

# Kernel Approximation via Empirical Orthogonal Decomposition for Unsupervised Feature Learning

Yusuke Mukuta  
The University of Tokyo  
7-3-1 Hongo Bunkyo-ku, Tokyo, Japan  
mukuta@mi.t.u-tokyo.ac.jp

Tatsuya Harada  
The University of Tokyo  
7-3-1 Hongo Bunkyo-ku, Tokyo, Japan  
harada@mi.t.u-tokyo.ac.jp

## A. Feature functions assuming Gaussian distribution

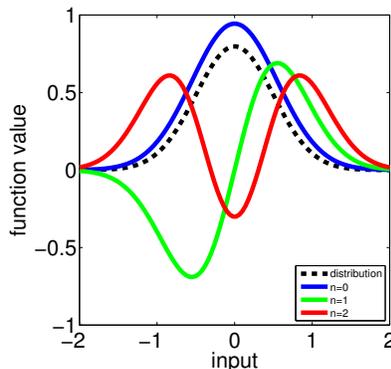


Figure 1. Eigenfunctions for a Gaussian kernel and Gaussian distribution. Dashed line represents the distribution and the solid lines represent the feature functions.

## B. List of architectures used in the experiments of unsupervised feature learning

Setting	Input	$N$	$m_1$	$p_1$	$\gamma_1$	$m_2$	$p_2$	$\gamma_2$
MNIST								
1	Patch	2	$5 \times 5$	50	2	$2 \times 2$	200	2
2	Grad	2	$1 \times 1$	12	2	$3 \times 3$	50	2
3	Grad	2	$1 \times 1$	12	2	$3 \times 3$	400	4
CIFAR-10, CIFAR-100, SVHN								
1	Grad	2	$1 \times 1$	12	2	$2 \times 2$	800	4
2	Patch	2	$2 \times 2$	100	2	$2 \times 2$	800	4
3	Patch	1	$3 \times 3$	800	10	—	—	—

Table 1. List of architectures reported in the paper. With regard to the Input column, "Patch" indicates that the network works on patches. "Grad" indicates that the network works on gradient maps.  $N$  represents the number of layers.  $p_i$  represent the number of filters for  $i$ -th layer;  $m_i$  represent the size of the patches;  $\gamma_i$  is the subsampling factor.