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| **Started on** | Tuesday, 30 July 2024, 11:16 AM |
| **State** | Finished |
| **Completed on** | Tuesday, 30 July 2024, 11:18 AM |
| **Time taken** | 2 mins 18 secs |
| **Marks** | 7/7 |
| **Grade** | **10** out of 10 (**100**%) |

**Question 1**

Correct

Mark 1 out of 1

Let's recall what is so special about the covariance matrix of a (finite) dataset $X = (x_1, \dots, x_N) \in \mathbb{R}^{N \times n}$: Which of the following statements are correct?

- [x] a. Its Eigenvectors define the rotation operation needed to generate $X$ from whitened data.
- [ ] b. The diagonal entry $\mathrm{Cov}(X)_{i,i}$ in the $i$th row holds the standard deviation of the $i$th feature.
- [x] c. $\mathrm{Cov}(X)$ is defined as $\frac{1}{N}(X - \mathrm{mean}_{x \in X}(x))(X - \mathrm{mean}_{x \in X}(X))^T$
- [x] d. The entries $\mathrm{Cov}(X)_{i,j}$ at row $i$, column $j$ hold the covariance of the $i$th with the $j$th feature.
- [x] e. The covariance matrix of decorrelated data is a diagonal matrix.
- [ ] f. Its Eigenvectors define the operation needed to whiten $X$.
- [ ] g. $\mathrm{Cov}(X)_{i,j} = -\mathrm{Cov}(X)_{j,i}$

Your answer is correct.

Correct

Marks for this submission: 1/1.

**Question 2**

Correct

Mark 1 out of 1

The vanilla PCA formulation requires to find $m$ Eigenvalues of the (possibly huge) covariance matrix of the data $X$. Even though this can done iteratively, this still is a pretty expensive problem. Which of the following methods will reduce the computational effort necessary without substantial sacrifice of accuracy of the solution?

- [x] a. Solve the Eigenvalue equation for the matrix $X^TX$ instead of $XX^T$.
- [ ] b. Kernel PCA: Apply the transformation that projects $x$ to its first $m$ components prior to PCA.
- [ ] c. Reduce $|X|$: Randomly remove half of the samples.
- [x] d. Reduce $m$: Stop early when the Eigenvalues get small.
- [x] e. Use EM: skip finding the Eigenvalues by employing EM to the Bayesian net formulation.

Your answer is correct.

Correct

Marks for this submission: 1/1.

**Question 3**

Correct

Mark 5 out of 5

Dimensionality reduction generally pursues the goal to represent data points of a high dimensionality $n$ as points in a lower dimensional space. In the lecture, we have seen many different approaches to formulate this goal. For example, PCA takes a probabilistic perspective: The data points are sampled from a normally distributed population, with negligible variance into some dimensions (projection perspective).

Let's have a look at the ideas underlying some non-linear dimensionality reduction methods: Match underlying modeling ideas to the method.

| | |
|---|---|
| There exists a mapping from $X$ to a lower-dimensional space that locally preserves distribution of similarity. | t-SNE |
| My data points all lie close to an $m$-dimensional compact submanifold. The embedding of this submanifold can be described by the mapping on selected key points. | Self-organizing maps |
| There is a mapping $e$ to a lower-dimensional space for which an approximate inverse $d$ exists s.t. $d(e(x)) \approx x$ for $x \in X$. | Autoencoder |
| After some transformation, my data is approximately a Gaussian and can be whitened by finding a rotation onto its covariance Eigenvectors. | Kernel PCA |
| The data is generated from lower-dimensional data that is sampled from Gaussian population with unit covariance, using a non-linear embedding. | Non-linear PCA |

Your answer is correct.

Correct

Marks for this submission: 5/5.

◀ 10. Quiz - Unsupervised Clustering

Jump to...

12. Quiz - Time Series Analysis ▶