

# Kernel PCA and De-Noising in Feature Spaces

Presented by

Jökull Jóhannsson  
Kristófer Hannesson  
Xinyi Lin

Sudhanshu Mittal  
Samuel Murray

# Kernel PCA and De-Noising in Feature Spaces

- Linear/Kernel PCA
- The method
- Experiment results
- Discussion

# Linear vs Kernel PCA

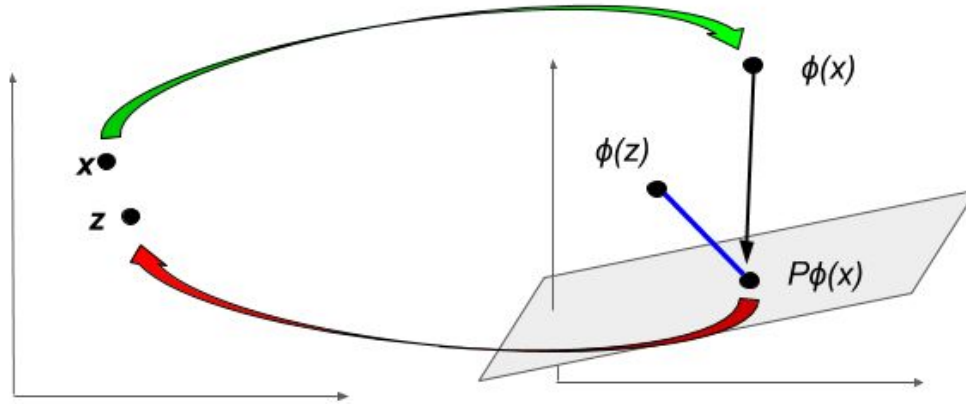
## Applications

- compression
- reconstruction
- de-noising

## What we explored

- Nonlinear de-noising
- Connection between feature space expansions and meaningful patterns in input space.

# Linear vs Kernel PCA



## Kernel PCA

- Map to feature space using function  $\Phi$
- Do PCA in the feature space - calculate projection  $P$
- Results may not have pre-images in the input space
  - Solution: Find approximate pre-image ( $z$ )

# Methodology

$$N\lambda\alpha = K\alpha, \quad \text{PCA} \\ K = C, N=1$$

$$k(x, y) = \exp(-||x - y||^2/c)$$

$$\beta_k := V^k \cdot \Phi(x)$$

$$P_n\Phi(x) = \sum_{k=1}^n \beta_k V^k$$

## Input Space

$k$  - Gaussian kernel function

$\mathbf{z}$  - pre-image of vector  $\mathbf{x}$  in input space

$\Phi$  - mapping

## Feature Space

$\mathbf{a}$  - eigenvectors

$\mathbf{V}$  - normalized eigenvectors

$\beta$  - projection on principal components

$\gamma$  - weight of each training point

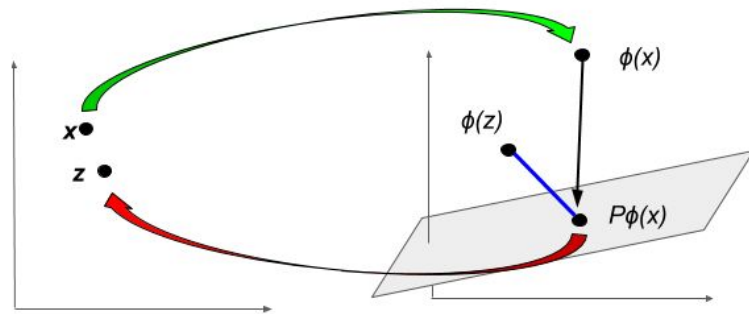
$\mathbf{n}$  - number of top components

# Pre-images for Gaussian Kernels

$$\gamma_i = \sum_{k=1}^n \beta_k \alpha_i^k.$$

Minimize :  $\rho(z) = \|\Phi(z) - P_n \Phi(x)\|^2$

$$\nabla_z \rho(z) = 0$$



Using Fixed-point Iterative method, we calculate:

$$z_{t+1} = \frac{\sum_{i=1}^N \gamma_i \exp(-\|z_t - x_i\|^2/c) x_i}{\sum_{i=1}^N \gamma_i \exp(-\|z_t - x_i\|^2/c)}$$

# Experiments

- Toy examples
- Reconstruction and denoising of digits

# Toy example: Denoising in $\mathbb{R}^2$

## Linear PCA

- 1 or 2 components
- 2 components reproduces all noise!



# Toy example: Denoising in $\mathbb{R}^2$

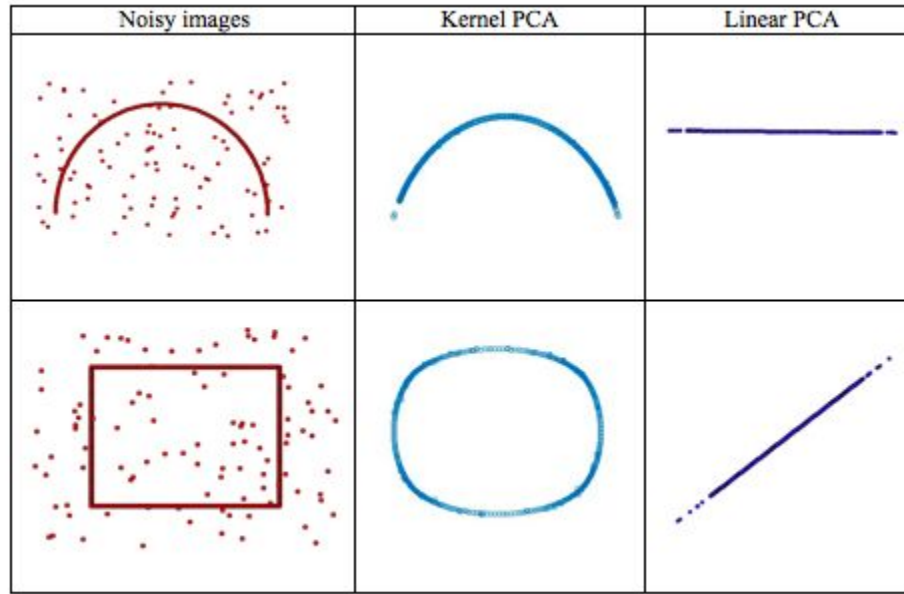
## Linear PCA

- 1 or 2 features
- 2 features reproduces all noise!

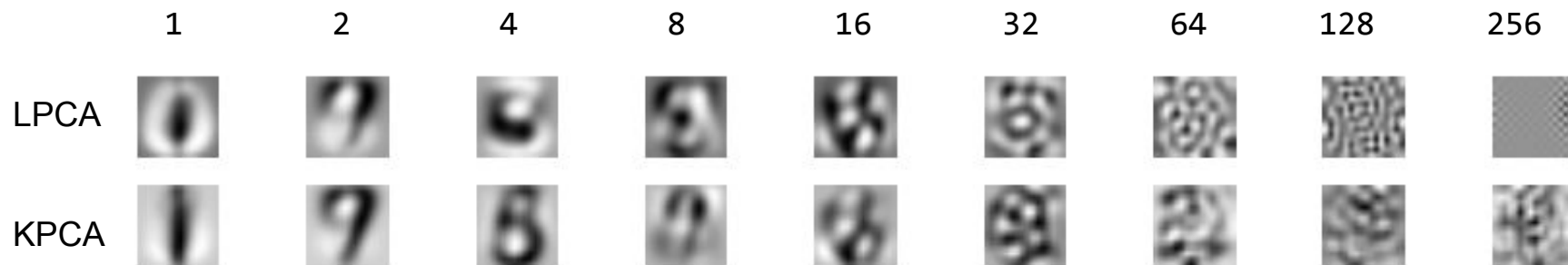
## Kernel PCA

- As many components as training points!

# Toy example: Denoising in $\mathbb{R}^2$































































































































































































































# Eigenvectors for components $2^0, \dots, 2^8$





# Denoising comparison

	Gaussian noise										'salt & pepper' noise									
orig.	0	1	2	3	4	5	6	7	8	9	0	1	2	3	4	5	6	7	8	9
noisy																				
n = 1																				
4																				
16																				
64																				
256																				
n = 1																				
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# Discussion

## Advantages

- Captures complex nonlinear structure in the data
- Allows projection of data to high dimensional space
- Can be used for application of reconstruction, denoising and compression.

## Disadvantages

- Suffers from numerical instability or local minima problem.
- Dependent on initial guess.
- For the fixpoint method, the kernel function needs to be smooth.
- Computationally intensive compared to PCA

# Summary

- Performs PCA on data in feature space
- Iterative process to get pre-image
- Can de-noise and reconstruct non-linear data

THANK YOU