Principal Component Analysis

Quiz, 5 questions

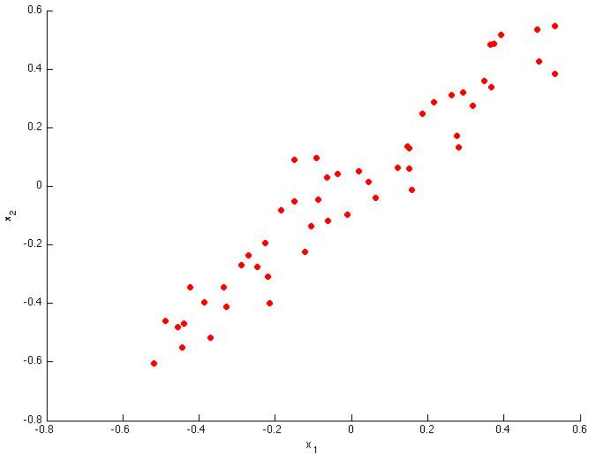
5/5 points (100%)

Congratulations! You passed!

Next Item

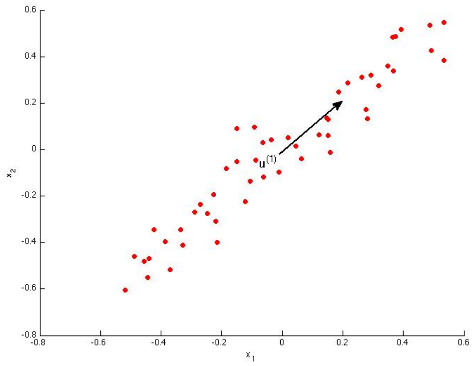
1 / 1 point

1. Consider the following 2D dataset:



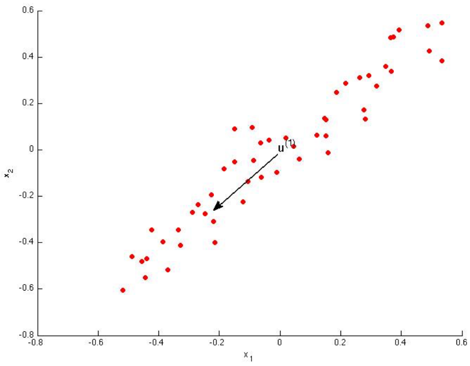
Which of the following figures correspond to possible values that PCA may return for $u^{(1)}$ (the first eigenvector / first principal component)? Check all that apply (you may have to check more than one figure).

- [ ]



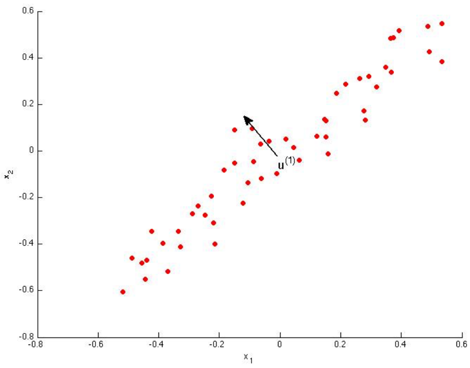
Correct

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

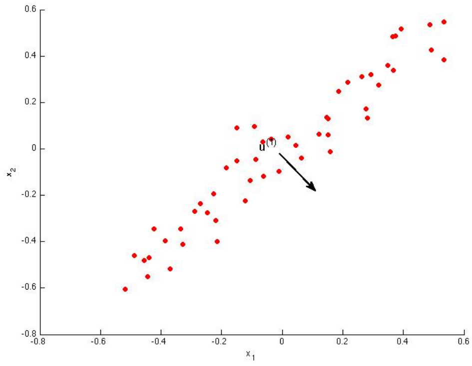


Correct

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



Un-selected is correct



Un-selected is correct

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1 / 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.)

- Use the elbow method.
- 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.

- [ ] Choose k to be 99% of m (i.e., $k = 0.99 * m$, rounded to the nearest integer).

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1 / 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?

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

Correct
This is the correct formula.

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

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1 / 1 point

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

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

Un-selected is correct

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

Un-selected is correct

☐ 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.

☐ 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.

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

1 / 1 point

☐ As a replacement for (or alternative to) linear regression: For most learning applications, PCA and linear regression give substantially similar results.

Un-selected is correct

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

Un-selected is correct

- [ ] 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 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.