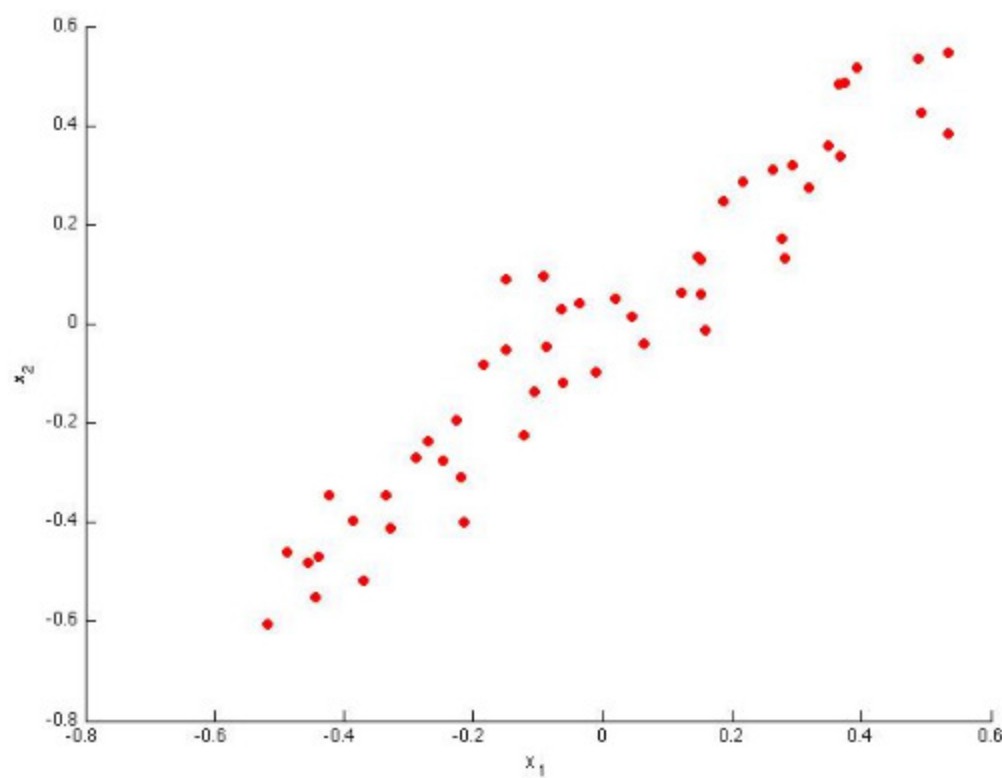
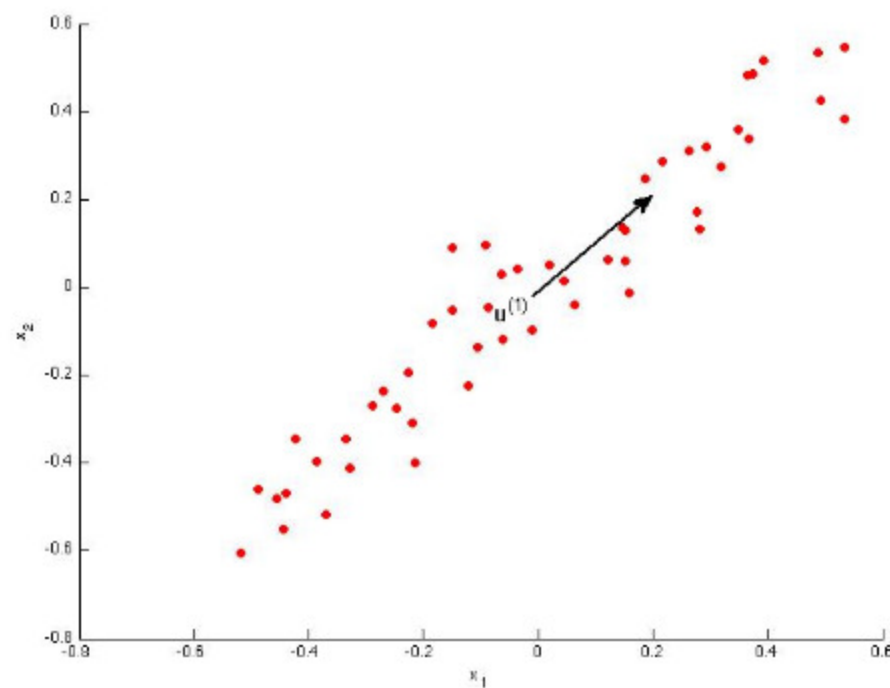
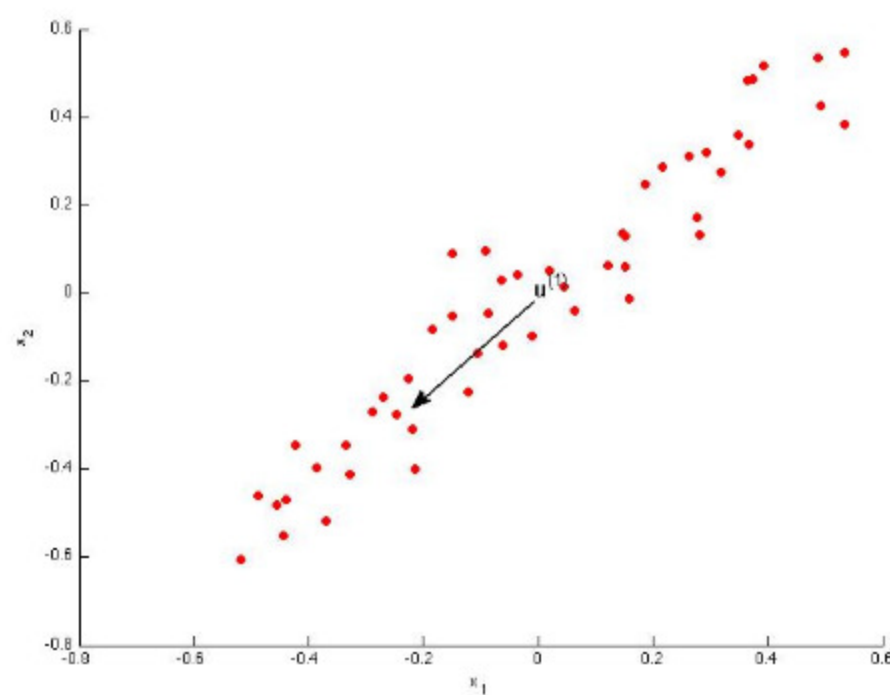
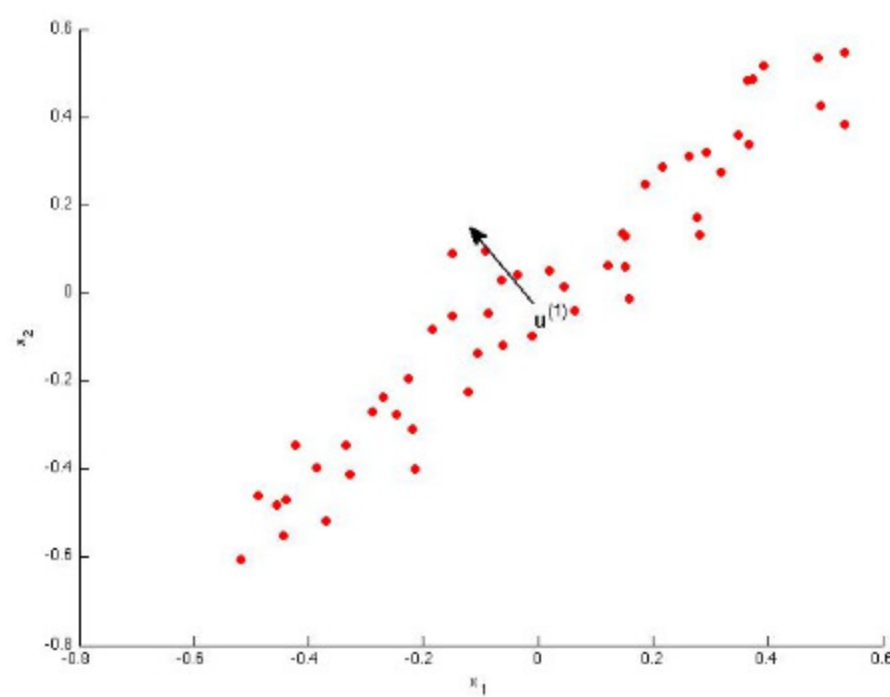
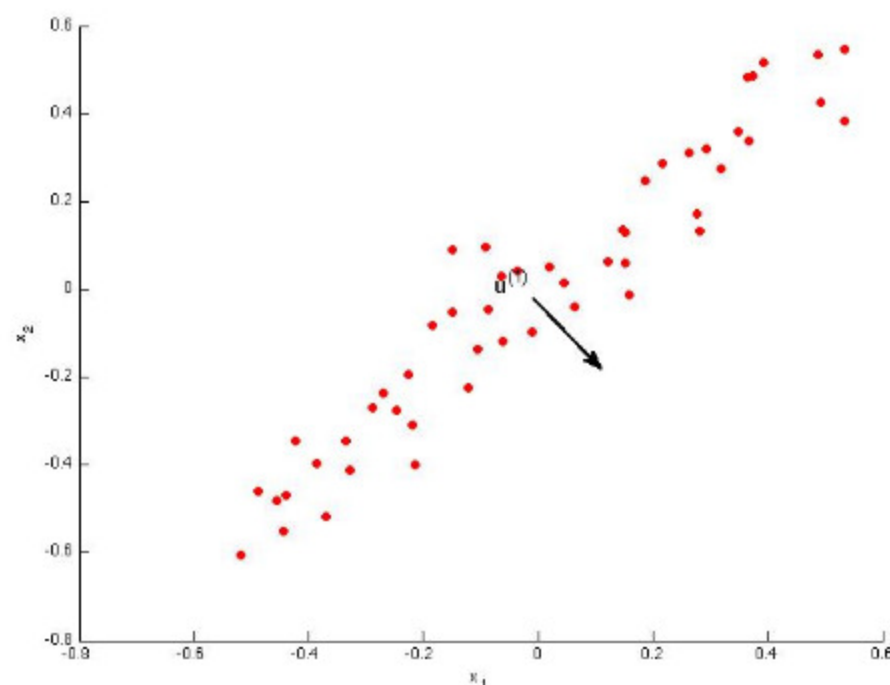


1 point

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).

☒☒☐☐

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

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?

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

1 point

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

- ☐ Given only  $z^{(i)}$  and  $U_{\text{reduce}}$ , there is no way to reconstruct any reasonable approximation to  $x^{(i)}$ .
- ☒ Given input data  $x \in \mathbb{R}^n$ , it makes sense to run PCA only with values of  $k$  that satisfy  $k \leq n$ . (In particular, running it with  $k = n$  is possible but not helpful, and  $k > n$  does not make sense.)
- ☒ 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.
- ☐ PCA is susceptible to local optima; trying multiple random initializations may help.

1 point

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

- ☒ Data compression: Reduce the dimension of your data, so that it takes up less memory / disk space.
- ☒ Data visualization: Reduce data to 2D (or 3D) so that it can be plotted.
- ☐ To get more features to feed into a learning algorithm.
- ☐ Preventing overfitting: Reduce the number of features (In a supervised learning problem), so that there are fewer parameters to learn.

☐ Entiendo que enviar trabajo que no es mío resultará en la desaprobación permanente de este curso y la desactivación de mi cuenta de Coursera.

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