The background of the slide is a photograph of a server room. On the left, several server racks are visible, with blue light emanating from them. The right side of the image is heavily blurred, creating a bokeh effect with out-of-focus light sources in shades of blue and yellow. The title text is overlaid on the right side of the image.

# Feature Selection And PCA In Data Mining

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# Unveiling The Power Of Dimensionality Reduction In Data Mining

# Introduction- The Challenge of High-Dimensional Data

## The Data Deluge

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- Modern datasets often contain a vast number of features (dimensions).
- **Curse of Dimensionality:**
  - Increased computational cost and time.
  - Difficulty in visualization.
  - Degraded model performance (overfitting, sparsity).
  - More data required to achieve statistical significance.





# What is Dimensionality Reduction?

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## The Core Idea

- Process of reducing the number of random variables under consideration.
- Transforms data from a high-dimensional space to a low-dimensional space.
- Aims to preserve meaningful properties of the original data as much as possible.



# Two Main Categories

## Two Main Categories

- 1.Feature Selection:** Selecting a subset of the original features.
- 2.Feature Extraction:** Transforming features into a new, smaller set of features.

# Feature Selection- Definition & Goal

## Feature Selection

```
graph TD; A[Feature Selection] --> B[Definition: The process of choosing a subset of relevant features for use in model construction.]; B --> C[Goal:]; C --> D[Improve model accuracy.]; C --> E[Reduce training time.]; C --> F[Enhance model interpretability.]; C --> G[Mitigate the curse of dimensionality.]; C --> H[Reduce overfitting.];
```

**Definition:** The process of choosing a subset of relevant features for use in model construction.

## Goal:

Improve model accuracy.

Reduce training time.

Enhance model interpretability.

Mitigate the curse of dimensionality.

Reduce overfitting.

# Types of Feature Selection Methods

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## 1. Filter Methods

**Concept:** Select features based on their intrinsic properties (e.g., correlation, statistical scores) without involving any learning algorithm.

**Pros:** Computationally efficient, independent of the learning algorithm.

**Cons:** May select redundant features, ignores interaction with the model.

### Examples:

- Variance Threshold
- Chi-squared test ( $\chi^2$ )
- Information Gain
- Correlation Coefficient



# Wrapper Methods

- **Concept:** Use a specific machine learning algorithm to evaluate the performance of different subsets of features.
- **Pros:** Account for model bias, often yield better predictive accuracy.
- **Cons:** Computationally intensive, prone to overfitting to the specific model.
- **Examples:**
  - Forward Selection
  - Backward Elimination
  - Recursive Feature Elimination (RFE)



# Embedded Methods

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- **Concept:** Feature selection is integrated into the model training process itself.
- **Pros:** Less computationally expensive than wrappers, considers feature interactions.
- **Cons:** Method-dependent.
- **Examples:**
  - Lasso Regression (L1 regularization)
  - Ridge Regression (L2 regularization)
  - Decision Trees (feature importance)



# Principal Component Analysis (PCA)

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- **Definition:** A statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components.
- **Goal:**
  - Reduce dimensionality while retaining as much variance as possible.
  - Visualize high-dimensional data.
  - Remove noise from data.
  - Pre-processing for other machine learning algorithms.

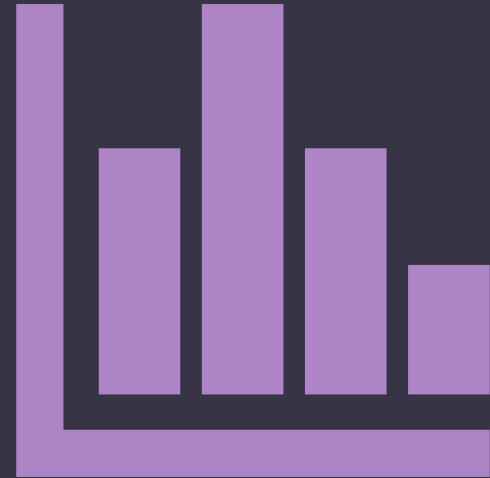


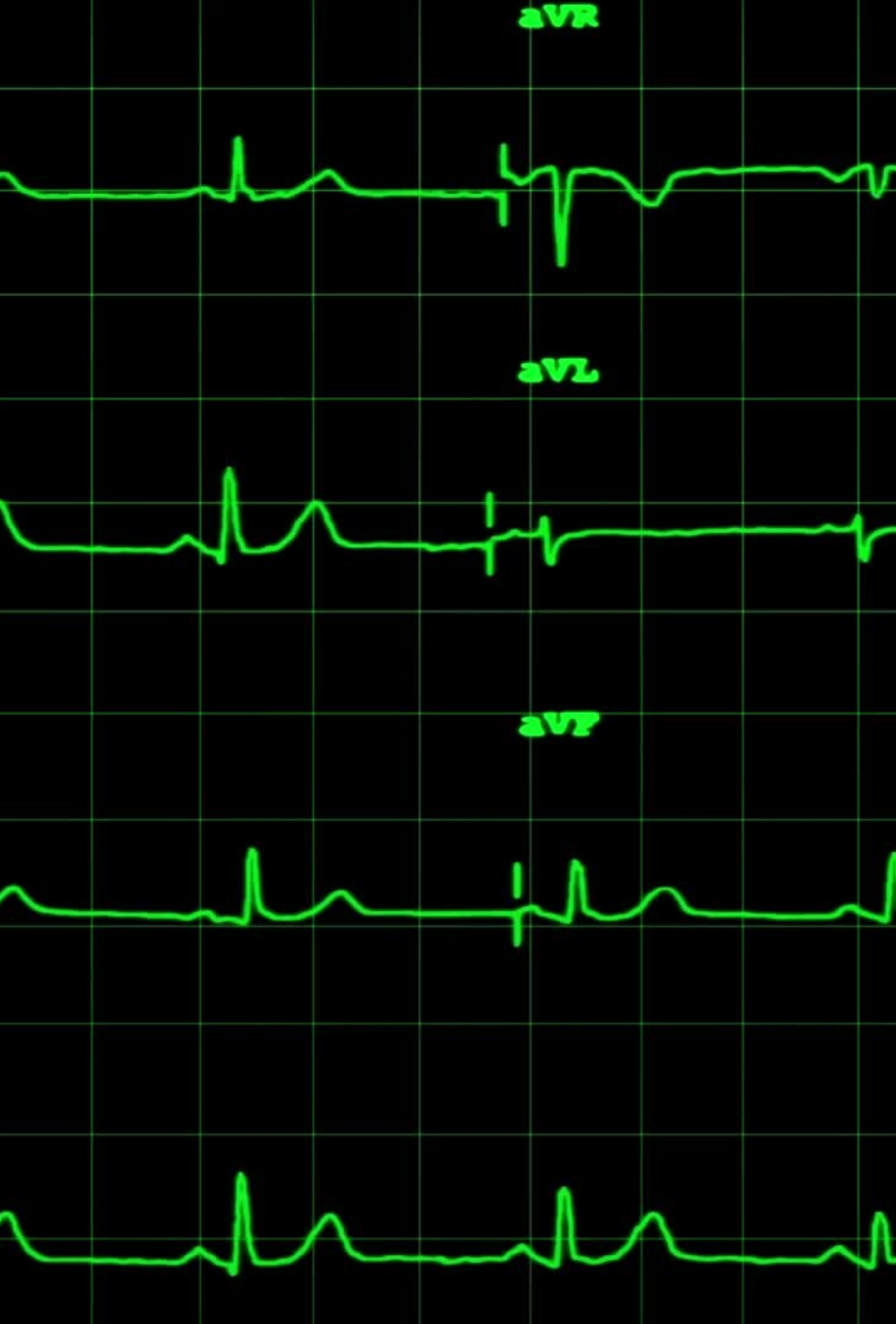
# How PCA Works (Simplified)

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## The Core Steps

- 1. Standardize the Data:** Ensure all features contribute equally by scaling them.
- 2. Calculate the Covariance Matrix:** Understand how features vary with respect to each other.
- 3. Compute Eigenvectors and Eigenvalues:**
  - 1. Eigenvectors:** Represent the directions (principal components) of maximum variance.
  - 2. Eigenvalues:** Indicate the magnitude of variance along each eigenvector.
- 4. Sort Eigenvalues:** Order principal components by their explained variance (from highest to lowest).
- 5. Select Principal Components:** Choose the top 'k' eigenvectors that capture a significant amount of variance.
- 6. Transform the Data:** Project the original data onto the new subspace defined by the selected principal components.





# PCA- Key Concepts

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## Principal Components

- New variables that are linear combinations of the original variables.
- Orthogonal (uncorrelated) to each other.
- The first principal component accounts for the largest possible variance, and each succeeding component accounts for the highest remaining variance.

## Explained Variance Ratio

- Indicates the proportion of variance in the original data that is captured by each principal component.
- Helps in determining the optimal number of components to retain.