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Grade received 80% To pass 80% or higher

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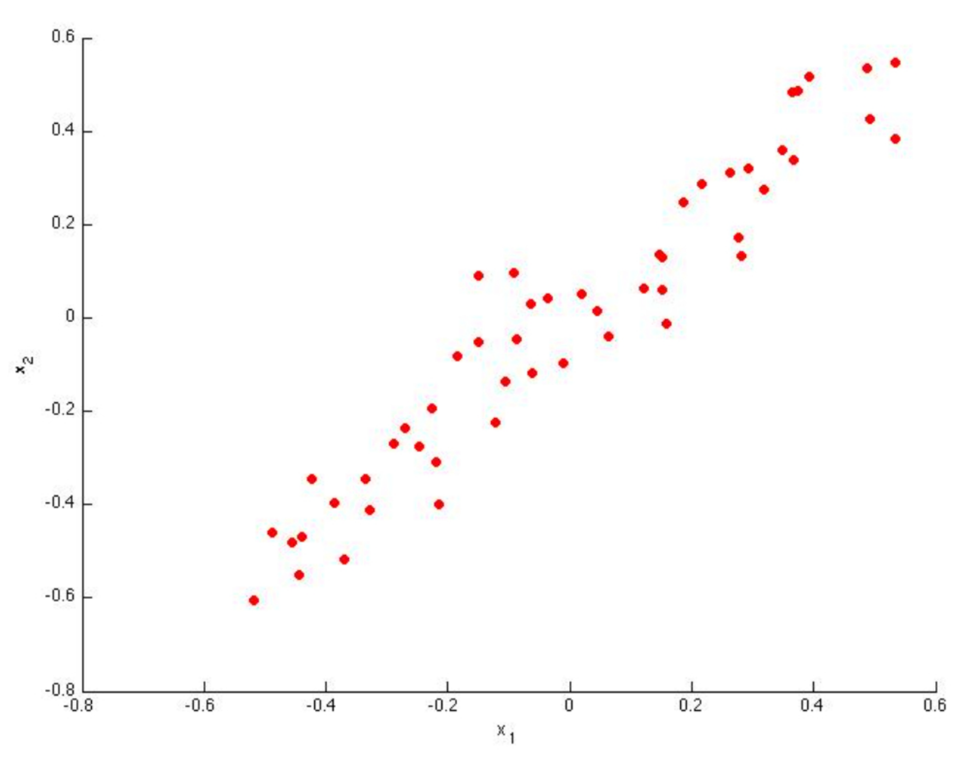
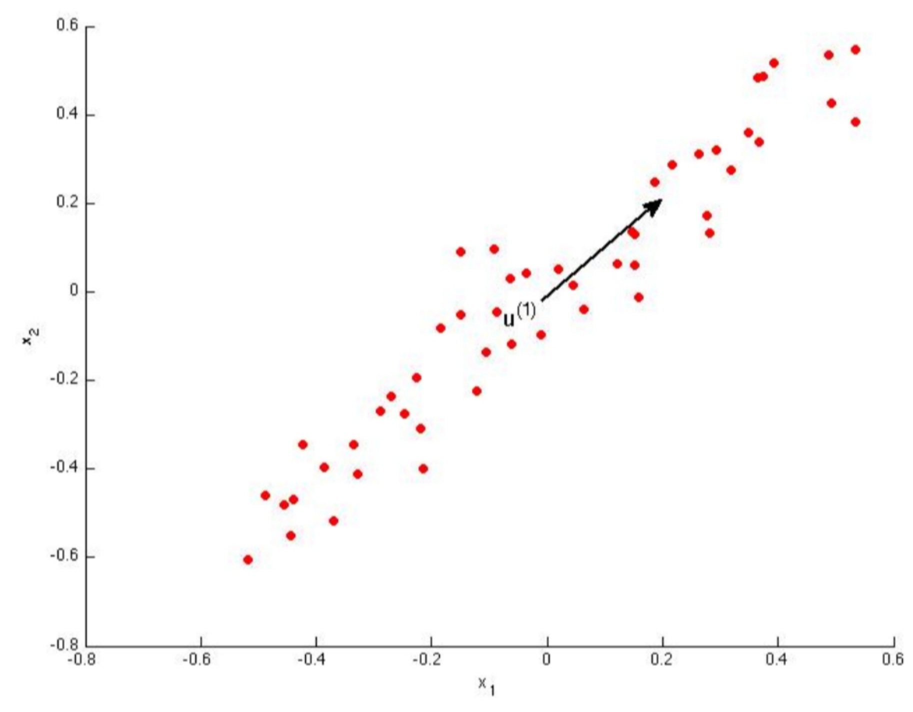
Principal Component Analysis

Latest Submission Grade 80%

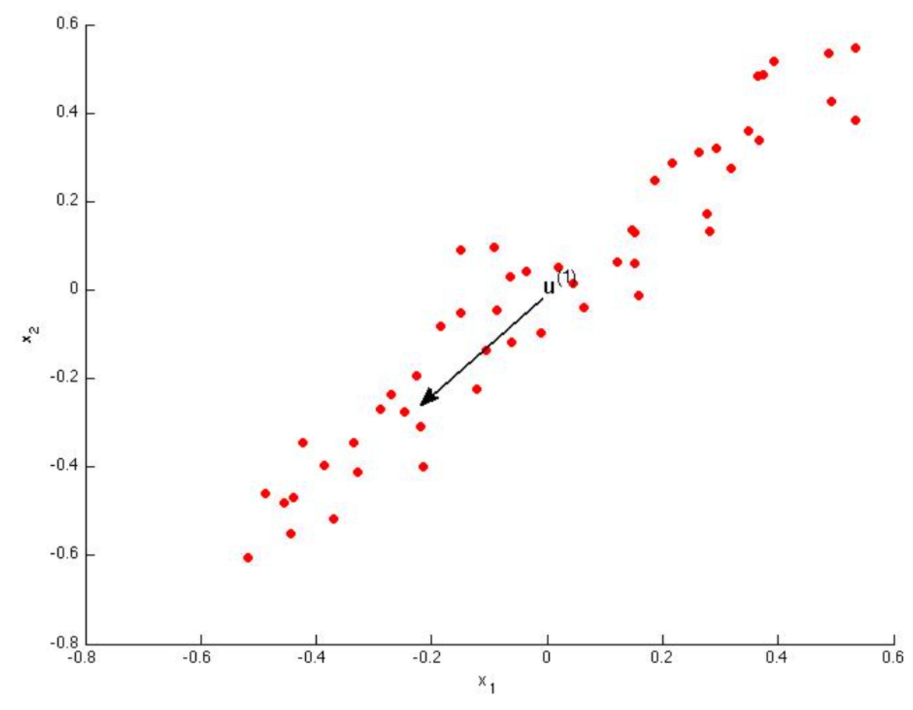
1. Consider the following 2D dataset: **1 / 1 point**



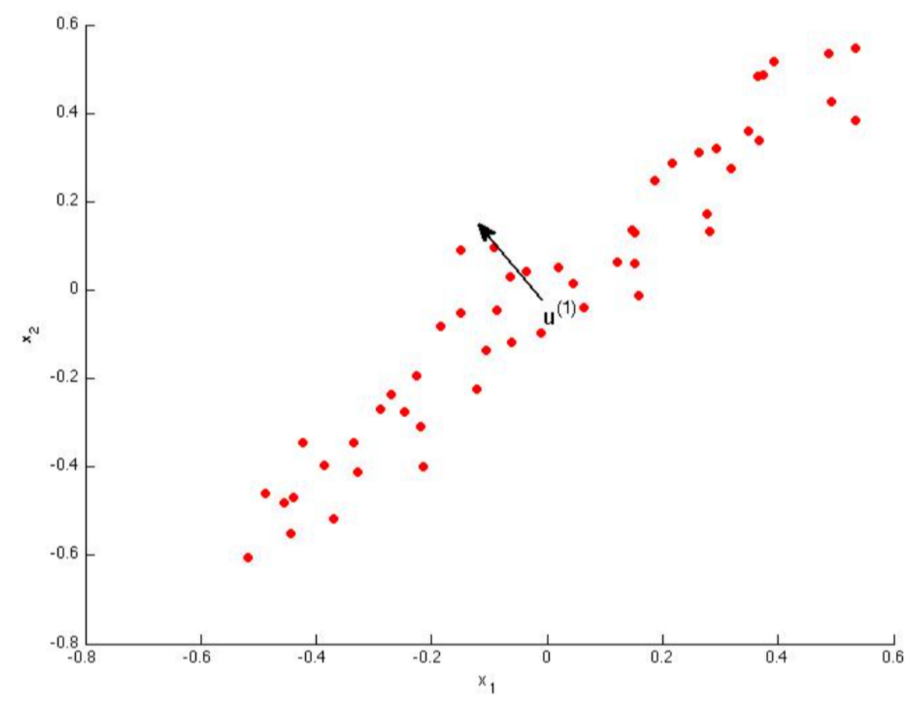
Which of the following figures correspond to possible values that PCA may return for $u^{(1)}$ (the first eigenvector / first principal component)? Check all that apply (you may have to check more than one figure).

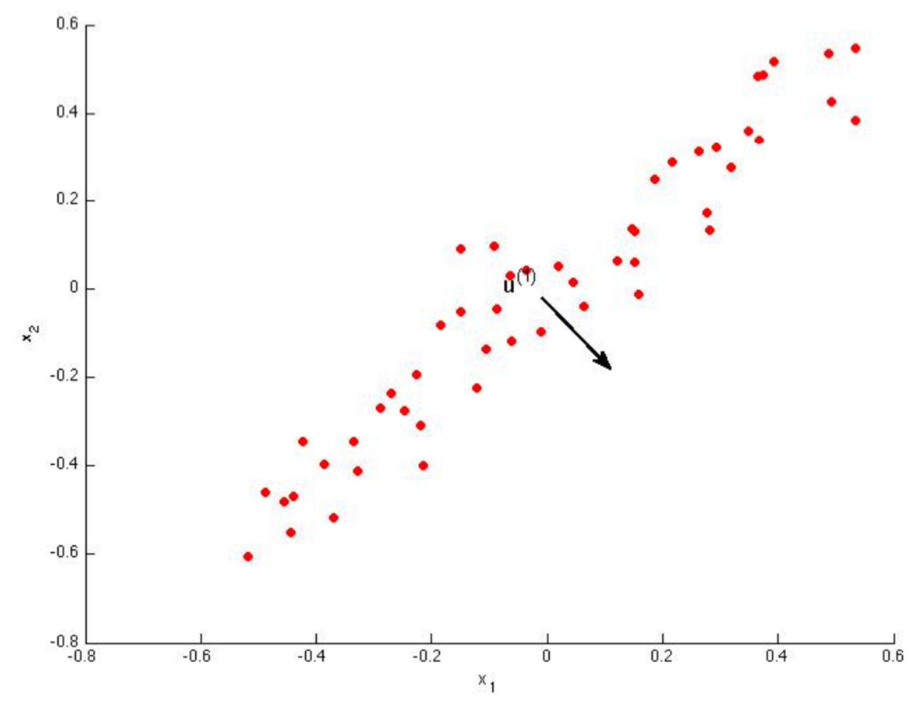
- [x] 

Correct
The maximal variance is along the y = x line, so this option is correct.

- [x] 

Correct
The maximal variance is along the y = x line, so the negative vector along that line is correct for the first principal component.

- [ ] 

- [ ] 

2. Which of the following is a reasonable way to select the number of principal components k? **1 / 1 point**

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

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

Correct
This is correct, as it maintains the structure of the data while maximally reducing its dimension.

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? **1 / 1 point**

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

Correct
This is the correct formula.

4. Which of the following statements are true? Check all that apply. **1 / 1 point**

- [ ] Feature scaling is not useful for PCA, since the eigenvector calculation (such as using Octave's $\texttt{svd(Sigma)}$ routine) takes care of this automatically.
- [x] Given an input $x \in \mathbb{R}^n$, PCA compresses it to a lower-dimensional vector $z \in \mathbb{R}^k$.

Correct
PCA compresses it to a lower dimensional vector by projecting it onto the learned principal components.

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

Correct
Feature scaling prevents one feature dimension from becoming a strong principal component only because of the large magnitude of the feature values (as opposed to large variance on that dimension).

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

5. Which of the following are recommended applications of PCA? Select all that apply. **0 / 1 point**

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

This should not be selected
You should use PCA to visualize data with dimension higher than 3, not data that you can already visualize.

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

Correct
If memory or disk space is limited, PCA allows you to save space in exchange for losing a little of the data's information. This can be a reasonable tradeoff.