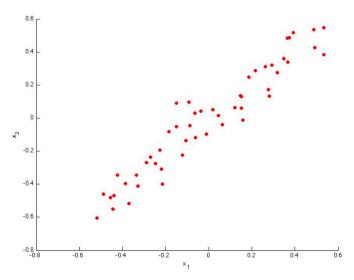
## **Principal Component Analysis**

TOTAL POINTS 5

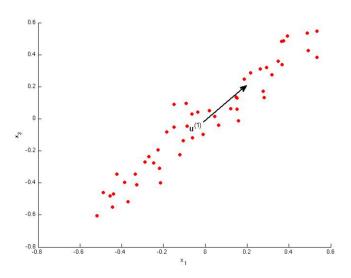
1. Consider the following 2D dataset:

1 point

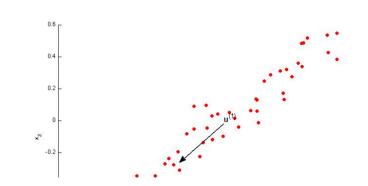


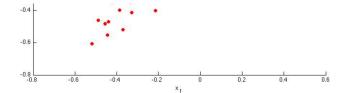
Which of the following figures correspond to possible values that PCA may return for  $u^{(1)}$  (the first eigenvector / first principal component)? Check all that apply (you may have to check more than one figure).

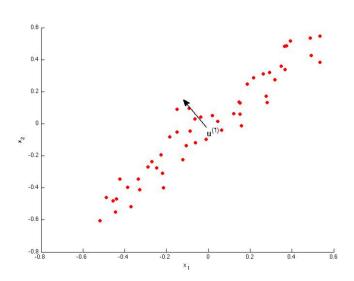
**~** 

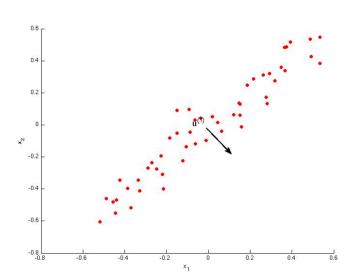


**~** 









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.)

- $\bigcirc$  Choose k to be the largest value so that at least 99% of the variance is retained
- $\bigcirc$  Choose k to be 99% of m (i.e., k=0.99\*m, rounded to the nearest integer).
- $\bigcirc \ \ \, \text{Choose} \, k \text{ to be the smallest value so that at least 99\% of the variance is retained}.$
- O 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

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

$$\frac{\frac{1}{m}\sum_{i=1}^{m}||x^{(i)}-x_{\text{inprox}}^{(i)}||^{2}}{\frac{1}{m}\sum_{i=1}^{m}||x^{(i)}||^{2}} \ge 0.9$$

$$\frac{\frac{1}{m}\sum_{i=1}^{m}||x^{(i)}-x_{\text{inprox}}^{(i)}||^{2}}{\frac{1}{m}\sum_{i=1}^{m}||x^{(i)}||^{2}} \ge 0.0$$

$$\frac{1}{m}\sum_{i=1}^{m}||x^{(i)}-x_{\text{inprox}}^{(i)}||^{2}}{\frac{1}{m}\sum_{i=1}^{m}||x^{(i)}-x_{\text{inprox}}^{(i)}||^{2}} \ge 0.0$$

4	M/bich of	f+bo	following	statements	are true?	Chack	all that	annl.
4.	VVIIICII O	ı ure	TOHOWINE	Statements	are true:	CHECK	all tilat	appiv.

1 point

- igspace Given an input  $x\in\mathbb{R}^n$ , PCA compresses it to a lower-dimensional vector  $z\in\mathbb{R}^k$ .
- ✓ 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.
- $5. \quad \text{Which of the following are recommended applications of PCA? Select all that apply.}$

1 point

- Clustering: To automatically group examples into coherent groups.
- ightharpoonup 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.
- ✓ Data visualization: Reduce data to 2D (or 3D) so that it can be plotted.
- I, Noel Brambila Jr, understand that submitting another's work as my own can result in zero credit for this assignment. Repeated violations of the Coursera Honor Code may result in removal from this course or deactivation of my Coursera account.



Learn more about Coursera's Honor Code

Save

Submit