

可信机器学习

Trustworthy Machine Learning

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School of Computer Science, Fudan University

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Course Info



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Time&Palce: Class 11-13, 18:30pm – 21:05pm
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Office Hours: Tuesday Afternoon

Course page: <https://trustworthymachinelearning.github.io/>

Personal page: <https://xingjunma.com>



Syllabus

- Week 1: Intro, Basics of Machine Learning
- Week 2: Explainability and Robustness to Common Corruptions
- Week 3: Adversarial Examples, Attacks and Explanations
- Week 4: Adversarial Defense (Part I), Adversarial Example Detection
- Week 5: Adversarial Defense (Part II), Early Defense Methods, Adversarial Training
- Week 6: Adversarial Defense (Part III), Certifiable Adversarial Defense
- Week 7: Data Poisoning Attack and Defense
- Week 8: Backdoor Attack and Defense
- Week 9: Data Leakage and Model Stealing
- Week 10: Differential Privacy
- Week 11: Federated Learning
- Week 12: Machine Learning Fairness
- Week 13: Data Manipulation and Deepfakes
- Week 14: Model Intellectual Property Protection
- Week 15: Guest Lectures on Research Frontiers
- Week 16: Project Report
- Week 17: Project Report



Assessment

考核形式* Assessment Criteria	权重 Percentage	评定标准 Assessment Standard
出勤 Attendance	10%	全勤10分，缺席1次扣1分
课堂表现 Participation	0%	
作业/实验/实践 Assignment(s)	20%	基于Kaggle的课堂对抗攻防赛（20%）
课程论文 Course Paper	60%	学生自选研究题目，解决一个可信机器学习问题，设计自己的方法与基线方法比较。 40分以上：选题新颖，方法创新，具备学术价值和现实意义、写作规范，行文流畅。 30分以上：选题合理，观点明确，思路清晰，方法具有一定的创新。 30分以下：背景知识缺乏了解，选题、方法设计、分析不能达到基本要求。
开卷考试 Open-book exam	0%	
闭卷考试 Close-book exam	0%	
其他 Other(s)	10%	开源社区贡献（10%），包括但不限于收集各研究方向的论文、设计开源示例、整合并复现各研究方向的基线方法、建设开源社区等。



Assessment

◆ 基于Kaggle的课堂对抗攻防赛（占比20%）

- 计划第5-6周发布，可能会提前
- 请同学们自行寻找计算资源（GPU）
- 比赛内容：
 - ✓ 对抗攻击一个鲁棒训练的模型
 - ✓ 数据集为CIFAR-10
 - ✓ 衡量攻击成功率和效率，各占50%

- 得分：安排名进行评分，**第一名100分，最后一名50分**

◆ 自选研究题目（占比60%）

- 有4-5个备选题目，第10周左右发布
- **需要组队：博士1-2人、硕士2-3人**
- **需要做实验**
- **需要写报告**（英文报告加分）
- **需要课堂作展示，每个组5分钟**

- 得分：结合创新性、报告质量、展示质量三个方面综合评分

没卡的同学建议使用Google Colab：<https://colab.research.google.com/>



Textbook

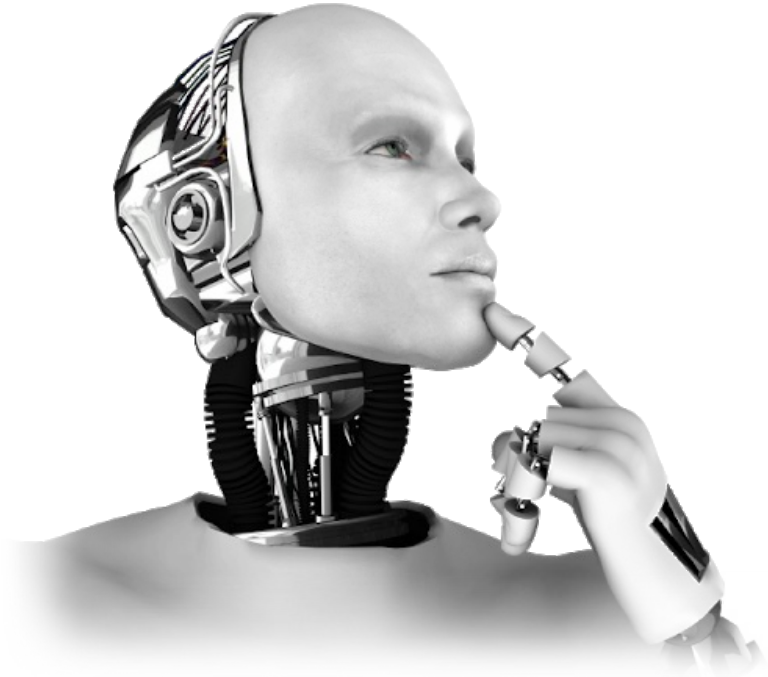
- ◆ 自编教材《人工智能数据与模型安全》
 - 由Fudan Vision and Learning Lab编写
 - 未经允许不能分享给课外人员
 - 教材还在优化中，部分章节缺失
 - 同学可参与到教材的优化中来（算开源贡献）：发现错误、改正错误，至少需要完成一个二级章节（2、4、5、6、7）中的三级章节（例如：5.3），章节由老师来制定
 - 教材优化的同学不多于10人

下周发布BaiduPan下载链接

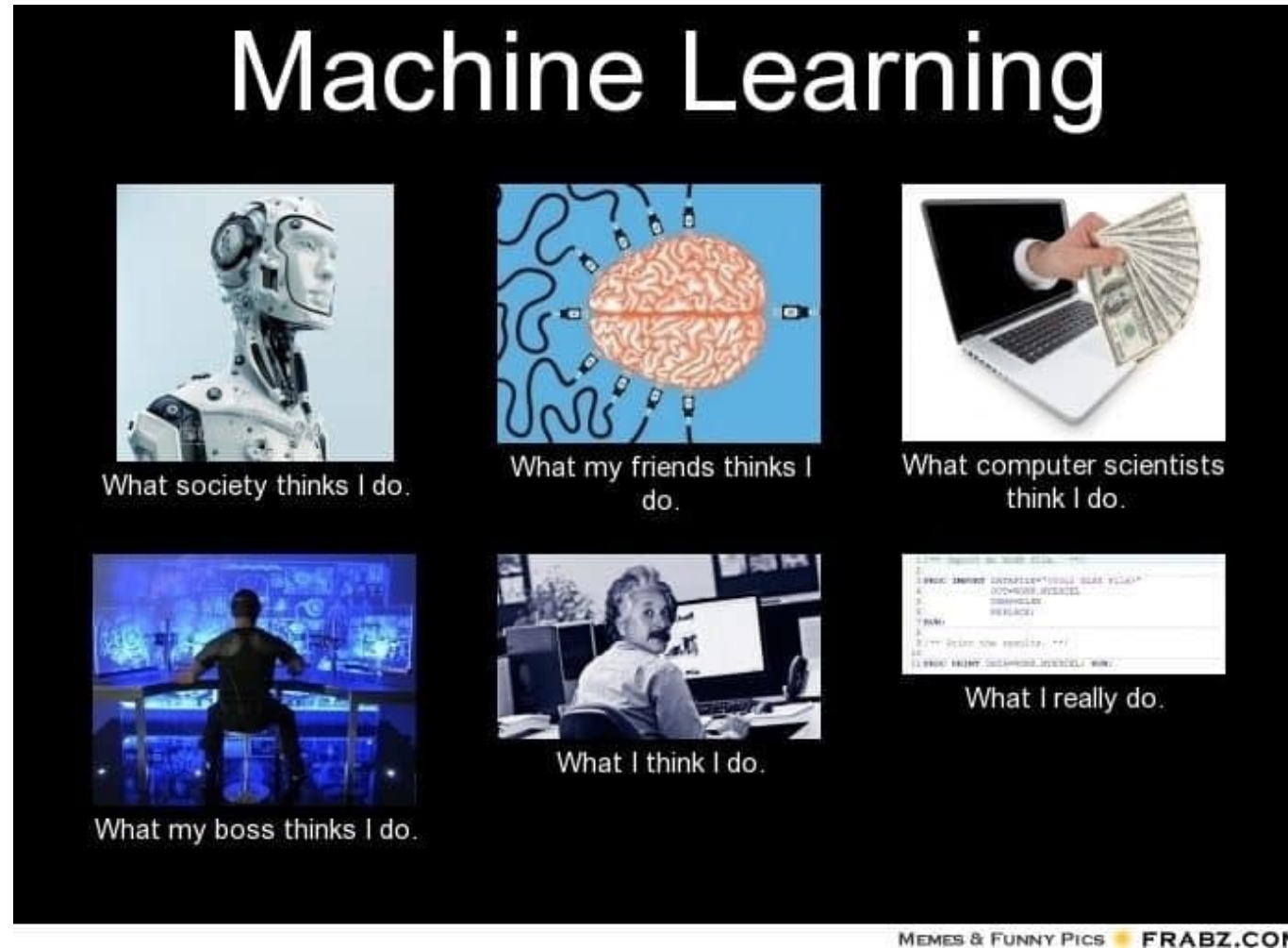


Week 1: Machine Learning Basics

1. What is Machine Learning
2. Machine Learning Paradigms
3. Loss Functions
4. Optimization Methods



What Is Machine Learning



<https://carllepelaars.nl/2018/10/15/100daysofmlcode-summary/>

What Is Machine Learning



‘Cat’



‘Dog’

<https://www.image-net.org/>

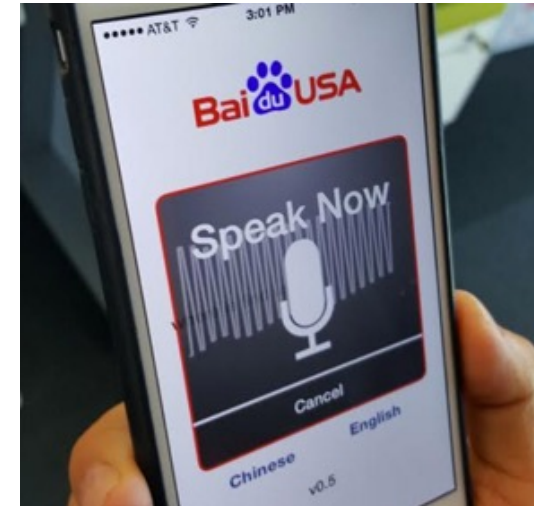
What Is Machine Learning



Million-scale Image Recognition

<https://www.image-net.org/>

What Is Machine Learning



Speech Recognition

<https://machinelearning.apple.com/research/hey-siri;>

What Is Machine Learning



Strategy Games

<https://www.deepmind.com/research/highlighted-research/alphago;>

<https://www.deepmind.com/blog/alphazero-shedding-new-light-on-chess-shogi-and-go>



What Is Machine Learning



Million-scale Facial Recognition

<https://www.face-benchmark.org/>

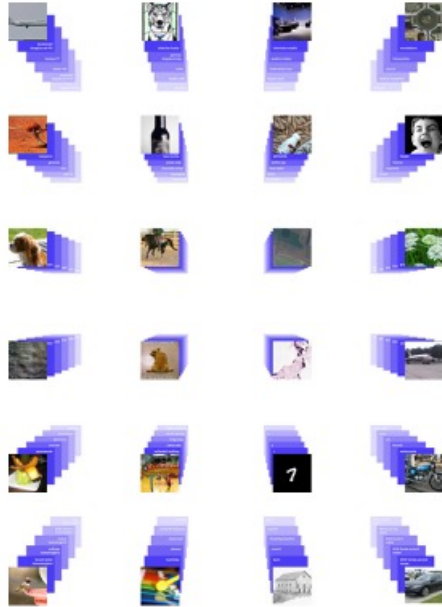
What Is Machine Learning



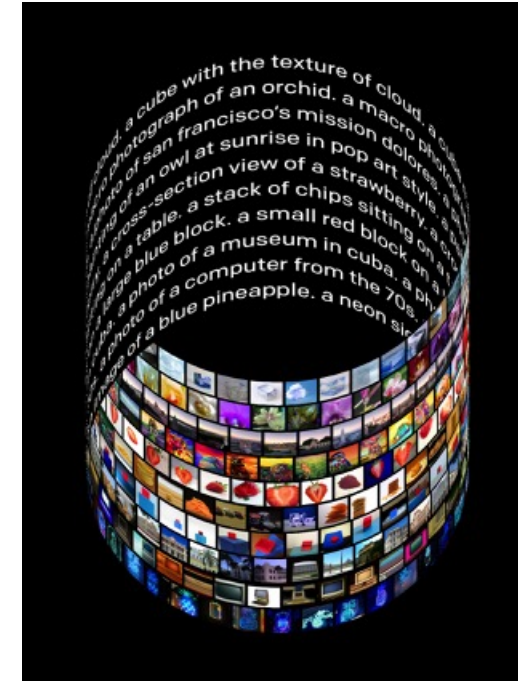
Large-scale Visual-Speech Learning

https://www.robots.ox.ac.uk/~vgg/data/lip_reading/lrs3.html

What Is Machine Learning



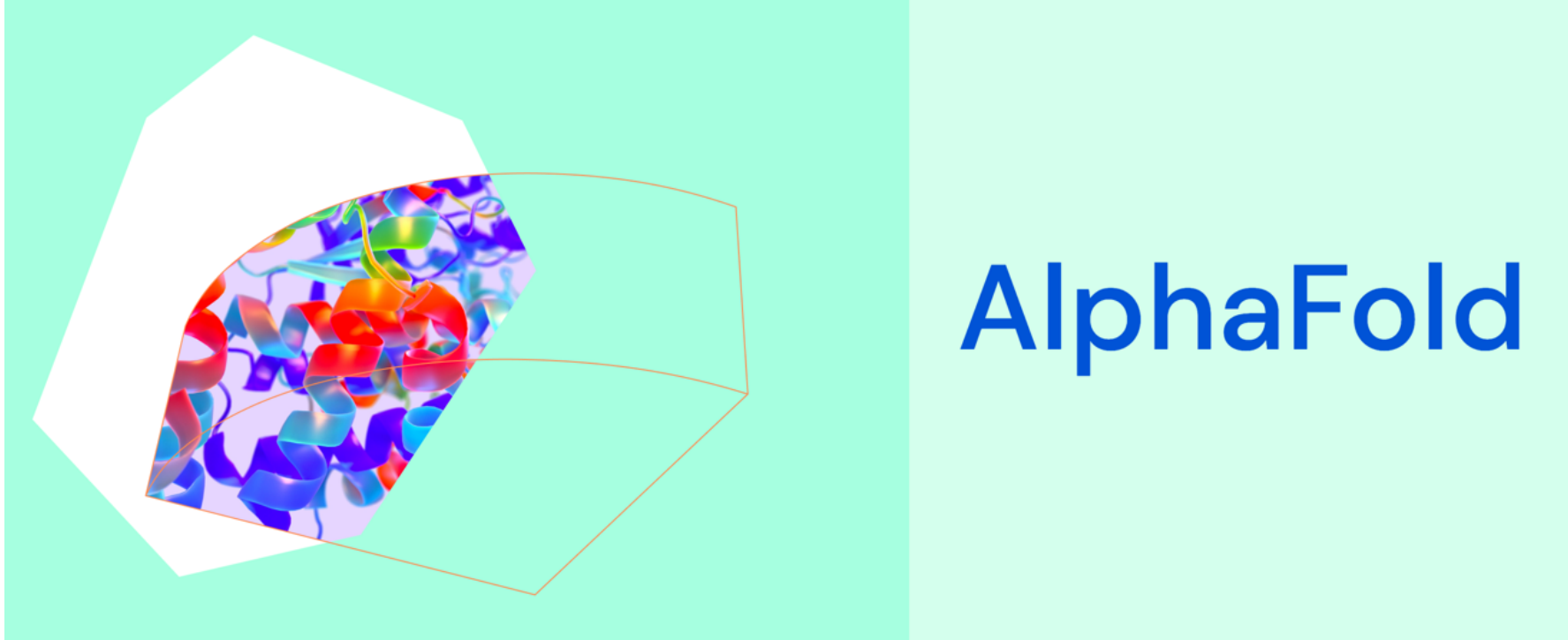
CLIP: Connecting Text and Images



DALL-E: Creating Images from Text

<https://openai.com/research/>

What Is Machine Learning



<https://www.deepmind.com/blog/alphafold-reveals-the-structure-of-the-protein-universe>

Machine Learning Is Everywhere



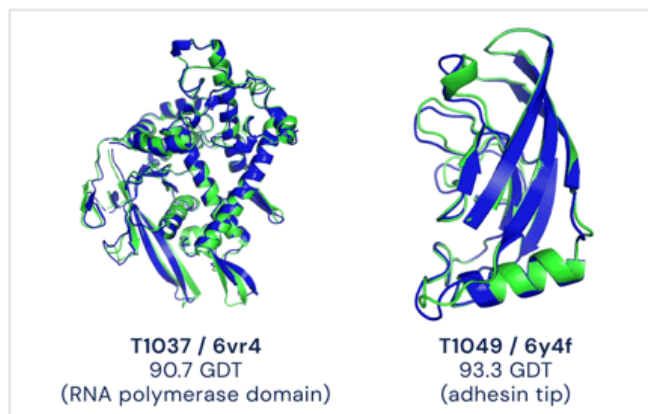
智慧教育



智慧医疗



自动驾驶



生物信息



智能制造



智慧金融

Elements of Machine Learning

❖ 语音识别 $f(\text{audio waveform}) = \text{“天气不错”}$

❖ 人脸识别 $f(\text{face image}) = \text{“小明”}$

❖ 语义分割 $f(\text{scene image}) = \text{segmented image}$



Data describes the problem

Model describes the brain of the machine

Algorithm describes the learning mechanism

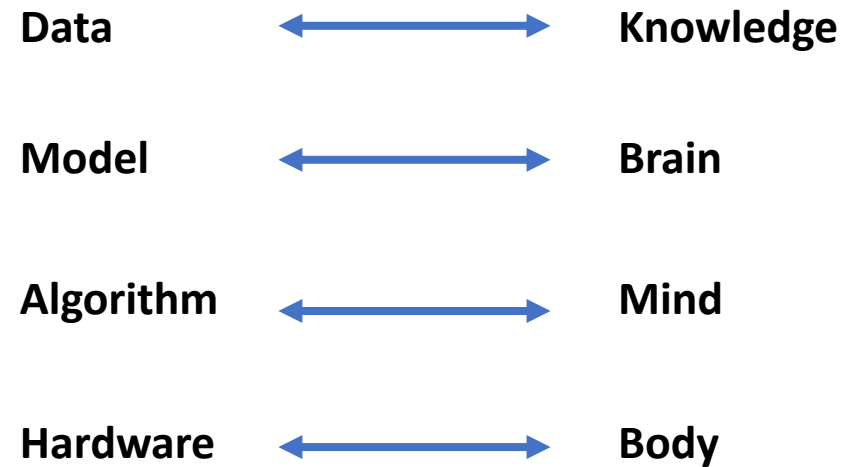
Hardware accelerates the learning

Learning Patterns From A Given Dataset Using An Algorithm

机器学习四要素：数据、模型、算法、算力



Elements of Machine Learning



10 Questions of Machine Learning

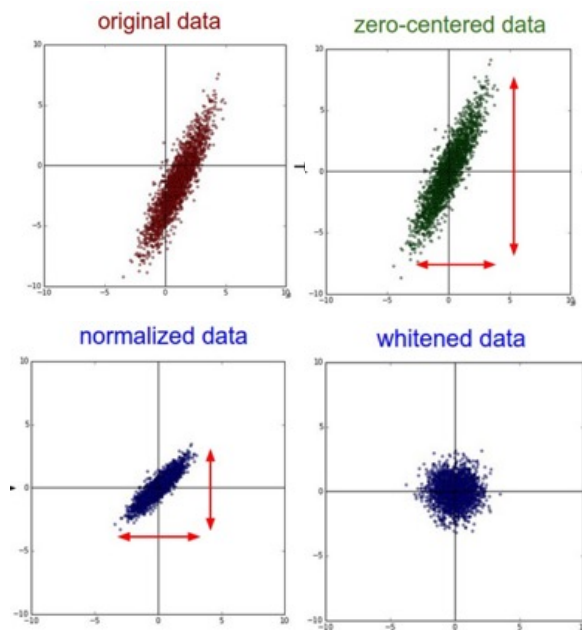
1. What is the task?
2. What is the objective?
3. What is the data?
4. How much data do we have?
5. What is the model?
6. What are the inputs and outputs?
7. What needs to be learned?
8. How is the model trained?
9. How is the model tested?
10. How is the model deployed?



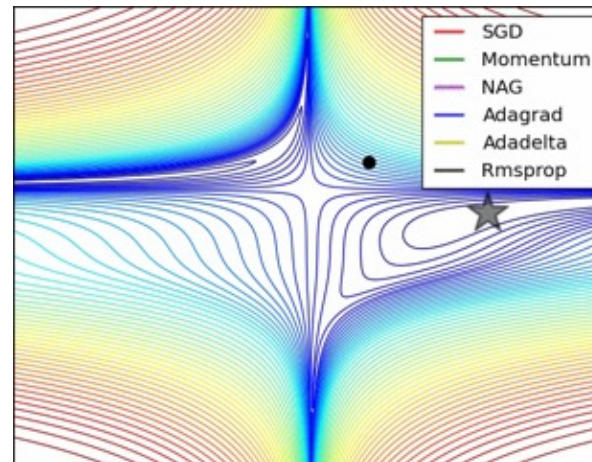
1. Problem definition
2. Learning objective
3. Training/Test data
4. Scale of learning
5. Model Architecture
6. Function Family
7. Features/Representations
8. Training Method
9. Evaluation Metrics
10. Generalization

Machine Learning Pipeline

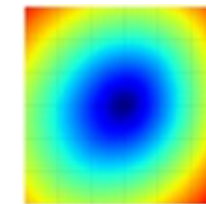
setup the input



setup the optimiser



setup the loss

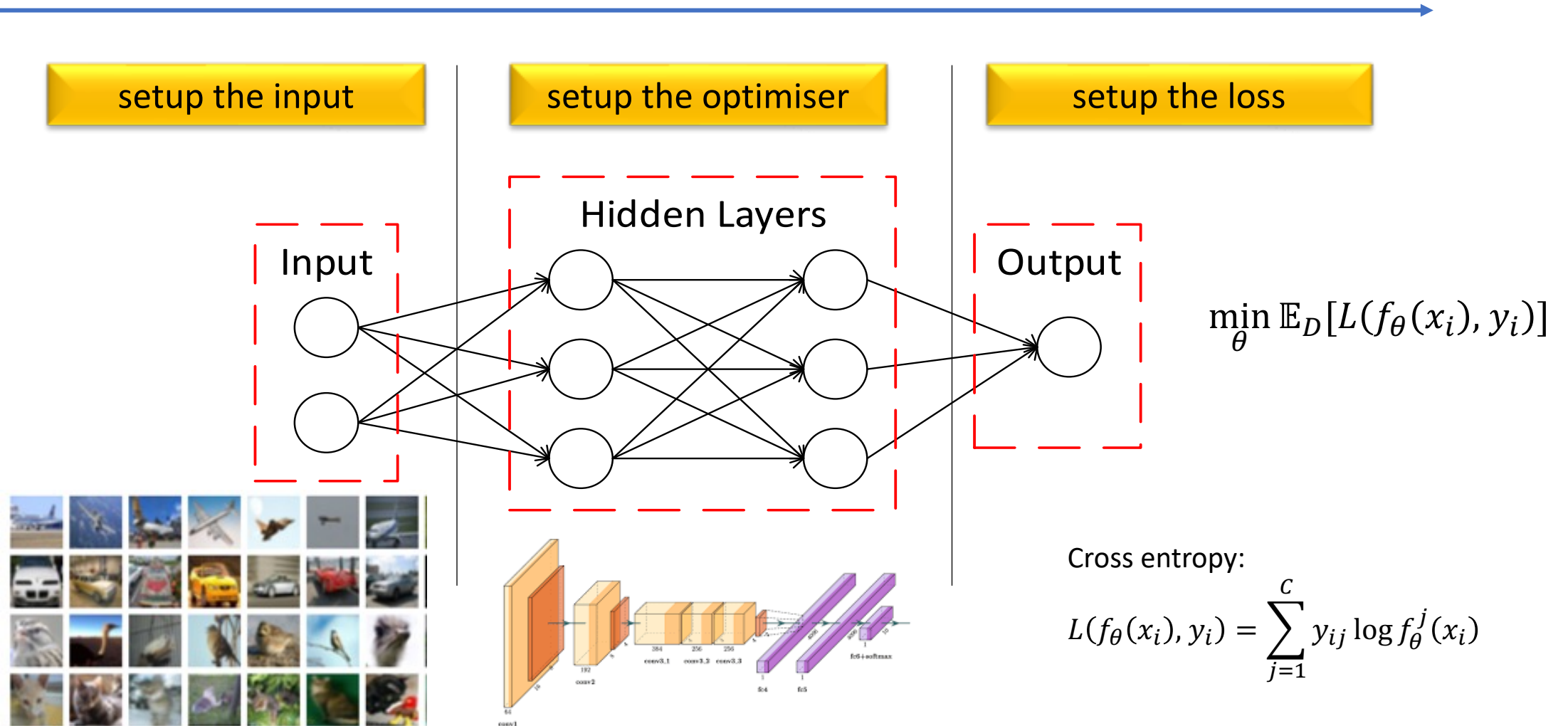


landscape of a loss function, it varies w.r.t. data, the function itself



regularization makes decision region smoother

Machine Learning Pipeline



Machine Learning Concepts

Data

Training data
Test data
Samples
IID/Non-IID
Domain
Feature
Representation
Noise
Corruptions
...

Model

SVM/RF/LR
DNN
RNN
CNN
FWN
Layers, neurons,
blocks, module
Activations, logits,
probabilities
Model capacity,
parameters
...

Algorithm

Learning method
Standard learning
Curriculum learning
Supervised learning
Unsupervised learning
Reinforcement learning
Continual learning
Self-supervised learning
Representation learning
Contrastive learning
...



Learning Is Optimizing

❖ 语音识别 $f(\text{audio waveform}) = \text{“天气不错”}$

❖ 人脸识别 $f(\text{face image}) = \text{“小明”}$

❖ 语义分割 $f(\text{photo of sheep}) = \text{segmented image}$

Learning is the process of empirical risk minimization (ERM)

$$\hat{\theta} = \operatorname{argmin}_{\theta} \frac{1}{N} \sum_{i=1}^N \mathcal{L}(f_{\theta}(\mathbf{x}_i), y_i)$$

Mapping function: $Y = f(X)$

Hypothesis space: $\mathcal{F} = \{f | Y = f_{\theta}(X), \theta \in R^m\}$

Expected risk: $R_{exp}(f) = \mathbb{E}_P[\mathcal{L}(Y, f(X))] = \int_{X \times Y} \mathcal{L}(f(\mathbf{x}), y) P(\mathbf{x}, y) d\mathbf{x} dy$

Empirical risk: $R_{emp}(f) = \mathbb{E}_{(\mathbf{x}, y) \in D} \mathcal{L}(f(\mathbf{x}), y) = \frac{1}{N} \sum_{i=1}^N \mathcal{L}(f(\mathbf{x}_i), y_i)$

Input $\rightarrow X$
Output $\rightarrow Y$

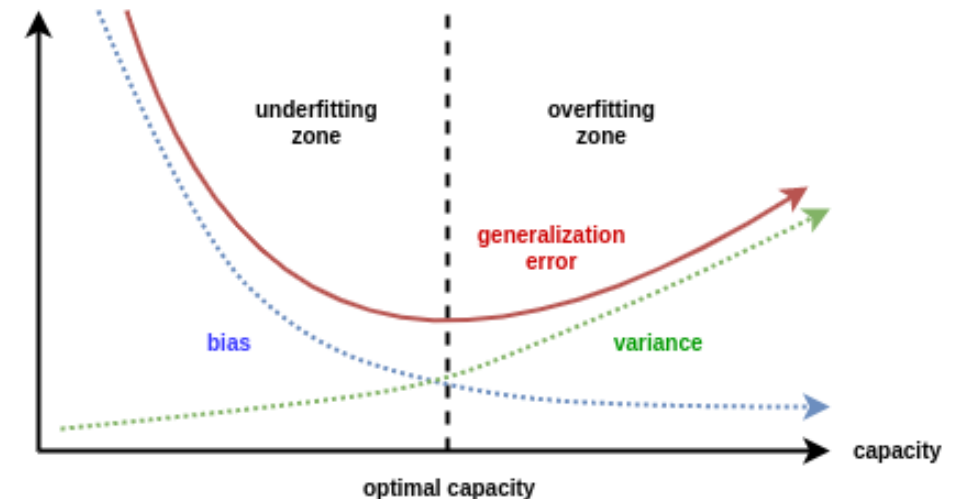
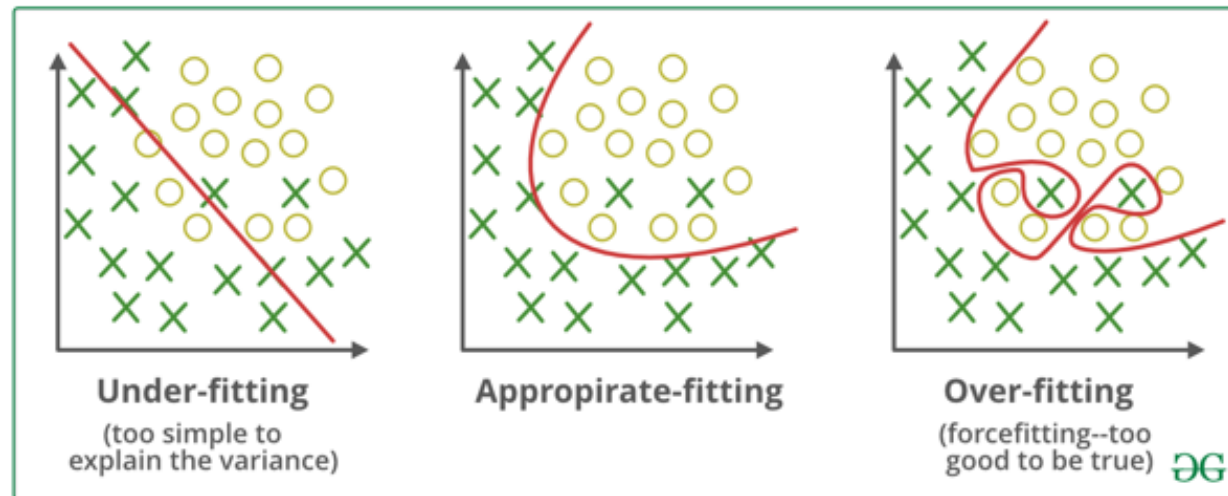
$f(X) \Rightarrow$ mapping function
 $Y = f(X)$

Fitting, Overfitting, Underfitting

Bias: assumptions made by a model to make learning easier **Training Error**

Variance: difference between training and test error **Test Error – Training Error** Generalization gap

$$\text{Generalization error} = \text{expected loss} = \text{test error} = \text{Bias} + \text{Variance}$$



<https://www.geeksforgeeks.org/underfitting-and-overfitting-in-machine-learning/>



Regularization

One solution to the **Overfitting** problem

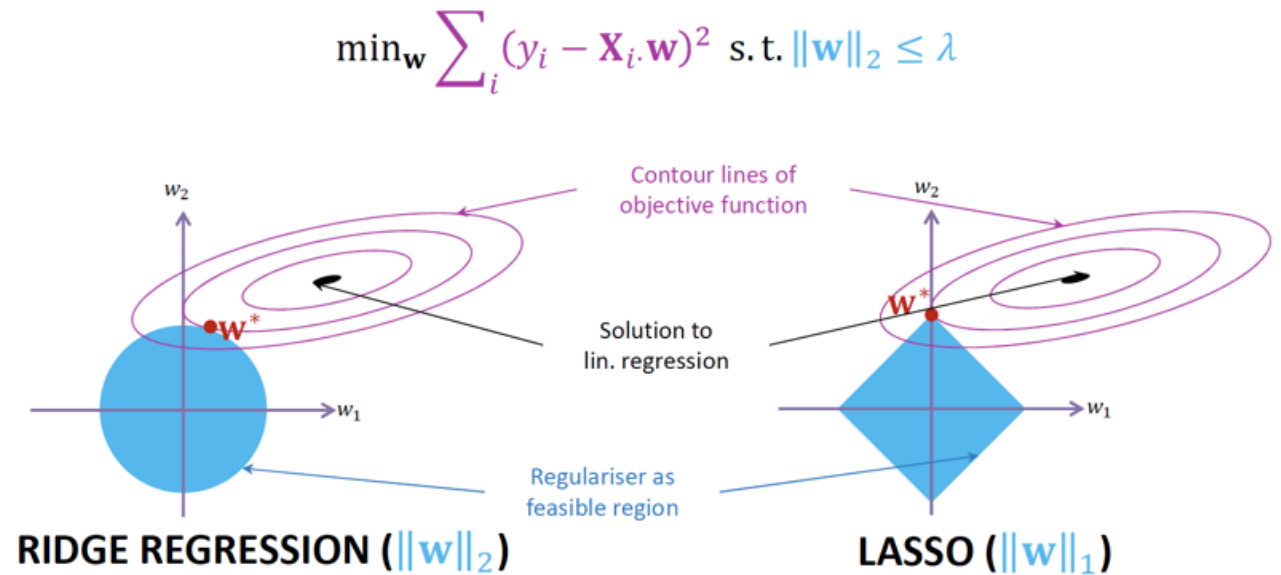
结构风险最小化

Structural Risk Minimization

$$R_{srm}(f) = R_{emp} + \lambda \cdot \Omega(\theta) :$$

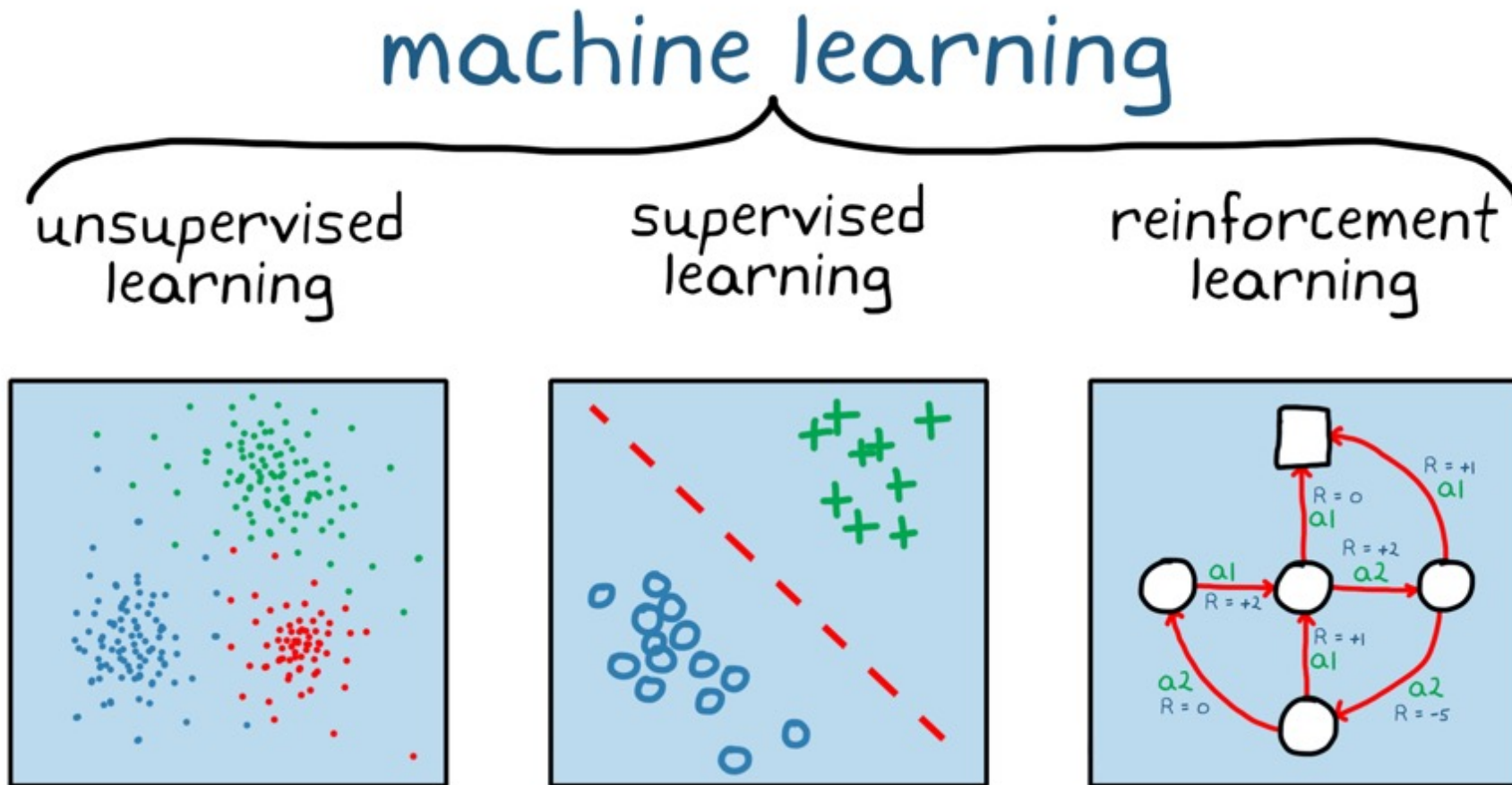
$$L_1 : \Omega(\theta) = \|\theta\|_1 = \sum_i |\theta_i|$$

$$L_2 : \Omega(\theta) = \|\theta\|_2 = \sum_i \theta_i^2$$



L_1 -regularisation encourages solutions \mathbf{w}^* to sit on axes
→ \mathbf{w}^* will have components equal zero → **\mathbf{w}^* will be sparse!**

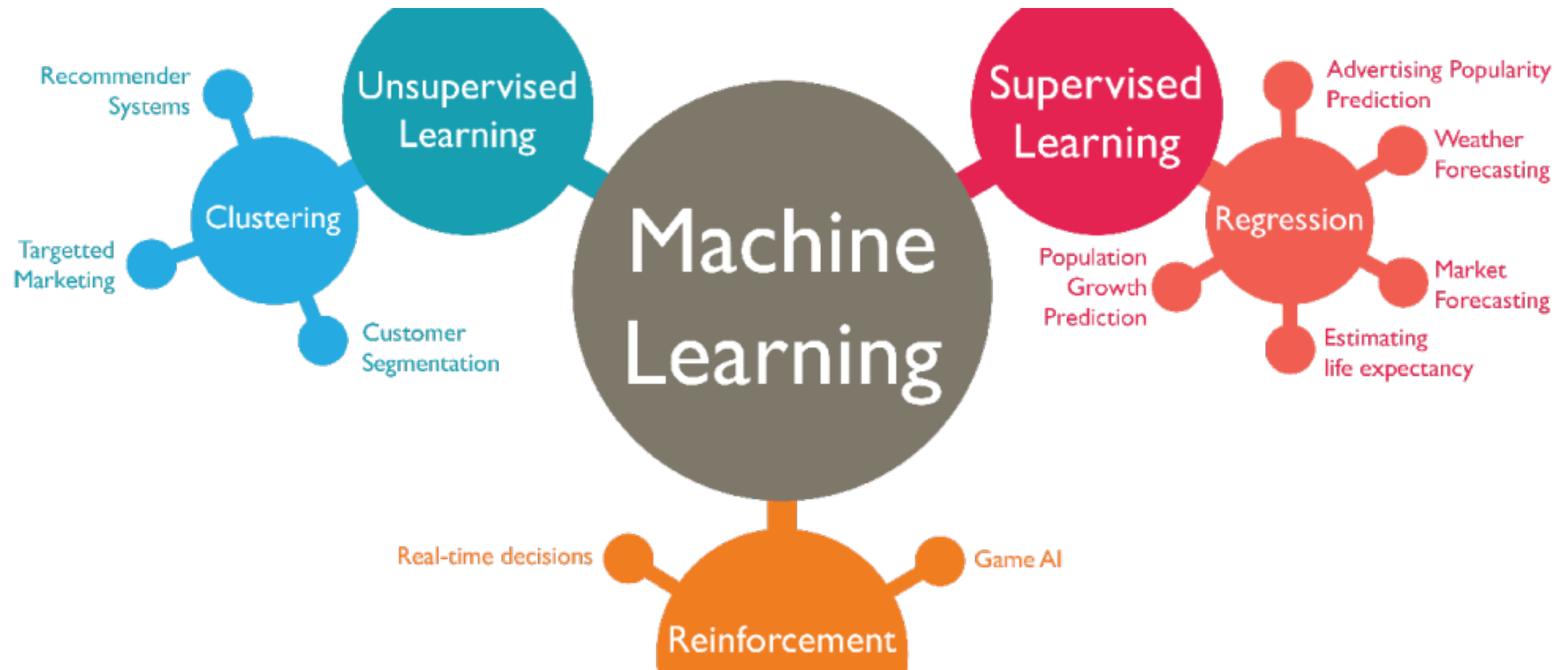
Learning Paradigms



<https://ww2.mathworks.cn/discovery/reinforcement-learning.html>



Learning Paradigms



<https://dev.to/afozbek/supervised-learning-vs-unsupervised-learning-4b65>



Supervised Learning



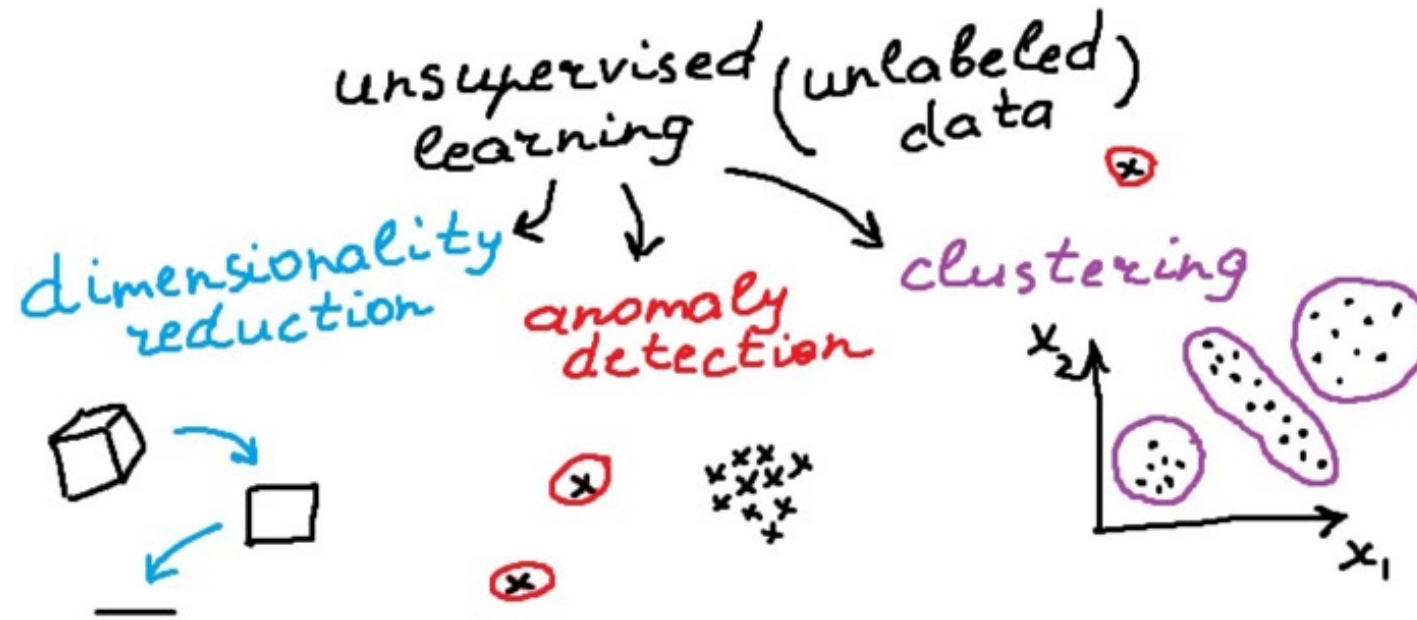
'dog'



'cat'

$$\min_{\theta} \mathbb{E}_{(x,y) \in D} \mathcal{L}(f(x), y) \quad D = \{x_i, y_i\}_{i=1}^n$$

Unsupervised Learning



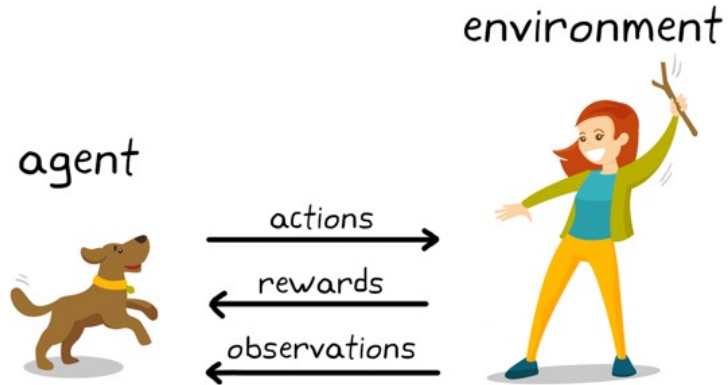
Step 1: $A(X) \rightarrow f$

Step 2: $f(x \in X^*) \rightarrow t$

$$D = \{x_i\}_{i=1}^n$$

<https://towardsdatascience.com/unsupervised-learning-algorithms-cheat-sheet-d391a39de44a>

Reinforcement Learning



History: $H_t = A_1, O_1, R_1, \dots, A_t, O_t, R_t$

State: $S_t = f(H_t)$ S_t^e S_t^a S_t

Markov State: $\mathbb{P}[S_{t+1}|S_t] = \mathbb{P}[S_{t+1}|S_1, \dots, S_t]$

Policy: Deterministic : Stochastic :

$$a = \pi(s) \qquad \pi(a|s) = \mathbb{P}[A_t = a|S_t = s]$$

Value Function: $v_\pi(s) = \mathbb{E}_\pi[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \dots | S_t = s]$

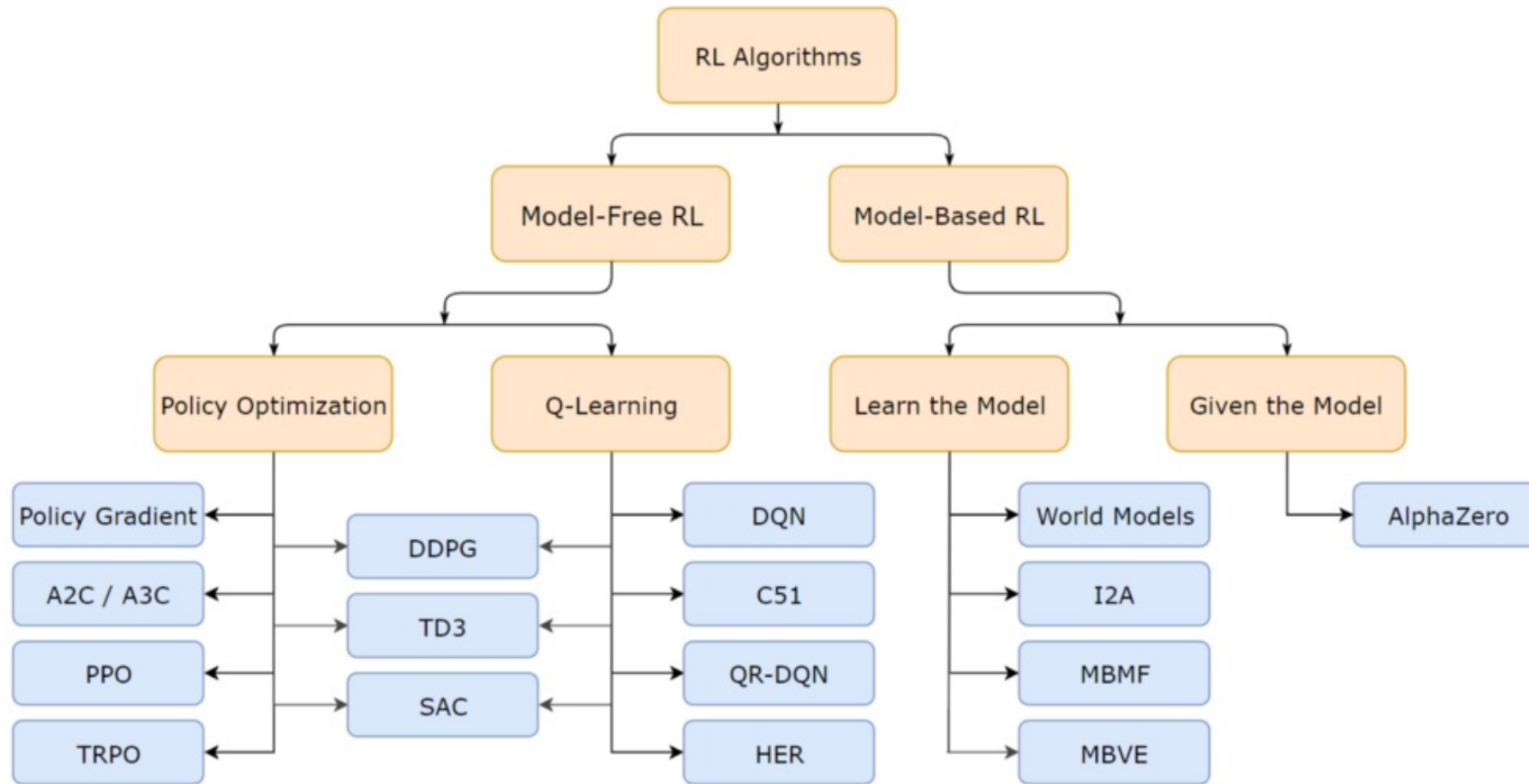
Model: $p_{ss'}^a = \mathbb{P}[S_{t+1} = s', A_t = a]$

$$p_s^a = \mathbb{E}[R_{t+1} | S_t = s, A_t = a]$$

<https://ww2.mathworks.cn/discovery/reinforcement-learning.html>; <https://towardsdatascience.com/reinforcement-learning-an-introduction-to-the-concepts-applications-and-code-ced6fbfd882d>



Types of Reinforcement Learning

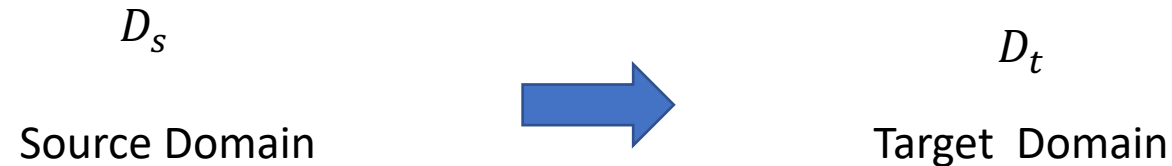


https://spinningup.openai.com/en/latest/spinningup/rl_intro2.html



Other Popular Learning Paradigms

Transfer Learning



$$\min_{\theta} [\mathbb{E}_{(x,y) \in D^s} \mathcal{L}(f(\mathbf{x}), y) + \mathcal{L}_{dis}(g(D^s), g(D^t))] \quad \text{Feature Transfer}$$

$$\min_{\theta} [\mathbb{E}_{(x,y) \in D^s} \mathcal{L}(f \circ X_{s \rightarrow t}(\mathbf{x}), y)] \quad \text{Sample Transfer}$$

$$\min_{\theta \subset \theta_g \cup \theta_{h^*}} [\mathbb{E}_{(x,y) \in D^t} \mathcal{L}^*(h^* \circ g(\mathbf{x}), y)] \quad \text{Model Transfer}$$

f 为模型, g 为特征编码器, h 为任务头, θ 为模型参数, $\mathcal{L}(f(\mathbf{x}), y)$ 对应任务损失函数, $g(D)$ 为数据集 D 的样本特征集合, \mathcal{L}_{dis} 为衡量特征集合分布差异的函数



Other Popular Learning Paradigms

Online Learning

$$D_{old} = \{\mathbf{x}_i^{old}, y_i^{old}\}_{i=1}^{n_{old}}$$

Existing Data



$$D_{new} = \{\mathbf{x}_i^{new}, y_i^{new}\}_{i=1}^{n_{new}}$$

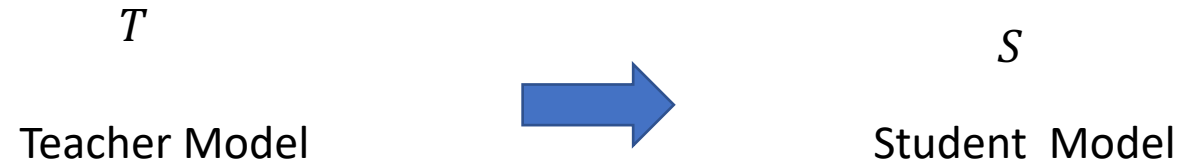
New Data

$$\min_{\theta} [\mathbb{E}_{(x,y) \in D_{old}} \mathcal{L}(f(\mathbf{x}), y) + \mathbb{E}_{(x,y) \in D_{new}} \mathcal{L}(f(\mathbf{x}), y)]$$

Key problem: catastrophic forgetting

Other Popular Learning Paradigms

Knowledge Distillation



$$\min_{\theta_s} \mathbb{E}_{(x,y) \in D} \mathcal{L}_{sim}(S_{\theta_s}(\mathbf{x}), T_{\theta_t}(\mathbf{x}))$$

KL-divergence loss is the most commonly used distillation loss

Losses

Regression Losses

MSE:
$$\mathcal{L}(f(X), Y) = \frac{1}{N} \sum_{i=1}^N (y_i - f(\mathbf{x}_i))^2$$

MAE:
$$\mathcal{L}(f(X), Y) = \frac{1}{N} \sum_{i=1}^N |y_i - f(\mathbf{x}_i)|$$

Huber Loss:
$$\mathcal{L}_\delta(f(\mathbf{x}), y) = \begin{cases} \frac{1}{2}(f(\mathbf{x}) - y)^2 & |f(\mathbf{x}) - y| < \delta \\ \delta|f(\mathbf{x}) - y| - \frac{1}{2}\delta^2 & \text{otherwise} \end{cases}$$



Losses

Classification Losses

Cross Entropy: $\mathcal{L}_{CE}(y, \mathbf{p}) = - \sum_{c=1}^C \mathbb{I}(c \equiv y) \cdot \log(\mathbf{p}_c) = -\log(\mathbf{p}_y)$

Binary Cross Entropy: $\mathcal{L}_{BCE}(y, p) = y \cdot \log(p) + (1 - y) \cdot \log(1 - p)$

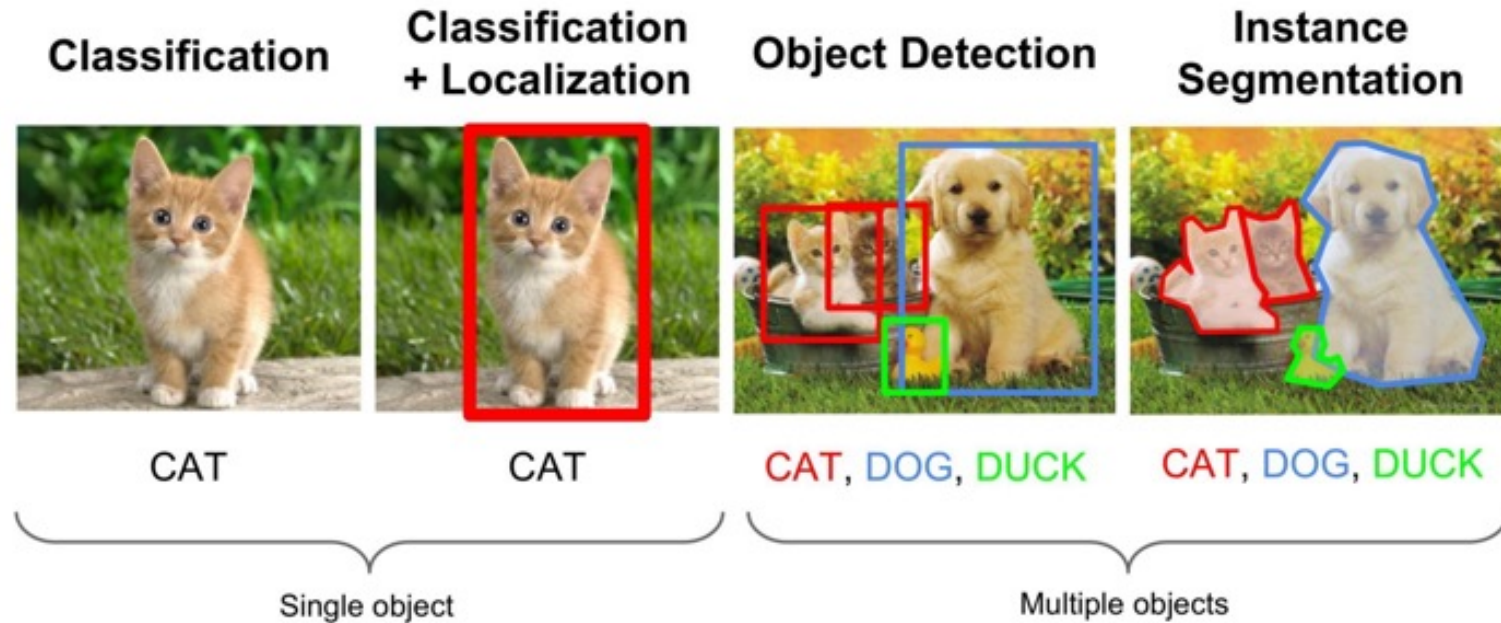
Generalized Cross Entropy: $\mathcal{L}_q(f(\mathbf{x}; \boldsymbol{\theta}), y) = \frac{1 - f_j(\mathbf{x})^q}{q}, \quad q \in (0, 1]$

Symmetric Cross Entropy: $SCE = \alpha H(\mathbf{q}, \mathbf{p}) + \beta H(\hat{\mathbf{p}}, \mathbf{q})$

Focal Loss: $FL(\mathbf{p}_y) = -(1 - \mathbf{p}_y)^\gamma \log(\mathbf{p}_y), \gamma \geq 0$

Losses

Object Detection Losses



Bounding Box Regression + Classification

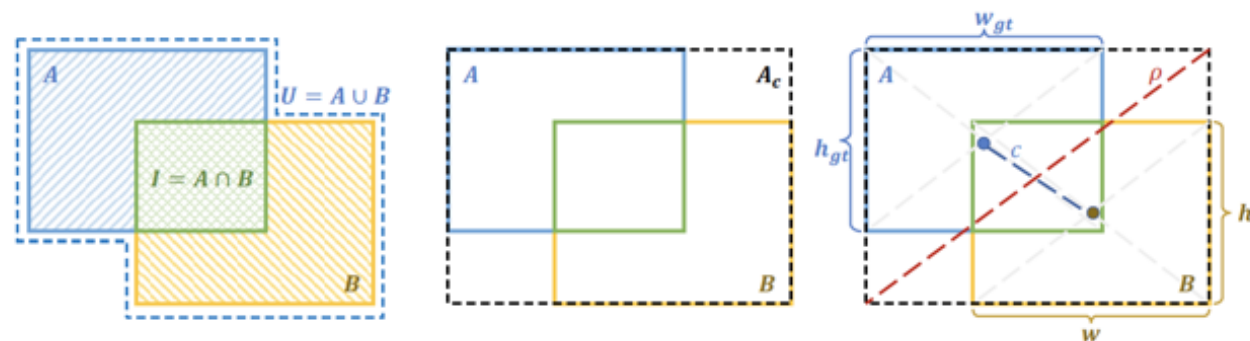
<https://medium.com/zylapp/review-of-deep-learning-algorithms-for-object-detection-c1f3d437b852>



Losses

Object Detection Losses

方法名称	*IoU 定义	损失函数
IoU-loss	$IoU = A \cap B / A \cup B $	$\mathcal{L}_{IoU} = 1 - IoU$
GIoU-loss	$GIoU = IoU - A_c - U / A_c $	$\mathcal{L}_{GIoU} = 1 - GIoU$
DIoU-loss	$DIoU = IoU - \rho^2(b, b^{gt}) / c^2$	$\mathcal{L}_{DIoU} = 1 - DIoU$
CIoU-loss	$CIoU = DIoU - \beta v$ $v = \frac{4}{\pi^2} \left(\arctan \frac{w^{gt}}{h^{gt}} - \arctan \frac{w}{h} \right)^2$	$\mathcal{L}_{CIoU} = 1 - CIoU$



$$\mathcal{L}_{\alpha IoU} = 1 - IoU^\alpha + P^\alpha(b, b^{gt})$$



$$\begin{cases} \mathcal{L}_{\alpha-IoU} = 1 - IoU^\alpha \\ \mathcal{L}_{\alpha-GIoU} = 1 - IoU^\alpha + \left(\frac{|A_c - U|}{|A_c|} \right)^\alpha \\ \mathcal{L}_{\alpha-DIoU} = 1 - IoU^\alpha + \frac{\rho^{2\alpha}(b, b^{gt})}{c^{2\alpha}} \\ \mathcal{L}_{\alpha-CIoU} = 1 - IoU^\alpha + \frac{\rho^{2\alpha}(b, b^{gt})}{c^{2\alpha}} + (\beta v)^\alpha \end{cases}$$

Losses

Generative Losses

- ◆ 自回归模型 (Autoregressive)
- ◆ 能量模型 (Energy based models)
- ◆ 流模型 (Flows)
- ◆ 变分自编码器 (VAE , variational autoencoder)
- ◆ 生成对抗网络 (GAN , generative adversarial network)
- ◆ 扩散模型 (Diffusion models)

方法	损失函数
GAN	$\mathcal{L}_D = -(\mathbb{E}_{x \sim p_{data}(x)}[\log(D(x))] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))])$ $\mathcal{L}_G = \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))]$
LSGAN	$\mathcal{L}_D = (\mathbb{E}_{x \sim p_{data}(x)}[(D(x) - 1)^2] + \mathbb{E}_{z \sim p_z(z)}[(D(G(z)))^2])$ $\mathcal{L}_G = \mathbb{E}_{z \sim p_z(z)}[(D(G(z)) - 1)^2]$
WGAN	$\mathcal{L}_D = (\mathbb{E}_{z \sim p_z(z)}[D(G(z))] - \mathbb{E}_{x \sim p_{data}(x)}[D(x)])$ $\mathcal{L}_G = -\mathbb{E}_{z \sim p_z(z)}[D(G(z))]$ $\theta_D = \text{clip}(\theta_D, -c, c)$, c 是截断参数
Hinge Loss	$\mathcal{L}_D = -\mathbb{E}_{x \sim p_{data}(x)}[\min(0, -1 + D(x))]$ $-\mathbb{E}_{z \sim p_z(z)}[\min(0, -1 - D(G(z)))]$ $\mathcal{L}_G = -\mathbb{E}_{z \sim p_z(z)}D(G(z))$



Optimizers

Gradient Descent (GD)

$$\theta' = \theta - \eta \nabla_{\theta} = \theta - \eta \frac{1}{N} \sum_{i=1}^N \nabla_{\theta} \mathcal{L}(y_i, f(\mathbf{x}_i); \theta)$$

Stochastic Gradient Descent (SGD) for mini-batch based training

$$\theta' = \theta - \eta \nabla_{\theta} = \theta - \eta \frac{1}{N'} \sum_{i=1}^{N'} \nabla_{\theta} \mathcal{L}(y_i, f(\mathbf{x}_i); \theta)$$

SGD with Momentum

$$\mathbf{v}_t = \gamma \mathbf{v}_{t-1} + \eta \nabla_{\theta} J(\boldsymbol{\theta}_t)$$

$$\boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t - \mathbf{v}_t$$

SGD with Nesterov Acceleration

$$\mathbf{v}_t = \gamma \mathbf{v}_{t-1} + \eta \nabla_{\theta} J(\boldsymbol{\theta}_t - \gamma \mathbf{v}_{t-1})$$

$$\boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t - \mathbf{v}_t$$



Optimizers

AdaGrad

$$\theta_{t+1,i} = \theta_{t,i} - \frac{\eta}{\sqrt{\sum_t g_t^2 + \epsilon}} \cdot g_{t,i}$$

RMSprop

$$E[g^2]_t = \gamma E[g^2]_{t-1} + (1 - \gamma) g_t^2$$
$$\theta_{t+1,i} = \theta_{t,i} - \frac{\eta}{\sqrt{E[g^2]_{t,i} + \epsilon}} \cdot g_{t,i}$$

Adadelta

$$\theta_{t+1,i} = \theta_{t,i} - \frac{\sqrt{E[\Delta\theta^2]_{t,i} + \epsilon}}{\sqrt{E[g^2]_{t,i} + \epsilon}} \cdot g_{t,i}$$

Adam

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t + \epsilon}} \hat{m}_t$$

谢谢！下周见！

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