

# Machine Learning

Abdelhak Mahmoudi  
[abdelhak.mahmoudi@um5.ac.ma](mailto:abdelhak.mahmoudi@um5.ac.ma)

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# Content

## 1. The Big Picture

## 2. Supervised Learning

- Linear Regression, Logistic Regression, Support Vector Machines, Trees, Random Forests, Boosting, Artificial Neural Networks

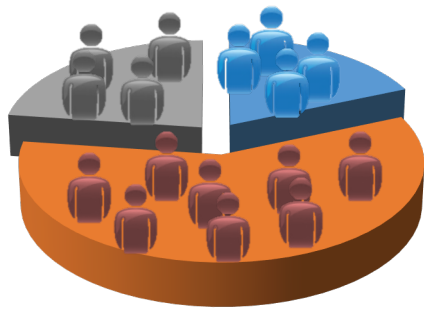
## 3. Unsupervised Learning

- Principal Component Analysis, K-means, Mean Shift

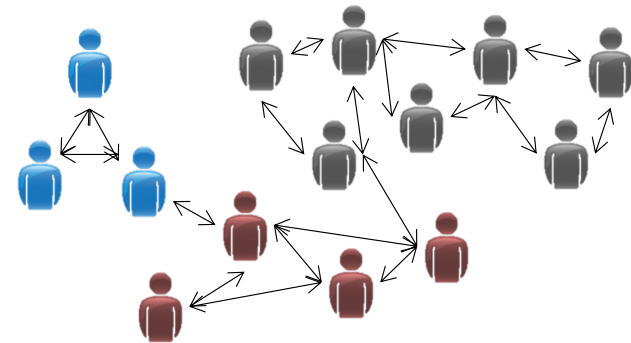
# Unsupervised Learning

- **Dimensionality Reduction**
  - **Principal Component Analysis (PCA)**
- Clustering
  - K-Means
  - Mean-Shift

# Unsupervised Learning



Market segmentation



Social network analysis



Organize computing clusters

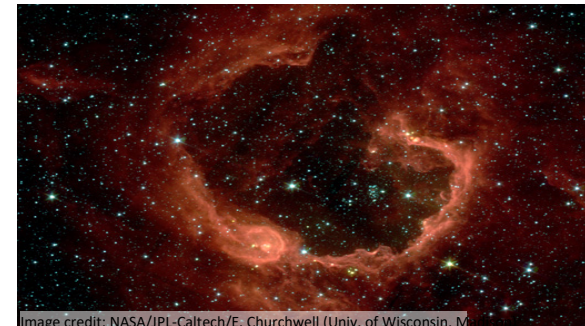
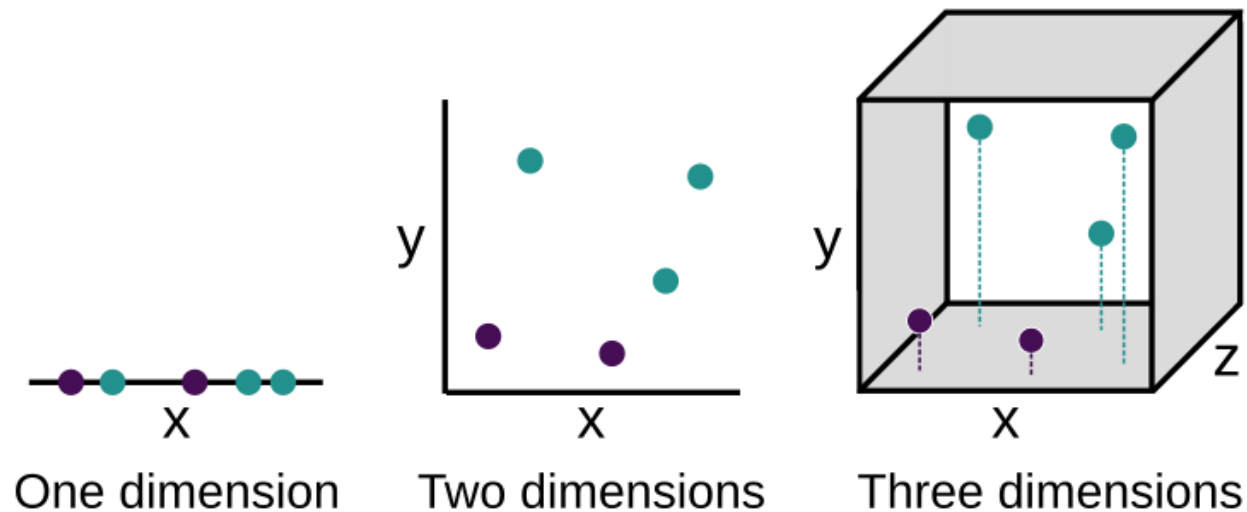


Image credit: NASA/JPL-Caltech/E. Churchwell (Univ. of Wisconsin, M...)

Astronomical data analysis

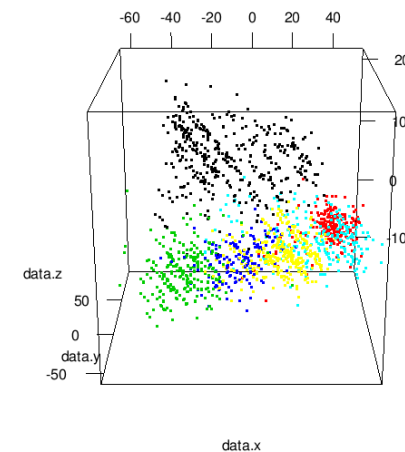
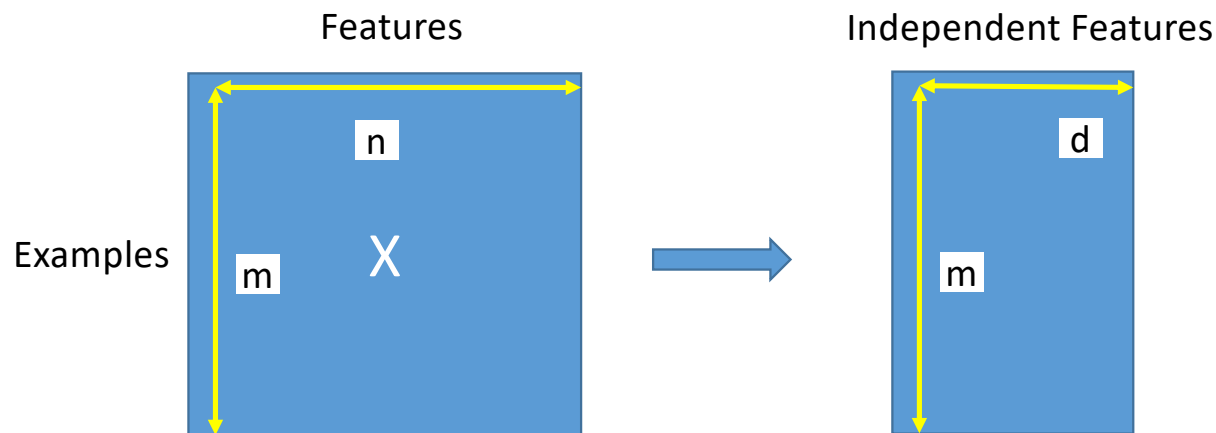
# Dimensionality Reduction

- Curse of dimensionality ( $n \gg m$ )
  - Data are at risk of being **very sparse** in high dimensional space
  - High risk of **overfitting**



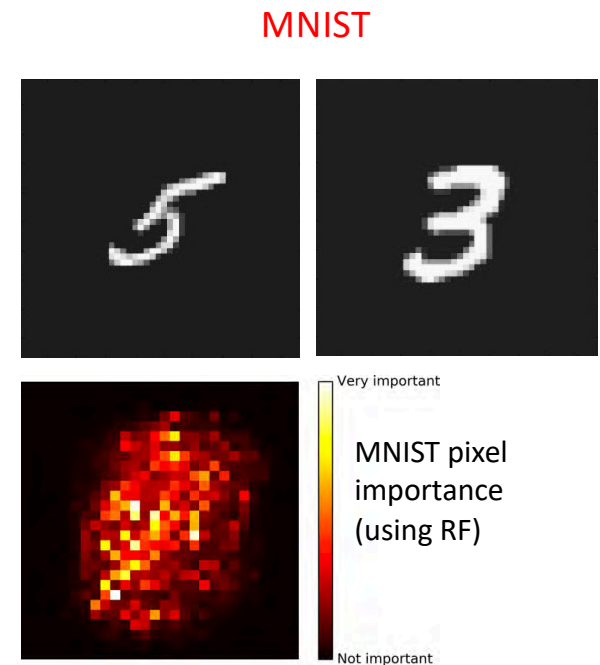
# Dimensionality Reduction

- Transforms feature space from  $n$  to  $k$  ( $k < n$ )
  - Some **features** are probably **corelated** (dependent)
  - Some **features** are almost **constant**
  - **Transform but preserve** the maximum of **variance**



# Dimensionality Reduction

- Transforms feature space from **n** to **k**
  - Some **features** are probably **corelated** (dependent)
  - Some **features** are almost **constant**
  - **Transform but preserve** the maximum of **variance**
- **MNIST** Example
  - Dropping some pixels without losing much information
  - Two neighboring pixels are often highly correlated -> use their average.



# Dimensionality Reduction

- Transforms feature space from **n** to **k**
  - Some **features** are probably **corelated** (dependent)
  - Some **features** are almost **constant**
  - **Transform but preserve** the maximum of **variance**
- **EOCD** example

Country	GDP (trillions of US\$)	Per capita GDP (thousands of intl. \$)	Human Dev Index	Life expectancy	...
Canada	1.577	39.17	0.908	80.7	...
China	5.878	7.54	0.687	73	...
India	1.632	3.41	0.547	64.7	...
Russia	1.48	19.84	0.755	65.5	...
Singapore	0.223	56.69	0.866	80	...
...	...	...	...	...	...

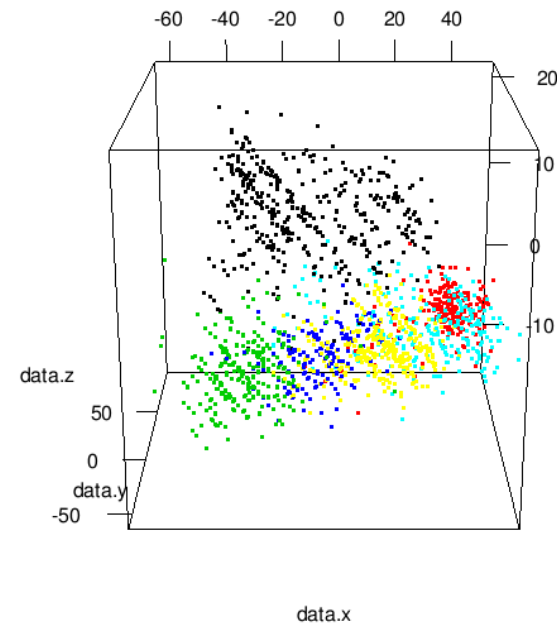


Country	z1	z2
Canada	1.6	1.2
China	1.7	0.3
India	1.6	0.2
Russia	1.4	0.5
Singapore	0.5	1.7
...	...	...

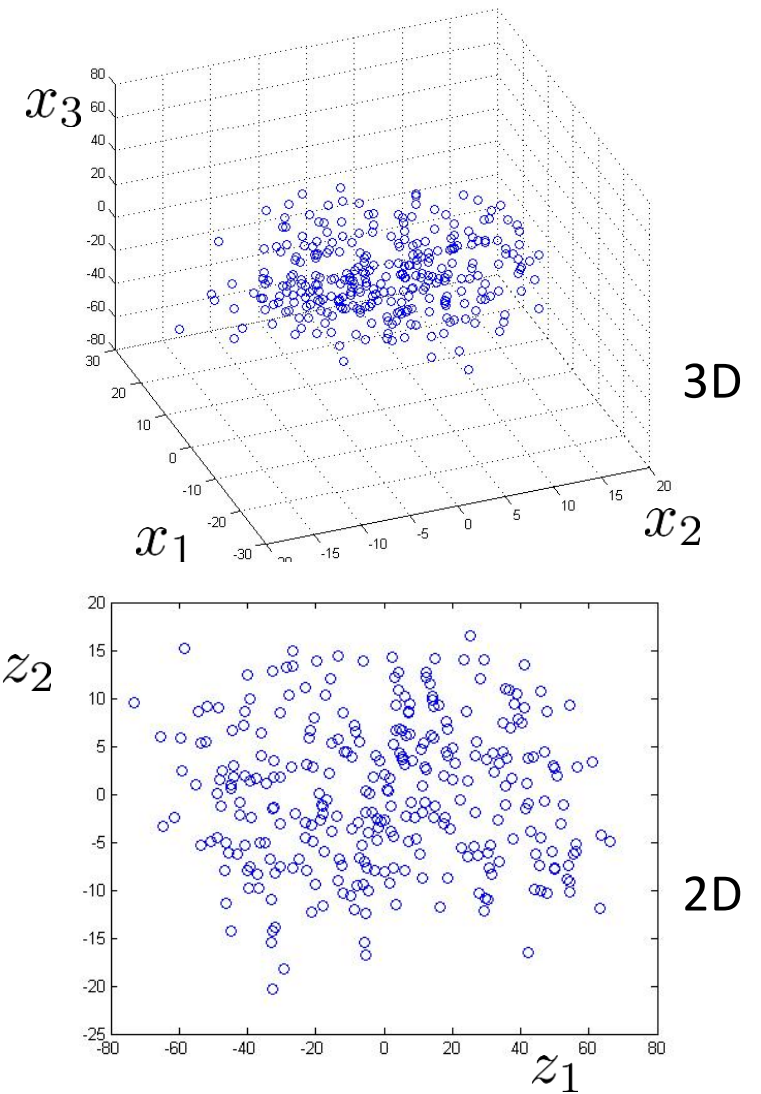
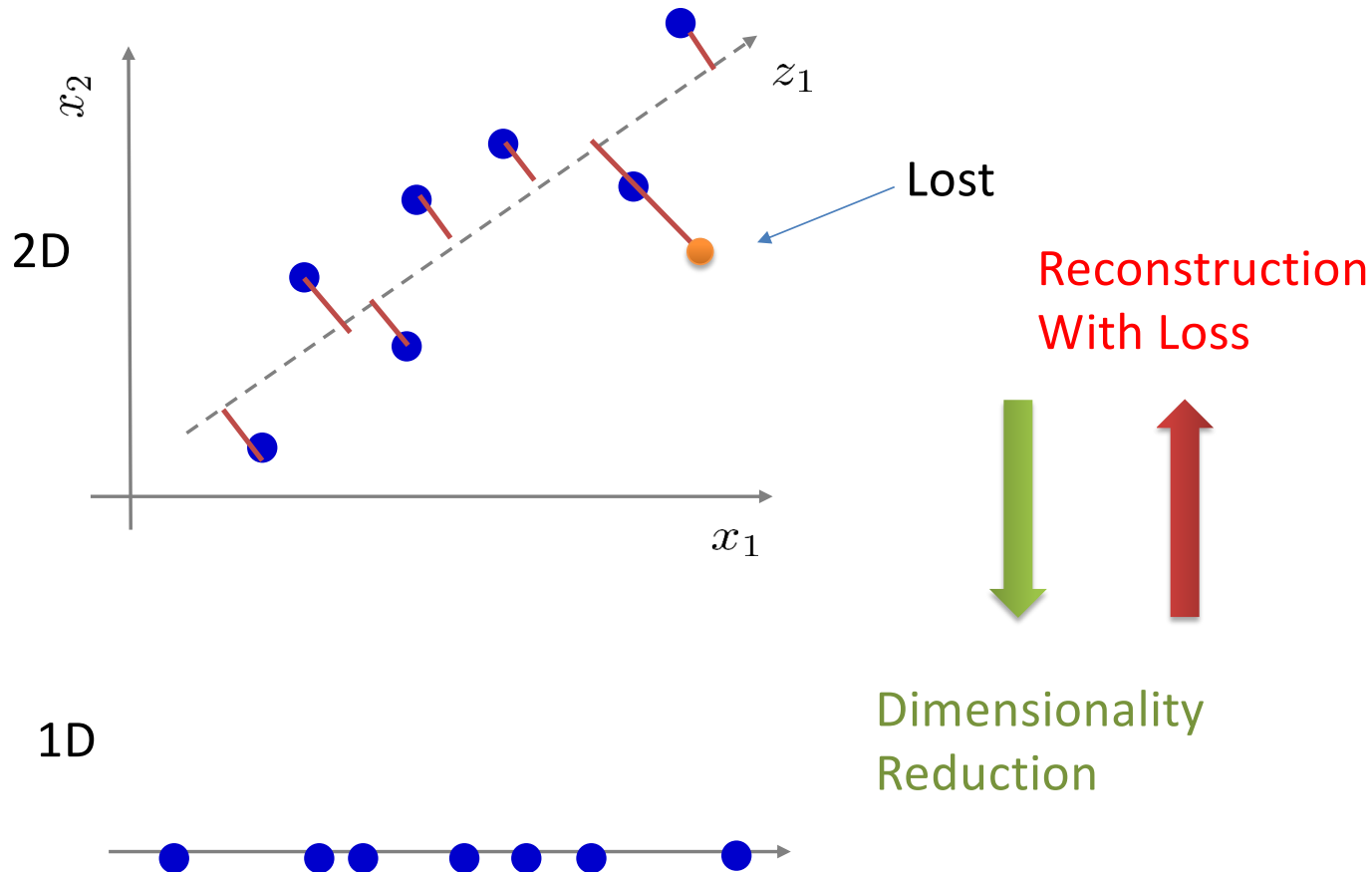


# Dimensionality Reduction

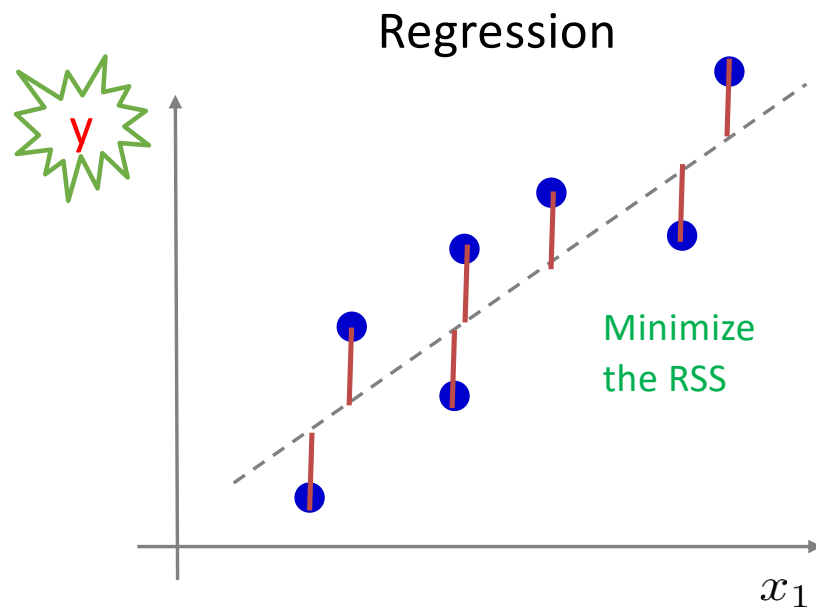
- Often
  - **Not** necessarily lead to **better performance**
  - **Not the better** way to address **overfitting !**
- Always
  - **Speed up** training
  - Allow **data compression**
  - Allow **data exploration**
  - Allow **data visualization** (DataViz)



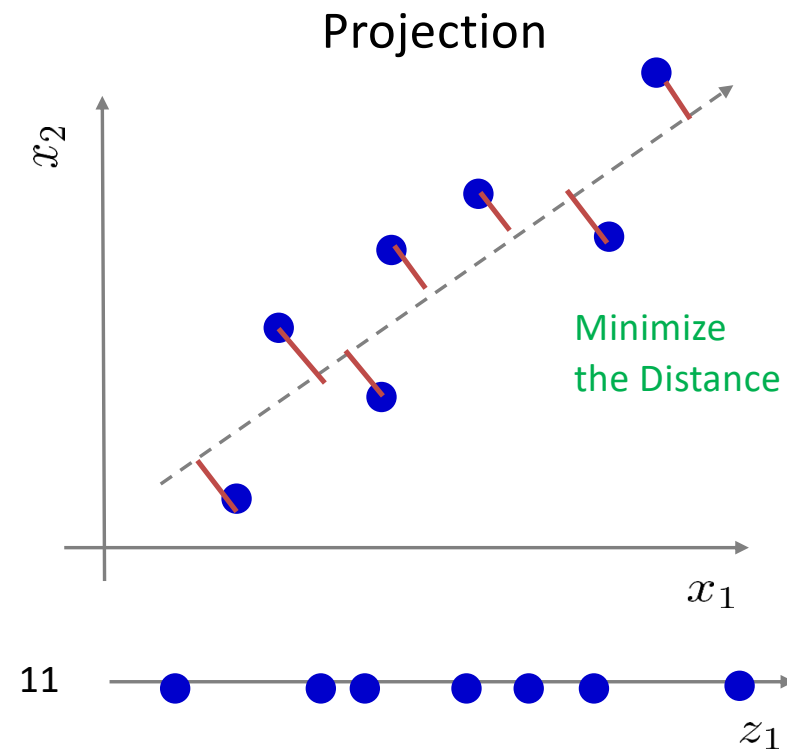
# Principal Component Analysis



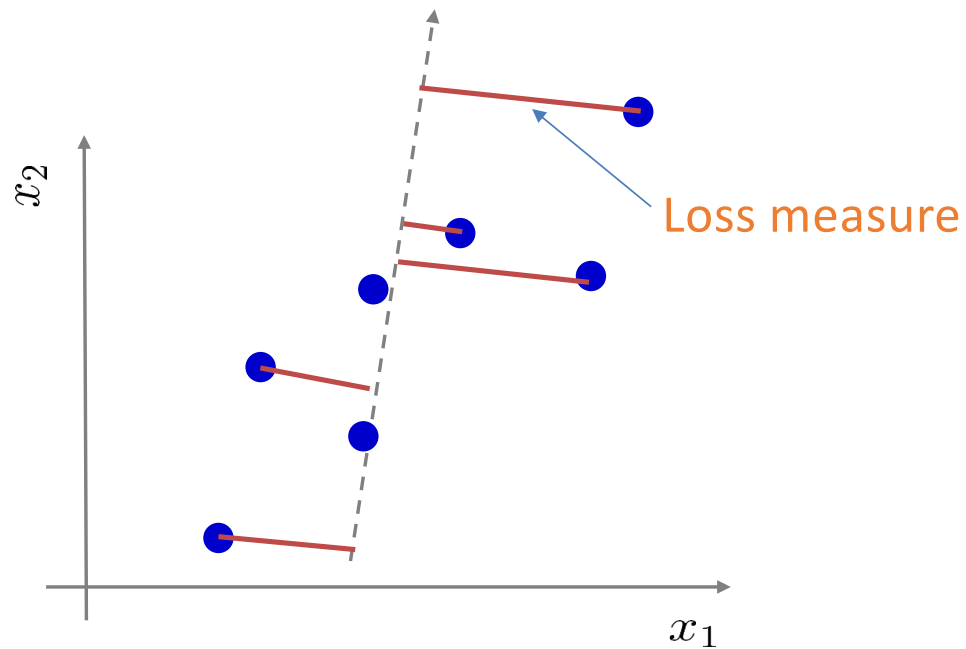
# Principal Component Analysis



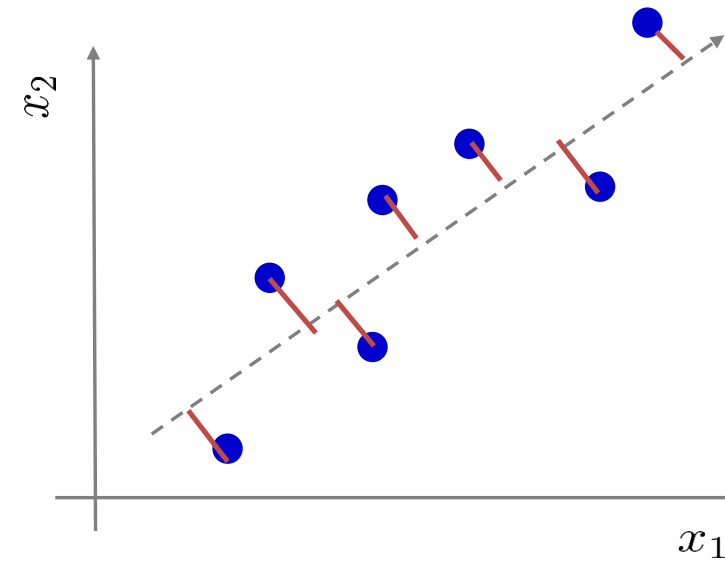
Don't be confused !



# Principal Component Analysis



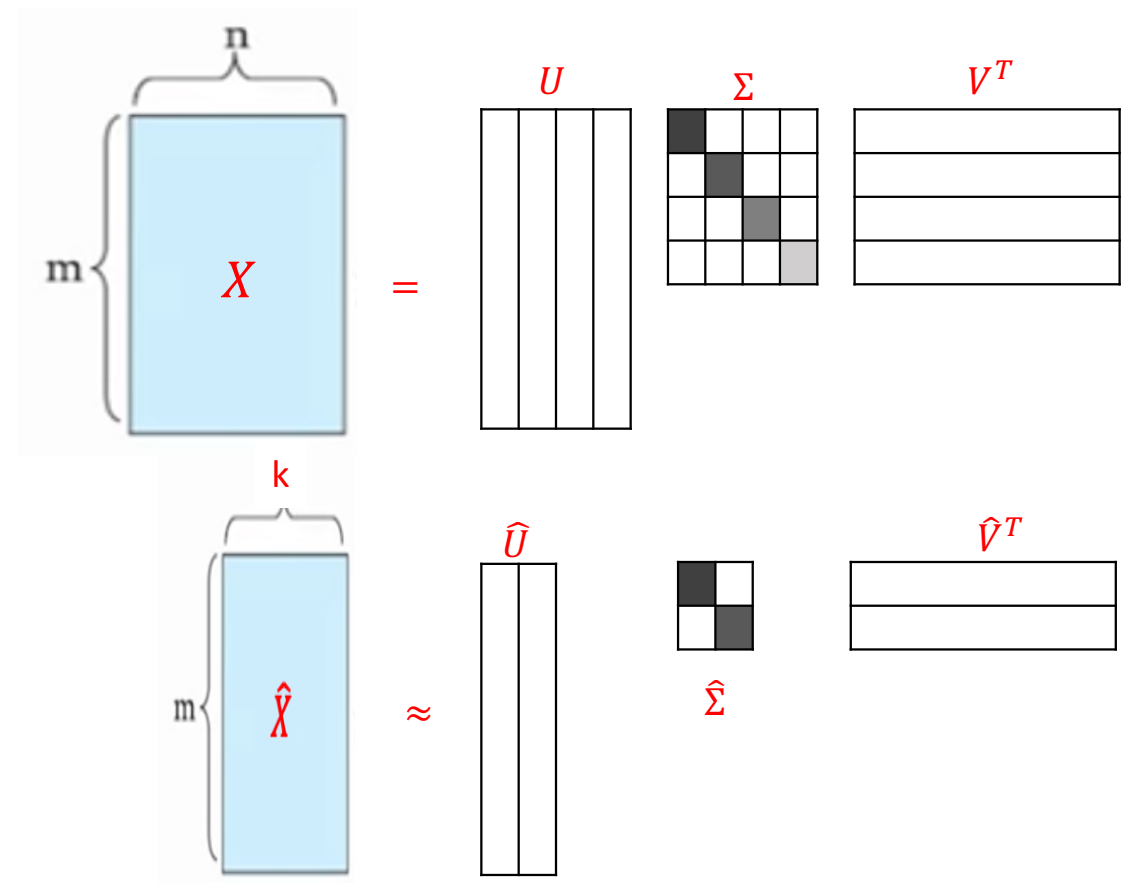
**Maximum** loss  
Less variance



**Minimum** loss  
More variance

# Principal Component Analysis

- Singular Value Decomposition
  - $X = U\Sigma V^T$
  - $\Sigma$  is **diagonal**, composed of ordered **positive singular values**
  - U and V form a **basis (are orthonormal)**
- k Principal Components
  - **k first vectors of U**
  - Corresponds to the **first k singular values**
- Explained Variance
  - Sum of the first **k singular values**
- Reconstruction
  - $\hat{X} = \hat{U}\hat{\Sigma}\hat{V}^T$



# Principal Component Analysis

- Singular Value Decomposition (SVD) (very costly)
  - Parallelization: Incremental PCA (fast), Randomized PCA (faster)
- PCA assumes that the dataset is centered around the origin
- How many dimensions to preserve?
  - Reduce dimensions that add up to a sufficiently large portion of the variance (e.g., 99%)
- Kernel PCA (kPCA): use the kernel trick like SVM
- In practice, use kPCA to transform the feature space, then perform classification or regression.

# Principal Component Analysis

- Hyper-Parameters Tuning
  - $d$ : polynomial Kernel
  - $\gamma$ : RBF kernel
  - $K$ : Number of retained principal components
  - Etc.

# Other Dimensionality Reduction Methods

- Multidimensional Scaling (MDS)
- Isomap
- t-Distributed Stochastic Neighbor Embedding (t-SNE)
- Manifold Learning
  - Locally Linear Embedding (LLE)
- Etc.

