PROJECT REPORT

DEEP LEARNING

ASSIGNMENT PCA

BY

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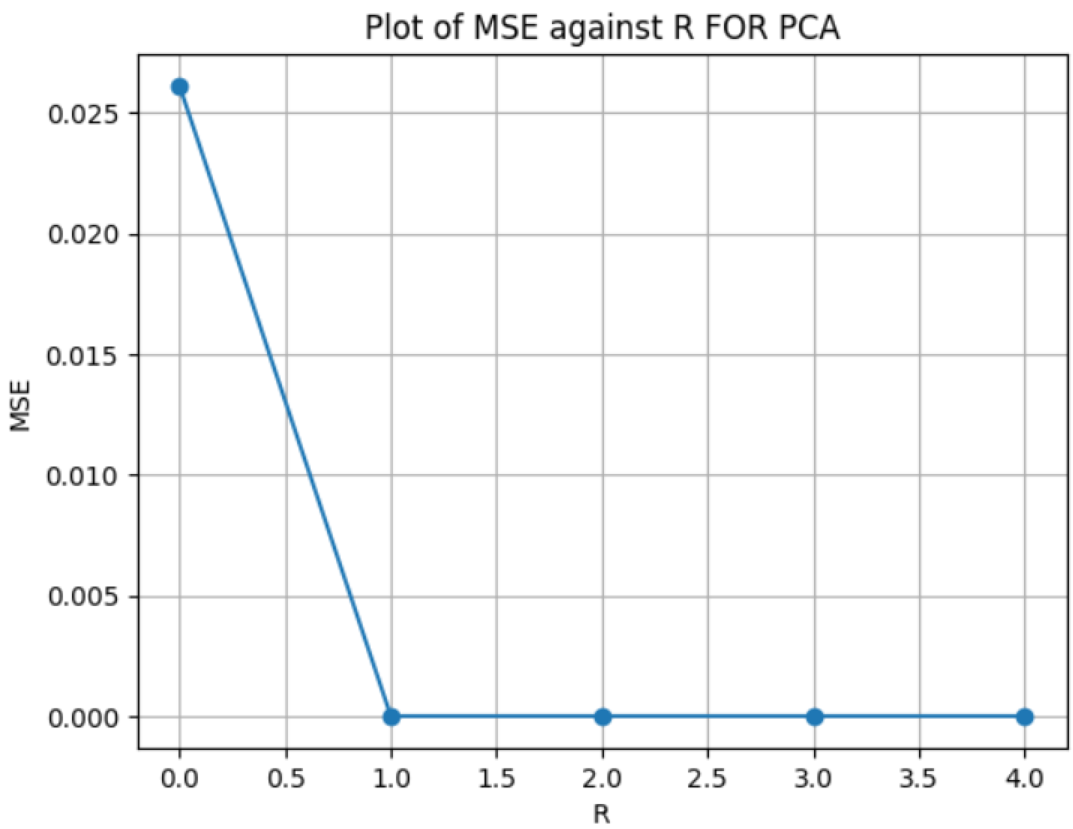
Q1. Compare the principle directions obtained from Mode shape approach and PCA approach.

Ans.

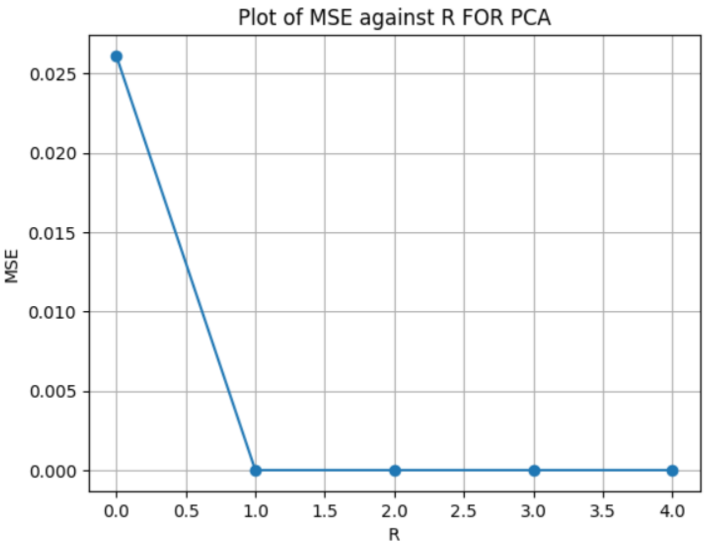
- It is expected that the primary directions derived from the PCA Approach and Mode Shape Approach would differ.
- The Mode Shape Approach determines the directions of vibration or deformation by concentrating on the mechanical characteristics of the system.
- PCA, on the other hand, takes into account the variability in the applied forces and determines which directions have the most variability.
- As a result, although both strategies seek to lower the problem's dimensionality, they do it from various angles and using various standards.
- There's a chance that the major directions found by both methods will coincide in some way, particularly if particular force patterns cause particular modes of vibration in the system. They are not, however, anticipated to be identical in general.

Q2. For PCA approach, plot the mean square error with respect to ’r’ and explain it.



- This figure makes it easier to see how the MSE varies with the number of maintained primary components (r).
- It enables us to evaluate the trade-off between the PCA model's accuracy (measured by MSE) and model complexity (represented by r).
- Though there may be a point of diminishing returns when adding more principle components does not materially enhance the model's performance, generally speaking, we expect the MSE to drop as r grows.
- This figure assists in determining the ideal value of r that strikes a balance between prediction accuracy and model complexity.

Q3. Lets consider the case where displacement data is coming with noise of +/-8 percent. Does the noise affect the performance of the PCA.



Without Noise

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Mean Displacement using PCA= 0.01930647052601078
Mean Displacement Orginal= 0.0137903360900077
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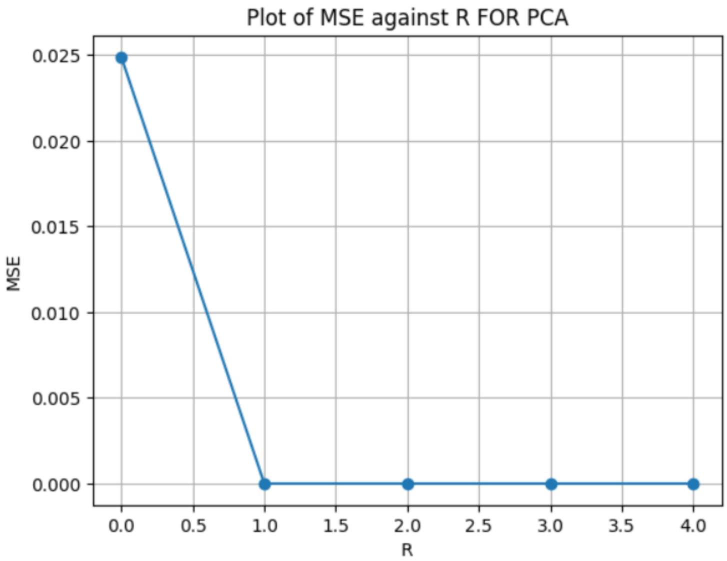

With Noise

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Mean Displacement usin PCA= 0.018738771100366335
Mean Displacement Orginal= 0.0137903360900077
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In the context of the provided problem, if the displacement data is contaminated with noise of +/-8 percent, PCA may still be able to provide dimensionality reduction, but the accuracy and reliability of the reduced-dimensional representation is compromised compared to a scenario with clean data. It's essential to evaluate the trade-offs and consider the suitability of PCA in the presence of noise based on the specific characteristics of the dataset and the objectives of the analysis.

Q4. Is it possible to find the a force distribution for which PCA works fine,but the mode shape approach fails? If yes, state such distribution and verify that indeed PCA works better than mode shape.

Ans. In situations where the force distribution introduces a significant amount of noise or variability that is not well aligned with the natural modes of vibration that the Mode Shape Approach captures, PCA may indeed perform better than the Mode Shape Approach. In these situations, the Mode Shape Approach, which depends on identifying dominant modes of vibration, may not offer as strong a representation of the system dynamics as PCA, which finds directions of maximum variance in the force distribution. This can be confirmed by simulating the system with the specified force distribution and comparing the outcomes from the two methods to evaluate how accurate and consistent they are with the data that is observed.

An example scenario would be to think of a spring-mass system with three masses connected by springs and several degrees of freedom. Assume for the moment that this system's inherent modes of vibration are simple harmonic motion along each of its degrees of freedom.
Let us now consider the application of a force distribution that introduces random variability or noise into the system. It is possible that this force distribution is not well aligned with the natural modes of vibration that the Mode Shape Approach is able to capture. In the event that random forces are applied to every mass block in the force distribution, for example, the system may exhibit complex and irregular motion that is poorly captured by the mode shapes.

Q5. Is it possible to find the a force distribution for which mode shape approach works fine, but the PCA approach fails? If yes, state such distribution and verify that indeed mode shape works better than PCA.

Ans. Yes, it is possible for the Mode Shape Approach to outperform PCA in scenarios where the force distribution aligns well with the natural modes of vibration captured by the Mode Shape Approach but introduces noise or variability that PCA struggles to handle. In such cases, the Mode Shape Approach, which directly identifies dominant modes of vibration, may provide more accurate results compared to PCA, which may struggle to differentiate between signal and noise. To verify this, we can simulate the system with the given force distribution and compare the results obtained using both approaches, assessing their accuracy and alignment with observed data.

An example scenario would be to think of a spring-mass system with three masses connected by springs and several degrees of freedom. Assume for the moment that this system's inherent modes of vibration are simple harmonic motion along each of its degrees of freedom.

Let's say that we now apply a force distribution that precisely matches the natural vibrational modes that the Mode Shape Approach was able to identify. Harmonic forces that match the frequencies and patterns of the mode shapes could be applied to each mass block as part of the force distribution, for example.

Q6.Summary

Ans.The following essential concepts about PCA have been taught to us via this exercise and its comparison with the Mode Shape Approach:

Flexibility: By determining the directions of maximum variance in the data, PCA provides flexibility in the reduction of dimensionality. Compared to the Mode Shape Approach, it may be more resilient in managing intricate or noisy datasets because of this.

Robustness to Noise: Although PCA can partially handle noisy datasets, noise can still affect its performance, particularly if it overpowers the signal and masks the data's underlying structure.

Flexibility vs. Interpretability: By identifying dominant modes of vibration that are physically significant, the Mode Shape Approach yields results that are interpretable. PCA, on the other hand, is more flexible but may not be directly interpretable, especially if the principal components don't correspond to quantities that make sense physically.

Applicability: Depending on the features of the problem and the type of data, one may choose to use the Mode Shape Approach or PCA. While the Mode Shape Approach is better suited for comprehending the physical behaviour of systems, PCA may be preferred for complex or noisy data.

Trade-off: Interpretability and accuracy are subject to trade-offs. In some situations, PCA might perform better, but the Mode Shape Approach offers direct physical insights into the behaviour of the system.