S&DS 265 / 565

Introductory Machine Learning

Language Models

October 25

Yale

Welcome back!

For today:

- Where have we been? Where are we going?
- Language models

Checking in

- Midterms scores posted
- Provisional grades announced
- Happy to meet to discuss grading, standing...
- Assignment 3 due next Tues, Nov. 1
- Assignment 4 out this Thursday

Where we've been

1	Sept 1	Course overview		Sept 1: Course overview		
2	Sept 6, 8	Python and background concepts	Python elements Covid trends	Sept 6: Python elements Sept 8: Pandas and linear regression	Data8 Chapters 3, 4, 5	Thu: Quiz 1
3	Sept 13, 15	Linear regression and classification	Covid trends (revisited) Classification examples	Sept 13: Regression concepts Sept 15: Classification	ISL Sections 3.1, 3.2, 3.5 Notes on regression ISL Sections 4.3, 4.4 Notes on classification	Thu: Assn 1
4	Sept 20, 22	Stochastic gradient descent	SGD examples	Sept 20: Classification (continued) Sept 22: Stochastic gradient descent	ISL Section 6.2.2 ISL Section 10.7.2	Thu: Quiz 2
5	Sept 27, 29	Bias and variance, cross-validation	Bias-variance tradeoff Covid trends (revisited) California housing	Sept 27: Bias and variance Sept 29: Cross-validation	ISL Section 2.2 ISL Section 5.1	Thu: Assn 1 in Assn 2 out
6	Oct 4, 6	Tree-based methods	Trees and forests Visualizing trees Bagging operations	Oct 4: Trees Oct 6: Forests	ISL Sections 8.1, 8.2	Thu: Quiz 3
7	Oct 11, 13	PCA and dimension reduction	PCA examples PCA revisited Used for regression	Oct 11: PCA Oct 13: PCA and review	ISL Section 12.2	Thu: Assn 2 in Assn 3 out
8	Oct 18	Midterm exam (in class)			On Canvas: Practice midterms / Sample solns Midterm / Sample	

Where we’re going

8	Oct 18	Midterm exam (in class)			On Canvas: Practice midterms / Sample solns Midterm / Sample soln	
9	Oct 25, 27	Language models, word embeddings	CO Word embeddings	Oct 25: Language models Oct 27: Word embeddings		CO Assn 4 out
10	Nov 1, 3	Bayesian inference, topic models	CO Mixtures CO Bayesian inference CO Topic models	Nov 1: Bayesian inference Nov 3: Bayes and topic models	Notes on Bayesian inference Notes on simulation	Tue: Assn 3 in Thu: Quiz 4
11	Nov 8, 10	Introduction to neural networks	CO Minimal neural network CO Regression examples	Nov 8: Topic models Nov 10: Neural networks	ISL Sections 10.1, 10.2	Thu: Assn 4 in CO Assn 5 out
12	Nov 15, 17	Deep neural networks	Tensorflow playground CO Autoencoder examples	Nov 15: Neural networks (continued) Nov 17: Autoencoders	ISL Section 10.7 Notes on backpropagation	Thu: Quiz 5
13	Nov 22, 24	No class, Thanksgiving break				
14	Nov 29, Dec 1	Reinforcement learning	CO Q-learning	Nov 29: Reinforcement learning Dec 1: Deep reinforcement learning		Thu: Assn 5 in CO Assn 6 out
15	Dec 6, 8	Societal issues for machine learning		Dec 6: Societal issues Dec 8: Course wrap up		Thu: Quiz 6
16	Dec 15					Thu: Assn 6 in
17	Mon, Dec 19, 7pm	Final exam			Registrar: Final exam schedule Practice final, sample solution	

For Today

- Language models
- Concepts...no new methods

When you text someone

- Take out your cell phone...

When you text someone

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- Text someone

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 language models

- Speech recognition

Often built using Bayes' rule: $P(\text{signal} \mid \text{words}) \propto P(\text{words} \mid \text{signal}) \cdot P(\text{words})$

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- Mind reading from fMRI

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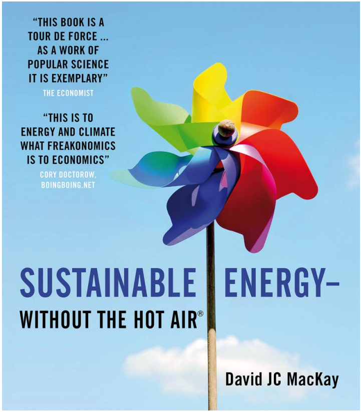
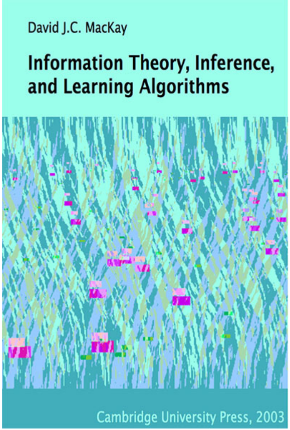
David MacKay





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

Mind reading from fMRI

https://youtu.be/Ecvv-EvOj8M?t=663

Human brain mapping and brain decoding, Jack Gallant, TEDxSanFrancisco

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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?

One approach: Grouping histories

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- What are some example groupings?

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- 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/

Specious species

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- What is the chance I'll find a new species?
- What if Wilson observes 100 unique species?

Missing species: Good-Turing

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https://en.wikipedia.org/wiki/Good-Turing_frequency_estimation

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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.

https://en.wikipedia.org/wiki/Good-Turing_frequency_estimation

Map of Life

YaleNews EXPLORE TOPICS ▾

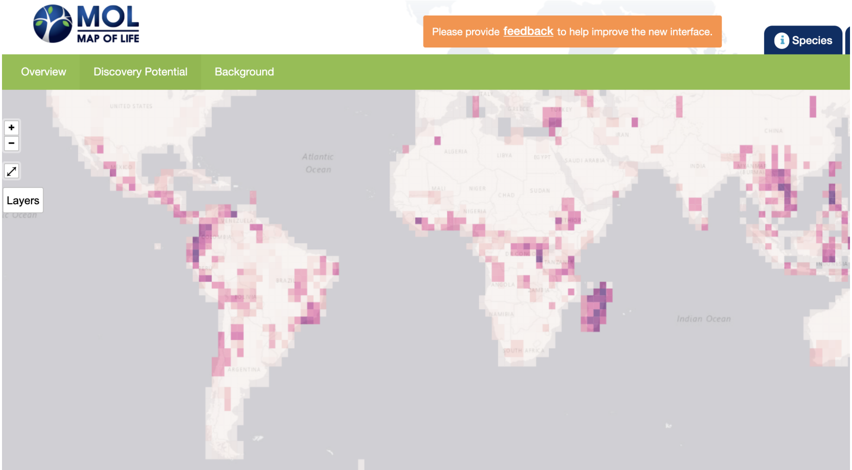
Yale researchers create map of undiscovered life

By Bill Hathaway | MARCH 22, 2021

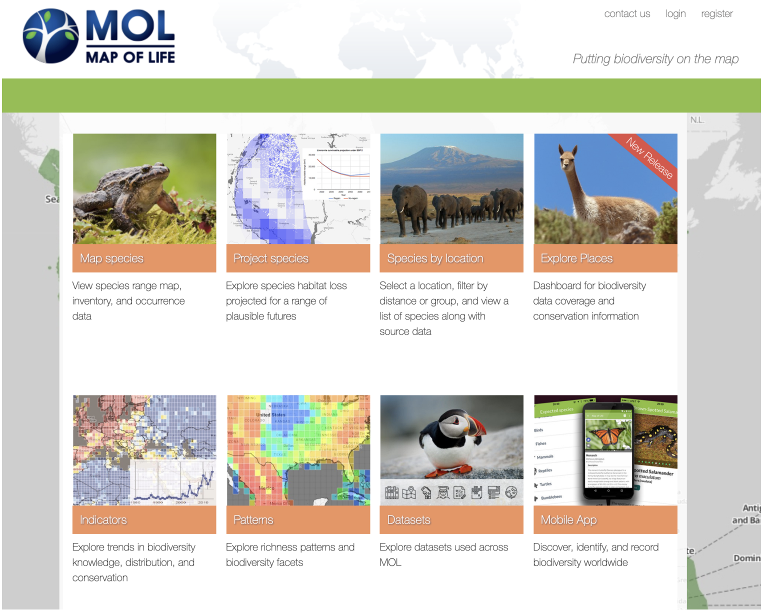
Less than a decade after unveiling the "Map of Life," a global database that marks the distribution of known species across the planet, Yale researchers have launched an ambitious and perhaps even more important project — creating a map of where life has yet to be discovered.

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

Sparse data: Species $\approx$ words in vocabulary

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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.

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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* of 1/4, 4, 8 is

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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

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Modern language models

Suppose a computer program assigns a “score” to possible next words:

$$s(v;\ \underbrace{w_1, \ldots, w_n}_{\text{word history}}\ )$$

https://en.wikipedia.org/wiki/Softmax_function

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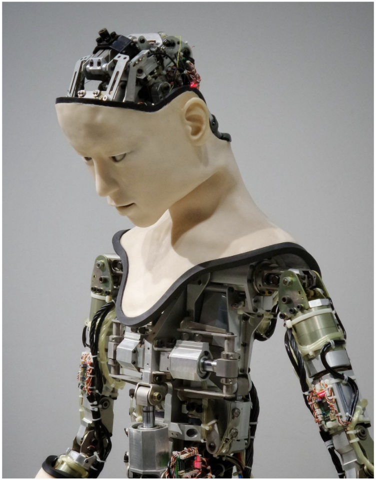
In GPT-3, the function $s(v; w_{1:n})$ is learned on large amounts of text (unsupervised) using a type of deep neural network called a *transformer*.

https://en.wikipedia.org/wiki/Softmax_function

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.

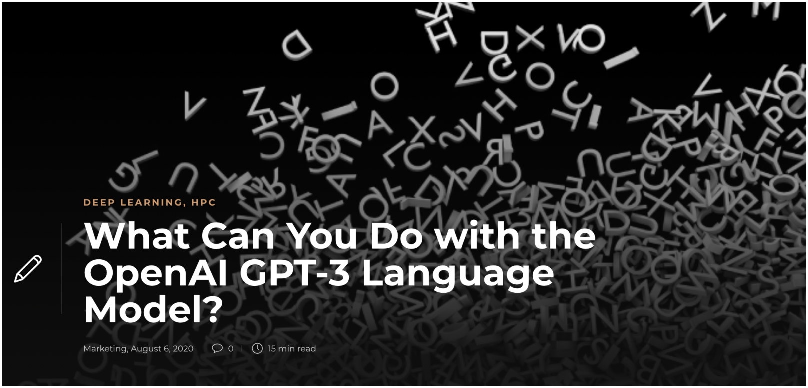
David Pereira Jul 25, 2020 · 6 min read ★



Introduction

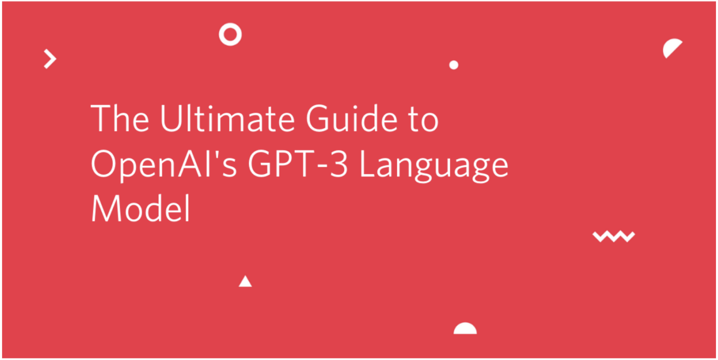
Let's start with the basics. GPT-3 stands for Generative Pretrained Transformer version 3, and it is a sequence transduction model. Simply put, sequence transduction is a technique that transforms an input sequence to an output sequence.

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

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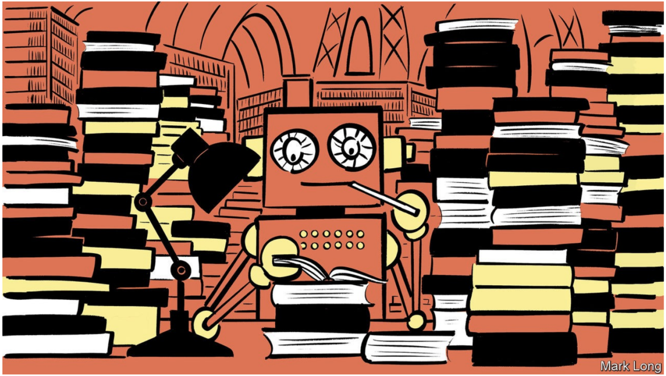
Science & technology

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



Mark Long

≡ 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 current frontier of AI