

K-Means

Randomly initialize \rightarrow reassign \rightarrow mean value
 iterate until it converge

Spectral Clustering

to find densely linked clusters

2 groups $A, B = V \setminus A$, then $\text{cut}(A) = \sum_{i \in A, j \notin A} w_{ij}$
 Optimize: $\frac{\min \left\{ \sum_{(i,j) \in E; i \in A, j \notin A} w_{ij} \right\}}{\min \{ \text{vol}(A), 2m - \text{vol}(A) \}}$ (undirected)

where $\text{vol}(A)$: total weight of edges with at least 1 endpoint in A

A: adjacency mat ; $A\vec{x} = \vec{y}$, $y_i = \sum_{(i,j) \in E} x_j$
 property: symmetric, Eig vector — real & orthogonal

D: degree mat . 对角阵

L: Laplacian mat $L = D - A$ — The first eig $\lambda = 0$
 property: Symmetric, eig $> 0 \wedge \in \mathbb{R}$, Eig vec $\in \mathbb{R}$

SVM

to separate data using a line
 Maximize the Margin, line: $\vec{w} \cdot \vec{x} + b = 0$

point A(x_1, x_2), $w = (w_1, w_2) / \|w\|$

$$y_i = (\vec{w} \cdot \vec{x}_i + b)$$

Then goal: $\max \gamma$, $\forall i, y_i(\vec{w} \cdot \vec{x}_i + b) \geq \gamma$
 re-define $\gamma = \frac{1}{\|\vec{w}\|} (\vec{w} \cdot \vec{x}_0 + b)$, $\|\vec{w}\| = 1$ for support

$$\text{Then } \gamma = \frac{1}{\|\vec{w}\|}$$

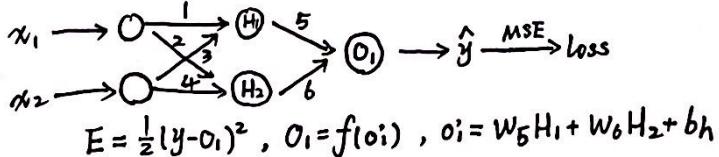
The final goal for hard margin:

$$\min_w \frac{1}{2} \|w\|^2, (\forall i, y_i(\vec{w} \cdot \vec{x}_i + b) \geq 1)$$

Fully connect

$$\vec{Output} = \vec{W} \vec{Input} + \vec{b}, \vec{Output} = f(\vec{Output})$$

$$\text{sigmoid } f(z) = \frac{1}{1+e^{-z}}, f'(z) = f(z)(1-f(z))$$



$$\frac{\partial E}{\partial w_5} = (o_1 - y) f'(o_1) \cdot H, \quad \text{update } w_i \\ \frac{\partial E}{\partial o_i} \triangleq \delta o_i$$

$$H_1 = f(h_1), h_1 = w_1 x_1 + w_3 x_2 + b$$

$$\frac{\partial E}{\partial w_1} = \frac{\partial E}{\partial H} \cdot \frac{\partial H}{\partial h_1} \cdot \frac{\partial h_1}{\partial w_1} = \delta o_1 \cdot w_5 \cdot f'(h_1) \cdot x_1$$

$$\text{return } \frac{\partial E}{\partial H}$$

Conv NN

$$32 \times 32 \times 3 \xrightarrow[6 \text{ } 5 \times 5 \times 3 \text{ filters}]{\text{CONV, RELU}} 28 \times 28 \times 6 \longrightarrow \dots$$

$$\text{output size} = \frac{\text{Input} + 2 \cdot \text{pad} - \text{kernel_size}}{\text{stride}} + 1$$

Numbers of parameters: e.g., 10 5×5 filters for $32 \times 32 \times 3$
 $N \cdot P = 10 \times (5 \times 5 \times 3 + 1) \rightarrow \text{bias}$

To conclude,

$$W_1 \times H_1 \times D_1 \xrightarrow[\text{stride } S, \text{ zero Padding } P]{\text{Filters-Number } K, \text{ Spatial extent } F} W_2 \times H_2 \times D_2$$

$$\text{where } W_2 = \frac{W_1 - F + 2P}{S} + 1, H_2 \text{ 同理}, D_2 = K$$

Common settings: K : powers of 2
 $(F, S, P) = (3, 1, 1) / (5, 1, 2) / (5, 2, ?) / (1, 2, 0)$

Architecture

$$\text{LeNet: } \begin{matrix} \text{CONV} & \rightarrow & \text{POOL} & \rightarrow & \text{CONV} & \rightarrow & \text{POOL} & \rightarrow & \text{FC} \end{matrix} \rightarrow \text{FC} \rightarrow \text{FC} \rightarrow \text{FC}$$

$$\begin{matrix} 16 & 5 \times 5 \\ 6 & 5 \times 5 \end{matrix} \xrightarrow[2 \times 2 \text{ stride 2}]{} \begin{matrix} 120 \\ 84 \end{matrix} \xrightarrow{} \begin{matrix} 84 \\ 10 \end{matrix}$$

AlexNet: 双层，最后反互 / 在特定位置交互
 $(\text{CONV} \rightarrow \text{MAX POOL} \rightarrow \text{NORM}) \times 2 \rightarrow \text{CONV} \times 3 \rightarrow \text{FC} \times 3$

VGGNet: 两个 3×3 相当于一个 5×5 ，以此类推
 更少参数

Inception:

(Google) to compute loss

layer: previous $\rightarrow 1 \times 1 \text{ conv} \rightarrow$ Filter concatenation
 $\begin{matrix} 1 \times 1 \text{ C} & \rightarrow & 3 \times 3 \text{ C} \\ \downarrow & & \uparrow \end{matrix} \xrightarrow{1 \times 1 \text{ C}} \xrightarrow{3 \times 3 \text{ max pooling}} \xrightarrow{1 \times 1 \text{ C}}$

ResNet:
 (Residual)
 $x \xrightarrow{\text{relu}} F(x) \xrightarrow{\text{relu}} \oplus \xrightarrow{\text{relu}} H(x) = F(x) + x$

DenseNet — connected to every other layer

KNN: $N \times k$ \triangleq 最近的 k 个 point

$$\hat{y}(x) = \frac{1}{k} \sum_{i \in N_k(x)} y_i, \text{ bias } \uparrow \text{ variance } \downarrow$$

decide k : split data into Train, validation & Test
 or "fold"s

补充：

$$\text{solve } (w_0, b_0) = \arg \min \|w\|^2 \text{ s.t. } \forall i, y_i(\langle w, x_i \rangle + b) \geq 1$$

output: $\hat{w} = \frac{w_0}{\|w_0\|}, \hat{b} = \frac{b_0}{\|w_0\|}$ is a solution of $\max_{\|w\|=1} \min_i y_i(\langle w, x_i \rangle + b)$

$$\text{proof: } (w^*, b^*), y^* = \min_i y_i(\langle w^*, x_i \rangle + b^*)$$

$$\Rightarrow y_i(\langle w^*, x_i \rangle + \frac{b^*}{\gamma^*}) \geq 1$$

Therefore, $\|w\| \leq \frac{1}{\gamma^*}$ which means $\gamma^* \leq \frac{1}{\|w\|}$

$$\Rightarrow y_i(\langle \hat{w}, x_i \rangle + b) = \frac{1}{\|\hat{w}\|} y_i(\langle w_0, x_i \rangle + b_0) \geq \frac{1}{\|w_0\|} \geq \gamma^*$$

$$\Sigma x_i = 0, \Sigma x_i^2 = 1, \gamma^* = \frac{\sqrt{\lambda_2}}{\sqrt{\lambda_1}} = \sqrt{\frac{\sum_{(i,j) \in E} (x_i - x_j)^2}{\sum x_i^2}}$$

第2小特征根 \rightarrow eig vec 可分类。where \star is eig vec