Time Series and NLP

Today

Time series and NLP

Core components

- Embeddings
- Recurrent Neural Nets (RNNs)

The real world is mostly time series

Predict: energy demand, inventory, network utilization

Control a robot

Identify who is speaking in a video

Translate English to Chinese, **speech to text**

Answer a question

Hold a **conversation**

Time series require special handling

Everything we have seen so far has a fixed input dimensionOr here...

Time series do not, so they are often

Truncated and padded to give a uniform size

Embedded: mapped to a vector

Modeled using recurrence

Embedding

A mapping from anything to a vector

Image2vec

Word2vec

Person2vec

Such that ‘similar’ items are close in the embedding space

Recurrent neural nets take advantage of invariances in the world

CNNs: nearby pixels are correlated and images are translational invariant

the kernels serve as 2-D, local, translationally invariant feature detectors

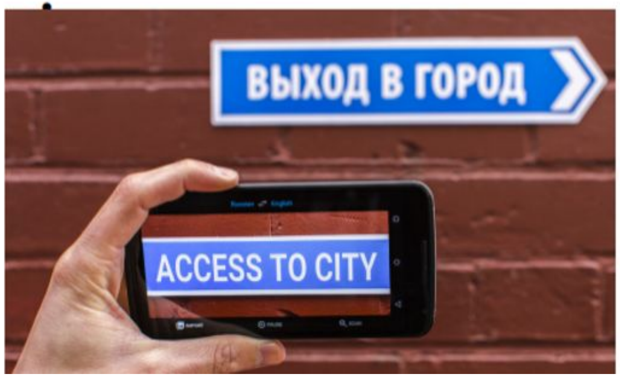
RNNs: time is 1-D and translationally invariant ("stationary")

So predict the future based on a "hidden state" that summarizes the past

What is Natural Language Processing (NLP)?

Why Natural Language Processing?

To



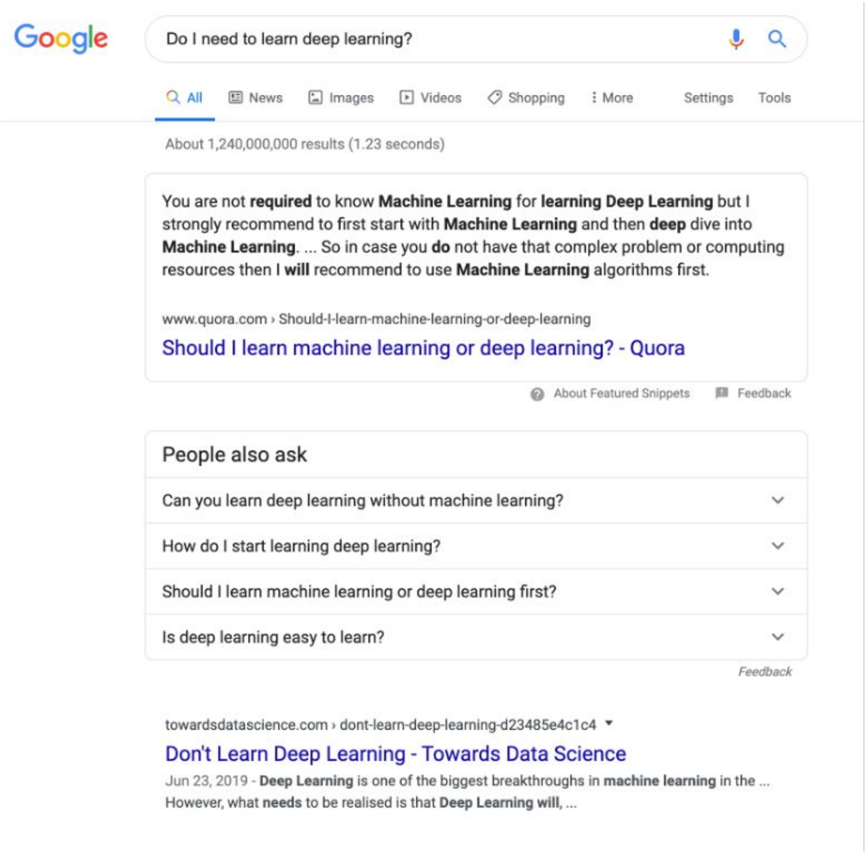
To let machines communicate with us.

Image credits: google, amazon

NLP tasks

Information retrieval	query (+corpus)	➜ document
Information extraction	query (+corpus)	➜ fact (tuple)
Machine translation	source text	➜ translation
Speech recognition	sounds	➜ words
Question answering	question	➜ answer
Summarization	text	➜ summary
Conversational agents	prompt	➜ response (and repeat)

Information Retrieval



Information Extraction

Natural Language Generation

Input: write a message to convince someone to get a covid vaccine.

Output: Covid vaccines are essential in order to protect yourself and others from the virus. They are safe and effective, and have been shown to reduce the severity of symptoms. Get the vaccine to protect yourself and your loved ones!

Lyle Ungar
using GPT-3

NLP component tasks

Tokenizing

Part of Speech Tagging (POS tagging)

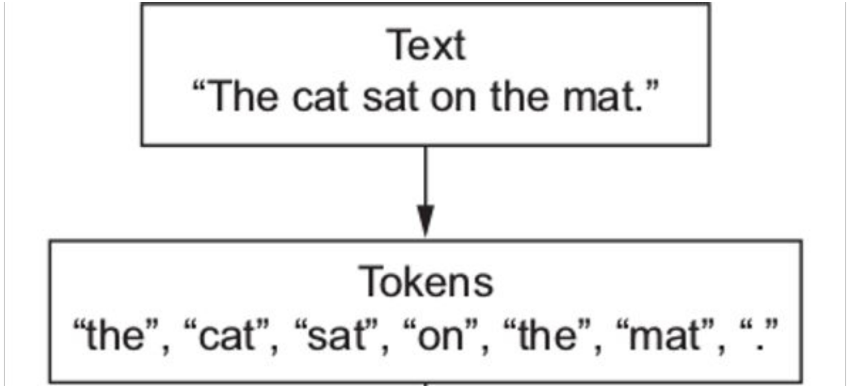
Named Entity Recognition (NER)

Co-reference detection

Parsing

Tokenization

Split sequence of characters into “tokens”.



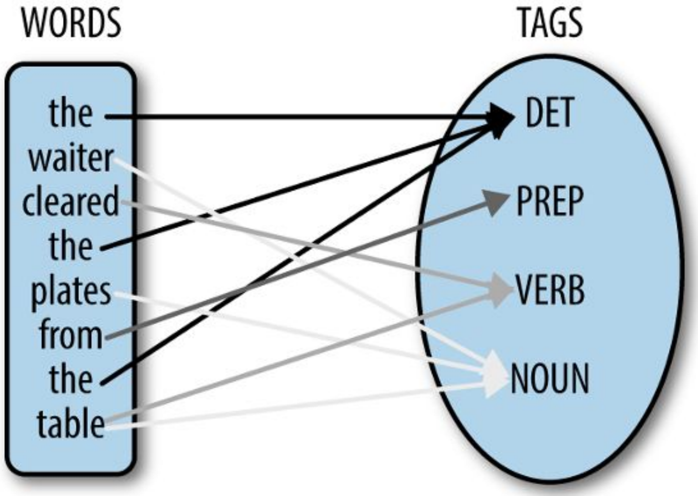
Nomenclature: the ***word*** “the” occurs twice above;

It is the 1st and the 5th ***token***.

POS (Part-of-speech) Tagging: check copyright

POS tagging is the process of marking the words in the corpus to its corresponding part of a speech tag (noun, verb, adjective, etc), based on its context and definition.

https://spacy.io/usage/linguistic-features



https://spacy.io/usage/linguistic-features

Named entity recognition

https://arxiv.org/abs/1511.08308

Coreference

Tom was happy that **he** got a present.

Tom gave **Bill** a present but **he** didn't like it.

Language models

Language Models compute the probability of the next word.

More formally,

Given a sequence of words $x^{(1)}$ .... $x_{(t)}$, compute the probability of the occurrence of $x^{(t+1)}$

$$P(\boldsymbol{x}^{(t+1)} | \boldsymbol{x}^{(t)}, \ldots, \boldsymbol{x}^{(1)})$$

where $\boldsymbol{x}^{(t+1)}$ can be any word in the vocabulary $V = \{\boldsymbol{w}_1, ..., \boldsymbol{w}_{|V|}\}$

https://www.cs.bgu.ac.il/~elhadad/nlp18/nlp02.html

Language model use: autocompletion

Probability of a sentence

Language models also assign probability to the entire text.

Given text containing words $x^{(1)}$ .... $x^{(T)}$. Then the probability of that text is

$$P(\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(T)}) = P(\boldsymbol{x}^{(1)}) \times P(\boldsymbol{x}^{(2)} | \, \boldsymbol{x}^{(1)}) \times \cdots \times P(\boldsymbol{x}^{(T)} | \, \boldsymbol{x}^{(T-1)}, \ldots, \boldsymbol{x}^{(1)})$$
$$= \prod_{t=1}^{T} P(\boldsymbol{x}^{(t)} | \, \boldsymbol{x}^{(t-1)}, \ldots, \boldsymbol{x}^{(1)})$$

Natural Language Processing

Details of tokenization

Representations

Words/tokens: context-free or context-sensitive embeddings

Sub-word encoding (e.g., Byte Pair Encoding, BPE): frequent character sequences are treated as "words"

"bbibtech" might be three words "b" + "bib" + "tech"

Special tokens:

- **sep_token**: separates different strings
- **unk_token**: unknown token
- **pad_token**: padding
- **cls_token**: token for the entire sequence

Typical NLP pipeline

1) **Tokenize (or extract byte pair encodings)**
2) **Map tokens to embeddings using something trained on a huge corpus (word2vec, Bert,...)**
3) **Train a neural net with embeddings as the input**
    a) **optionally: "fine tune" the embeddings to better fit the task**

Embeddings rule!

We often map objects to vectors

Similar objects should be close in the embedding space

Many things can be embedded

- embed images by using the penultimate output of the CNN
- embed a word, sentence or document
- embed a product or a person

Word embeddings

The simplest word embeddings (word2vec, Glove), map each word to a 300 dimensional vector such that words that are tend to show up in the same contexts have embeddings that are close to each other.

Distributional similarity

Words that occur in similar contexts are similar

He ate the **sandwich.**

He ate the **shrudlu**.

The **Shrudla** ate the sandwich.

“sandwich” and “shrudlu” are distributionally similar, as are “he” and “Shrudla”

One-Hot Word Representation

Before the deep learning era, we tended to treat each word as a separate symbol.

one-hot encoding example

Hotel = [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]

Motel = [0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0]

But all one-hot words are equally similar

How can we know that two words (or sentences) mean similar things?

Vector embeddings as dimensionality reduction: LSA

Latent Semantic Analysis (LSA):
context is the document the words appear in

Run SVD on a word x document matrix
Maps every word to a k-dimensional vector so that words that tend to appear in the same documents will be close

related words will be close: doctor, hospital, nurse, cancer

LSA

1) **I ate ham and cheese**
2) **You ate cheese and crackers**
3) **he went to hospital with covid**
4) **she came home from the hospital after her operation**

	Document				
	1	**2**	**3**	**4**	**...**
ate	1	1	0	0	...
cheese	1	1	0	0	...
I	1	0	0	0	...
hospital	0	0	1	1	...

Vector embeddings as dimensionality reduction: word2vec

Modern vector embeddings (word2vec)
context is the words to the left and right of each token

Run SVD on word x context matrix
Maps every work to a k-dimensional vector so that words that tend to appear in the same contexts will be close

similar words will be close: doctor, nurse

Eigenwords (like word2vec)

I ate ham
You ate cheese
You ate

	Word Before					Word After				
	ate	cheese	ham	I	You	ate	cheese	ham	I	You
ate	0	0	0	1	2	0	1	1	0	0
cheese	1	0	0	0	0	0	0	0	0	0
ham	1	0	0	0	0	0	0	0	0	0
I	0	0	0	0	0	1	0	0	0	0
You	0	0	0	0	0	2	0	0	0	0

Similar words are close

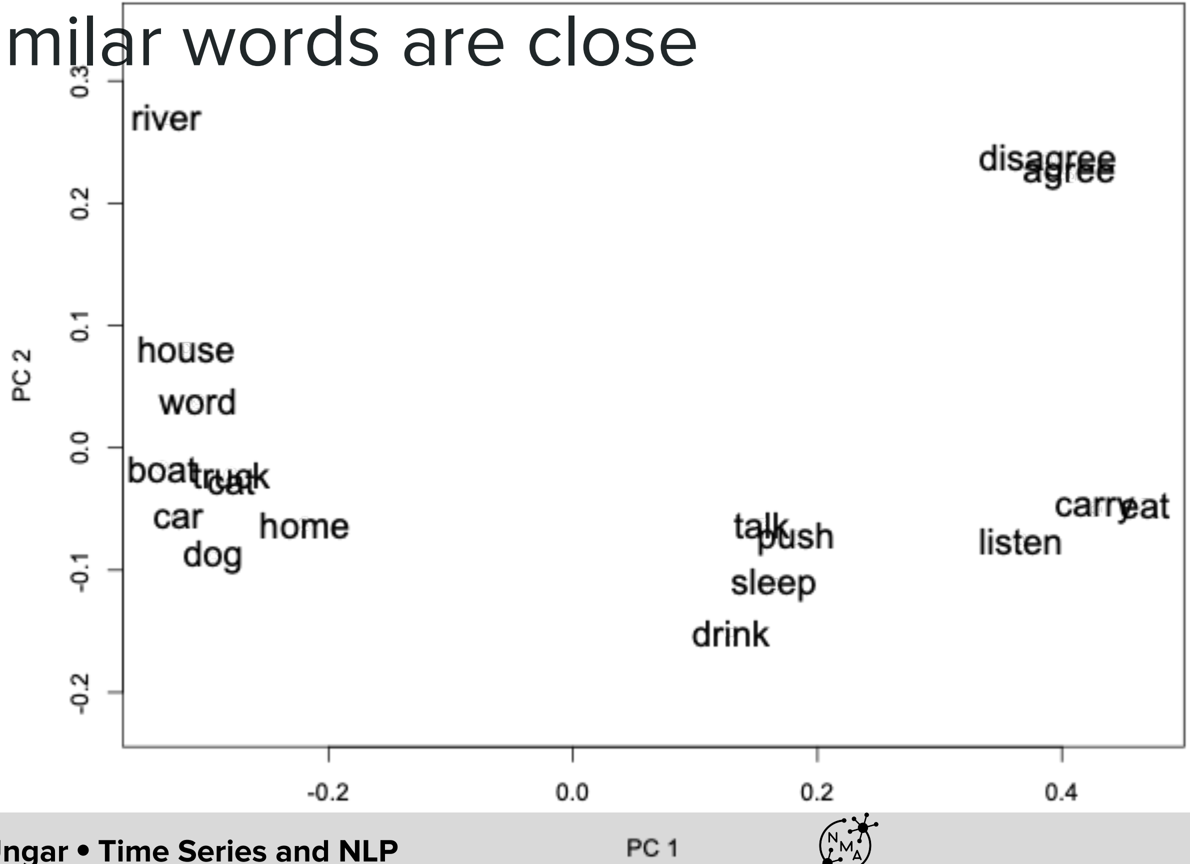


Image credit: lyle ungar

One can embed words in different languages into the same space

similar words will be close: doctor, nurse

Or even embed images and words into the same space

Distributional Similarity and Vector Embeddings

Context oblivious and context sensitive

Context free vs. context sensitive embeddings

Words have different meanings depending on their context

Distributional similarity (again)

Words that occur in similar contexts are similar

He drank the port.

He visited the port.

He’s on the port (not starboard!) side of the boat.

He needs to port the code to pytorch.

What we want of a good similarity

Similar words should be close in embedding space

But be careful: what does “similar” mean

meaning?

style?

emotion?

For now: similar means “distributionally similar”

Later: we will “fine tune” embeddings for different tasks

Two kinds of embeddings

context oblivious: embed words

LSA, word2vec, Glove, fastText

map each of e.g. 1,000,000 words to a 300-D vector

context sensitive: embed tokens in context

Bert, Elmo, and friends

map token and surrounding tokens to a 768-D vector

Many of these actually use Byte Pair Encoding

Using Embeddings

Embeddings: what to use when

context oblivious: mostly of historical interest for text

LSA, word2vec, fastText

Still used for images

context sensitive: pick a popular embedding from Hugging Face

BERT and other transformer models

These use a context oblivious Byte Pair or Word Part Encoding as input

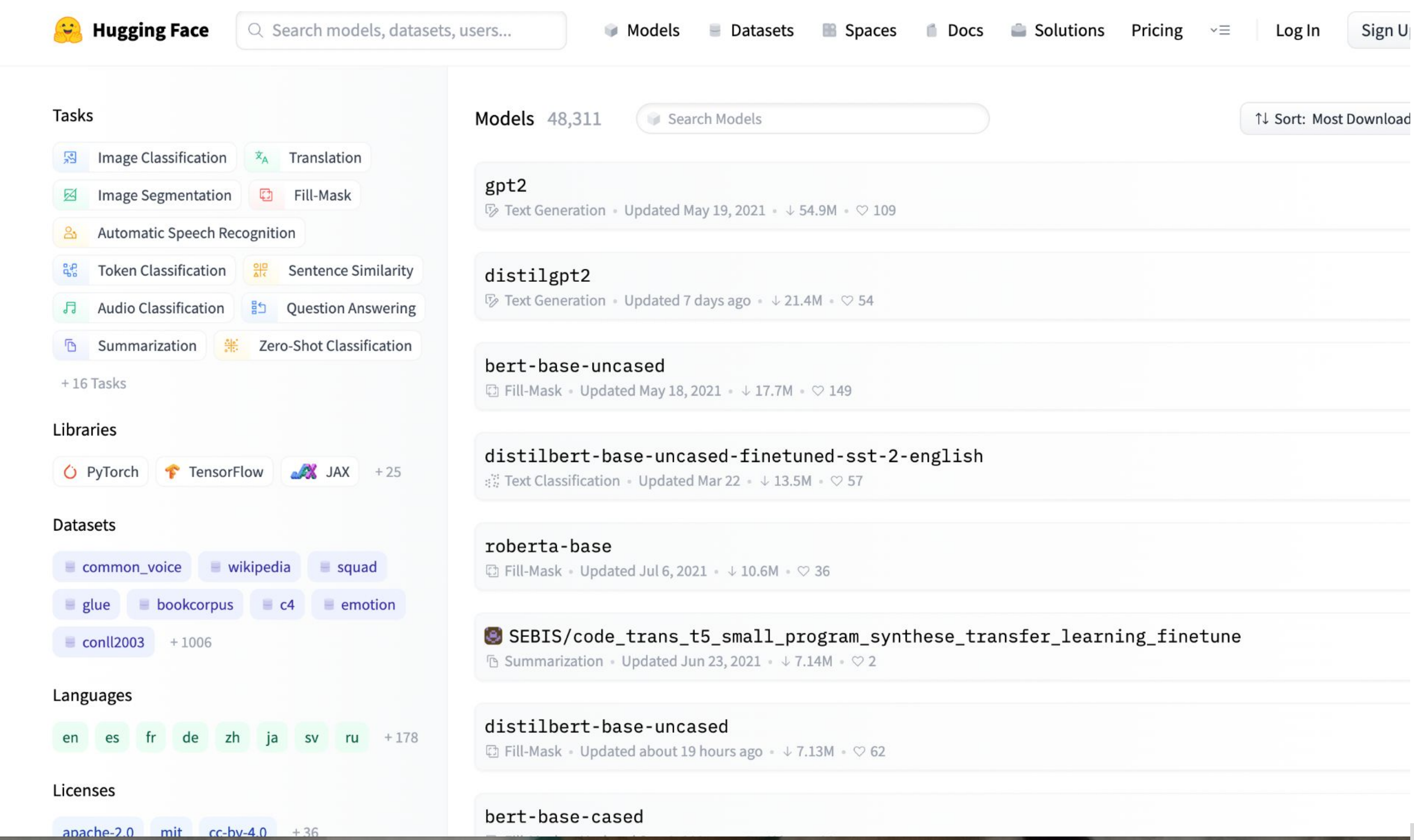
Hugging Face

Tasks

Problems solvers

Thousands of creators work as a community to solve Audio, Vision, and Language with AI.

Task	Models
Image Classification	488 models
Object Detection	28 models
Question Answering	1745 models
Summarization	409 models
Text Classification	6721 models
Translation	1584 models


Hugging Face
Search models, datasets, users...
Models
Datasets
Spaces
Docs
Solutions
Pricing
Log In
Sign Up
Tasks
Image Classification
Translation
Image Segmentation
Fill-Mask
Automatic Speech Recognition
Token Classification
Sentence Similarity
Audio Classification
Question Answering
Summarization
Zero-Shot Classification
+ 16 Tasks
Libraries
PyTorch
TensorFlow
JAX
+ 25
Datasets
common_voice
wikipedia
squad
glue
bookcorpus
c4
emotion
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+ 1006
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distilgpt2
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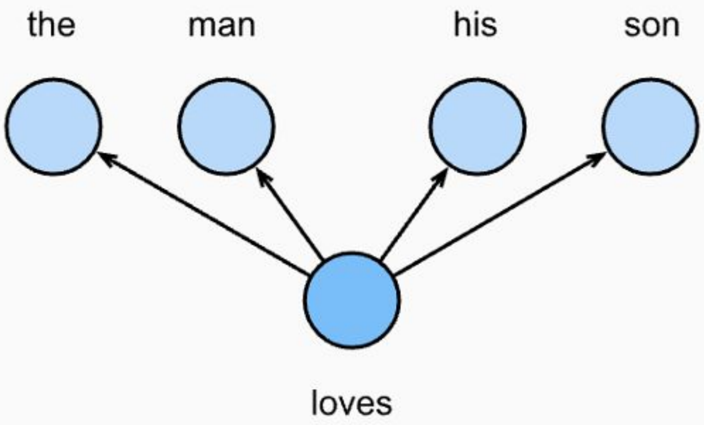
Fill-Mask • Updated May 18, 2021 • 17.7M • 149
distilbert-base-uncased-finetuned-sst-2-english
Text Classification • Updated Mar 22 • 13.5M • 57
roberta-base
Fill-Mask • Updated Jul 6, 2021 • 10.6M • 36
SEBIS/code_trans_t5_small_program_synthese_transfer_learning_finetune
Summarization • Updated Jun 23, 2021 • 7.14M • 2
distilbert-base-uncased
Fill-Mask • Updated about 19 hours ago • 7.13M • 62
bert-base-cased

Skip-gram-based embeddings

$$P(\text{"the"} \mid \text{"loves"}) \cdot P(\text{"man"} \mid \text{"loves"}) \cdot P(\text{"his"} \mid \text{"loves"}) \cdot P(\text{"son"} \mid \text{"loves"}).$$



Skip-gram-based embeddings

maximize the log-likelihood of neighboring words

$$-\sum_{t=1}^{T} \sum_{-m \leq j \leq m,\ j \neq 0} \log P(w^{(t+j)} \mid w^{(t)}).$$

where probabilities are estimated based on the embedding of the word and its context words

$$P(w_o \mid w_c) = \frac{\exp(\mathbf{u}_o^\top \mathbf{v}_c)}{\sum_{i \in \mathcal{V}} \exp(\mathbf{u}_i^\top \mathbf{v}_c)},$$

use “negative sampling” to approximate the background distribution

Continuous Bag of Words (CBOW)

Flips the dependencies