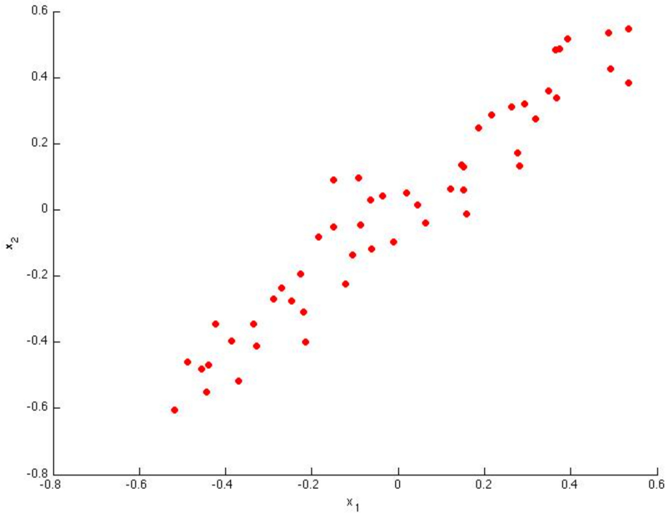
Principal Component Analysis

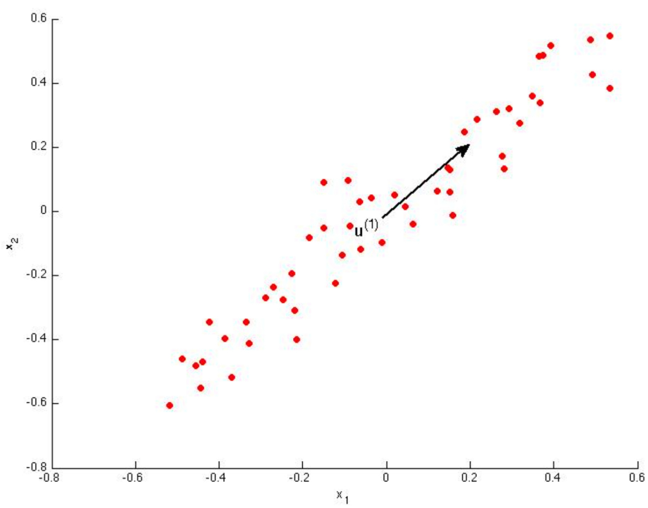
TOTAL POINTS 5

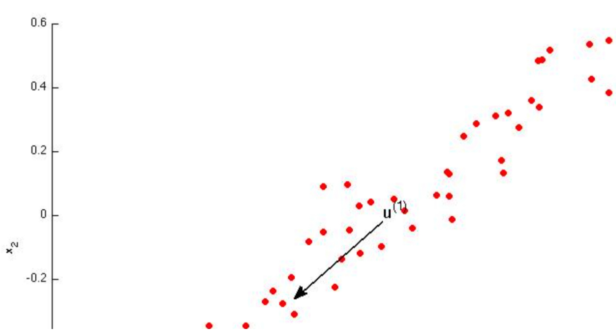
1. Consider the following 2D dataset:

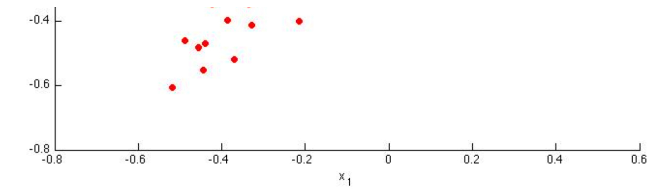
1 point

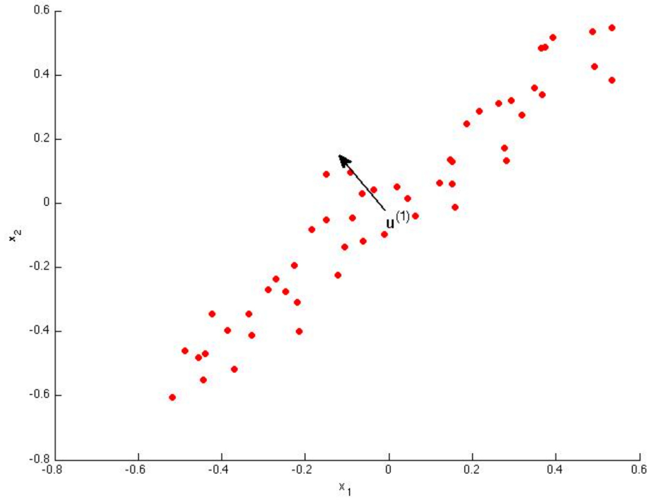


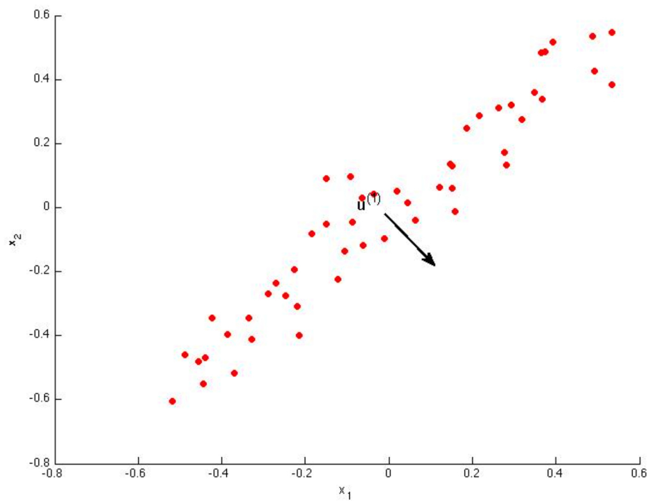
Which of the following figures correspond to possible values that PCA may return for $u^{(1)}$ (the first eigenvector / first principal component)? Check all that apply (you may have to check more than one figure).

- [x] 

- [x] 



- [ ] 

- [ ] 

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

   1 point

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

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 point

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

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

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

1 point

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

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

1 point

- [ ] Clustering: To automatically group examples into coherent groups.
- [x] 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.
- [x] Data visualization: Reduce data to 2D (or 3D) so that it can be plotted.
