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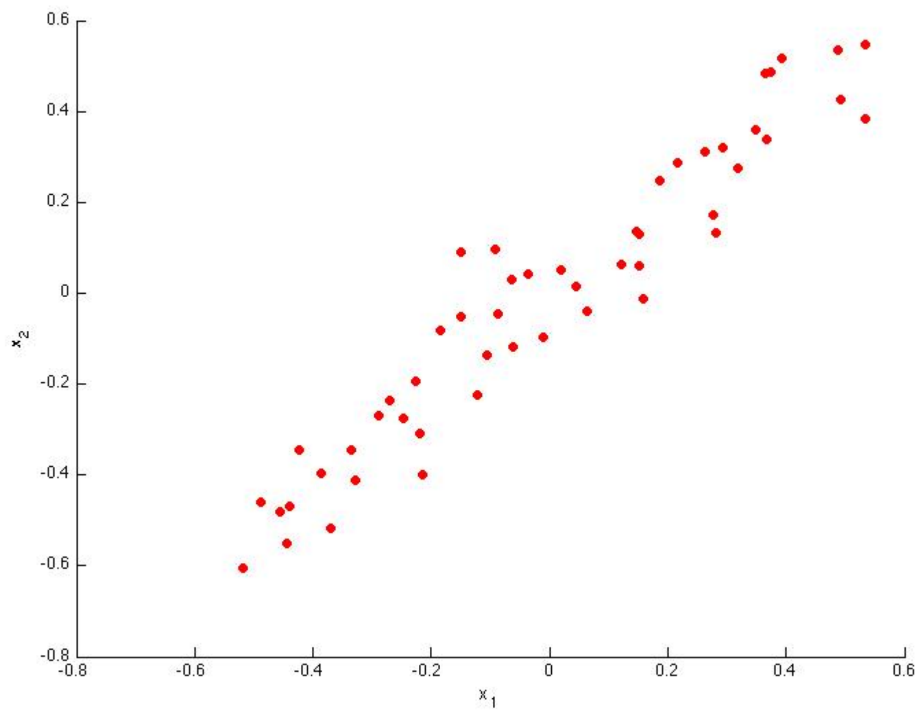
Principal Component Analysis

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).

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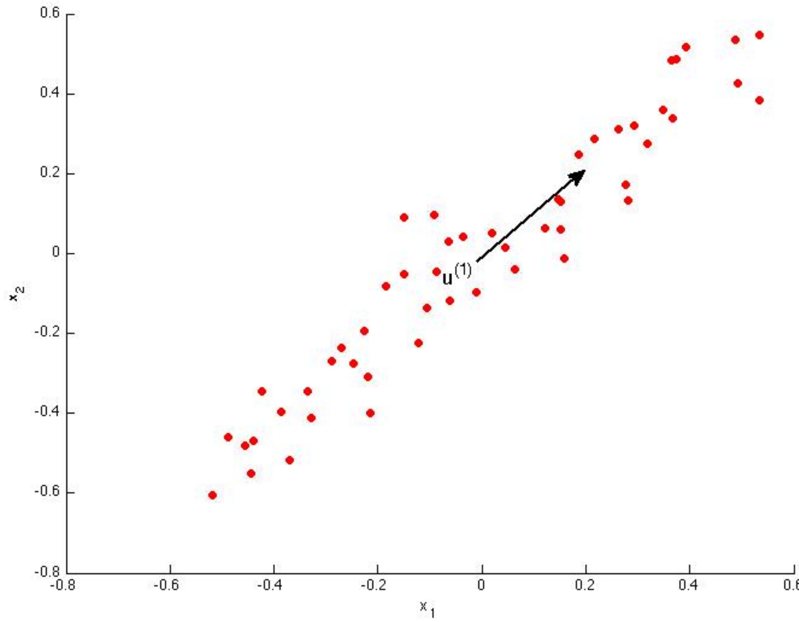
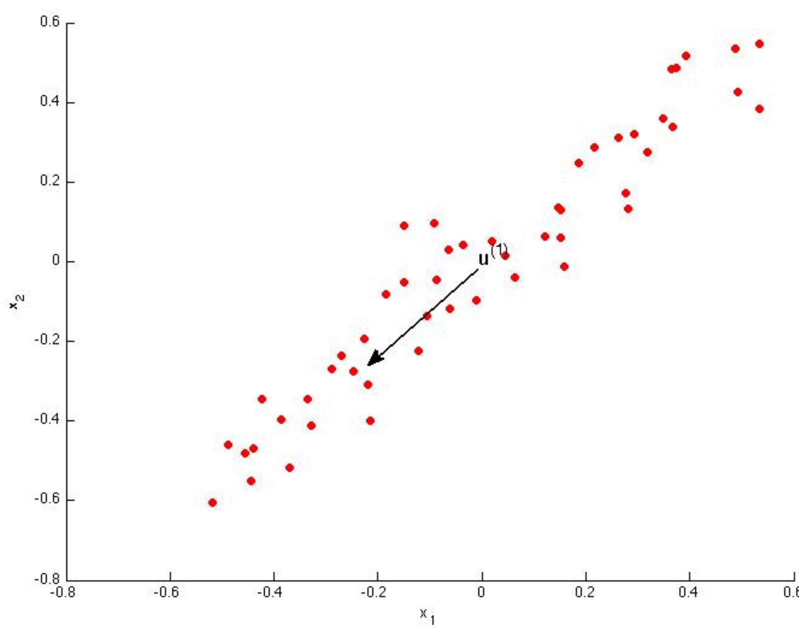


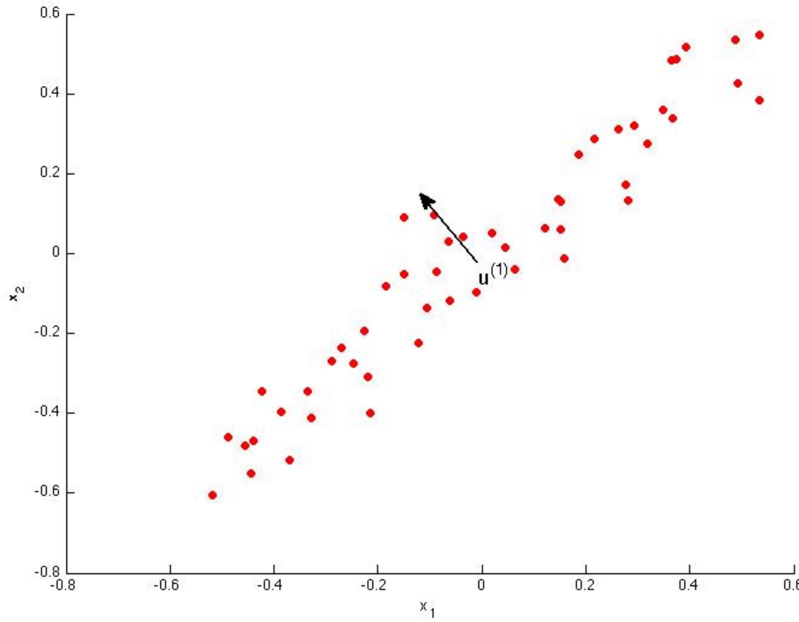
$u^{(1)}$
x_1
x_2

☐



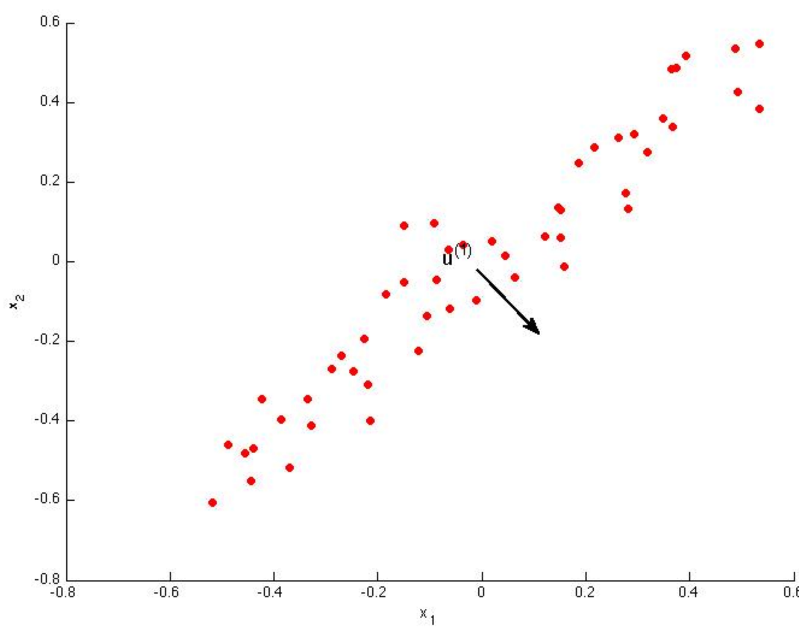
$u^{(1)}$
x_1
x_2

☐



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

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 the value of k that minimizes the approximation error $\frac{1}{m}\sum_{i=1}^{m}||x^{(i)} - x_{\text{approx}}^{(i)}||^2$.
- Choose k to be the smallest value so that at least 1% of the variance is retained.
- Choose k to be the smallest value so that at least 99% of the variance is retained.
- Choose k to be 99% of n (i.e., $k = 0.99 * n$, rounded to the nearest integer).

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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?

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

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1 point

4.
Which of the following statements are true? Check all that apply.

- [ ]

PCA can be used only to reduce the dimensionality of data by 1 (such as 3D to 2D, or 2D to 1D).

- [ ] Given an input $x \in \mathbb{R}^n$, PCA compresses it to a lower-dimensional vector $z \in \mathbb{R}^k$.

- [ ] Feature scaling is not useful for PCA, since the eigenvector calculation (such as using Octave's `svd(Sigma)` routine) takes care of this automatically.

- [ ] If the input features are on very different scales, it is a good idea to perform feature scaling before applying PCA.

1
point

5.
Which of the following are recommended applications of PCA? Select all that apply.

- [ ] As a replacement for (or alternative to) linear regression: For most learning applications, PCA and linear regression give substantially similar 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).

- [ ] Data visualization: To take 2D data, and find a different way of plotting it in 2D (using k=2).

- [ ] Data compression: Reduce the dimension of your data, so that it takes up less memory / disk space.

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