AI Uses in Education Research

AERA Virtual Research Learning Series
June 11, 2024

Min Sun, Lovenoor (Lavi) Aulck,
Jing Liu, Shawon Sarkar

Institute of Education Sciences

UNIVERSITY of WASHINGTON eScience Institute
ADVANCING DATA-INTENSIVE DISCOVERY IN ALL FIELDS

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Outline

- Intro
- What is ML? What is AI?
- Use case examples part 1
- Use case examples part 2
- Summary

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ISEA

- Innovation Science for Education Analytics (ISEA)
  - Funded by IES and the Department of Education
  - www.amplifylearn.ai/isea/

With the rise of artificial intelligence (AI) in all aspects of society, there has been an increasing talent gap in AI and machine learning, especially in applying these tools in education. Through a collaboration between the UW College of Education, the UW eScience Institute, and faculty from other higher education institutions including the University of Oregon, the University of Maryland, and Vanderbilt University, a training program called Innovation Science for Education Analytics (ISEA) will launch in January 2024 thanks to a 3-year grant from the Institute of Education Sciences (IES).

ISEA seeks to advance computational and analytic capacity in K-12 education. The program will recruit a cohort of 15-20 fellows each year with the goal of developing a new pool of talented individuals who have integrated expertise across engineering, statistics, and K-12 education. ISEA is designed as a targeted training program that emphasizes state-of-the-art data analytics informed by education domain knowledge, computational workflows, immediate applications, and career advising.

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Multiple Paradigms of Regression

- Statistics/economics: explain a relationship
  - Ties in with the idea of inference

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- Statistics/economics: explain a relationship
  - Ties in with the idea of inference
- Machine learning: predict the future
  - Ties in with the idea of prediction

Example: Earnings

- Inference
  - What are the determinants of income?
  - Do people with children earn more?
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- Prediction
  - What is the predicted income for person X?
  - What are the descriptors of a person with income Y?

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- Have we measured the causal effect of an additional year of education on wages?
  - With another year of education, will I definitely earn $2,518 more?

The Model Is Right…?

> “All models are wrong but some are useful”
>
> \- George Box

> “… all models are limited by the validity of the assumptions on which they ride”
>
> \- Collier, Sekhon, and Stark

> “Assumptions behind models are rarely articulated, let alone defended.”
>
> \- David Freedman

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- A critical concern of machine learning is the ability to build models that accurately generalize while a critical concern of econometrics is the ability to build models that capture relationships

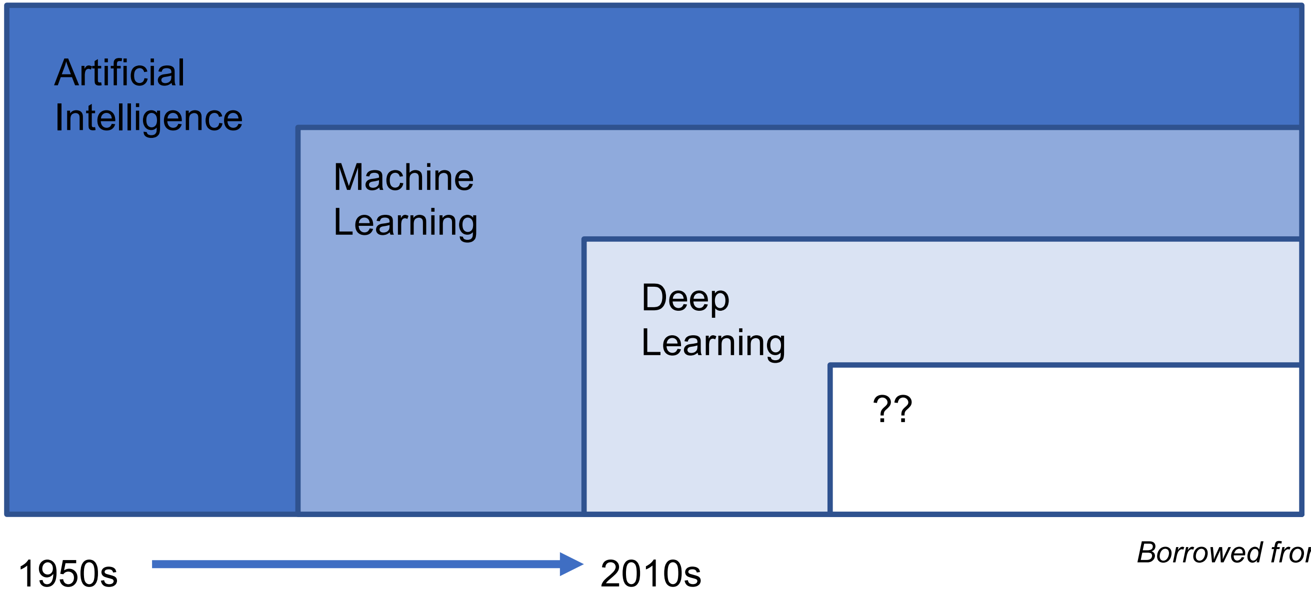
What is Machine Learning?

> Machine learning is the science of getting computers to act without being explicitly programmed

> Machine learning is a scientific discipline that explores the construction and study of algorithms that learn from data

> Machine learning is a natural outgrowth at the intersection of computer science and statistics

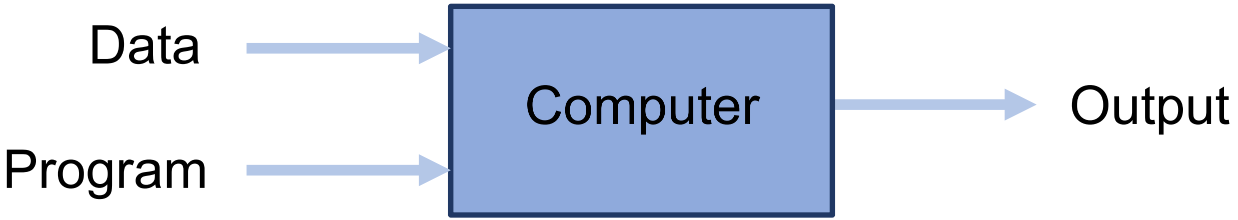
What is Machine Learning?



Borrowed from Nvidia

What is Machine Learning?

Traditional Programming



Machine Learning

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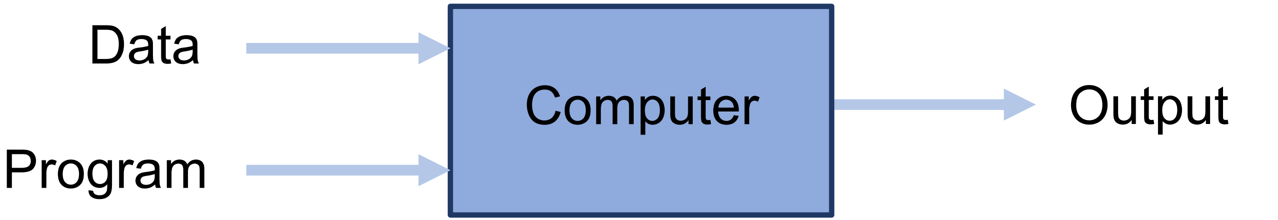
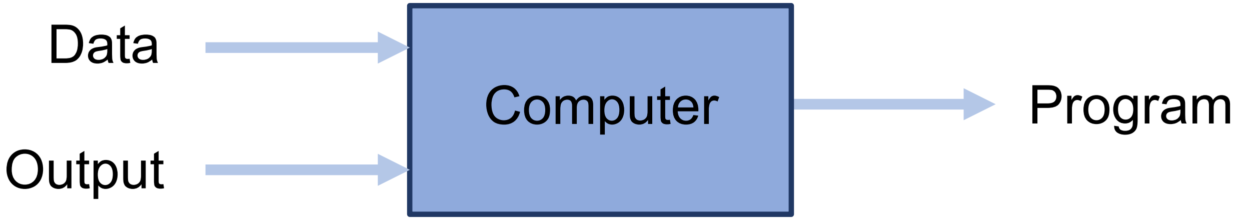


Machine Learning



“Flavors” of Machine Learning

- Supervised learning
- Unsupervised learning
- Semi-supervised learning
- Reinforcement learning

Supervised Learning

- We know the "correct" answer for values
  - We're trying to model the input (independent) variables as they relate to the output (dependent) variables
- Examples
  - Predicting whether a student will graduate from a university
  - Predicting salary upon graduation
  - Other examples?

Unsupervised Learning

- We don't know the "correct" answer for values
  - We're trying to discover underlying structure
- Examples
  - Extracting topics/themes from textual surveys of students
  - Understanding the relationships between different departments/programs
  - Finding bottlenecks in student course offerings

"Pop" Quiz

Would you address each of the below with a supervised or unsupervised learning algorithm?

- Given email labelled spam or not, build a spam detector
- Given news articles on the web, group them into sets based on topic
- Given a database of customer data, find market segments/customer groups
- Given patients with a disease, determine if new patients have the disease
- Given phone records of individuals, determine which are the wealthiest
- Given phone records of individuals and survey data about their income, predict the incomes of new subscribers

Semi-supervised Learning

- We know the “correct” answer for some values
  - The input data contains both labelled and unlabeled instances
- Examples?

Reinforcement Learning

- We develop “agents” that seek to maximize “reward”
  - We’re trying to build models that will seek to maximize some gain
- Examples
  - Creating personalized curricula for students
  - Creating educational content for students

ML Basics

- Thousands of ML algorithms
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- Thousands of ML algorithms
  - No one knows them all
  - Often tweaks or small improvements to existing approaches
- Every ML algorithm has three components
  - The representation (the model)
  - The evaluation (the cost/objective function)
  - The optimization (the search)

Designing for Prediction: Key Ideas

- Generalization and overfitting
- Training, validation, and test data
- Evaluation metrics
- Baselines
- Error analysis

Determining Model Fit

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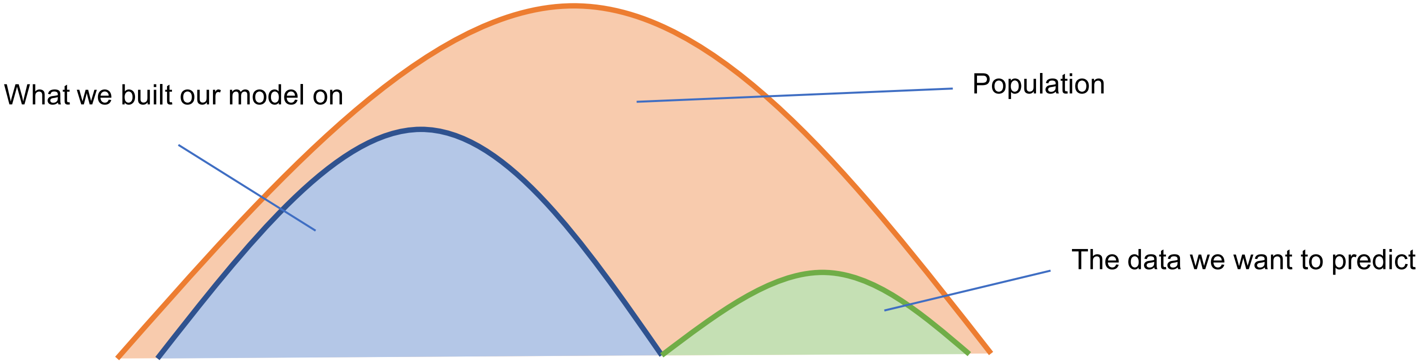
> Should we keep adding features? Is this what we want?

The ML Dilemma

- We want to find a balance between modeling the data we have while also being able to generalize to unseen data



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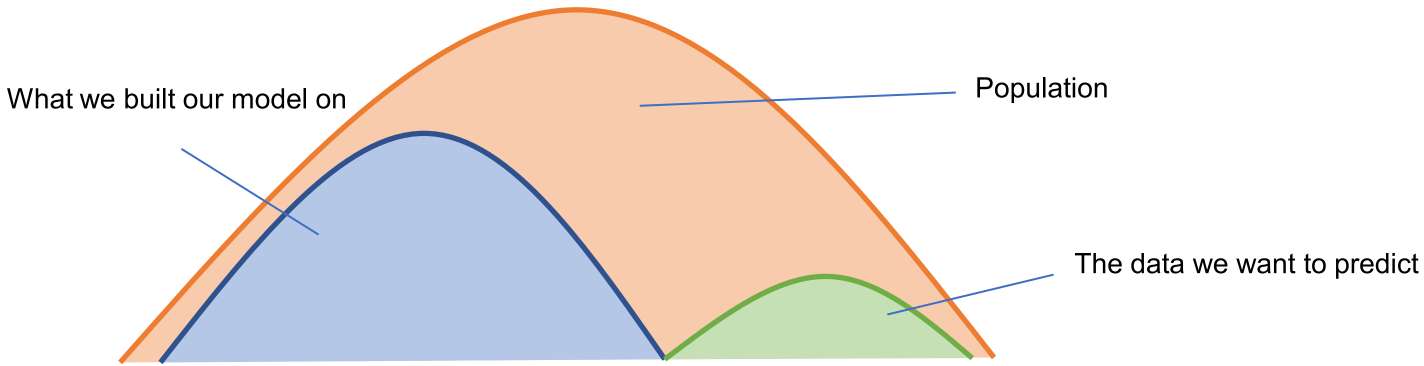
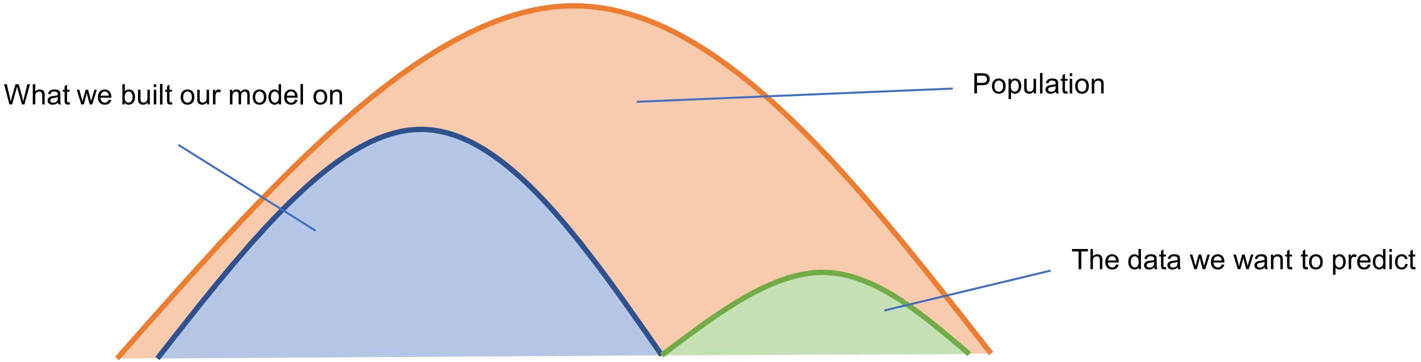


The ML Dilemma

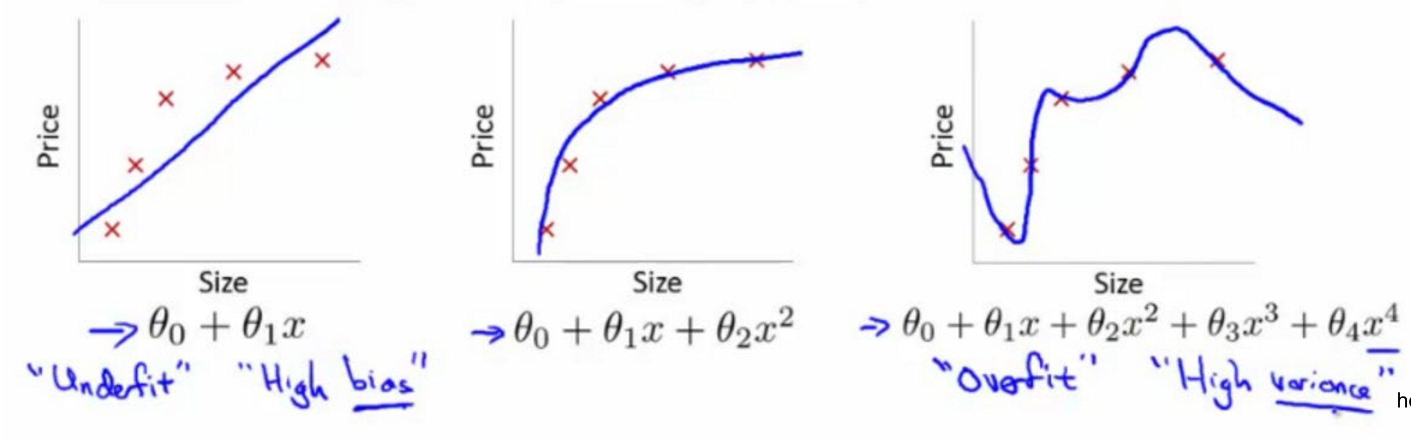
variance

> We want to find a balance between modeling the data we have while also being able to generalize to unseen data

bias



Bias - Variance Tradeoff



holehouse.org

Bias-Variance Tradeoff: the problem of simultaneously minimizing two sources of error that prevent generalization

Overfitting and Underfitting

- More formally: <u>overfitting</u> is when we have too high of variance in our model with respect to bias

- More formally: <u>underfitting</u> is when we have too high of bias in our model with respect to variance

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- How do we know? Validation!

Training, Validation, and Test Data

- **Training set**: a set of examples used for learning, to which we fit parameters of a model

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Test Data

Until you're ready to report final results…

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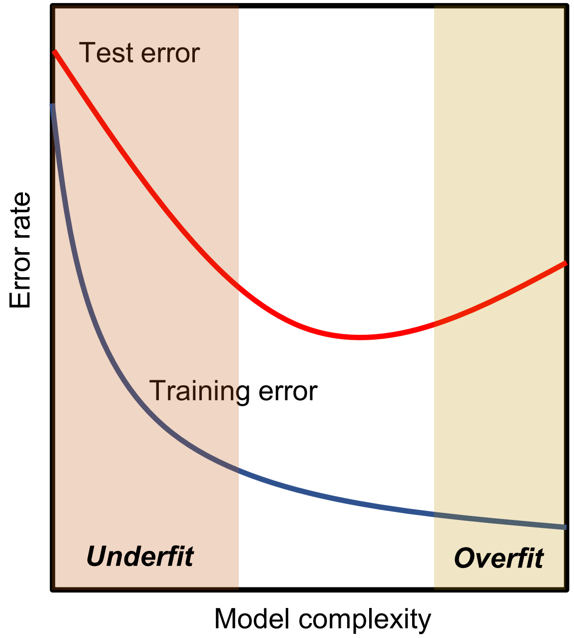
How Prediction Experiments Work

- ML experiments typically separate data into a training/test set
- Model is fit on training set
  - Validation set is often used to fine tune
- Performance is measured on the test set
  - This gives something of a “real-world” approximation of how well the model performs



A Typical (Supervised) ML Experiment

> Data with labelled instances
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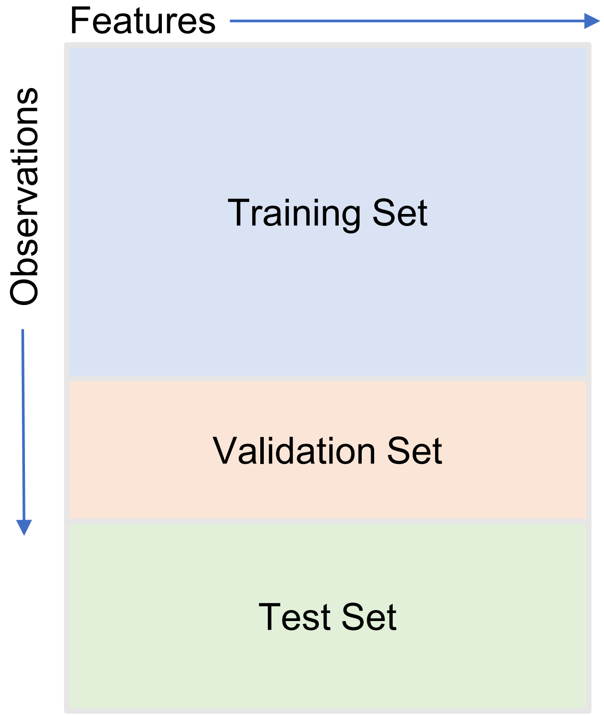

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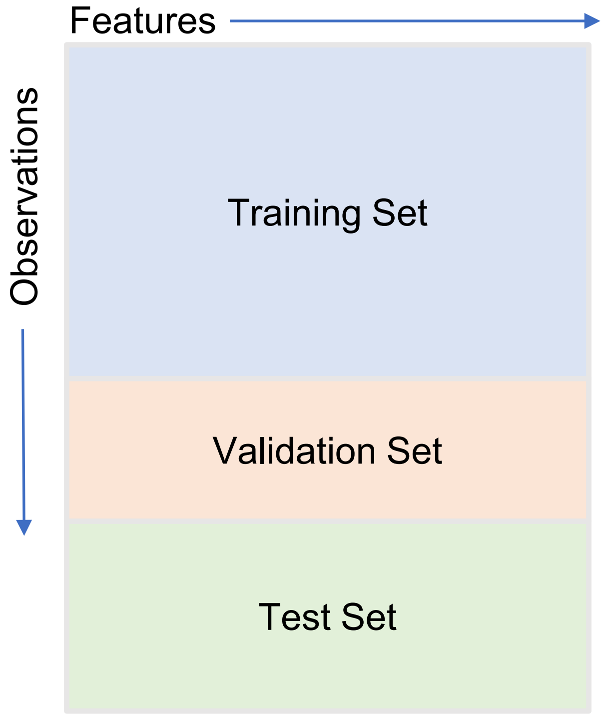

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- Training your model
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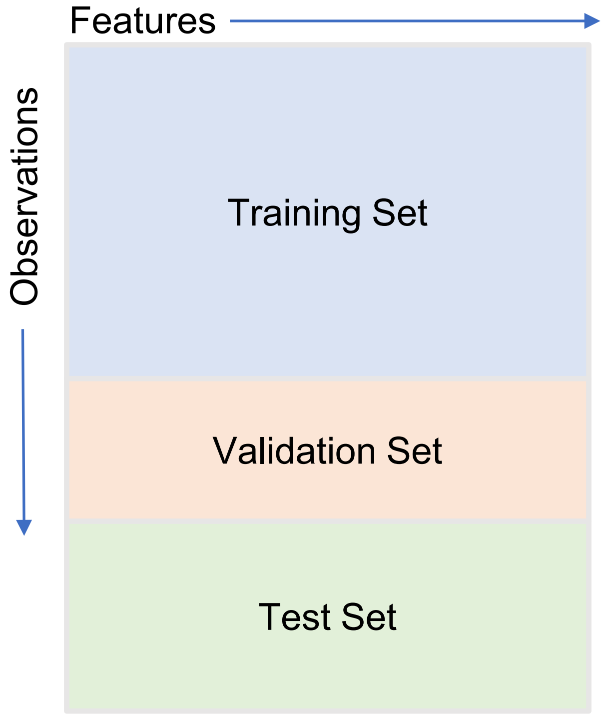
- Evaluation
  - Many metrics and context-dependent
  - Ideally, what we use to train should be our final evaluation criteria



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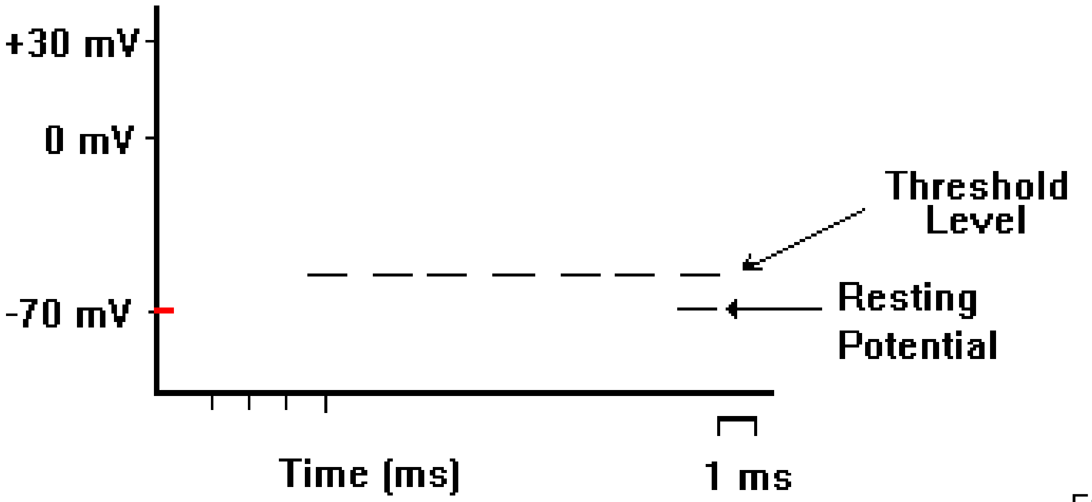
- These action potentials move along axons and activate synaptic connections with other neurons

Neurons



Eric Chudler

The Perceptron

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  - Keep this process in mind! It is central to how neural networks work!

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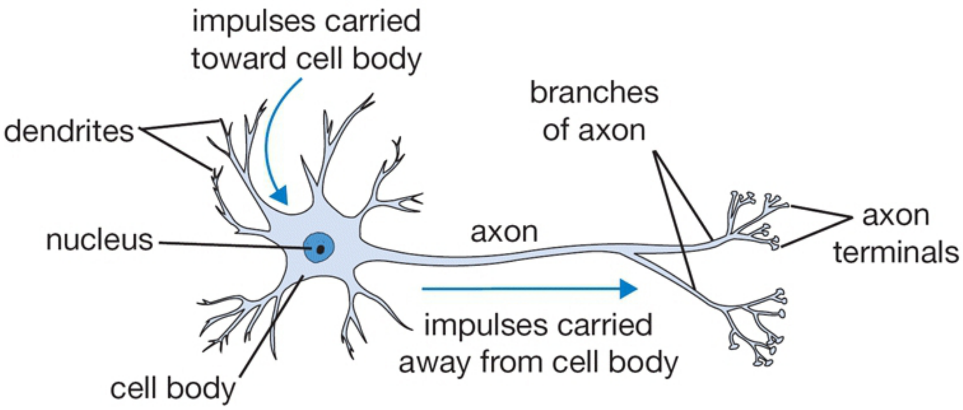
- Rosenblatt's (a psychologist's) attempt at trying to mathematically model a neuron
- The perceptron takes in a set of inputs, multiplies them by a weight, and then aggregates
  - Keep this process in mind! It is central to how neural networks work!
- Perceptron "fires" if the aggregate reaches some threshold
  - Very much like the all-or-nothing response of a neuron

The Perceptron



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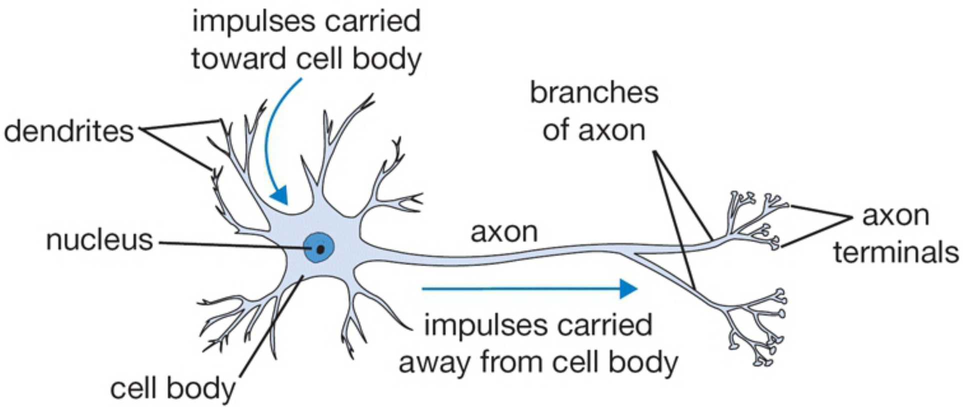
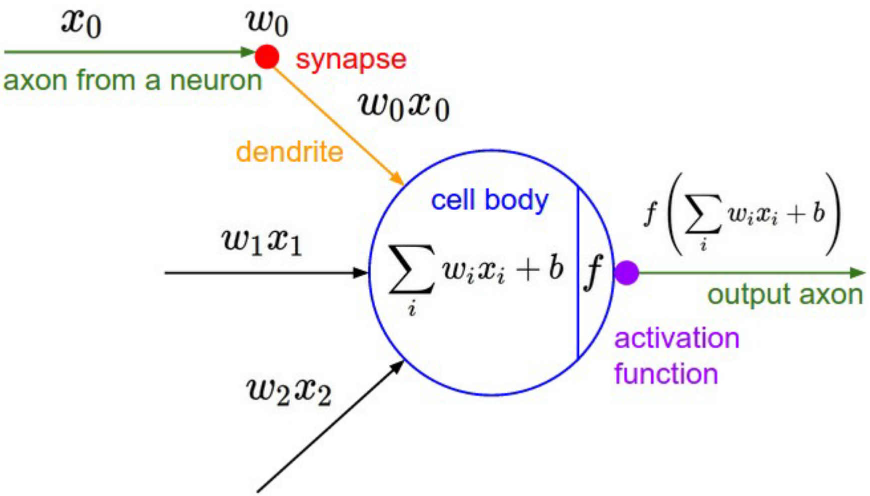
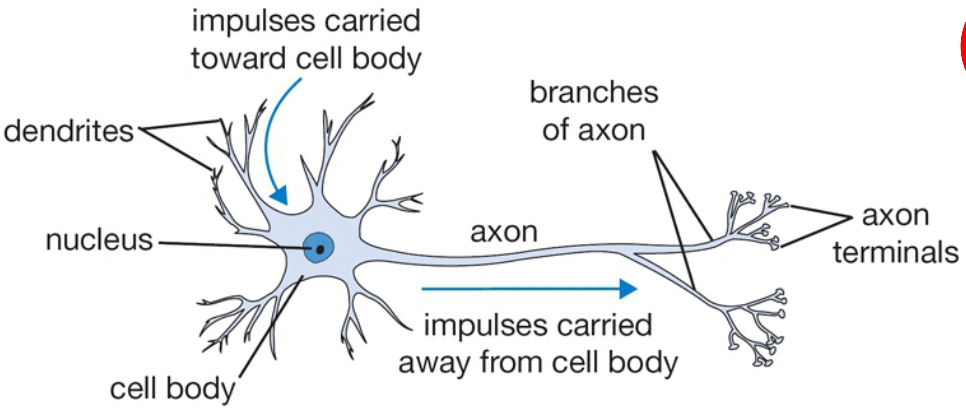
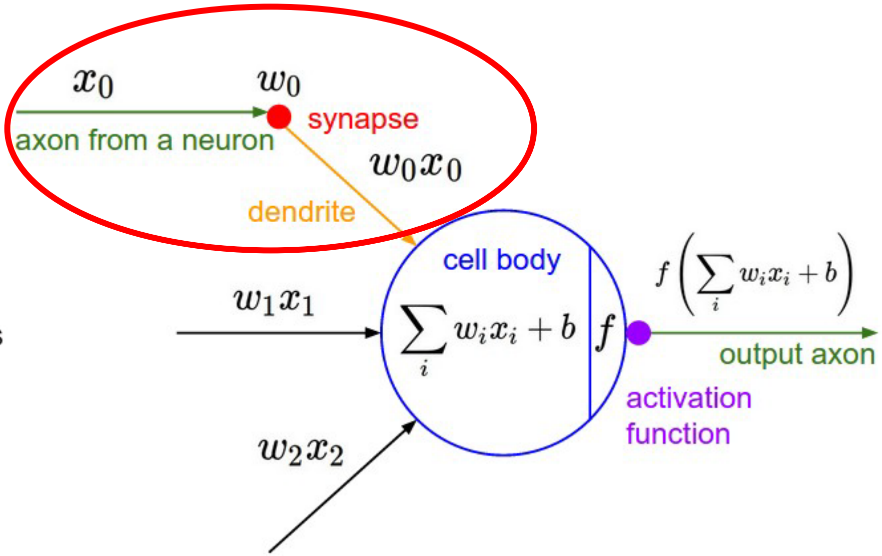




Stanford CS231n

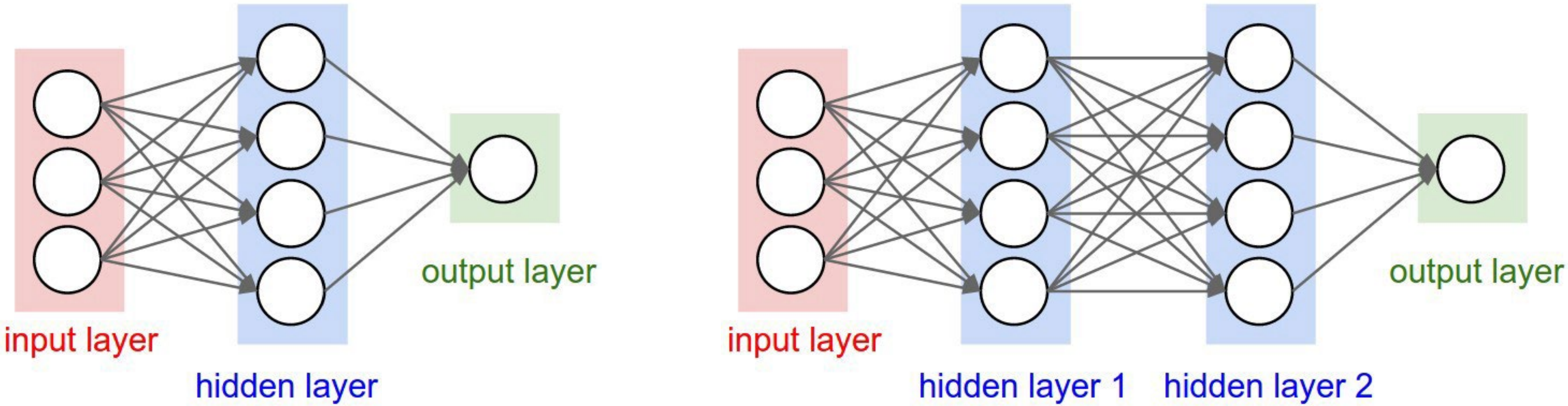
The Perceptron





Stanford CS231n

Multi-Layer Networks



Modified from Stanford CS231n

Taking A Step Back

- Neural networks are just that – a network of neurons
  - Neurons are represented as perceptrons
  - Sometimes also called artificial neural networks (ANNs)
  - Sometimes also called multi-layer perceptrons (MLPs; though MLPs are often vanilla architectures)
  - Neurons are also called “units”

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- What is deep learning?
  - Generally, neural networks with a large number of hidden layers! (thus, “deep”)

Training Multi-Layer Networks

- Forward propagation
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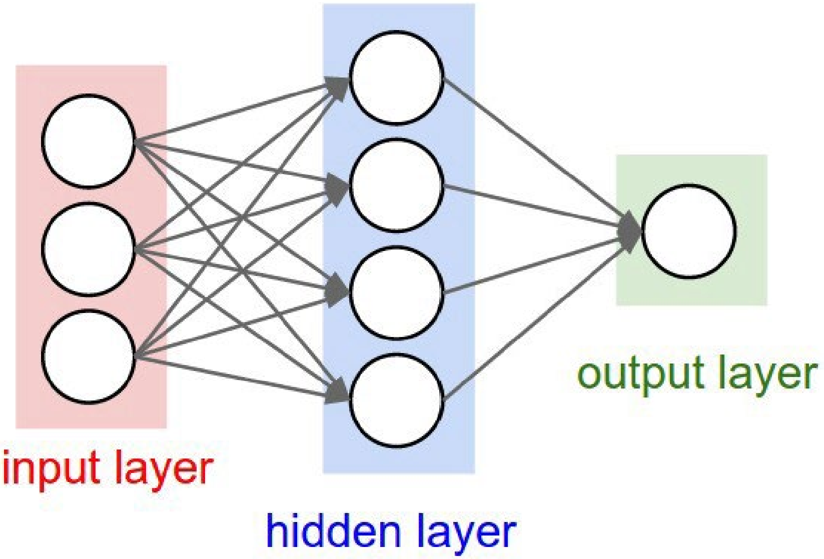
  - Determine how far off from y we are with ŷ
- Backpropagation (Backward propagation)
  - Update weights/biases based on the error

Training Multi-Layer Networks



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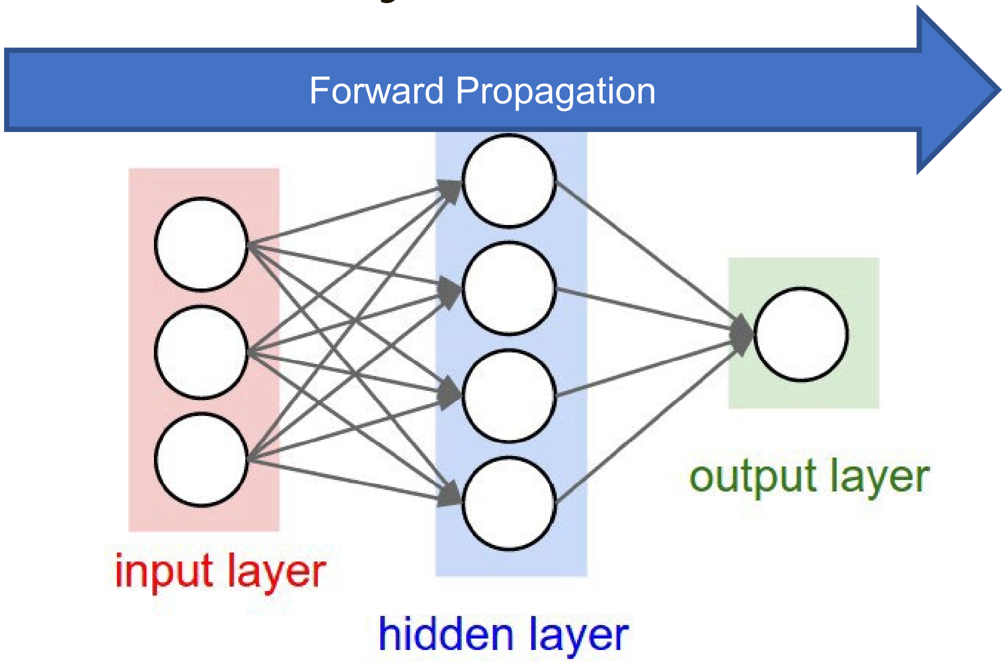

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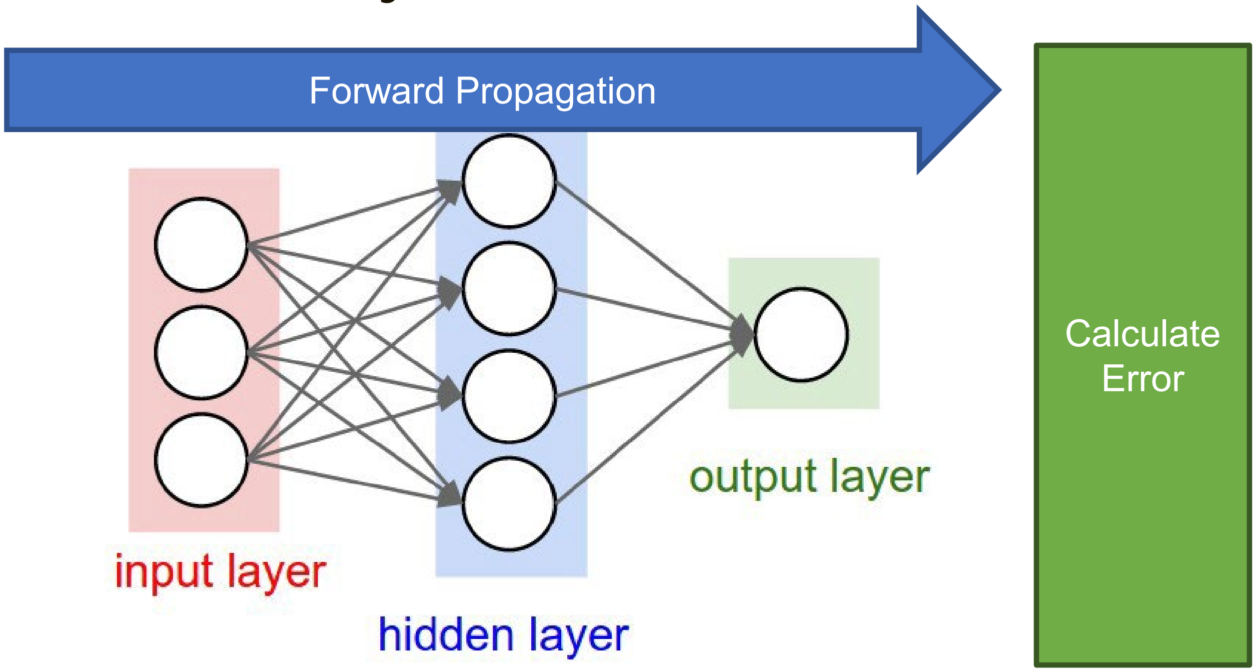

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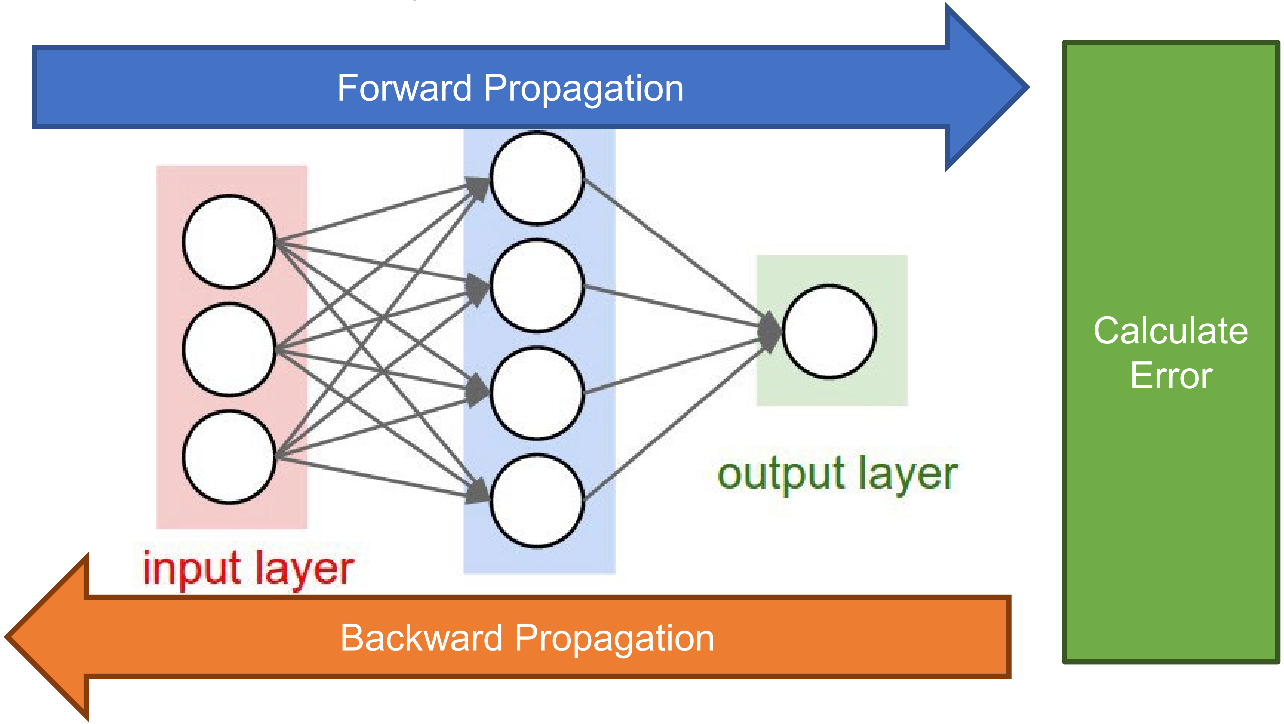

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- General idea:
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  - Attention: allows a model to pay “attention” to different parts of a sequence at once

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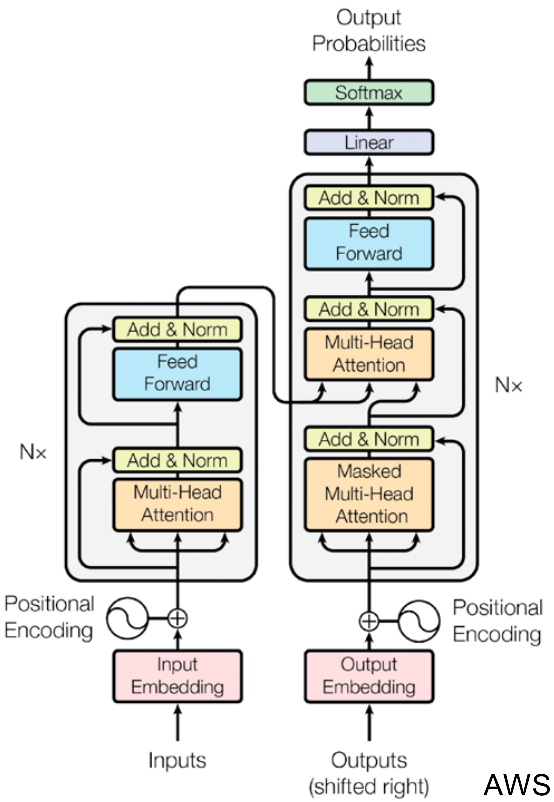
- General idea:
  - A neural network that learns context by tracking relationships in sequential data
  - Traditional AI frameworks often rely on encoder/decoder relationships
  - Attention: allows a model to pay “attention” to different parts of a sequence at once
- What most of the examples will leverage
  - Keep in mind the basics of ML and deep learning!

Transformers



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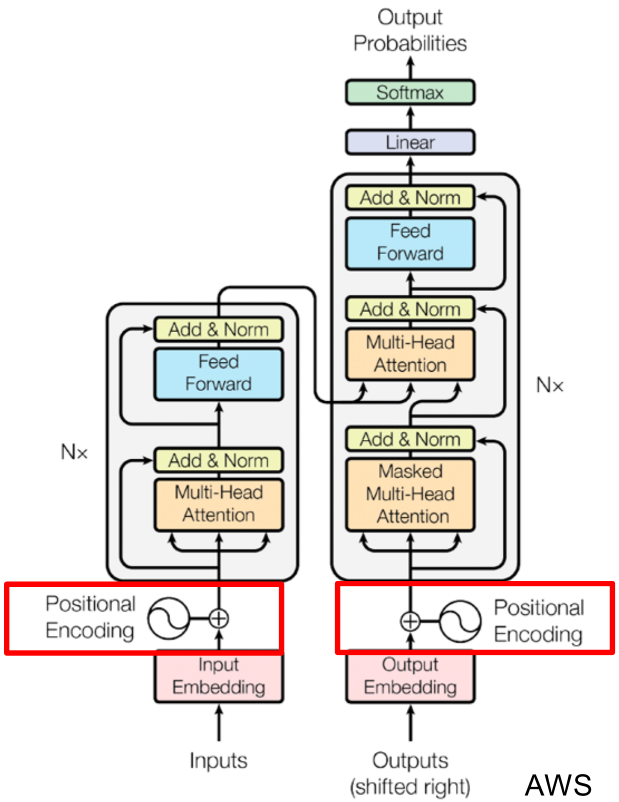

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Transformers

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What Is a Transformer Model?

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Transformer: A Novel Neural Network Architecture for Language Understanding

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