

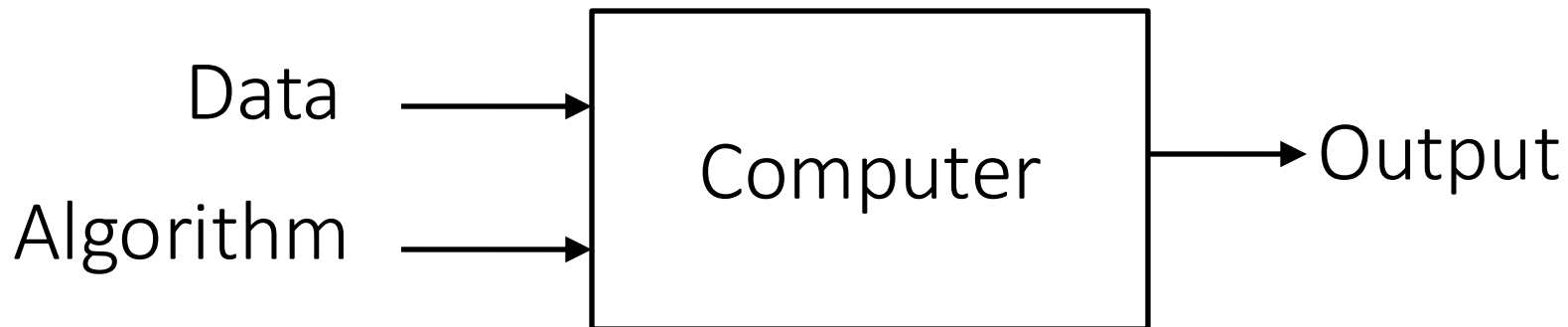
# UVA CS 4774: Machine Learning

## S0: Lecture 00: Weekly Quiz and QA

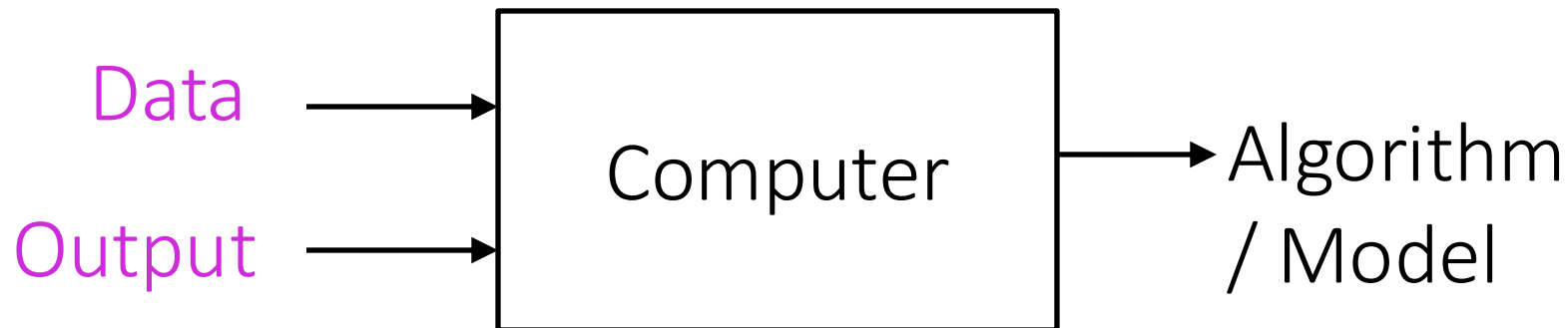
Dr. Yanjun Qi

University of Virginia  
Department of Computer Science

## Traditional Programming



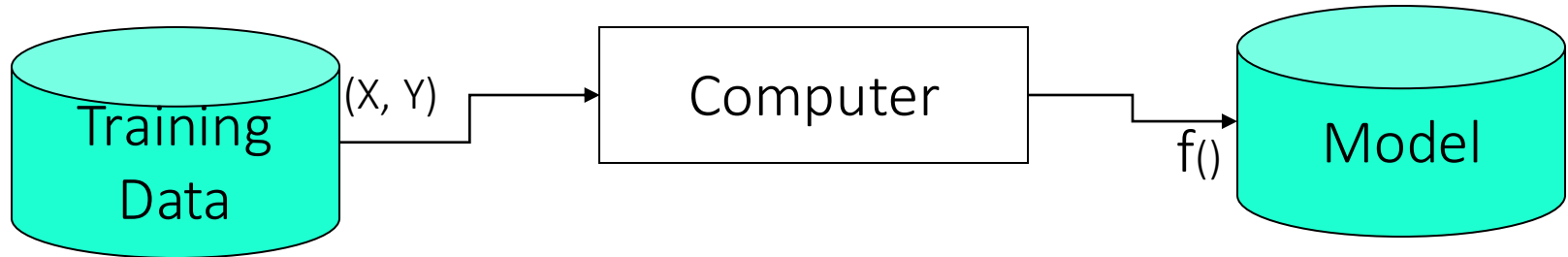
## Machine Learning



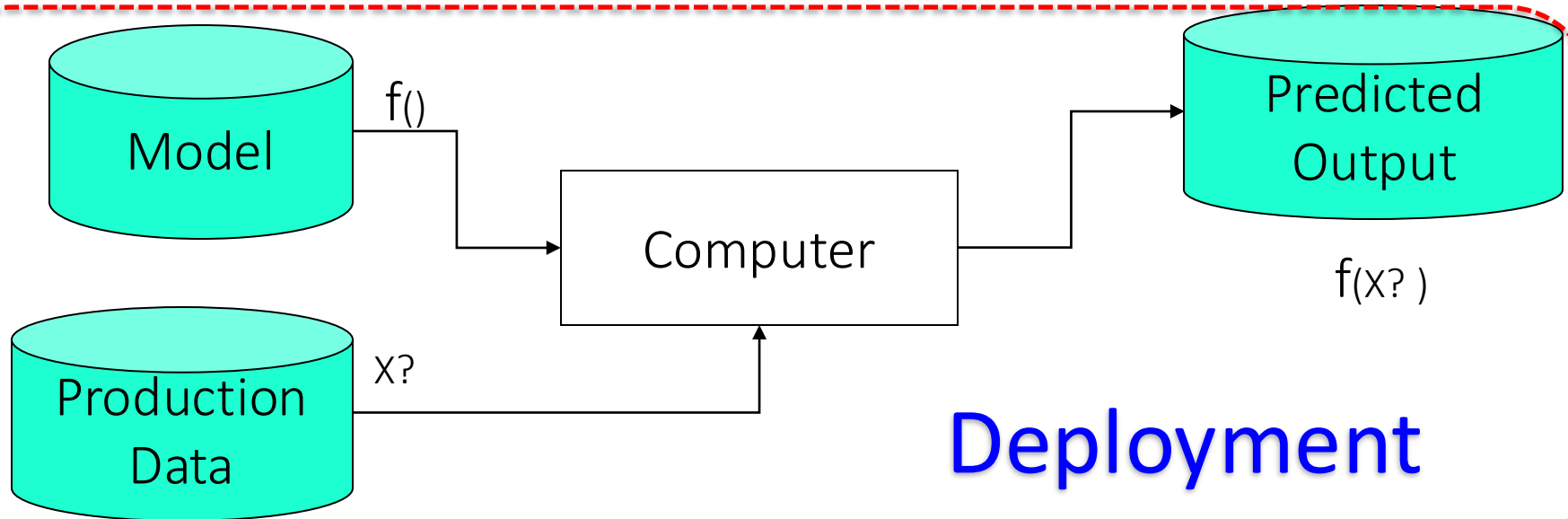
# Two Modes of Machine Learning

Consists of **input-output** pairs

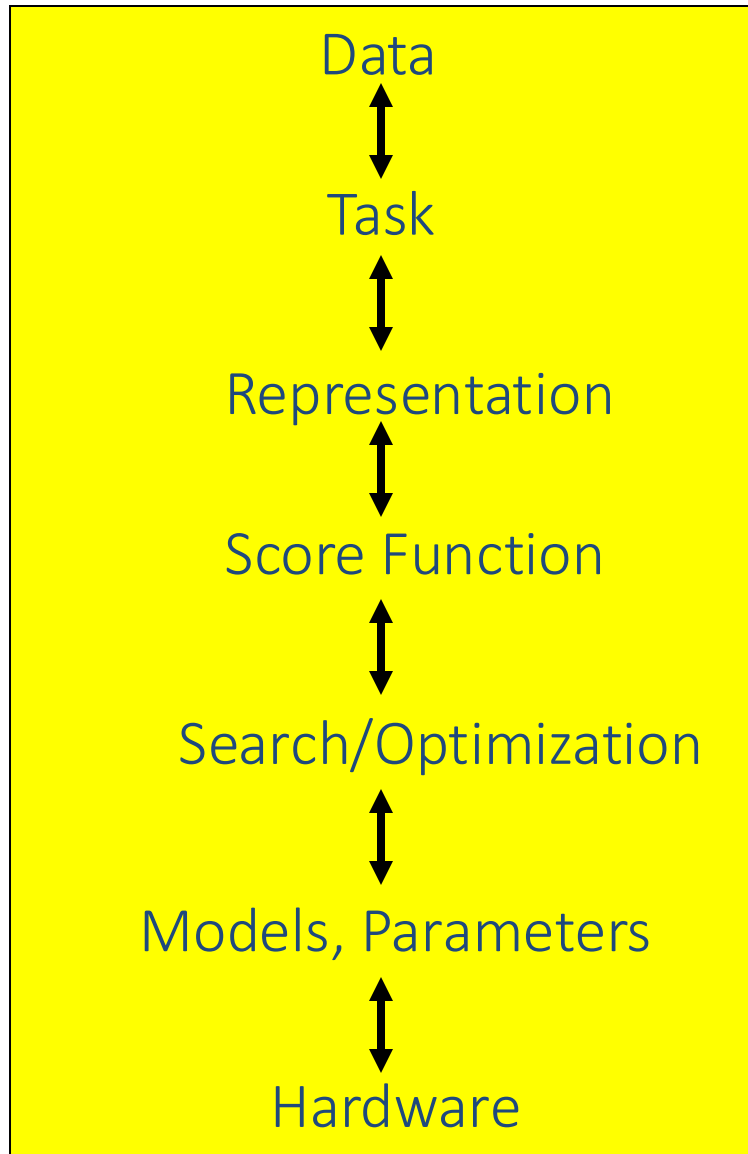
## Training



## Deployment



# Machine Learning in a Nutshell



ML grew out of  
work in AI

Optimize a  
performance criterion  
using example data or  
past experience,

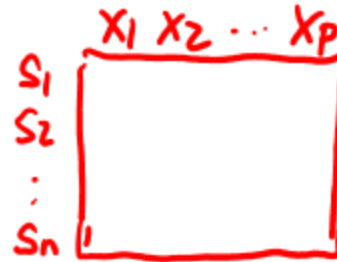
Aiming to generalize to  
unseen data

# Rough Sectioning of this Course

- S1. Basic Supervised Regression + Tabular Data
- S2. Basic Deep Learning + 2D Imaging Data
- S3. Generative and Deep + 1D Sequence Text Data
- S4. Advanced Supervised learning + Tabular Data
- S5. Not Supervised
- S6: Wrap Up + (a few invited tasks, e.g. on AWS)

# Course Content Plan → Regarding Data

❑ Tabular / Matrix



❑ 2D Grid Structured: Imaging



❑ 1D Sequential Structured: Text

❑ Graph Structured (Relational)

❑ Set Structured / 3D /

# Course Content Plan → Regarding Tasks

❑ Regression (supervised)

Y is a continuous

❑ Learning theory

About  $f()$

❑ Classification (supervised)

Y is a discrete

❑ Unsupervised models

NO Y

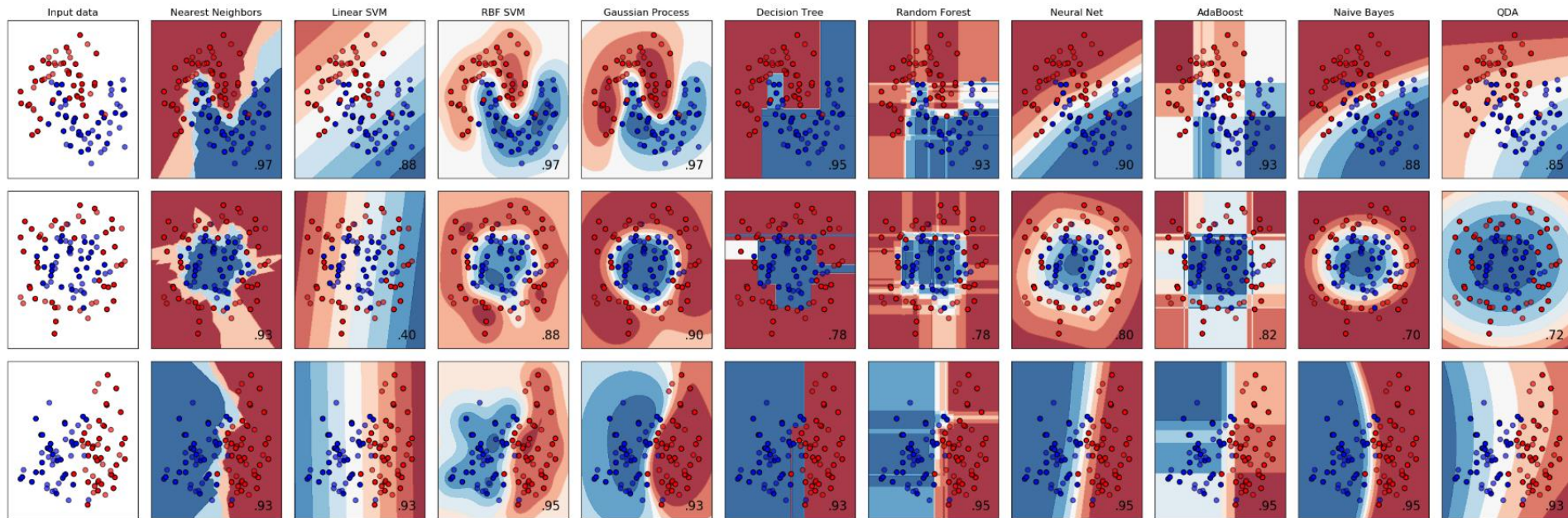
❑ Graphical models

About interactions among  $Y, X_1, \dots, X_p$

❑ Reinforcement Learning

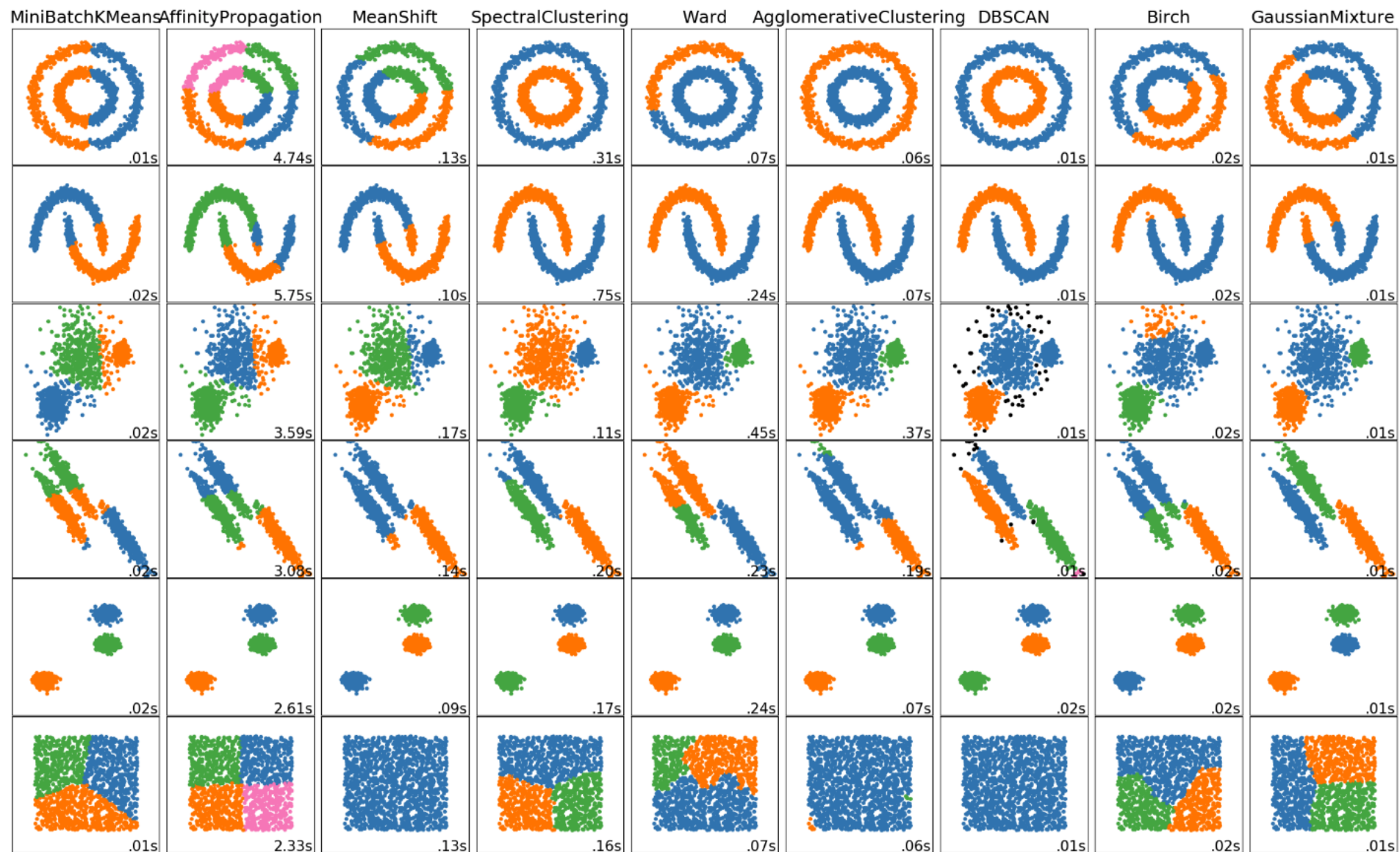
Learn to Interact with environment

[https://scikit-learn.org/stable/auto\\_examples/classification/plot\\_classifier\\_comparison.html](https://scikit-learn.org/stable/auto_examples/classification/plot_classifier_comparison.html)



- ✓ different assumptions on data
- ✓ different scalability profiles at **training** time
- ✓ different latencies at prediction (**test**) time
- ✓ different model **sizes** (embedability in mobile devices)
- ✓ different level of model **interpretability / robustness**





- ✓ different assumptions on data
- ✓ different scalability profiles
- ✓ different model **sizes** (embedability in mobile devices)

# Quiz 1

☑ Choose correct answers:

Q1: Given the definitions of A and B below, compute AB.

2 points

$$A = \begin{bmatrix} 1 & 2 & -1 \\ 0 & 3 & 4 \end{bmatrix}, \quad B = \begin{bmatrix} 2 & 1 \\ -1 & 0 \\ 5 & 2 \end{bmatrix}$$

Option 1

☒  $\begin{bmatrix} -5 & -1 \\ 17 & 8 \end{bmatrix}$  ✓

Option 2

☐  $\begin{bmatrix} -5 & 1 \\ -17 & 8 \end{bmatrix}$

Option 3

☐  $\begin{bmatrix} -3 & 1 \\ 15 & 8 \end{bmatrix}$

# Quiz 1

Q2: For conformable matrices A and B, which of the following always holds?

2 points

☒  $(AB)^T = (B^T)(A^T)$



☐  $(AB)^T = AB$

☐  $(AB)^T = AB^T$

# Quiz 1

 Choose correct answers:

Q3:

2  points

If a matrix  $D \in R^{5 \times 7}$ , which of the following must always be true?

- ☐ Rank(D) = 5
- ☐ Rank(D) = 7
- ☒ Rank(D)  $\leq 5$
- ☐ Rank(D)  $\geq 5$
- ☐ Rank(D)  $\geq 7$



# Quiz 2

1. In  $f:X \rightarrow Y$ , which represents the model?

☒ f

☐ X

☐ Y

2. How does unsupervised learning differ from supervised learning?

☐ No input X is provided

☒ No label Y is provided

☐ Label y is continuous

☐ Label y is discrete

# Quiz 2

3. Generalization refers to how well your model performs on

- ☒ The testing set
- ☐ The training set
- ☐ Both the training and testing set

4. The difference between classification and regression is?

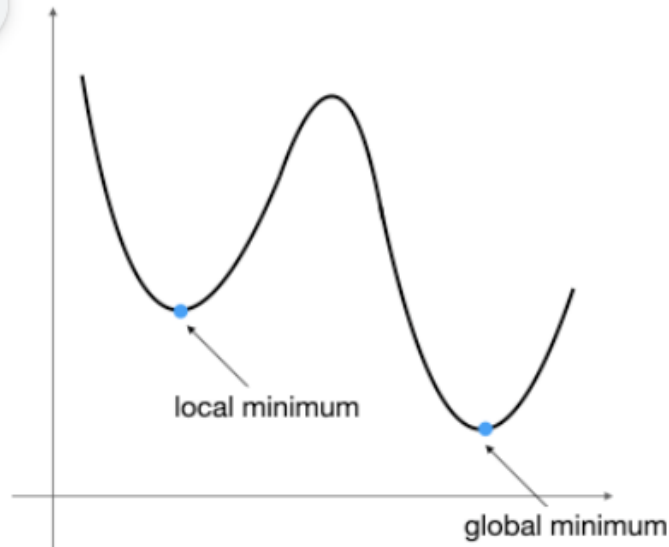
- ☐ Different types of input
- ☒ Different types of output
- ☐ Different types of model
- ☐ Different types of programs

# Quiz 3 Plus

2. True or False? Gradient descent always finds the global minimum. (Hint: Imagine the initial value starts from local minimum, the gradient there is 0)



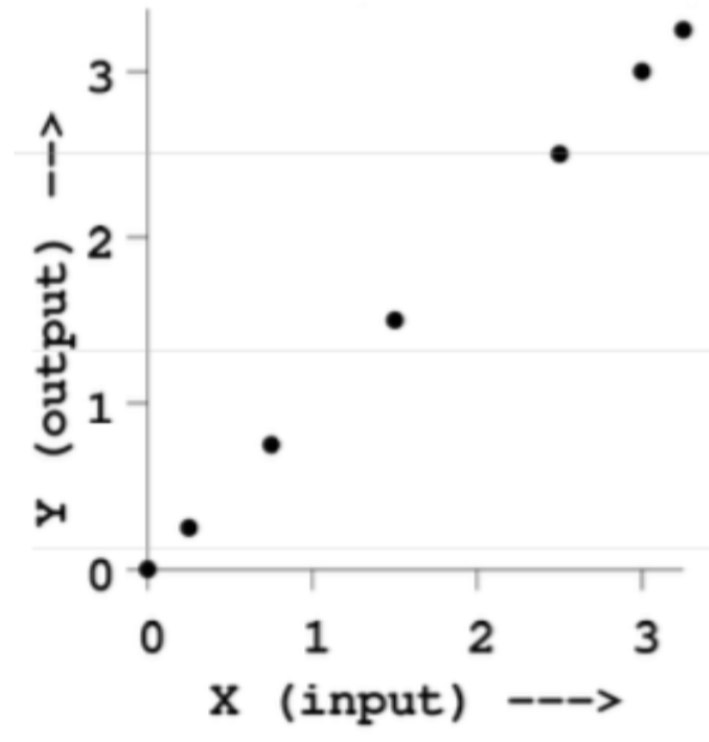
☒ Multiple choice



☐ False

☐ True

### Question 3.1. Linear Regression+ Train-Test Split



Quiz 3 Plus



Figure 1: A reference dataset for regression with one real-valued input (x as horizontal axis) and one real-valued output (y as vertical axis).

What is the mean squared training error when running linear regression to fit the data ? (i.e., the model is  $y = \beta_0 + \beta_1 x$ ). Assuming the rightmost three points are in the test set, and the others are in the training set. (you can eyeball the answers.)



# L 3,4- Reading Questions

## 1. Fundamentals of Linear Regression

- What does it mean for a dataset to be a good fit for linear regression?
- Does linear supervised regression only work with data that is already somewhat linear?
- When is it a good time to use linear regression, and under what conditions will it perform best?
- Where is linear regression used in real-world applications today?
- What challenges exist in making linear regression models robust and trustworthy?
- How should we interpret regression coefficients when features are correlated? Does GD handle multicollinearity?
- What does the “bias” term represent conceptually?

# L 3,4- Reading Questions

- 2. Loss / Cost Functions
- What exactly is the meaning of Mean Squared Error (MSE), Mean Absolute Error (MAE), Sum of Squared Errors (SSE)?
- When is MSE preferred over MAE, and what are the trade-offs?
- Why is SSE chosen in linear regression instead of MAE?
- What is the purpose of the  $\frac{1}{2}$  factor in quadratic loss?
- How do loss functions differ for convex, concave, and saddle point graphs?
- Where did the SSE loss measurement originate from?
- What is the difference between objective, cost, and loss function terminology?
- How do we choose performance metrics (MSE, MAE,  $R^2$ , others) and when should multiple metrics be combined?

# L 3,4- Reading Questions

- 3. Gradient Descent & Optimization
- How does gradient descent (GD) work conceptually?
- What's the difference between GD, stochastic GD (SGD), and mini-batch GD?
- How do we choose learning rate ( $\alpha$ ) values? Are they fixed or dynamic?
- How do we pick good starting points for GD?
- How does GD behave near local minima, saddle points, or flat regions?
- Are there ways for SGD to escape local minima/saddle points?
- What are good batch sizes, and how do they affect convergence?
- What are the limitations of GD and strategies to overcome them?
- How do we evaluate convergence and know when to stop?
- Could you show a full worked-out example of optimizing with GD step by step?

# L 3,4- Reading Questions

- **4. Normal Equation vs Iterative Methods**
- When should we use the Normal Equation versus Gradient Descent or SGD?
- What are the computational trade-offs between closed-form (Normal Eq.) and iterative (GD/SGD) methods?
- What happens if the feature matrix  $X$  does not have full rank?
- Why is Strassen's algorithm for matrix multiplication not always the default, despite being faster in theory?
- **5. Model Selection & Trade-offs**
- How do we know when to choose linear regression vs. more complex models (e.g., Random Forest, SVC)?
- How do we evaluate trade-offs between generalization, efficiency, scalability, and interpretability?
- How does context influence model selection and visualization choices?
- How are these classical regression/optimization topics applied to modern LLMs like ChatGPT or Alexa?

# L 3,4- Reading Questions

## • 6. Training, Testing, and Generalization

- How do we decide the split between training and testing data? (e.g., 80/20 rule)
- Is there an optimal ratio of training to test size?
- What does it mean for a model to generalize well? Does it just mean low error?
- Why is performance on training data not a good indicator of generalization?
- What happens if train/test sets have slightly different distributions (distribution shift)?
- When should validation sets be introduced in addition to train/test splits?
- How does generalization relate to overfitting/underfitting (residual patterns, feature poisoning examples)?

## • 7. Matrix & Representation Issues

- Why represent regression in matrix form? How does it help computation and parallelization?
- What's the difference between summation form and matrix form of the loss function?
- How do row vs. column vectors work in NumPy?
- What does it mean for a matrix to be full rank, and why does it matter?

# Matrix Representation (p53-)

## Lecture 3: Linear Regression Basics

Many architecture details and Algorithm details to consider

- (1): Data parallelization through CPU SIMD / Multithreading/ GPU parallelization / ....
- (2): Memory hierarchical / locality
- (3): Better algorithms, like Strassen's Matrix Multiply and many others

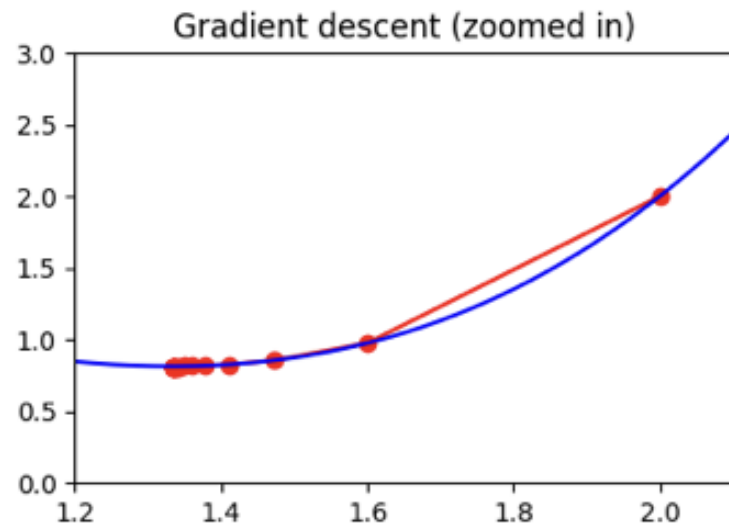
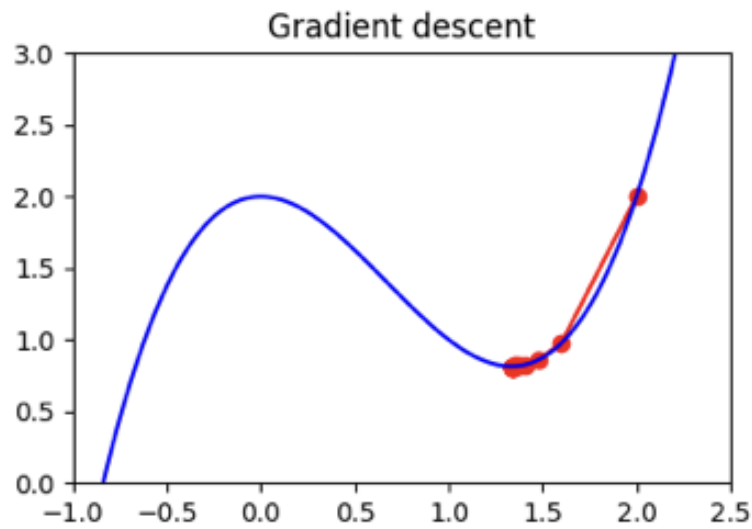
# Learning Rate Code Run



L4\_stochastic\_gradient\_descent.ipynb ☆ ☁

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# Quiz 3

1. how can we find the best  $\theta$  that minimizes loss function  $J(\theta)$  in linear regression? (check all that apply)

- ☐ Take derivative of  $J(\theta)$  and set it to 0, solving for  $\theta$
- ☐ Calculate the gradient of  $J(\theta)$  and use gradient descent iteratively
- ☐ Use binary search to find best  $\theta$
- ☐ Add option or [add "Other"](#)



Checkboxes





# Quiz 3

...

2. Suppose loss function  $J(x) = x^2$ , the initial value  $x_0=1$ , learning rate is 0.1, what will be  $x_1$  if we apply gradient descent?



Multiple choice

☐  $x_1 = -1$ ☐  $x_1 = 0$ ☐  $x_1 = 0.8$ ☐ Add option or [add "Other"](#)[Answer key](#) (2 points)

Required



# Quiz 3

3. Suppose we apply gradient descent with a learning rate that is too large. What is the most likely outcome?



Multiple choice

- ☐ Convergence will be faster and guaranteed
- ☐ The algorithm may overshoot and fail to converge
- ☐ The algorithm will converge to a local minimum instead of a global minimum
- ☐ The final solution will always be the closed-form solution
- ☐ Add option or [add "Other"](#)



# Quiz 3

4. Comparing SGD, GD, minibatch-GD, what is the most important difference?

- ☐ Error metric/ Loss function
- ☐ The number of data used for each update
- ☐ Total number of epochs
- ☐ Add option or [add "Other"](#)



Multiple choice



# Quiz 3 Plus

1. True or False: For linear regression, the loss function (sum of squared errors) is convex, meaning gradient descent is guaranteed to find the global minimum if the learning rate is chosen appropriately.

☒ True

☐ False

# Quiz 3 Plus

2. In linear regression, what is the role of the intercept term?

- ☐ It scales the input features
- ☒ It shifts the regression line vertically
- ☐ It reduces the variance of predictions
- ☐ It normalizes the input data

# Quiz 3 Plus

4. Suppose we want to minimize the function  $f(w)=w^2+4w$  using gradient descent. The initial value is  $w_0=2$ , and the learning rate is  $\alpha=0.1$ . What will be the value of  $w_1$  after one gradient descent update?

☐  $w_1 = 1.6$

☐  $w_1 = 2.4$

☐  $w_1 = -2$

☒  $w_1 = 1.2$

 [Add answer feedback](#)

# Quiz 3 Plus

3. Given the model and loss function, which of the following will be iteratively optimized to minimize the loss by gradient descent?



Multiple choice

- ☐ Input and output
- ☐ Model type (e.g. linear model or nonlinear model)
- ☐ Model parameters
- ☐ Add option or [add "Other"](#)



# L5 – e.g. LR with radial-basis functions

- E.g.: LR with RBF regression:

$$\hat{y} = \theta_0 + \sum_{j=1}^m \theta_j \varphi_j(x) = \varphi(x)^T \theta$$

$$\varphi(x) := \left[ 1, K_{\lambda_1}(x, r_1), K_{\lambda_2}(x, r_2), K_{\lambda_3}(x, r_3), K_{\lambda_4}(x, r_4) \right]^T$$

$$\theta^* = \left( \varphi^T \varphi \right)^{-1} \varphi^T \bar{y}$$

$$\vec{\theta} = \left[ \theta_0, \underbrace{\theta_1, \theta_2, \theta_3, \theta_4}_{\substack{\text{hyper} \\ \text{para}}} \right]^T$$

$\underbrace{\begin{matrix} r_1 & r_2 & r_3 & r_4 \\ \lambda_1 & \lambda_2 & \lambda_3 & \lambda_4 \end{matrix}}_{\text{hyper para}}$

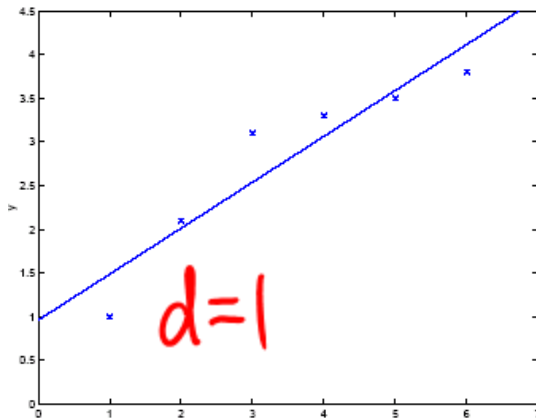


# L6: Main issues: Model Selection

- How to select the right model type? How to select hyperparameter for a model type?
  - E.g. what polynomial degree **d** for polynomial regression
  - E.g., where to put the centers for the RBF kernels? How wide?
  - E.g. which basis type? Polynomial or RBF?

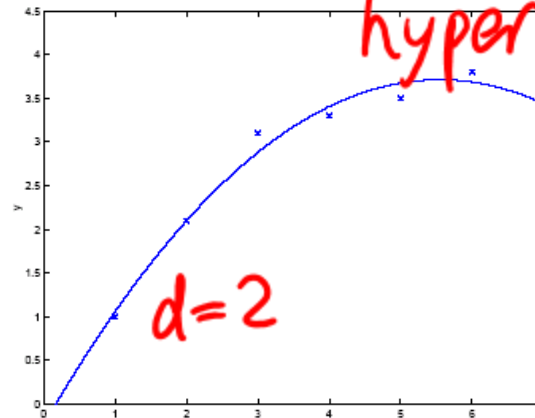
# What Model Order to Select?

Under fit



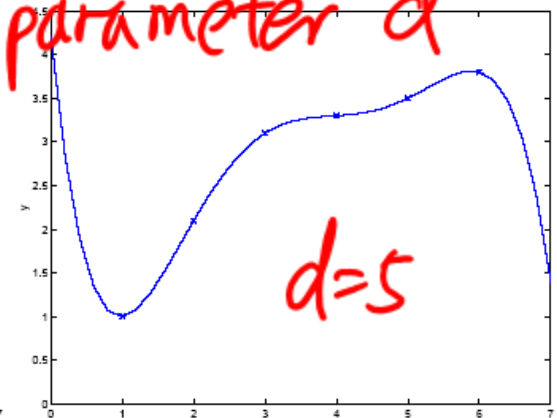
$$y = \theta_0 + \theta_1 x$$

Looks good



$$y = \theta_0 + \theta_1 x + \theta_2 x^2$$

Over fit



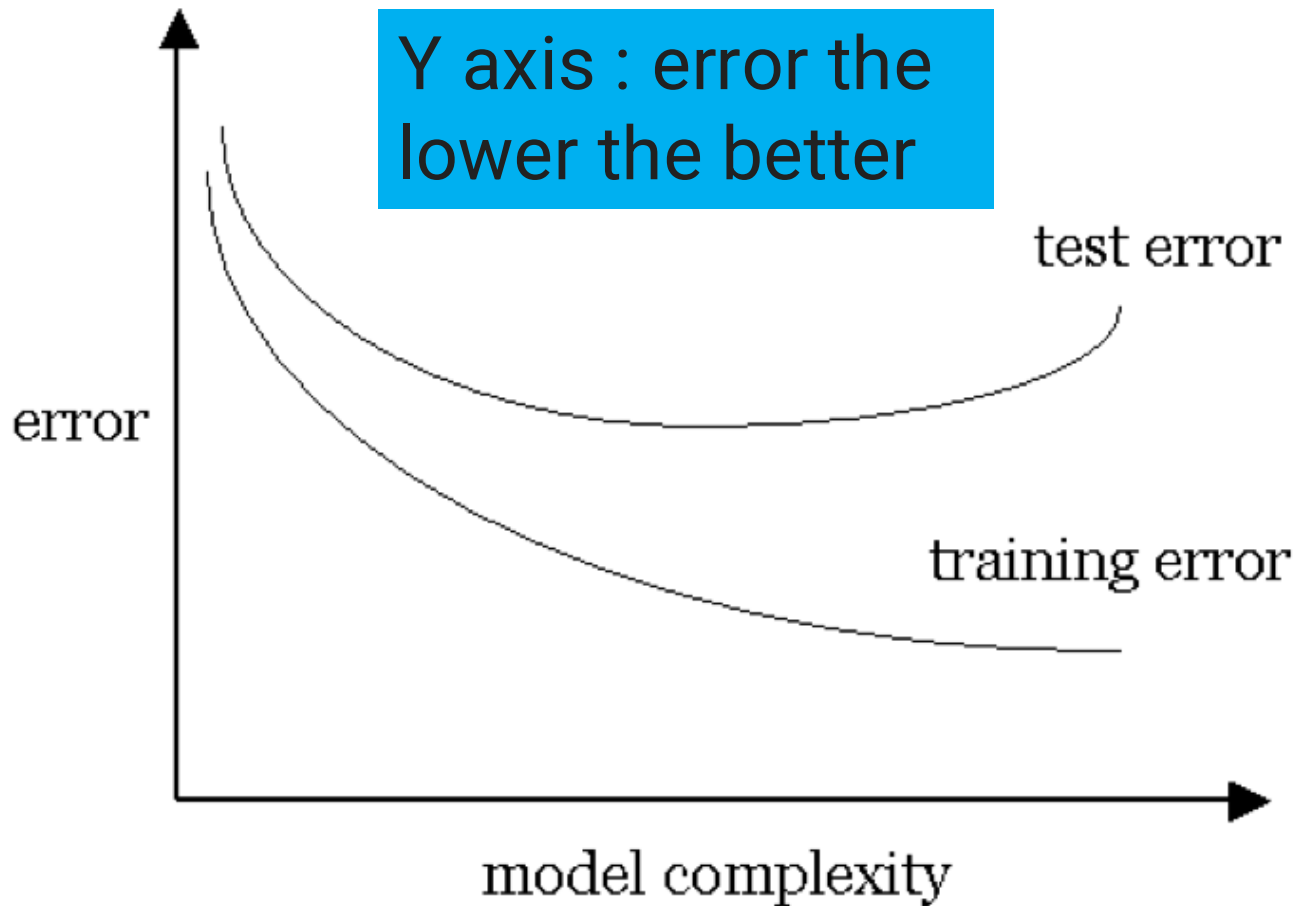
$$y = \sum_{j=0}^5 \theta_j x^j$$

hyperparameter  $d$

Generalisation: learn function / hypothesis from past data in order to “explain”, “predict”, “model” or “control” new data examples

(a) Train-validation /  
(b) K-fold Cross Validation /

# A Plot for Model Selection



k-CV on train to choose model and hyperparameter /  
then a separate test set to assess future performance

# Polynomial Regression Code Run

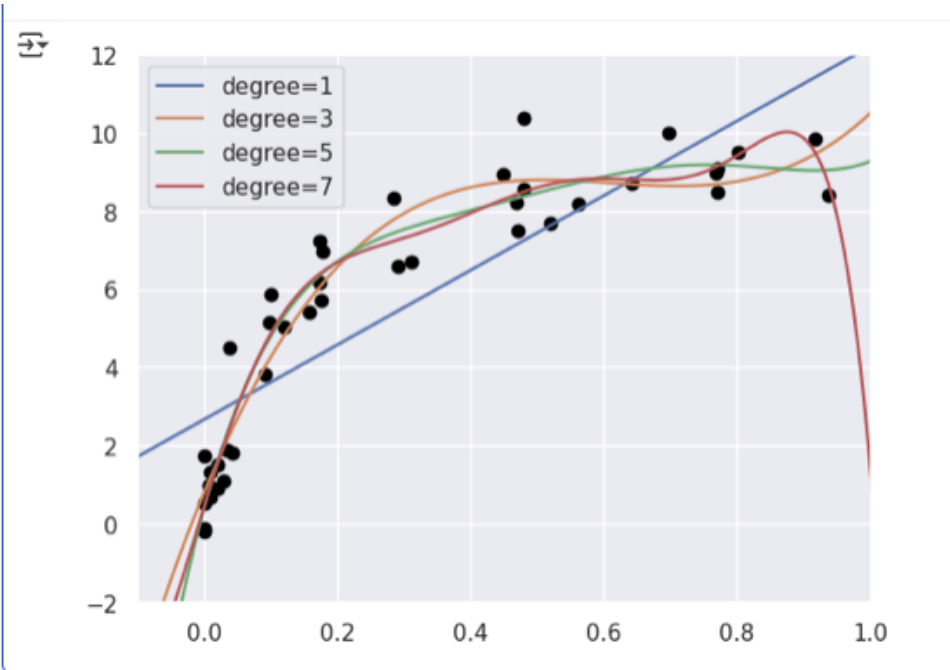
L5-Poly-Regression.ipynb ☆ ☁

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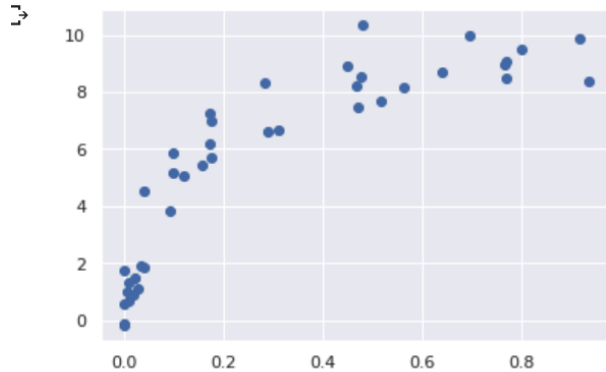
1 commands | + Code | + Text | ▶ Run all ▼

## More Regression / Modified from :

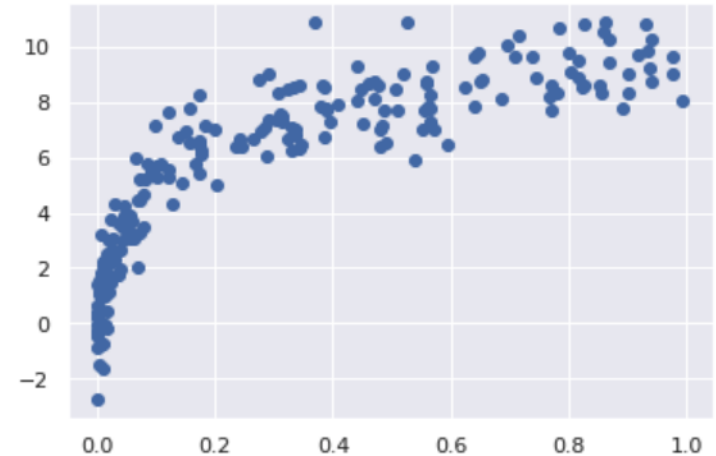
1. <https://github.com/jakevdp/PythonDataScienceHandbook>
2. <https://jakevdp.github.io/PythonDataScienceHandbook/05.03-hyperparameters-and-model-validation.html>



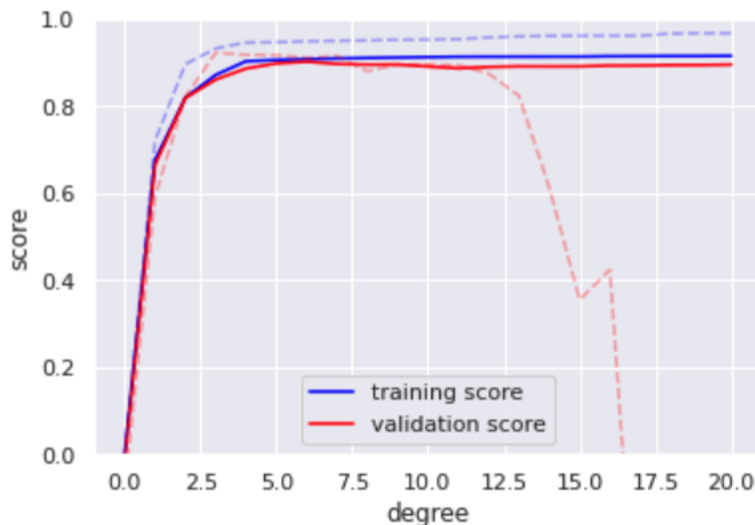
```
X, y = make_data(40)
plt.scatter(X, y);
```



```
X2, y2 = make_data(200)
plt.scatter(X2.ravel(), y2);
```



```
plt.plot(degree, np.median(train_score2, 1), color='blue',
plt.plot(degree, np.median(val_score2, 1), color='red', 1
plt.plot(degree, np.median(train_score, 1), color='blue',
plt.plot(degree, np.median(val_score, 1), color='red', al
plt.legend(loc='lower center')
plt.ylim(0, 1)
plt.xlabel('degree')
plt.ylabel('score');
```



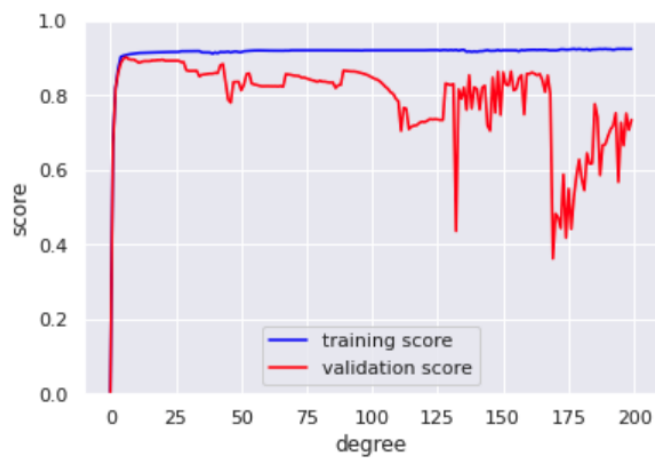
Behavior of the validation curve:

- the model complexity
- the number of training points

```
X2, y2 = make_data(200)
```

```
degree = np.arange(200)  
train_score2, val_score2 = validation_curve(PolynomialReg  
                                            'polynomialfe
```

```
plt.plot(degree, np.median(train_score2, 1), color='blue'  
plt.plot(degree, np.median(val_score2, 1), color='red', 1  
plt.legend(loc='lower center')  
plt.ylim(0, 1)  
plt.xlabel('degree')  
plt.ylabel('score');
```

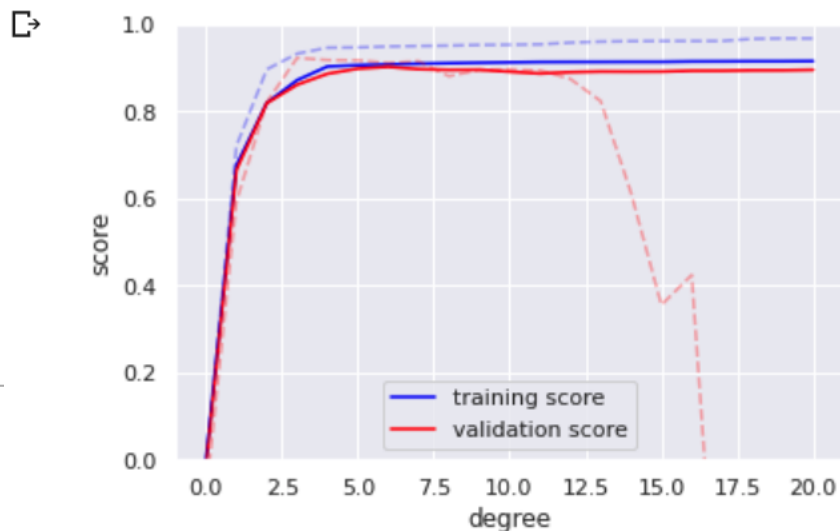


```
X2, y2 = make_data(200)
```

```
degree = np.arange(21)
```

```
train_score2, val_score2 = validation_curve(PolynomialReg  
                                            'polynomialfe
```

```
plt.plot(degree, np.median(train_score2, 1), color='blue'  
plt.plot(degree, np.median(val_score2, 1), color='red', 1  
plt.plot(degree, np.median(train_score, 1), color='blue', 1  
plt.plot(degree, np.median(val_score, 1), color='red', al  
plt.legend(loc='lower center')  
plt.ylim(0, 1)  
plt.xlabel('degree')  
plt.ylabel('score');
```



## Interesting Relation between


- the right range of model complexity
- the number of training points

# Quiz 4 plus

Which of the following statements about Leave-One-Out Cross Validation (LOOCV) is true?



☒ Multiple choice

- ☐ It wastes a large fraction of training data.
- ☐ It has low variance but high computational cost. 
- ☐ It provides the same estimate as a large k-fold CV with k close to 1.
- ☐ It is cheaper than k-fold cross validation.
- ☐ Add option or [add "Other"](#)

 **Answer key** (2 points)



Required



# need to make assumptions that are able to generalize

- **Underfitting:** model is too “simple” to represent all the relevant characteristics
  - High bias and low variance
  - High training error and high test error
- **Overfitting:** model is too “complex” and fits irrelevant characteristics (noise) in the data
  - Low bias and high variance
  - Low training error and high test error

A Gentle Touch of Bias - Variance Tradeoff

(More details ... Later)



# L 5/ L6 Readings