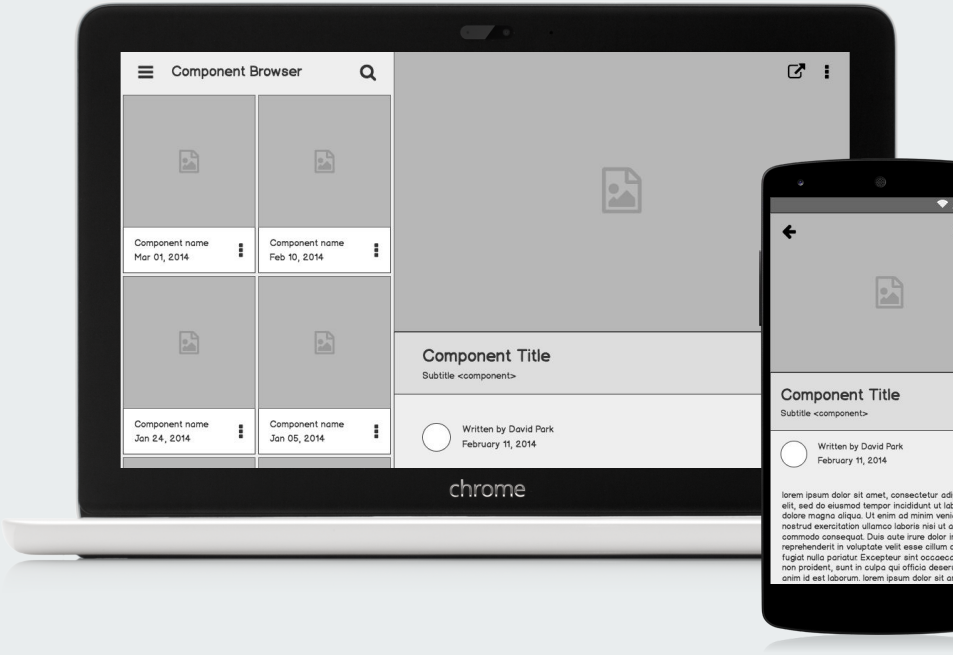
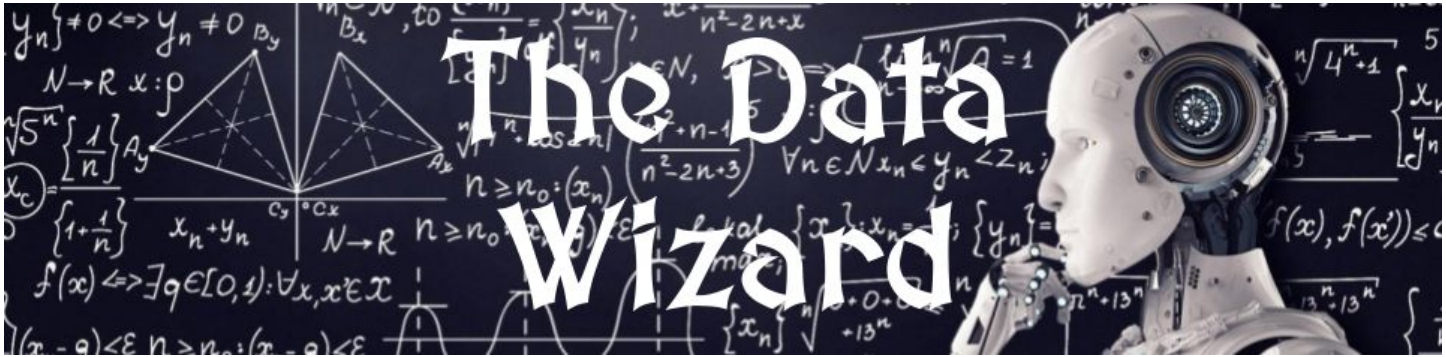
Enterprise Software Engineering Practices: AI/ML Real-World Applications



Lecture by: Brooks Christensen

ABOUT ME

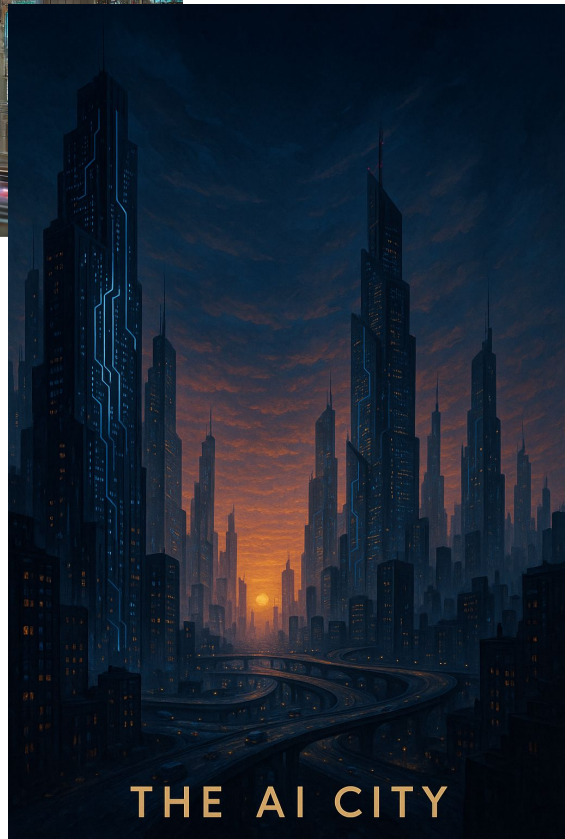


- Master's Degree in Physics from CU Boulder (2020)
- Applied Data Science Certificate from MIT PE Program (2022)
- AI / ML for Business Applications Certificate from UT Austin (2023)
- Nielsen Media Ratings (2021 - 2024)
- Freelance Data Scientist (2024 - Present)

Outline

- Intro to AI/ML Applications
- AI/ML Types
- AI Models
- Ensembles
- How AI/ML Systems Fail
- Ethical Considerations

“The AI City” - ChatGPT-4o (Oct 1, 2024)



“The AI City” - ChatGPT-5.1 (Nov 30, 2025)

Introduction to AI/ML Applications

U-Net: Convolutional Networks for Biomedical Image Segmentation

Olaf Ronneberger, Philipp Fischer, Thomas Brox

There is large consent that successful training of deep networks requires many thousand annotated training samples. In this paper, we pr
expanding path that enables precise localization. We show that such a network can be trained end-to-end from very few images and outp
(phase contrast and DIC) we won the ISBI cell tracking challenge 2015 in these categories by a large margin. Moreover, the network is fa

Extreme-Long-short Term Memory for Time-series Prediction

Sida Xing, Feihu Han, Suiyang Khoo

The emergence of Long Short-Term Memory (LSTM) solves the problems of vanishing gradient and exploding gradient in traditional Recurrent N
of LSTM can help to improve the efficiency in other application areas.
In this paper, we proposed an advanced LSTM algorithm, the Extreme Long Short-Term Memory (E-LSTM), which adds the inverse matrix part c
training rounds, thus reducing the overall training time.
In this research, the E-LSTM model is used for the text prediction task. Experimental results showed that the E-LSTM sometimes takes longer to
traditional LSTM, whilst also improving the training speed and the overall efficiency of the LSTM.

Deep Residual Learning for Image Recognition

Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun

Deeper neural networks are more difficult to train. We present a residual learning framework to ease the training of networks that are substantially dee
showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset we e
place on the ILSVRC 2015 classification task. We also present analysis on CIFAR-10 with 100 and 1000 layers.
The depth of representations is of central importance for many visual recognition tasks. Solely due to our extremely deep representations, we obtain a 2
detection, ImageNet localization, COCO detection, and COCO segmentation.

Attention Is All You Need

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llior

The dominant sequence transduction models are based on complex recu
recurrence and convolutions entirely. Experiments on two machine translation tas
the WMT 2014 English-to-French translation task, our model establishes a new single-m
limited training data.

Auto-Encoding Variational Bayes

Diederik P Kingma, Max Welling

How can we perform efficient inference and learning in directed probabilistic model
case. Our contributions are two-fold. First, we show that a reparameterization of th
an approximate inference model (also called a recognition model) to the intractable

Generative Adversarial Networks

Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley,

We propose a new framework for estimating generative models via an adversarial process, in wh
making a mistake. This framework corresponds to a minimax two-player game. In the space of ar
Markov chains or unrolled approximate inference networks during either training or generation of

Fashion-MNIST: a Novel Image Dataset for Benchmarking Mach

Han Xiao, Kashif Rasul, Roland Vollgraf

We present Fashion-MNIST, a new dataset comprising of 28x28 grayscale images of 70,000 fashion products from
algorithms, as it shares the same image size, data format and the structure of training and testing splits. The dataset

Recurrent Neural Networks (RNNs):

Robin M. Schmidt

State-of-the-art solutions in the areas of "Language Modelling & G
publications in those areas. In this work we give a short overview
Mechanism" or "Pointer Networks". We also give recommendatior

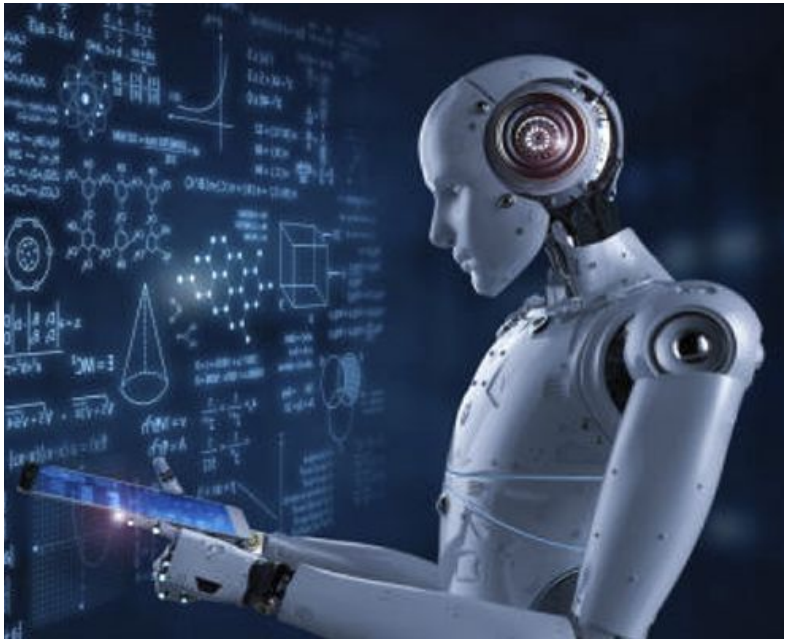
WaveNet: A Generative Model for Raw Audio

Aaron van den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Ale

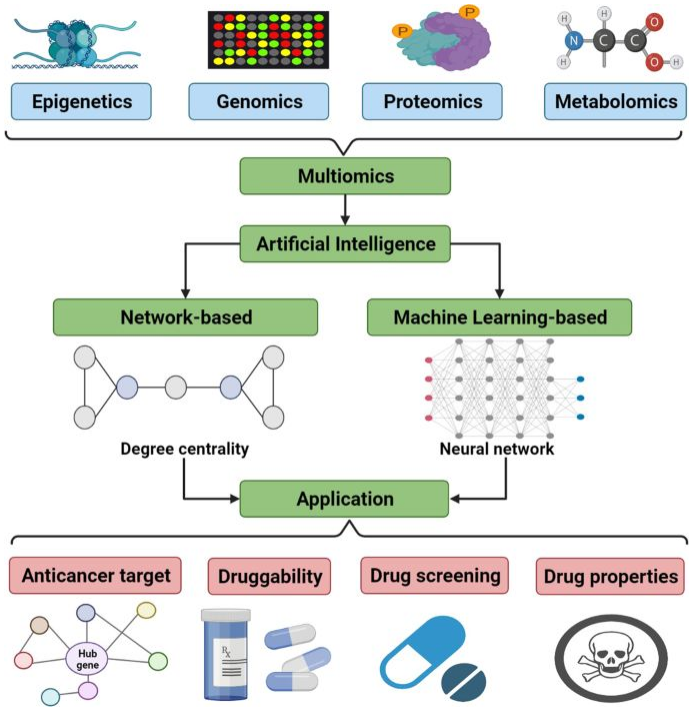
This paper introduces WaveNet, a deep neural network for generating raw audio waveforms. The n
speech, it yields state-of-the-art performance, with human listeners rating it as significantly more na
trained to model music, we find that it generates novel and often highly realistic musical fragments.

Examples of AI/ML Applications

- Large Language Models (ChatGPT, etc)
  - Machine Translation
  - Chatbots
  - Text Summarization
  - Sentiment Analysis
  - Content Creation
  - Knowledge Extraction and Question Answering
  - Personalization
  - Research & Development
  - **Retrieval Augmented Generation (RAG)**
- Traffic Management
- Food Production
- **Environmental Modeling and Sustainability**
- Creativity and Art
- Quantum Machine Learning

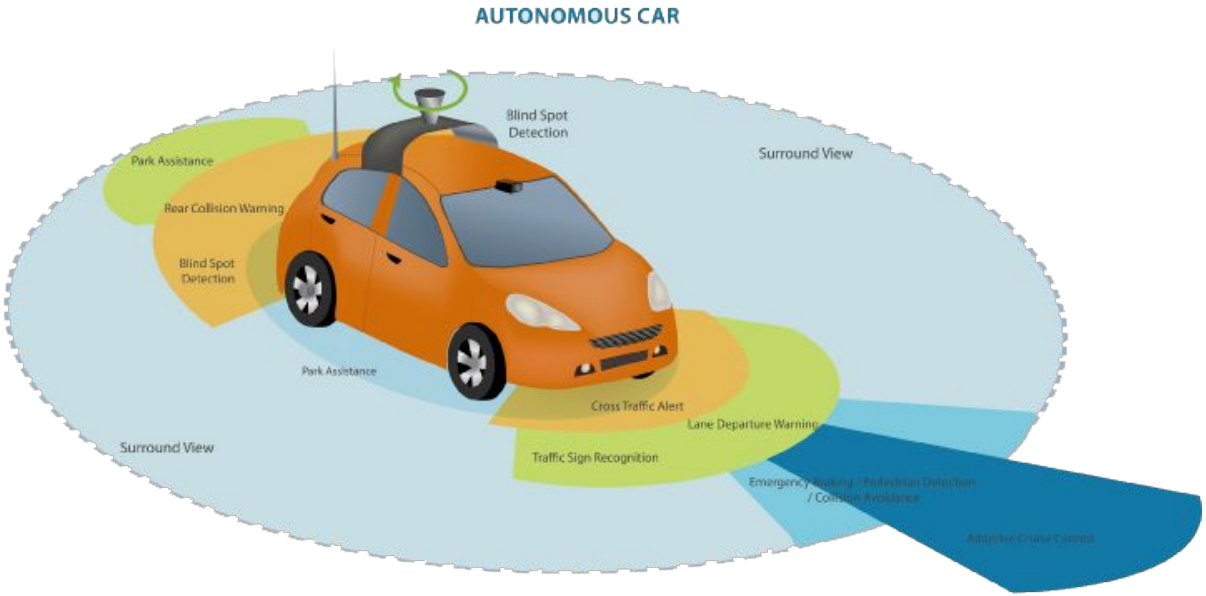


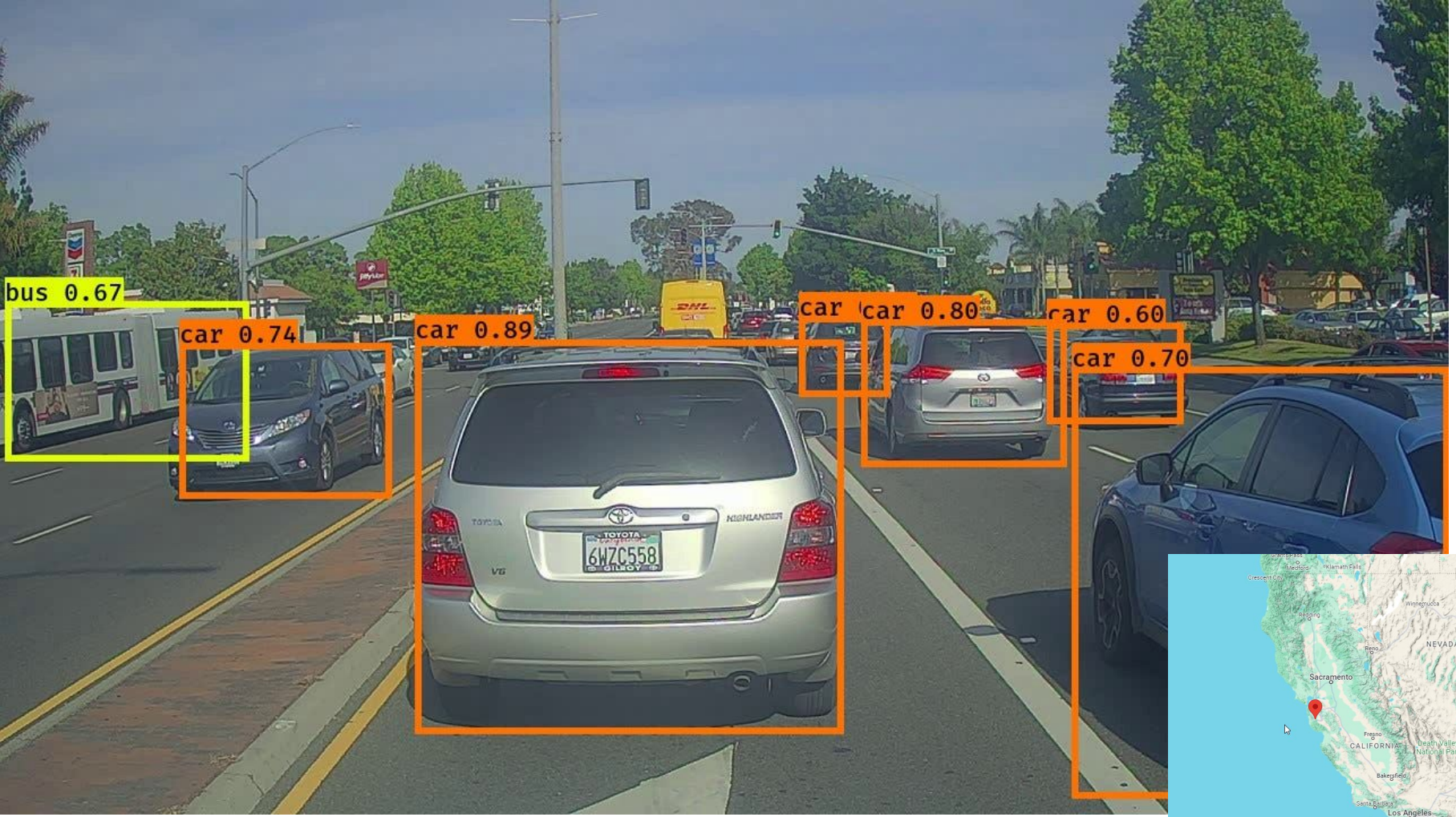
AI/ML Applications in Health Sciences



AI/ML Applications in Business & Finance

AI/ML Applications in Automation

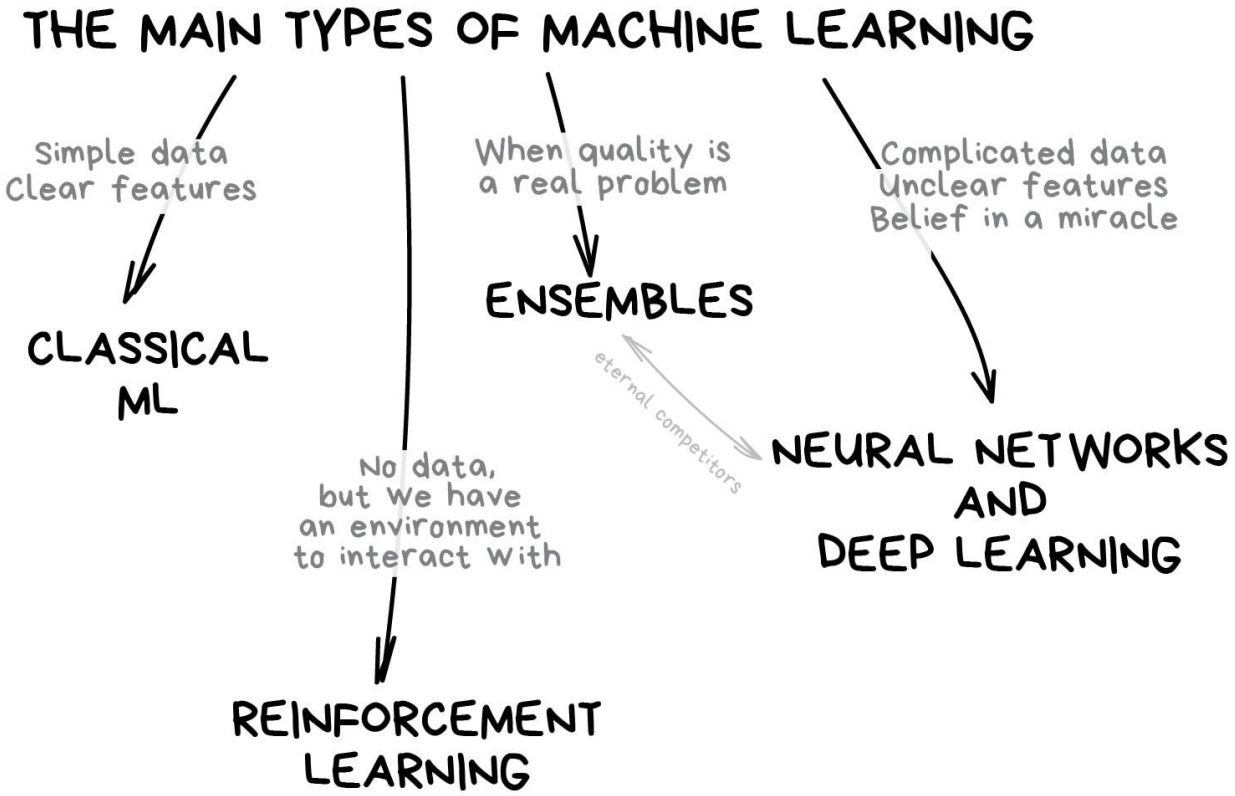


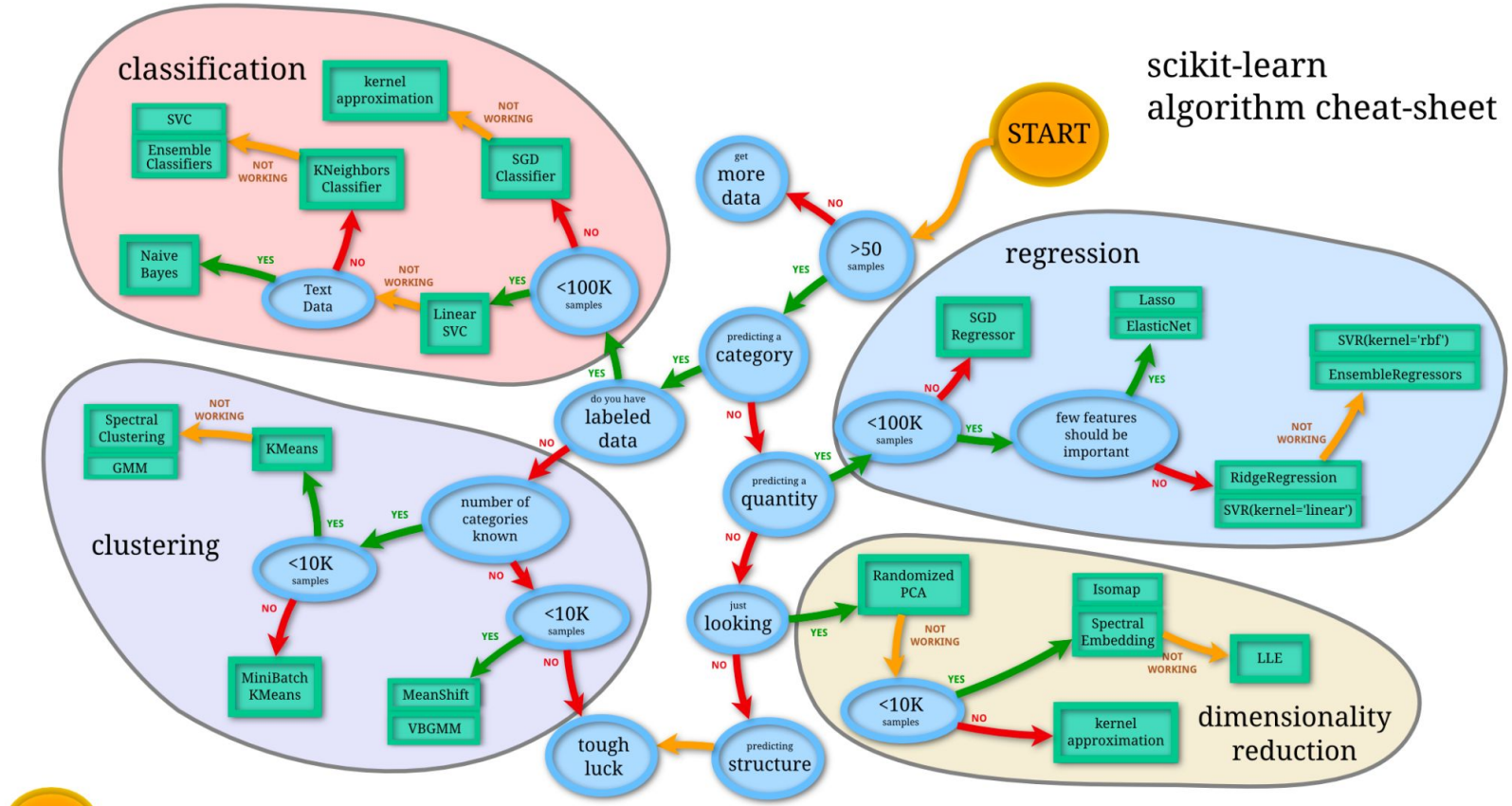

bus 0.67
car 0.74
car 0.89
car
car 0.80
car 0.60
car 0.70
TOYOTA
6WZC558
HIGHLANDER

NEVADA
Sacramento
CALIFORNIA
Las Vegas
Los Angeles
San Diego

AI/ML Types

Main Types of AI/ML

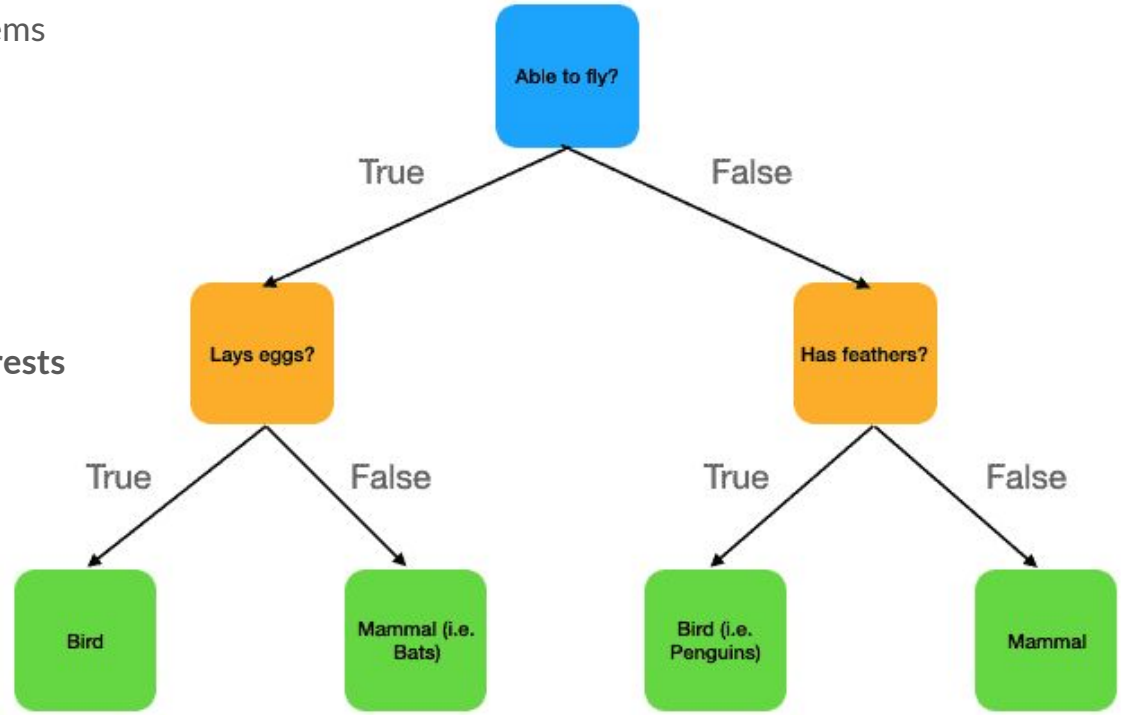




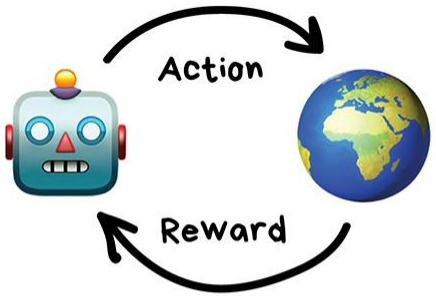
https://scikit-learn.org/1.3/_static/ml_map.png

Decision Trees

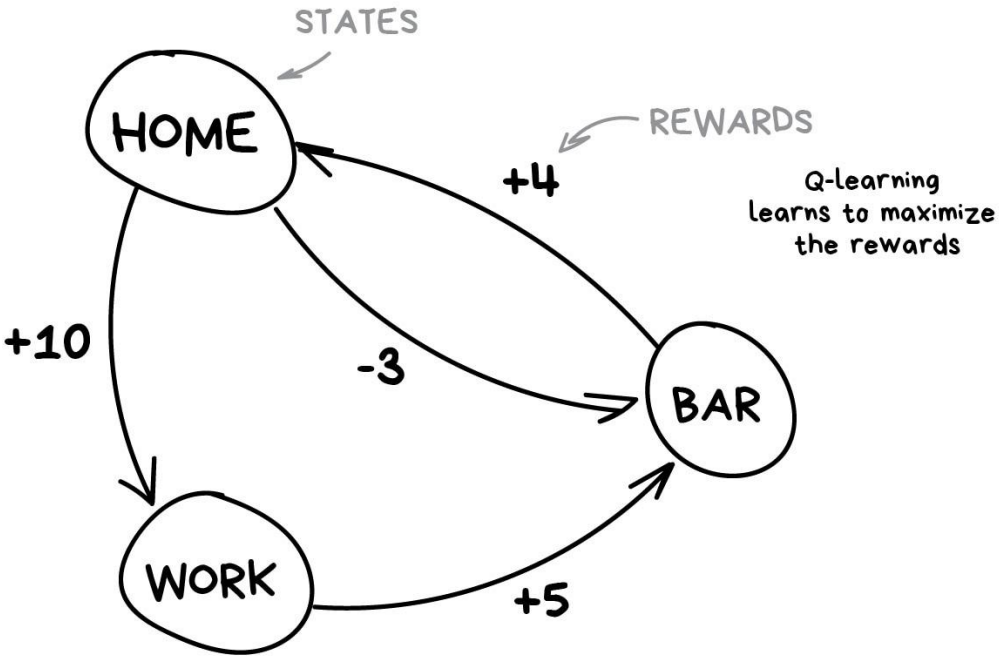
- Classical ML Technique
- Practical Solutions for **Many** Problems
- Useful for Tabular Data
- Not a Neural Network
- Classification or Regression
- Typically Better Performance in **Forests**



Reinforcement Learning



Reinforcement Learning



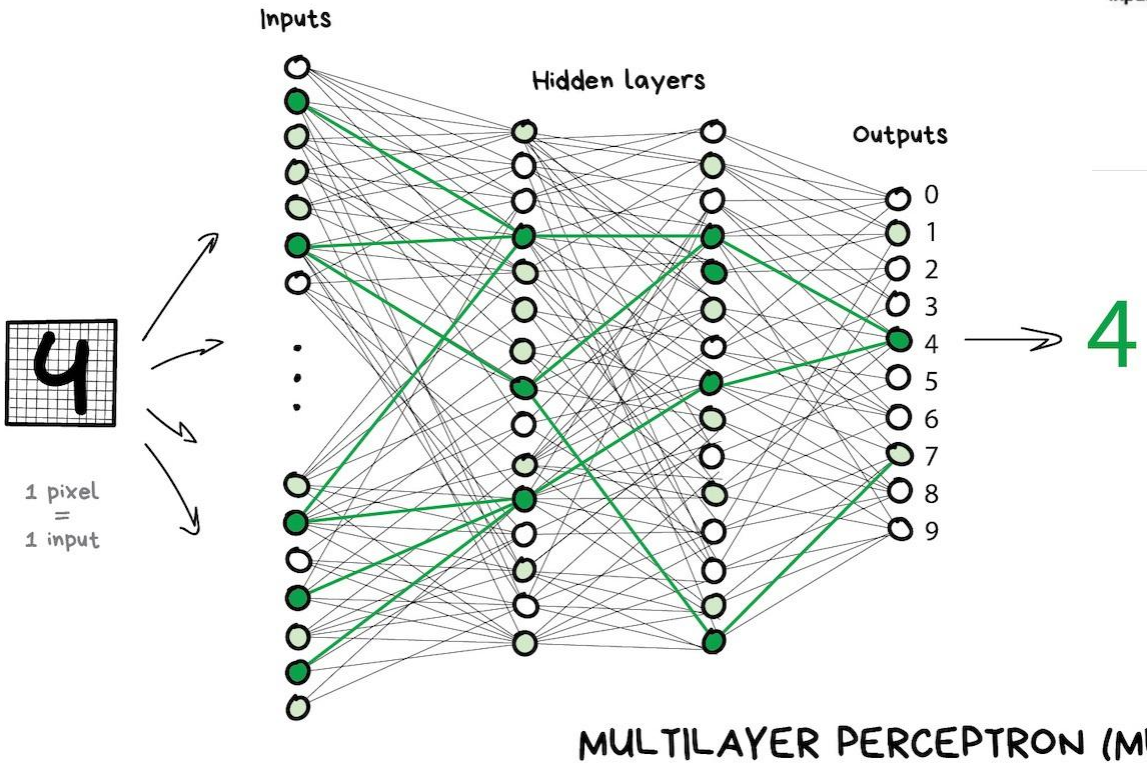
ROUTINE MARKOV PROCESS

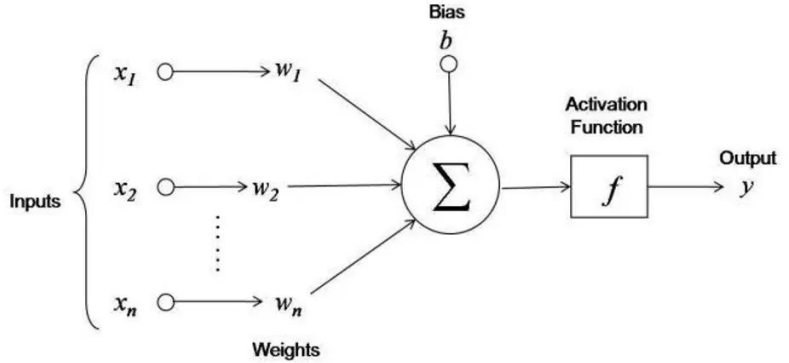
MICROSOFT / WEB / TL;DR

Twitter taught Microsoft's AI chatbot to be a racist asshole in less than a day

AI Models

AI Models - MLP





Activation Functions

Sigmoid
$\sigma(x) = \frac{1}{1+e^{-x}}$

tanh
$\tanh(x)$

ReLU
$\max(0, x)$

Leaky ReLU
$\max(0.1x, x)$

Maxout
$\max(w_1^T x + b_1, w_2^T x + b_2)$

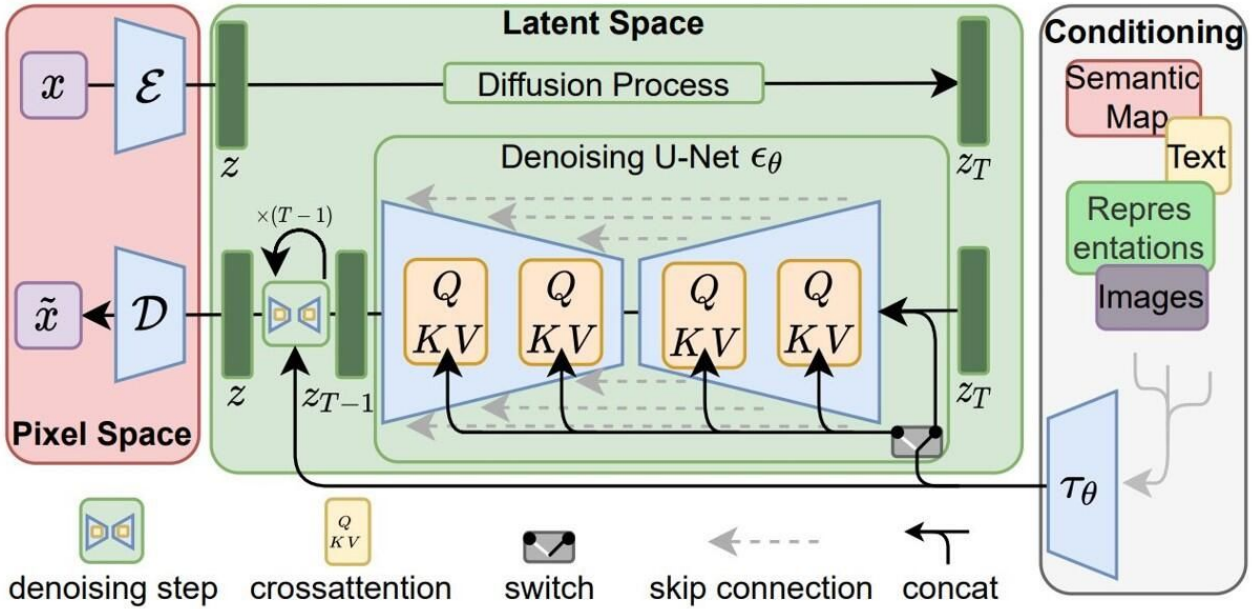
ELU
$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

Cross-Entropy Loss Function

$$H(P^* | P) = -\sum_i \underbrace{P^*(i)}_{\text{TRUE CLASS DISTIRBUTION}} \log \underbrace{P(i)}_{\text{PREDICTED CLASS DISTIRBUTION}}$$

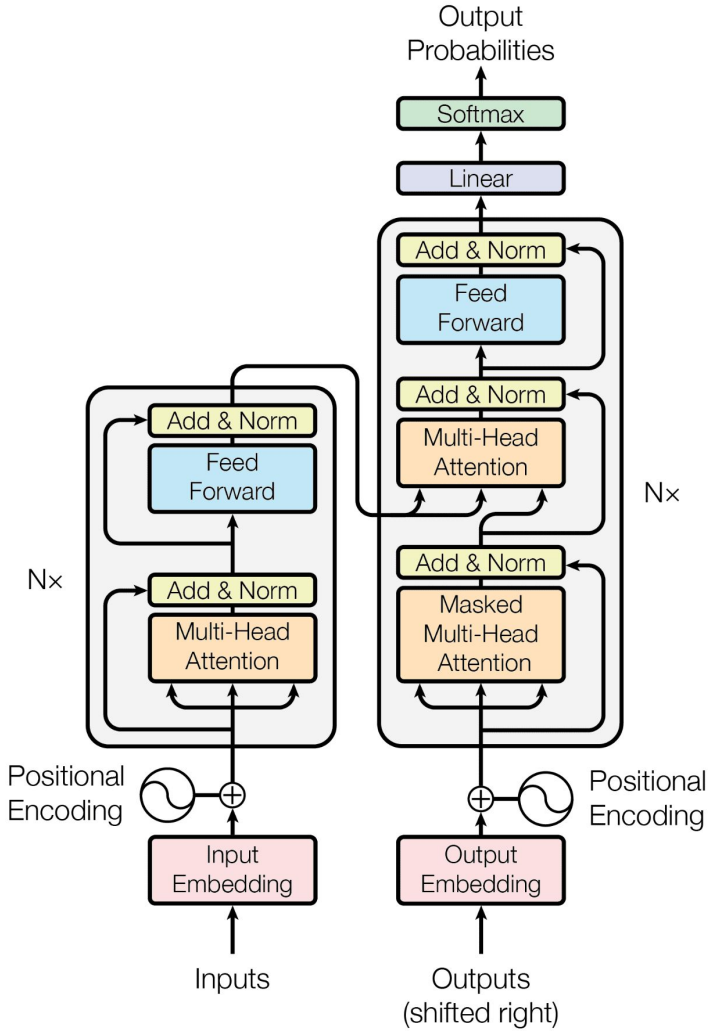
AI Models - Stable Diffusion

- Previous Image Generation Systems used SD-type Algorithms



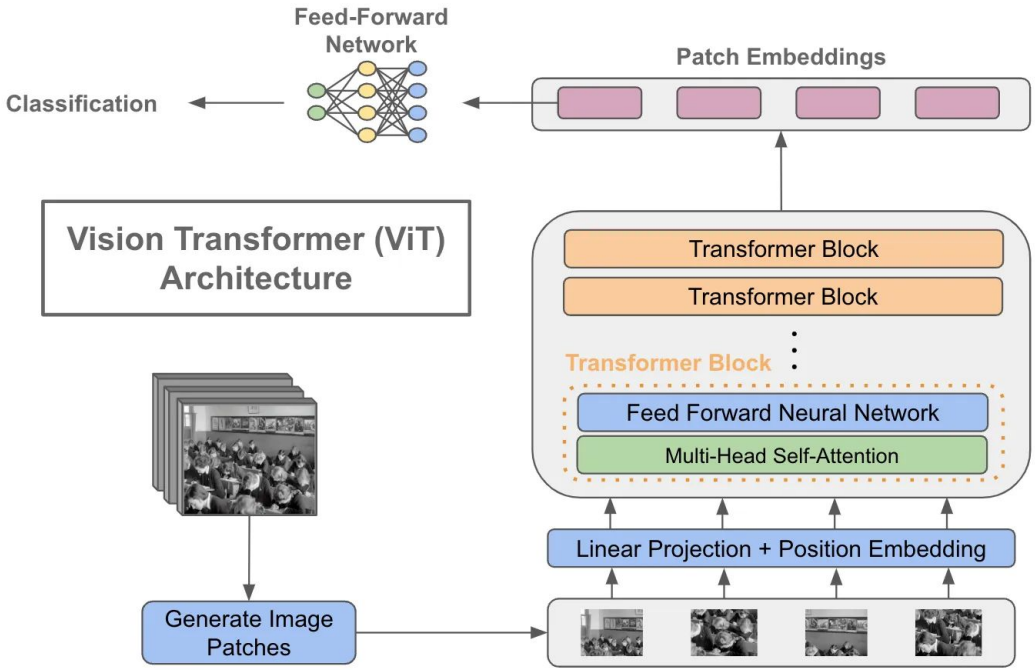
AI Models - Transformer

- “Attention is All You Need”, Vaswani, Et. al (2017)
- Original GPT Architecture
- Key, Query, Value
- Encoder/Decoder
- Positional Encoding
- Masking



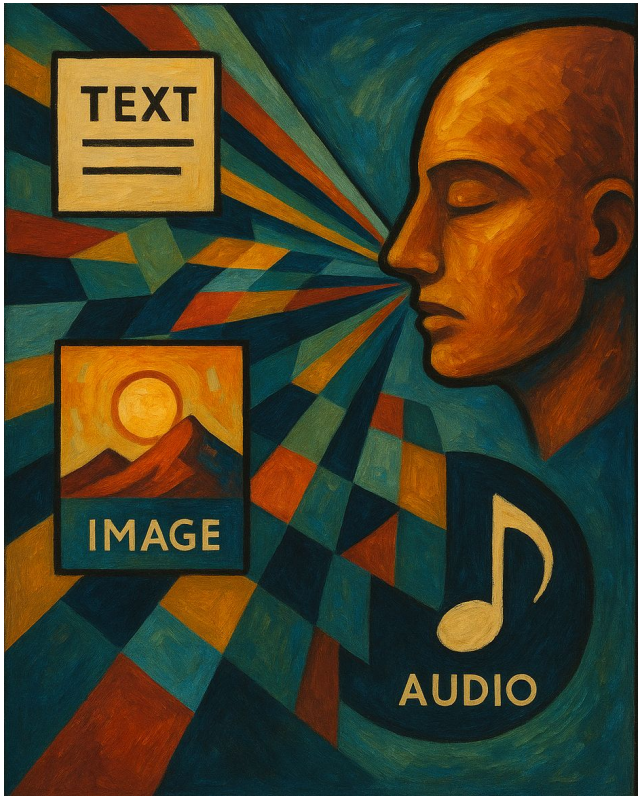
AI Models - Vision Transformer (ViT)

- Creates patches out of image
- Linear projection & position embedding
- Multiple transformer blocks:
  - Multi-head self-attention
  - FFNN (aka MLP)
- Patch embeddings act like tokens
- Final classification with FFNN (aka MLP)



AI Models - Multimodal Transformer-Based Generators

- Transformer-based Architectures that **Additionally** Support:
  - Vision
  - Language
  - Audio
  - Action
- Current GPT Architecture



“Multimodal Possibility” - ChatGPT-5.1 (Nov 30, 2025)

AI Models - Recommendation Systems

- Sparse matrix calculations
- Predicts which users will be interested in which products or services
- Individual user history is important to predicting future interest
- Examples:
  - Netflix
  - Amazon

AI Models -
Retrieval Augmented Generation (RAG)

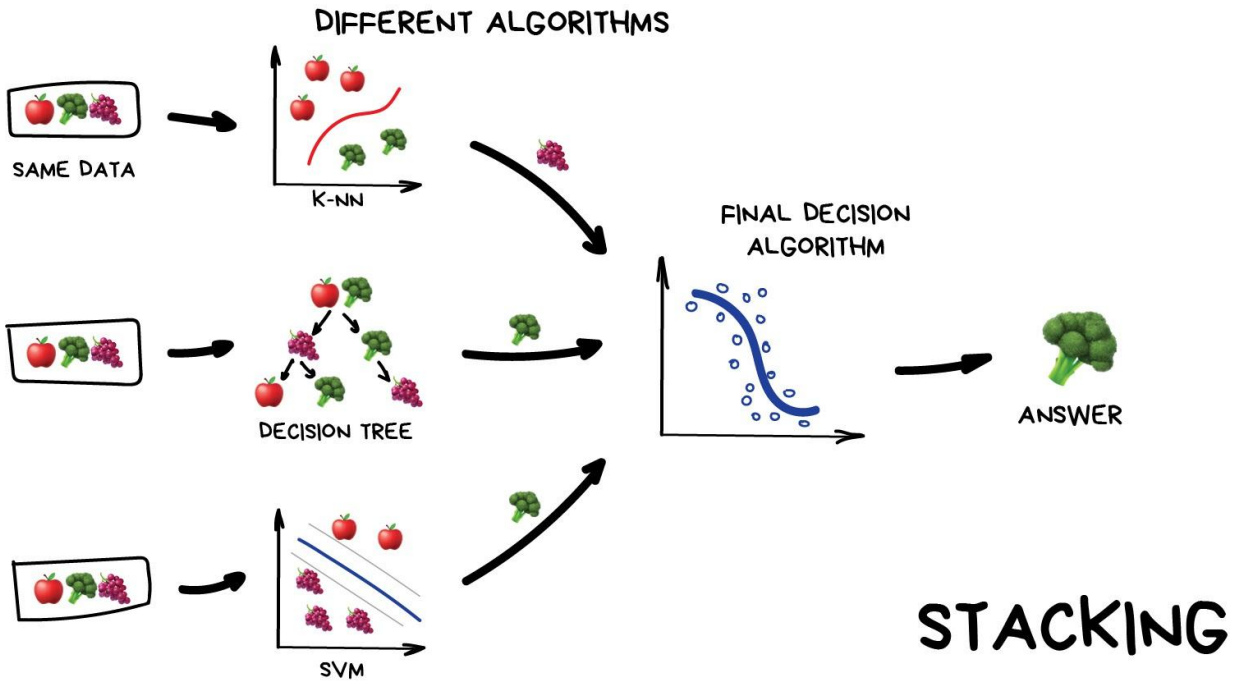
- Allows users to make queries about a **specific set** of existing data
- **Vectorization** allows for fast comparison between query and relevant text in corpus
  - FAISS is widely used
- Examples:
  - Search your emails
  - Search medical records
  - Make queries about legal documents

NEW
MODELS
EVERY DAY

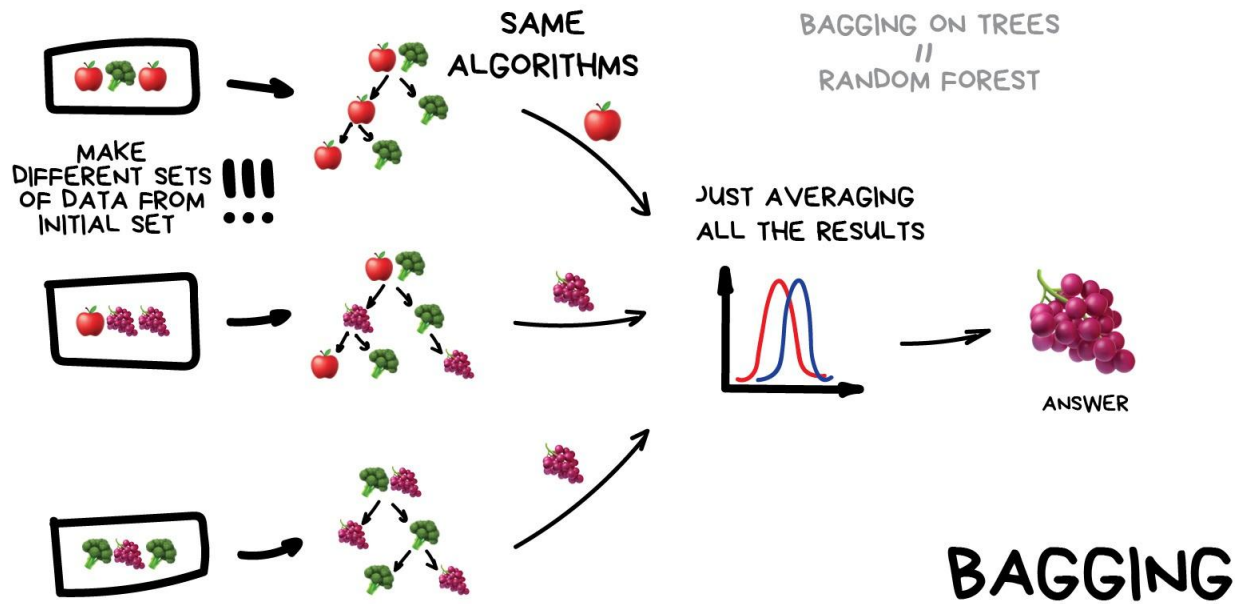
Ensembles

Ensembles

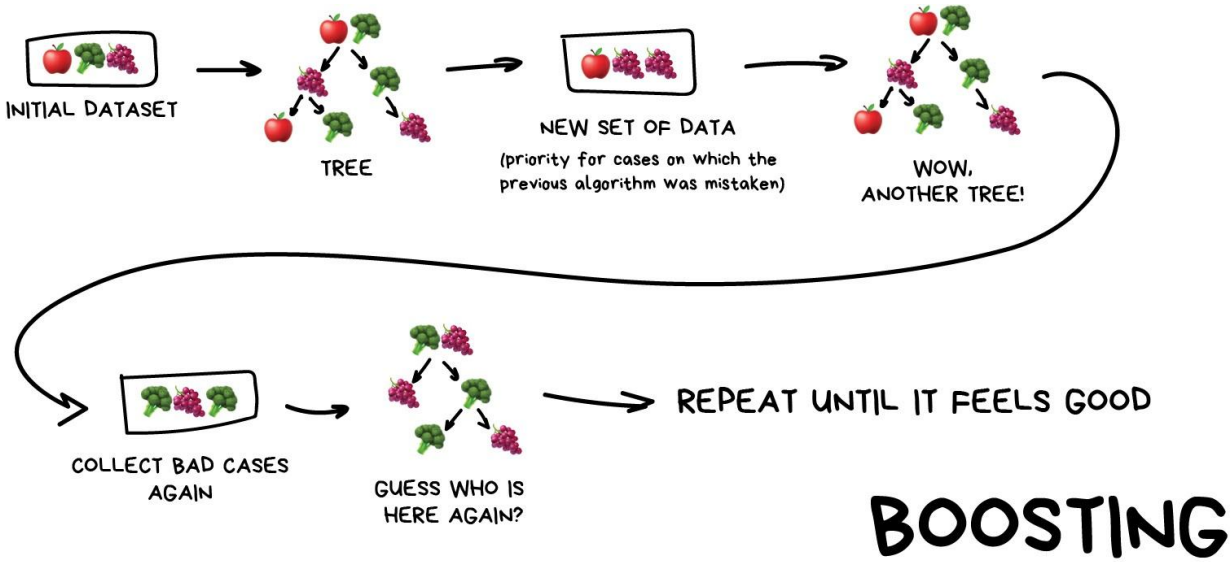
Ensembles - Stacking



Ensembles - Bagging



Ensembles - Boosting



How AI/ML Systems Fail

ARTIFICIAL INTELLIGENCE

Hundreds of AI tools have been built to catch covid. None of them helped.

What went wrong

Many of the problems that were uncovered are linked to the poor quality of the data that researchers used to develop their tools.

https://www.technologyreview.com/2021/07/30/1030329/machine-learning-ai-failed-covid-hospital-diagnosis-pandemic/

Traditional Software System Failures

- **Dependency failure –** A third party package no longer maintained
- **Hardware failure –** Hard-drive failure, CPU overheating, losing network access, etc
- **Downtime or Crashing –** Backend infrastructure outage

TECH

Dead Roombas, stranded packages and delayed exams: How the AWS outage wreaked havoc across the U.S.

PUBLISHED THU, DEC 9 2021·8:00 AM EST | UPDATED THU, DEC 9 2021·10:51 AM EST

https://www.cnbc.com/2021/12/09/how-the-aws-outage-wreaked-havoc-across-the-us.html

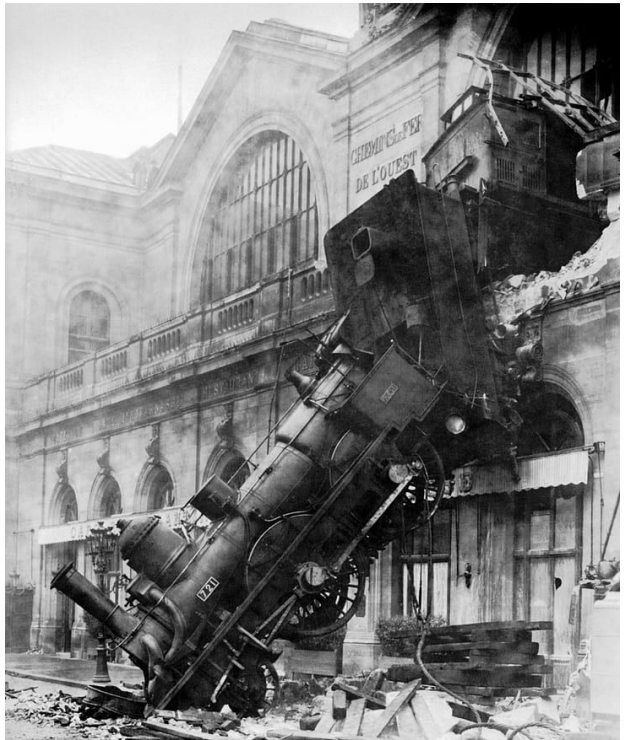
Raw Data Issues

- Sampling Errors
  - Convenience
  - Snowball
  - Judgement
  - Quota
- Imputation
- Data Leakage
- Duplicate Values
- Distribution Shifts

ML-Specific Failures

They account for a smaller proportion of failures but are **harder to detect and fix**:

- **Edge cases**
- **Data Distribution Shifts**
- **Degenerate feedback loops**



ML-Specific Failures – Edge Cases

ML-Specific Failures – Data Distribution Shifts

Consider a model estimating the likelihood of pets being adopted in a shelter. Let's call X the characteristics of a pet, Y whether its adopted or not, and P(Y|X) the likelihood of a pet being adopted

- **Covariate shift –** P(X) changes, P(Y|X) remains

A shelter takes in more older pets, but the likelihood of adoption remains the same by age.

- **Label shift –** P(Y) changes, P(X|Y) remains

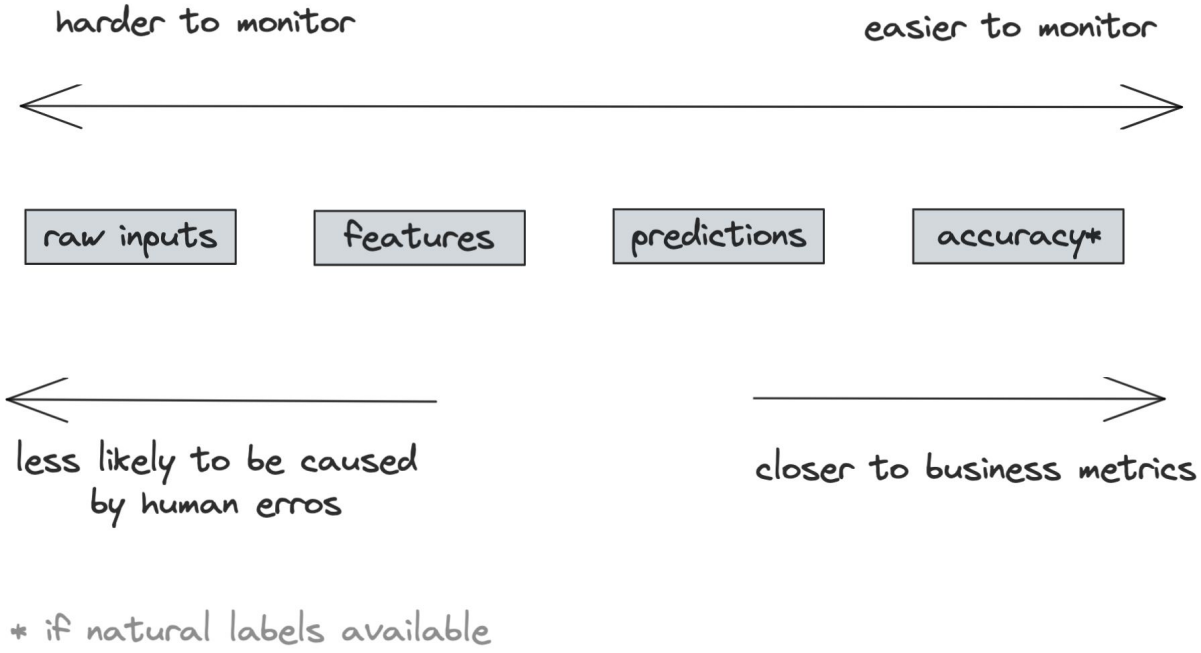
People want to adopt more pets, regardless of age.

- **Concept drift –** P(Y|X) changes, P(X) remains

People want to adopt more older pets, but the age of pets in the shelter remains the same.

ML-Specific Failures – Monitoring Data Distributions

Monitor data all along the inference pipeline over time

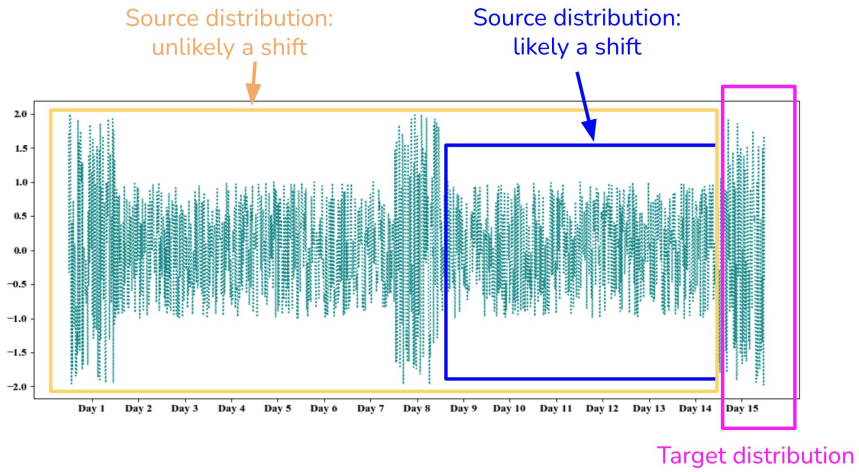


https://huyenchip.com/2022/02/07/data-distribution-shifts-and-monitoring.html

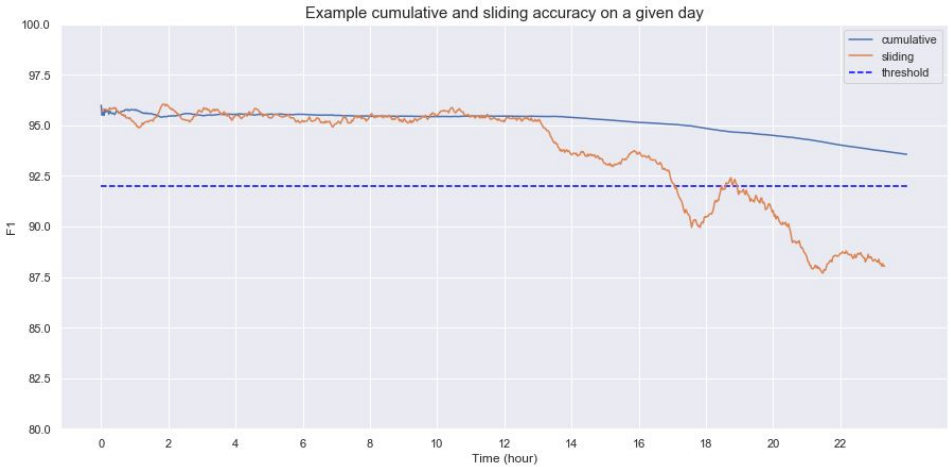
ML-Specific Failures – Detecting Data Distribution Shifts

A couple of monitoring pitfalls:

Consider seasonal variations



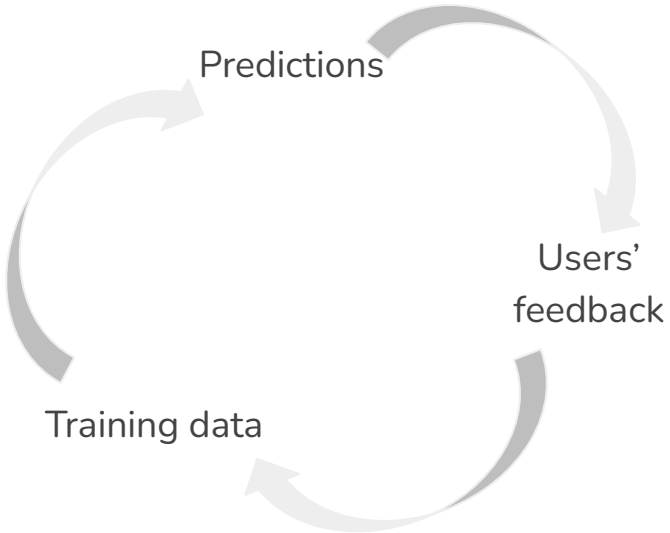
Cumulative statistics hide sudden shifts



https://huyenchip.com/2022/02/07/data-distribution-shifts-and-monitoring.html

ML-Specific Failures – Degenerate Feedback Loops (pt. 1)

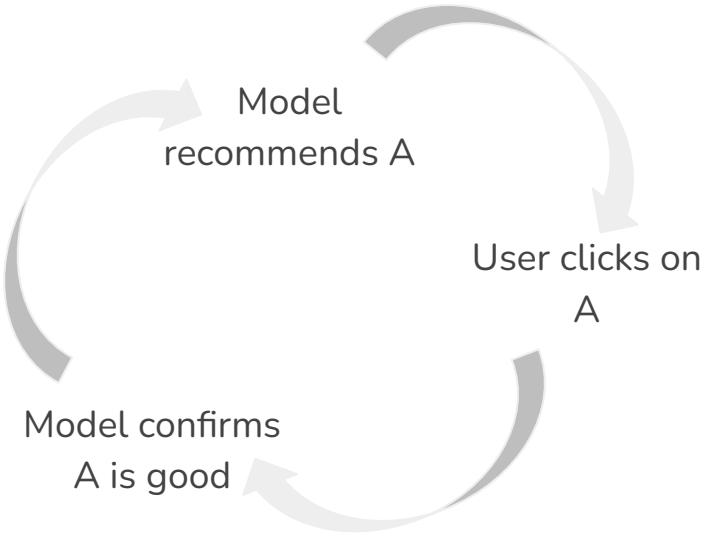
- Typical feedback loop:
  - User feedback from predictions used to train the next iteration of the model to create new predictions



Only arise once models are in production: hard to detect during development!

ML-Specific Failures – Degenerate Feedback Loops (pt. 2)

- Originally, A is ranked marginally higher than B: model recommends A;
- After a while, A is ranked much higher than B



Only arise once models are in production: hard to detect during development!

Ethics in AI

General Ethical Considerations

- Bias and Fairness
- Transparency and Explainability
- Privacy and Data Security
- Accountability
- Autonomy and Control
- Job Displacement and Economic Impact
- Weaponization of AI
- Environmental Impact

Case Study 1: Automated Grader’s Biases

- Summer 2020 - Pandemic
- UK A-level exams
- Failures:
  - Setting the Wrong Objective
  - Insufficient Evaluation
  - Lack of Transparency

Case Study 2: The Danger of “Anonymized” Data

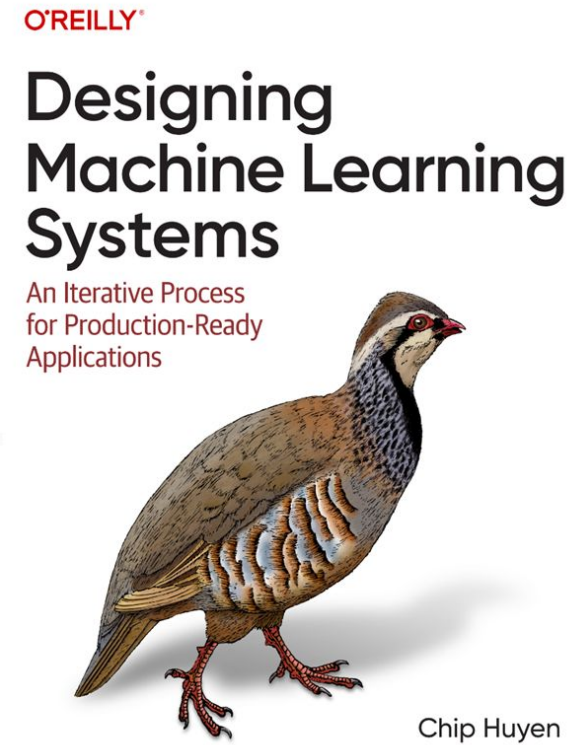
- Strava Fitness App (2018)
- PII was “Anonymized”
- Identified US Military Patrol Routes
- “opt-out” vs “opt-in” Confusion
- Further Potential for PII Misuse

Acknowledgement

- Vaswani, A. "Attention is all you need." *Advances in Neural Information Processing Systems* (2017).
- Huyen, Chip. *Designing machine learning systems*. "O'Reilly Media, Inc.", 2022.
- ChatGPT

“AI Dreams” - ChatGPT-4o (Oct 1, 2024)

“AI Dreams” - ChatGPT-5.1 (Nov 30, 2025)



Q&A