

Making Your Apps Smarter: Machine Learning & AI

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Software Design & Studio

Outline

- ① Web, App, and Business Intelligence
- ② What's Machine Learning & AI?
- ③ What's Deep Learning?
- ④ What's Generative AI?
- ⑤ Making Smart Apps

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Your Term Project

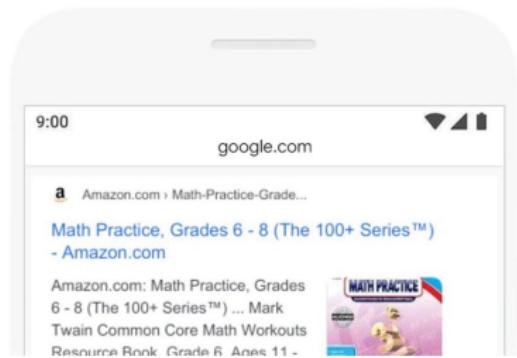
To *design & implement* an
intellectual app that solves *real
problems*.

Example: Intention Identification

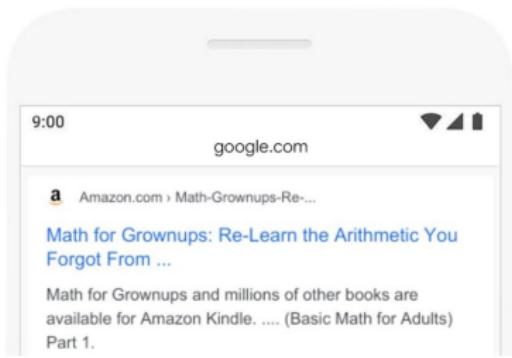


math practice books for adults

BEFORE



AFTER



Example: Spam Detection

The image shows two tweets from Donald J. Trump's official Twitter account (@realDonaldTrump). Both tweets express concerns about mail-in ballots being fraudulent.

Tweet 1: Donald J. Trump (@realDonaldTrump) · 12h
There is NO WAY (ZERO!) that Mail-In Ballots will be anything less than substantially fraudulent. Mail boxes will be robbed, ballots will be forged & even illegally printed out & fraudulently signed. The Governor of California is sending Ballots to millions of people, anyone.....
[Get the facts about mail-in ballots](#)

Tweet 2: Donald J. Trump (@realDonaldTrump)
....living in the state, no matter who they are or how they got there, will get one. That will be followed up with professionals telling all of these people, many of whom have never even thought of voting before, how, and for whom, to vote. This will be a Rigged Election. No way!
[Get the facts about mail-in ballots](#)

Example: Product Recommendation

Frequently Bought Together



Price For All Three: \$258.02

Add all three to Cart

- [This item: The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition \(Springer Series in Statistics\) by Trevor Hastie](#)
- [Pattern Recognition and Machine Learning \(Information Science and Statistics\) by Christopher M. Bishop](#)
- [Pattern Classification \(2nd Edition\) by Richard O. Duda](#)

Customers Who Bought This Item Also Bought



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Pattern Classification (2nd Edition) by Richard O. Duda
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Data Mining: Practical Machine Learning Tools and Algorithms by Ian H. Witten and Eibe Frank
★★★★★ (29) \$41.55



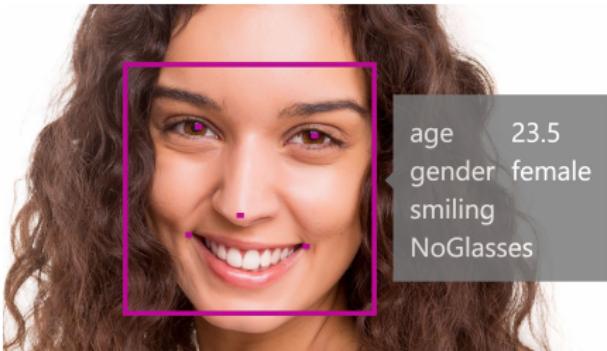
Bayesian Data Analysis, Second Edition (Texts in Statistical Science) by Andrew Gelman and John Carlin
★★★★★ (10) \$56.20



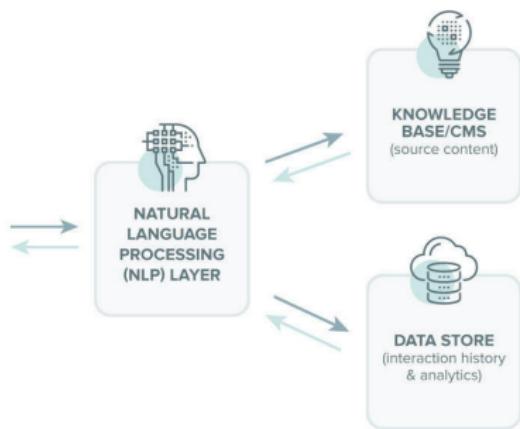
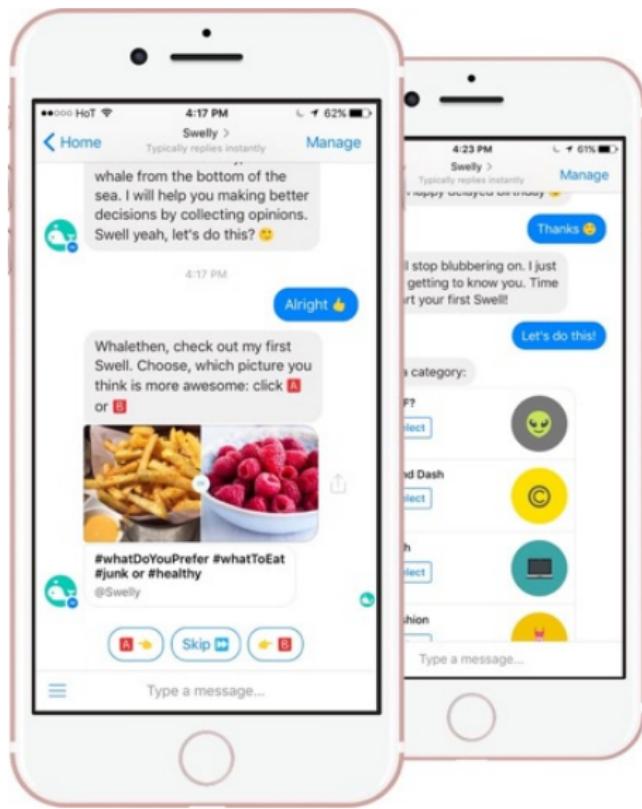
Data Analysis Using Regression and Multilevel Methods by Andrew Gelman and Jennifer Hill
★★★★★ (13) \$39.59

The screenshot shows a Spotify interface for a user named Moorissa Tjokro. On the left, there's a sidebar with navigation links like 'Browse', 'Radio', 'YOUR MUSIC', 'Your Daily Mix', 'Songs', 'Albums', 'Artists', 'Stations', 'Local Files', 'PLAYLISTS', and a 'Discover Weekly...' button. The main area features a large 'Discover Weekly' heading with a subtext about it being a weekly mixtape of new discoveries. Below this, there's a 'PAUSE' button, a 'FOLLOWING' button, and a '...' button. At the bottom, there's a track list with titles like 'Home (feat. Jeremy Camp)', 'Adam Cappa, Jeremy C...', and a timestamp '2 days ago'. To the right, there's a 'Download' toggle switch. On the far right, there's a sidebar with a 'See what your friends are playing' section showing friends like Julia Eger and Ben Khan.

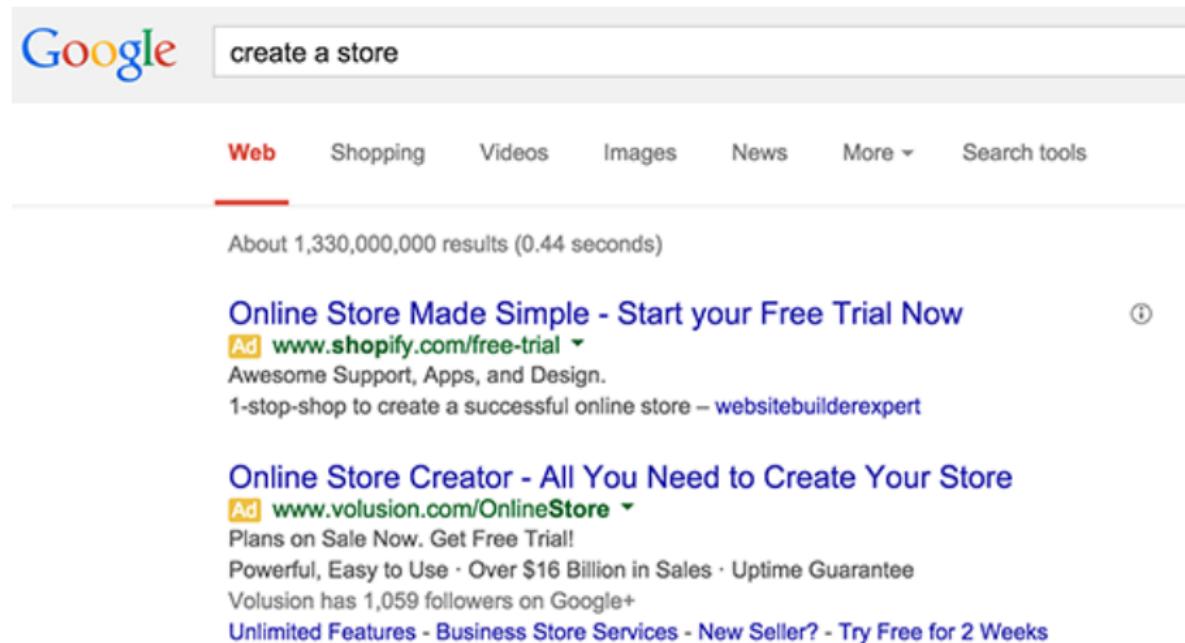
Example: Image Understanding



Example: Chat Bot & Service Automation



Example: Marketing & Advertisement



A screenshot of a Google search results page. The search query "create a store" is entered in the search bar. The results are filtered by "Web". Below the search bar, it says "About 1,330,000,000 results (0.44 seconds)". The first result is an advertisement for Shopify, titled "Online Store Made Simple - Start your Free Trial Now". It includes a link to www.shopify.com/free-trial, a snippet "Awesome Support, Apps, and Design.", and a description "1-stop-shop to create a successful online store – websitebuilderexpert". The second result is another advertisement for Volusion, titled "Online Store Creator - All You Need to Create Your Store". It includes a link to www.volusion.com/OnlineStore, a snippet "Plans on Sale Now. Get Free Trial!", and a description "Powerful, Easy to Use · Over \$16 Billion in Sales · Uptime Guarantee". Below these ads, there are several organic search results.

create a store

Web Shopping Videos Images News More Search tools

About 1,330,000,000 results (0.44 seconds)

Online Store Made Simple - Start your Free Trial Now Ⓞ
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Online Store Creator - All You Need to Create Your Store
Ad www.volusion.com/OnlineStore ▾
Plans on Sale Now. Get Free Trial!
Powerful, Easy to Use · Over \$16 Billion in Sales · Uptime Guarantee
Volusion has 1,059 followers on Google+
Unlimited Features - Business Store Services - New Seller? - Try Free for 2 Weeks

- All based on **Machine Learning** & **AI** technologies

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AI vs. Machine Learning

- Artificial Intelligence (AI): the goal
 - Creating systems that can function intelligently and independently
 - Mirroring or surpassing human capabilities
- Machine Learning (ML): a means of achieving AI
 - Enabling machines to *learn from data*

Prior vs. Posteriori Knowledge

- To solve a problem, we need an algorithm
 - E.g., sorting

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- Machine learning algorithms use the *a posteriori knowledge* to solve problems
 - Takes *examples* as additional input to algorithm

General ML Step 1: Data Preparation

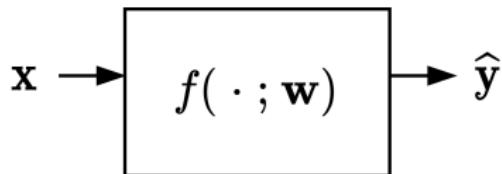
- Pre-process data (e.g., integration, cleaning, etc.)
- Define vector **features** to have a dataset:

$$\mathbb{X} = \{(\mathbf{x}^{(i)}, \mathbf{y}^{(i)})\}_{i=1}^N, \text{ where } \mathbf{x}^{(i)} \in \mathbb{R}^D \text{ and } \mathbf{y}^{(i)} \in \mathbb{R}^K,$$

- E.g., in toxic post detection:
 - $\mathbf{x}^{(i)}$ represents counts of different tokens
 - $\mathbf{y}^{(i)} \in \{0, 1\}$ indicates if the post $\mathbf{x}^{(i)}$ is toxic or not

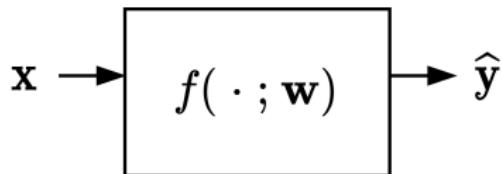


General ML Step 2: Model Development



- ① Assume a **model** $\{f(\cdot; \mathbf{w})\}_{\mathbf{w}}$ that is a collection of candidate functions f 's
 - Each f predicts label \hat{y} given an input x
 - f is assumed to be parametrized by \mathbf{w}

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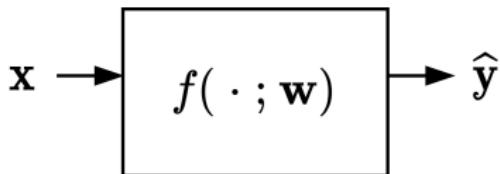


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$$C(\mathbf{w}; \mathbb{X})$$

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- ③ **Training**: employ an algorithm that solves

$$\mathbf{w}^* = \arg \min_{\mathbf{w}} C(\mathbf{w}; \mathbb{X})$$

- Where “learning” happens

General ML Step 3: Testing & Deployment

- ① **Testing**: evaluate the performance of the learned $f(\cdot; \mathbf{w}^*)$ using another, *unseen* test dataset \mathbb{X}'
 - Examples in \mathbb{X}' should have the same distribution with those in \mathbb{X}
 - A model minimizing $C(\mathbf{w}; \mathbb{X})$ does *not* necessarily give high test performance
- ② If $f(\cdot; \mathbf{w}^*)$ has satisfactory test performance, deploy it to solve real-world problem

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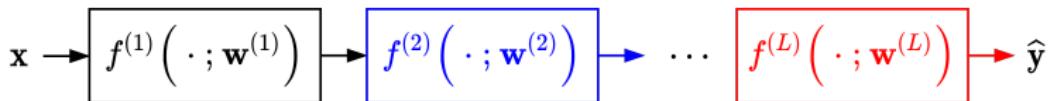
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What is Deep Learning?

- ML where an $f(\cdot; \mathbf{w})$ has many (deep) layers

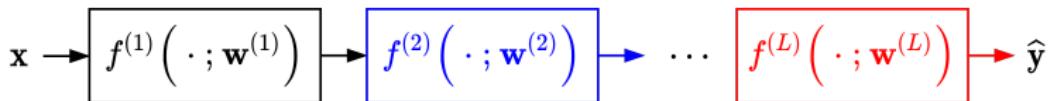
$$\hat{\mathbf{y}} = f^{(L)}(\dots f^{(2)}(f^{(1)}(\mathbf{x}; \mathbf{w}^{(1)}); \mathbf{w}^{(2)}) \dots; \mathbf{w}^{(L)})$$



What is Deep Learning?

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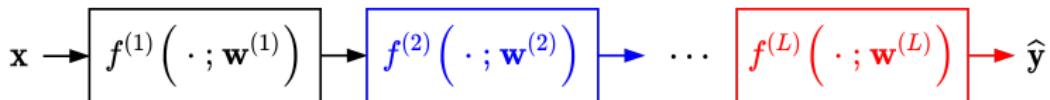
- Pros:

- Learns features from raw data automatically, called ***representation learning***
- Learns a complex function (e.g., visual objects to labels)

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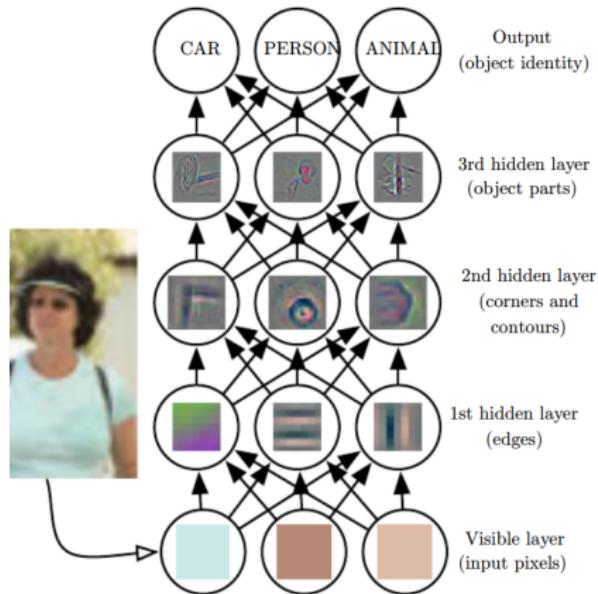
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- Pros:
 - Learns features from raw data automatically, called **representation learning**
 - Learns a complex function (e.g., visual objects to labels)
- Cons:
 - Usually needs large data to train a model well
 - High computation costs (at both training and test time); needs GPU acceleration

Representation Learning

- Automatically learned features also called *embeddings*
- Helps understanding what's learned
- Also enable new ways of using deep models
 - To be discussed later



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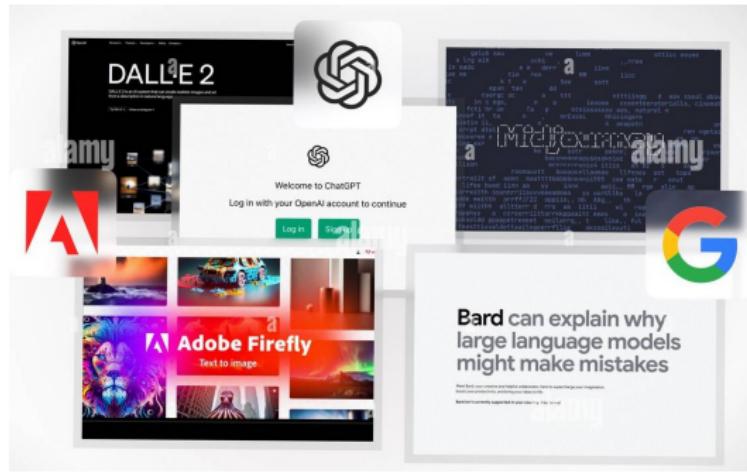
Generative AI

- The goal
- To generate ***structural*** and ***novel*** output (such as images, text, music, etc.) that cannot be deemed fake by humans



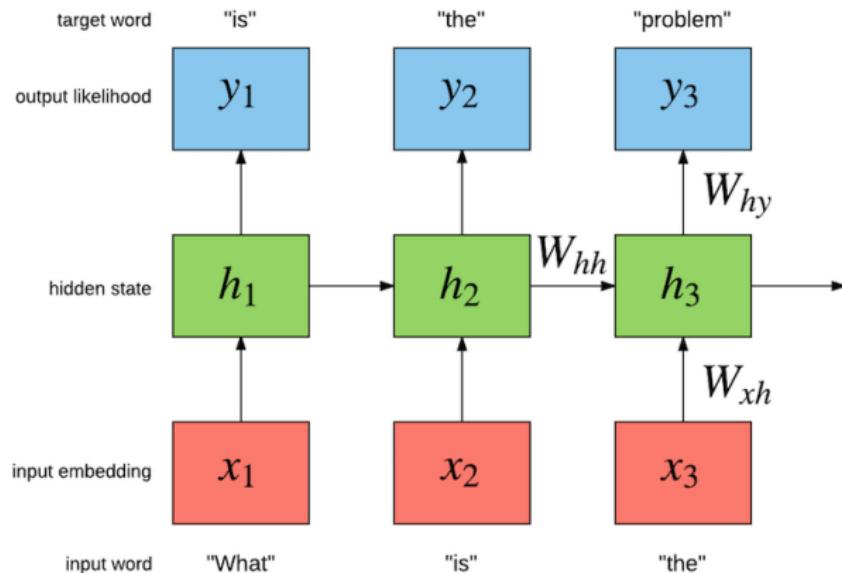
Generative Models

- The means
- Dataset: $\mathbb{X} = \{(\mathbf{x}^{(i)}, \mathbf{y}^{(i)})\}_{i=1}^N$, where $\mathbf{y}^{(i)}$ can be as complex as $\mathbf{x}^{(i)}$ and **cannot be exhausted**
- Image generation models (e.g., diffusion models)
- Text/language generation models (e.g., GPTs)
- Cross-modal generation models (e.g., GPT4 with vision)

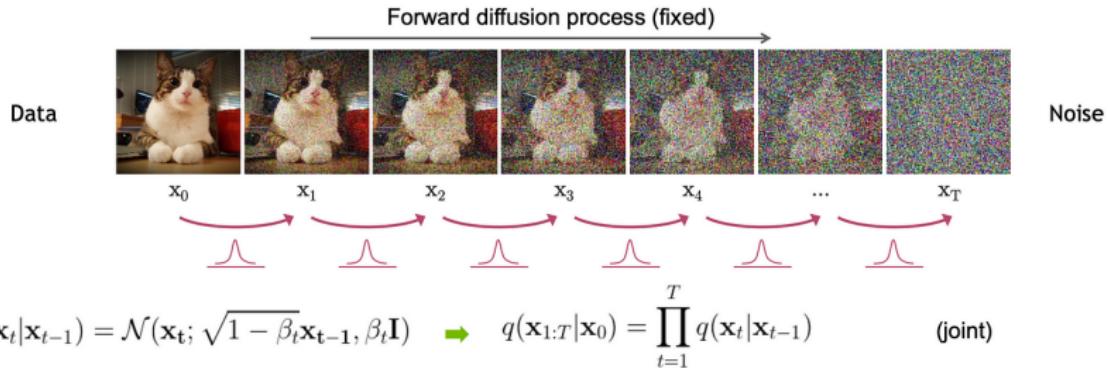


Autoregressive Models for Text Generation

- Text can be considered as 1D time-series data
- Autoregressive model** takes its previous output as current input
 - Learns the conditional transition distributions of tokens
 - Rather than the joint distribution of all tokens

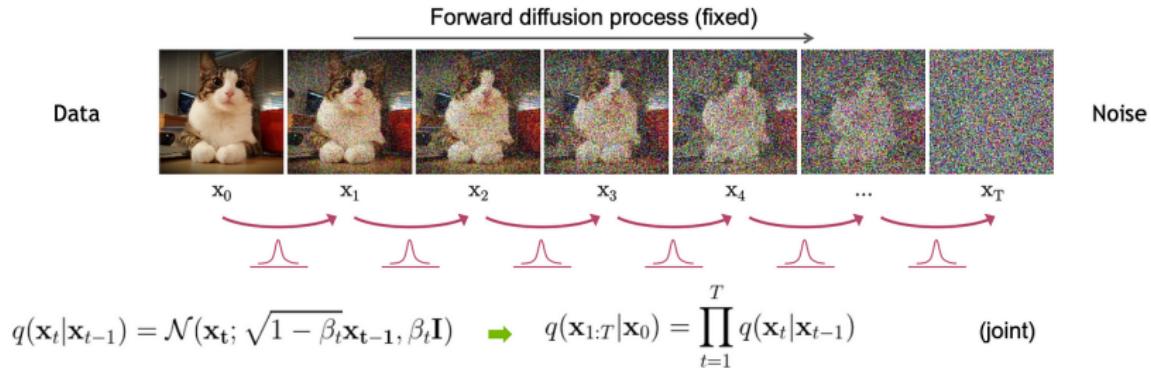


Diffusion Models for Image Generation



- Note a time-series data naturally; need other strategy to simplify learning

Diffusion Models for Image Generation



- Note a time-series data naturally; need other strategy to simplify learning
- Forward diffusion is stepwise and deterministic (no learning)
- Model learns to de-noise at each step to generate images
 - Input: noisy image \mathbf{x}_t , step t , and y (e.g., text prompt)
 - Output: less noisy image \mathbf{x}_{t-1}

Training Trick 1: Self-Supervised Pre-training

- Before training on $\mathbb{X} = \{(\mathbf{x}^{(i)}, \mathbf{y}^{(i)})\}_{i=1}^N$
- Pre-train model on $\mathbb{X}' = \{(\mathbf{x}^{(i,1)}, \mathbf{x}^{(i,2)})\}_{i=1}^M$, where $\mathbf{x}^{(i,1)}$ and $\mathbf{x}^{(i,2)}$ are parts of the same structural data point
 - Applicable to both text and images
- Why?



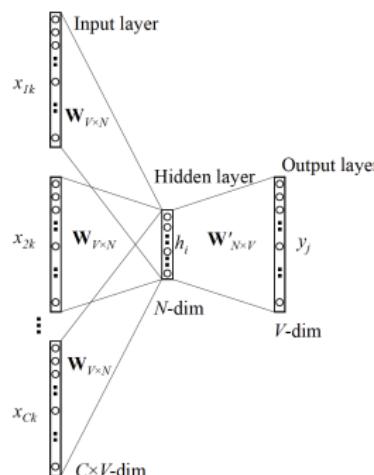
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 - Applicable to both text and images
- Why? $M \gg N$
 - GPT-4 is trained on ~ 13 trillion tokens (~ 10 trillion words)
 - LAION has 400 million 256X256 images
- Use “common sense” to learn $\mathbf{y}^{(i)}$ of limited numbers

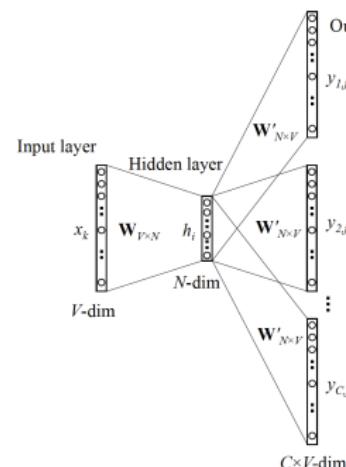


Byproduct: Semantic Embeddings

- After pre-training, embeddings of different data points have mutual distances reflecting human understanding
- E.g., word2vec [3, 2]: "... *the cat sat on*..."



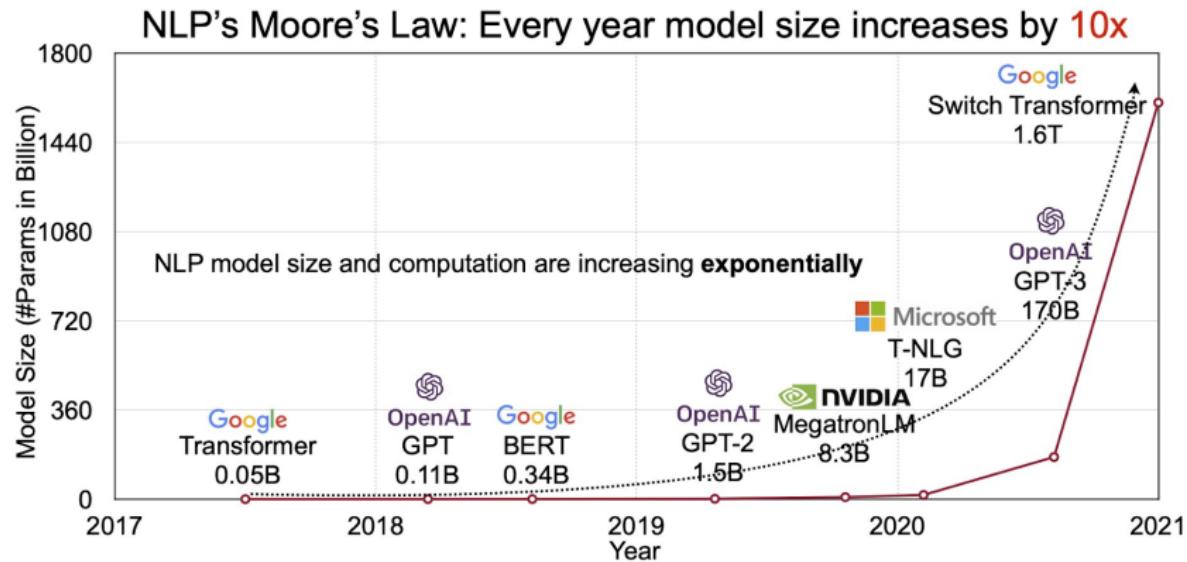
CBOW



Skip Gram

- Powers modern search and recommendation systems
 - Google Search, Instagram Feeds, Spotify playlists, etc.

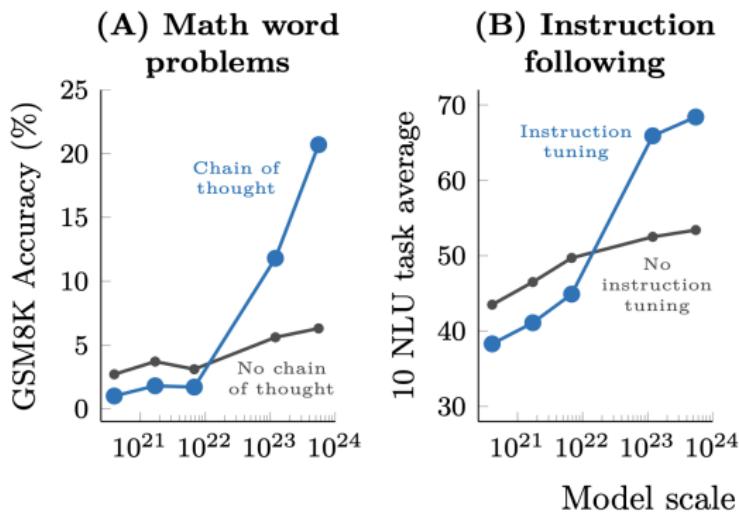
Training Trick 2: Large Models



- Training costs [4]:
 - 110M params: \$2.5k–\$50k
 - 340M params: \$10k–\$200k
 - 1.5B param: \$80k–\$1.6m

Size Does Matter!

- Emerging abilities of Large Language Models (LLMs) [5]



- A balance: 70B parameters + 1.4T training tokens [1]

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Using Existing ML Models

- Today, we can easily integrate the power of ML models into our apps to make impact
- Example: [Flutter warpper of ML Kit](#) from Google
 - Designed to be run **locally** on mobile devices
 - Supported image tasks:
 - Barcode scanning, doc scanning, face detection, image labeling, object detection, etc.
 - Supported NLP tasks:
 - Language identification, translation, entity (date/time/address/phone number) extraction, smart reply, etc.

Integrating Advanced Generative Models

- Example: [OpenAI's APIs](#)
 - Chat, image generation, embeddings, etc.
- Demo
 - Install the “http” package
 - Obtain your API key

Customizing Models (1/2)

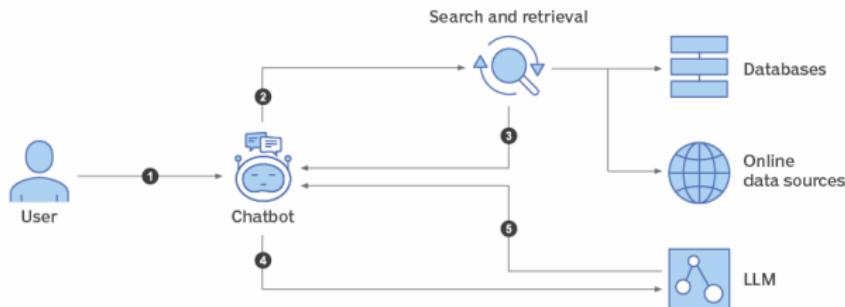
- How to customize a model for your specific tasks?

Customizing Models (1/2)

- How to customize a model for your specific tasks?
- Fine-tuning model using your own data
 - Not possible if weights are unavailable
- Write better prompts

Customizing Models (2/2)

- Enable *Retrieval Augmented Generation* (RAG) through Assistant API
 - Demo
 - Does not modify model's weights



- Ask model to perform “actions” defined by you via Function Calling API
 - E.g., “Code Interpreter” plugin of ChatGPT

Back to Your Project

To *design & implement* an
intellectual app that solves *real
problems*.

Homework: Find Problems Deserve to Solve

- Accounts for ***at least 20%*** of your term project score
- Our next lecture assumes you have found some already
- Tips:
 - What bothers ***you*** or people around you?
 - Make ***few*** people ***very*** happy
 - Avoid “platforms”
 - To have a good idea, you need ***many*** bad ones
 - Understand the ***root cause***
 - The “5 Whys” approach by Sakichi Toyoda

5 Whys

- ① Why do some people become the *King of Periods?*

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- ① Why do some people become the *King of Periods*?
 - Because they might not grasp the context or emotional subtleties
- ② Why might they not grasp the context or emotional subtleties?

5 Whys

- ① Why do some people become the *King of Periods*?
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 - Because they are more logic-oriented or straightforward thinkers
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 - Because they are complex and situation dependent
 - It's your turn!

Reference I

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