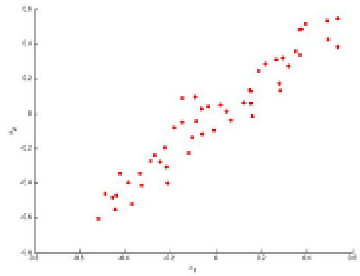
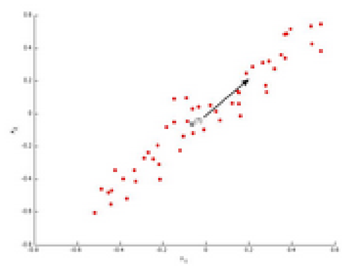
1. Consider the following 2D dataset:

1 / 1 point

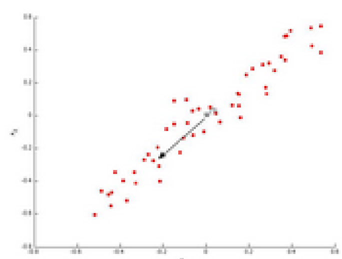


Which of the following figures correspond to possible values that PCA may return for $u^{(1)}$ (the first eigenvector / first principal component)? Check all that apply (you may have to check more than one figure).

- [x] 

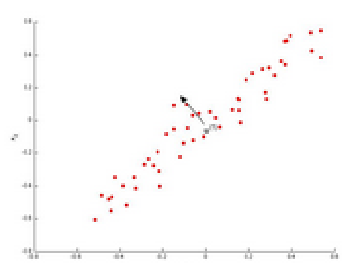
✓ **Correct**

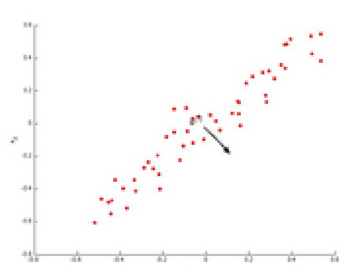
The maximal variance is along the y = x line, so this option is correct.

- [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?

(Recall that n is the dimensionality of the input data and m is the number of input examples.)

1 / 1 point

- ○ Choose the value of k that minimizes the approximation error $\frac{1}{m}\sum_{i=1}^{m}||x^{(i)} - x_{\text{approx}}^{(i)}||^2$.
- ○ Choose k to be 99% of n (i.e., $k = 0.99 * n$, rounded to the nearest integer).
- ◉ Choose k to be the smallest value so that at least 99% of the variance is retained.
- ○ Choose k to be the smallest value so that at least 1% 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

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

✓ **Correct**

This is the correct formula.

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

1 / 1 point

- [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.

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

- [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.

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

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.

- [ ] 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.

Correct

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