“...many problems are naturally classification problems”---Prof. Forsyth
Last time

- Review of Covariance matrix
- Dimension Reduction
- Principal Component Analysis
- Examples of PCA
Objectives

- Demo of Principal Component Analysis
- Introduction to classification
PCA an example

Step 1.

\[ D = \begin{bmatrix} 3 & -4 & 7 & 1 & -4 & -3 \\ 7 & -6 & 8 & -1 & -1 & -7 \end{bmatrix} \Rightarrow \text{mean}(D) = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \]

\[ m = \begin{bmatrix} 3 & -4 & 7 & 1 & -4 & -3 \\ 7 & -6 & 8 & -1 & -1 & -7 \end{bmatrix} \]

Step 2.

\[ \text{Covmat}(m) = \begin{bmatrix} 20 & 25 \\ 25 & 40 \end{bmatrix} \Rightarrow \lambda_1 \approx 57; \quad \lambda_2 \approx 3 \]

\[ U = \begin{bmatrix} 0.5606288 & -0.8280672 \\ 0.8280672 & 0.5606288 \end{bmatrix} \quad U^T = \begin{bmatrix} 0.5606288 & 0.8280672 \\ -0.8280672 & 0.5606288 \end{bmatrix} \]

\[ r = U^T m = \begin{bmatrix} 7.478 & -7.211 & 10.549 & -0.267 & -3.071 & -7.478 \\ 1.440 & -0.052 & -1.311 & -1.389 & 2.752 & -1.440 \end{bmatrix} \]

Step 3. \[ p = \begin{bmatrix} 7.478 & -7.211 & 10.549 & -0.267 & -3.071 & -7.478 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]
Reconstructing the data

- Given the projected data $\mathbf{p}_{d \times n}$ and $\text{mean}(\{\mathbf{x}\})$, we can approximately reconstruct the original data
  \[ \hat{\mathbf{D}} = \mathbf{U} \mathbf{p} + \text{mean}(\{\mathbf{x}\}) \]
- Each reconstructed data item $\hat{D}_i$ is a linear combination of the columns of $\mathbf{U}$ weighted by $\mathbf{p}_i$
- The columns of $\mathbf{U}$ are the normalized eigenvectors of the Covmat($\{\mathbf{x}\}$) and are called the principal components of the data $\{\mathbf{x}\}$
End-to-end mean square error

Each \( \mathbf{x}_i \) becomes \( \mathbf{r}_i \) by translation and rotation

Each \( \mathbf{p}_i \) becomes \( \mathbf{\hat{x}}_i \) by the opposite rotation and translation

Therefore the end to end mean square error is:

\[
\frac{1}{N-1} \sum_i \| \mathbf{\hat{x}}_i - \mathbf{x}_i \|^2 = \frac{1}{N-1} \sum_i \| \mathbf{r}_i - \mathbf{p}_i \|^2 = \sum_{j=s+1}^{d} \lambda_j
\]

\( \lambda_{s+1}, \ldots, \lambda_d \) are the smallest d-s eigenvalues of the Covmat(\{x\})
PCA: Human face data

- The dataset consists of 213 images
- Each image is grayscale and has 64 by 64 resolution
- We can treat each image as a vector with dimension $d = 4096 = 64 \times 64$

$n = 213$

Credit: Prof. Forsyth
How quickly the eigenvalues decrease?

Credit: Prof. Forsyth
What do the principal components of the images look like?

Mean image

The first 16 principal components arranged into images

Credit: Prof. Forsyth
Reconstruction of the image

1st row show the reconstructions using some number of principal components
2nd row show the corresponding errors

Mean

The original

Mean 1 5 10 20 50 100

mean(\{x_i\}) 4096 \times 213

Credit: Prof. Forsyth
Q. Which are true?

A. PCA allows us to project data to the direction along which the data has the biggest variance
B. PCA allows us to compress data
C. PCA uses linear transformation to show patterns of data
D. PCA allows us to visualize data in lower dimensions
E. All of the above
Q. Which of these is NOT true?

A. The eigenvectors of covariance can have opposite signs and it won’t affect the reconstruction
B. The PCA analysis in some statistical program returns standard deviation instead of variance
C. It doesn’t matter how you store the data in matrix
Demo: PCA of Immune Cell Data

- There are 38816 white blood immune cells from a mouse sample.
- Each immune cell has 40+ features/components.
- Four features are used as illustration.
- There are at least 3 cell types involved.

- T cells
- B cells
- Natural killer cells
There are 38816 white blood immune cells from a mouse sample.

Each immune cell has 40+ features/components.

Four features are used as illustration.

There are at least 3 cell types involved.

- **Dark red**: T cells
- **Brown**: B cells
- **Blue**: NK cells
- **Cyan**: other small population
PCA of Immune Cells

> res1
$values
eigenvalues
[1] 4.7642829 2.1486896 1.3730662 0.4968255

$eigenvectors
eigenvectors
$vectors
[1,] 0.2476698 0.00801294 -0.6822740 0.6878210
[2,] 0.3389872 -0.72010997 -0.3691532 -0.4798492
[3,] -0.8298232 0.01550840 -0.5156117 -0.2128324
[4,] 0.3676152 0.69364033 -0.3638306 -0.5013477
More features used

- There are 38816 white blood immune cells from a mouse sample
- Each immune cell has 42 features/components
- There are at least 3 cell types involved

\[42 \times 38816\]
Eigenvalues of the covariance matrix

![Graph showing eigenvalues (unscaled data)]
Large variance doesn’t mean important pattern

Principal component 1 is just cell length
Principal component 2 and 3 show different cell types
Principal component 4 is not very informative
Principal component 5 is interesting
Principal component 6 is interesting
Scaling the data or not in PCA

- Sometimes we need to scale the data for each feature have very different value range.
- After scaling the eigenvalues may change significantly.
- Data needs to be investigated case by case
Eigenvalues of the covariance matrix (scaled data)

Eigenvalues do not drop off very quickly
Principal component 1 & 2 (scaled data)

Even the first 2 PCs don’t separate the different types of cell very well.
Q. Which of these are true?

A. Feature selection should be conducted with domain knowledge
B. Important feature may not show big variance
C. Scaling doesn’t change eigenvalues of covariance matrix
D. A & B
Learning to classify

Given a set of feature vectors $x_i$, where each has a class label $y_i$, we want to train a classifier that maps unlabeled data with the same features to its label.
A binary classifier maps each feature vector to one of two classes.

For example, you can train the classifier to:

- Predict a gain or loss of an investment
- Predict if a gene is beneficial to survival or not
- ...
A multiclass classifier maps each feature vector to one of three or more classes.

For example, you can train the classifier to:
- Predict the cell type given cells’ measurement
- Predict if an image is showing tree, or flower or car, etc
- ...
Given our knowledge of probability and statistics, can you think of any classifiers?

Naive Bayes $\rightarrow$ MAP
Given our knowledge of probability and statistics, can you think of any classifiers?

- We will cover classifiers such as nearest neighbor, decision tree, random forest, Naïve Bayesian and support vector machine.
Nearest neighbors classifier

- Given an unlabeled feature vector
  - Calculate the distance from \( x \)
  - Find the closest labeled \( x_i \)
  - Assign the same label to \( x \)

- Practical issues
  - We need a distance metric
  - We should first standardize the data
  - Classification may be less effective for very high dimensions

Source: wikipedia
Variants of nearest neighbors classifier

- In k-nearest neighbors, the classifier:
  - Looks at the k nearest labeled feature vectors $x_i$
  - Assigns a label to $x$ based on a majority vote

- In (k, ℓ)-nearest neighbors, the classifier:
  - Looks at the k nearest labeled feature vectors
  - Assigns a label to $x$ if at least $\ell$ of them agree on the classification
How do we know if our classifier is good?

- We want the classifier to avoid some mistakes on unlabeled data that we will see in run time.

- **Problem 1**: some mistakes may be more costly than others
  We can tabulate the types of error and define a loss function

- **Problem 2**: It’s hard to know the true labels of the run-time data
  We must separate the labeled data into a training set and test/validation set
A binary classifier can make two types of errors:
- False positive (FP)
- False negative (FN)

Sometimes one type of error is more costly:
- Drug effect test
- Crime detection

We can tabulate the performance in a class confusion matrix:

```
<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Negative</td>
</tr>
<tr>
<td>Negative</td>
<td>True Negative</td>
</tr>
<tr>
<td>Positive</td>
<td>False Negative</td>
</tr>
</tbody>
</table>
```

```
<table>
<thead>
<tr>
<th></th>
<th>TP</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>TN</td>
<td>15</td>
<td>3</td>
</tr>
<tr>
<td>FN</td>
<td>7</td>
<td>25</td>
</tr>
</tbody>
</table>
```

```
Performance of a binary classifier

- A loss function assigns costs to mistakes
- The 0-1 loss function treats FPs and FNs the same
  - Assigns loss 1 to every mistake
  - Assigns loss 0 to every correct decision
- Under the 0-1 loss function
  - \( \text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \)
- The baseline is 50% which we get by random decision.
Performance of a multiclass classifier

- Assuming there are \( c \) classes:
- The class confusion matrix is \( c \times c \)
- Under the 0-1 loss function

\[
\text{accuracy} = \frac{\text{sum of diagonal terms}}{\text{sum of all terms}}
\]

ie. in the right example, accuracy = \( \frac{32}{38} = 84\% \)
- The baseline accuracy is \( 1/c \).

Source: scikit-learn
We expect a classifier to perform worse on run-time data. Sometimes it will perform much worse: an overfitting in training. An extreme case is: the classifier correctly labeled 100% when the input is in the training set, but otherwise makes a random guess.

To protect against overfitting, we separate training set from validation/test set.

- **Training set** for training the classifier
- **Validation/test set** is for evaluating the performance

It’s common to reserve at least 10% of the data for testing.
Cross-validation

- If we don’t want to “waste” labeled data on validation, we can use cross-validation to see if our training method is sound.

- Split the labeled data into training and validation sets in multiple ways

- For each split (called a fold)
  - Train a classifier on the training set
  - Evaluate its accuracy on the validation set

- Average the accuracy to evaluate the training methodology
How many trained models I can have for the leave one out cross-validation?

If I have a data set that has 50 labeled data entries, how many leave-one-out validations I can have?

A. 50
B. 49
C. 50*49
How many trained models can I have with this cross-validation?

If I have a data set that has 51 labeled data entries, I divide them into three folds (17,17,17). How many trained models can I have?

17 for testing
51-17 for training

How many $\binom{51}{17}$ of unique sets of 17?

*The common practice of using fold is to divide the samples into equal sized k groups and reserve one of the group as the test data set.*
The object classification **decision tree** can classify objects into multiple classes using sequence of simple tests. It will naturally grow into a tree.
Iris example. Which type is this?
Training a decision tree: example

The “Iris” data set

The Iris data set

- Setosa
- Versicolor
- Virginica

1? Where?

Petal Width< 1.75

<table>
<thead>
<tr>
<th>Petal.Length&lt; 2.45</th>
</tr>
</thead>
<tbody>
<tr>
<td>setosa 50/0/0</td>
</tr>
<tr>
<td>versicolor 0/49/5</td>
</tr>
<tr>
<td>virginica 0/1/45</td>
</tr>
</tbody>
</table>

Virginica

Setosa

Versicolor
Q: What is accuracy of this decision tree given the confusion matrix?

\[
\begin{bmatrix}
50 & 0 & 0 \\
0 & 49 & 5 \\
0 & 1 & 45
\end{bmatrix}
\]

A. \(\frac{6}{150}\)  
B. \(\frac{144}{150}\)  
C. \(\frac{145}{150}\)
Decision Boundary

Iris

Petal.Width

Petal.Length

2.45
Another Decision Boundary

Credit: Kelvin Murphy, “Machine Learning: A Probabilistic Perspective”, 2012
Assignments

🔹 Read Chapter 11 of the textbook
🔹 Next time: Decision tree, Random forest classifier
🔹 Prepare for midterm 2 exam (4/15)
  🔹 Lec 11-Lec 17, Chapter 6-10
Additional References


❖ Morris H. Degroot and Mark J. Schervish "Probability and Statistics"
See you next time

See You!