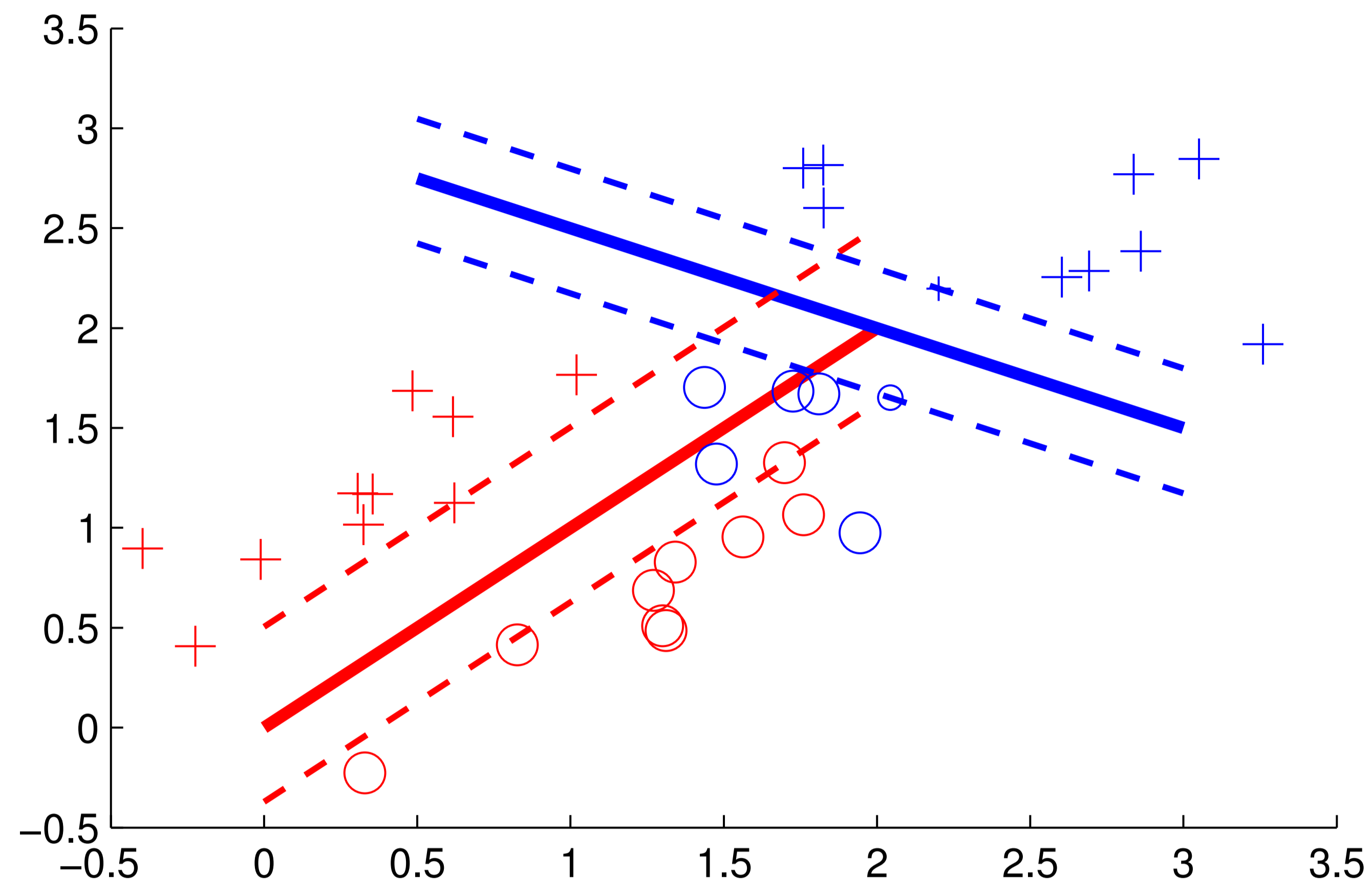


INFINITE SVM (Zhu et al., ICML 2011)

Infinite SVM: a supervised Bayesian nonparametric model



Exponential family likelihood model:

$$p(\mathbf{x}|\boldsymbol{\mu}) = \exp(-D_\varphi(\mathbf{x}, \boldsymbol{\mu}))f_\varphi(\mathbf{x}).$$

Chinese Restaurant Process nonparametric prior:

$$p(z_i = k|\boldsymbol{\alpha}, \mathbf{z}_{-i}) = \begin{cases} n_{-i,k} & \text{if } n_{-i,k} > 0 \\ \alpha_k & \text{otherwise} \end{cases}$$

Max-margin posterior regularization:

$$\min_{q(\Theta) \in \mathcal{P}} \text{KL}(q||p_0) - \mathbb{E}_q[\log p(\mathbf{X}|\Theta)] + 2c \cdot \mathcal{R}(q(\Theta), \mathbf{X}, \mathbf{y}),$$

$$\mathcal{R}(q(\Theta), \mathbf{X}, \mathbf{y}) = \sum_{i=1}^n \max(0, 1 - y_i \mathbb{E}_q[\boldsymbol{\eta}_{z_i}^\top \mathbf{x}_i]).$$

GIBBS SAMPLING

Averaging classifier vs. Gibbs classifier:

$$\mathcal{R}'(q(\Theta), \mathbf{X}, \mathbf{y}) = \sum_{i=1}^n \mathbb{E}_q[\max(0, 1 - y_i \boldsymbol{\eta}_{z_i}^\top \mathbf{x}_i)].$$

Data augmentation (Polson and Scott, 2011):

$$\phi(y_i|z_i, \boldsymbol{\eta}) = \int_0^\infty \frac{1}{\sqrt{2\pi\omega_i}} \exp\left(-\frac{(\omega_i + c\zeta_i^{z_i})^2}{2\omega_i}\right) d\omega_i.$$

Posterior distribution:

$$q(\Theta, \boldsymbol{\omega}) = \frac{p_0(\Theta) \prod_{i=1}^n p(\mathbf{x}_i|z_i, \boldsymbol{\mu}) \phi(y_i, \omega_i|z_i, \boldsymbol{\eta})}{Z(D)}.$$

SMALL-VARIANCE ASYMPTOTIC (SVA) ANALYSIS

1. For exponential family distributions (taking $\beta \rightarrow \infty$):

$$p(\mathbf{x}|\tilde{\boldsymbol{\theta}}(\boldsymbol{\mu})) = \exp(-\beta D_\varphi(\mathbf{x}, \boldsymbol{\mu}))f_\varphi(\mathbf{x}),$$

2. For existing clusters:

$$q(z_i = k|\mathbf{z}_{-i}, \beta) \propto n_{-i,k} f_\varphi(\mathbf{x}_i) \exp(-\beta D_\varphi(\mathbf{x}_i, \boldsymbol{\mu}_k) - 2c\beta'(\zeta_i^k)_+) \Rightarrow Q_i(k) = s \cdot D_\varphi(\mathbf{x}_i, \boldsymbol{\mu}_k) + 2c(\zeta_i^k)_+$$

3. For creating a new cluster:

$$q(z_i = z_{new}|\boldsymbol{\alpha}, \beta) \propto \alpha \cdot p(\mathbf{x}_i|\beta) \cdot \int \phi(y_i|\boldsymbol{\eta}, \beta') dp_0(\boldsymbol{\eta}) \Rightarrow Q_i(new) = \lambda + 2c(\zeta_i^*)_+ + \frac{\|\boldsymbol{\eta}^*\|^2}{\nu^2}$$

GIBBS-iSVM

Repeat until convergence:

- $q(\boldsymbol{\mu}_k) \propto \exp(-\kappa' D_\varphi((\tau + \bar{\mathbf{x}}_k)/\kappa', \boldsymbol{\mu}_k))$,
- $q(\boldsymbol{\eta}_k) = \mathcal{N}(\boldsymbol{\eta}_k; \boldsymbol{\lambda}_k, \boldsymbol{\Lambda}_k)$,
- $q(\omega_i^{-1}) = \mathcal{IG}(\omega_i^{-1}; 1/(c|\zeta_i^{z_i}|), 1)$,
- $q(z_i = k) \propto \begin{cases} n_{-i,k} p(\mathbf{x}_i|\boldsymbol{\mu}_k) \phi(y_i|\mathbf{x}_i, \boldsymbol{\eta}_k), & \text{if } n_{-i,k} > 0 \\ \alpha \cdot (x_i) \int \phi(y_i|\boldsymbol{\eta}) dp_0(\boldsymbol{\eta}), & \text{otherwise} \end{cases}$

MAX-MARGIN DP-MEANS

Repeat until convergence:

- $\boldsymbol{\mu}_k \leftarrow \bar{\mathbf{x}}_k = \sum_{i \in \mathcal{N}_k} \mathbf{x}_i$
- $\boldsymbol{\eta}_k \leftarrow \boldsymbol{\lambda}_k$
- $\omega_i \leftarrow c \cdot |\zeta_i^{z_i}| = c \max(0, 1 - y_i \boldsymbol{\eta}_{z_i}^\top \mathbf{x}_i)$,
- $z_i \leftarrow \text{argmin}_k Q_i(k)$.

EXPERIMENTS

1. Classification performance

		MNL	L-SVM	RBF-SVM	dpMNL	DP+SVM	Gibbs-iSVM	M ² DPM
<i>Synth. I</i>	Acc (%)	66.4	69.5	66.2	68.8	70.8	70.9	71.1
	Time (s)	0.1	0.1	0.2	29.8	0.1	4.2	0.1
<i>Synth. II</i>	Acc(%)	54.4	65.5	54.6	54.6	58.9	62.9	64.4
	Time (s)	11.1	14.3	1.2	126.2	2.4	40.7	3.6
<i>Protein</i>	F1 (%)	41.2	47.3	49.5	49.5	47.9	50.1	49.9
	Times (s)	2.9	0.5	1.6	98.2	0.2	223.4	8.1
<i>Parkinson</i>	Acc. (%)	85.6	87.2	87.2	87.7	86.2	88.9	88.7
	Time (s)	0.1	0.1	0.1	22.2	0.1	1.8	0.1

2. Nonparametric clustering performance on synthetic datasets

	n_0	100	300	1000	3000	10000
K_0	8	9	11	13	14	
K	8	8	11	12	14	

3. Clustering results on the Parkinson dataset

Group	I	II	III	IV	V
Avg. age	65.9	67.0	65.3	77.0	65.4
Avg. stage (0-4)	1.7	1.7	1.3	2.3	1.5