ENSIAS

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Machine Learning

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Content

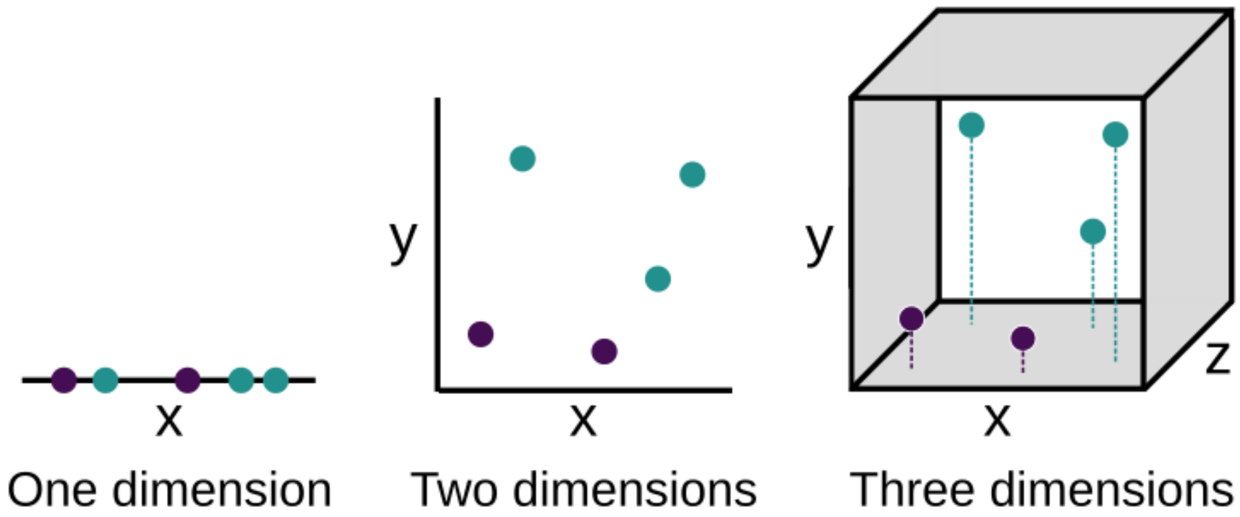
1. The Big Picture
2. Supervised Learning
   - Linear Regression, Logistic Regression, Support Vector Machines, Trees, Random Forests, Boosting, Artificial Neural Networks
3. **Unsupervised Learning**
   - Principal Component Analysis, K-means, Mean Shift

Unsupervised Learning

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

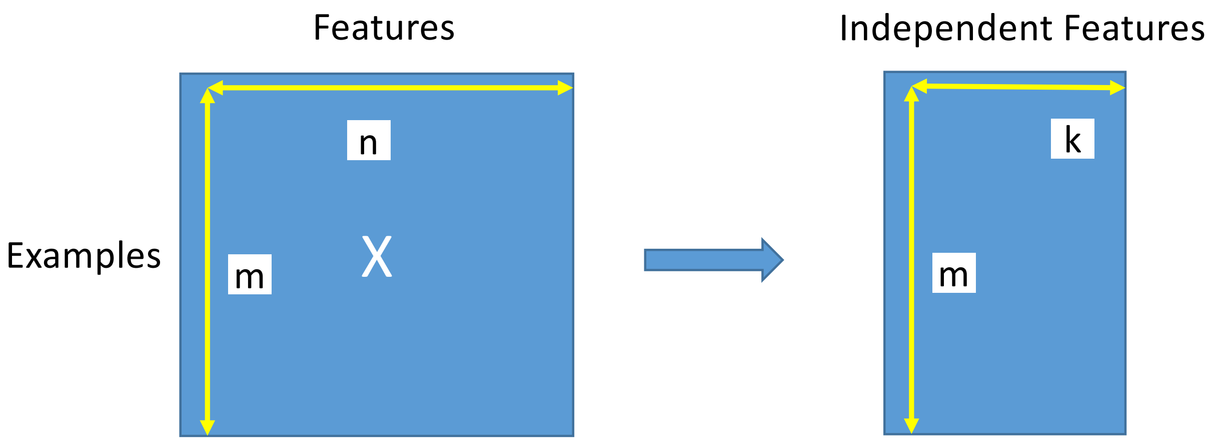
Dimensionality Reduction

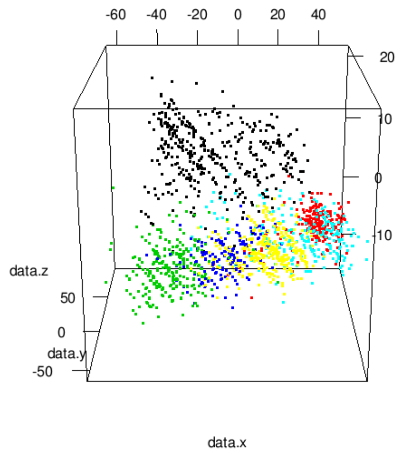
- Curse of dimensionality (n >> m)
  - Data are at risk of being very sparse in high dimensional space
  - High risk of overfitting



Dimensionality Reduction

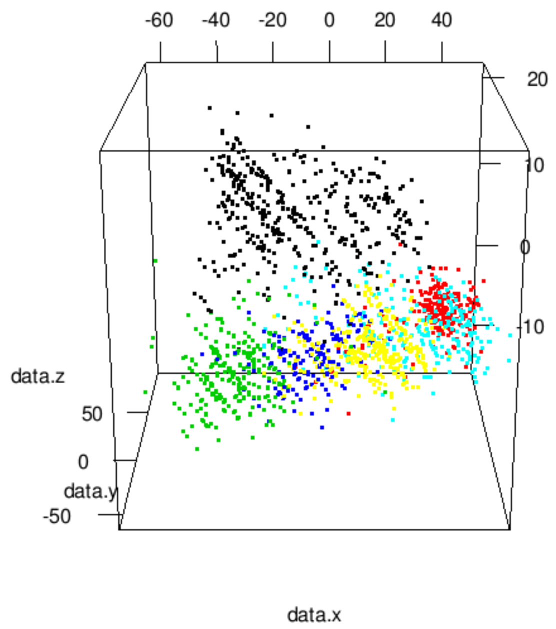
- Transforms feature space from n to k (k<n)
  - Some features are probably corelated (dependent)
  - Some features are almost constant
  - Transform but preserve the maximum of variance



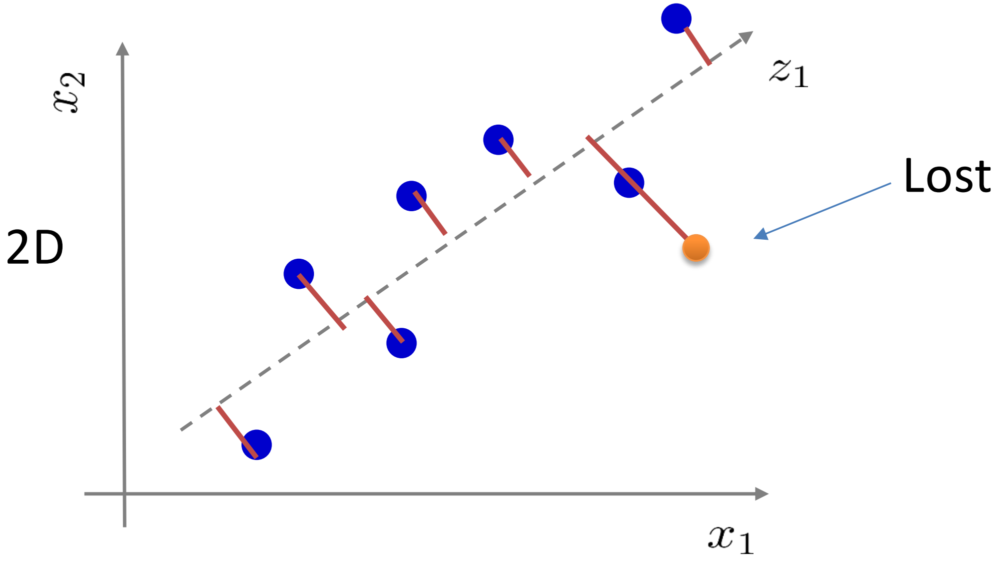


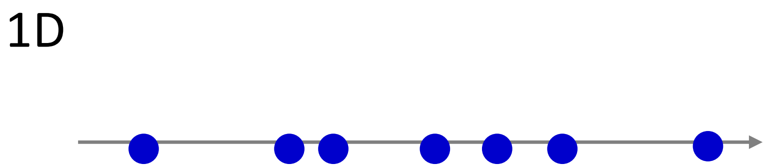
Dimensionality Reduction

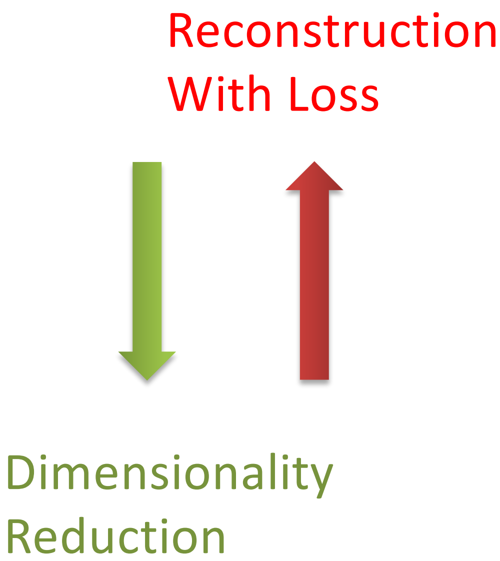
- Often
  - Not necessarily lead to better performance
  - Not the better way to address overfitting !
- Always
  - Speed up training
  - Allow data compression
  - Allow data exploration
  - Allow data visualization (DataViz)

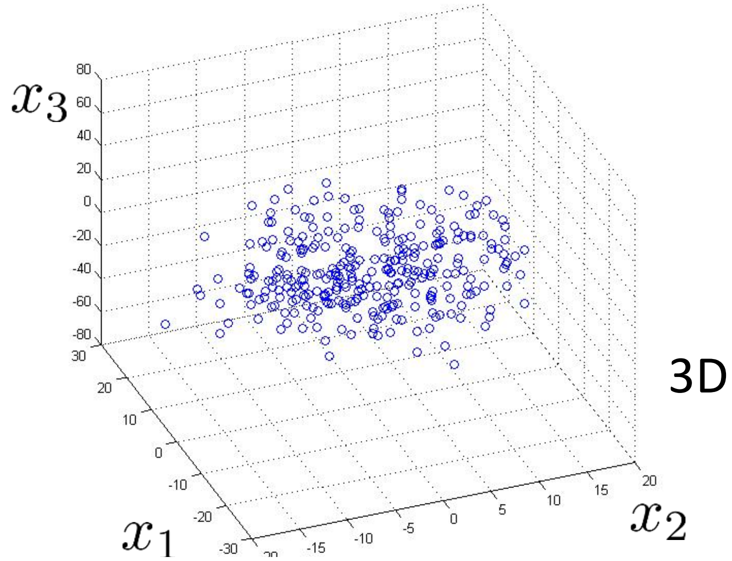


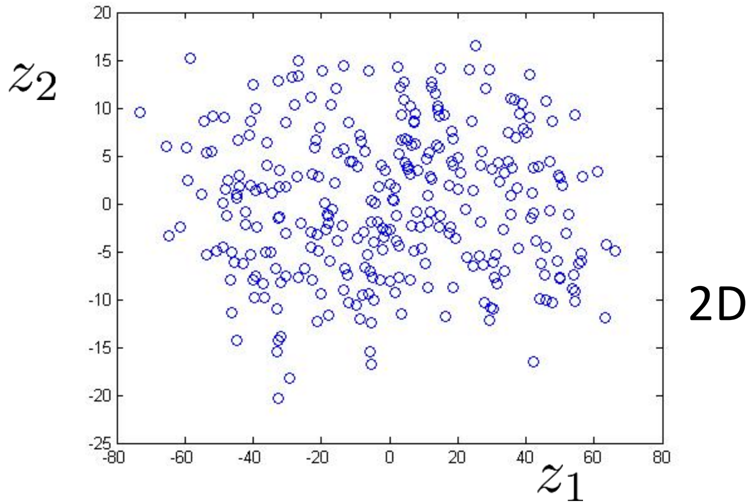
Principal Component Analysis



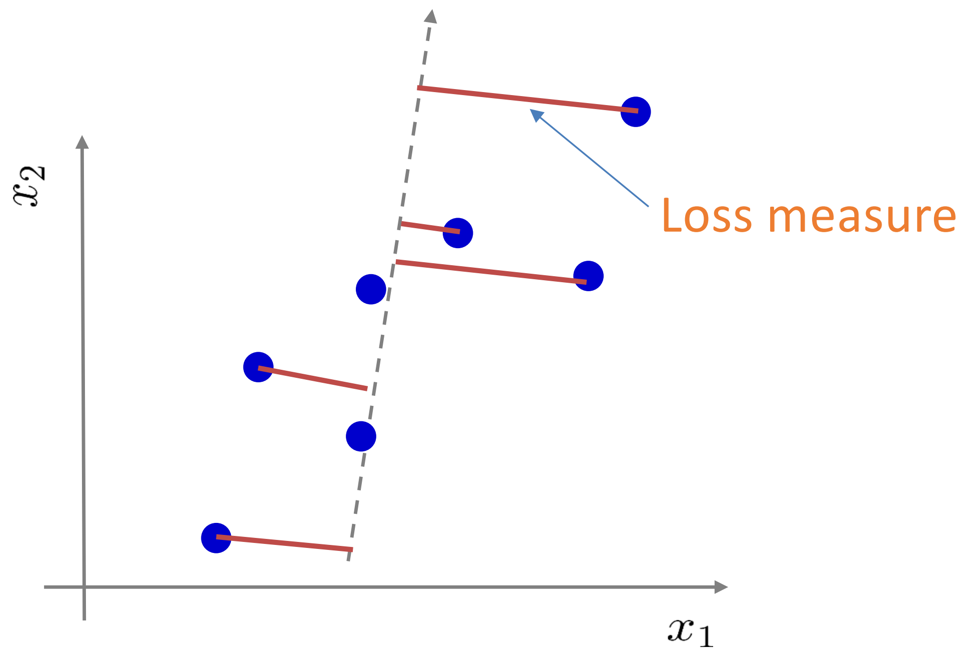


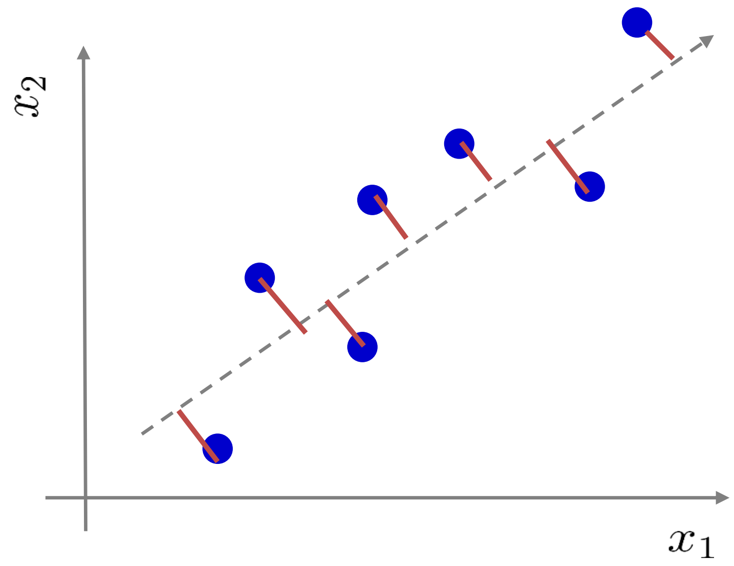






Principal Component Analysis





Maximum loss
Less variance

Minimum loss
More variance

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 explained 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 or clustering.

Principal Component Analysis

- Hyper-Parameters Tuning
  - d: polynomial Kernel
  - γ: RBF kernel
  - k: Number of retained principal components
  - Etc.

Unsupervised Learning

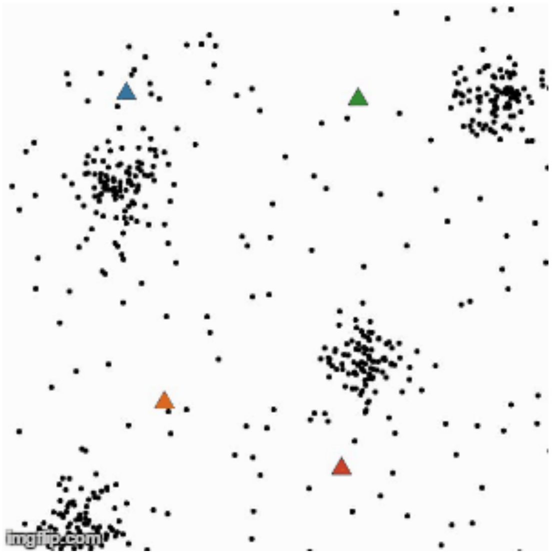
- Dimensionality Reduction
  - Principal Component Analysis (PCA)
- **Clustering**
  - **K-Means**
  - **Mean-Shift**

K-Means

- Pick a number of clusters k
- Initialize centroids randomly
- Problem of local optima
  - Run K-means a lot of times
- Sensible to initial conditions
- Have to specify k !

Repeat until convergence:

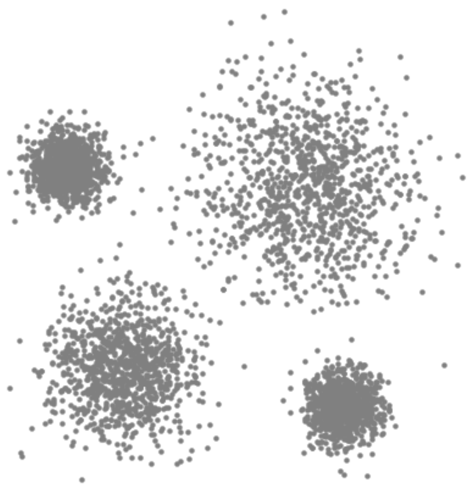
Assign each example to the cluster of the nearest centroid
Compute the mean in each cluster
Put the mean as the new centroid



Mean Shift

- Chose a radius r of the clusters
- Initialize centroids at each example
- No need to specify the number of clusters

For each example:
  Repeat until convergence:
    Compute the mean in its cluster with radius r
    Shift the cluster to the new mean centroid



Other Clustering methods

- Expectation Maximization (EM)
- Hierarchical Clustering
- Affinity Propagation (AP)
- Etc.