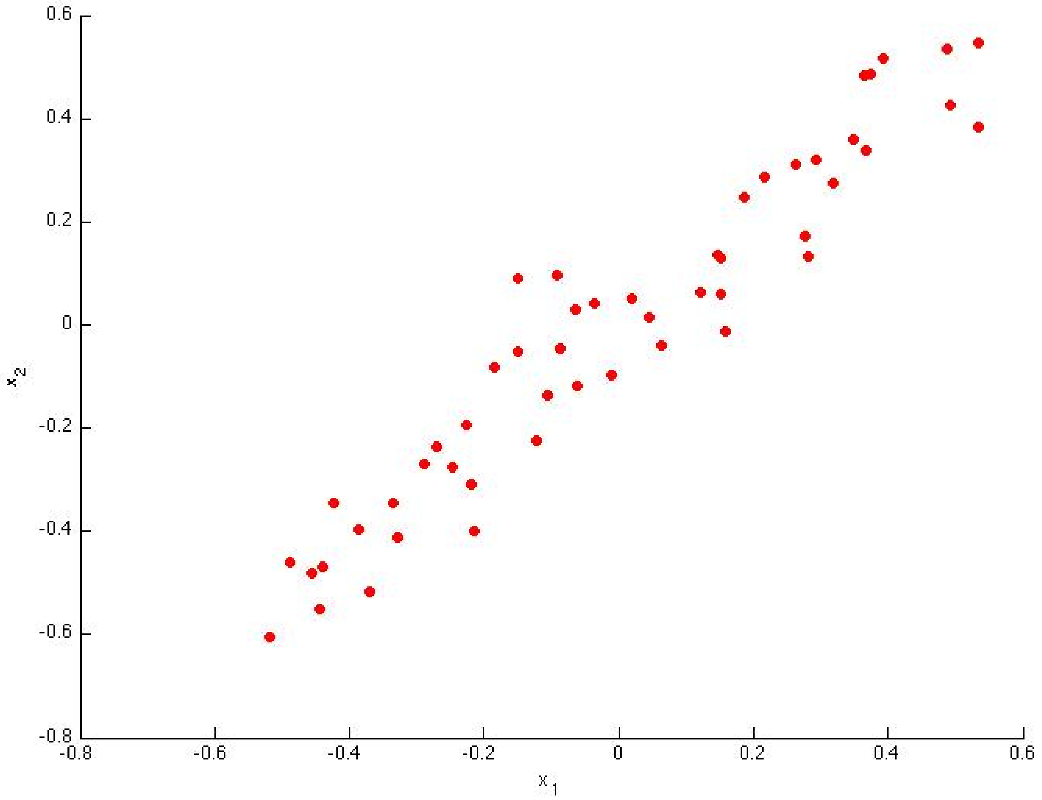
Feedback — XIV. Principal Component Analysis

Help Center

You submitted this quiz on **Wed 8 Apr 2015 9:18 AM CEST**. You got a score of **5.00** out of **5.00**.

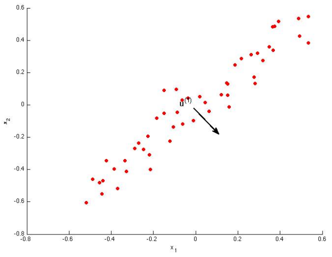
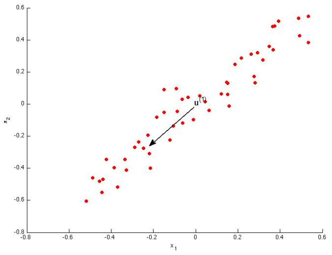
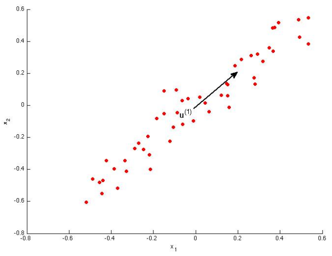
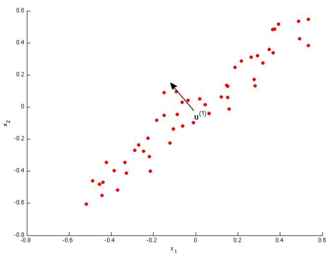
Question 1

Consider the following 2D dataset:



Which of the following figures correspond to possible values that PCA may return for $u^{(1)}$ (the first eigenvector / first principal component)? Check all that apply (you may have to check more than one figure).

Your Answer		Score	Explanation
☐	✔	0.25	The first principal component is aligned with the direction of maximal variance, but this is aligned with the direction of minimal variance.

			
☑ 	✔	0.25	The maximal variance is along the y = x line, so the negative vector along that line is correct for the first principal component.
☑ 	✔	0.25	The maximal variance is along the y = x line, so this option is correct.
☐ 	✔	0.25	The first principal component is aligned with the direction of maximal variance, but this is aligned with the direction of minimal variance.
Total		1.00 / 1.00	

Question 2

Which of the following is a reasonable way to select the number of principal components k?

(Recall that n is the dimensionality of the input data and m is the number of input examples.)

Your Answer		Score	Explanation
◉ Choose k to be the smallest value so that at least 99% of the variance is retained.	✔	1.00	This is correct, as it maintains the structure of the data while maximally reducing its dimension.

Choose k to be 99% of n (i.e., $k = 0.99 * n$, rounded to the nearest integer).

Use the elbow method.

Choose the value of k that minimizes the approximation error $\frac{1}{m}\sum_{i=1}^{m} ||x^{(i)} - x_{\text{approx}}^{(i)}||^2$.

Total	1.00 / 1.00	

Question 3

Suppose someone tells you that they ran PCA in such a way that "95% of the variance was retained." What is an equivalent statement to this?

Your Answer		Score	Explanation
$\frac{\frac{1}{m}\sum_{i=1}^{m} ||x^{(i)}-x_{\text{approx}}^{(i)}||^2}{\frac{1}{m}\sum_{i=1}^{m} ||x^{(i)}||^2} \geq 0.05$			
$\frac{\frac{1}{m}\sum_{i=1}^{m} ||x^{(i)}-x_{\text{approx}}^{(i)}||^2}{\frac{1}{m}\sum_{i=1}^{m} ||x^{(i)}||^2} \leq 0.95$			
$\frac{\frac{1}{m}\sum_{i=1}^{m} ||x^{(i)}||^2}{\frac{1}{m}\sum_{i=1}^{m} ||x^{(i)}-x_{\text{approx}}^{(i)}||^2} \leq 0.95$			
$\frac{\frac{1}{m}\sum_{i=1}^{m} ||x^{(i)}-x_{\text{approx}}^{(i)}||^2}{\frac{1}{m}\sum_{i=1}^{m} ||x^{(i)}||^2} \leq 0.05$	✔	1.00	This is the correct formula.
Total		1.00 / 1.00	

Question 4

Which of the following statements are true? Check all that apply.

Your Answer		Score	Explanation
☑ Given an input $x \in \mathbb{R}^n$, PCA compresses it to a lower-dimensional vector $z \in \mathbb{R}^k$.	✔	0.25	PCA compresses it to a lower dimensional vector by projecting it onto the learned principal components.

☑ Even if all the input features are on very similar scales, we should still perform mean normalization (so that each feature has zero mean) before running PCA.	✔	0.25	If you do not perform mean normalization, PCA will rotate the data in a possibly undesired way.
☐ PCA can be used only to reduce the dimensionality of data by 1 (such as 3D to 2D, or 2D to 1D).	✔	0.25	PCA can reduce data of dimension n to any dimension $k < n$.
☐ PCA is susceptible to local optima; trying multiple random initializations may help.	✔	0.25	PCA is a deterministic algorithm: there is no initialization and there are no local optima.
Total		1.00 / 1.00	

Question 5

Which of the following are recommended applications of PCA? Select all that apply.

Your Answer		Score	Explanation
☐ Preventing overfitting: Reduce the number of features (in a supervised learning problem), so that there are fewer parameters to learn.	✔	0.25	You should use regularization to prevent overfitting, not PCA.
☐ As a replacement for (or alternative to) linear regression: For most learning applications, PCA and linear regression give substantially similar results.	✔	0.25	PCA is not linear regression. They have different goals (and cost functions), so they give different results.
☑ Data compression: Reduce the dimension of your input data $x^{(i)}$, which will be used in a supervised learning algorithm (i.e., use PCA so that your supervised learning algorithm runs faster).	✔	0.25	If your learning algorithm is too slow because the input dimension is too high, then using PCA to speed it up is a reasonable choice.
☑ Data visualization: Reduce data to 2D (or 3D) so that it can be plotted.	✔	0.25	This is a good use of PCA, as it can give you intuition about your data that would otherwise be impossible to see.

Total	1.00 / 1.00