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Novelty Detection in Projected Spaces for Structural Health Monitoring

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Outline

- **Introduction to SHM**
  - Transmissibility features
- **Dimensionality reduction**
  - Random projections, Principal Component Analysis, Curvilinear Component Analysis
- **Novelty Detection**
  - k-NN, Gaussian, Mixture of Gaussians, Parzen
- **Experiments and Results**

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Introduction to Structural Health Monitoring

- Motivation and Scope
- Challenges

The scope of our project

- **Structural Health Monitoring**
  - monitor the condition of structures, like buildings, bridges, cranes, etc.
  - detect *damages* before they become apparent *faults*
- **Multidisciplinary research project: ISMO**
  - Intelligent Structural Health Monitoring System
- **Two major problems:**
  - no practical sensors to indicate damage
  - large structures require *wireless sensors*

Vibration-based SHM

- **Structures vibrate due to input excitation from the environment**
  - for example, traffic and wind cause bridges to shake
  - properties of the structure affect the response
- **Accelerometers for measuring the vibration output from the structure**
- **Major problem: input signal from the environment remains unknown!**
  - environmental variability vs. state of the structure?

Modeling disciplines

- **Physics-based models**
  - complex and detailed numerical models of structures
  - require lots of prior information: ”blueprints”
  - enable more elaborate damage assessment etc.
- **Data-based models**
  - simple and generic models
  - rely more on *machine learning* and acquired *data*
  - useful mainly for detecting damages

Transmissibility features

- **Ratio of vibration amplitudes**
  - one sensor location s_1 compared to another s_2
  - specific to a given frequency f

$$T(s_1, s_2, f) = \left| \frac{X_{s_1}(f)}{X_{s_2}(f)} \right|$$

- **Attempts to measure how well energy propagates between two points**
  - eliminates environmental variability (overall amplitude)
  - combinations of sensor pairs and monitoring frequencies lead to a ***large feature space***

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Dimensionality Reduction

- Random Projections
- Principal Component Analysis
- Curvilinear Component Analysis

Background

- **Previous results reported in [IDA2009]**
  - randomly selected feature sets of different sizes
  - supervised damage classification
  - result: damage detection possible with few transmissibility features (32 out of 6300)
- **However: supervised learning not realistic**
  - data from damaged structures not available IRL
  - novelty detection instead of pattern classification
  - feature selection not possible in advance, but how about projections to lower dimensions?

Random Projections

- **Select a random projection matrix** $R_{k \times d}$ **according to** $\begin{cases} P(r_{ij} = -\sqrt{3}) = 1/6 \\ P(r_{ij} = 0) = 2/3 \\ P(r_{ij} = \sqrt{3}) = 1/6 \end{cases}$
- **Project data from *d* to *k* dimensions by**

$$\mathbf{y} = R\mathbf{x}$$

- **Motivated by Johnson-Lindenstrauss lemma**
- **Computationally inexpensive**

Principal Component Analysis

- Classical signal decomposition method used in pattern recognition
- Selects a new orthogonal basis for the data points according to eigenvectors
- By selecting *k* leading eigenvalues and corresponding eigenvectors, most of the variance represented in the new basis
- Linear projection...

Curvilinear Component An.

- **Nonlinear projection method**
- **Based on a neural network**
  - an intermediate layer of model vectors
- **Cost function to minimize**
  - considers inter-point distances in both input and output space

$$E = \sum_{ij} \begin{cases} (D_{ij} - Y_{ij})^2 F_\lambda(Y_{ij}) & \text{if } Y_{ij} > D_{ij} \\ (D_{ij}^2 - Y_{ij}^2)^2 F_\lambda(Y_{ij}) / 4D_{ij}^2 & \text{if } Y_{ij} <= D_{ij} \end{cases}$$

- **Interpolation and extrapolation provided for projecting new data**

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Novelty Detection Methods

- k-Nearest Neighbor
- Gaussian
- Mixture of Gaussians
- Parzen density estimation

Nearest Neighbor method

- **Memorize all projected training data points**
- **Compute distance between the new point** x **and its (**k**th) nearest neighbor** $NN(x)$
- **As a reference, compute the distance between the nearest neighbor** $NN(x)$ **and its nearest neighbor** $NN(NN(x))$
- **Ratio of these distances is a novelty score**
  - assumes the distances are suitable for the projected feature space

Gaussian Densities

- **Fit a single multivariate normal distribution to the training data**
- **Assign the area of low density, below some threshold, to outliers**
  - unimodal, symmetric ellipsoid as decision boundary
- **"Rescales" the projected feature space according to the covariance matrix**

Mixtures of Gaussians

- **Fit a sum of several multivariate normal distributions to the training data**
  - achieved via Expectation Maximization algorithm
  - diagonal covariance matrices used
- **Assign the area of low density, below some threshold, to outliers**
  - several symmetric and axis-aligned ellipsoids as the decision boundary
- **Allows few (separate) clusters of data**

Parzen Density Estimation

- **Sum of multivariate normal distributions at *each* training data point**
  - spherical covariance used and the width parameter determined by Maximum Likelihood solution
- **Assign the area of low density, below some threshold, to outliers**
  - superposition of many spheres as decision boundary
- **Combines aspects of k-NN and MoG**

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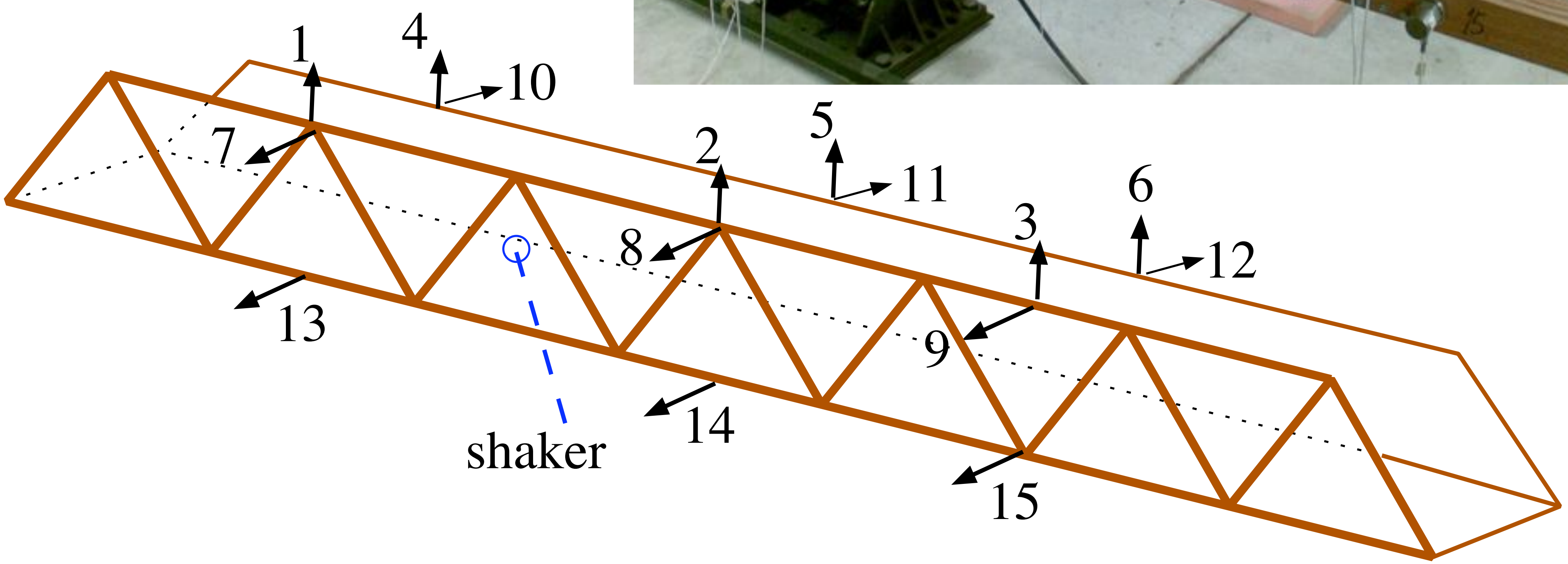
Experiments and Results

- The Bridge
- AUROC values for combinations of methods
- Examples of ROC curves

The Bridge

- Wooden model bridge used
- Shaker
- Wired sensors



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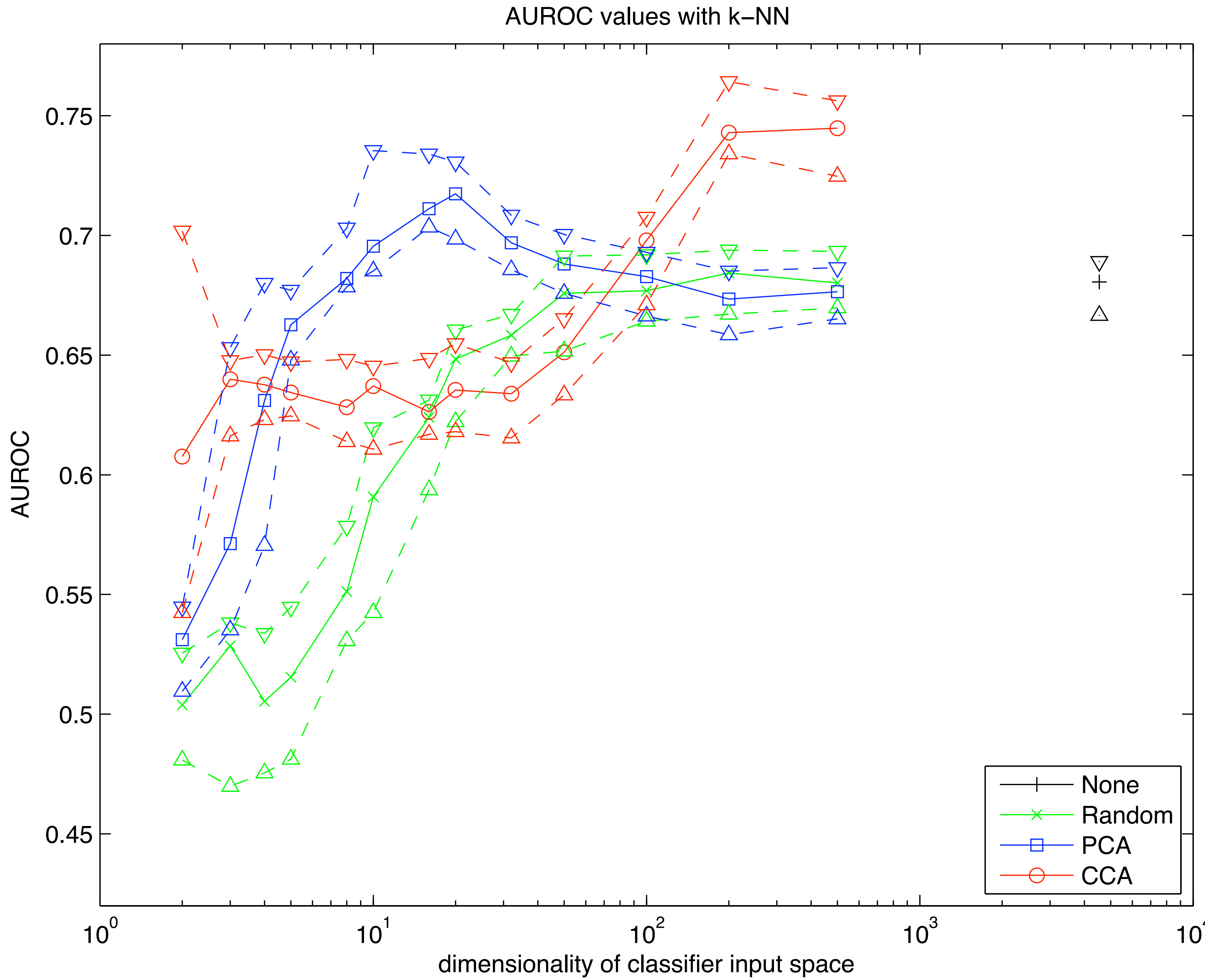
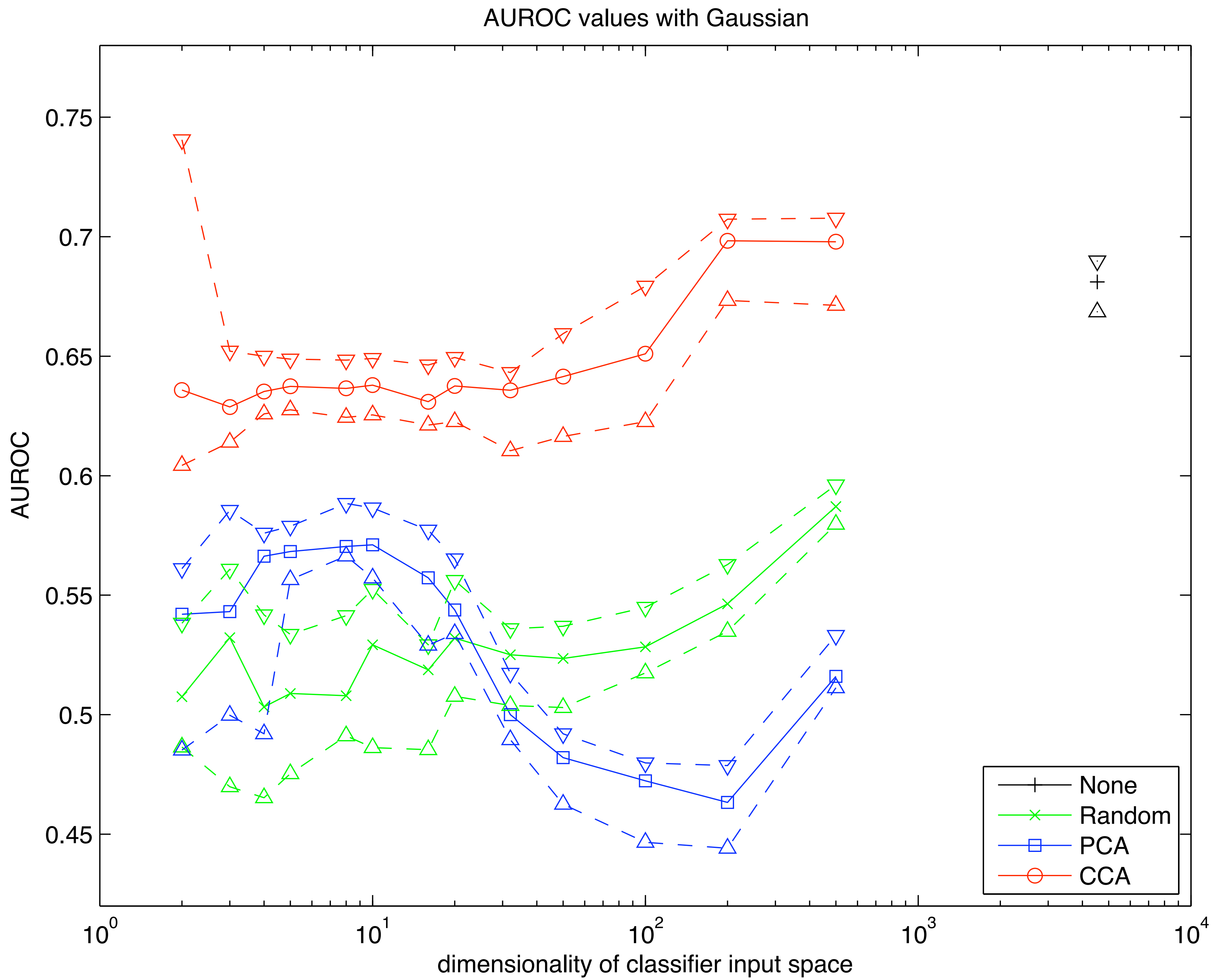
Data and Preprocessing

- **15 wired accelerometers produced**
  - 2509 time series of 32 seconds each
  - sampling frequency of 256 Hz
- **attached various small weights as damages**
  - masses range from 23.5 g to 193 g
- **transmissibility features extracted**
  - for 19 pairs of *adjacent* sensors (not for all 105 pairs)
  - with 512-point FFT, averaging each 8 blocks (16 s)
  - resulting data stream: 4541 feature values / 16 s

AUROC for k-NN



AUROC for Gaussian



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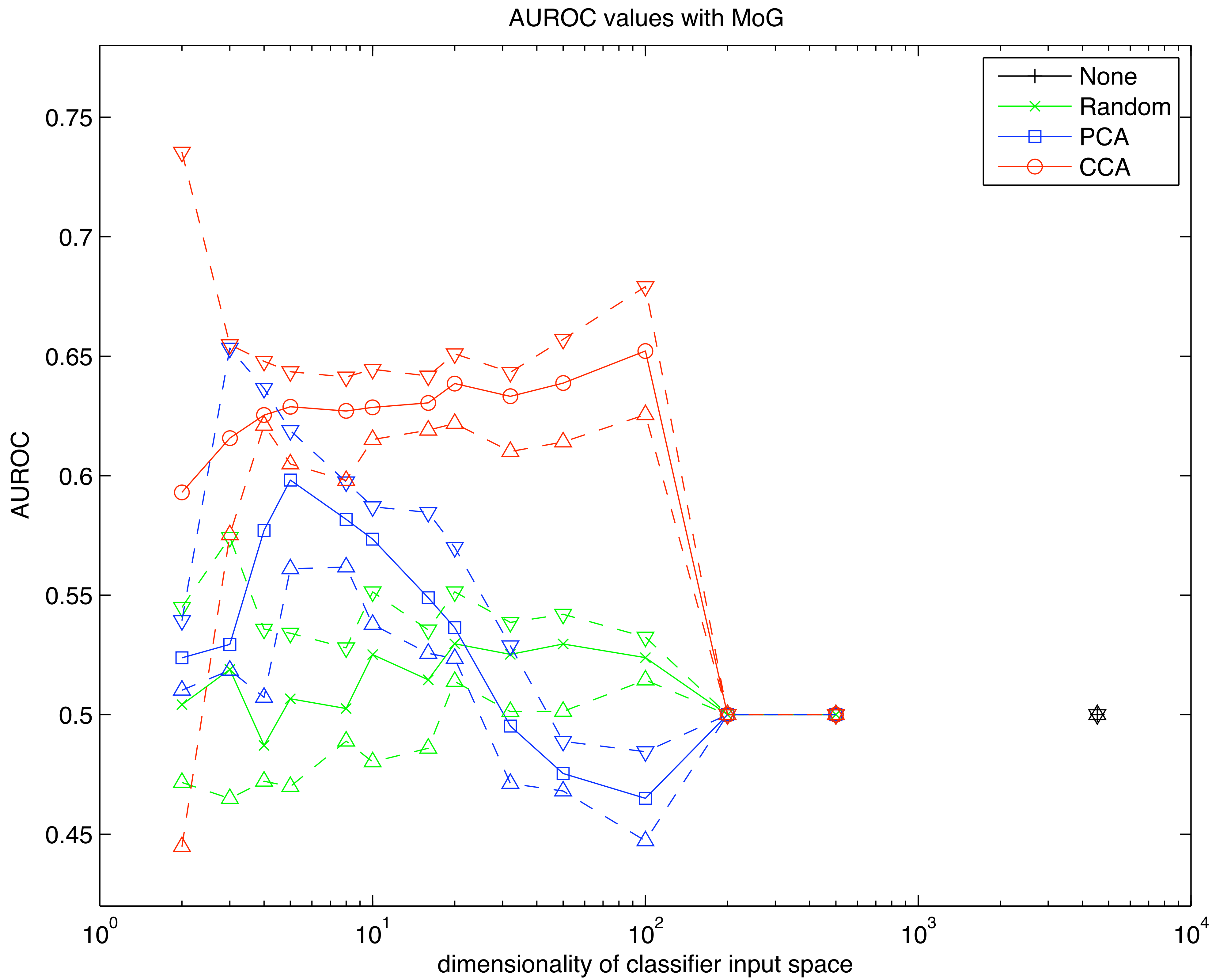
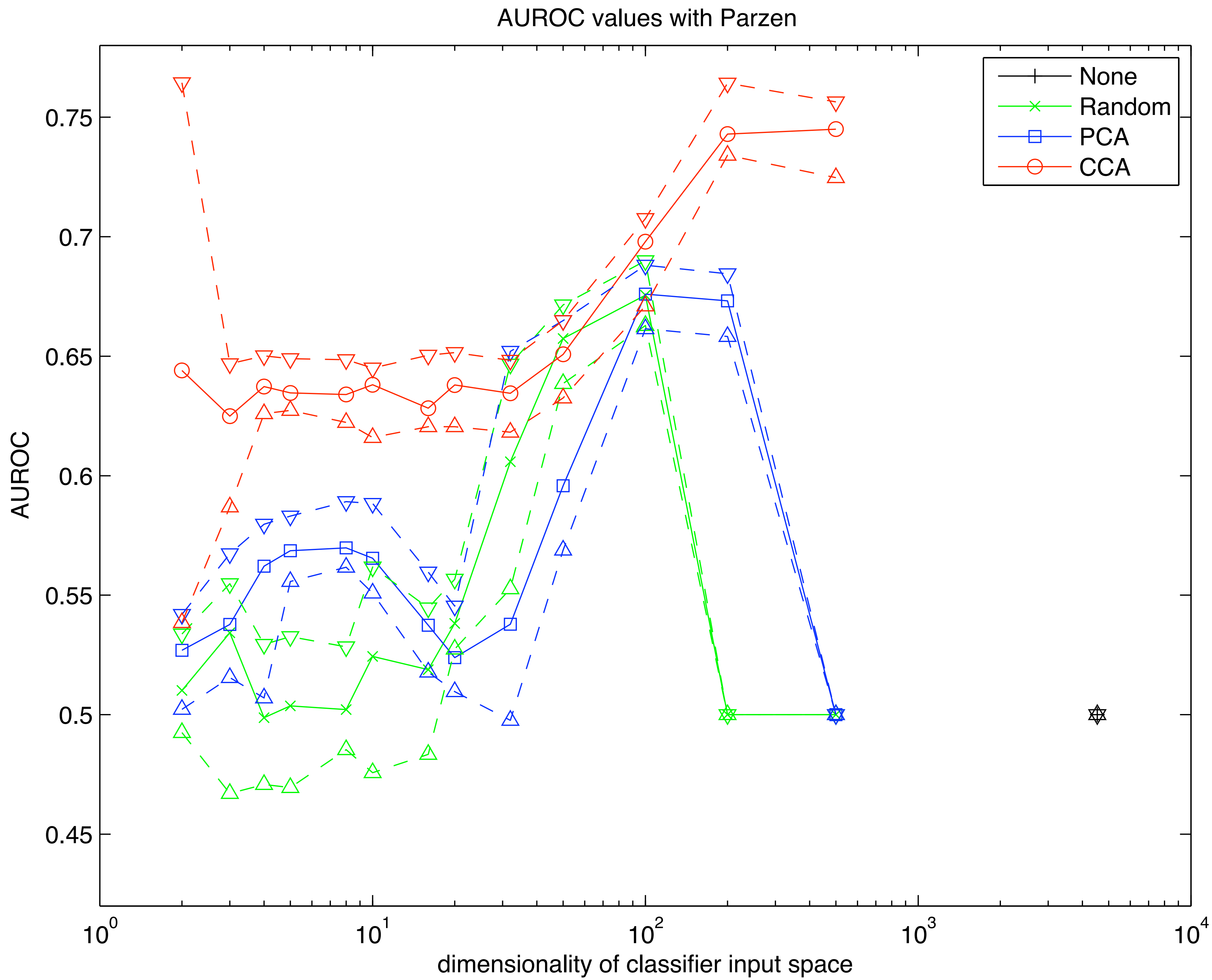
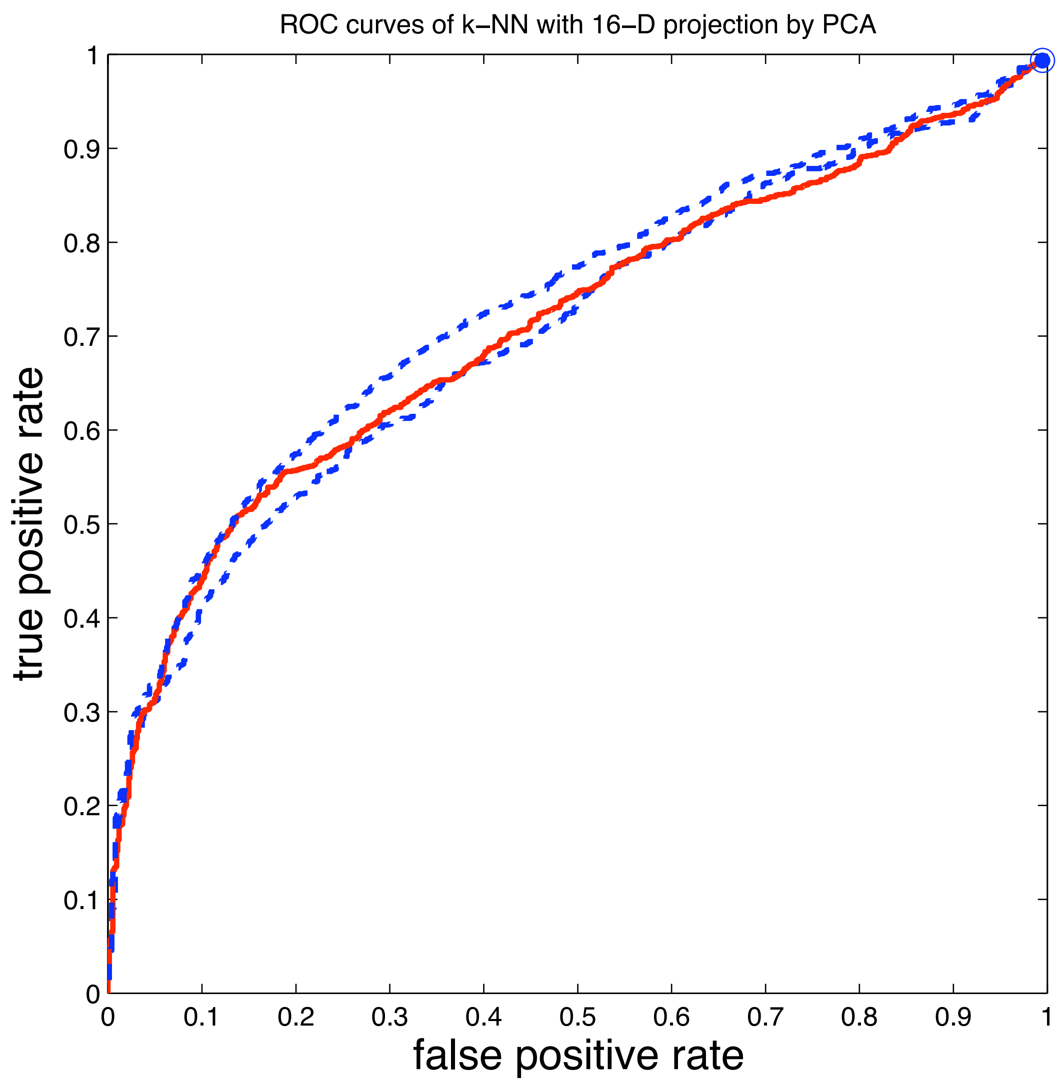
AUROC for MoG

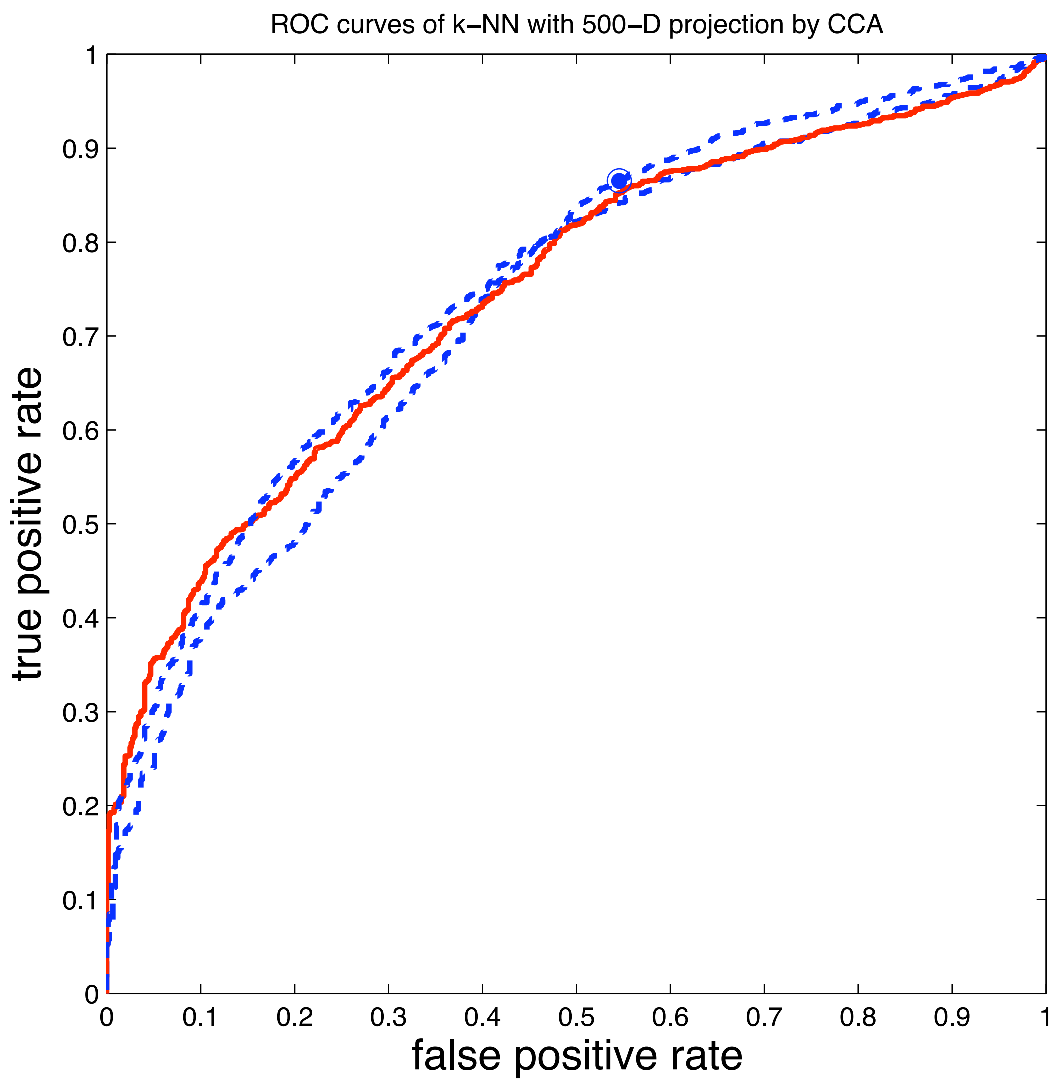


AUROC for Parzen Method



Examples of ROC with k-NN





- **16-dim. PCA versus 500-dim. CCA**
  - median AUROC of 0.7112 and 0.7448

Summary I

- **Application domain considered**
  - Need for dimensionality reduction
  - Need for novelty detection
- **General level solution as combination of projections and novelty detection methods**
  - The problem of distributing the computation still not considered at this stage
  - Application requirements were open: Will a certain combination of methods work in SHM, or not?

Summary II

- **Several combinations of methods benchmarked with a real-world data set**
  - Experience gained about the performance of several methods
  - Nonlinear projections reach better performance
  - k-NN and Parzen density estimates outperform simpler density-based novelty detection methods
- **More research still required**
  - Applicability domain of transmissibility features?
  - More and better data sets and density models?

Thanks for listening!

- ...any questions or comments?