Making Your Apps Smarter: Machine Learning & AI

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Outline

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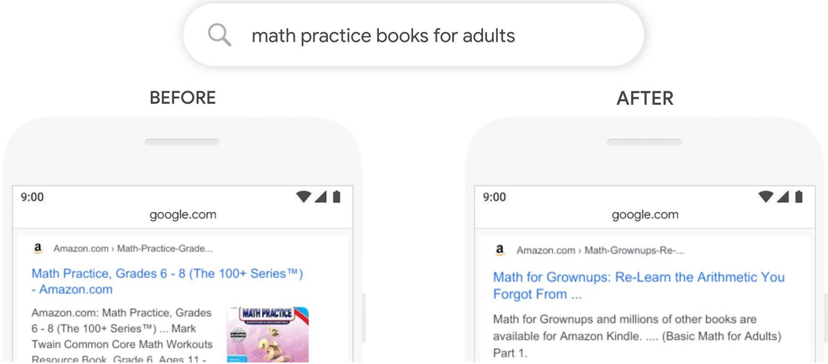
1. Web, App, and Business Intelligence
2. What's Machine Learning & AI?
3. What's Deep Learning?
4. What's Generative AI?
5. Making Smart Apps

Your Term Project

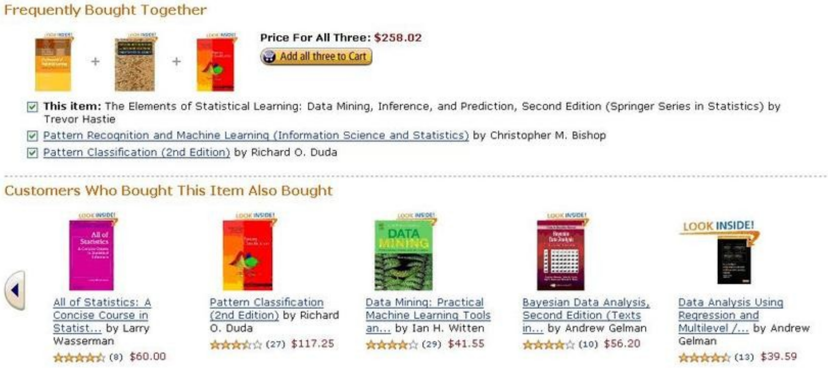
To ***design & implement*** an ***intellectual app*** that solves ***real problems***.

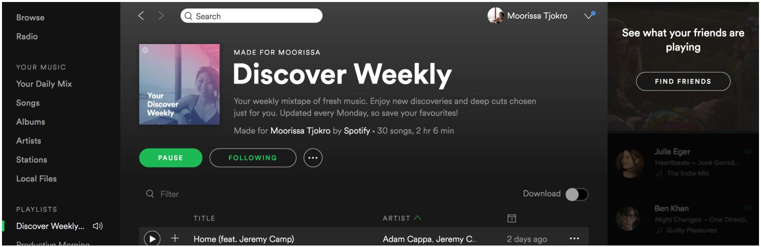
Example: Intention Identification



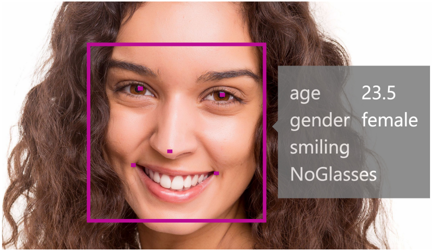
Example: Spam Detection

Example: Product Recommendation

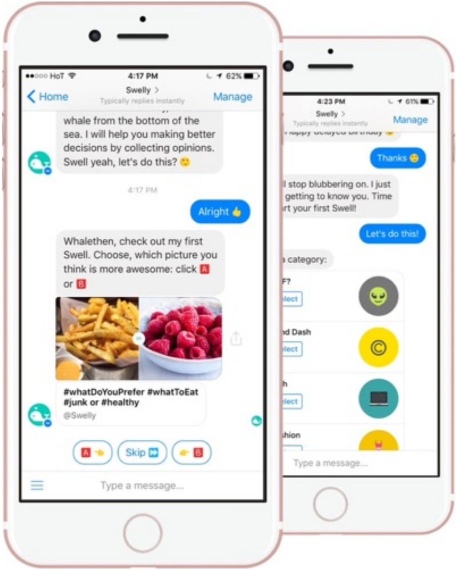


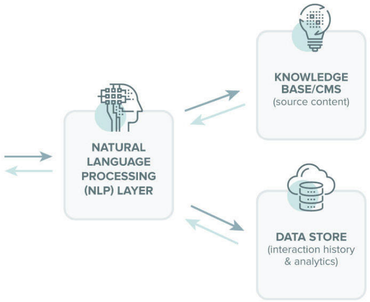


Example: Image Understanding

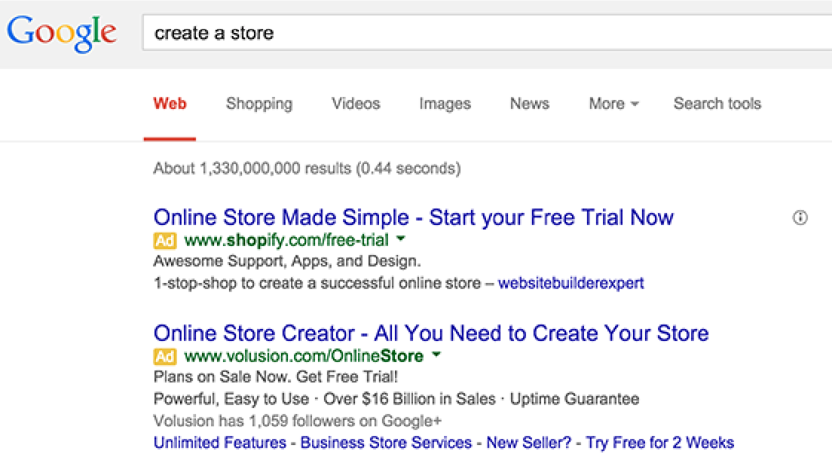


Example: Chat Bot & Service Automation





Example: Marketing & Advertisement



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

Outline

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***

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  - The correct answer varies in time and from site to site

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

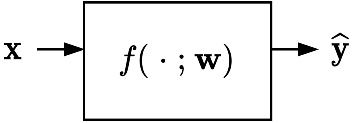
General ML Step 1: Data Preparation

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

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

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

General ML Step 2: Model Development



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

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   that measures "how good a particular $f(\cdot;\boldsymbol{w})$ can explain the training data $\mathbb{X}$" (posteriori knowledge)
3. ***Training***: employ an algorithm that solves
   $$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} C(\boldsymbol{w};\mathbb{X})$$
   - Where "learning" happens

General ML Step 3: Testing & Deployment

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

Outline

What is Deep Learning?

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

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

$$\mathbf{x} \rightarrow \boxed{f^{(1)}\left(\,\cdot\,;\mathbf{w}^{(1)}\right)} \rightarrow \boxed{f^{(2)}\left(\,\cdot\,;\mathbf{w}^{(2)}\right)} \rightarrow \cdots \boxed{f^{(L)}\left(\,\cdot\,;\mathbf{w}^{(L)}\right)} \rightarrow \widehat{\mathbf{y}}$$

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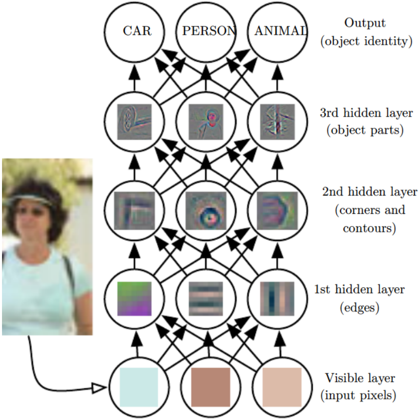
- Pros:
  - Learns features from raw data automatically, called ***representation learning***
  - Learns a complex function (e.g., visual objects to labels)
- Cons:
  - Usually needs large data to train a model well
  - High computation costs (at both training and test time); needs GPU acceleration

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



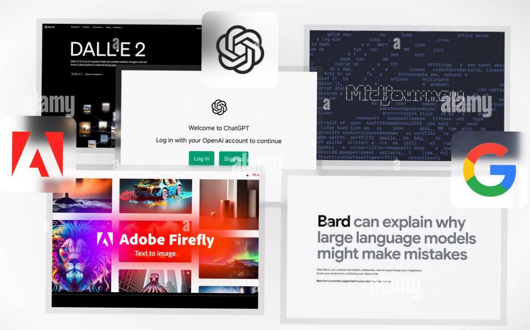
Outline

Generative AI

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

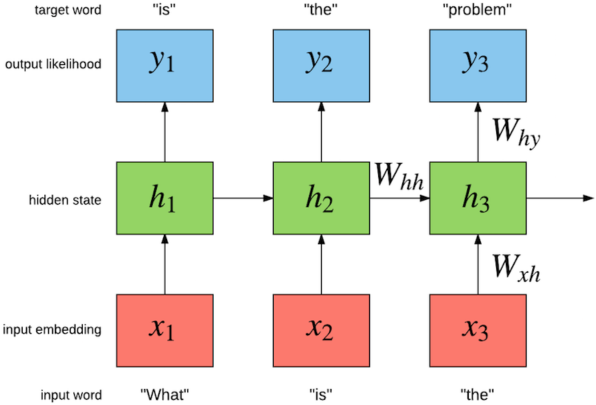
Generative Models

- The means
- Dataset: $\mathbb{X} = \{(\boldsymbol{x}^{(i)}, \boldsymbol{y}^{(i)})\}_{i=1}^{N}$, where $\boldsymbol{y}^{(i)}$ can be as complex as $\boldsymbol{x}^{(i)}$ 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)

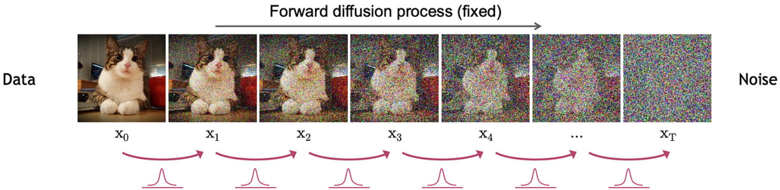


Autoregressive Models for Text Generation

- 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 join distribution of all tokens



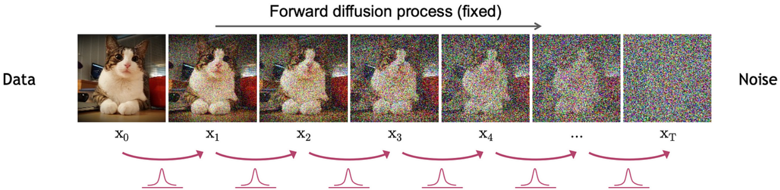
Diffusion Models for Image Generation



$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x_t}; \sqrt{1-\beta_t}\mathbf{x_{t-1}}, \beta_t\mathbf{I}) \quad \Rightarrow \quad q(\mathbf{x}_{1:T}|\mathbf{x}_0) = \prod_{t=1}^{T} q(\mathbf{x}_t|\mathbf{x}_{t-1}) \qquad \text{(joint)}$$

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

Diffusion Models for Image Generation



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- 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 $\boldsymbol{x}_t$, step t, and $\boldsymbol{y}$ (e.g., text prompt)
  - Output: less noisy image $\boldsymbol{x}_{t-1}$

Training Trick 1: Self-Supervised Pre-training

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

$\boldsymbol{x}^{(i)}$

$\boldsymbol{y}^{(i)}$

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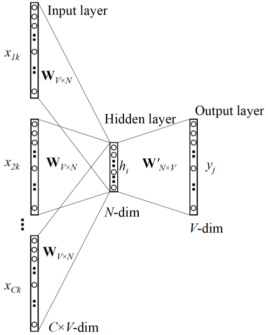
  - Applicable to both text and images
- Why? $M \gg N$
  - GPT-4 is trained on ~13 trillion tokens (~10 trillion words)
  - LAION has 400 million 256X256 images
- Use "common sense" to learn $\boldsymbol{y}^{(i)}$ of limited numbers

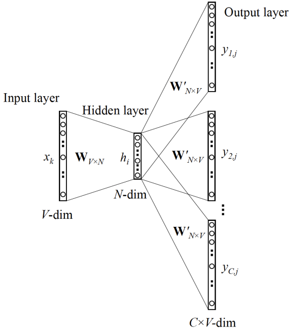
$\boldsymbol{x}^{(i)}$  $\boldsymbol{y}^{(i)}$

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***..."



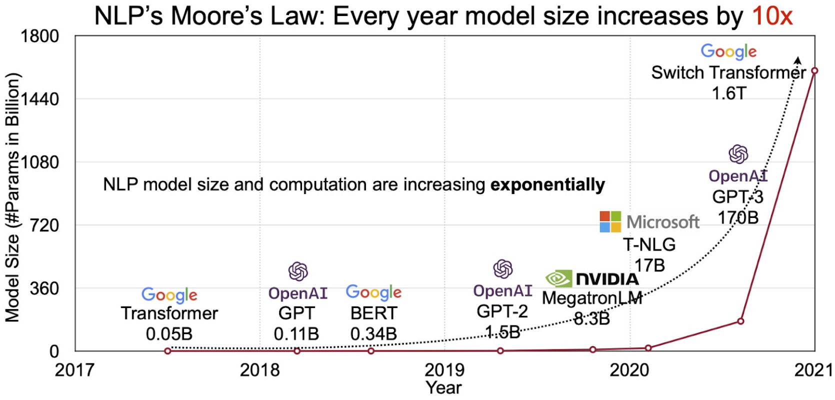
CBOW



Skip Gram

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

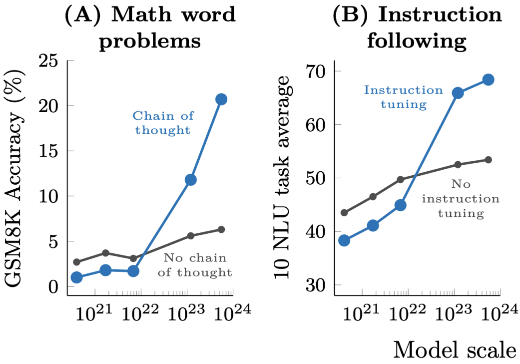
Training Trick 2: Large Models



- 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]

Outline

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?

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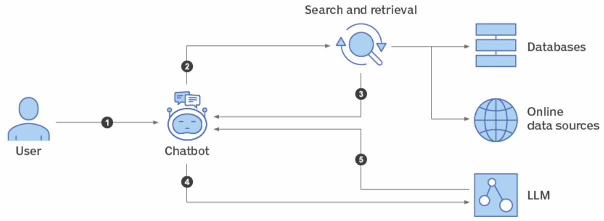
- How to customize a model for your specific tasks?
- Fine-tuning model using your own data
  - Not possible if weights are unavailable
- Write better prompts

Customizing Models (2/2)

- Enable ***Retrieval Augmented Generation*** (RAG) though 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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   - Because they might not grasp the context or emotional subtleties
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2. Why might they not grasp the context or emotional subtleties?
    - Because they more logic-oriented or straightforward thinkers
3. Why are they more logic-oriented or straightforward thinkers?

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4. Why does our education emphasize logic more to these people?

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    - Because the subtle art of emotional navigation is overshadowed
5. Why are there no educational tools for emotional subtleties?

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- It's your turn!

Reference I

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