

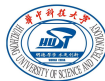
# Multimodal semi-supervised learning for image classification

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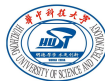
## ① Introduction

## ② Multimodal Semi-supervised Learning

Supervised Learning

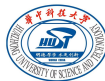
Semi-supervised Learning

Alternative approaches



# Motivation

- Increasing quantity and diversity of hand-labelled images improves the performance of classifier.
- Labelling images is time consuming and unrealistic in some scenario.
- Motivation: Using other information sources to aid learning process on limited amount of labelled images.



# Supervised Learning I

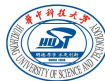
Train a SVM on labelled images:

$$f(x) = \sum_i \alpha_i k(x, x_i) + b \quad (1)$$

where  $k(\cdot, \cdot)$  is kernel function.

Class label:

$$y \in \{-1, +1\} = \text{sign}(f(x))$$



# Combine visual and textual representations

Combined kernel:

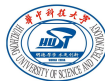
$$k_c(\cdot, \cdot) = d_v k_v(\cdot, \cdot) + d_t k_t(\cdot, \cdot) \quad (2)$$

where  $k_v(\cdot, \cdot)$  is visual kernel,  $k_t(\cdot, \cdot)$  is textual kernel,  $d_v, d_t > 0$  and  $d_v + d_t = 1$ .

**Multiple kernel learning(MKL) framework** allows joint learning of kernel combination weights  $d_v, d_t$  and the parameters  $\{\alpha_i\}$  and  $b$ .

**The SVM based on combined kernels:**

$$f_c(x) = \sum_i \alpha_i k_c(x, x_i) + b \quad (3)$$

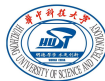


# Semi-supervised Learning I

Notation:  $\mathcal{L}$  is set of labelled images;  $\mathcal{U}$  is set of unlabelled images.

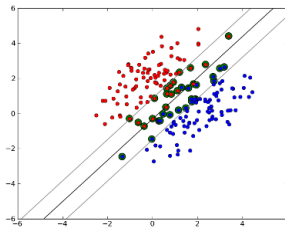
## Processing tactics

- 1 Learn a joint visual-textual classifier  $f_c$  from  $\mathcal{L}$  using MKL;
- 2 Predict class labels for images in  $\mathcal{U}$  with  $f_c$ ;
- 3 Train a visual-only SVM classifier  $f_v$  from  $\mathcal{L}$  and  $\mathcal{U}$ ;
- 4 Complete image classification task with  $f_v$ .

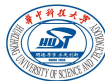


# First Alternative

**Intention:** Only add the confidently classified examples in  $\mathcal{U}$ , those fall outside the margin with  $|f_c(x)| \geq 1$ .



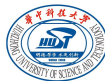
They have the less possibility of changing the MKL classifier.



## Second Alternative

**Intention:** Approximate the joint classification function  $f_c$ .  
Perform a least square regression (LSR) on MKL scores  $f_c(x)$  for all examples in  $x \in \mathcal{L} \cup \mathcal{U}$  to find the function

$$f_v(x) = \sum_i \alpha_i k_v(x, x_i) + b$$





# Pseudo-code of the algorithm

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**Algorithm 1:** Procedure for learning a semi-supervised MKL+LSR visual classifier.

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**Input:** Labeled data  $\mathcal{L}$  and unlabeled data  $\mathcal{U}$ , visual kernel  $k_v$  and textual kernel  $k_t$ .

**Output:** Visual classifier  $\alpha$  using kernel  $k_v$ .

```

1  $f_c \leftarrow \text{MKL}(\mathcal{L}, \{k_v, k_t\})$    /* Learn MKL classifier */
2 foreach  $x \in \mathcal{L} \cup \mathcal{U}$  do           /* Center scores */
3    $s(x) \leftarrow f_c(x) - \langle f_c(x') \rangle_{x' \in \mathcal{L} \cup \mathcal{U}}$ 
4 end
5 foreach  $x, x' \in \mathcal{L} \cup \mathcal{U}$  do /* Center kernel columns */
6    $K_v(x, x') \leftarrow k_v(x, x') - \langle k_v(x, x'') \rangle_{x'' \in \mathcal{L} \cup \mathcal{U}}$ 
7 end
8  $U \Lambda V^\top = K_v$                /* SVD of  $K_v$  */
9 for  $i = 1$  to  $|\mathcal{L} \cup \mathcal{U}|$  do     /* Pseudo-invert  $K_v$  */
10    $\bar{\Lambda}_{ii} \leftarrow \begin{cases} 0 & \text{if } \Lambda_{ii} < \epsilon \\ \Lambda_{ii}^{-1} & \text{otherwise} \end{cases}$ 
11 end
12  $\alpha \leftarrow V \bar{\Lambda} U^\top s$    /* Least-squares regression of  $s$  */
```

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