# Stat 115 Lab 4

PCA, SVM, BWA

(your name)

February 13-14, 2018

## Roadmap

- Dimension reduction: summarizing complicated data.
- Classification: Predicting  $y \in \{0, 1\}$  from **X**.
- Read mapping: finding regions of the genome where short reads map to.

### **Install and Load Packages**

```
# install packages from bioconductor
source("https://bioconductor.org/biocLite.R")
biocLite("sva")
biocLite("bladderbatch") # for the example data
install.packages("class")
install.packages("e1071")
install.packages("ggplot2")
install.packages("cowplot")
install.packages("caret")
# etc.
library(sva)
library(bladderbatch)
library(limma)
library(ggplot2)
library(cowplot)
library(class)
library(e1071)
library(caret)
```

#### Load Data

- Gene expression data from investigation into bladder cancer.
- Outcome: finding differentially expressed genes that are associated with cancer status (0/1 in the variable hasCancer).
- Already normalized with RMA.

```
data(bladderdata)
pheno <- pData(bladderEset)
pheno$hasCancer <- as.numeric(pheno$cancer == "Cancer")
edata <- exprs(bladderEset)
head(pheno)

## sample outcome batch cancer hasCancer
## GSM71019.CEL 1 Normal 3 Normal 0
## GSM71020.CEL 2 Normal 0</pre>
```

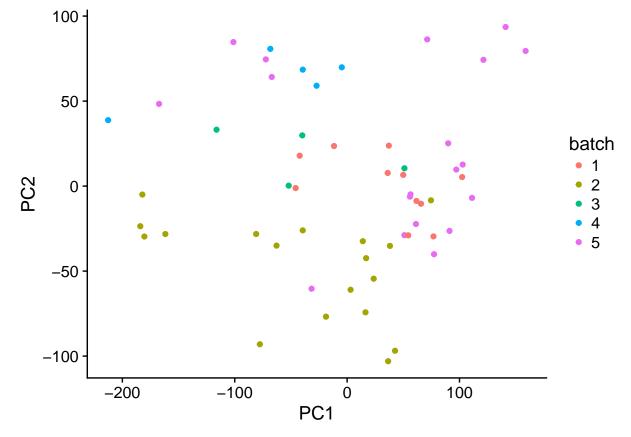
```
## GSM71021.CEL
                                     2 Normal
                         Normal
                                                       0
                                     3 Normal
## GSM71022.CEL
                         Normal
                                                       0
                                     3 Normal
## GSM71023.CEL
                         Normal
                                                       0
## GSM71024.CEL
                                     3 Normal
                                                       0
                         Normal
```

#### **PCA**

- Finds the best linear combinations of the variables.
- "Best" means optimally describing the variance.
- Can produce lower-dimensional summaries of the data.
- Useful for visualization, among other things.

#### PCA

- Main function: prcomp.
- Definitely want to center and scale your data: e.g. for car data, you might have 4-8 cylinders, but weight could be measured in kilograms or grams.



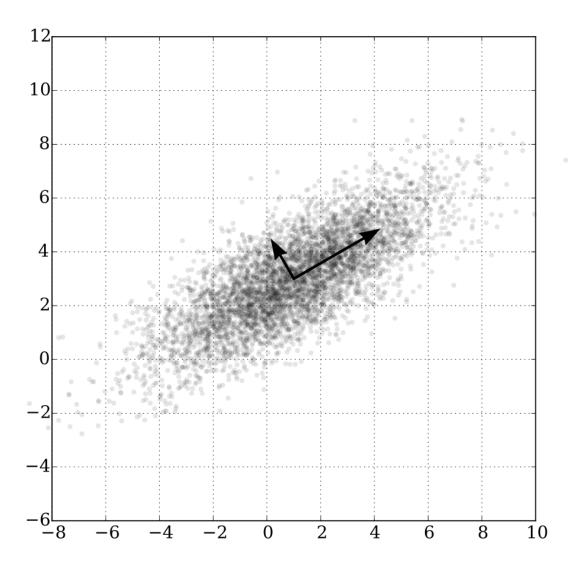
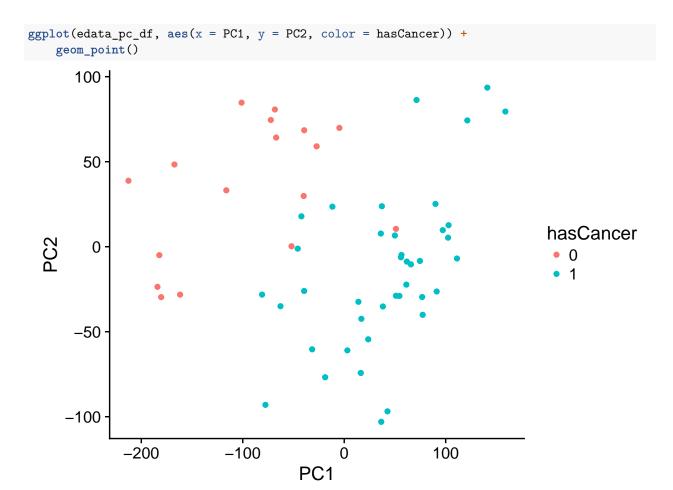


Figure 1: Source: https://en.wikipedia.org/wiki/File:GaussianScatterPCA.svg



#### PCA Variance Explained

- Linear algebra result:  $\mathrm{trace}(\Sigma) = \sum_i \lambda_i$
- $\operatorname{trace}(\Sigma)$  can be thought of as total variance.
- Variance of  $PC_i$  is  $\lambda_i$
- So variance explained by PCs 1 to k is  $\frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{K} \lambda_i}$
- Denominator is sum of all eigenvalues
- Given the formula here, can you write code to plot the variance explained from 1 to k, for all possible values of k (1, 2, ..., 57)?

### PCA Variance Explained: Your turn

```
# your turn
```

## PCA After ComBat: Does it change?

```
# your turn
# run combat on edata to remove batch effect (see Lab 3)
```

```
# your turn
# run PCA on the data from ComBat, draw a plot of the result
```

#### **SVM Overview**

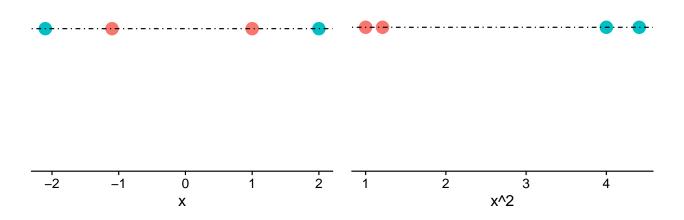
- SVM is a type of classifier (can also be used for regression)
- Predict binary y from covariates X.
- Different from clustering: in clustering, only have covariates X, no labels y.
- Can run SVM on our data to predict cancer status.
- kernel = "linear" means SVM draws a linear decision boundary. Will this work for our data?

#### **SVM:** Nonlinear

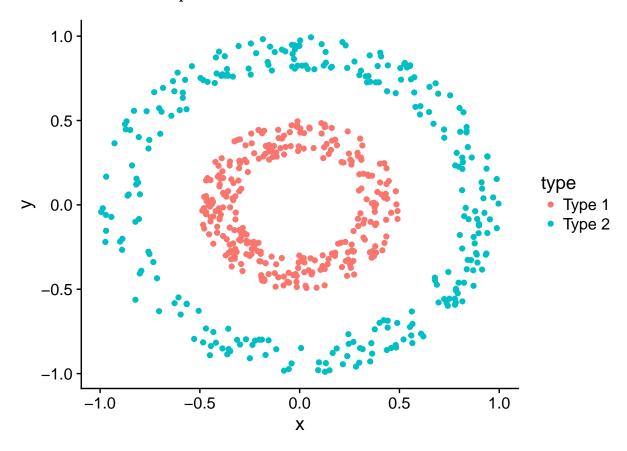
- Power of SVM comes in when we use different kernels
- Example: SVM can also draw circular decision boundaries.
- Intuition:

## **Plot of Original Data**

Plot of Data^2



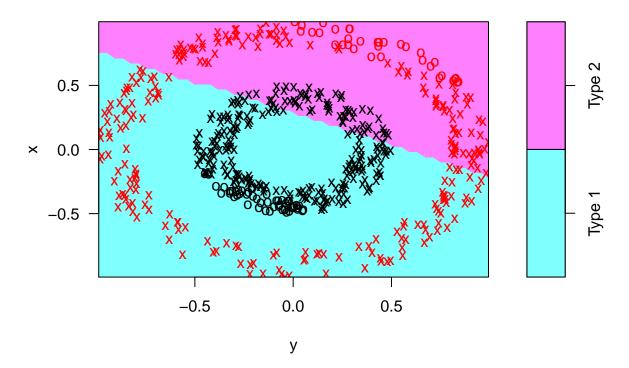
# SVM: Nonlinear example



# SVM: Using Linear kernel

```
## Reference
## Prediction Type 1 Type 2
## Type 1 231 145
## Type 2 67 136
```

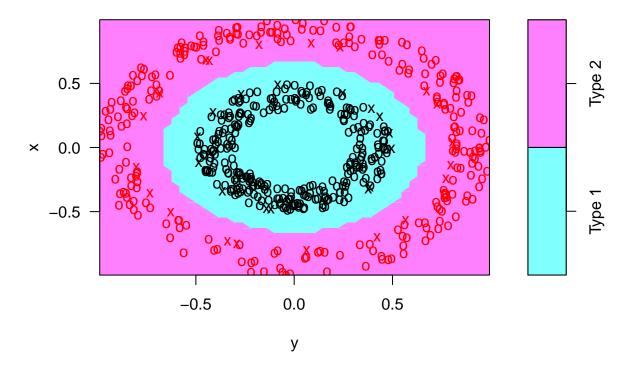
# **SVM** classification plot



# SVM: Using Radial Kernel

##	Reference					
##	${\tt Prediction}$		Туре	1	Туре	2
##	Туре	1	29	98		0
##	Type	2		0	28	31

## **SVM** classification plot



#### **BWA**

- 3 different versions:
  - BWA-backtrack (aln/samse/sampe)
  - BWA-SW (bwasw)
  - BWA-MEM (mem)
- Different recommendations depending on data:
  - BWA-backtrack: Illumina reads up to 100bp
  - BWA-SW / BWA-MEM: longer sequeces from 70bp to 1Mbp
  - BWA-MEM latest version, recommended since generally faster and more accurate
  - BWA-MEM better than BWA-backgrack for 70-100bp Illumina reads
- How to run:

bwa aln index.fa sample.fastq > sample.sai
bwa samse index.fa sample.1M.sai sample.fastq > sample.sam
samtools flagstat sample.sam

#### Odyssey

- What is Odyssey? Lots of computers stringed together
- Advantage: More storage, can run many things in parallel (e.g. use 10 computers to process 10 samples at a time)
- Disadvantage: a lot of overhead to get things to work (have to make sure your stuff doesn't interfere with other people's stuff)
- Can't just run stuff through the terminal on Odyssey—login node.
- Have to submit job using srun or sbatch (preferred)
- My tip: start off by requesting very few resources and doing a test run on a small file.

## **Odyssey Logistics**

YOUR\_COMMANDS\_HERE

- Login using ssh (Mac/Linux) or PuTTY (Windows)
- Transfer files using Filezilla
- Details: https://www.rc.fas.harvard.edu/resources/odyssey-quickstart-guide/
- Matt will discuss more next week.

## **Example Submission Script**

- Save this to a file, e.g. submit.sbatch.
- Submit by running sbatch submit.sbatch.

```
#!/bin/bash
#SBATCH -n 1 # Number of cores requested
#SBATCH -N 1 # Ensure that all cores are on one machine
#SBATCH -t 15 # Runtime in minutes
#SBATCH -p serial_requeue # Partition to submit to
#SBATCH --mem=100 # Memory per cpu in MB (see also --mem-per-cpu)
#SBATCH --open-mode=append
#SBATCH -o output_%j.out # Standard out goes to this file
#SBATCH -e error_%j.err # Standard err goes to this file
LOAD_MODULES
# example:
module load bwa
module load samtools
```