S&DS 265 / 565

Introductory Machine Learning

Language Models

Tuesday, October 26

Yale

Checkpoint

- Midterms scores posted
- Provisional grades announced
- Happy to meet to discuss grading, standing...
- Assignment 4 due week from today

Here we are

8	Oct 19	Midterm exam (in class)			Practice midterm (Canvas) Sample solutions (Canvas)
9	Oct 26, 28	Language models, word embeddings	CO Word embeddings		Oct 26: Language models Oct 28: Word embeddings
10	Nov 2, 4	Bayesian inference, topic models	CO Bayesian inference CO Topic models	Tue: Assn 4 in; Assn 5 out	
11	Nov 9, 11	Introduction to neural networks	CO Minimal neural network	Thu: Assn 5 in; Assn 6 out	

For Today

- Language models
- Channel models
- Concepts...no new methods

When you text someone

- Take out your cell phone...

When you text someone

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When you text someone

- Take out your cell phone...
- Text someone
- What did you notice?

Language models

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Language models

- A language model is a way of *generating* any sequence of words

$$
\begin{aligned}
&P(\text{“the whole forest had been anesthetized”}) = \\
&P(\text{“the”}) \times P(\text{“whole”} \mid \text{“the”}) \\
&\times P(\text{“forest”} \mid \text{“the whole”}) \\
&\times P(\text{“had”} \mid \text{“the whole forest”}) \\
&\times P(\text{“been”} \mid \text{“the whole forest had”}) \\
&\times P(\text{“anesthetized”} \mid \text{“the whole forest had been”})
\end{aligned}
$$

Remixing Noon

Text generated from Channel Skin by Jeff Noon

"The whole forest had been anesthetised, her temples wired, her senses stimulated, her eyes were not on Eva, not on Eva, not on Eva, not on anybody in that same realm, the land of dreams and nightmares."

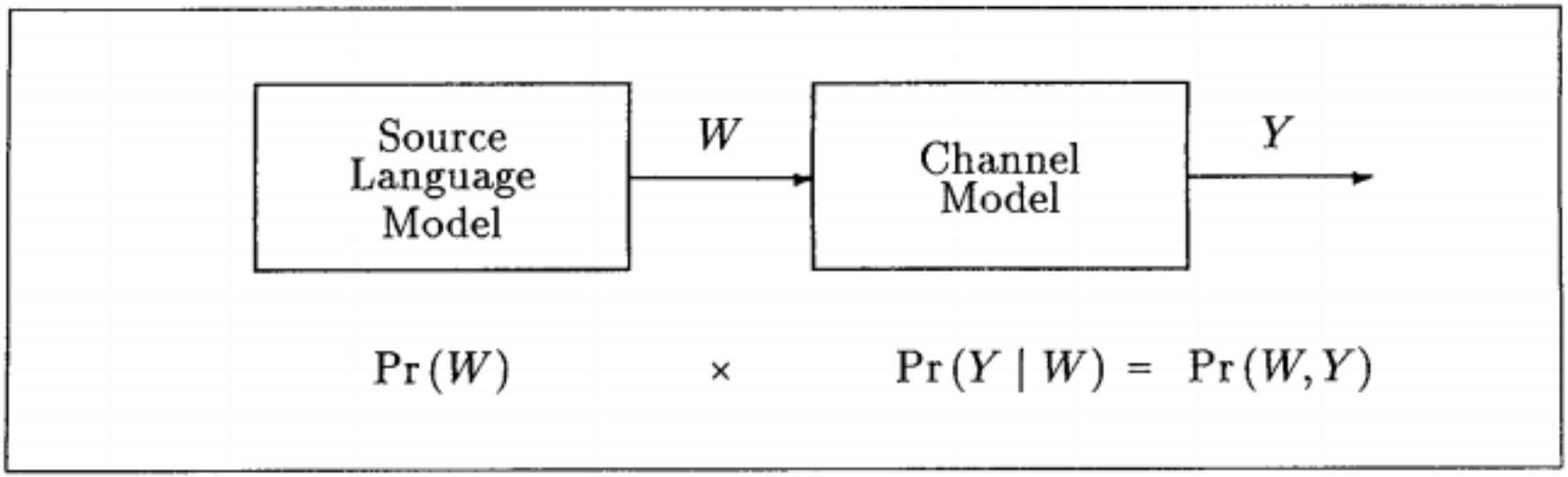
Viability: 0.000000326%

https://revdancatt.com/2017/03/01/markov_noon

Text generation

- Words generated one-by-one
- A word is chosen by sampling from a probability distribution
- Then treated as if it were “real,” as in dreaming
- Result is purely synthetic text

Uses of LMs: The source-channel framework



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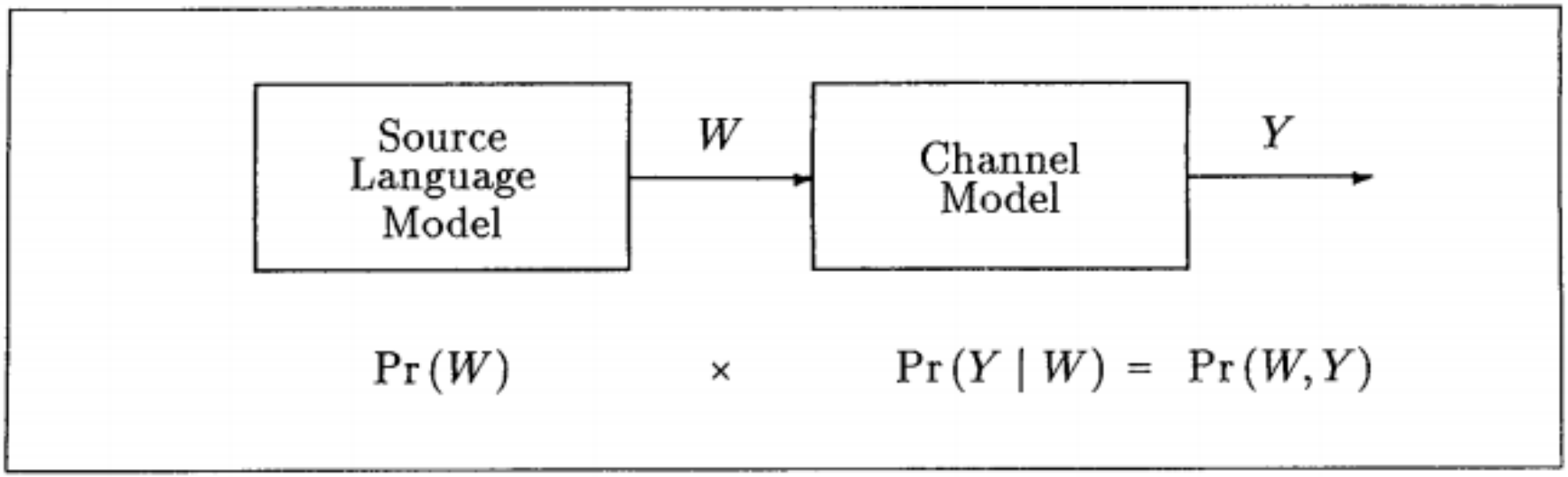

What are some examples?

The source-channel framework

- Speech recognition

The source-channel framework

- Speech recognition
- Machine translation

The source-channel framework

- Speech recognition
- Machine translation
- Texting

The source-channel framework

- Speech recognition
- Machine translation
- Texting
- Email completion

The source-channel framework

- Speech recognition
- Machine translation
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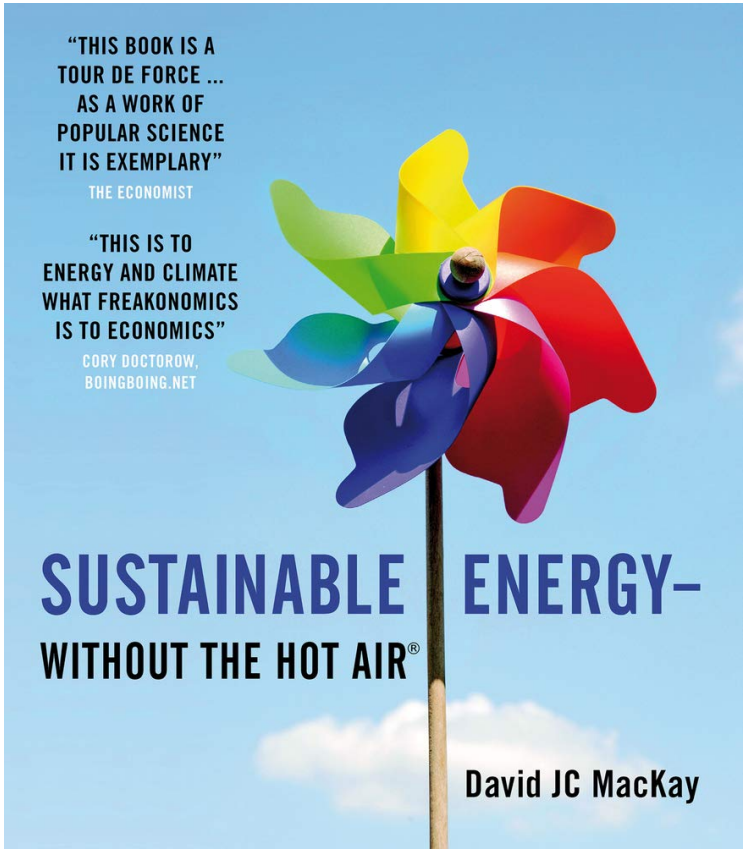
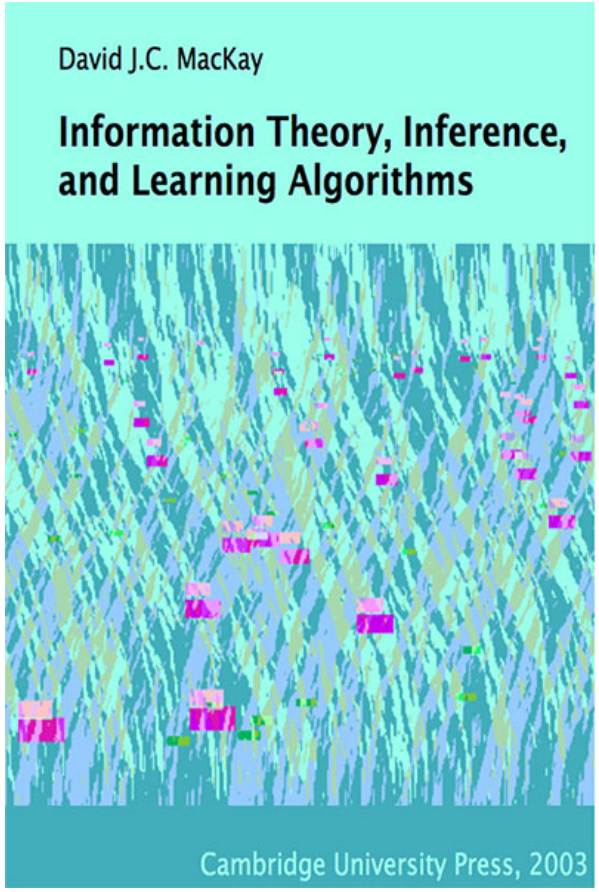
- Email completion
- Image captioning

The source-channel framework

- Speech recognition
- Machine translation
- Texting
- Email completion
- Image captioning
- Mind reading from fMRI

David MacKay





Dasher: LMs for assistive devices

Language models enable new modes of text input:

https://www.youtube.com/watch?v=quw_Kci4fUg

https://youtu.be/QxFEUk3J89Q?t=72

Dasher poetry:

https://www.youtube.com/watch?v=x-WLiY2p1LQ

Dasher for text input, David Mackay, University of Cambridge

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- The number of *histories* grows as V^{n-1}. Number of parameters in model grows as V^n, where V is number of words in vocabulary.
- What are some ways of reducing the number of parameters?

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- What are some example groupings?

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- Bigrams: $g(w_1, \ldots, w_n) = w_n$.
- Trigrams: $g(w_1, \ldots, w_n) = (w_{n-1}, w_n)$.
- Number of parameters grows as $O(V)$, $O(V^2)$, and $O(V^3)$, respectively.

Estimating parameters

- The maximum likelihood estimate of a trigram model:

$$\widehat{p}(w_3 \mid w_1, w_2) = \frac{\text{count}(w_1, w_2, w_3)}{\text{count}(w_1, w_2)}$$

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- What are some problems with this model?

Sparse data problem

The next group of slides present one way of quantifying the problem of sparse data in language modeling

Half Earth

Aug 06, 2018 *by Foundation Staff* *0 Comment* *Google Earth, Half-Earth Project, Map of Life*

By Jeremy Malczyk, Michelle Duong, Ajay Ranipeta, Chris Heltne, Walter Jetz of Map of Life, Yale University, and the E.O. Wilson Biodiversity Foundation Half-Earth Project

This article originally in *Medium,* July 30, 2018

half-earth project

Learn how you can be part of bringing Half-Earth to life.

The Significance of Biodiversity

Narrow-billed Tody, Todus angustirostris. Photo by Julie Hart.

https://eowilsonfoundation.org/mapping-species-for-half-earth/

https://www.half-earthproject.org/

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- A naturalist (say, Edward O. Wilson) explores a region and observes animals (organisms).

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- What if Wilson observes 100 unique species?

Missing species: Good-Turing

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- Good-Turing: Estimate of the probability that the next animal is a new species? $\widehat{p}_{GT} = 100/100,000 = 10^{-3}$.
- This is an estimate of the missing probability mass.

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Map of Life

YaleNews EXPLORE TOPICS ▾

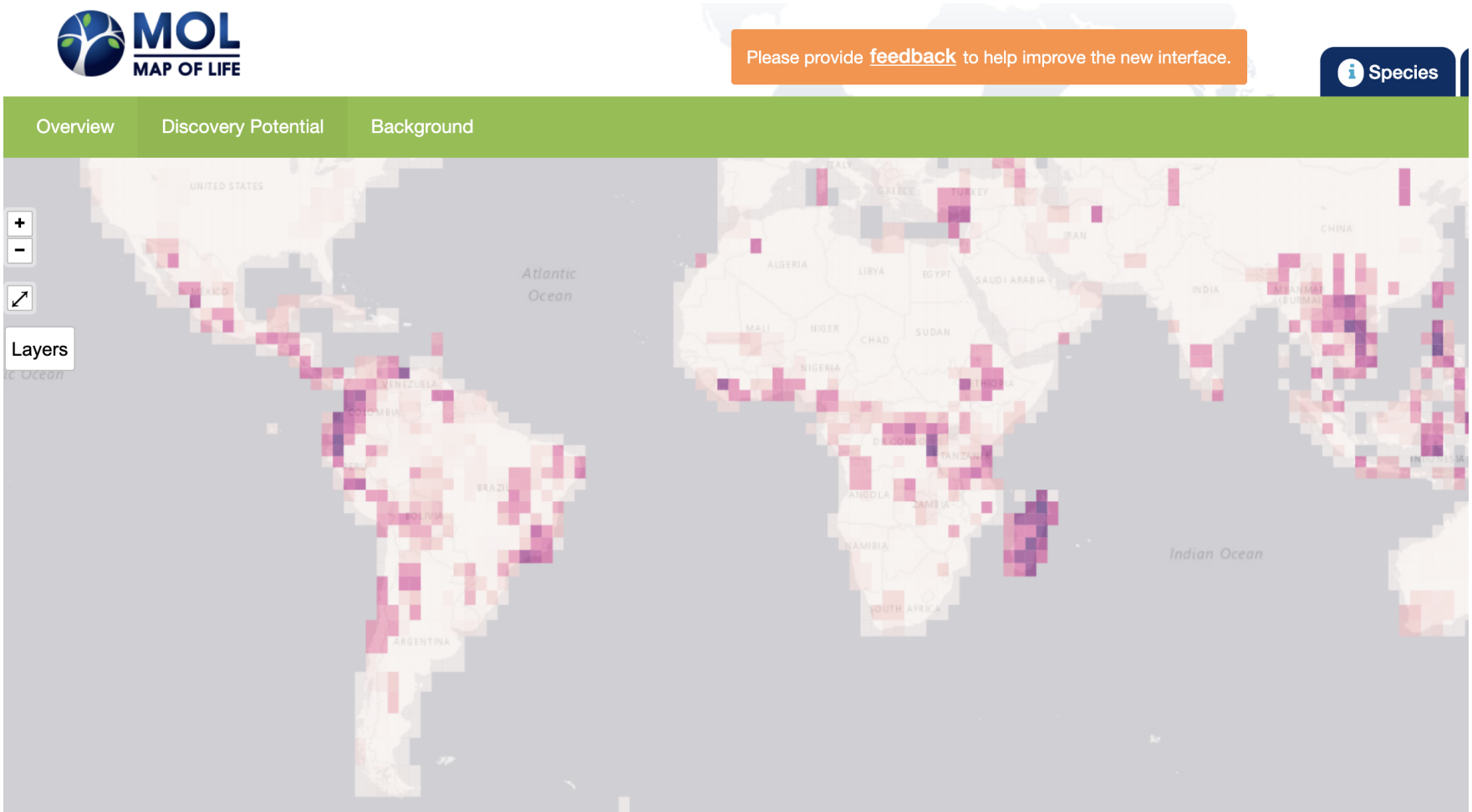
Yale researchers create map of undiscovered life

By Bill Hathaway | MARCH 22, 2021

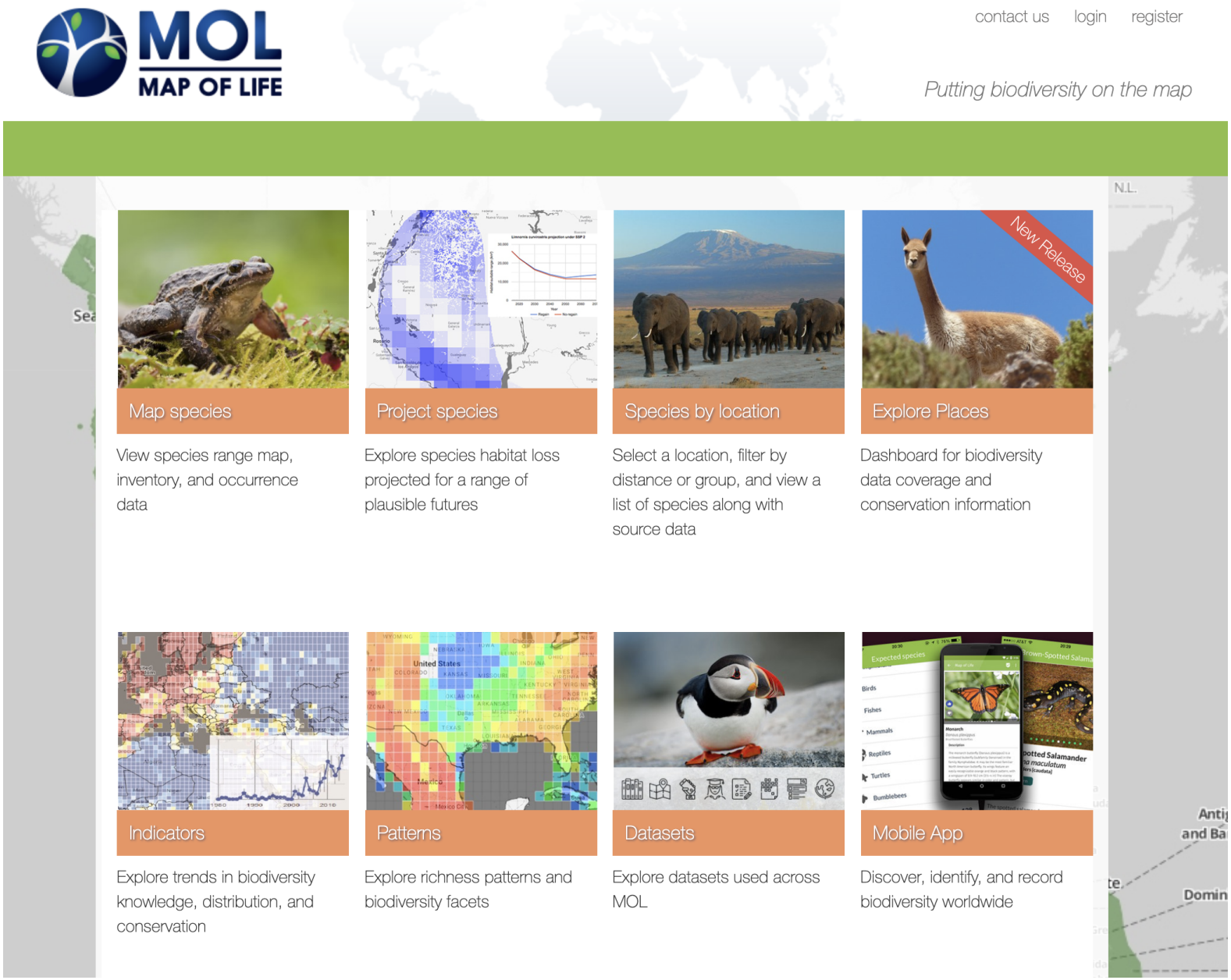
Less than a decade after unveiling the "Map of Life," a global database that marks the distribution of known species across the planet, Yale researchers have launched an ambitious and perhaps even more important project — creating a map of where life has yet to be discovered.

For Walter Jetz, a professor of ecology and evolutionary biology at Yale who spearheaded the Map of Life project, the new effort is a moral imperative that can help support biodiversity discovery and preservation around the world.

Map of Life


MOL
MAP OF LIFE
Please provide feedback to help improve the new interface.
Species
Overview
Discovery Potential
Background
Layers
Atlantic Ocean
Indian Ocean

Map of Life


MOL
MAP OF LIFE
contact us
login
register
Putting biodiversity on the map
New Release
Map species
View species range map, inventory, and occurrence data
Project species
Explore species habitat loss projected for a range of plausible futures
Species by location
Select a location, filter by distance or group, and view a list of species along with source data
Explore Places
Dashboard for biodiversity data coverage and conservation information
Indicators
Explore trends in biodiversity knowledge, distribution, and conservation
Patterns
Explore richness patterns and biodiversity facets
Datasets
Explore datasets used across MOL
Mobile App
Discover, identify, and record biodiversity worldwide

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- Suppose we have a corpus of 500 million words. I count trigrams and find that 50 million of them are unique.

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- The MLE is supported on the observed data. We need to spread out the probability over unseen events.

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- Some kind of “shrinkage” or smoothing needs to be done.
- How else can the model be strengthened?

Interpolation

Linear interpolation:

$$p(w_3 \mid w_1, w_2) = \lambda_3 \widehat{p}(w_3 \mid w_1, w_2) + \lambda_2 \widehat{p}(w_3 \mid w_2) + \lambda_1 \widehat{p}(w_3)$$

where $\lambda_1 + \lambda_2 + \lambda_3 = 1$.

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where $\lambda_1 + \lambda_2 + \lambda_3 = 1$.

This is a type of “mixture model”

How good is a language model?

The next group of slides present a useful way of quantifying how good a language model is

Recall: Geometric mean

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The geometric mean is no greater than the arithmetic mean

Recall: Geometric mean

The *geometric mean* of $x_1, \ldots, x_n$ is

$$\sqrt[n]{x_1 x_2 \cdots x_n} = \left(\prod_{i=1}^{n} x_i \right)^{\frac{1}{n}}$$

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How good is a language model? Perplexity

Perplexity is defined as

$$\text{Perplexity}(\theta) = \left(\prod_{i=1}^{n} p_\theta(w_i \mid w_{1:i-1}) \right)^{-\frac{1}{n}}$$

where $w_1, w_2, \ldots, w_n$ is a large chunk of text that wasn't used to train the language model.

How good is a language model? Perplexity

- Perplexity is the inverse of the geometric mean of the word probabilities
- If the perplexity is 100, the model predicts, on average, as if there were 100 equally likely words to follow
- This is the (geometric) average “branching factor” for the model on real text

Remixing Noon

Text generated from Channel Skin by Jeff Noon

"The whole forest had been anesthetised, her temples wired, her senses stimulated, her eyes were not on Eva, not on Eva, not on Eva, not on anybody in that same realm, the land of dreams and nightmares."

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Modern language models

Suppose a computer program assigns a "score" to possible next words:

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Can convert this to a language model by the "softmax" operation:

$$p(w \mid w_1, \ldots, w_n) = \frac{\exp(s(w; w_1, \ldots, w_n))}{\sum_{v \in V} \exp(s(v; w_1, \ldots, w_n))}$$

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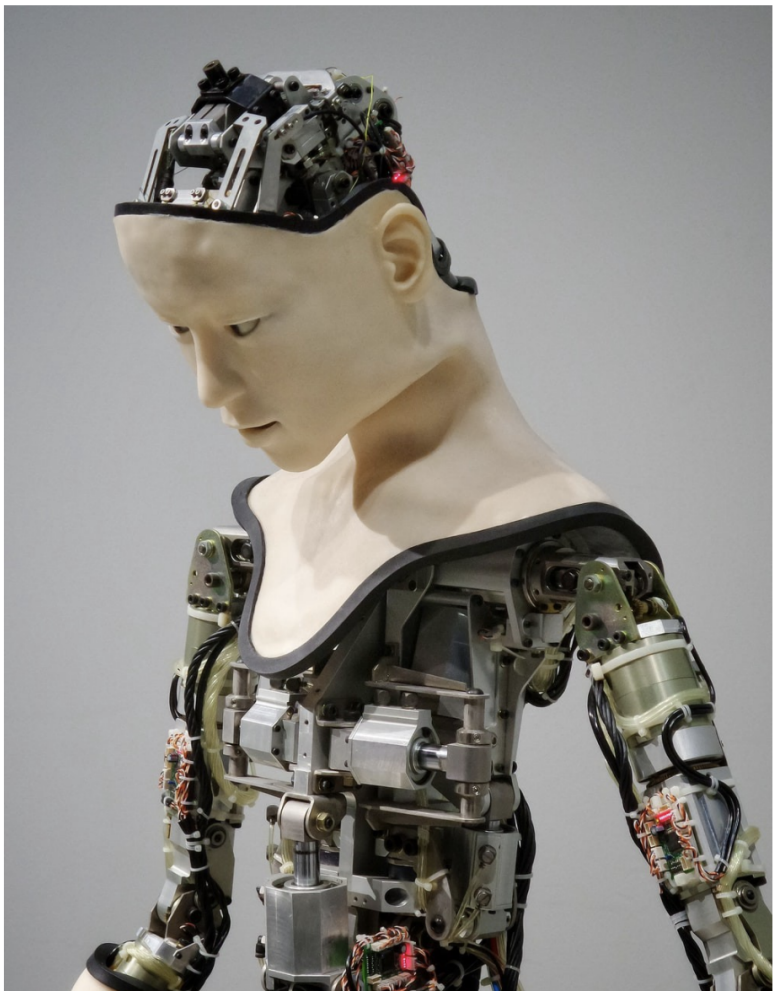
In GPT-3, the function $s(v; w_{1:n})$ is learned on large amounts of text (unsupervised) using a type of deep neural network called a *transformer*.

GPT-3 101: a brief introduction

It has been almost impossible to avoid the GPT-3 hype in the last weeks. This article offers a quick introduction to its architecture, use cases already available, as well as some thoughts about its ethical and green IT implications.

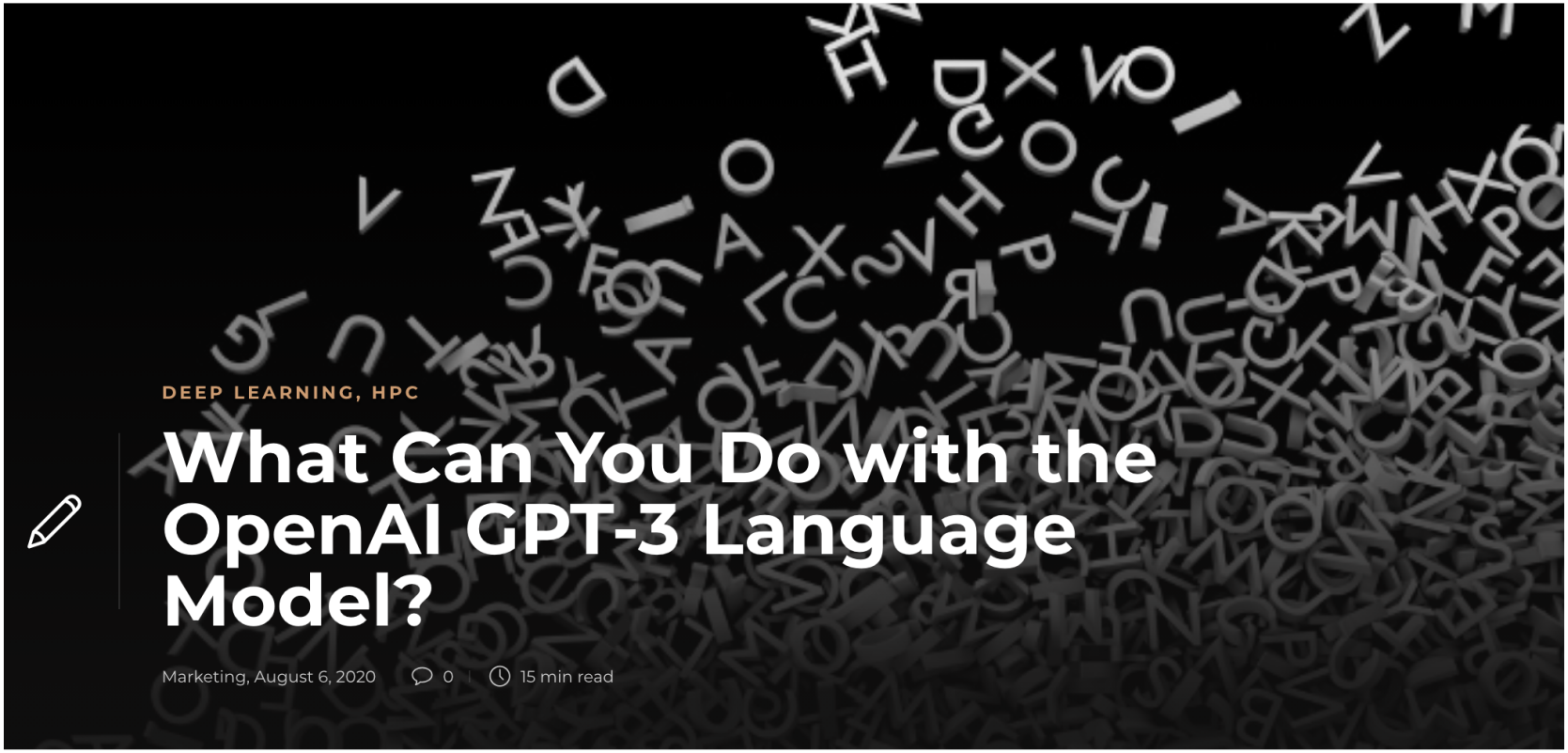
David Pereira Jul 25, 2020 · 6 min read ★



Introduction

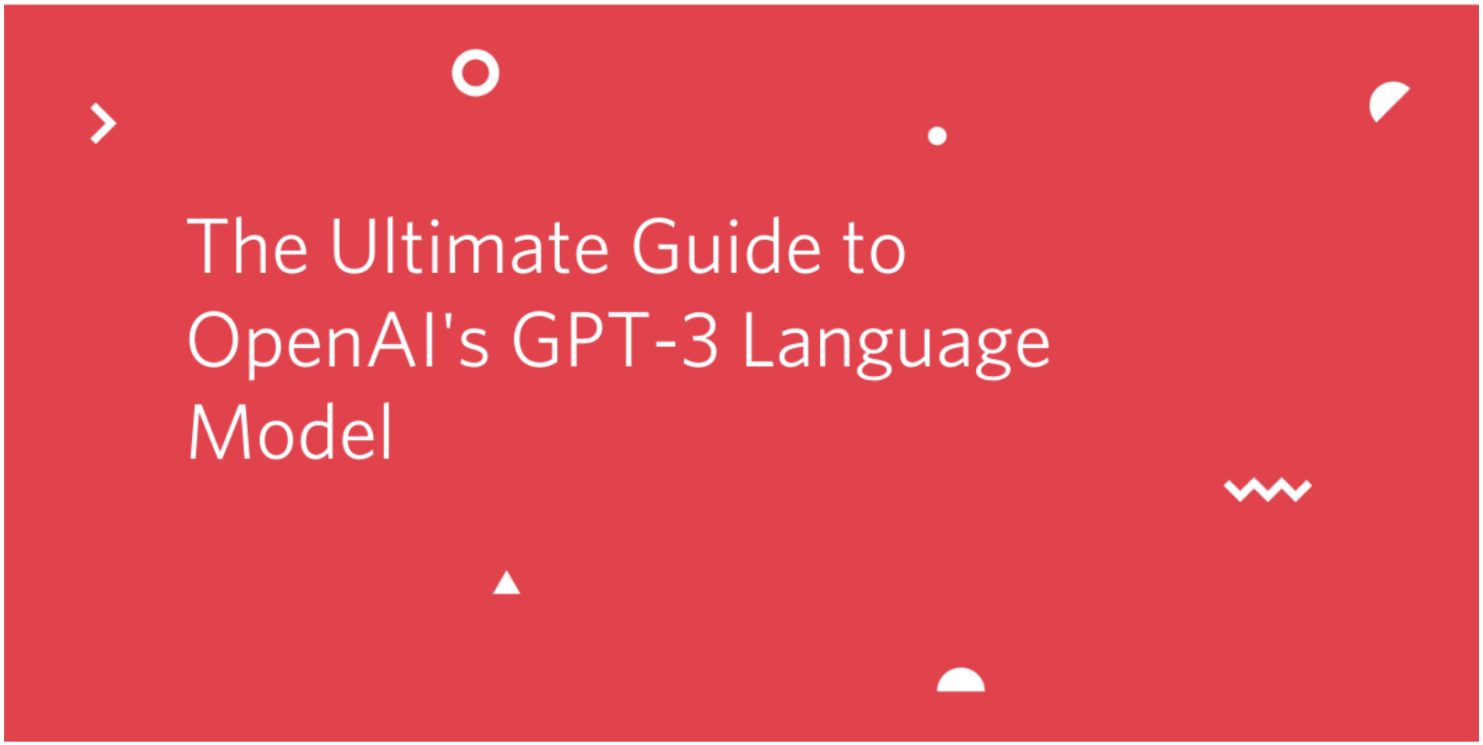
Let's start with the basics. GPT-3 stands for Generative Pretrained Transformer version 3, and it is a sequence transduction model. Simply put, sequence transduction is a technique that transforms an input sequence to an output sequence.

GPT-3 is a language model, which means that, using sequence transduction, it can predict the likelihood of an output sequence given an input sequence. This can be used, for instance to predict which word makes the most sense given a text sequence.



Exploring GPT-3: A New Breakthrough in Language Generation

The Ultimate Guide to OpenAI's GPT-3 Language Model



Generative Pre-trained Transformer 3 (GPT-3) is a new language model created by OpenAI that is able to generate written text of such quality that is often difficult to differentiate from text written by a human.

Opinion

How Do You Know a Human Wrote This?

Machines are gaining the ability to write, and they are getting terrifyingly good at it.

By Farhad Manjoo
Opinion Columnist

July 29, 2020

342

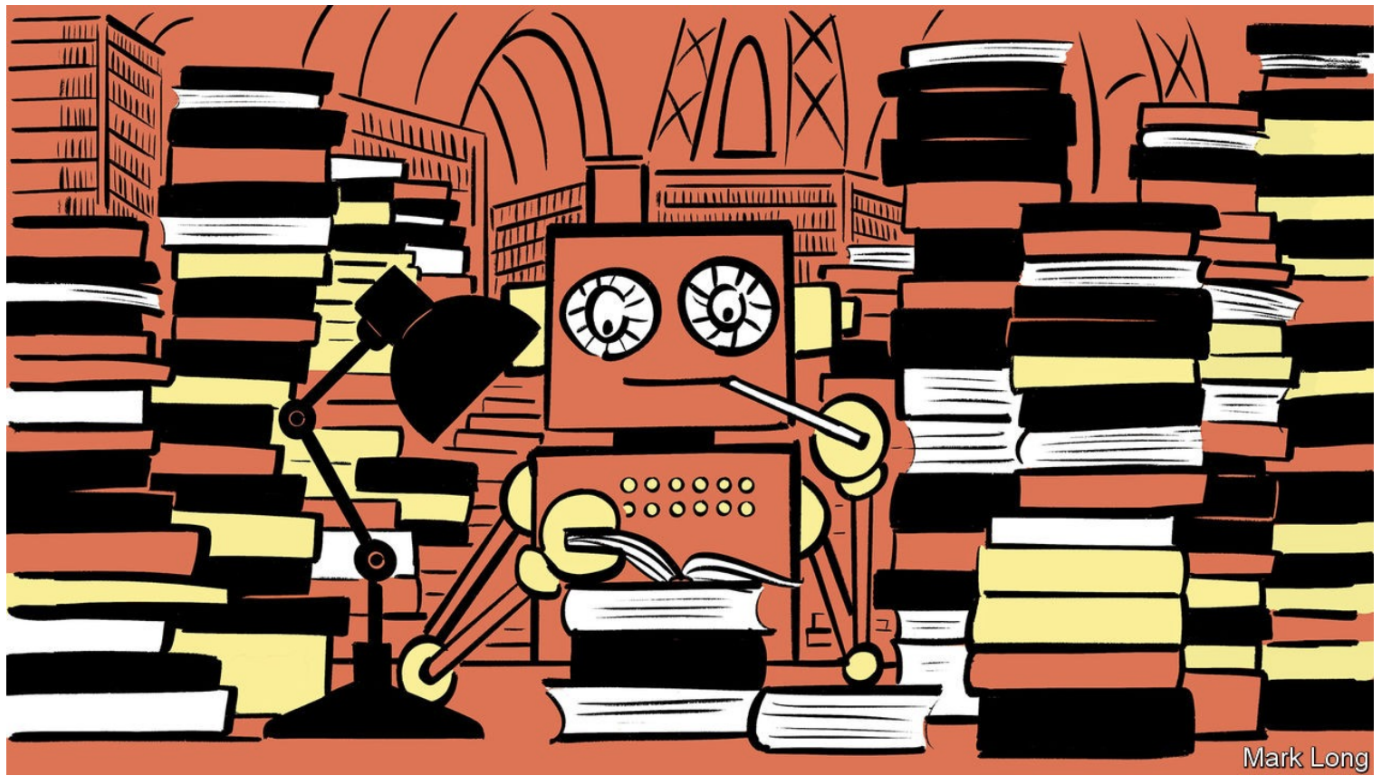
Science & technology

Aug 6th 2020 edition ›

Artificial intelligence

A new AI language model generates poetry and prose

GPT-3 can be eerily human-like—for better and for worse



The New York Times

Account

Meet GPT-3. It Has Learned to Code (and Blog and Argue).

The latest natural-language system generates tweets, pens poetry, summarizes emails, answers trivia questions, translates languages and even writes its own computer programs.

Key intuition

- Words that have similar neighbors will be similar
- Note, recursive notion of similarity!
- This will be an intuition behind “word embeddings”

Pointwise mutual information (PMI)

Can cluster words based on "pointwise mutual information" (PMI)

$$\log\left(\frac{p_{\text{near}}(w_1, w_2)}{p(w_1)p(w_2)}\right)$$

- How likely are specific words/clusters to co-occur together within some window, compared to if they were independent?

Example clusters from PMI

we our us ourselves ours
question questions asking answer answers answering
performance performed perform performs performing
tie jacket suit
write writes writing written wrote pen
morning noon evening night nights midnight bed
attorney counsel trial court judge
problems problem solution solve analyzed solved solving
letter addressed enclosed letters correspondence
large size small larger smaller
operations operations operating operate operated
school classroom teaching grade math
street block avenue corner blocks
table tables dining chairs plate
published publication author publish writer titled
wall ceiling walls enclosure roof
sell buy selling buying sold

Shortcomings of word clusters

- Clusters are still “categorical”
- Can’t use vector space operations
- “One hot” representation wasteful
- These are addressed with *distributed representations* (next)

Insight of embeddings

- Use PMI-like scores to get embedding vectors.
- Can be applied whenever have large amounts of cooccurrence data.
- We'll go further into this next time

Summary of today: Language models

- A language model is used to predict or generate the next word
- Used many different places, channel models
- Probabilities need to be “smoothed” to avoid zeros
- Perplexity is a measure of a language model’s predictive power
- Surprising amount of information captured by purely local cooccurrence counts
- GPT-3 is a hint at the future of AI