Text Data in Economics

Warwick QAPEC Summer School

9. Embedding Sequences with Attention

Outline

Intro

Embedding Layers

Sequence Models

- Neural networks $\leftrightarrow$ deep learning models
  - solve machine learning problems, just like logistic regression or gradient boosted machines
  - use tensorflow, torch, or huggingface, rather than sklearn or xgboost.

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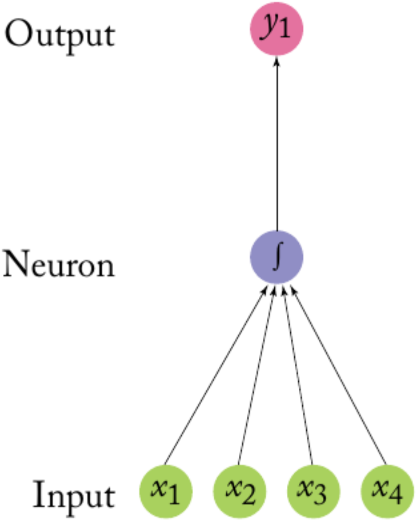
- **why not use neural nets?**
  - usually worse than standard ML on standard problems
  - models are often more challenging/labor-intensive to implement
  - outputs are a black box and difficult to interpret
  - computational constraints: training requires specialized hardware.

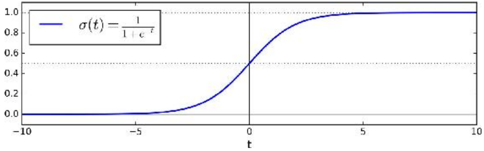
A “Neuron”



- applies dot product to vector of numerical inputs:
    - multiplies each input by a learned weight (parameter or coefficient)
    - sums these products
- applies a non-linear “activation function” to the sum
    - (e.g., the $\int$ shape indicates a sigmoid transformation)
- passes the output.

Logistic Regression ≈ "Neuron"

$$\hat{y} = \text{sigmoid}(\boldsymbol{x} \cdot \theta) = \frac{1}{1 + \exp(-\boldsymbol{x} \cdot \theta)}$$



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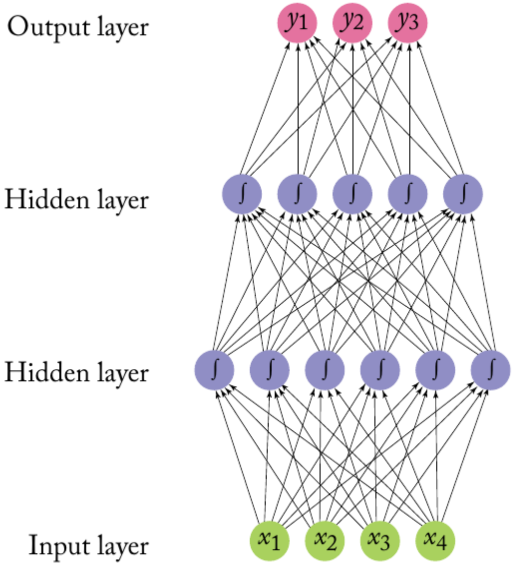
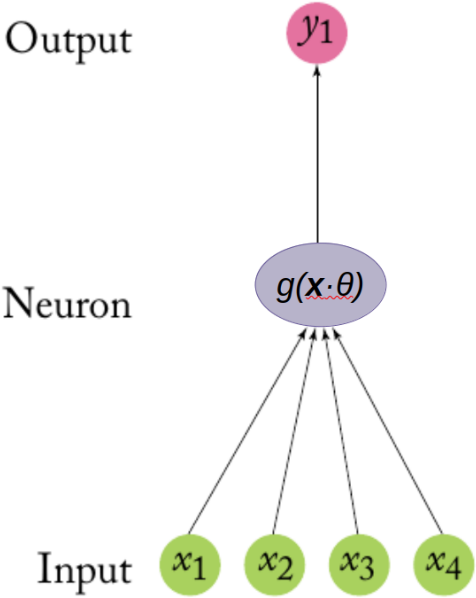
Multi-Layer Perceptron (MLP)



- A multilayer perceptron (also called a feed-forward network or sequential model) stacks neurons horizontally and vertically.
- alternatively, think of it as a stacked ensemble of logistic regression models.
- this vertical stacking is the “deep” in “deep learning”!

Activation functions $g(\boldsymbol{x} \cdot \theta)$



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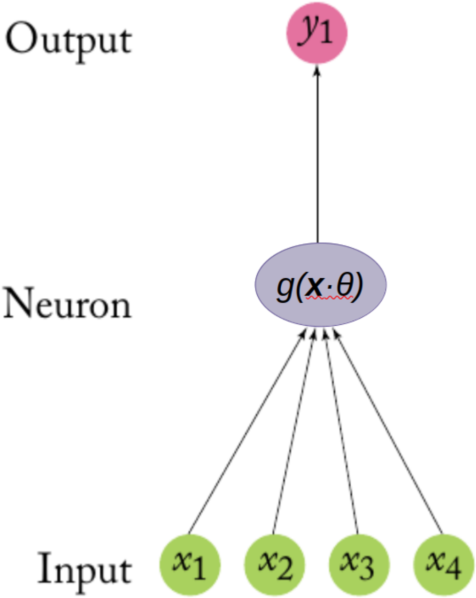

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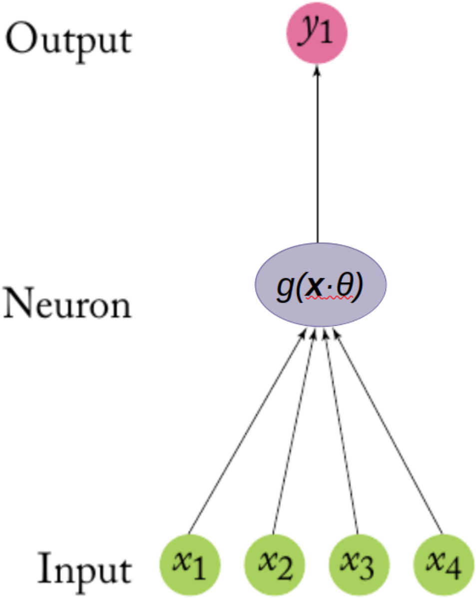

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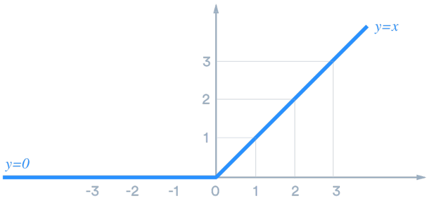
ReLU (rectified linear unit) function:

$$g(\boldsymbol{x} \cdot \theta) = \text{ReLU}(\boldsymbol{x} \cdot \theta) = \max\{0, \boldsymbol{x} \cdot \theta\}$$



Equation Notation: Multi-Layer Perceptron

- An multi-layer perceptron (MLP) with two hidden layers is

$$\boldsymbol{y} = \boldsymbol{g}_2(\boldsymbol{g}_1(\boldsymbol{x} \cdot \boldsymbol{\omega}_1) \cdot \boldsymbol{\omega}_2) \cdot \boldsymbol{\omega}_y$$

$$\boldsymbol{y} \in \{0,1\}^{n_y}, \boldsymbol{x} \in \mathbb{R}^{n_x}, \boldsymbol{\omega}_1 \in \mathbb{R}^{n_x \times n_1}, \boldsymbol{\omega}_2 \in \mathbb{R}^{n_1 \times n_2}, \boldsymbol{\omega}_y \in \mathbb{R}^{n_2 \times n_y}$$

  - $n_1, n_2 =$ dimensionality in first and second hidden layer.
  - $\boldsymbol{\omega}_1, \boldsymbol{\omega}_2, \boldsymbol{\omega}_y =$ set of learnable weights for the first hidden, second hidden, and output layer
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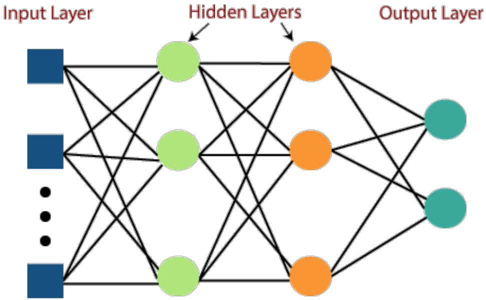
- Can also be written in decomposed notation:

$$\boldsymbol{h}_1 = \boldsymbol{g}_1(\boldsymbol{x} \cdot \boldsymbol{\omega}_1)$$
$$\boldsymbol{h}_2 = \boldsymbol{g}_2(\boldsymbol{h}_1 \cdot \boldsymbol{\omega}_2)$$
$$\boldsymbol{y} = \boldsymbol{h}_2 \cdot \boldsymbol{\omega}_y$$

where $\boldsymbol{h}_l$ indicate hidden layers.



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What is an Embedding?

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- Embeddings:
  - PCA reductions of the word count vectors
  - LDA topic shares
  - word embeddings from GloVe

Categorical Embeddings = dense representations of categorical variables

Say we have a binary classification problem with outcome Y:

- we have a high-dimensonal categorical variable (e.g. area of law with 1000 categories)
- including dummy variables A for each category in your ML model is computationally expensive.

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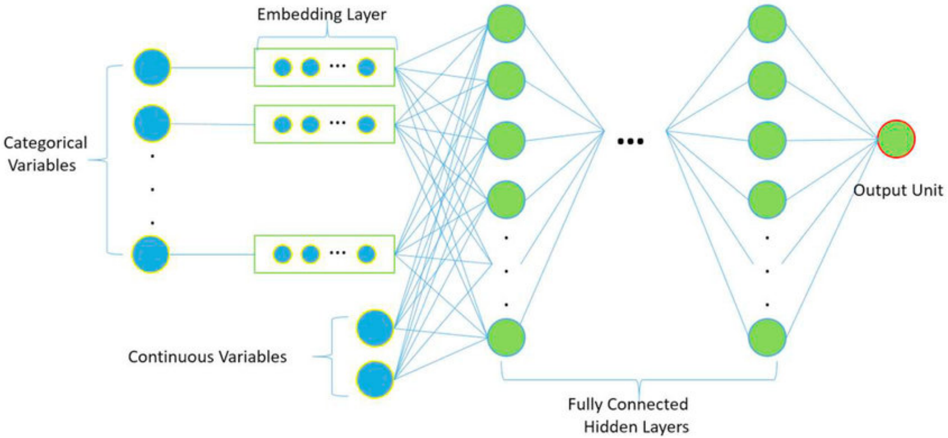
(2) is quite close to what embedding layers do in neural nets.



An embedding layer is efficient matrix multiplication:

$$\underbrace{h_1}_{n_E \times 1} = \underbrace{\omega_E}_{n_E \times n_w} \cdot \underbrace{x}_{n_x \times 1}$$

- x = a categorical variable (e.g., representing a word)
  - one-hot vector with a single item equaling one. Input to the embedding layer.
- h_1 = the first hidden layer of the neural net
  - The output of the embedding layer.

The embedding matrix ω_E encodes predictive information about the categories; it has a spatial interpretation when projected to two dimensions.

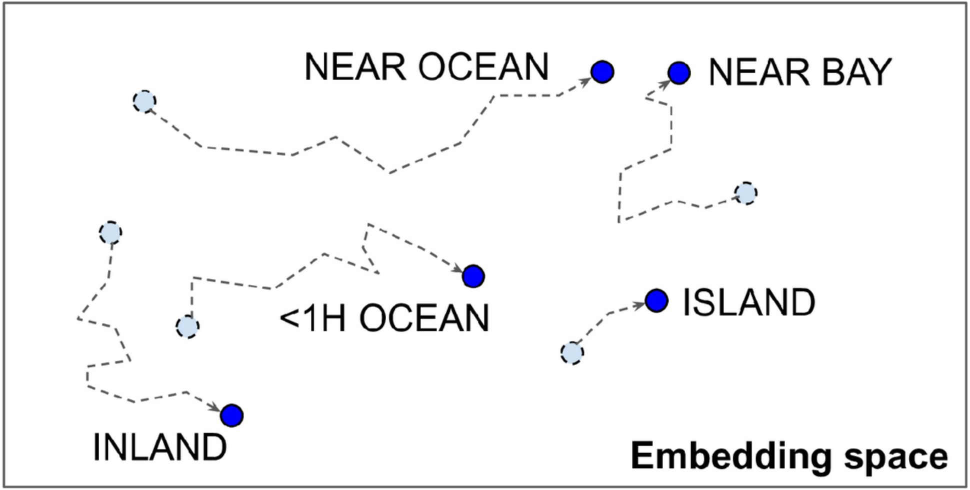


Figure 13-4. Embeddings will gradually improve during training

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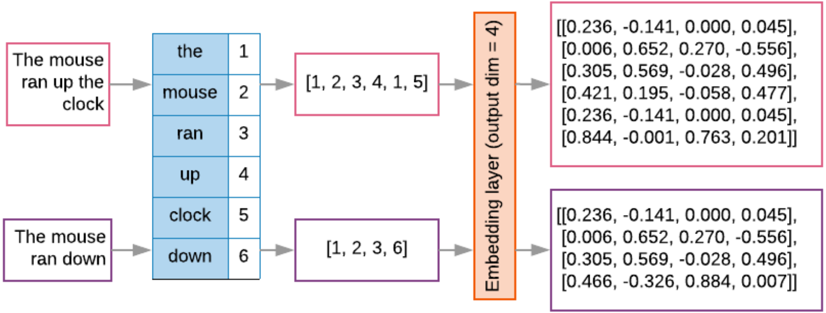
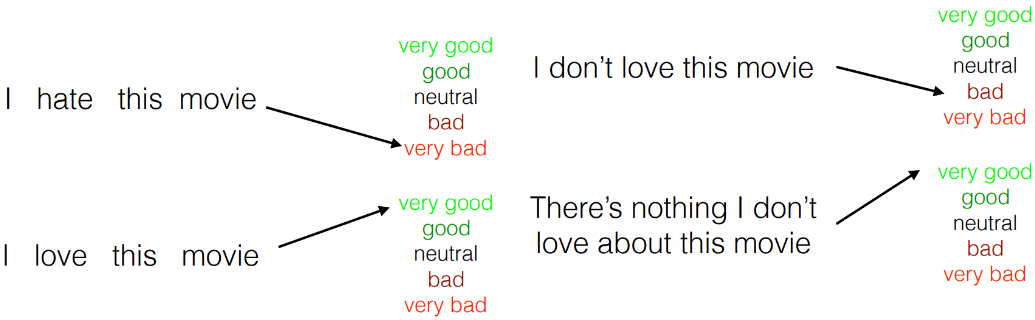


Outline

The Classic Sentence Classification Problem



Source: Graham Neubig slides.

- bag-of-words models won't capture the importance of "don't love" or "nothing I don't love", even with interactions / hidden layers.
- N-grams have a large feature space (especially with 4-grams) and don't share information across similar words/n-grams.

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  - Rather than inputting **counts over words** $\boldsymbol{x}$, take as input a **sequence of tokens** $\{w_1, ..., w_t, ... w_n\}$.
- "Traditional" architectures:
  - Convolutional neural nets (CNNs)
  - Recurrent Neural Nets (RNNs)
- Since 2018, CNNs and RNNs (as currently implemented) usually get worse performance than transformers (<u>attentional</u> neural nets).

Universal Sentence Encoder (USE) Produces Embeddings that are Sensitive to Word Order and Context

```
import tensorflow_hub as hub

embed = hub.Module("https://tfhub.dev/google/"
    "universal-sentence-encoder/1")

embedding = embed([
    "The quick brown fox jumps over the lazy dog."])
```

Listing 1: Python example code for using the universal sentence encoder.

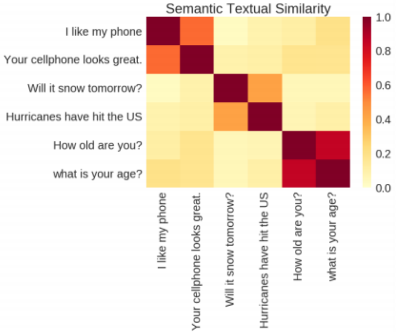

Figure 1: Sentence similarity scores using embeddings from the universal sentence encoder.

- Neural net architecture with embeddings pre-trained on:
  - Identifying co-occuring sentences
  - Identifying message-response pairs (Henderson et al 2017)
  - Some supervised learning tasks (see Cer et al 2018).

Multilingual Encoders

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  - Trained on a similar array of tasks in all languages, so that it can be used out-of-the-box.
- Facebook's LASER encoder produces vectors for 90 languages with a single model.
  - bidirectional LSTM architecture
  - trained on multilingual machine translation task

Sentence-BERT

- The document embeddings produced by BERT do not perform well for sentence similarity tasks.
- S-BERT (Reimers and Gurevych 2019):
  - fine-tune BERT embeddings to classify sentence pairs in textual entailment task.
  - significantly improves performance of sentence embeddings on standard tasks.

SentenceTransformers

- SentenceTransformers (sbert.net) is an amazing python package for embedding texts or short documents.
- Initially based on S-BERT but expanded to many additional models, including embeddings trained on other tasks besides entailment:
  - paraphrase identification
  - semantic textual similarity
  - duplicate question detection
  - question-answer retrieval
- monolingual and multilingual models (for over 100 languages)

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- Recurrent neural nets can process whole documents word-by-word:
  - but they have to sweep through the whole document at each training epoch, so they learn too slowly.
- Transformers overcome these limitations:
  - intuitively, they provide a way to efficiently read in an entire document and learn the meaning of all words and all interactions between words.

Self-Attention – the fundamental computation underlying transformers

- Consider a sequence of tokens with fixed length n_L, $\{w_1, ..., w_i, ..., w_{n_L}\}$
- We have word embedding vectors $x_i = E(w_i)$ with dimension n_E, producing a sequence of vectors

$$\{x_1, ..., x_i, ..., x_{n_L}\}$$

- In previous models, the sequence $x_{1:n_L}$ could be flattened to an $n_L n_E$-dimensional vector and piped to the hidden layers for use in the task, e.g. sentiment classification.

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- A **self-attention layer** transforms $x_{1:n_L}$ into a second sequence $h_{1:n_L}$, where
$$h_i = \sum_{j=1}^{n_L} a(x_i, x_j) x_j$$
  - where $a(\cdot)$ is an attention function such that $a(\cdot) \geq 0$, $\sum a(\cdot) = 1$.
  - $\rightarrow$ each h_i becomes a weighted average of the whole sequence.
- $h_{1:n_L}$ is flattened and piped to the network's hidden layers, rather than $x_{1:n_L}$.

Basic Self-Attention

Setup:

1. Sequence of tokens $\{w_1, ..., w_i, ..., w_{n_L}\}$
2. Sequence of (trainable) embedding vectors $\{x_1, ..., x_i, ..., x_{n_L}\}$
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Basic self-attention specifies

$$a(x_i, x_j) = \frac{\exp(x_i \cdot x_j)}{\sum_{k=1}^{n_L} \exp(x_i \cdot x_k)}$$

- the dot-product $x_i \cdot x_j$, normalized with softmax such that $\sum_j a(\cdot) = 1$.

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- the dot-product $x_i \cdot x_j$, normalized with softmax such that $\sum_j a(\cdot) = 1$.
- Putting it together:

$$h_i = \sum_{j=1}^{n_L} \frac{\exp(x_i \cdot x_j)}{\sum_{k=1}^{n_L} \exp(x_i \cdot x_k)} x_j$$

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Note the following simplifications:

- **basic self-attention has no learnable parameters**.
  - self-attention works indirectly through allowing the word embeddings to interact with each other
- **basic self-attention ignores word order.**

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The big initial gain from transformers, relative to RNNs, came from basic self-attention.

- The successful models (e.g. BERT, GPT) do add parameters and word order information to $a(\cdot)$

Self-attention allows words to interact with each other

- Consider a sentence

  the, cat, walks, on, the, street

  with embeddings

  $$\boldsymbol{x}_{\text{the}}, \boldsymbol{x}_{\text{cat}}, \boldsymbol{x}_{\text{walks}}, \boldsymbol{x}_{\text{on}}, \boldsymbol{x}_{\text{the}}, \boldsymbol{x}_{\text{street}}$$

- Feeding this sentence into the self-attention layer produces

  $$\boldsymbol{h}_{\text{the}}, \boldsymbol{h}_{\text{cat}}, \boldsymbol{h}_{\text{walks}}, \boldsymbol{h}_{\text{on}}, \boldsymbol{h}_{\text{the}}, \boldsymbol{h}_{\text{street}}$$

  where $\boldsymbol{h}_i = \sum_{j=1}^{n} \frac{\exp(\boldsymbol{x}_i \cdot \boldsymbol{x}_j)}{\sum_k \exp(\boldsymbol{x}_i \cdot \boldsymbol{x}_k)} \cdot \boldsymbol{x}_j$.

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Embedding layer will learn vectors $\boldsymbol{x}$ that tend to have **attention dot products** that contribute to the task at hand.

- For example, most transformers are pre-trained on a language modeling task (predicting a left-out word or sentence)
- in this task, stopwords like "the" will not be helpful.
  - the learned embedding $\boldsymbol{x}_{\text{the}}$ will tend to have a low or negative dot product with more informative words.

Autoregressive vs Autoencoding Language Models

- **Autoregressive models**:
  - e.g. **GPT = "Generative Pre-Trained Transformer"**:
  - pretrained on classic language modeling task: guess the next token having read all the previous ones.
  - during training, attention heads only view previous tokens, not subsequent tokens.
  - ideal for text generation.
- **Autoencoding models**
  - e.g. **BERT = "Bidirectional Encoder Representations from Transormers"**
  - pretrained by dropping/shuffling input tokens and trying to reconstruct the original sequence.
  - usually build bidirectional representations and get access to the full sequence.
  - can be fine-tuned and achieve great results on many tasks, e.g. text classification.

Shortcut: Using BERT-Based Pre-Trained Models

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```
from transformers import pipeline
sentiment_analysis = pipeline(“sentiment-analysis”)

pos_text = "I enjoy studying computational algorithms."
neg_text = "I dislike sleeping late everyday."

pos_sent = sentiment_analysis(pos_text)[0]
print(pos_sent['label'],0 pos_sent['score'])

neg_sent = sentiment_analysis(neg_text)[0]
print(neg_sent['label'], neg_sent['score'])
```

- also straightforward to fine-tune BERT for your own classification tasks.
- see notebooks for full details / explanation.

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- GPT-2 (2019):
  - all articles linked from Reddit with at least 3 upvotes (8 million documents, 40 GB of text)
  - dispense with supervised learning task, make some other architectural adjustments
  - make model much bigger

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- GPT-1: the first autoregressive transformer model (2018)
  - trained on the Books corpus.
  - train on a language modeling task, as well as a multi-task that adds a supervised learning task.
- GPT-2 (2019):
  - all articles linked from Reddit with at least 3 upvotes (8 million documents, 40 GB of text)
  - dispense with supervised learning task, make some other architectural adjustments
  - make model much bigger
- GPT-3 (2020):
  - use an even bigger corpus (Common Crawl, WebText2, Books1, Books2 and Wikipedia)
  - make model much, much bigger

OPENAI'S NEW MULTITALENTED AI WRITES, TRANSLATES, AND SLANDERS

A step forward in AI text-generation that also spells trouble

By James Vincent | Feb 14, 2019, 12:00pm EST

Howard, co-founder of Fast.AI agrees. "I've been trying to warn people about this for a while," he says. "We have the technology to totally fill Twitter, email, and the web up with reasonable-sounding, context-appropriate prose, which would drown out all other speech and be impossible to filter."

Applications: GPT-3

Stammbach and Ash (2020), "e-FEVER: Explanations and Summaries for Automated Fact Checking"

Claim	Extractive Summary	Abstractive Summary
Marnie was directed by someone who was "The Master of Nothing".	+ Alfred Hitchcock + Sir Alfred Joseph Hitchcock (13 August 1899 - 29 April 1980) was an English film director and producer , at times referred to as " The Master of Suspense " . + Marnie (film) + Marnie is a 1964 American psychological thriller film directed by Alfred Hitchcock ."	Marnie was directed by Alfred Hitchcock, who was "The Master of Suspense".
Colin Kaepernick is a poker player.	+ Colin Kaepernick + Colin Rand Kaepernick (born November 3 , 1987) is an American football quarterback who is currently a free agent . + American football + American football , referred to as football in the United States and Canada , and also known as " gridiron football " or simply " gridiron " , is a sport played by two teams of eleven players on a rectangular field with goalposts at each end .	Colin Kaepernick is a football player, not a poker player.

Stammbach, Antoniak, and Ash (2022), "Heroes, Villains, and Victims, and GPT-3"

Who is the villain in the following text?

Text: In questioning the use of hydraulic fracturing in New York to help produce natural gas, you do not note that the technology has been employed and continuously improved for more than 50 years and that studies by the Environmental Protection Agency and the Ground Water Protection Council have not identified a single instance of groundwater contamination. Wells where fracturing is used are specially constructed to protect drinking water sources. Regulatory oversight is extensive. The fluids mostly water that are forced into a well to create pressure to fracture rock are pushed back out by the oil and gas flowing upward for safe processing. Protecting our water supplies is important, as are reductions in greenhouse gas emissions through use of clean-burning natural gas. Banning hydraulic fracturing would be unwarranted and shortsighted, preventing production of large amounts of natural gas that could directly benefit New York consumers for decades and create thousands of good jobs.

Villain: **The villain in this text is the person who is questioning the use of hydraulic fracturing in New York.**

Movie	Hero	Victim	Villain
101 Dalmatians	Roger Dearly	The Dalmatian Puppies	Cruella de Vil
Aladdin	Aladdin	Aladdin	Jafar
Cinderella	Cinderella	Cinderella	Lady Tremaine
Alice In Wonderland	Alice	Alice	The Queen of Hearts
The Jungle Book	Mowgli	Mowgli	Shere Khan, a man-eating Bengal tiger
Sleeping Beauty	Prince Phillip	Aurora	Maleficent
The Lion King	Simba	Mufasa	Scar
Peter Pan	Peter Pan	Wendy, John, Michael, and the Lost Boys	Captain Hook
Mary Poppins	Mary Poppins	Mr. Banks	Mr. Dawes
The Little Mermaid	Ariel	Ariel	Ursula
Snow White	Snow White	Snow White	The Queen

Table 2: Results for Wikipedia plots of widely known Disney Movies

BERT (and RoBERTa)

- BERT = Bidirectional Encoder Representations from Transformers
  - RoBERTa = Robust BERT
- Architecture:
  - a stack of transformer blocks with a self-attention layer and an MLP.
  - The largest BERT model has 24 blocks, embedding dimension of 1024, and 16 attention heads.
    $\approx$ 340M parameters to learn.

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- Corpus:
  - 800M words from English books (modern work, from unpublished authors), by Zhu et al (2015).
  - 2.5B words of text from English Wikipedia articles (without markup).

Application: Climate-Related Corporate Disclosures (Bingler, Kraus, and Leippold 2021)

- Fine-tunes RoBERTa ("Robust BERT") to classify texts related to corporate climate disclosures (using hand-annotated sample).

Table 3. Out-of-sample performance comparison between baseline models and our proposed ClimateBERT. Performance is reported in precision for each category.

	Governance	Strategy	Risk Management	Metrics & Targets	General Language	Overall Accuracy
Tf-idf	0.43	0.00	0.40	0.35	0.00	0.24
Sentence Enc.	0.19	0.57	0.15	0.24	0.00	0.23
RoBERTa Para.	0.26	0.25	0.25	0.25	0.07	0.22
RoBERTa Sent.	0.96	0.92	0.84	0.74	0.32	0.75
ClimateBERT	0.94	0.90	0.79	0.77	0.65	0.81

- model applied to large sample, shows that most disclosures are about more subjective / less verifiable aspects of climate disclosures.