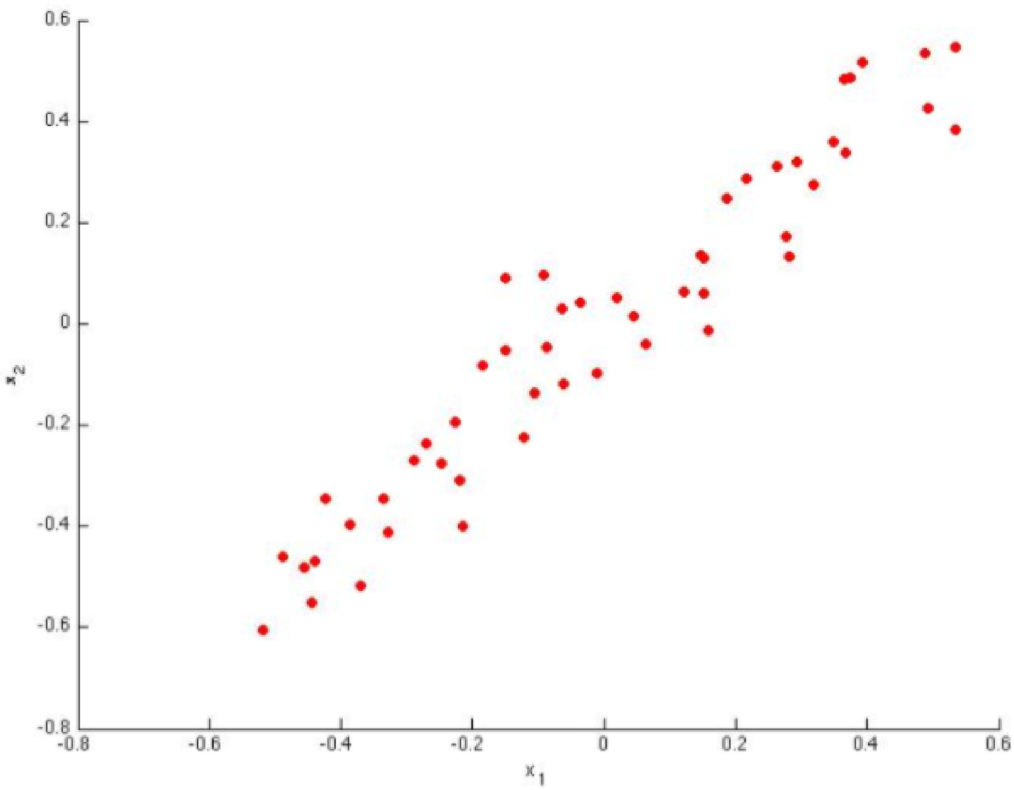
Principal Component Analysis

LATEST SUBMISSION GRADE

100%

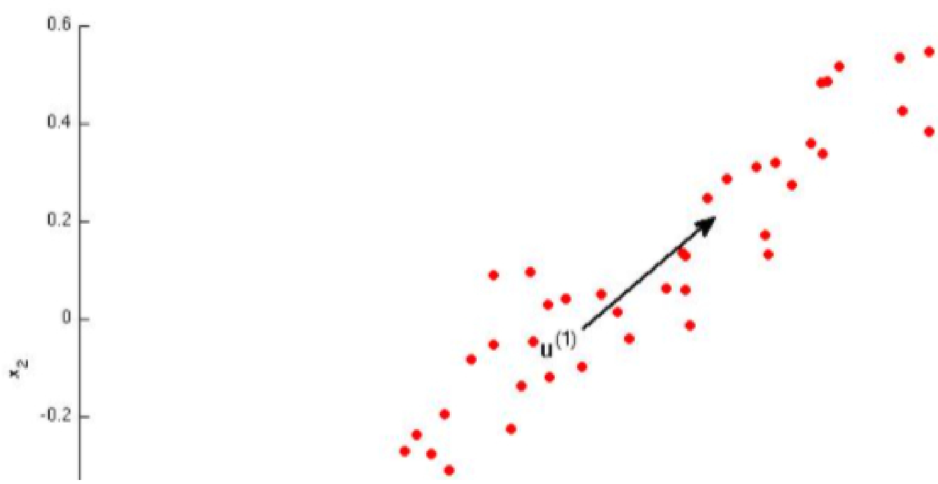
1. Consider the following 2D dataset:

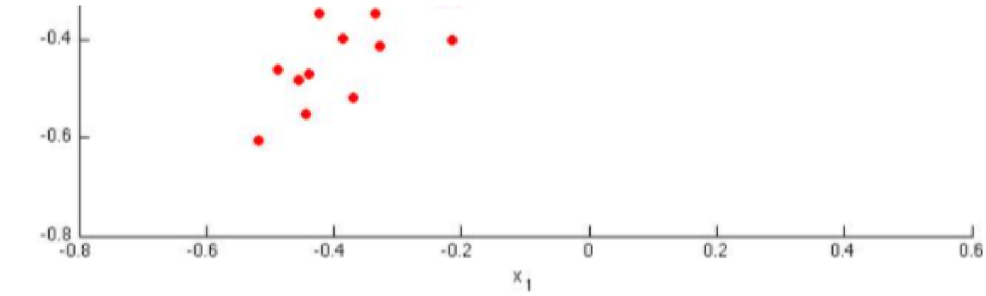
1 / 1 point



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).

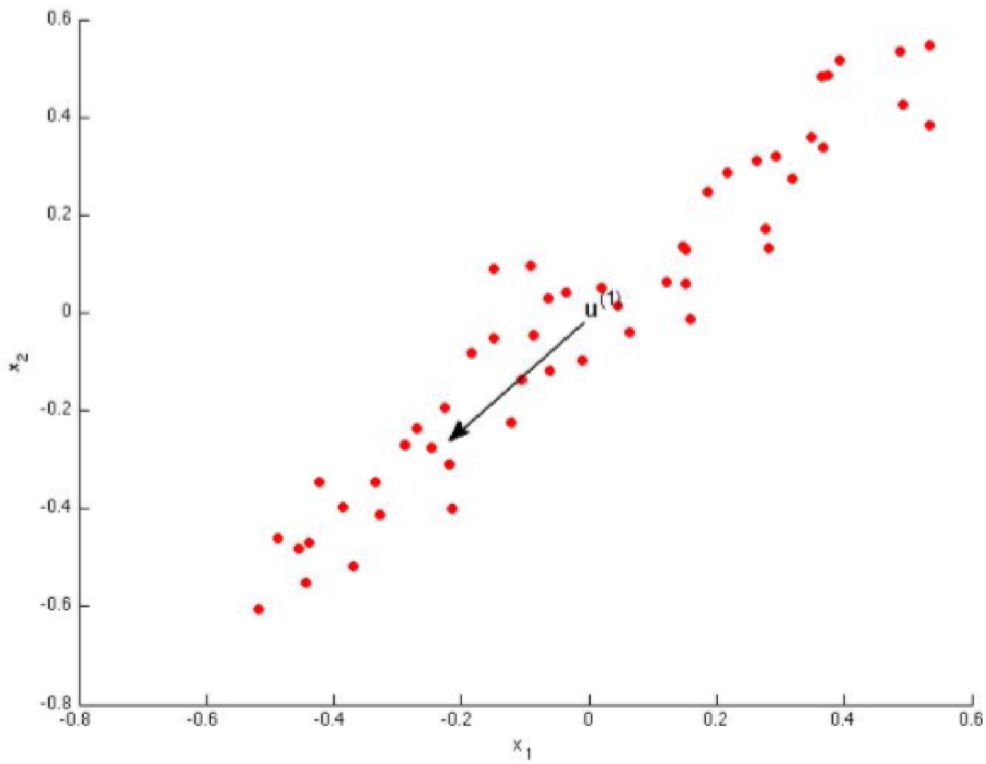
- [x]





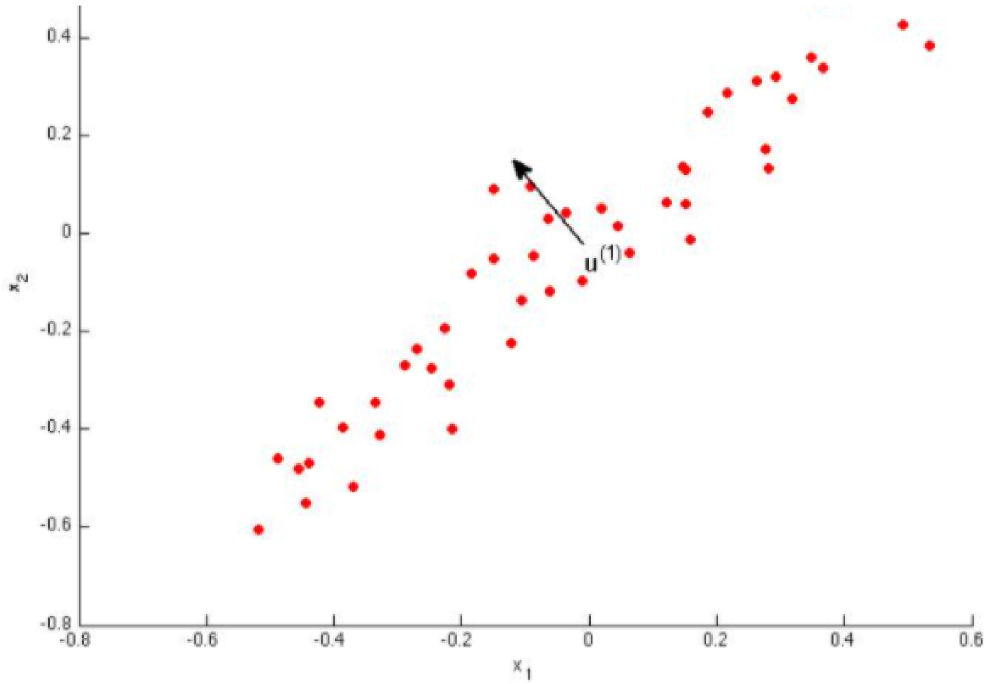
Correct

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



Correct

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



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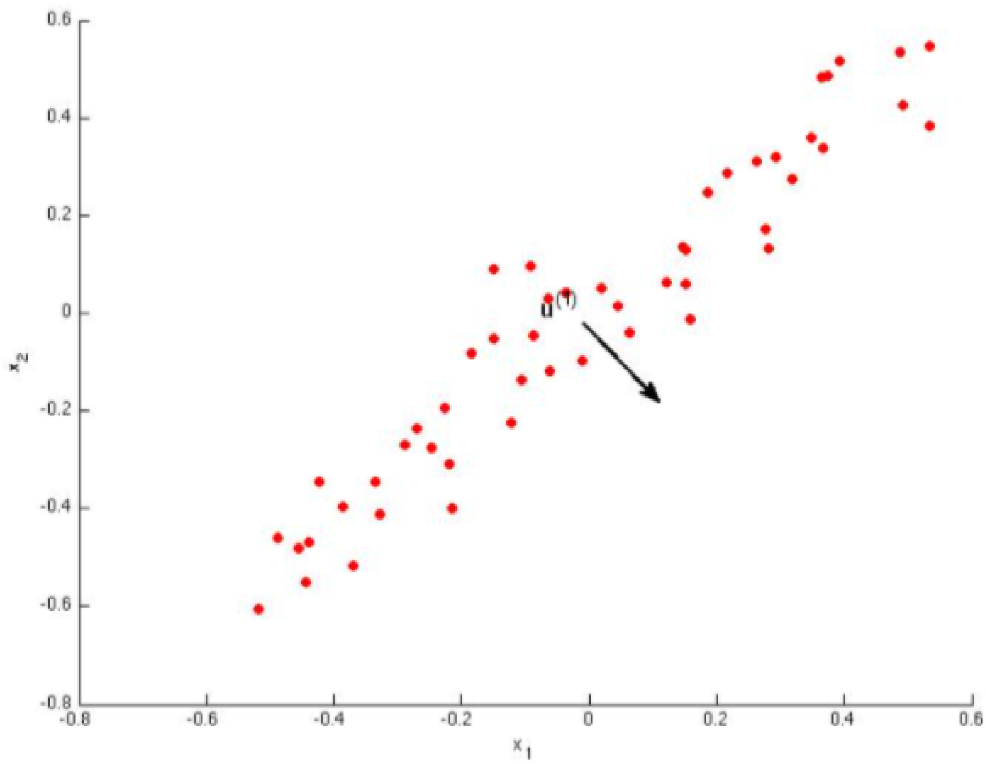

2. Which of the following is a reasonable way to select the number of principal components k?

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 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).

> ✓ **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**

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

> ✓ **Correct**
> This is the correct formula.

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

- [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.

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

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

- [ ] Preventing overfitting: Reduce the number of features (in a supervised learning problem), so that there are fewer parameters to learn.

- [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.

- [x] Data visualization: Reduce data to 2D (or 3D) so that it can be plotted.

Correct
This is a good use of PCA, as it can give you intuition about your data that would otherwise be impossible to see.

- [ ] To get more features to feed into a learning algorithm.