Congratulations! You passed!

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| 1. | Which one of the following is an intrinsic property of an object? | 1 / 1 point |
|----|--|-------------|
| | O Pose | |
| | Shape | |
| | Orientation | |
| | ○ Illumination | |
| | ✓ Correct Pose, illumination, and orientation of the object are extrinsic variables that are independent of the object itself. | |
| 2. | Our database consists of images for 60 objects with 100 different lighting directions and 200 different poses, how much time would it take to find the closest match for an input image using naïve template matching if performing each template match takes $10ms$? | 1/1 point |
| | lacksquare 200min | |
| | $\bigcirc \ 20min$ | |
| | $\bigcirc \ 2min$ | |
| | \bigcirc 12 s | |
| | | |

We need to search the entire database to find the closest match to the image. The entire database consists of $60 \times 200 \times 100$ = 1200000 images. To search through 1200000 images, it takes 1200000×0.01 = 12000 s = 200 min

| 3. | Which of the following statements best describes dimensionality reduction? | 1/1 point |
|----|---|-----------|
| | O It reduces the length of all vectors formed by connecting all data points to the origin. | |
| | O It projects data points to a higher dimensional space such that the underlying information is preserved. | |
| | O It transforms the data points to reduce the variance between all points. | |
| | It projects data points to a lower dimensional space such that the underlying information is preserved. | |
| | Correct By definition, dimensionality reduction attempts to represent the same information using fewer dimensions. | |
| 4. | Why is dimensionality reduction especially useful for the appearance matching problem? | 1/1 point |
| | O Since there are many different combinations of orientations and illuminations for each object, dimensionality reduction must be used to reduce the number of images required to represent each object | |
| | Since many images of the same object are taken under different orientations and illuminations, we expect the data to be highly correlated and therefore each image could be represented with fewer features | |
| | When there are many objects in the dataset, dimensionality reduction can | |
| | decompose each object into simple shapes | |
| | decompose each object into simple shapes None of the above | |

✓ Correct

The second choice best matches the motivation for dimensionality reduction in appearance matching.

5. Which of the following statements about Principal Component Analysis is false?

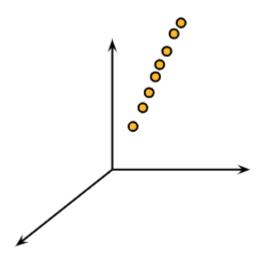
1/1 point

- The first principal component is also the axis of maximum variance from the mean of the features
- All the principal components are orthogonal to each other
- The principal components are the eigenvectors of the covariance matrix
- lacktriangle The principal components are the singular values of the feature matrix F
 - **⊘** Correct

The principal components do not correspond to the singular values of ${\cal F}$, they are the eigenvectors of ${\cal F}{\cal F}^T$.

6. Given the set of 3D points below, what is the minimum number of principal components sufficient to represent these points?

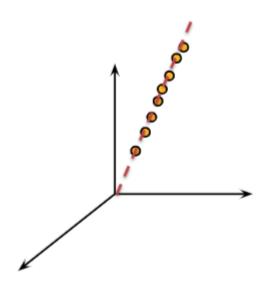
2 / 2 points



 \bigcirc

- 2
- \bigcirc
- ✓ Correct

Since all the points lie on a straight line, they can be represented by a single number. With a 1D line (see red line below) as the axis, each point can be represented as a unique distance along this line.



7. Given a dataset of n images of size $d \times d$, what are the dimensions of the covariance matrix R whose eigenvectors are the principal components of the dataset?

1 / 1 point

- $\bigcap n \times d^2$
- \bigcap $n \times n$
- $\bigcirc d \times d$
- $d^2 \times d^2$

✓ Correct

For this dataset, each feature vector will be a $d^2 imes 1$ vector, so the matrix F of feature vectors will be $d^2 imes n$. Since $R = FF^T$, the dimensions of R will be $d^2 imes d^2$.

8. Given a dataset of 1500 images of size 10x10, what is the maximum number of non-zero eigenvalues we can get from Principal Component Analysis?

1 / 1 point

- 1500
- 100
- \bigcirc 15000
- \bigcirc 10

✓ Correct

Each image of size 10x10 image forms a 100-dimensional vector. If we had N such images in the dataset, the covariance matrix of the $100 \times N$ dataset is 100×100 . A full-rank matrix gives the maximum number of non-zero eigenvalues. Hence, the answer is 100.

9. If a dataset is composed of 5000 copies of the same image (of size 10×10), how many non-zero eigenvalues do we get from the covariance matrix of this dataset?

1/1 point

- 1
- \bigcirc 10
- O 100
- **5000**

⊘ Correct

Since the dataset contains copies of the same image, we essentially only have one data point within the dataset. We only need one principal component (hence, one non-zero eigenvalue) to represent this data point.

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|---------------|---|--------------|
| 10. Gi | iven a set of images I_1,I_2,\cdots,I_n (as $m^2	imes 1$ feature vectors), let | 0 / 2 points |
| F | $\Gamma = [I_1 \cdots I_n]$. If the mean of the set is large and the variance is small, then which | |
| of | the following is $\emph{approximately}$ the first eigenvector of FF^T ? | |
| C | The mean image | |
| • | The first principal component | |
| C | The first moment of inertia of the points | |

⊗ Incorrect

None of the above