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Topic Model Kernel: An Empirical Study Towards Probabilistically Reduced Features For Classification

Tien-Vu Nguyen, Dinh Phung, Svetha Venkatesh

Center for Pattern Recognition and Data Analytics (PRaDA)

Deakin University, Australia

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Content

1. Introduction
2. Support Vector Machine
3. Topic Model Feature
4. Topic Model Kernel for Classification
5. Experiments
6. Question & Answer

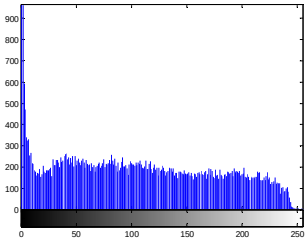
1. Introduction

Classification.

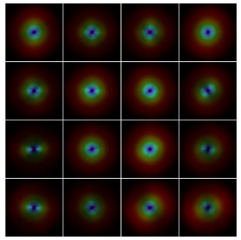
- The low-level features may not able to semantically represent the data well.

Low-level representation
(high-dimensional feature)

High-level representation
(low-dimensional feature)



Color Histogram



GIST

RBM
Neuron Network
Topic Models
…

1. Introduction

Classification.

- The low-level features may not able to semantically represent the data well.
- The integrated classification framework:
  - (1) discovering the “high-level” features (e.g. topic models)
  - (2) do classification with supervised learning method (e.g. SVM, ...).
- We propose the Topic Model Kernel (TMK) for SVM classification with the topic model feature.

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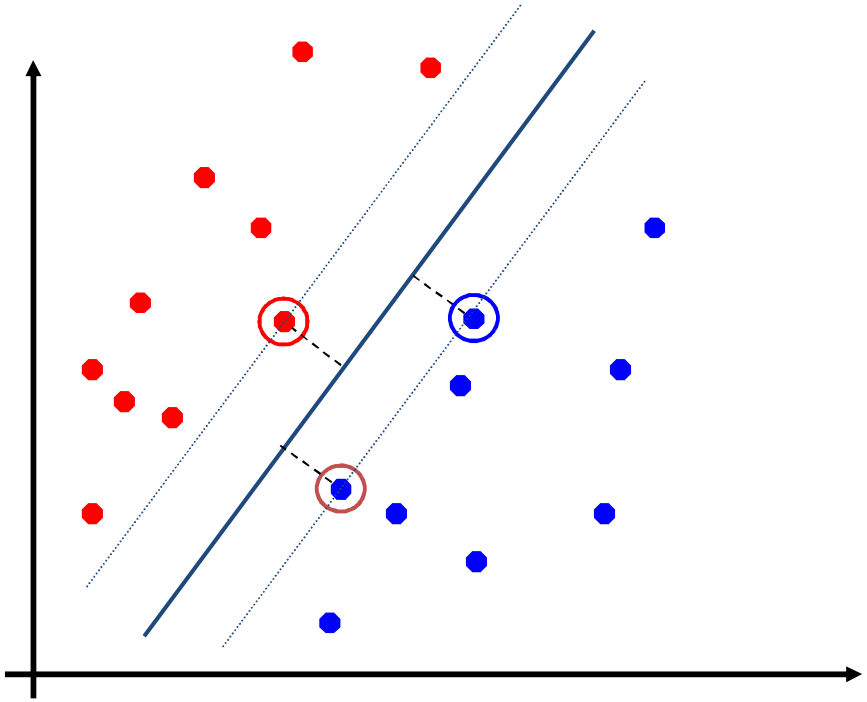
2. Support Vector Machine

- Supervised learning technique.
- Finding the line that maximizes the margin between classes.



Machine Learning Group
University of Texas Austin

3. Topic Model

discovering the main “topics” from collections of “documents”

“documents”

Applications

- Summarization
- Classification
- Information retrieval

3. Example of Topics learned by Topic Model

sky sea water rocks sand beach

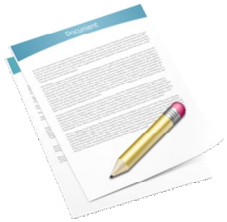
door window balcony

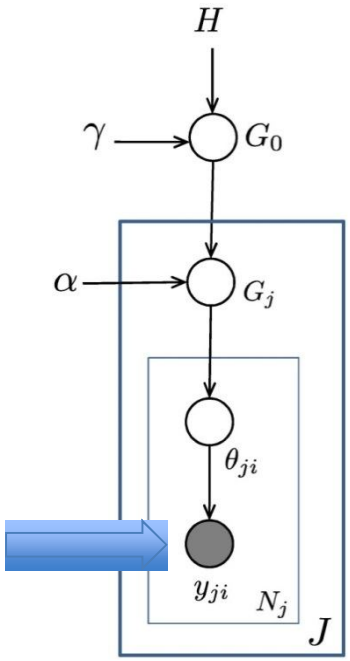
person walking building poster plants

Topic Models

Parametric: Latent Dirichlet Allocation (LDA), TOT, sLDA…
Nonparametric: Hierarchical Dirichlet Process (HDP), CDDP…

Hierarchical Dirichlet Processes

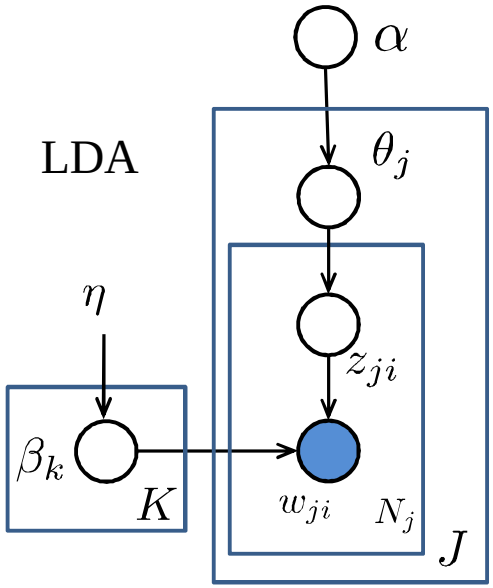




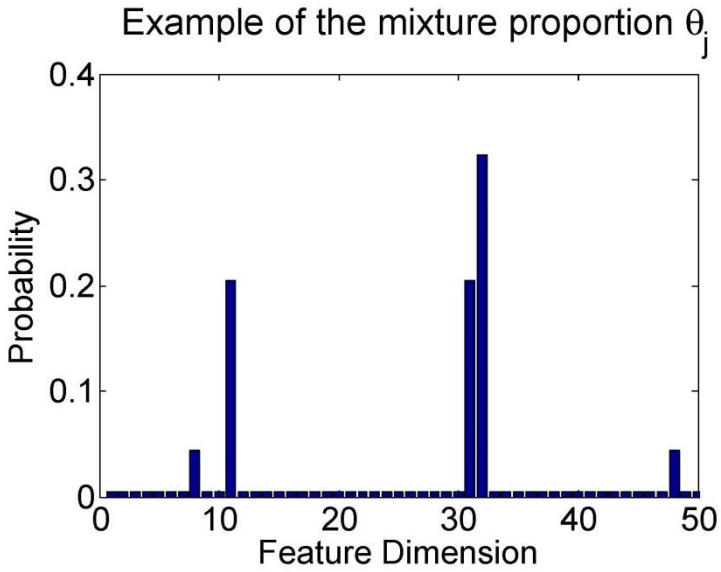
Dirichlet Process

Automatically identify number of topic

Topic Model Feature



Reduced from original dimension of 65,483 to 50



Topic model feature, high-level representation, follows Multinomial distribution.

Topic model features are condensed in low dimension,
they are more semantically informative and discriminative for classification

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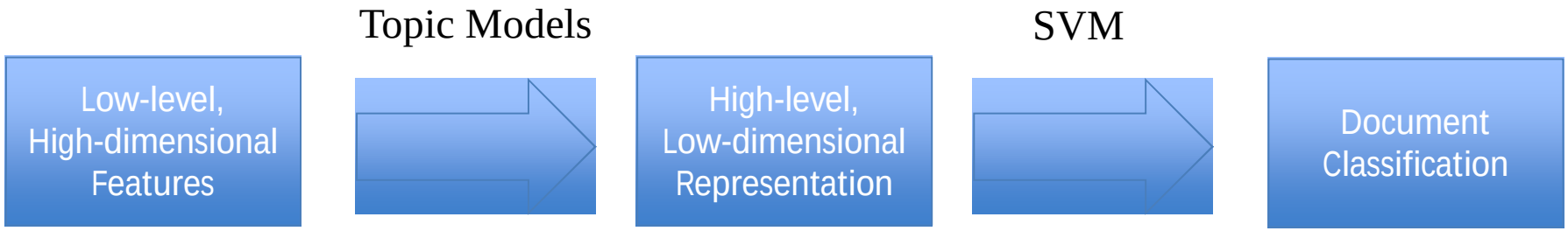
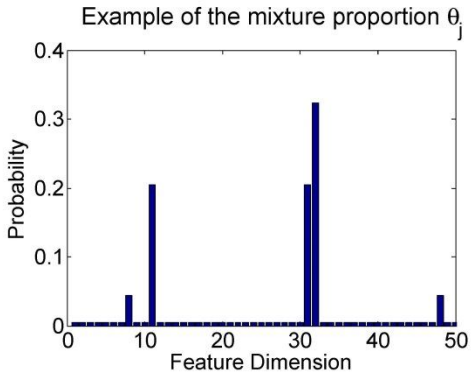
Classification with Topic Model Feature





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4. Topic Model Kernel

P and Q are two probabilistic distributions (e.g. Multinomial, Gaussian).

Kullback–Leibler (KL) Divergence

$$D_{KL}\left(P \parallel Q\right) = \sum_{i} P(i) \ln \frac{P(i)}{Q(i)}$$

Is not a metric

Jensen-Shanon (JS) Divergence

$$D_{JS}\left(P, Q\right) = \pi D_{KL}\left(P \parallel M\right) + \left(1 - \pi\right) D_{KL}\left(Q \parallel M\right)$$

$$M = \tfrac{1}{2}\left(P + Q\right)$$

JS squared root is a metric for two probability distributions. (D. Endres, J. Schindelin, 2003)

It is negative definite on $R_+ \times R_+$ (Topsoe, 2003)

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4. Topic Model Kernel

X and Y are two (non-negative) feature vectors.(e.g Topic Model Feature)

$$K_{TM}(X,Y) = \exp\left\{-\frac{1}{\sigma^2} \times D_{JS}(X,Y)\right\}$$

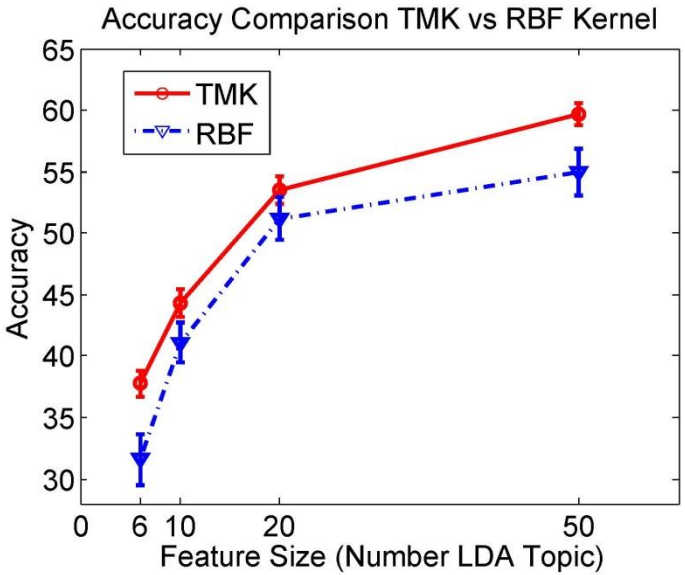
$$= \exp\left\{-\frac{1}{\sigma^2} \times \left[\frac{1}{2}\sum_i X(i) \ln \frac{X(i)}{M(i)} + \frac{1}{2}\sum_i Y(i) \ln \frac{Y(i)}{M(i)}\right]\right\}$$

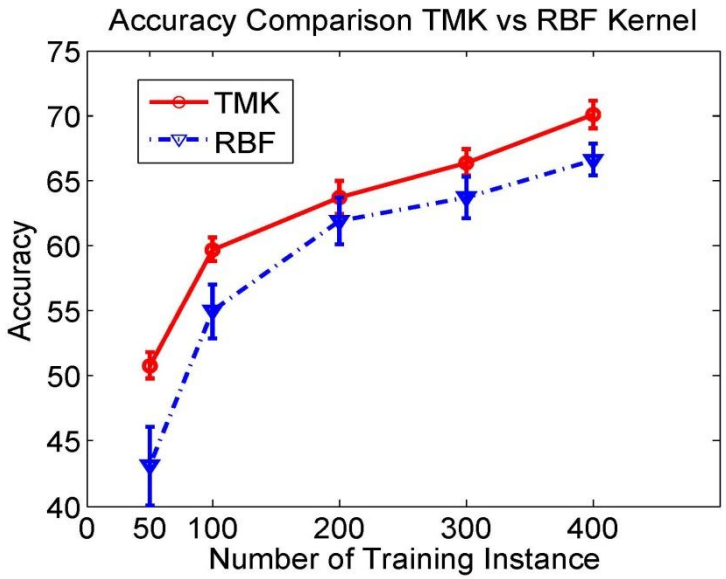
It satisfied a positive semi definite condition to be a kernel.

5. Experimental Results

Livejournal corpus: classify communities

8758 posts in 65,483-dimension raw feature
using LDA…
8758 posts in k-dimension (e.g 6,10,20,50…)





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5. Experimental Results on Topic Model Features

Dataset	TMK	RBF	Linear	Polynomial	Sigmoid
Livejournal	**58.1 (2.1)**	54.9 (4.9)	54.4 (5.2)	52.6 (6.6)	51.8 (5.1)
Reuter21578	**81.3 (0.2)**	79.0 (0.5)	78.2 (0.1)	77.9 (0.1)	77.4 (0.4)
LabelMe	**72.3 (1.9)**	70.8 (1.9)	71.5 (1.8)	62.7 (4.2)	69.8 (1.6)

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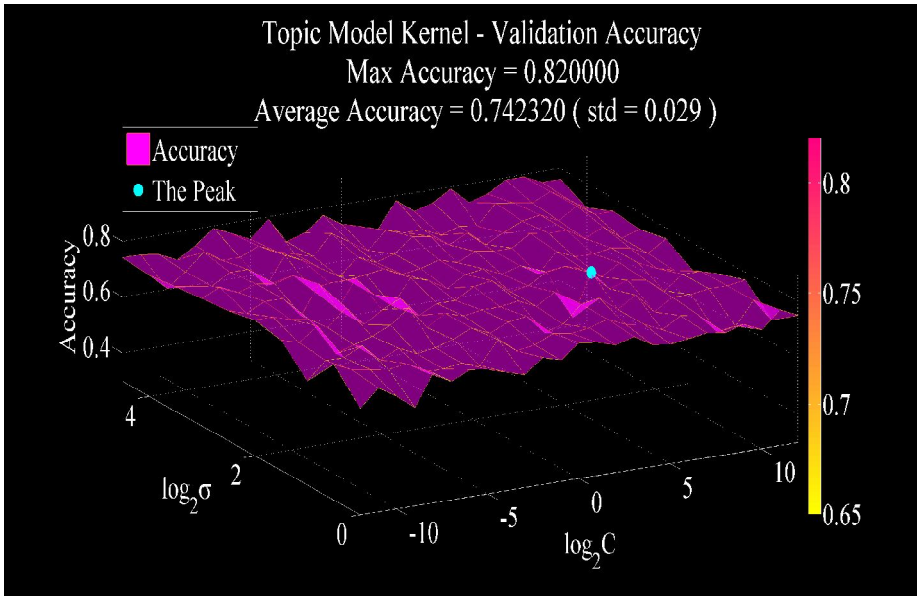
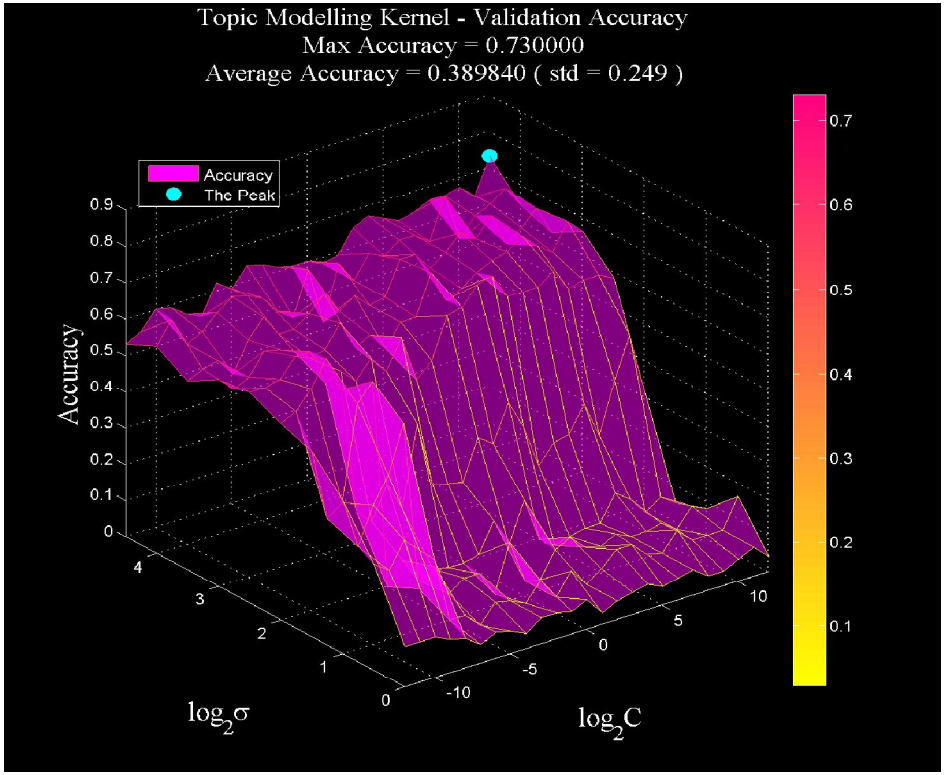
5. Experimental Results on Generic Features

Dataset	TMK	RBF	Linear	Polynomial	Sigmoid
MNIST (at default parameter)	88.4(0.9)	82.2(1.9)	**91.3(0.5)**	83.7(2.6)	79.6(3.4)
MNIST (at optimal parameter by cross-validation)	**90.8(2.25)**	89.3(2.5)	89.8(2.7)	88.7(2.9)	85.8(2.7)

5. Experimental Results





Excellent performance
Robust on topic model features
(LabelMe)

Very good performance
but not stable on generic feature
(MNIST)

Summary

- Document classification with two steps:
  1. Topic Models for extracting low-dimentional feature.
  2. Do classification by SVM with Topic Model Kernel.

- TMK is superior on Topic Model feature, comparable on other types of feature.

TMK Matlab code is available at author website.
prada-research.net/~tienvu/code

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