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Graded Quiz • 30 min

**Due** Jan 17, 1:29 PM IST

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**Grade received** 100% **To pass** 80% or higher

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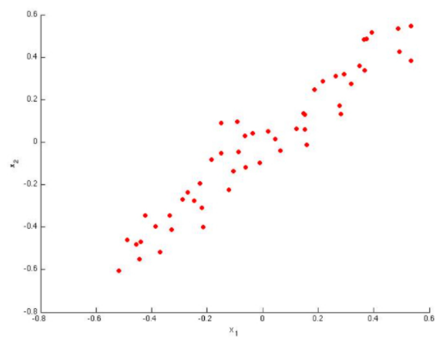
## Principal Component Analysis

**Latest Submission Grade 100%**

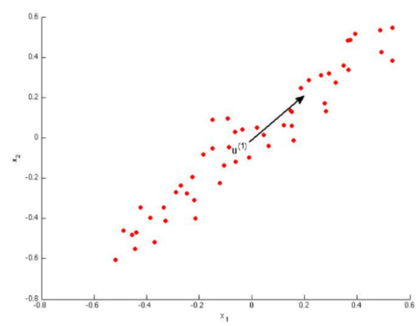
**1.** Consider the following 2D dataset:

1 / 1 point



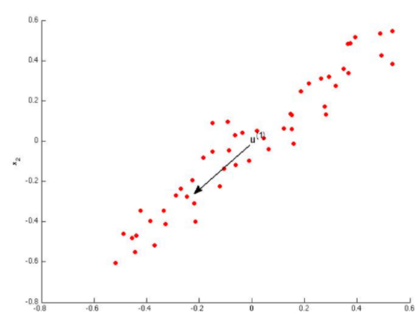

Which of the following figures correspond to possible values that PCA may return for $u^{(1)}$ (the first eigenvector / first principal component)? Check all that apply (you may have to check more than one figure).

- [x]



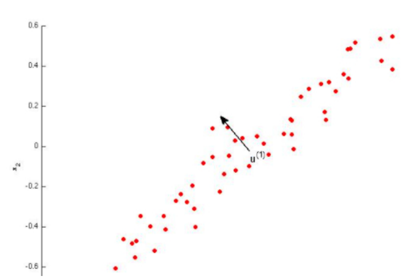

Correct
The maximal variance is along the y = x line, so this option is correct.

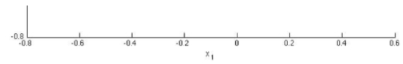
- [x]



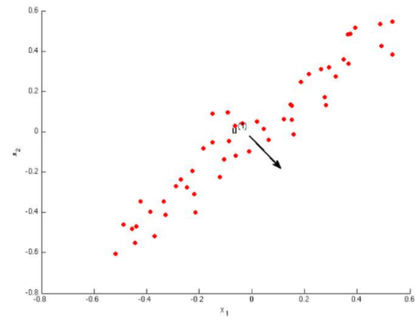

Correct
The maximal variance is along the y = x line, so the negative vector along that line is correct for the first principal component.

- [ ]






- [ ] 




**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 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
- ◉ Choose $k$ to be the smallest 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

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

**Correct**
This is the correct formula.

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

1 / 1 point

- [ ] PCA is susceptible to local optima; trying multiple random initializations may help.
- [x] 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.)

**Correct**
The reasoning given is correct: with $k = n$, there is no compression, so PCA has no use.

- [ ] Given only $z^{(i)}$ and $U_{\text{reduce}}$, there is no way to reconstruct any reasonable approximation to $x^{(i)}$.
- [x] 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.

**Correct**
If you do not perform mean normalization, PCA will rotate the data in a possibly undesired way.

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

1 / 1 point

- [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 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).

**Correct**
If your learning algorithm is too slow because the input dimension is too high, then using PCA to speed it up is a reasonable choice.

- [ ] Data visualization: To take 2D data, and find a different way of plotting it in 2D (using k=2).
- [ ] As a replacement for (or alternative to) linear regression: For most learning applications, PCA and linear regression give substantially similar results.