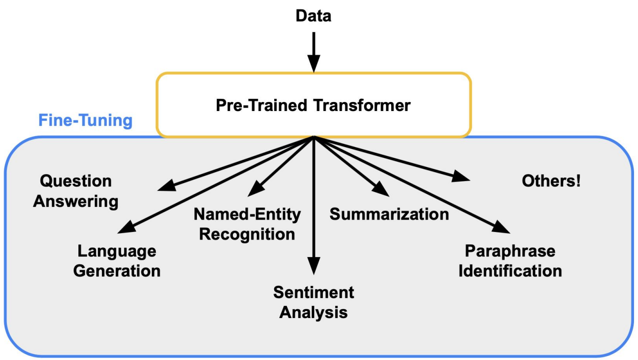
Fine-Tuning:

- task specialization
- domain adaptation
- cheap and requires much less data

This paradigm is not limited to NLP, it is also well-known in Computer Vision (see ImageNet challenge)

BERT[2]: A Pre-Trained Language Model





... it is a function approximation!

[2] Devlin et al, BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, 2018, Arxiv

Pre-Trained Language Models

=

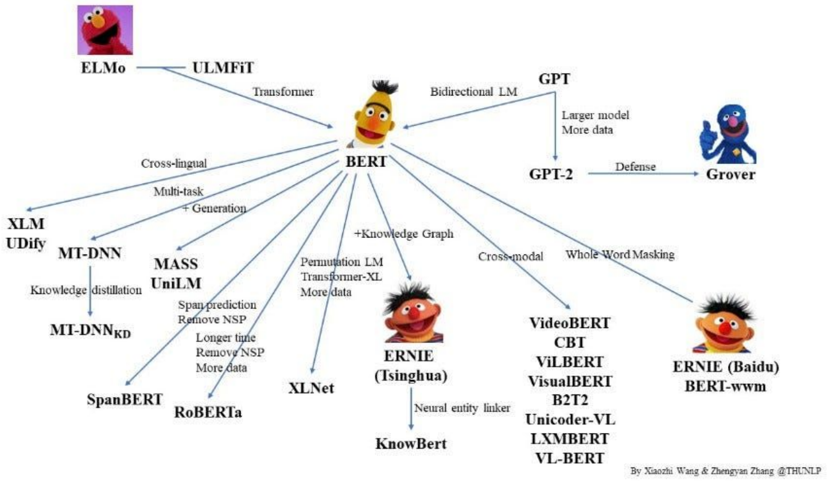
Distributional Hypothesis

+

Deep Learning

+

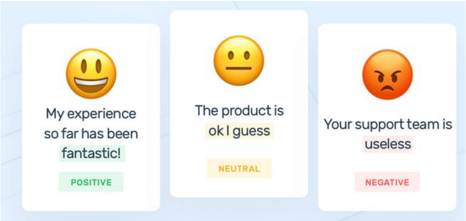
Pre-Training



NLP Tasks


NLP Tasks
Text Preprocessing
Coreference Resolution
Part Of Speech Tagging
Word Sense Disambiguation
Grammatical Error Correction
Feature Extraction
Text-to-Data and viceversa
Speech-to-Text
Text-to-Image
Text-to-Speech
Data-to-Text
Fake News and Hate Speech Detection
Fake News Detection
Stance Detection
Hate Speech Detection
Text Reasoning
Common Sense Reasoning
Natural Language Inference
Chatbots
Slot Filling
Intent Detection
Keyword Extraction
Topics and Keywords
Keyword Extraction
Topic Modeling
Knowledge Bases, Entities and Relations
Relation Extraction
Relation Prediciton
Named Entity Recognition
Entity Linking
Text-to-Text Generation
Machine Translation
Text Generation
Text Summarization
Text Simplification
Lexical Normalization
Paraphrase Generation
Information Retrieval and Document Ranking
Sentence/Document Similarity
Question Answering
Classification
Text Classification
Sentiment Analysis

Sentiment Analysis



Is used to determine whether data is positive, negative or neutral.

Approaches:

- **lexicon-based:** counts the number of positive, neutral, and negative words and assigns a score based on intensity and frequency
- **rule-based:** depends on handcrafted rules and lexicons that might not apply for all texts
- *** machine-learning based**: patterns identification on hand-crafted features
- *** deep-learning based:** uses DL to automatically extract features
- *** PTLMs based:** like DL but exploits the power of transfer learning

*supervised approaches: need training data

Challenges:

- tone:
- sarcasm
- negations
- emojis

Semantic Text Simality

Text similarity calculates how two documents are close to each other. Closeness may be **lexical** or in **meaning**

- The dog bites the man
- The man bites the dog

lexical similarity very high… almost identical
semantic similarity is very low … totally different

Approaches:

- **Knowledge base methods**: leverages lexical structured representation of concepts connected by semantic relations, further offering an ambiguity free semantic measure
- **Corpus based**: use the distributional hypothesis to get rid of ambiguity
- **DL methods and PT LMs:** exploit transfer learning power along with DL architectures

Usages:

- Information Retrieval
- Document Similarity and Clustering

My Proposal

Sentiment Analysis and Semantics Analysis

Problem characteristics:

- italian language
- no labelled data
- extremely small data points
- words definitions as input

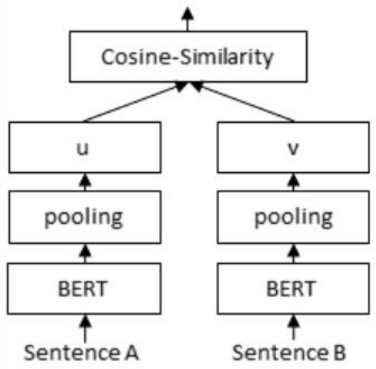
proposal:

- sentiment analysis
- semantic analysis

- already trained models for SA and STS
- Italian words definitions as a compass

Semantic Text Similarity: SBERT [3]

Sentence BERT uses Bi-Encoders.
They pass to a BERT **independently** the sentences A and B, which result in the sentence embeddings u and v. These sentence embedding can then be compared using cosine similarity.



Training data:
multilingual translation of the STS benchmark dataset

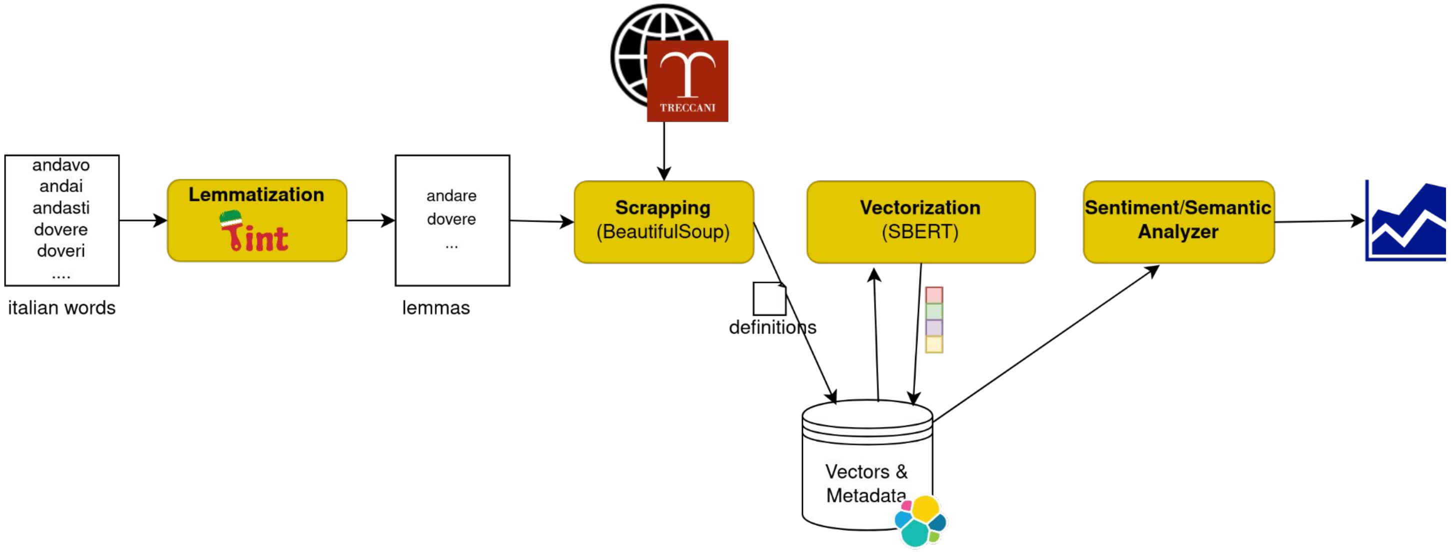
score	2 example sentences	explanation
5	*The bird is bathing in the sink.* *Birdie is washing itself in the water basin.*	The two sentences are completely equivalent, as they mean the same thing.
4	*Two boys on a couch are playing video games.* *Two boys are playing a video game.*	The two sentences are mostly equivalent, but some unimportant details differ.
3	*John said he is considered a witness but not a suspect.* *"He is not a suspect anymore." John said.*	The two sentences are roughly equivalent, but some important information differs/missing.
2	*They flew out of the nest in groups.* *They flew into the nest together.*	The two sentences are not equivalent, but share some details.
1	*The woman is playing the violin.* *The young lady enjoys listening to the guitar.*	The two sentences are not equivalent, but are on the same topic.
0	*The black dog is running through the snow.* *A race car driver is driving his car through the mud.*	The two sentences are completely dissimilar.

Sentiment Analysis

- neuraly/bert-base-italian-cased-sentiment:
  - base model: BERT based italian cased
  - fine-tuning data: Sentipolc EVALITA 2016. (45K pre-processed tweets)
- citizenlab/twitter-xlm-roberta-base-sentiment-finetunned:
  - base model: Multilingual XLM-Roberta
  - fine-tuning data: toxicity prediction dataset
- cardiffnlp/twitter-xlm-roberta-base-sentiment:
  - base model: multilingual XLM-roBERTa-base
  - fine-tuning data: 198M multilingual tweets
- lxyuan/distilbert-base-multilingual-cased-sentiments-student:
  - Teacher model: MoritzLaurer/mDeBERTa-v3-base-mnli-xnli
  - Teacher hypothesis template: "The sentiment of this text is {}."
  - Student model: distilbert-base-multilingual-cased

the chosen one

Logical Architecture



Demo: http://2.44.8.105:8501/

Conclusions

- Sentiment Analysis
  - differences are evident but motivations are not always clear
- Semantic Analysis
  - SBERT is a good model to be used for Semantic Text Similarity
  - differences and similarities between participants are evident
  - .. however there are some cases where is hard to explain similarity
  - coherence and incoherence is visible

Understanding and communication phenomena result in different conceptualisations

This is a nice way to show differences about people understanding… but IMHO going further requires a psychological analysis

Limitations & Future Work

Human limitations:

- **exhaustivity**: is what has been written really what the participants know?
- **expressivity**: did the participants express themselves well?
- **commitment**: did the participants make a serious effort?

Models limitations:

- Sentiment analysis domain differences: tweets vs definitions
- Semantics analysis domain differences: Treccani definitions vs custom definitions
- a SBERT model trained on definitions would work better

Future Work:

- Exploit knowledge from LLMs to get embeddings
- use LLMs to rephrase Treccani definitions and fine-tune a SBERT model
- Try to use prompting to get sentiment scores

Links

- https://www.pinecone.io/learn/series/nlp/sentence-embeddings/
- https://www.sbert.net/examples/applications/cross-encoder/README.html
- https://www.searchcandy.uk/nlp/sentence-bert/