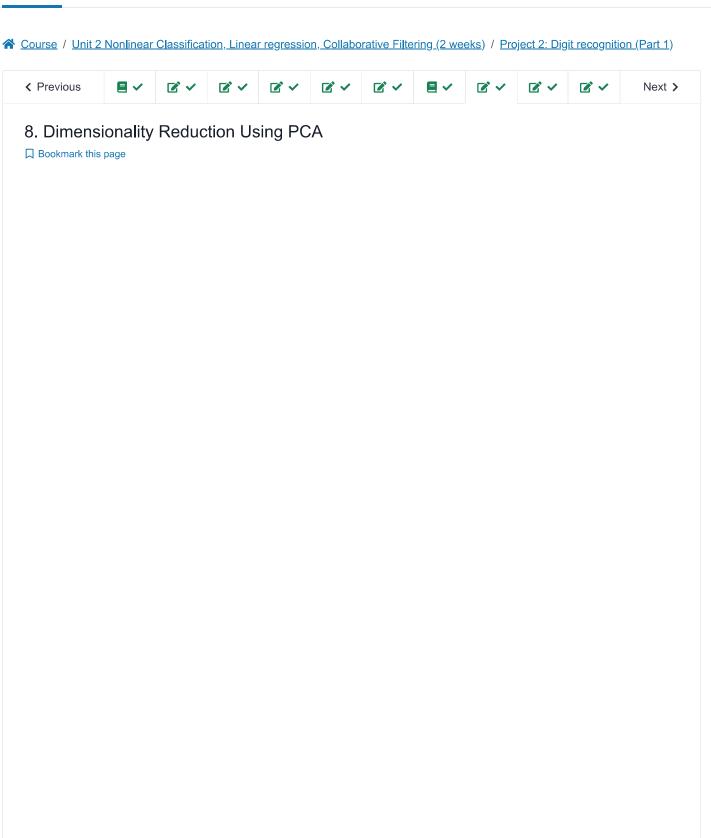


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Project due Oct 21, 2020 05:29 IST Completed

PCA finds (orthogonal) directions of maximal variation in the data. In this problem we're going to project our data onto the principal components and explore the effects on performance.

You will be working in the files part1/main.py and part1/features.py in this problem

## **Project onto Principal Components**

3.0/3.0 points (graded)

Fill in function  $[project\_onto\_PC]$  in **features.py** that implements PCA dimensionality reduction of dataset X.

Note that to project a given  $n \times d$  dataset X into its k-dimensional PCA representation, one can use matrix multiplication, after first centering X:

## $\widetilde{X}V$

where  $\widetilde{X}$  is the centered version of the original data X using the mean learned from training data and V is the  $d \times k$  matrix whose columns are the top k eigenvectors of  $\widetilde{X}^T\widetilde{X}$ . This is because the eigenvectors are of unit-norm, so there is no need to divide by their length.

**Function input::** You are given the full principal component matrix V' as pcs and the features mean computed from the training data set as  $feature_means$  in this function. Note that  $feature_means$  are learned from the training data set, which should not be computed in this function using  $feature_means$  are learned from the training data set, which should not be computed in this function using  $feature_means$  are learned from

**Available Functions:** You have access to the NumPy python library as <code>np</code> .

**Correction on features.py and main.py:** Please download a corrected version of the project archive <u>mnist.tar.gz</u> or correct these files as decribed above before this problem.

```
1 def project_onto_PC(X, pcs, n_components, feature_means):
 2
3
      Given principal component vectors pcs = principal_components(X)
4
      this function returns a new data array in which each sample in \boldsymbol{X}
5
      has been projected onto the first n\_components principcal components.
      \ensuremath{\text{\#}} TODO: first center data using the feature_means
7
8
      # TODO: Return the projection of the centered dataset
9
               on the first n_components principal components.
10
              This should be an array with dimensions: n x n_components.
      # Hint: these principal components = first n_components columns
12
              of the eigenvectors returned by principal_components().
13
      #
               Note that each eigenvector is already be a unit-vector,
14
               so the projection may be done using matrix multiplication.
15
      try:
                         center data(X)
```

Press ESC then TAB or click outside of the code editor to exit

Correct

### Test results

```
CORRECT

See full output

See full output

You have used 1 of 25 attempts
```

**Note:** we only use the training dataset to determine the principal components. It is **improper** to use the test dataset for anything except evaluating the accuracy of our predictive model. If the test data is used for other purposes such as selecting good features, it is possible to overfit the test set and obtain overconfident estimates of a model's performance.

# **Testing PCA**

1.0/1.0 point (graded)

Use project\_onto\_PC to compute a 18-dimensional PCA representation of the MNIST training and test datasets, as illustrated in main.py.

Retrain your softmax regression model (using the original labels) on the MNIST training dataset and report its error on the test data, this time using these 18-dimensional PCA-representations rather than the raw pixel values.

If your PCA implementation is correct, the model should perform nearly as well when only given 18 numbers encoding each image as compared to the 784 in the original data (error on the test set using PCA features should be around 0.15). This is because PCA ensures these 18 feature values capture the maximal amount of variation from the original 784-dimensional data.

Submit

You have used 2 of 5 attempts

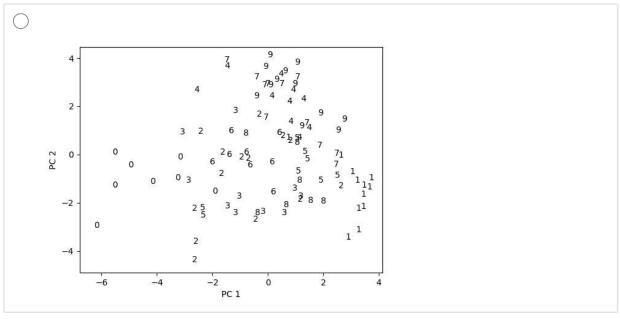
• Answers are displayed within the problem

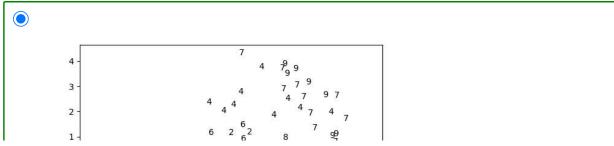
## Testing PCA (continued)

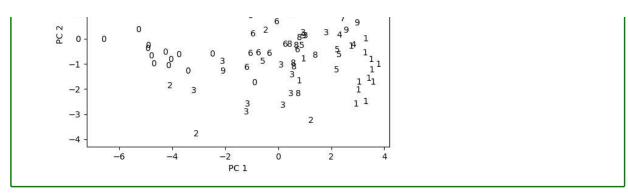
1.0/1.0 point (graded)

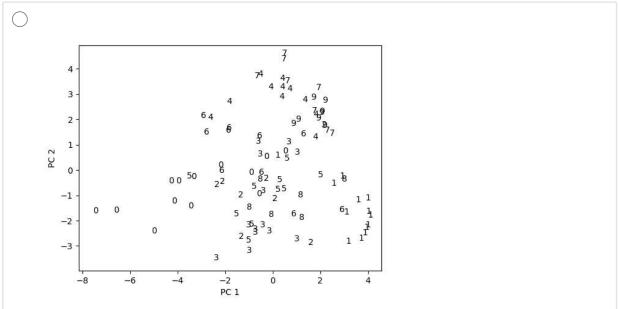
Use plot\_PC in **main.py** to visualize the first 100 MNIST images, as represented in the space spanned by the first 2 principal components of the training data.

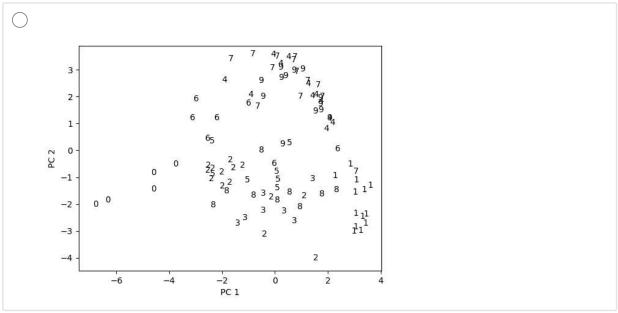
What does your PCA look like?

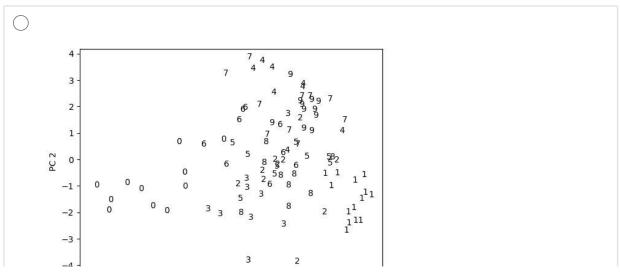














Use the calls to <code>plot\_images()</code> and <code>reconstruct\_PC</code> in **main.py** to plot the reconstructions of the first two MNIST images (from their 18-dimensional PCA-representations) alongside the originals.

Submit You have used 1 of 2 attempts

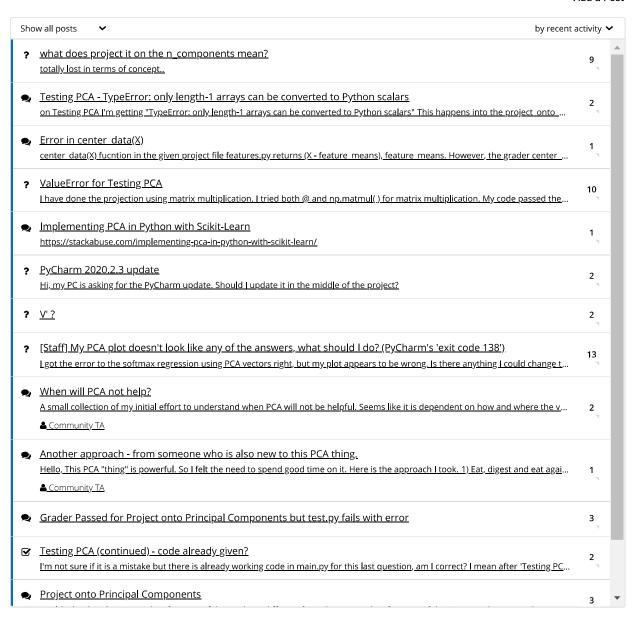
#### **1** Answers are displayed within the problem

**Remark:** Two dimensional PCA plots offer a nice way to visualize some global structure in high-dimensional data, although approaches based on nonlinear dimension reduction may be more insightful in certain cases. Notice that for our data, the first 2 principal components are insufficent for fully separating the different classes of MNIST digits.

# Discussion Hide Discussion

**Topic:** Unit 2 Nonlinear Classification, Linear regression, Collaborative Filtering (2 weeks):Project 2: Digit recognition (Part 1) / 8. Dimensionality Reduction Using PCA

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