COMP 6611C: Advanced Topics in Embedded Al Systems

Lecture 1: Machine Learning Basics

Xiaomin Ouyang

Assistant Professor

Department of Computer Science and Engineering, HKUST



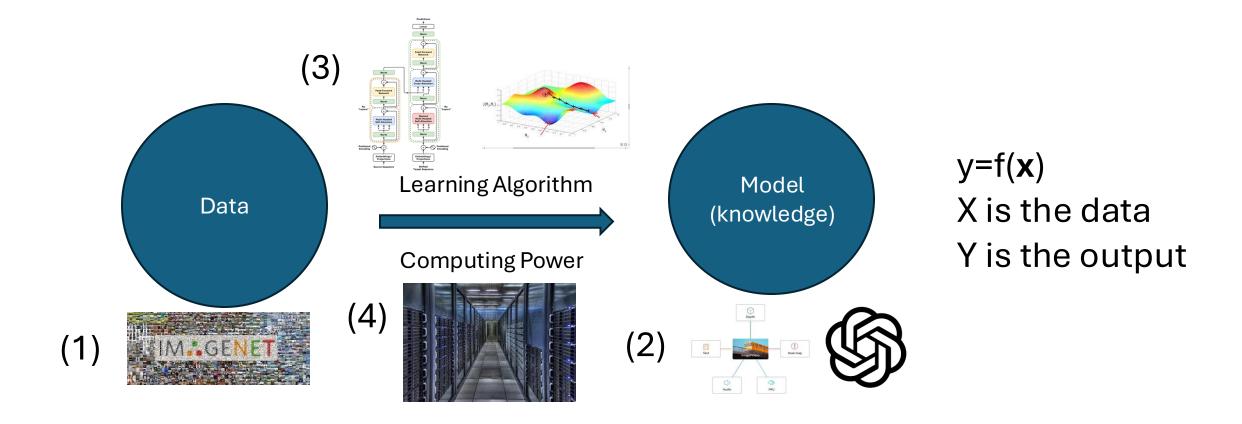
Recap

- ➤ Auditing students:
 - > please email me your name/email/ID for joining canvas
- ➤ Late submission policy:
 - 20% reduction per day, request approval if having emergency
 - Only for project report and paper reviews, pre slides are more casual
- ➤ Q&A recording <u>spreadsheet</u>

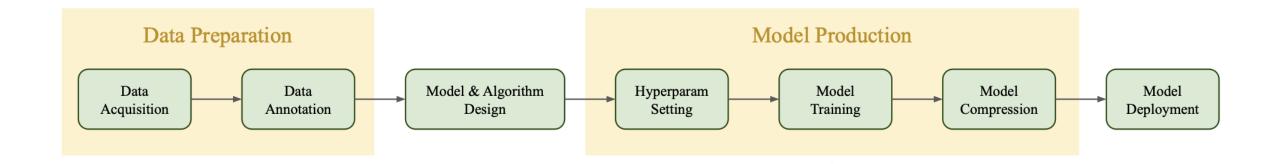
Outline

- > Overview of Machine Learning
- ➤ Machine Learning Paradigms
- ➤ Model Architectures
- ➤ Machine Learning Systems
- ➤ Applications

What is Machine Learning



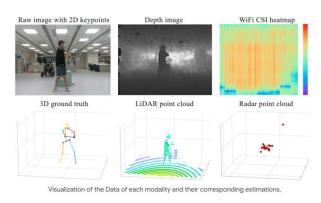
Workflow of Machine Learning



- Data Preparation
- Model & Algorithm Design
- Model Training
- Model Deployment and Inference

Data Preparation

➤ Data Acquisition



Captured by sensors



Crawled from web Synthetic data

➤ Data Annotation





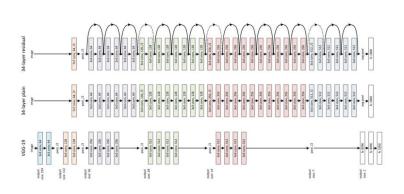
➤ Data Preprocess

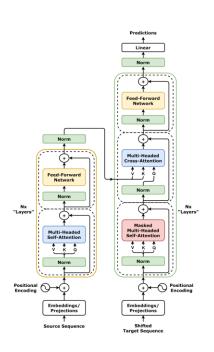
- Normalization
- Feature selection
- Crop, resize
- Augmentation
- ...

Model & Algorithm Design

➤ Model Architecture

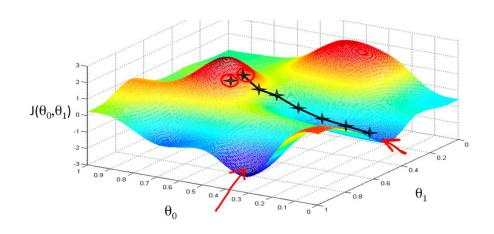
- MLP
- CNN
- RNN
- ResNet
- Transformers





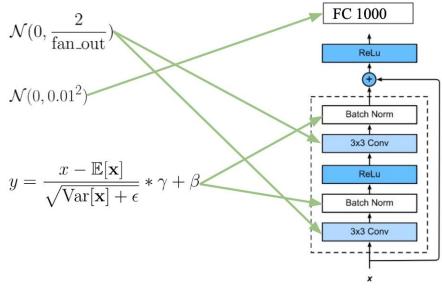
➤ Learning Algorithms

- Gradient Descent
- Stochastic Gradient Descent (SGD)
- Adaptive Moment Estimation (Adam)



Model Training

➤ Weight Initialization



- Zero Initialization
- Random Initialization
- Kaiming initialization
- Gaussian distribution

> Hyperparameters

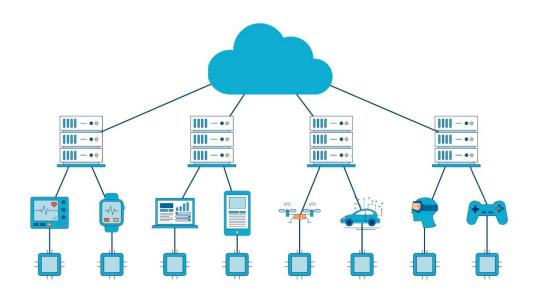
- Model design
 - the number of layers
 - the size of each layer
 - other layer parameters
 - activation functions
- Learning algorithm
 - choice of optimizers
 - learning rate
 - batch size
 - dropout ratios

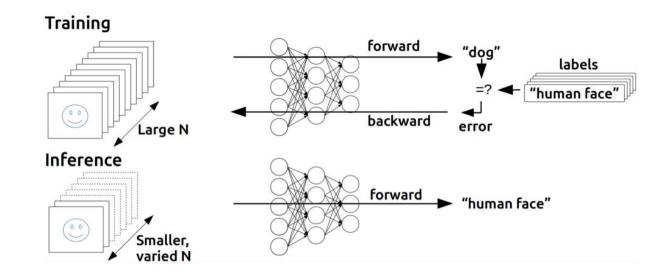
•

Model Deployment and Inference

➤ Model Deployment

➤ Model Inference





- Cloud-Edge-Devices
- Model compression/partition
- Model finetuning and adaptation

Accuracy, latency, energy, memory

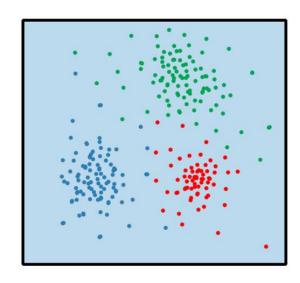
Outline

- ➤ Overview of Machine Learning
- **➤ Machine Learning Paradigms**
- ➤ Model Architectures
- ➤ Machine Learning Systems
- ➤ Applications

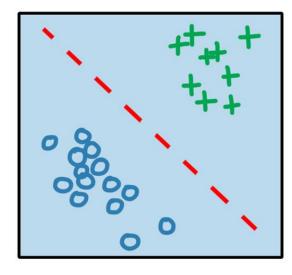
Types of Machine Learning

machine learning

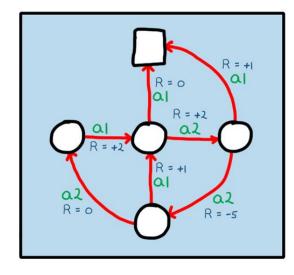
unsupervised learning supervised learning reinforcement learning



Data-driven



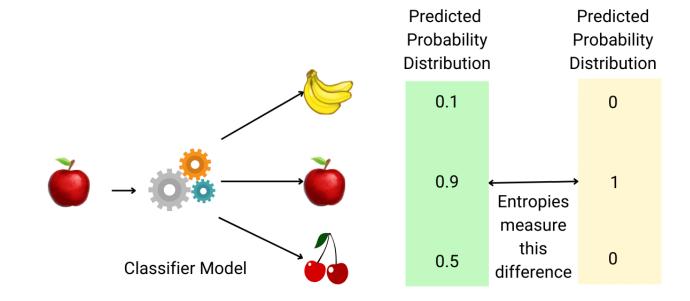
Task-driven



Learn from mistakes

Supervised Learning

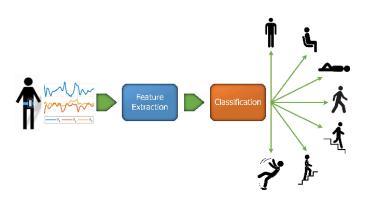
> Given a dataset with data and labels (x, y), find a function that maps x -> y



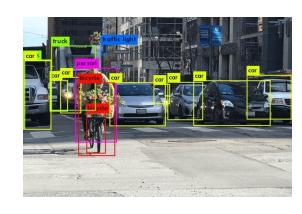
Training Loss is calculated by comparing predictions with y, e.g., cross entropy loss

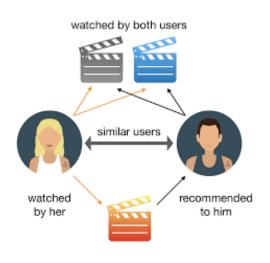
Supervised Learning

➤ Applications









Classification

Regression

Detection

Recommendation

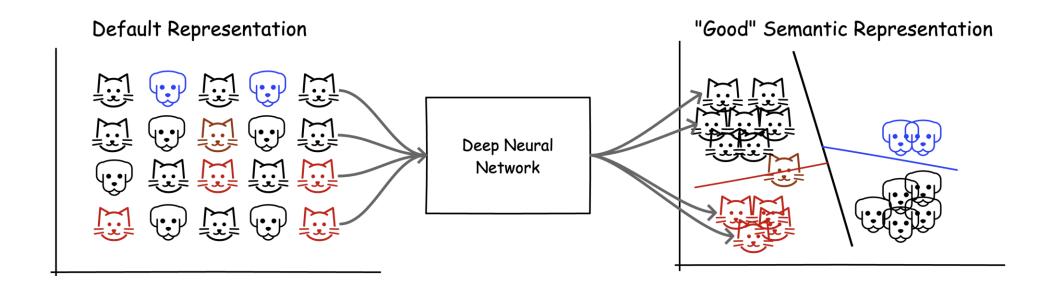
Supervised Learning

> Approaches

- Linear Regression,
- Logistic Regression
- Decision Tree
- Random Forests
- Support Vector Machines (SVM)
- K-Nearest Neighbors (KNN)
- Naive Bayes
- Neural Networks

Unsupervised Learning

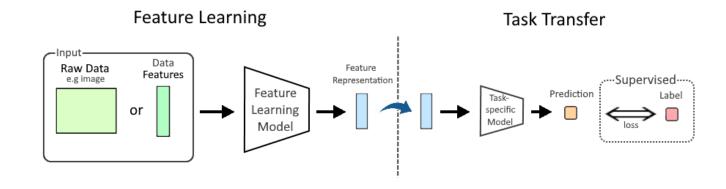
> Given a dataset with only data x, learn an effective representation of x



Unsupervised Learning

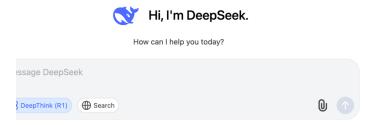
> Applications

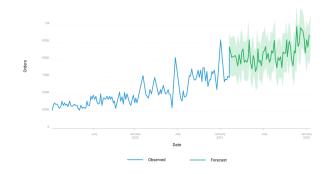
Finetuned for Downstream Tasks



Generation

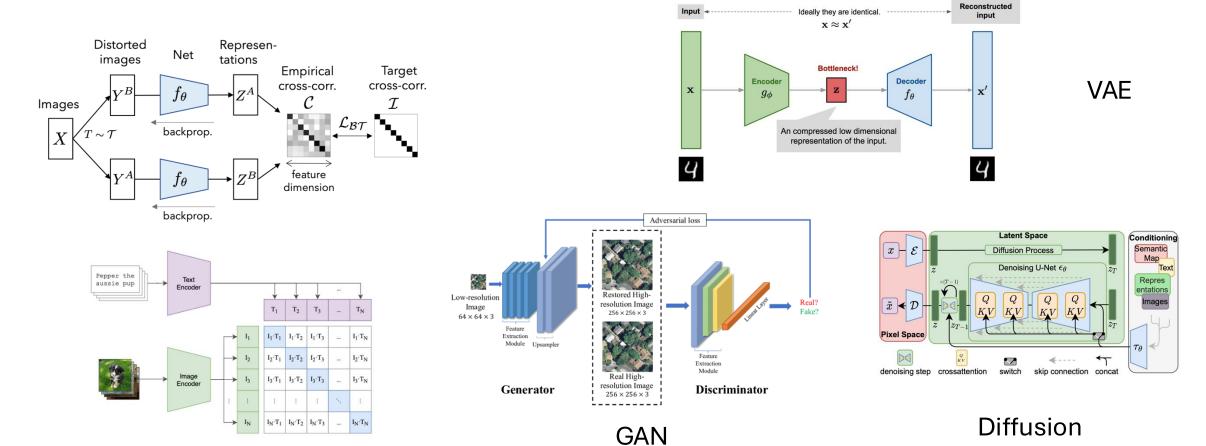






Unsupervised Learning

> Approaches

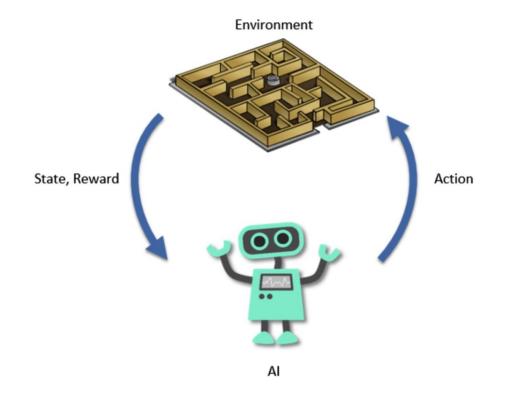


Contrastive Learning

Reconstruction

Reinforcement Learning

➤ Given a dataset with state, action and reward (**s**, **a**, r), find a function to **maximize the reward** r



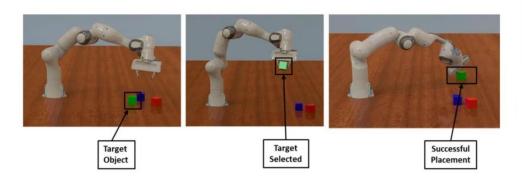
Reinforcement Learning

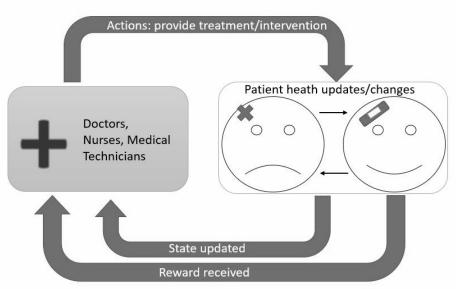
> Applications

Alpha Go



Robotic Control



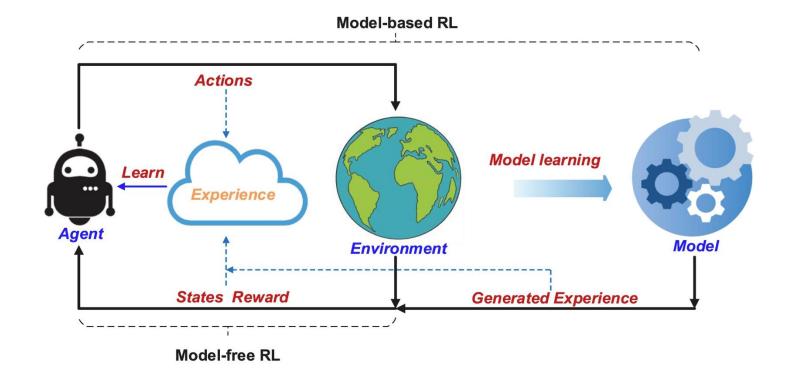


Health Intervention

Reinforcement Learning

> Approaches

Model-based RL: build a model for the environment, sample-efficient Model-free RL: learn directly from environment, simpler to implement



How to choose different paradigms

➤ Lots of **labelled data**: supervised learning

> Lots of unlabelled data: unsupervised learning

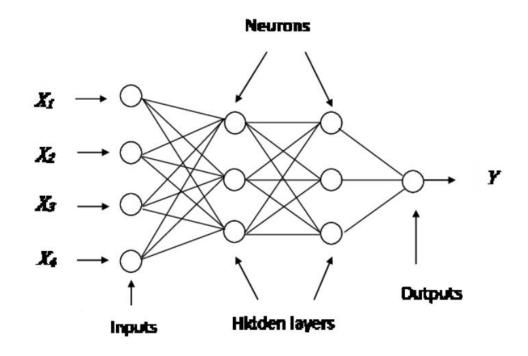
> No data labels, only **feedback signals**: reinforcement learning

Outline

- ➤ Overview of Machine Learning
- ➤ Machine Learning Paradigms
- > Model Architectures
- ➤ Machine Learning Systems
- ➤ Applications

Multi-Layer Perceptron (MLP)

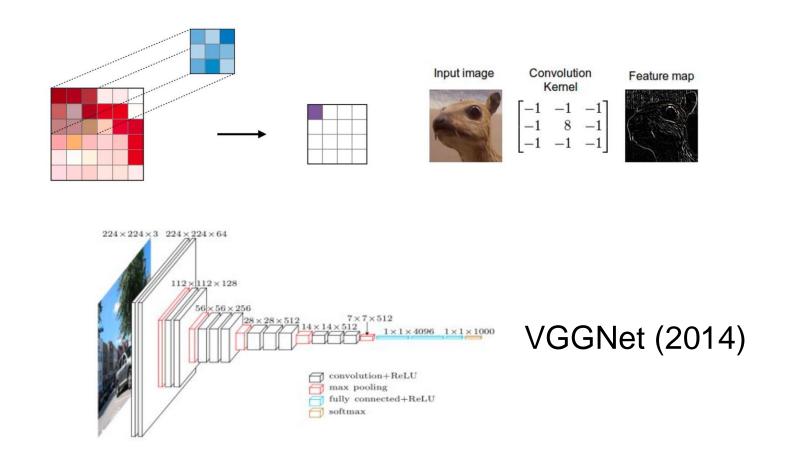
➤ Consists of multiple layers of neurons (fully connected layers), each taking the output of previous as input and generating outputs for the next layer.



$$\begin{aligned}
 b_0 &= x \\
 z_1 &= W_1 h_0 + b_1 & h_1 &= \sigma(z_1) \\
 & \cdots & \cdots \\
 z_L &= W_L h_{L-1} + b_L & h_L &= \sigma(z_L) \\
 & y &= h_L
 \end{aligned}$$

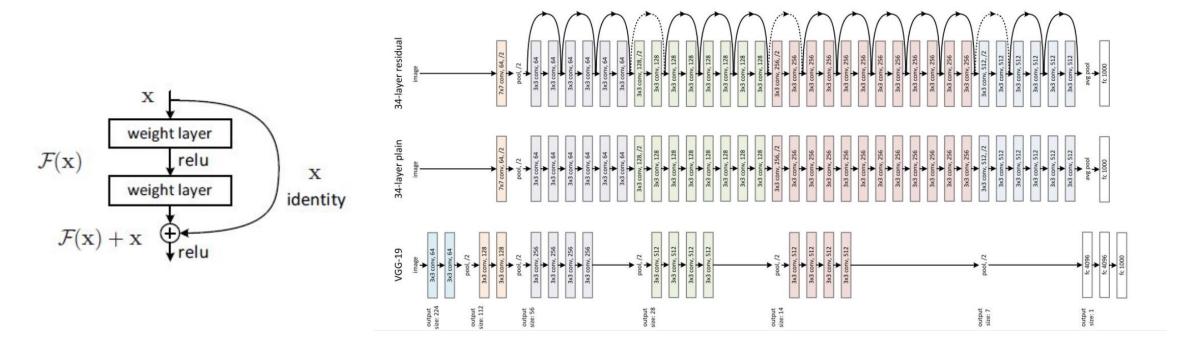
Convolutional Neural Network (CNN)

> Extracts feature on small local receptive fields with shared kernel weights.



Residual Networks (ResNet)

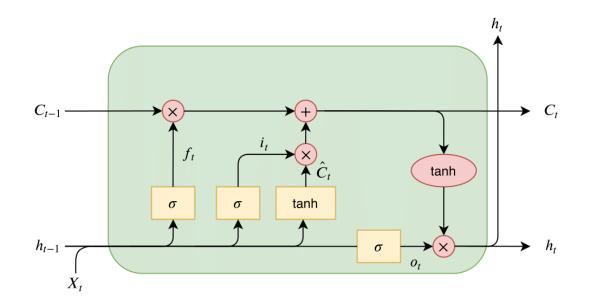
➤ Introduces shortcut connections based on its residual learning paradigm and dramatically increases network depth above 1000.



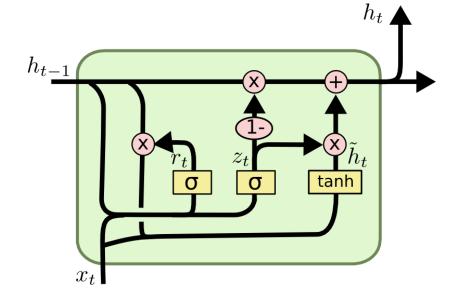
Given a target mapping H(x) and a network F(x). Fitting the full mapping F(x) = H(x) is harder than just fitting the residual F(x) = H(x)-x.

Recurrent Neural Network (RNN)

> Processing sequential data: connections between nodes form a sequence



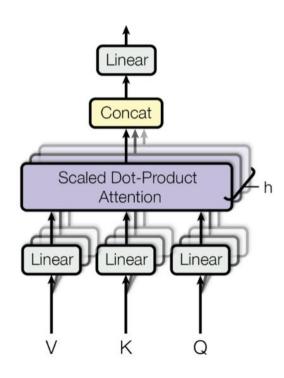
Long short-term memory (LSTM)



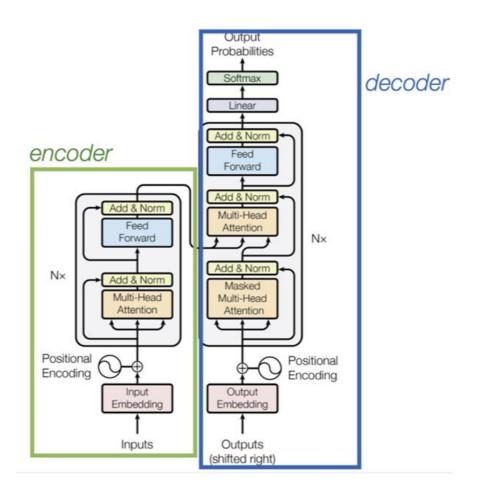
Gated Recurrent Unit (GRU)

Transformer

> Encoder-decoder architecture based on the multi-head Self-Attention



Multi-Head Self-Attention



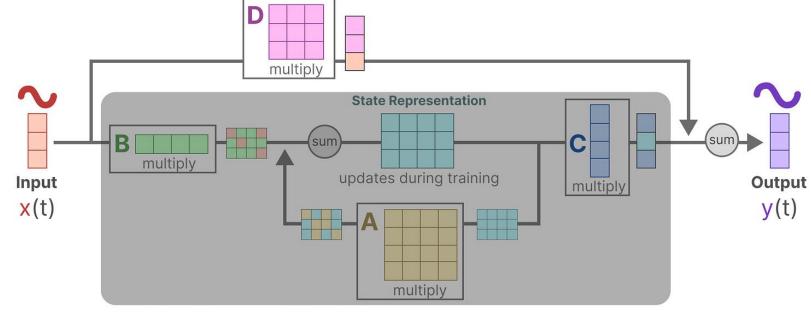
State Space Model (Mamba)

> From control theory: model a dynamic system via state representations

State equation
$$h'(t) = Ah(t) + Bx(t)$$

Output equation y(t) = Ch(t) + Dx(t)

Handle very long sequences, generally with a lower number of parameters



State Space Model

Efficiently Modeling Long Sequences with Structured State Spaces. Mamba: Linear-Time Sequence Modeling with Selective State Spaces.

How to choose different models

➤ General data: MLP, CNN, ResNet, Transformer

> Sequential data: RNN, Transformer, State Space Models

Outline

- ➤ Overview of Machine Learning
- ➤ Machine Learning Paradigms
- ➤ Model Architectures
- **➤ Machine Learning Systems**
- ➤ Applications

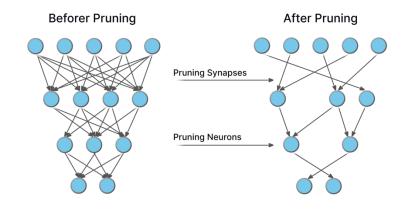
Machine Learning Systems

> Optimizing system performance of ML models

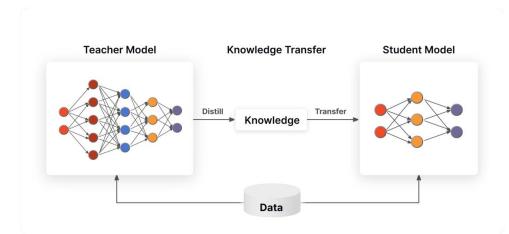
- Model Compression
- Parallel and Distributed Computing
- Hardware Acceleration
- Inference Optimization

Model Compression

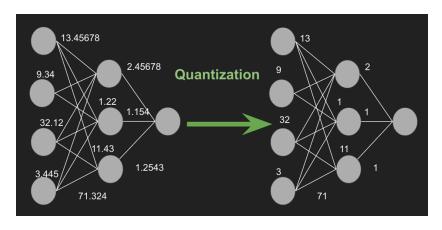
> Pruning



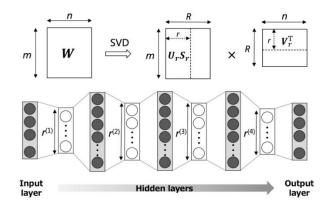
➤ Knowledge Distillation



➤ Quantization



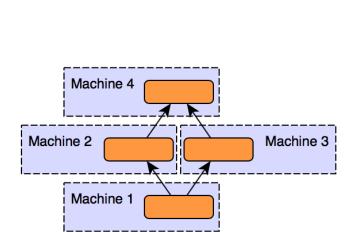
➤ Low-rank factorization



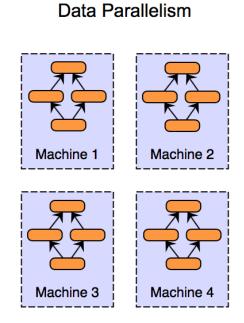
Parallel and Distributed Computing

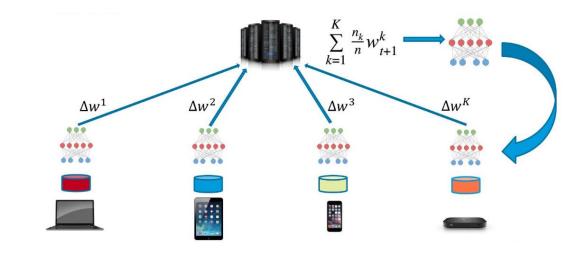
➤ Distributed Training

> Federated Learning



Model Parallelism





Hardware Acceleration

➤ GPUs, TPUs, and FPGAs



CPU

- Small models
- Small datasets
- Useful for design space exploration



GPU

- Medium-to-large models, datasets
- Image, video processing
- Application on CUDA or OpenCL



TPU

- Matrix computations
- Dense vector processing
- No custom TensorFlow operations

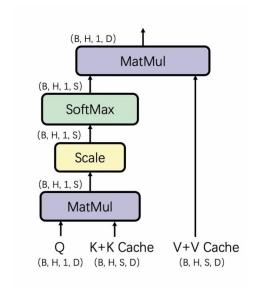


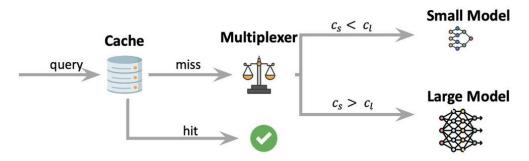
FPGA

- Large datasets, models
- Compute intensive applications
- High performance, high perf./cost ratio

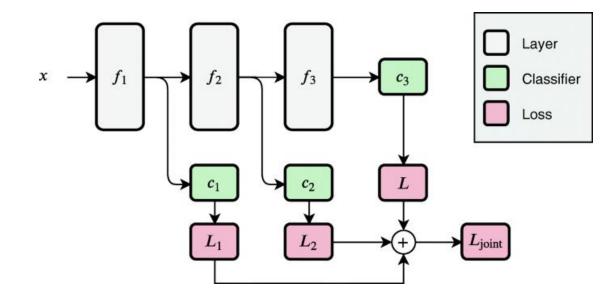
Inference Optimization

> Caching





➤ Progressive Inference



How to optimize ML systems

- > Task requirements: Accuracy, Latency
- > Resource constraints: Memory, Energy
 - Model Compression
 - Parallel and Distributed Computing
 - Hardware Acceleration
 - Inference Optimization

Outline

- ➤ Overview of Machine Learning
- ➤ Machine Learning Paradigms
- ➤ Model Architectures
- ➤ Machine Learning Systems
- > Applications

Smart Health

> Behavior monitoring, early disease diagnosis, personalized intervention





Fitness Tracking



Sleep Monitoring



Cognition Impairment Detection

Smart Home & Building

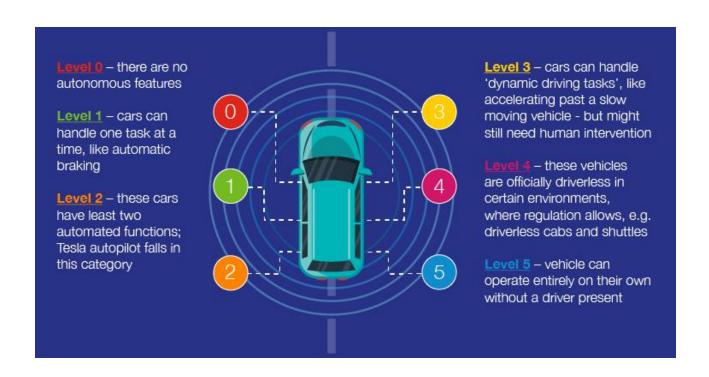
> Occupant detection, environment monitoring, localization, adaptive control

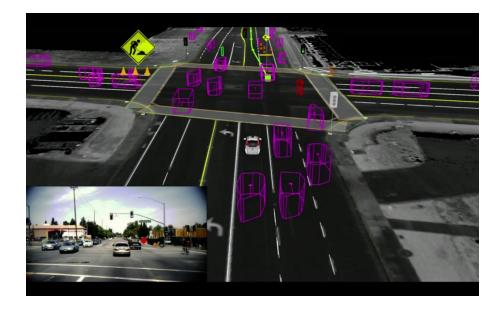




Autonomous Driving

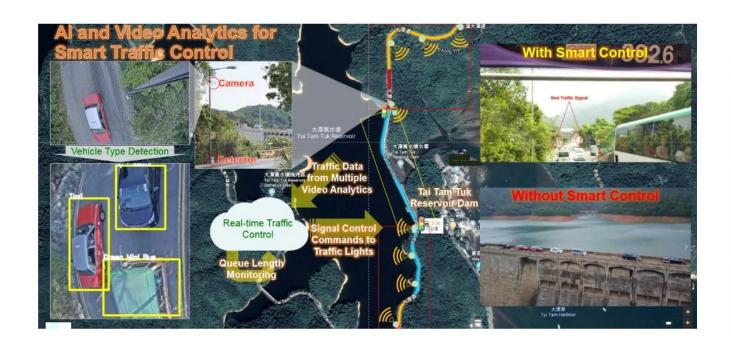
➤ Object detection, control





Smart City

> Traffic management, sustainability, public security





Other Applications

➤ Smart Manufacturing



➤ Smart Agriculture



Break

- > Next lecture: Challenges in Embedded AI Systems
- > Website:
 - > A shared spreadsheet for paper pre to be released on Weekends
 - > Course APP and dataset to be released next Tuesday
- > Any questions?