

PLAME: Piecewise-Linear Approximate Measure for Additive Kernel SVM



Tsz Nam Chan

Shenzhen University

edisonchan@szu.edu.cn

Zhe Li

Alibaba Cloud

huoju.lz@alibaba-inc.com

Leong Hou U

University of Macau

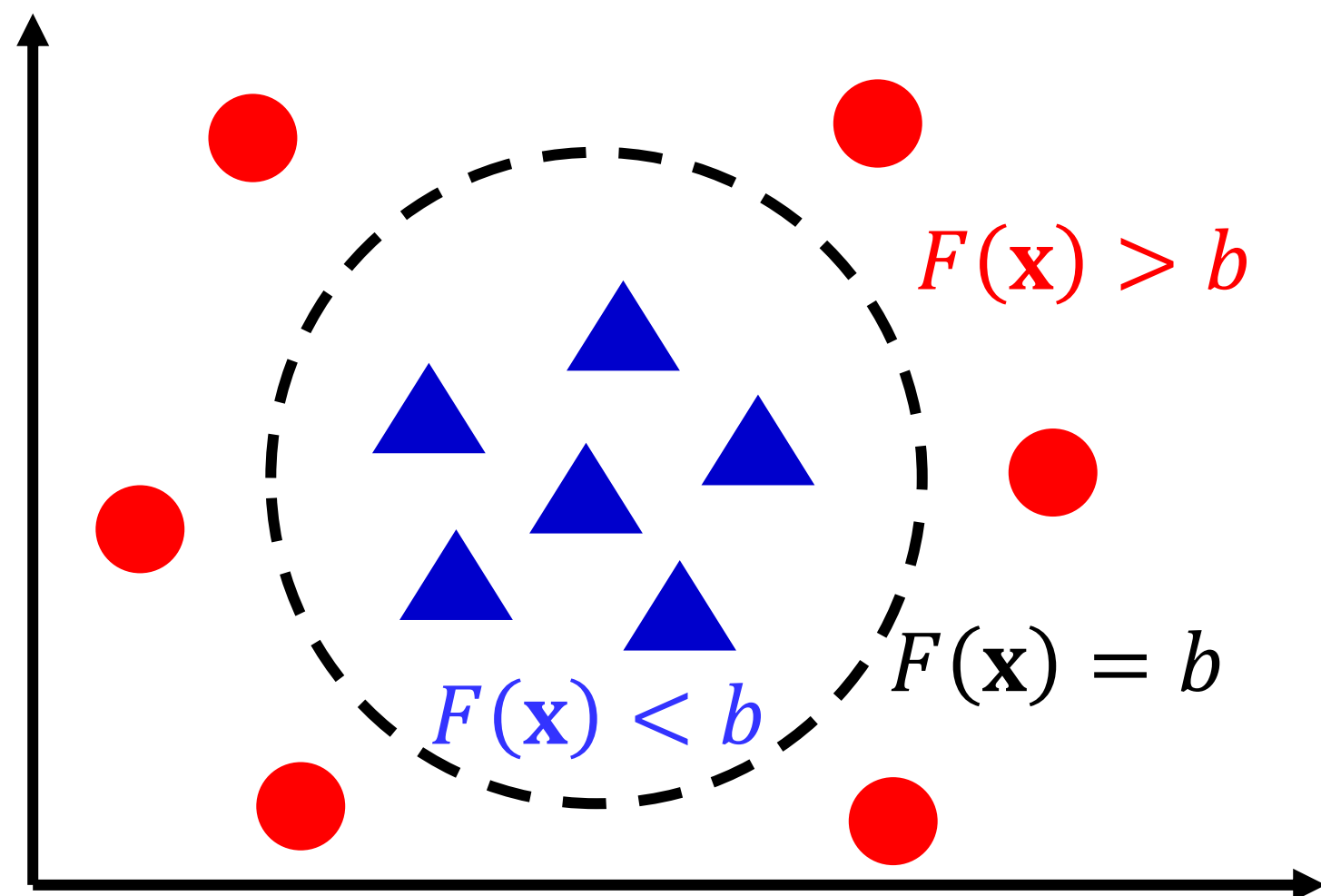
ryanlu@um.edu.mo

Reynold Cheng

The University of Hong Kong

ckcheng@cs.hku.hk

Overview of Kernel SVM



$F(\mathbf{x}) = \sum_{i=1}^n \alpha_i y_i K(\mathbf{x}, \mathbf{x}_i)$ is the kernel SVM classifier, where:

- (\mathbf{x}_i, y_i) denotes the i^{th} training data point (y_i can be +1 or -1).
- n denotes the number of training data points.
- d denotes the dimensionality of training data points.

Goal: Obtain α_i and b .

Overview of Additive Kernels

Kernel name	$K(\mathbf{x}_i, \mathbf{x})$
χ^2	$\sum_{\ell=1}^d \frac{2x_i^{(\ell)} x^{(\ell)}}{x_i^{(\ell)} + x^{(\ell)}}$
JS	$\sum_{\ell=1}^d \frac{1}{2} x_i^{(\ell)} \log_2 \left(\frac{x_i^{(\ell)} + x^{(\ell)}}{x_i^{(\ell)}} \right) + \frac{1}{2} x^{(\ell)} \log_2 \left(\frac{x_i^{(\ell)} + x^{(\ell)}}{x^{(\ell)}} \right)$
Intersection	$\sum_{\ell=1}^d \min(x_i^{(\ell)}, x^{(\ell)})$
Hellinger	$\sum_{\ell=1}^d \sqrt{x_i^{(\ell)} x^{(\ell)}}$

Additive kernels are demonstrated to be useful in many application domains, including human activity detection and pedestrian detection.

Guo et al. [a] "... we train a SVM classifier with chi-square kernel for multi-class recognition task, which is beneficial for classifying the histogram features."

[a] Y. Guo, Y. Li, and Z. Shao. DSRF: A flexible trajectory descriptor for articulated human action recognition. Pattern Recognition, 76: 137-148, 2018.

Existing Methods of Additive Kernel SVM and PLAME

Method	Classification error	Memory space	Training time
Kernel SVM solver [13]	low	low	high
Linear SVM solver [23], [28]	high	low	low
Feature approximation [35], [47], [59], [60] [7], [17], [33], [64]	high	high	low
Function approximation [69], [71], [75]	high	low	low
PLAME (ours)	low	low	low

Existing SVM training methods (those references in the above table can be found in our TKDE paper.) cannot simultaneously fulfill these three conditions.

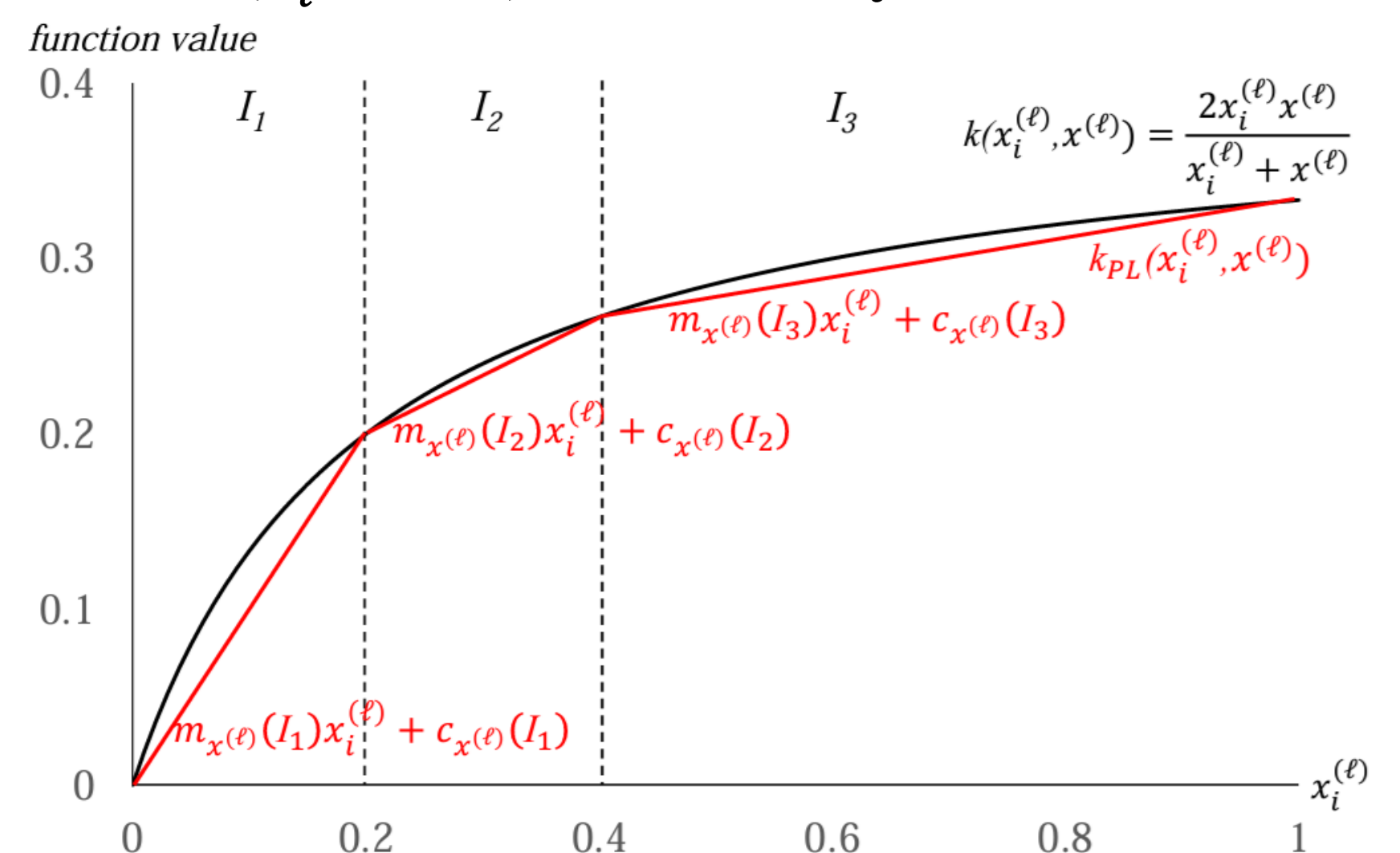
- Low classification error
- Low memory space
- Low training time

PLAME is the **first approach** that can achieve these three conditions.

Our observation: Every additive kernel can be represented by d one-dimensional additive kernel functions.

$$K(\mathbf{x}, \mathbf{x}_i) = \sum_{\ell=1}^d k(x_i^{(\ell)}, x^{(\ell)})$$

Core idea of PLAME: Use a **piecewise-linear function** to approximate $k(x_i^{(\ell)}, x^{(\ell)})$ and modify the linear SVM solver.



Experimental Evaluation

Accuracy of all methods

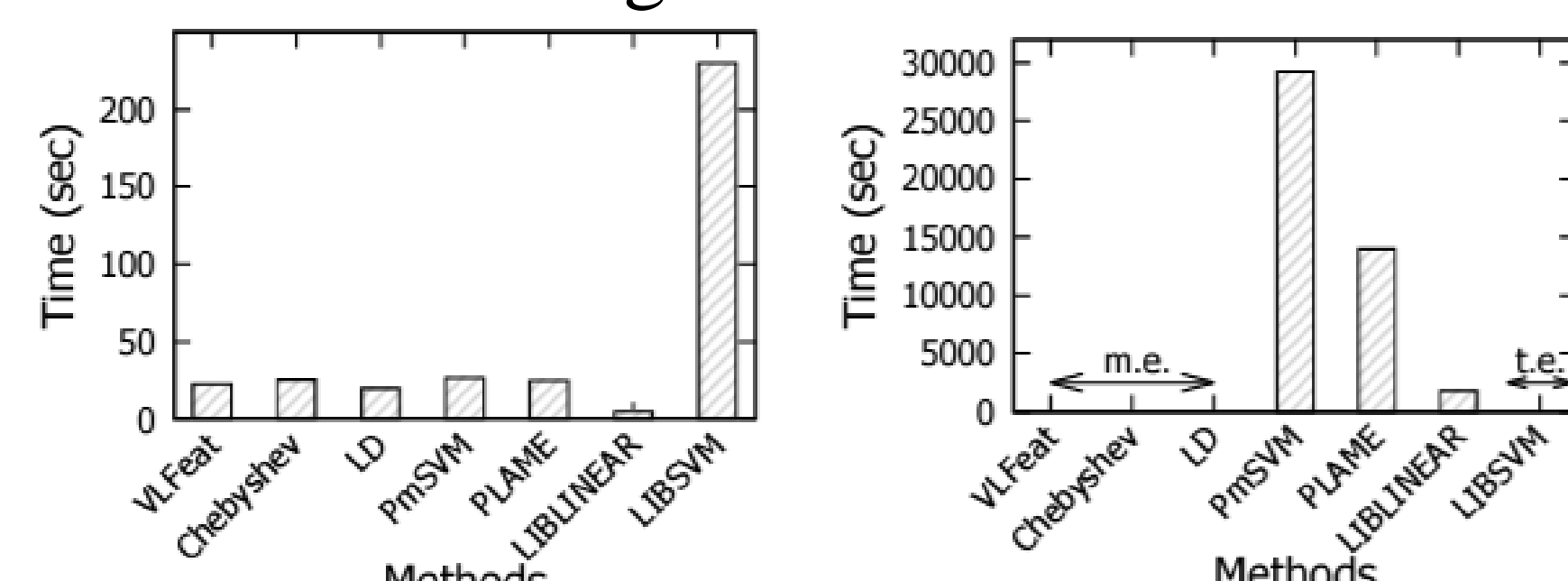
Method	LIBSVM	LIBLINEAR	VLFeat	Chebyshev	LD	PmSVM	PLAME
skin	0.992	0.895	0.927	0.942	0.949	0.919	0.988
casas	t.e.	0.71	m.e.	m.e.	m.e.	0.728	0.78

Remark:

t.e.: more than three days for training

m.e.: more than 16 GB for training

Training time of all methods



(a) skin

(b) casas