

Making Your Apps Smarter: Machine Learning & AI

Shan-Hung Wu
shwu@cs.nthu.edu.tw

Department of Computer Science,
National Tsing Hua University, Taiwan

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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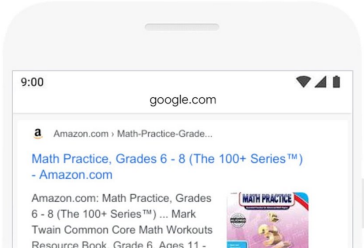
Your Term Project

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

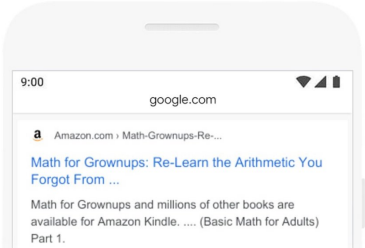
Example: Intention Identification

math practice books for adults

BEFORE



AFTER



Example: Spam Detection



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.....

 [Get the facts about mail-in ballots](#)

 31.2K  29.2K  100.8K 

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



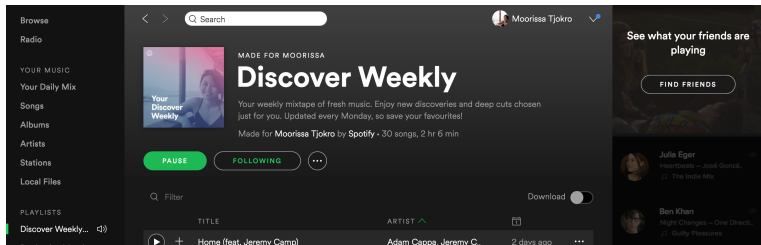
Price For All Three: \$258.02

Add all three to Cart

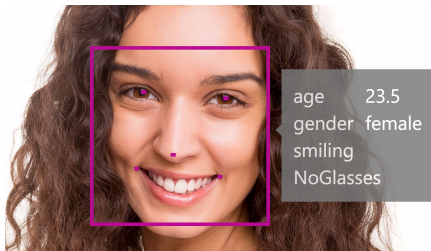
- This item:** [The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition \(Springer Series in Statistics\)](#) by Trevor Hastie
- [Pattern Recognition and Machine Learning \(Information Science and Statistics\)](#) by Christopher M. Bishop
- [Pattern Classification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

Customers Who Bought This Item Also Bought

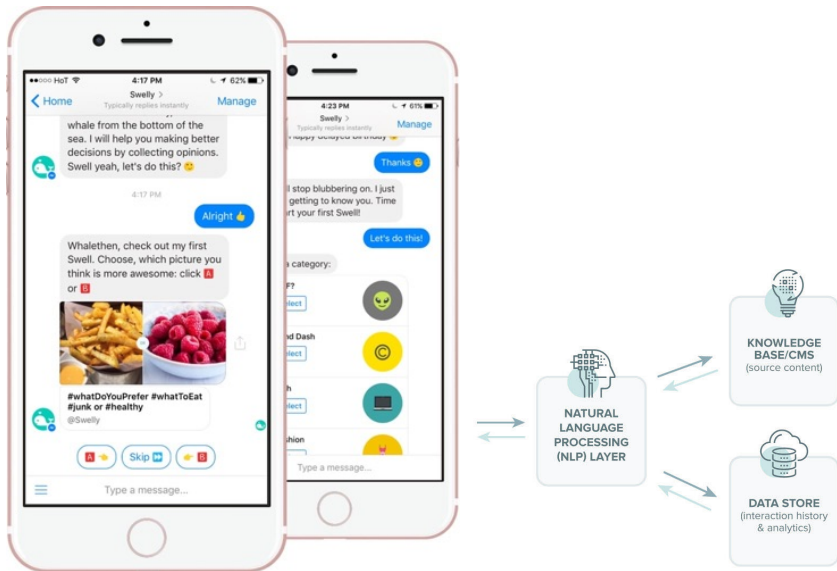
All of Statistics: A Concise Course in Statist... by Larry Wasserman	Pattern Classification (2nd Edition) by Richard O. Duda	Data Mining: Practical Machine Learning Tools an... by Ian H. Witten	Bayesian Data Analysis, Second Edition (Texts in... by Andrew Gelman	Data Analysis Using Regression and Multilevel /... by Andrew Gelman
★★★★☆ (9) \$60.00	★★★★☆ (27) \$117.25	★★★★☆ (29) \$41.55	★★★★☆ (10) \$56.20	★★★★☆ (13) \$39.59



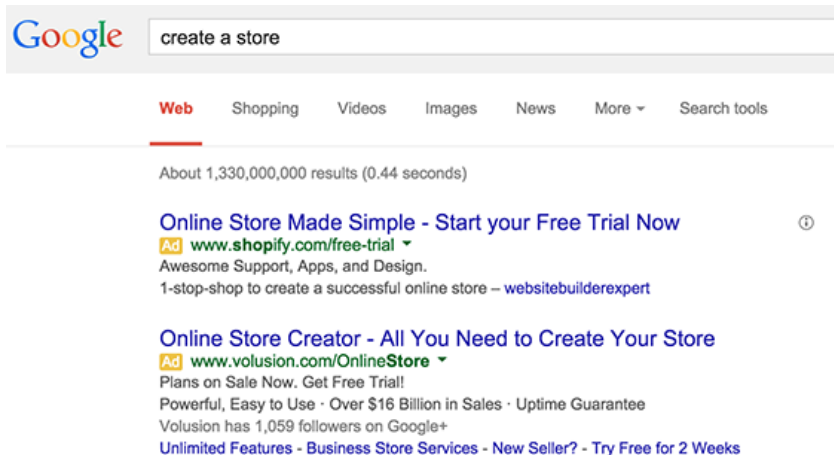
Example: Image Understanding



Example: Chat Bot & Service Automation



Example: Marketing & Advertisement



Google 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 ⓘ
Ad www.shopify.com/free-trial ▾
Awesome Support, Apps, and Design.
1-stop-shop to create a successful online store – [websitebuilderexpert](#)

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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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

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

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 - E.g., sorting

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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

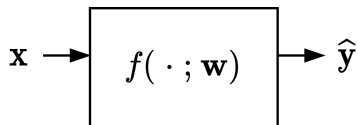
- Pre-process data (e.g., integration, cleaning, etc.)
- Define vector *features* to have a dataset:

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

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

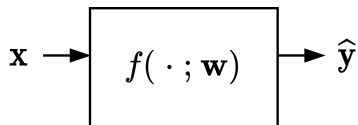


General ML Step 2: Model Development



- 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}

General ML Step 2: Model Development

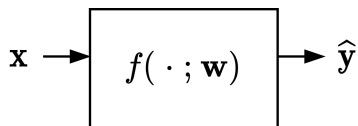


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that measures “how good a particular $f(\cdot; \mathbf{w})$ can explain the training data \mathbb{X} ” (posteriori knowledge)

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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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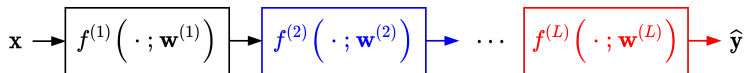
④ What's Generative AI?

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What is Deep Learning?

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

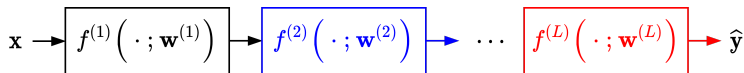
$$\hat{\mathbf{y}} = f^{(L)}(\dots f^{(2)}(f^{(1)}(\mathbf{x}; \mathbf{w}^{(1)}); \mathbf{w}^{(2)}) \dots; \mathbf{w}^{(L)})$$



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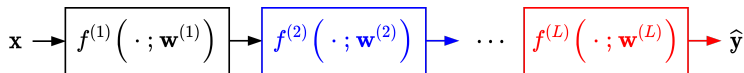


- Pros:
 - Learns features from raw data automatically, called **representation learning**
 - Learns a complex function (e.g., visual objects to labels)

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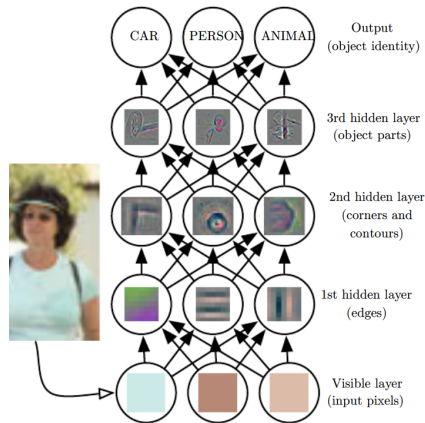
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- Pros:
 - Learns features from raw data automatically, called **representation learning**
 - Learns a complex function (e.g., visual objects to labels)
- Cons:
 - Usually needs large data to train a model well
 - High computation costs (at both training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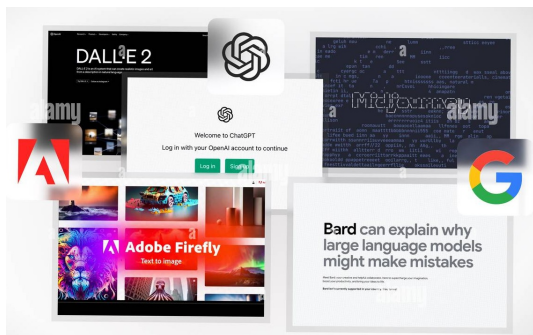
Generative AI

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



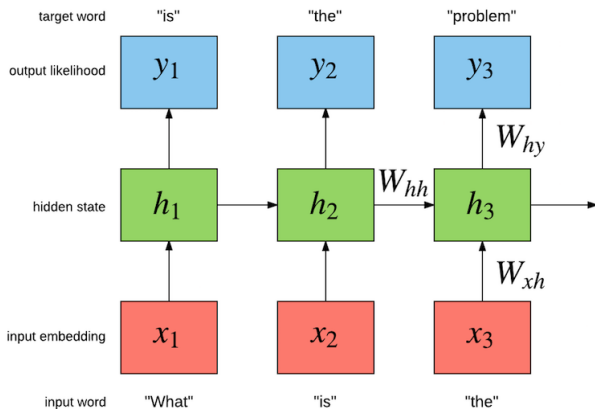
Generative Models

- 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)

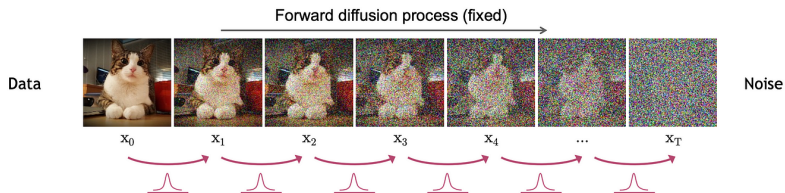


Autoregressive Models for Text Generation

- 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



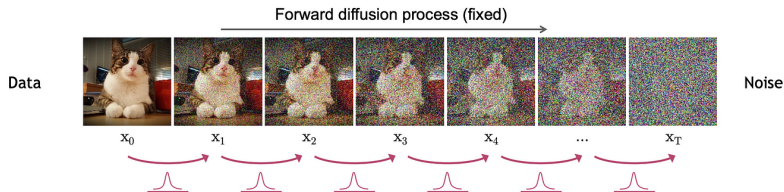
Diffusion Models for Image Generation



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

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

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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 \mathbf{x}_t , step t , and \mathbf{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?



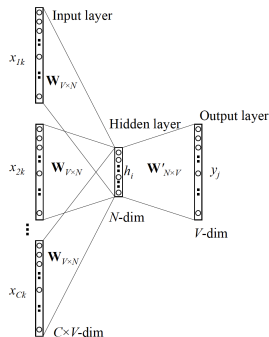
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 - Applicable to both text and images
- Why? $M \gg N$
 - GPT-4 is trained on ~ 13 trillion tokens (~ 10 trillion words)
 - LAION has 400 million 256X256 images
- Use “common sense” to learn $\mathbf{y}^{(i)}$ of limited numbers

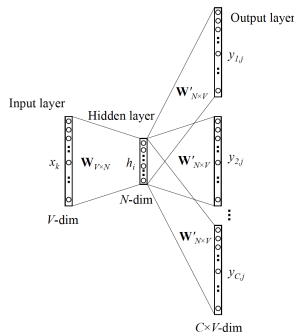


Byproduct: Semantic Embeddings

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



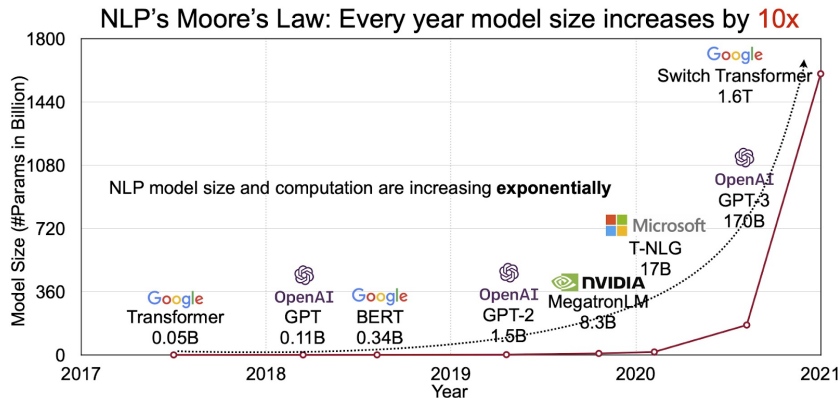
CBOW



Skip Gram

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

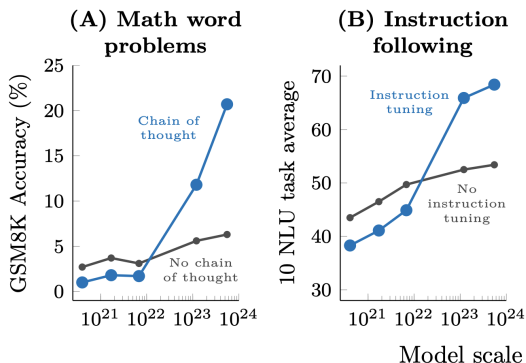
Training Trick 2: Large Models



- 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 wrapper 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)

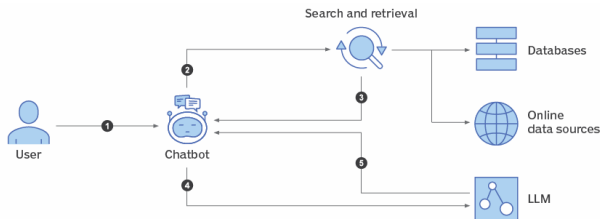
- How to customize a model for your specific tasks?

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

Reference I

- [1] Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, et al.
Training compute-optimal large language models.
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- [2] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean.
Efficient estimation of word representations in vector space.
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Distributed representations of words and phrases and their compositionality.
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Reference II

- [4] Or Sharir, Barak Peleg, and Yoav Shoham.
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- [5] Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, et al.
Emergent abilities of large language models.
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