



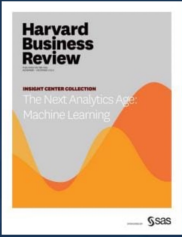
Machine Learning

Prof. Adil Khan

Who Am I?

- Adil Khan
- Professor in Innopolis University (IU), Russia
- Expertise: Machine Learning, Deep Learning
- Head of Machine Learning Lab at IU
- Director of the Institute of AI at IU





WHITE PAPER

The Next Analytics Age: Machine Learning

A Harvard Business Review Insight Center Collection

The top most emerging trend in Computing and Information Technology

Machine Learning

Large Scale Academic Research

One of the largest number of start-ups

Has changed business in almost every industry

Active Recruitment of ML Engineers

To Effectively use Machine Learning

- One must understand:
 - What is machine learning?
 - The available machine learning methods at your disposal
 - Characteristics of those methods
 - Circumstances under which a method would be most effective
 - Their theoretical underpinnings

Course Objectives

1. Teach you how to **implement** important machine learning methods and **apply** them for solving real-world problems
2. Provide you with both the **theoretical** and **practical** knowledge of machine learning methods
3. **Supervised Methods** (Linear, Polynomial and Logistic Regression, Decision Trees, ANNs, CNNs, etc.)
4. **Unsupervised Methods** (k-means, kmeans++, Hierarchical Clustering, etc.)
5. **Working with ML Models** (Regularization, Dimensionality Reduction, Ensemble Learning)

Prerequisites

- Basics of
 - Python programming
 - Linear algebra
 - Calculus
 - Probability

Plan for Today

- Foundations of Machine Learning
 - What does it mean for machines to learn?
 - ❖ Task, Experience and Performance
 - Regression
 - Classification
 - Train and Test Error
 - Overfitting and Underfitting
 - Bias-Variance Tradeoff

What Does it Mean for a Machine to Learn?

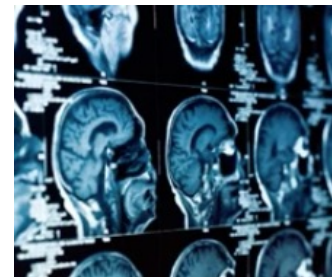
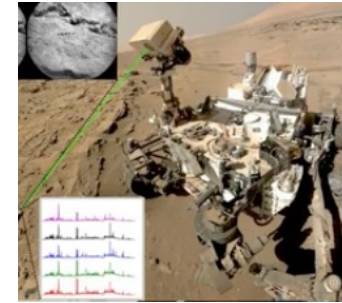
- If you downloaded a copy of Wikipedia, has your computer really learned something?
- Did it make your computer any smarter?

What is Machine Learning?

Machine Learning

- Computer programs that improve their performance at some task through experience

Usual Examples of **Tasks** where ML is being Used



Experience

Targets: For example, malware or Not

Data

$$D = \{(x_i, y_i)\}_{i=1}^N$$

Number of
available examples

Predictors: For example, execution behavior of a program

$$x \in \mathbb{R}^d$$

Examples of Predictors and Response

| Input (x) | Output (y) | Application |
|-------------------|------------------------|---------------------|
| Home Features | Price | Real Estate |
| Ad, User info | Click ad? (0/1) | Online Advertising |
| Image | Object (1, ..., 1000) | Photo Tagging |
| Audio | Text Transcript | Speech Recognition |
| English | Chinese | Machine Translation |
| Image, Radar Info | Position of other cars | Autonomous Driving |

Performance

- Needs to be defined according to the given task
- For example: the ratio of correctly identified malwares

Goal of Learning

- Learning or inferring a “functional” relationship between predictors and target


$$D = \{(\mathbf{x}_i, y_i)\}_{i=1}^N$$

$$\mathbf{x} \in \mathbb{R}^d$$

$$y = f(\mathbf{x})$$

$$\hat{f} \approx f \quad \textit{Goal of learning}$$

Putting It All Together (1)

$$D = \{(\mathbf{x}_i, y_i) \in X \times Y : 1 \leq i \leq N\}$$


Learning
Algorithm



$$\hat{f}: X \rightarrow Y$$

Putting It All Together (2)

$$D = \{(\mathbf{x}_i, y_i) \in X \times Y : 1 \leq i \leq N\}$$

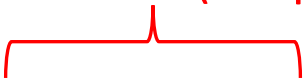
The diagram illustrates the supervised learning process. A blue arrow points from the data set D to a gray box labeled "Supervised Learning Algorithm". Another blue arrow points from the gray box to the learned function $\hat{f}: X \rightarrow Y$.

“Supervised”
Learning
Algorithm

$$\hat{f}: X \rightarrow Y$$

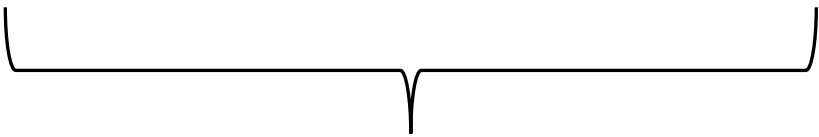
Example: Dataset 1

Dependent Variable
(Response)



| Country | Age | Salary | Purchased |
|---------|-----|--------|-----------|
| France | 44 | 72000 | No |
| Spain | 27 | 48000 | Yes |
| Germany | 30 | 54000 | No |
| Spain | 38 | 61000 | No |
| Germany | 40 | | Yes |
| France | 35 | 58000 | Yes |
| Spain | | 52000 | No |
| France | 48 | 79000 | Yes |
| Germany | 50 | 83000 | No |
| France | 37 | 67000 | Yes |

Independent Variables
(Predictors)



Exampe: Dataset 2

Dependent Variable (Response)

| YearsExperience | Salary |
|-----------------|--------|
| 1.1 | 39343 |
| 1.3 | 46205 |
| 1.5 | 37731 |
| 2 | 43525 |
| 2.2 | 39891 |
| 2.9 | 56642 |
| 3 | 60150 |
| 3.2 | 54445 |
| 3.2 | 64445 |

Independent Variables (Predictors)

Compare the Response Variable

| Country | Age | Salary | Purchased |
|---------|-----|--------|-----------|
| France | 44 | 72000 | No |
| Spain | 27 | 48000 | Yes |
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$$y = \{c_1, c_2, \dots, c_k\}$$

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$$y \in \mathbb{R}$$

Classification and Regression

| Country | Age | Salary | Purchased |
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Classification

| YearsExperience | Salary |
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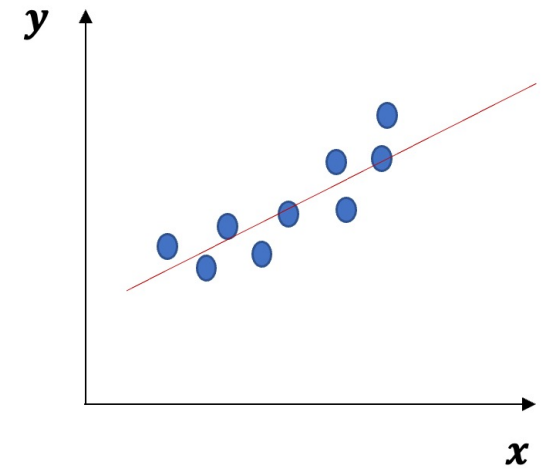
Regression

Estimating f

$$y = f(x; \text{parameters})$$


$$y = f(x; \mathbf{w})$$

$$y = f(x; w_0, w_1) = w_0 + w_1 x$$



$$\underbrace{y = w_0 + w_1 x}_f$$

Assessing the Quality of Learning

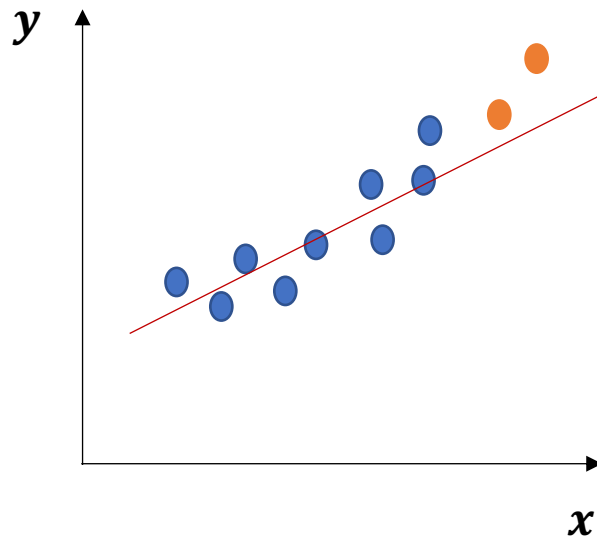
- Let $T_r = \{x_i, y_i\}_{i=1}^N$ be the training data we used to estimate $\hat{f}(x)$.
- To assess the quality of estimate, we can compute

$$\text{MSE}_{\text{Tr}} = \text{Ave}_{i \in \text{Tr}} [y_i - \hat{f}(x_i)]^2$$

- But this is **not a reliable** approach

What can go wrong?

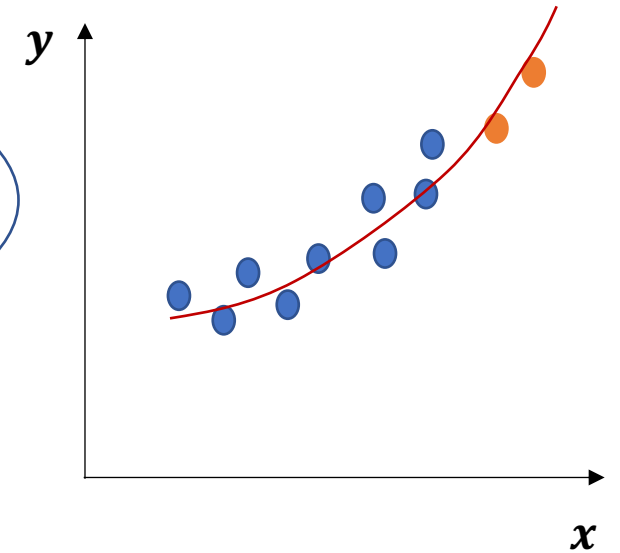
- Training Data
- Unseen Test Data



$$\frac{y = w_0 + w_1 x}{f}$$

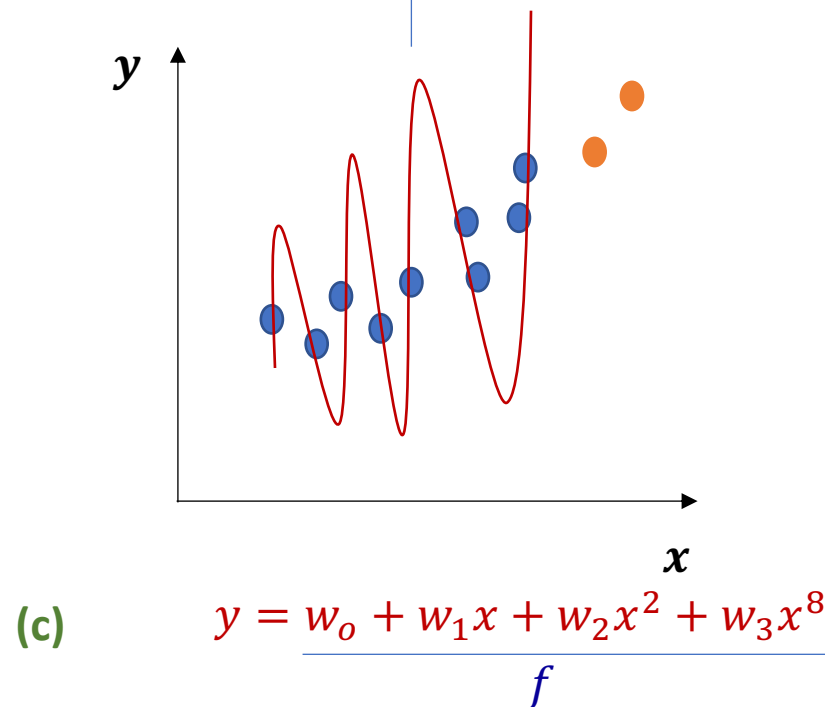
(a)

Smallest Training Error
Most Complex
Largest Test Error



$$\frac{y = w_0 + w_1 x + w_2 x^2}{f}$$

(b)

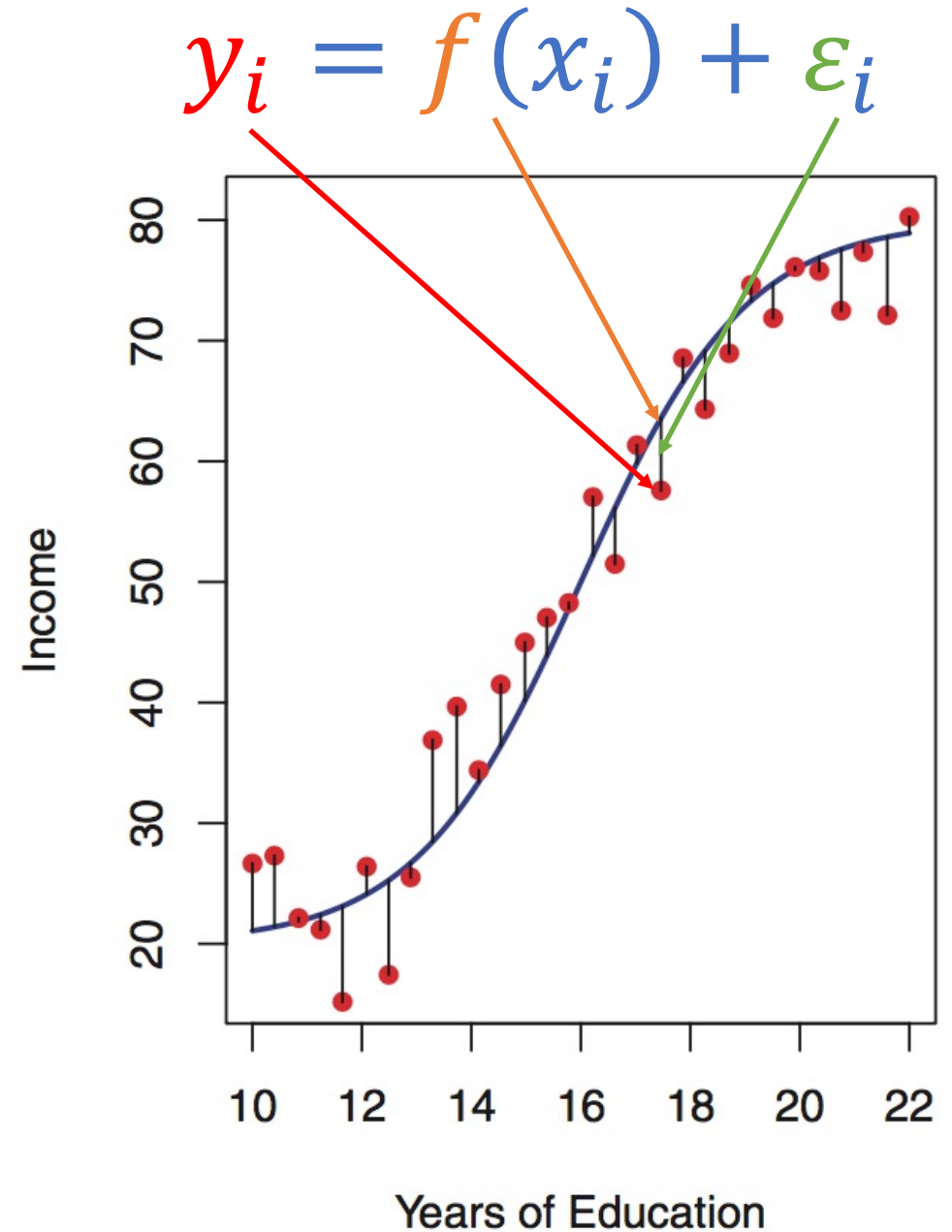


(c)

$$\frac{y = w_0 + w_1 x + w_2 x^2 + w_3 x^8}{f}$$

Why Does it Happen?

- Data is inherently **noisy**




Thus Use Separate Test Data

- Thus, if possible, we should try to use the test data $T_e = \{x_i, y_i\}_{i=1}^M$


$$\text{MSE}_{T_e} = \text{Ave}_{i \in T_e} [y_i - \hat{f}(x_i)]^2$$

Putting It All Together (3)

Training Phase

$$Tr = \{(\mathbf{x}_i, y_i) \in X \times Y : 1 \leq i \leq N\}$$


“Supervised”
Learning
Algorithm

$$\hat{f}: X \rightarrow Y$$


Evaluation Phase

$$Te = \{(\mathbf{x}_i, y_i) \in X \times Y : 1 \leq i \leq n\}$$


Learned
Model

Important Take-away (1)

Goal of Machine Learning

Learn how do features relate to labels?

$$f: x \rightarrow y$$

$$D = \{(x_i, y_i)\}_{i=1}^N$$

Features

Labels

For example: risk score of the patient

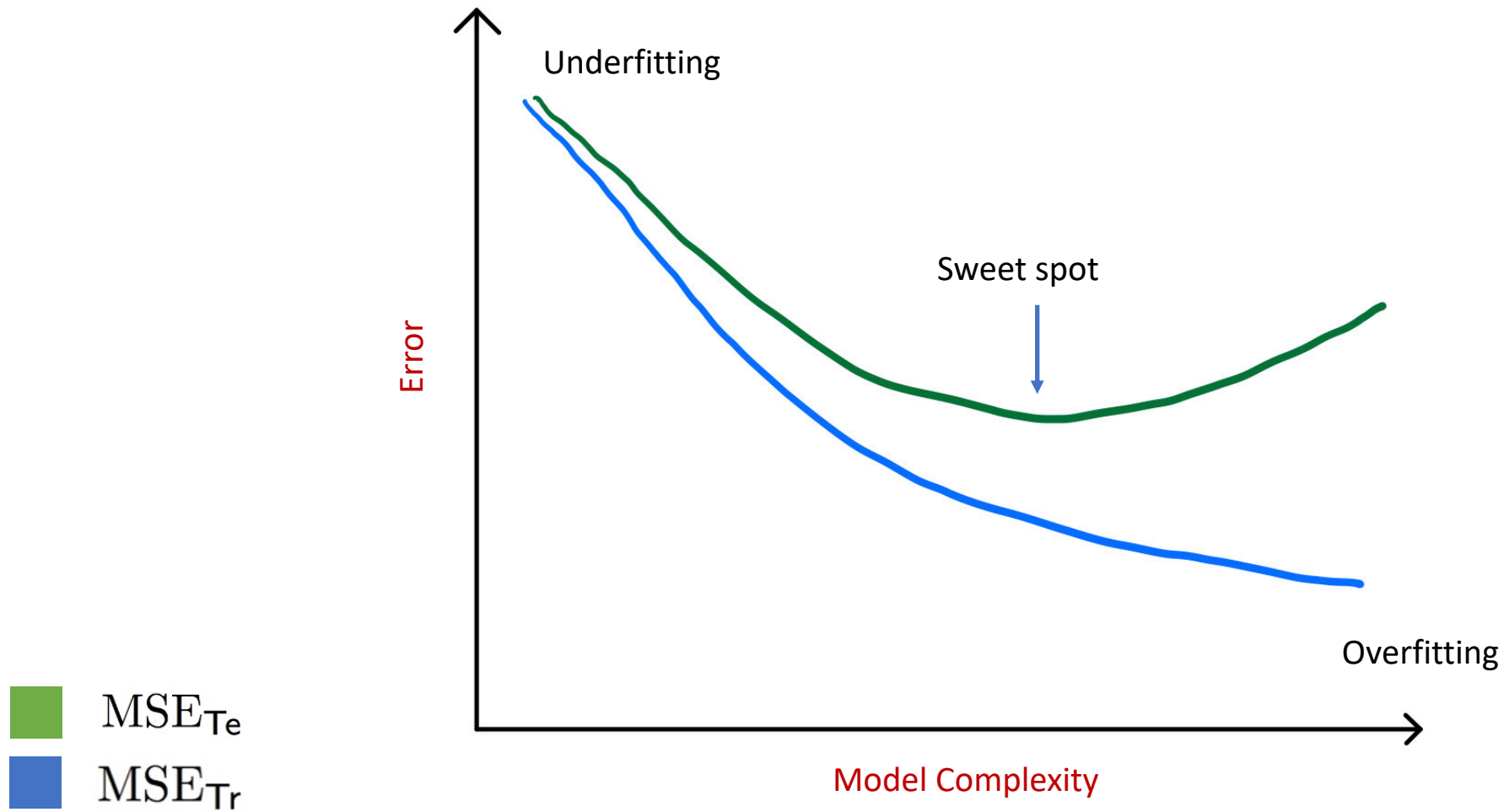
$$y \in \mathbb{R} \quad \text{Regression}$$

For example: COVID + OR COVID -

$$y \in \{c_i\}_{i=1}^k \quad \text{Classification}$$

For example: clinical Data of a patient

Important Take-away (2)



Bias Variance Tradeoff

$$E \left(y_0 - \hat{f}(x_0) \right)^2 = \text{Var}(\hat{f}(x_0)) + [\text{Bias}(\hat{f}(x_0))]^2 + \text{Var}(\epsilon).$$

Where (x_0, y_0) is a test observation

Typically, as the **flexibility or complexity** of \hat{f} increases, its variance increases, and its bias decreases. So choosing the flexibility based on average test error amounts to a **bias-variance trade-off**.

Summary

- Course Introduction
- Overview of Machine Learning
 - Three components: Task, Experience, Performance
 - Predictors and Response
 - Goal of Learning
 - Classification and Regression
 - Parametric Models
 - Model Evaluation
 - Bias-Variance Tradeoff