

# MMD

$$\min_{\beta^T \hat{P} = b} \left\| \frac{1}{p+b} \left( \sum_{x_j \in P} \phi(x_j) + \sum_{x_i \in \hat{P}} \beta_i g_i \phi(x_i) \right) - \frac{1}{\hat{p}-b} \left( \sum_{x_j \in \hat{P}} \phi(x_j) - \sum_{x_i \in \hat{P}} \beta_i g_i \phi(x_i) \right) \right\|_H^2$$

$P$ : 已标记正例集合,  $p = |P|$

$\hat{P}$ : 预测正例集合,  $\hat{p} = |\hat{P}|$

$b$ : 批量查询的个数

$\beta$ :  $\beta_i \in \{0,1\}$

$g$ :  $g_i = f(x_i)$

# MMD

查询在预测正例中具有代表性的样本

$$\left\| \frac{1}{p+b} \left( \sum_{x_j \in P} \phi(x_j) + \sum_{x_i \in \hat{P}} \beta_i g_i \phi(x_i) \right) - \frac{1}{\hat{p}-b} \left( \sum_{x_i \in \hat{P}} (1 - \beta_i g_i) \phi(x_i) \right) \right\|_H^2$$

$$\frac{1}{2} \langle \beta \circ g \rangle^T K_{\hat{P}\hat{P}} \langle \beta \circ g \rangle - \frac{p+b}{p+\hat{p}} \mathbf{1}_{\hat{P}}^T K_{\hat{P}\hat{P}} \langle \beta \circ g \rangle + \frac{\hat{p}-b}{\hat{p}+p} \mathbf{1}_P^T K_{P\hat{P}} \langle \beta \circ g \rangle + const$$

$$\beta_i \in \{0,1\}, g_i = f(x_i)$$

进一步简写为  $\boldsymbol{\beta}^T K_1 \boldsymbol{\beta} + k \boldsymbol{\beta}$

# If Query a Negative Example

现有的PU经验风险公式：

$$R_{emp}(f) = \frac{\pi}{p} \sum_{x_i \in D_P} \tilde{l}(f(x_i), 1) + \frac{1}{u} \sum_{x_i \in D_U} l(f(x_i), -1), \text{ where } p = |D_P|, u = |D_U|$$



$$R_{emp}(f) = \frac{\pi}{p} \sum_{x_i \in D_P} \tilde{l}(f(x_i), 1) + \frac{1}{u} \sum_{x_i \in D_U} l(f(x_i), -1) + \frac{c}{n} \sum_{x_i \in D_N} l(f(x_i), -1),$$

$$\text{where } p = |D_P|, u = |D_U|, n = |D_N|$$

为了让分类器将已标注的负类样本分对，设置一个较大的 $c$ 值，加大对负类样本分错的惩罚力度。

$$f^* = \arg \min_{f \in H_k} \left\{ R_{emp}(f) + \lambda \|f\|_{H_k}^2 \right\}$$

# Cost-sensitive PU Learning

$$\begin{aligned} &+ \quad \text{U} \quad \text{Q} \quad - \\ &\frac{\pi}{p} \sum_{x_i \in P} \tilde{l}(f(x_i), 1) + \frac{1}{u} \sum_{x_i \in U \setminus Q} l(f(x_i), -1) + \frac{1}{b} \sum_{x_i \in Q} l(f(x_i), -1) + \frac{c}{n} \sum_{x_i \in N} l(f(x_i), -1) \\ &= \frac{\pi}{p} \sum_{x_i \in P} \tilde{l}(f(x_i), 1) + \frac{1}{u} \sum_{x_i \in U} l(f(x_i), -1) + \frac{c}{n} \sum_{x_i \in N} l(f(x_i), -1) \end{aligned}$$

# Square Loss

$$l(f(x), y) = \frac{1}{4}(f(x) - y)^2$$

$$\tilde{l}(f(x), y) = l(f(x), y) - l(f(x), -y) = \frac{1}{4}(f(x) - y)^2 - \frac{1}{4}(f(x) + y)^2 = -yf(x)$$

$$\frac{\pi}{p} \sum_{x_i \in P} \tilde{l}(f(x_i), 1) + \frac{1}{u} \sum_{x_i \in U} l(f(x_i), -1) + \frac{c}{n} \sum_{x_i \in N} l(f(x_i), -1)$$



$$-\frac{\pi}{p} \sum_{x_i \in P} f(x_i) + \frac{1}{u} \sum_{x_i \in U} \frac{1}{4}(f(x_i) + 1)^2 + \frac{c}{n} \sum_{x_i \in N} \frac{1}{4}(f(x_i) + 1)^2$$

# Vectorization

$$-\frac{\pi}{p} \sum_P f(x_i) + \frac{1}{u} \sum_U \frac{1}{4} (f(x_i) + 1)^2 + \frac{c}{n} \sum_N \frac{1}{4} (f(x_i) + 1)^2$$

$$\min_{\mathbf{a}} \left\{ -\frac{\pi}{p} \sum_{x_i \in P} \mathbf{a}^T \phi(x_i) + \frac{1}{4u} \sum_{x_i \in U} (\mathbf{a}^T \phi(x_i) + 1)^2 + \frac{1}{4n} \sum_{x_i \in N} (\mathbf{a}^T \phi(x_i) + 1)^2 + \lambda \|\mathbf{a}\|^2 \right\}$$

$$\min_{\mathbf{a}} \left\{ -\frac{\pi}{p} \mathbf{1}_P^T \phi_P \mathbf{a} + \left( \frac{1}{4u} \mathbf{a}^T \phi_U^T \phi_U \mathbf{a} + \frac{1}{2u} \mathbf{1}_U^T \phi_U \mathbf{a} \right) + \left( \frac{c}{4n} \mathbf{a}^T \phi_N^T \phi_N \mathbf{a} + \frac{c}{2n} \mathbf{1}_N^T \phi_N \mathbf{a} \right) + \lambda \mathbf{a}^T \mathbf{a} \right\}$$