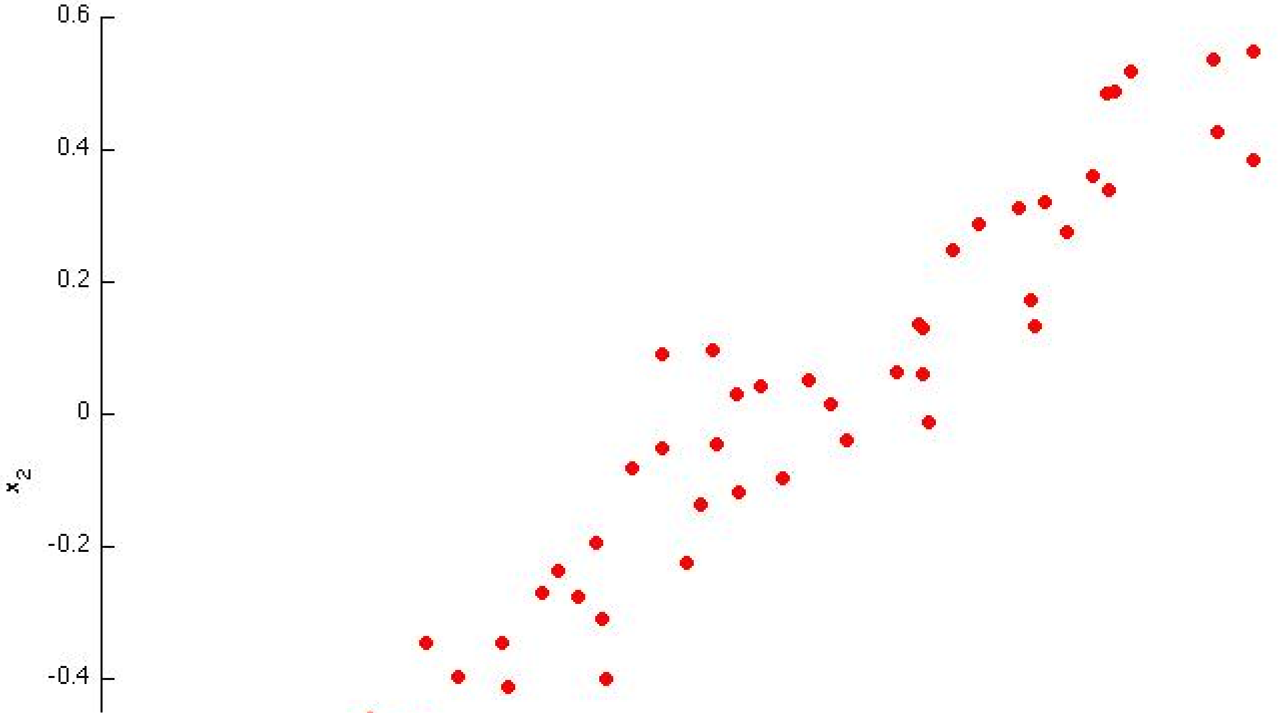
Principal Component Analysis

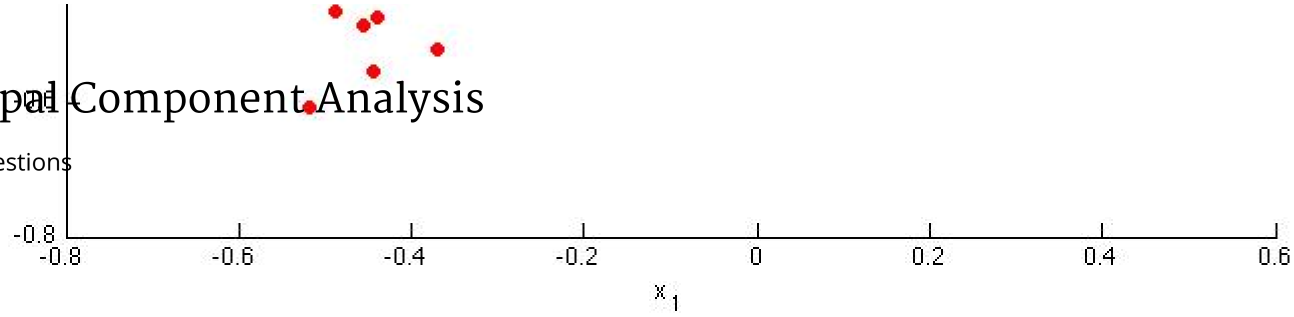
Quiz, 5 questions

1
point

1.

Consider the following 2D dataset:



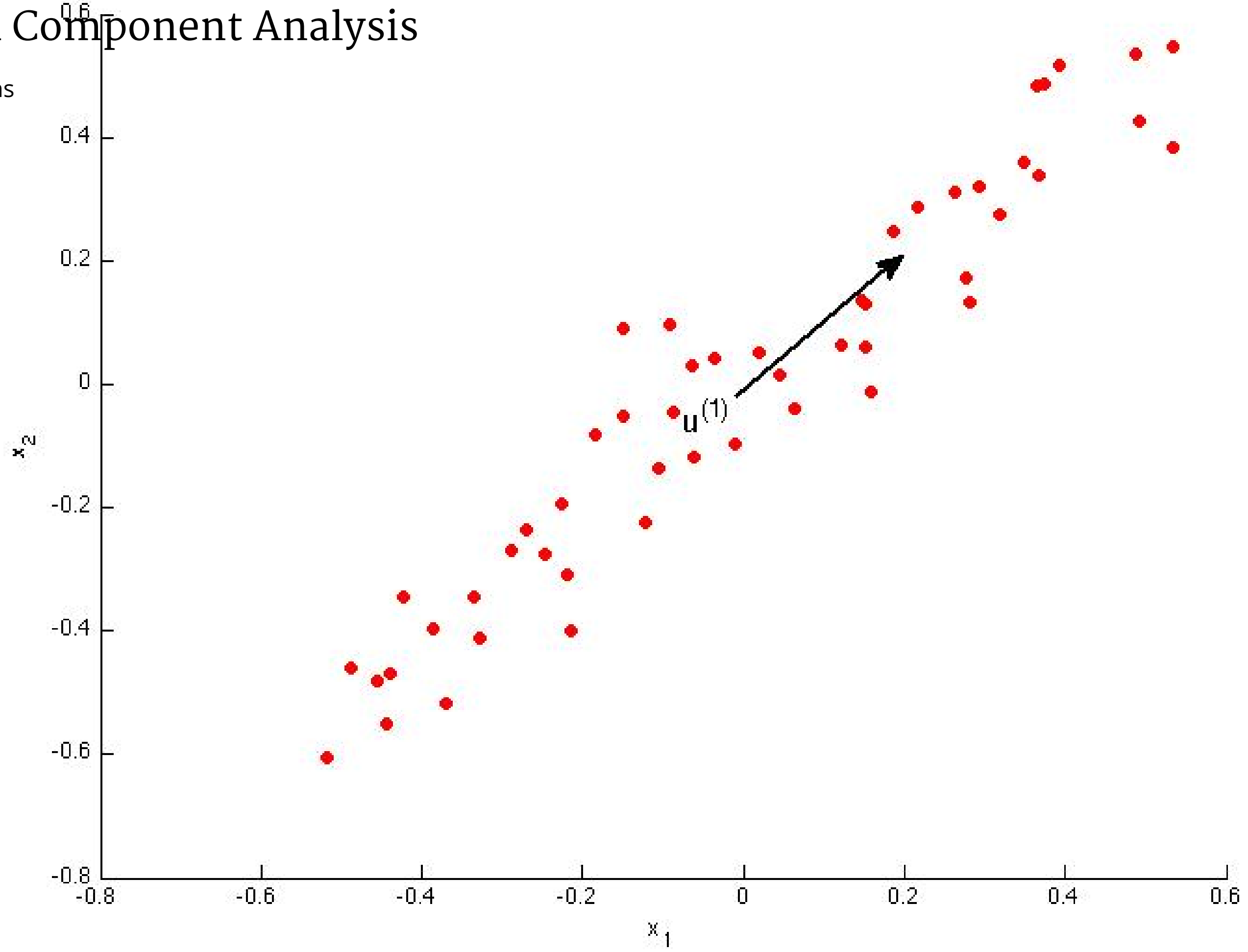


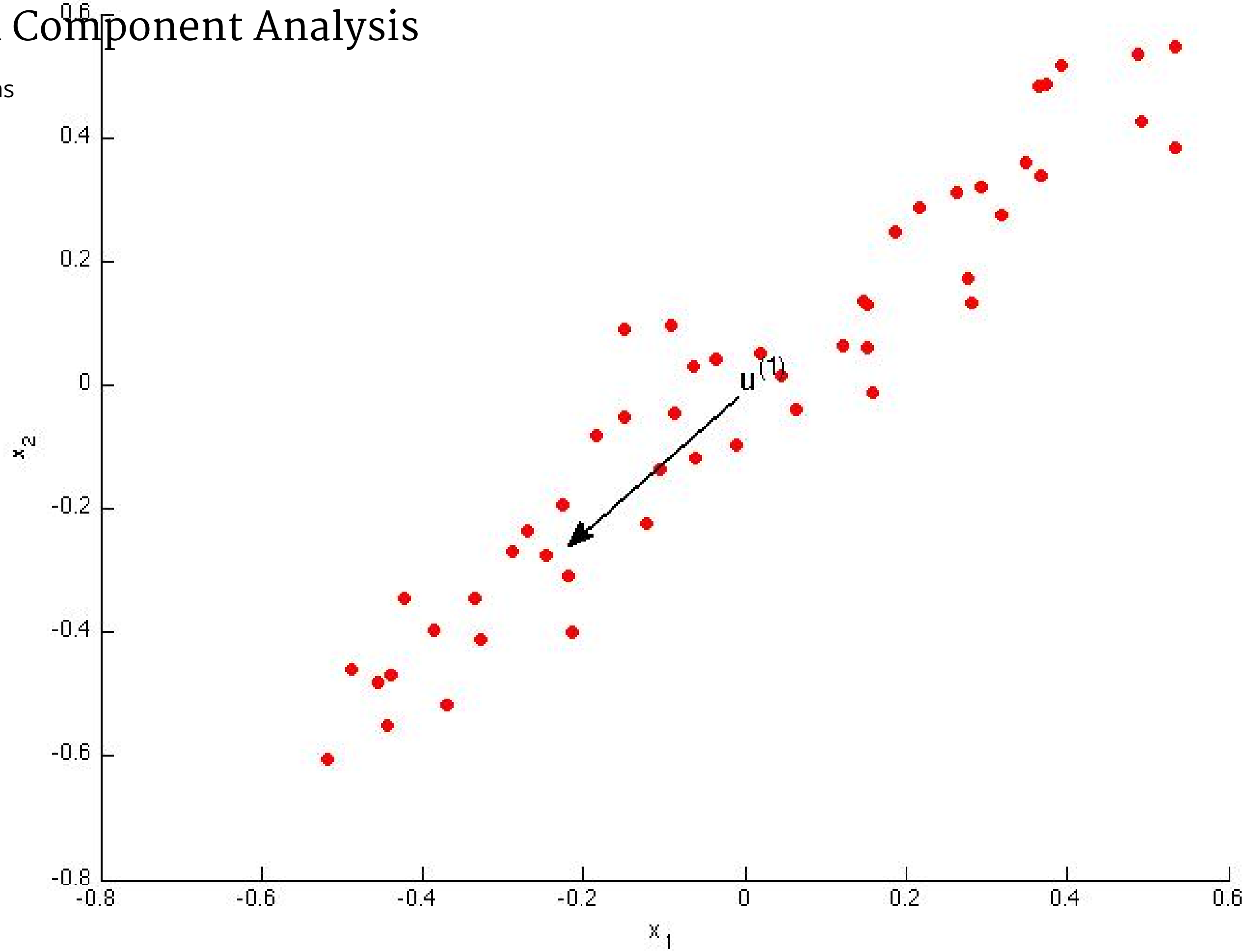
Which of the following figures correspond to possible values that PCA may return for $u^{(1)}$ (the first eigenvector / first principal component)? Check all that apply (you may have to check more than one figure).

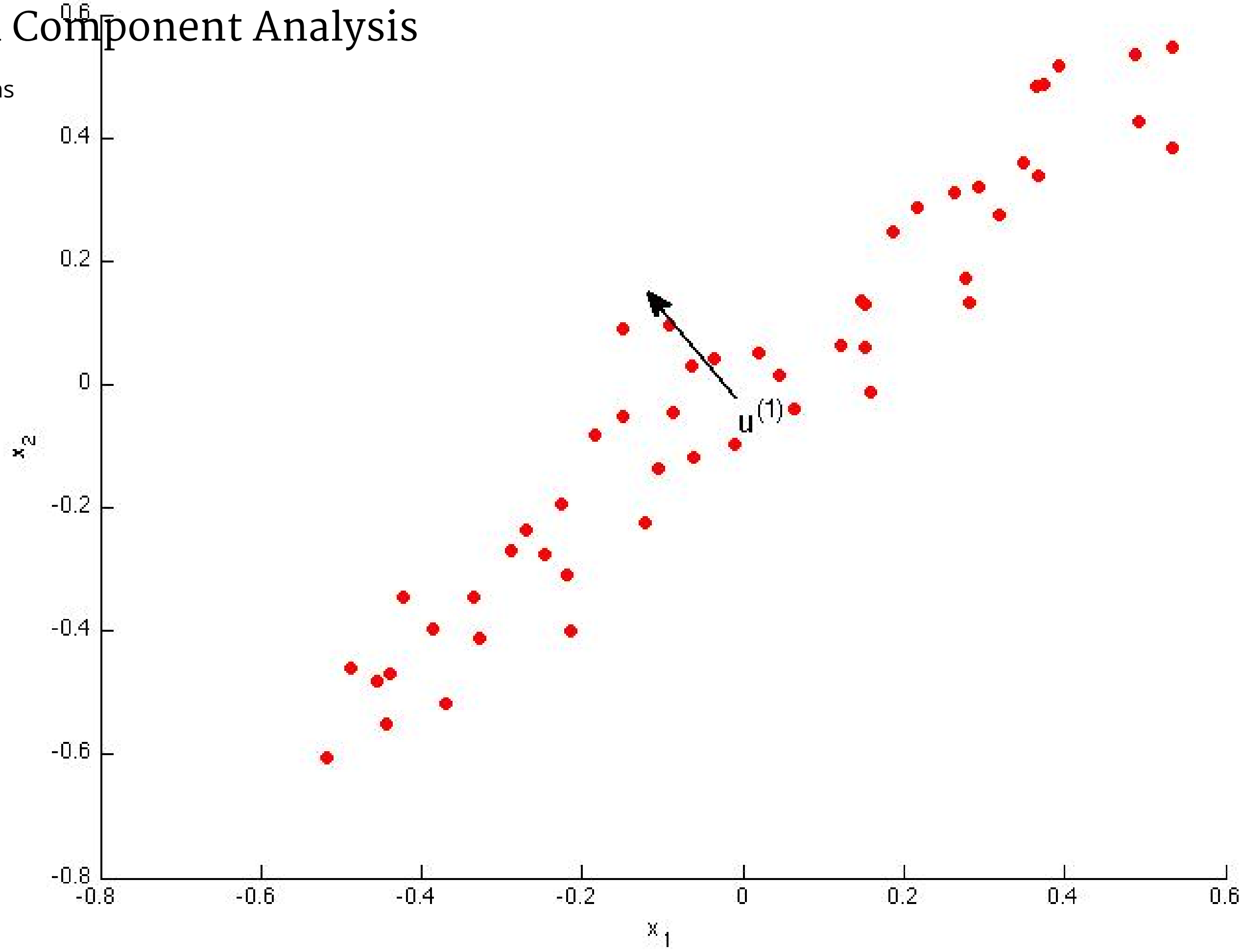
☐

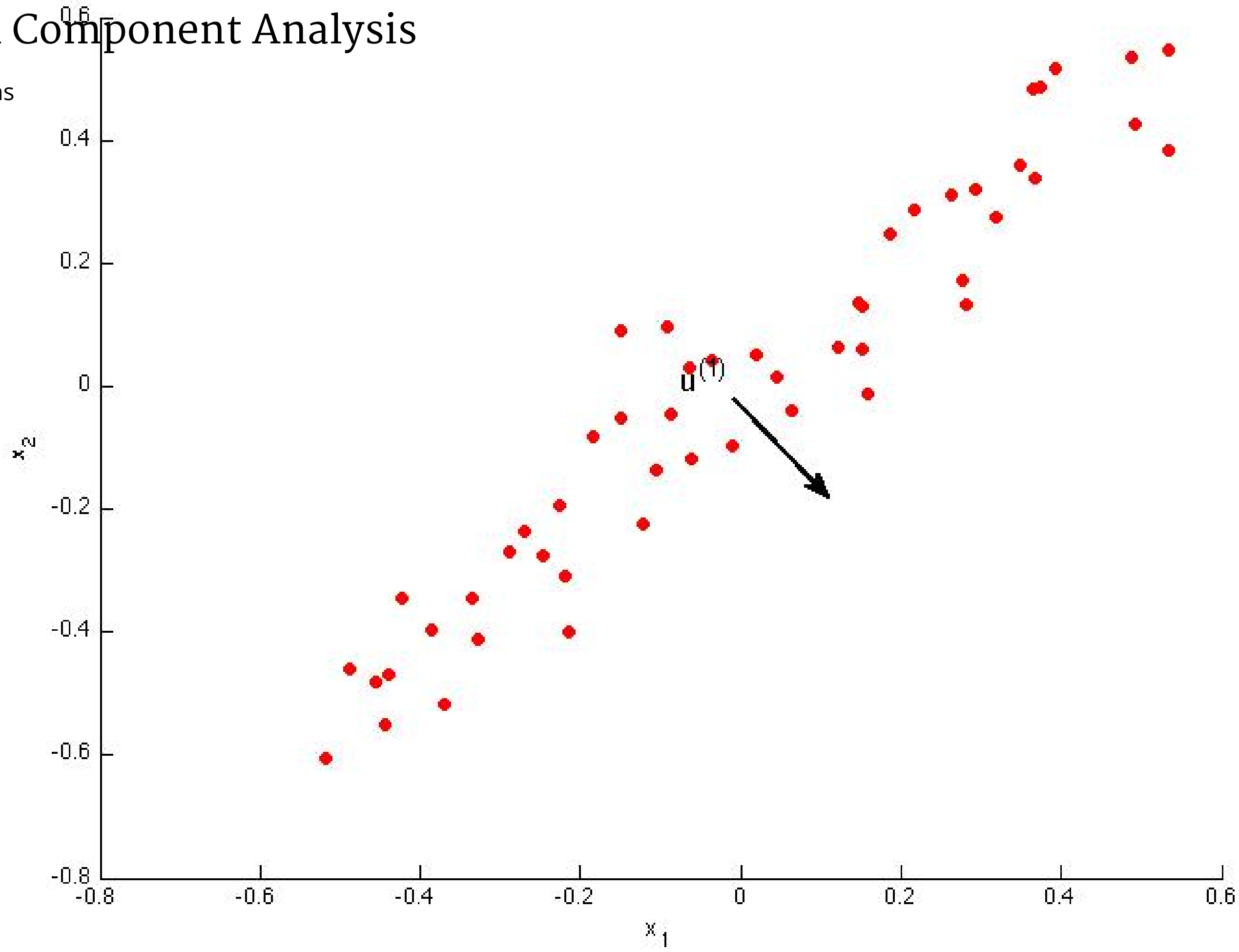
Principal Component Analysis

Quiz, 5 questions




0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
x_1
x_2
$u^{(1)}$


0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
x_2
$u^{(1)}$
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
x_1



1
point

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.)

- ◯ Choose k to be the largest value so that at least 99% of the variance is retained
- ◯ Choose k to be the smallest value so that at least 99% of the variance is retained.
- ◯ Use the elbow method.
- ◯ Choose k to be 99% of m (i.e., $k = 0.99 * m$, rounded to the nearest integer).

---

1 point

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?

- ◯ $\frac{\frac{1}{m}\sum_{i=1}^{m}||x^{(i)}-x_{\text{approx}}^{(i)}||^2}{\frac{1}{m}\sum_{i=1}^{m}||x^{(i)}||^2} \leq 0.95$
- ◯ $\frac{\frac{1}{m}\sum_{i=1}^{m}||x^{(i)}-x_{\text{approx}}^{(i)}||^2}{\frac{1}{m}\sum_{i=1}^{m}||x^{(i)}||^2} \leq 0.05$
- ◯ $\frac{\frac{1}{m}\sum_{i=1}^{m}||x^{(i)}-x_{\text{approx}}^{(i)}||^2}{\frac{1}{m}\sum_{i=1}^{m}||x^{(i)}||^2} \geq 0.95$
- ◯ $\frac{\frac{1}{m}\sum_{i=1}^{m}||x^{(i)}-x_{\text{approx}}^{(i)}||^2}{\frac{1}{m}\sum_{i=1}^{m}||x^{(i)}||^2} \geq 0.05$

1
point
Principal Component Analysis

4 Quiz, 5 questions

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

- [ ] Given an input $x \in \mathbb{R}^n$, PCA compresses it to a lower-dimensional vector $z \in \mathbb{R}^k$.
- [ ] If the input features are on very different scales, it is a good idea to perform feature scaling before applying PCA.
- [ ] Feature scaling is not useful for PCA, since the eigenvector calculation (such as using Octave's `svd(Sigma)` routine) takes care of this automatically.
- [ ] PCA can be used only to reduce the dimensionality of data by 1 (such as 3D to 2D, or 2D to 1D).

1
point

5.

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

- [ ] Data visualization: Reduce data to 2D (or 3D) so that it can be plotted.
- [ ] Clustering: To automatically group examples into coherent groups.
- [ ] 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).
- [ ] To get more features to feed into a learning algorithm.
