

MachineLearnAthon - Microlecture

Types of Classification Models

Classification

15.10.2024

Recap previous microlecture Classification-1

- Types of Machine Learning Tasks
- Stages of Supervised Machine Learning Pipeline
- Proper Machine Learning Modeling

Learning outcomes of today

After successfully completing this micro-lecture, you are able to....

- Identify the different types of machine learning models.
- Understand the distinction of Deep Learning from Machine Learning.

Agenda for today

- Defining a supervised ML task
- Linear Models
- Non-Linear Models
 - Deep Neural Networks

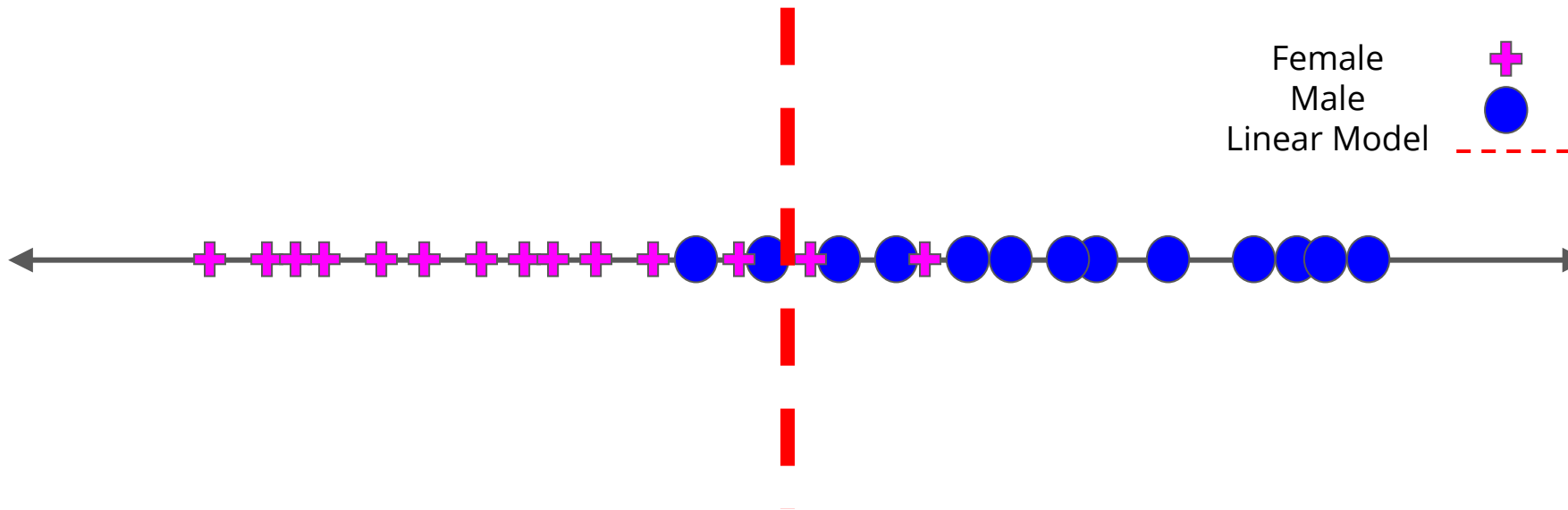
What is ML Model?

NB! Notations can vary across authors

- \mathbf{X} - input space (set of all possible instances)
- Y - output space (all possible labels / target)
- $f : \mathbf{X} \rightarrow Y$ - **any such function is a classifier/regressor**
- $\mathbf{x} \in \mathbf{X}$ - instance
- $y \in Y$ - actual / true label/target of an instance \mathbf{x}
- $f(\mathbf{x}) = \hat{y}$ - predicted label/target of instance \mathbf{x}

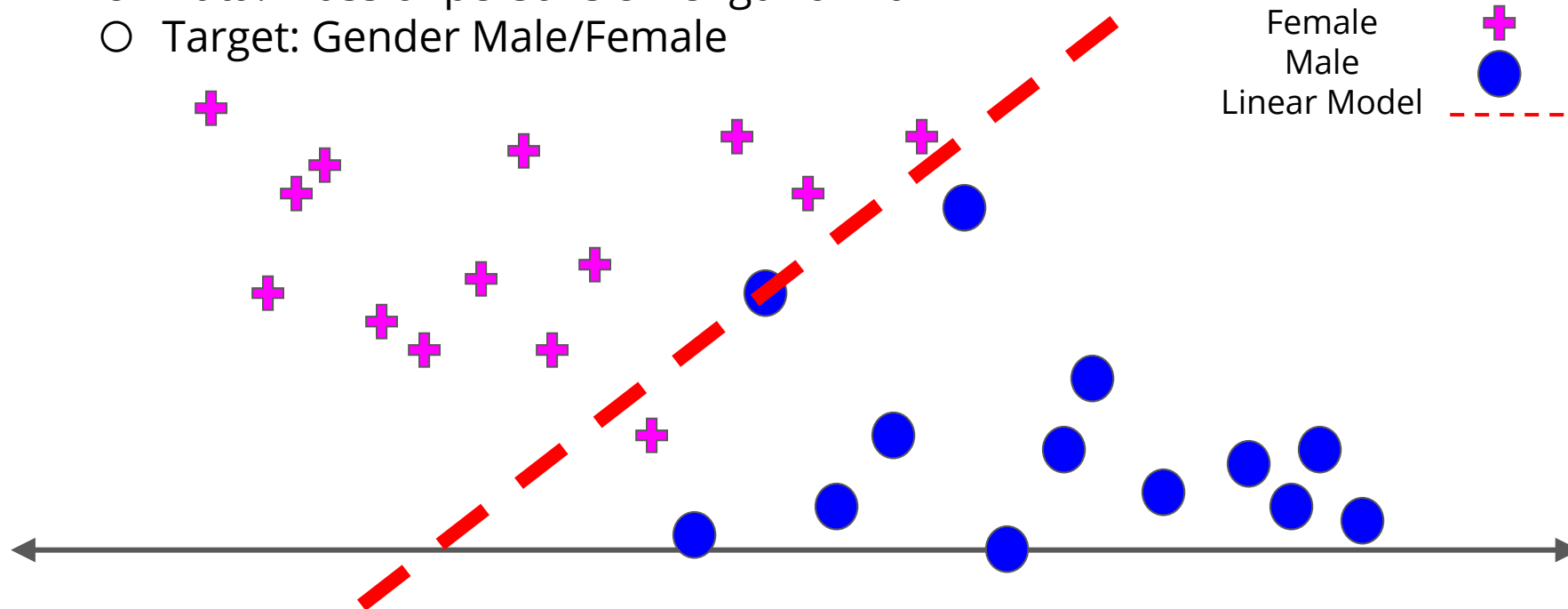
Linear Models in 1D

- Linear Models: $f(\mathbf{x}) = \text{Linear Function of } \mathbf{x}$
- Suppose:
 - Data: Mass of persons
 - Target: Gender Male/Female



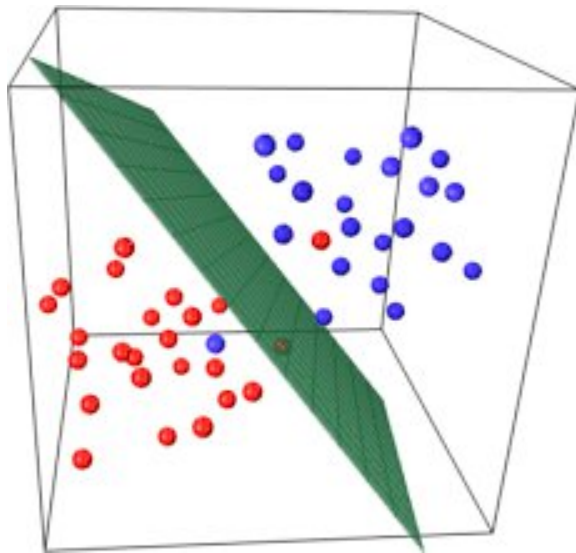
Linear Models in 2D

- Linear Models: $f(x)$ = Linear Function of x
- Suppose:
 - Data: Mass of persons & Length of Hair
 - Target: Gender Male/Female



Linear Models in 3D

- Linear Models: $f(x)$ = Linear Function of x
- Suppose:
 - Data: Mass of persons & Length of Hair & Height
 - Target: Gender Male/Female

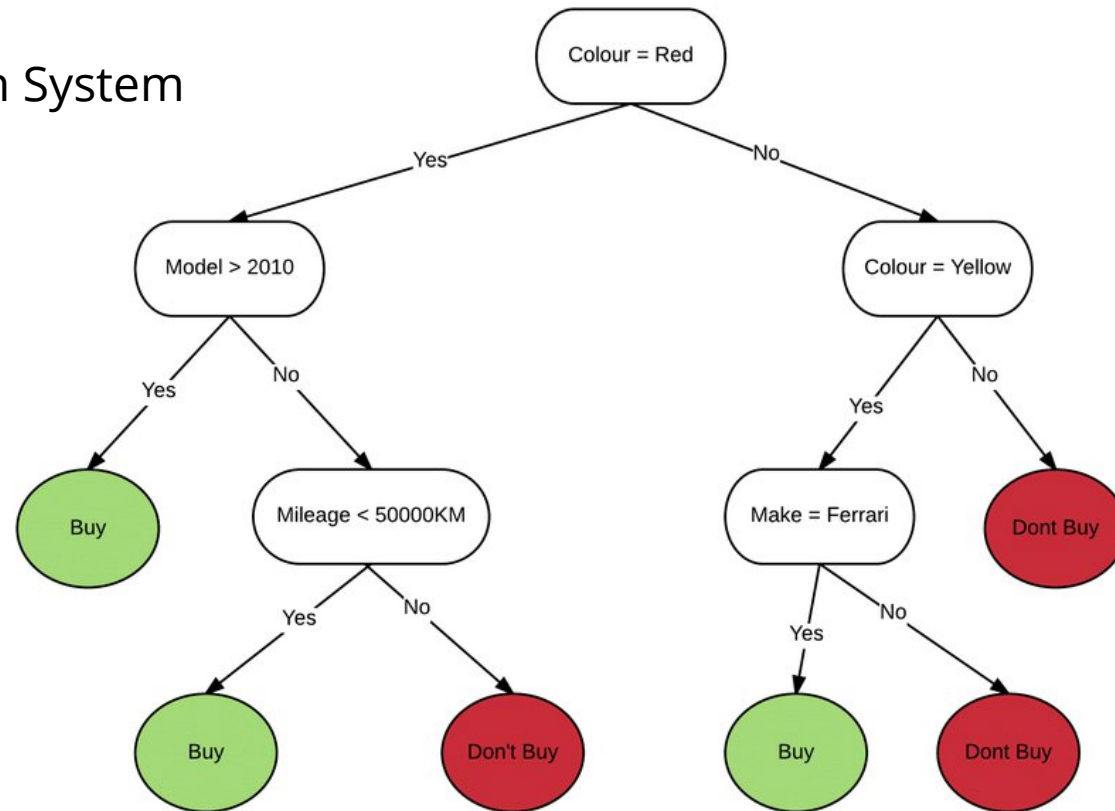


- Finds the best fitting hyper-plane in n-dimensional space
- Examples:
 - SVM: find best linear function maximizing margins with support vector instances
 - Logistic Regression
 - Perceptron

Bishop, C. M., & Nasrabadi, N. M. (2006). *Pattern recognition and machine learning* (Vol. 4, No. 4, p. 738). New York: springer.

Non-Linear Models

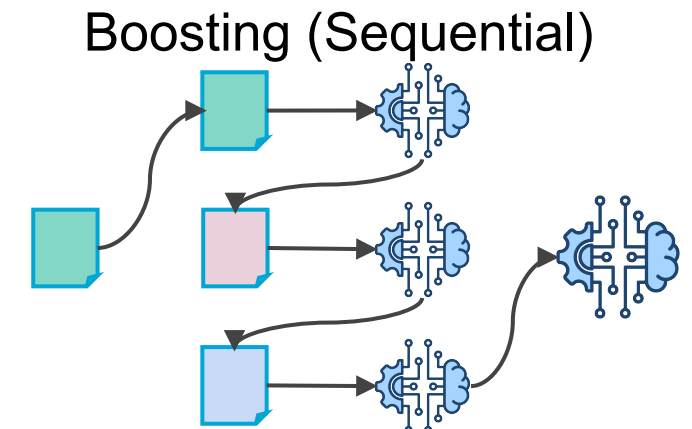
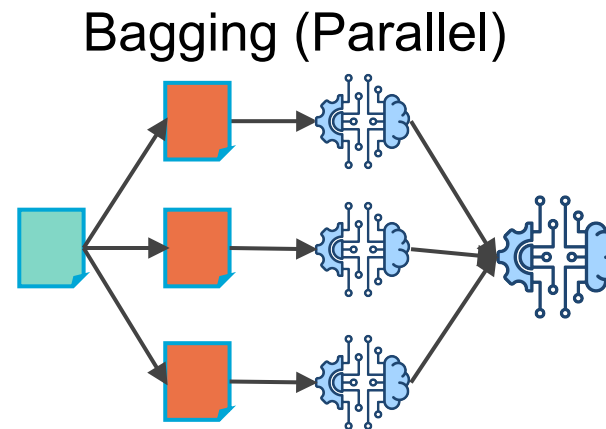
- Decision Trees
 - Car Recommendation System
- Examples:
 - ID3
 - C4.5
 - C5.0
 - CART



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Non-Linear Models

- Ensemble Models
- **Majority Voting:** Weighted average of predictions of different models.
- **Bagging:** Average of multiple versions of the same model trained on random splits of the training data with replacement.
- **Boosting:** Sequential Learning from the same model where each model tries to fix the errors made by the previous models.
- Examples:
 - Random Forest
 - Xgboost
 - Gradient Boosting



Non-Linear Models

- Bayesian Machine Learning: Domain knowledge can be explicitly entered into learning in the form of the prior

- Based on Bayes Rule:
$$P(M | D) = \frac{P(D | M)P(M)}{P(D)}$$

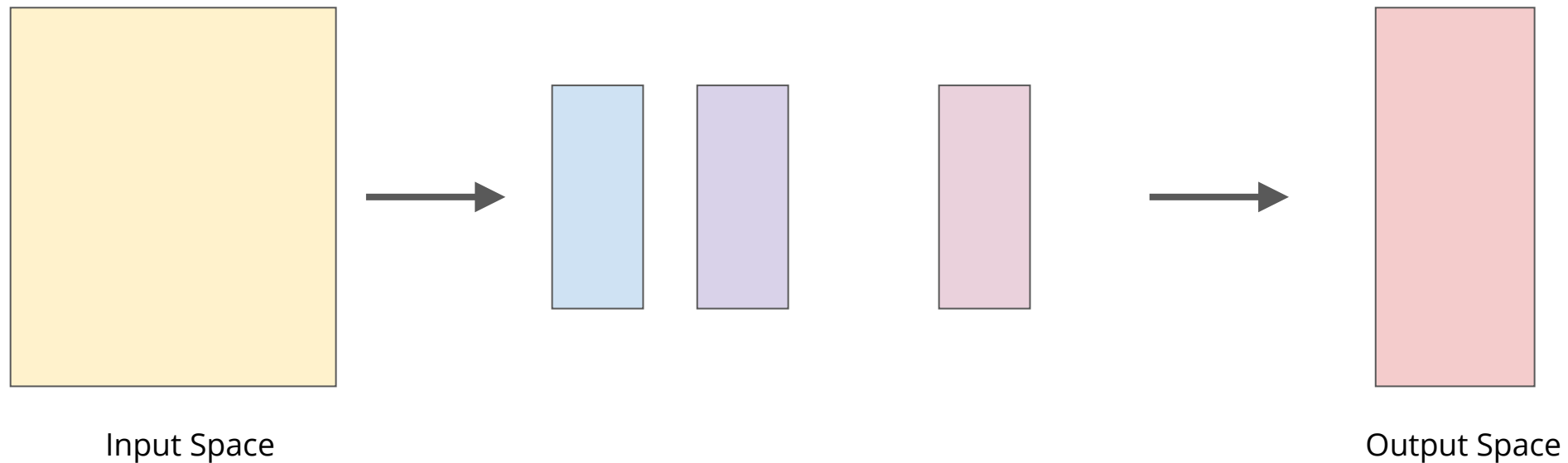
- **P(M)**: How probable would we consider model M before seeing any data D (our inductive bias!)
- **P(D | M)**: model likelihood
- **P(D)**: normalizer, ensures P(M | D) adds up to 1
- **P(M | D)**: How probable is model M after seeing the data

- Generate Predictions:
$$P(Y | D) = \sum_M P(Y | M)P(M | D)$$

- Examples:
 - Gaussian Processes
 - Bayesian Ridge

Non-Linear Models

- Artificial Neural Network Methods that learn multiple levels of representation to model the relation between input data and the output = **Automatic Feature Selection+Extraction+Modeling**.
- ANN is a collection of simple trainable mathematical units that collaborate to compute a complicated function

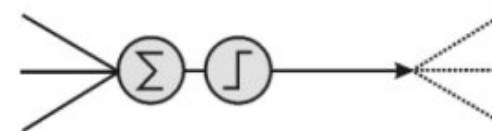
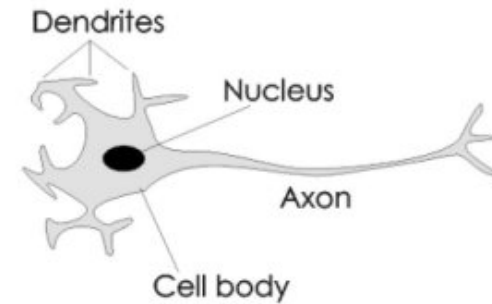
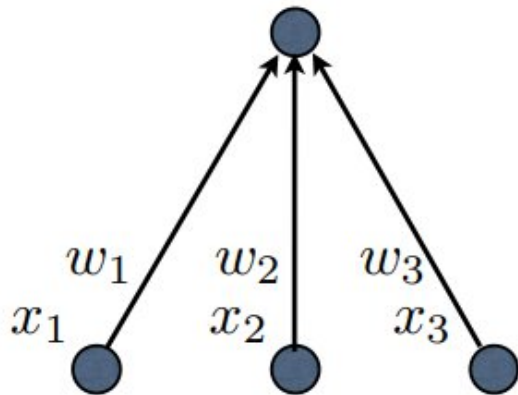


Non-Linear Models

- Linear part = sum [weights (Ws) * inputs (Xs)]
- Non-Linear part = Activation Function = F ()

$$y_i = F \left(\sum_i w_i x_i \right)$$

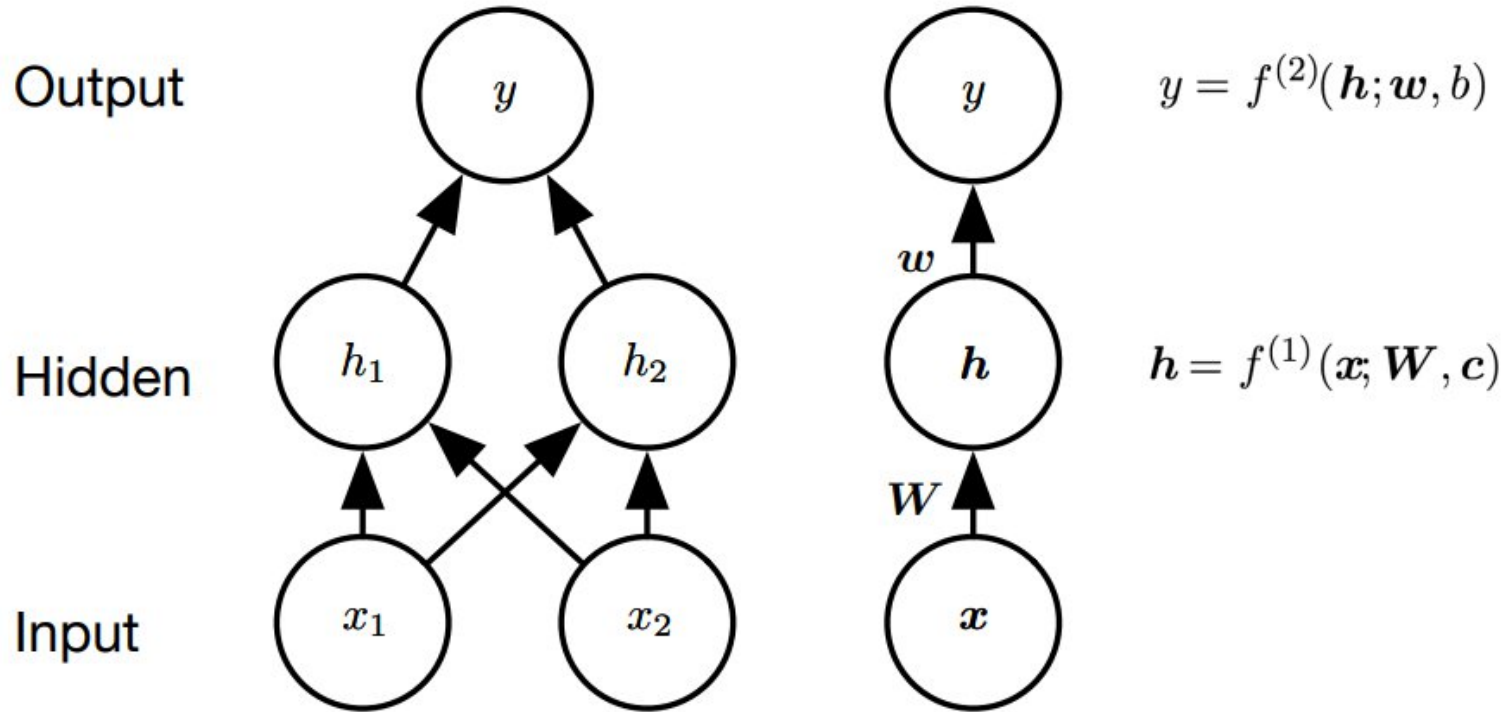
$$F(x) = \frac{1}{1 + \exp(-x)}$$



Norman, J. M. McCulloch & pits publish the first mathematical model of a neural network.

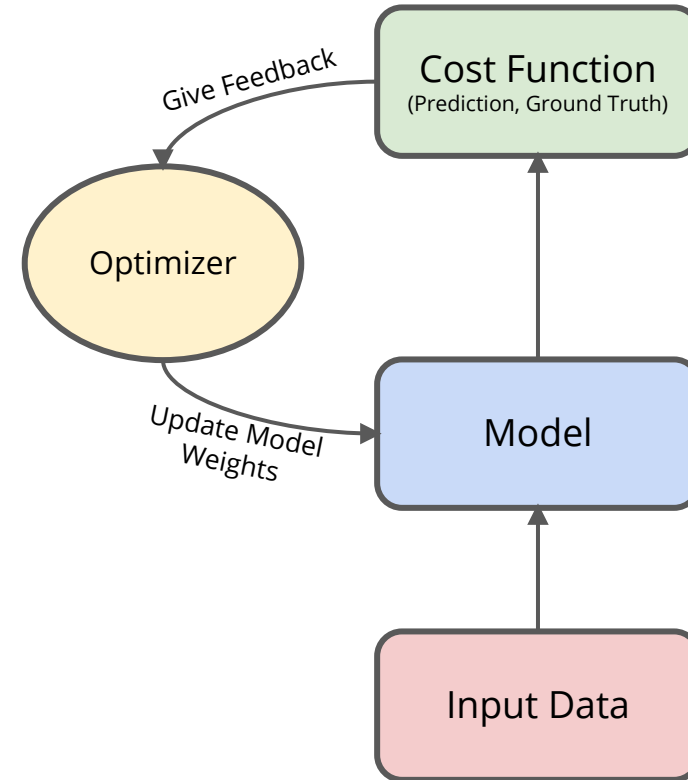
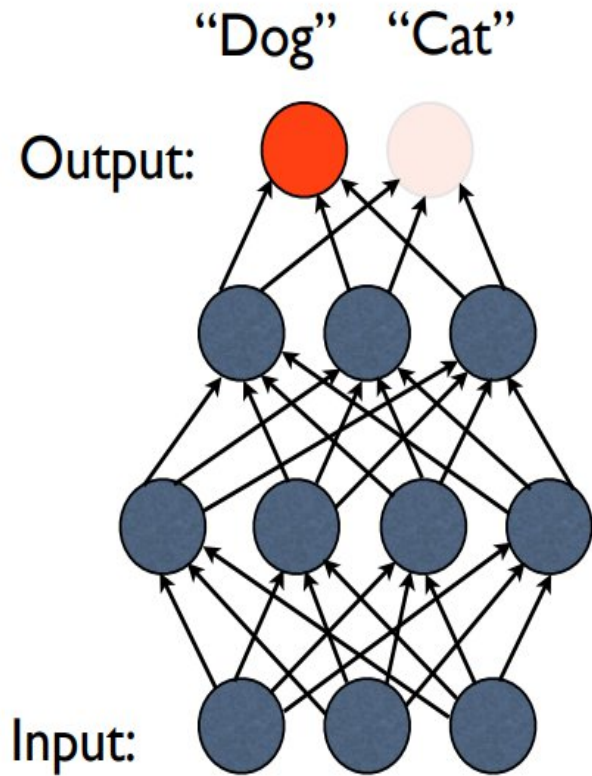


Non-Linear Models



$$f(\mathbf{x}; \mathbf{W}, \mathbf{c}, \mathbf{w}, b) = f^{(2)}(f^{(1)}(\mathbf{x}))$$

Non-Linear Models

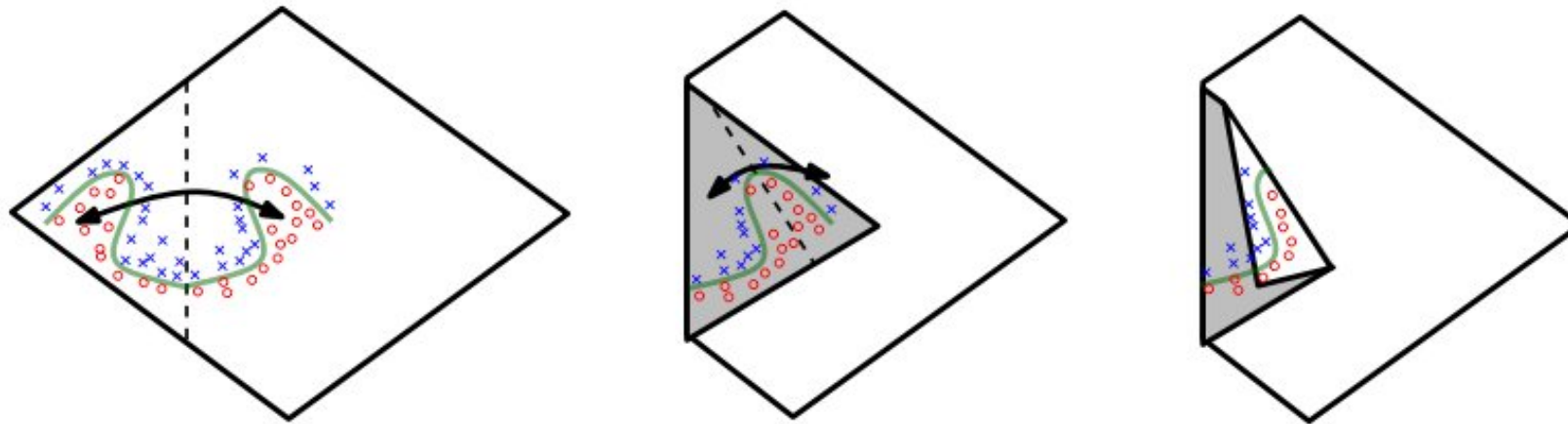


Non-Linear Models

Universal approximation Theorem [\[Wikipedia\]](#):

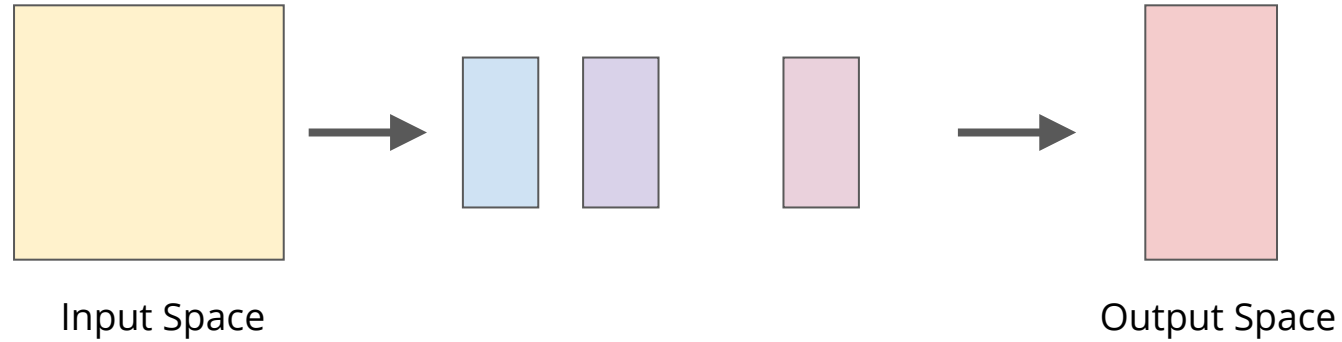
A feed-forward network with a **single hidden layer** containing a finite number of neurons can approximate continuous functions, under mild assumptions of the activation functions.

So, Why DEEP?

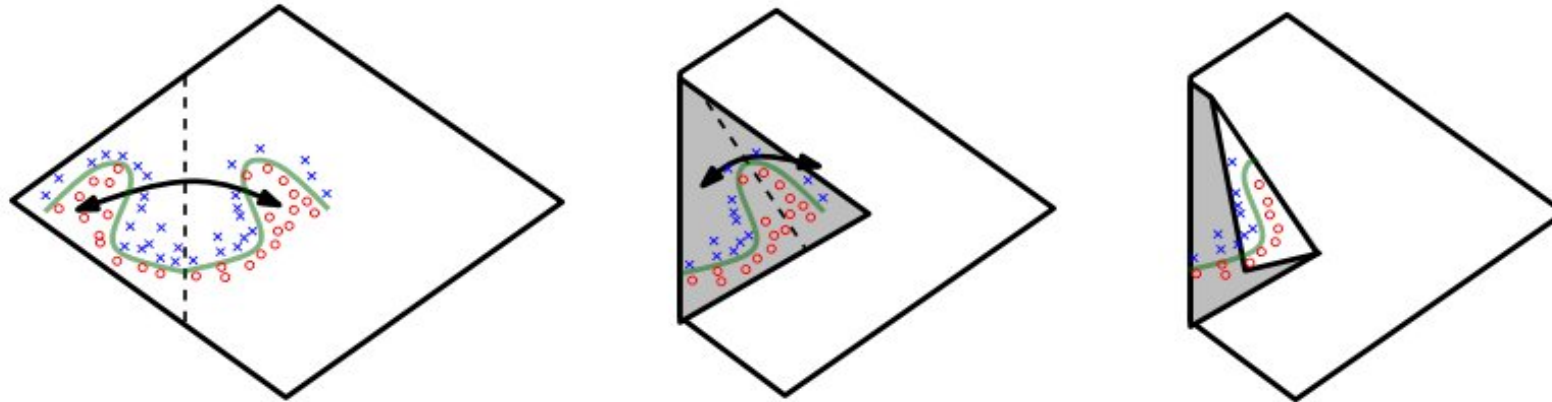


Heaton, J. (2018). Ian goodfellow, yoshua bengio, and aaron courville: Deep learning: The mit press, 2016, 800 pp, isbn: 0262035618. *Genetic programming and evolvable machines*, 19(1), 305-307.

Non-Linear Models

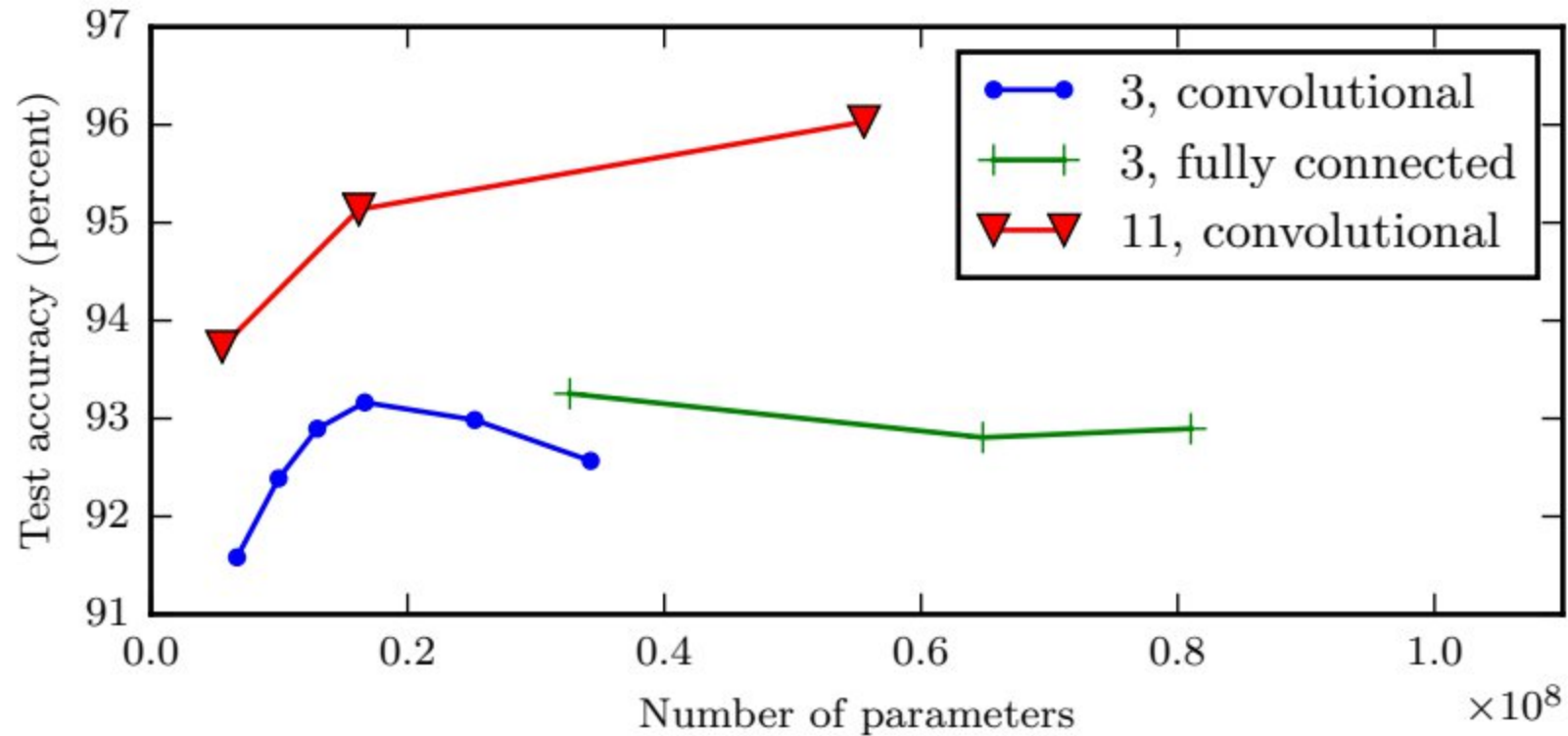


So, Why DEEP?



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Non-Linear Models



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Deep Learning: When to use ML? | When to use DL?

Machine Learning



- Relatively Small Volume of Data.
- Domain experience or knowledge how to do feature engineering.
- Better Interpretability / Explainability
- Faster execution

Deep Learning

- Large Volume of Data. Otherwise, highly susceptible to overfitting.
- Difficult to do feature engineering
- Complex Relation between inputs and outputs
 - Computer Vision Tasks
 - NLP Tasks

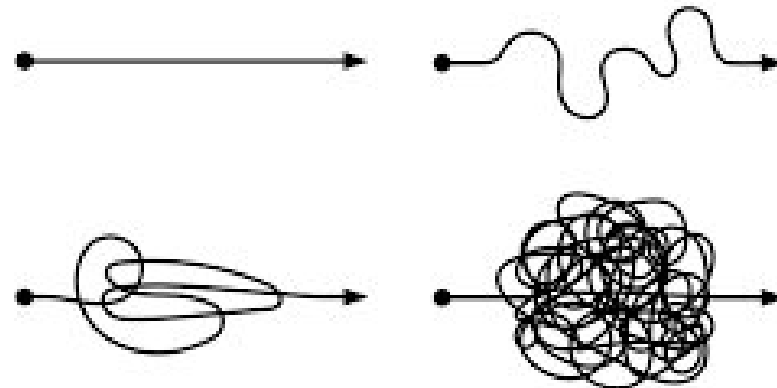


Types of Deep Learning Architectures

- Feed Forward Neural Networks
 - Suitable for tabular data
- Convolutional Neural Networks
 - Suitable for computer vision tasks
 - Image classification
 - Image Segmentation
- Recurrent Neural Networks
 - Suitable for sequential data
 - Time-Series Data
 - Machine Translation
- Attention-based Neural Networks (Transformers)
 - Boosting performance of NLP tasks
- Graph Neural Networks
 - Suitable for graph data structures (E.g. Traffic Flow Networks)

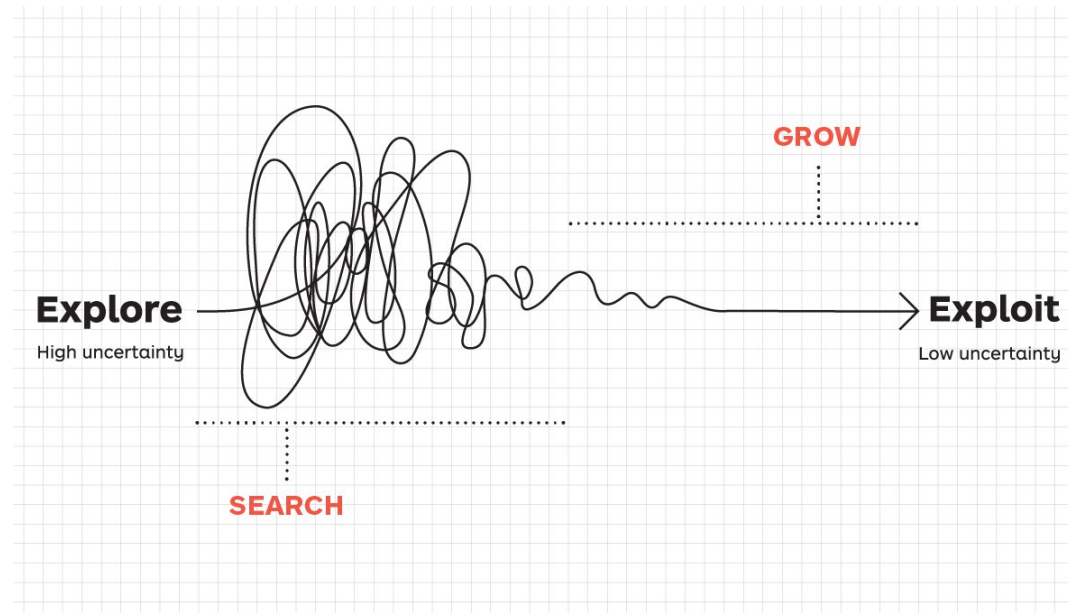
Linear Vs Non-Linear Models

- Simpler models are more able to generalize well on new data.
- If linear models have good performance, Why to go for complex models?!
- Rule of Thumb:
 - If SVM = 98%,
 - If Deep Neural Network = 98.2%
 - **Use the SVM**



How to choose your model?

- Start with a single model out of each family. **(Explore)**
- Get recommendations from AutoML tools. **(Explore)**
- Start focusing and tuning on the best performing families. **(Exploit)**



Recap this lecture

After successfully completing this lecture, you are able to....

- Identify the different types of machine learning models.
- Understand the distinction of Deep Learning from Machine Learning.



Outlook: What will the tutorial be about?

- we'll explore how different classification models—from linear ones like Logistic Regression to non-linear ones like Decision Trees—learn to separate data points.
- You'll see how linear models draw straight boundary lines (hyper-planes),
- while non-linear models create more complex, flexible boundaries.
- By the end, you'll understand the strengths of each approach and know when to use linear vs. non-linear classifiers to solve your classification problems!

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