Week 14

## Other numerical methods in biology

## Scatter plot

Shows the relation between two variables


Can we quantitatively measure the strength of relationship between variables?

Linear regression is a form of regression in which one exploratory variable is used to predict the outcome of a response variable.

Covariance

Does Y get larges (smalleR) as Y increase?


Covariance $>0$ if X and Y variables gets larger

Covariance $<0$ if X and Y variables moves opposite direction


Correlation coefficient always lies between -1 to +1

## Fitlm and polyfit functions

b = fitlm(hist',genetrial')

| New to MATLAB? See resources for Getting Started. |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| $y \sim 1+x 1$ |  |  |  |  |
| Estimated Coefficients: |  |  |  |  |
|  | Estimate | SE | tstat | pValue |
| (Intercept) | 42.933 | 2.1767 | 19.724 | $4.544 \mathrm{e}-08$ |
| $\times 1$ | 3.2303 | 0.35081 | 9.2082 | $1.5659 \mathrm{e}-05$ |

Number of observations: 10, Error degrees of freedom: 8
Root Mean Squared Error: 3.19
R-squared: 0.914, Adjusted R-Squared: 0.903
F-statistic vs. constant model: 84.8, p-value $=1.57 \mathrm{e}-05$
fx $\gg$
[co,S]=polyfit(hist,genetrial,1)

```
\(\mathrm{co}=\)
```

$3.2303 \quad 42.9333$
$\mathrm{S}=$
struct with fields:
R: [ $2 \times 2$ double]
df: 8
normr: 9.0124

## Correlation sets



Remember that correlation coefficient is an indicator of the strength of a linear relationship between two variables, but its value generally does not completely characterize their relationship

## $r^{2}$ IN REGRESSION

The square of the correlation, $r^{2}$, is the fraction of the variation in the values of $y$ that is explained by the least-squares regression of $y$ on $x$.

$$
r^{2}=\frac{\text { variance of predicted values } y}{\text { variance of observed values } y}
$$

## Properties of r2

$0=<r^{2}=<1$
if $r^{2}=1$, it represents a straight line
if $r^{2}=0$, it indicates no correlation between $y$ and $x$
Larger the $r^{2}$ means higher correlation, but not always

R2 gets smaller by the size of
Slope $=1.63$
Intercept = -3.35


## Gene expression in different cells



What is the covariance between different cell types?


## MULTIVARIATE REGRESSION

In linear regression, a single independent variable was present. A total of two variables. In multiple regression, y dependent variable (response variable) depends on a many explanatory independent variables.

Now we can define linear function as

$$
Y=\operatorname{constant}(a)+\beta_{1} x_{1}+\beta_{2} x_{2}+\beta_{3} x_{3} \ldots .+\beta_{k} x_{n}
$$

## It is also called as population regression equation.

y varies normally with a mean given by the population regression equation

- y - dependent variable or also called response variable
- $\mathrm{x}_{1}, \mathrm{x}_{2}, \mathrm{x}_{3} \ldots, \mathrm{x}_{\mathrm{n}}$ are called independent variables


## or explanatory variables.

- X values can either quantitative or categorical.

$$
Y=\operatorname{constant}(a)+\beta_{1} x_{1}+\beta_{2} x_{2}+\beta_{3} x_{3} \ldots .+\beta_{k} x_{n}
$$

## Examples of multivariate regression

2. Dependence of cancer risk to several genes (biology)
3. Dependence of home price to location, size, type etc. (home market)
4. Dependence of hormone levels to genes
(health)
5. Dependence of reading score to mothers educaiton, age, gender, family income etc. (social science)

In Matlab
$m d l=$ fitlm $(X, Y)$

## Dependence of cell growth to expression of geneX, geneY and geneZ

```
\begin{tabular}{|c|c|c|c|c|}
\hline \multicolumn{5}{|l|}{Linear regression model:
\[
-x \sim 1+x 1+x 2+x 3
\]} \\
\hline Estimated Coeff & ents: Estimate & SE & tStat & pValue \\
\hline (Intercept) & 47.153 & 26.499 & 1.7794 & 0.078342 \\
\hline x1 & 0.28602 & 0.069679 & 4.1048 & 8.4971e-05 \\
\hline x2 & -0.0033967 & 0.0047938 & -0.70856 & 0.48031 \\
\hline x3 & -0.3098 & 0.071258 & -4.3476 & 3.4254e-05 \\
\hline
\end{tabular}
Number of observations: 100, Error degrees of freedom: 96
Root Mean Squared Error: 1.74
R-squared: 0.994, Adjusted R-Squared 0.993
F-statistic vs. constant model: 4.95e+03, p-value \(=4.52 \mathrm{e}-105\)
>>
Cell growth \(=47+0.28\) geneX -0.003 gene \(Y-0.30\) geneZ
```


## Dependence of hormone levels to expression of geneX, geneY and geneZ

|  | 1 | 2 | 3 | 4 |
| :---: | :---: | :---: | :---: | :---: |
| 1 | 120 | 140 | 249 |  |
| 2 | 120 | 218 | 245 |  |
| 3 | 123 | 124 | 244 |  |
| 4 | 125 | 248 | 243 |  |
| 5 | 128 | 186 | 241 |  |
| 6 | 129 | 207 | 241 |  |
| 7 | 130 | 190 | 240 |  |
| 8 | 131 | 177 | 240 |  |
| 9 | 132 | 172 | 238 |  |
| 10 | 132 | 149 | 237 |  |
| 11 | 133 | 162 | 237 |  |
| 12 | 134 | 204 | 233 |  |
| 13 | 136 | 215 | 232 |  |
| 14 | 137 | 123 | 230 |  |
| 15 | 138 | 166 | 229 |  |
| 16 | 139 | 168 | 227 |  |
| 17 | 140 | 135 | 227 |  |
| 18 | 141 | 142 | 224 |  |
| 19 | 141 | 177 | 221 |  |
| $? 0$ | 147 | 148 | 221 |  |
| $? 1$ | 147 | 167 | 221 |  |
| $? 2$ | 148 | 209 | 221 |  |
| $? 3$ | 153 | 221 | 220 |  |
| 24 | 154 | 164 | 218 |  |
| $? 5$ | 155 | 122 | 216 |  |
| $? 6$ | 155 | 140 | 215 |  |
| $? 7$ | 156 | 157 | 215 |  |


|  |  | 1 |
| :--- | :--- | :--- |
| 1 | 2 | 2 |
| 2 |  | 6 |
| 3 |  | 7 |
| 4 | 7 |  |
| 5 | 8 |  |
| 6 | 9 |  |
| 7 | 11 |  |
| 8 | 14 |  |
| 9 | 18 |  |
| 10 | 19 |  |
| 11 | 21 |  |
| 12 | 21 |  |
| 13 | 21 |  |
| 14 | 21 |  |
| 15 | 22 |  |
| 16 | 22 |  |
| 17 | 22 |  |
| 18 | 24 |  |
| 19 | 26 |  |
| 20 | 26 |  |
| 21 | 27 |  |
| 22 | 27 |  |
| 23 | 27 |  |
| 24 | 27 |  |
| 25 | 27 |  |
| 26 | 27 |  |
| 27 | 28 |  |

## Lets predict cell growth

We conclude that geneX and gene $Z$ contain useful information for predicting cell growth

Let's find the predicted cell growth for a sample with an 0.3 average in geneX and 0.6 in geneZ.
The explanatory variables are geneX and geneY. The predicted cell growth is

$$
\begin{aligned}
& \text { Cell growth }=47+0.28 \text { geneX }-0.003 \text { geneY- } 0.30 \text { geneZ } \\
& \text { Cell growth }=47+0.28 \text { gene- } 0.3 \text { geneZ } \\
& \text { Cell growth }=47+0.28(0.3)-0.30(0.6)
\end{aligned}
$$

## Logistic Regression



It is used to determine model parameters when dependent variables are binary rather than continuous

For example, cell division, 0 or 1
Cancer diagnostic, cancer/not
Voting yes/no
Mortality alive/death
Product-marketing, sold/not sold
Arrived/delayed

The results of these data is not continuous as you have seen in multivariable linear regression

## Logistic model can be used to make prediction for binary results

If a response variable such as yes/no or success/failure response variables., we cannot use linear regression models where it assumes a normal distribution.

Think about a cancer patient diagnosis whether a patient either have a cancer or not a cancer

One type of model that can be used is called logistic regression. We think in terms of a binomial model for the two possible values of the response variable and use one or more explanatory variables to explain the probability of success.

$$
P(Y=1 \mid b e t a)=\exp (b(1)+b(2) x) / 1+\exp (b(1)+b(2) x)
$$

$\mathrm{x}=$ binary or cont
$y=$ binary
$\mathrm{b}(1)$ and $\mathrm{b}(2)$ are coefficients
if $y$ response variable is discrete

$f(x)$ or $y$ values always falls in range between 0 and 1

## Solutions: Logistic regression

Logistic regression is the best model if response variable is binomial. Because it uses a fitting method that is appropriate for the binomial distribution.
Predicted proportions/probability values are present in the range from 0 to 1 .


In matlab we use glmfit function to fit our data to a logistic model. This function returns coefficient estimates for a linear regression of the responses $Y(f(x))$ on the independent variable $X$

## In Matlab,

```
%logistic regression
[logitCoef,dev,stats] = glmfit(geneX, [cancer
tested],'binomial','logit');
```


## geneX $=\left[\begin{array}{lll}2180 & 24502640273031003120332036103800\end{array}\right.$

 $\%$ The number of patients tested at each levels (intervals) tested $=\left[\begin{array}{lllll}57443733 & 3221 & 2319161821\end{array}\right]^{\prime \prime} ;$\% The number of cancer patients at each test
cancer $=\left[\begin{array}{ll}1 & 2 \\ 2\end{array} 48141717151721\right.$ 1];
\%logistic regression
[logitCoef,dev,stats] = glmfit(geneX,[cancer tested],'binomial','logit'); logitFit = glmval(logitCoef,geneX,'logit');
figure(3)
plot(geneX,proportion,'bs', geneX,logitFit,'r-','markersize',16);

## Glmval is uses to compute the predicted values for the model



| $\begin{aligned} & \frac{\text { stats } \times}{} \text { logitfit } \times 12 \times 1 \text { double } \end{aligned}$ |  |  |  |
| :---: | :---: | :---: | :---: |
|  |  |  |  |
|  | 1 | 2 | 3 |
| 1 | 0.0141 |  |  |
| 2 | 0.0391 |  |  |
| 3 | 0.0782 |  |  |
| 4 | 0.1073 |  |  |
| 5 | 0.3345 |  |  |
| 6 | 0.3519 |  |  |
| 7 | 0.5406 |  |  |
| 8 | 0.7831 |  |  |
| 9 | 0.8827 |  |  |
| 10 | 0.9308 |  |  |
| 11 | 0.9725 |  |  |
| 12 | 0.9871 |  |  |
| 13 |  |  |  |
| 14 |  |  |  |

## glmfint: Logistic model coefficients



| stats $\times$ | logitFit $\times$ | dev $x$ | logitCoef |  |
| :---: | :---: | :---: | :---: | :---: |
| 固 1x1 struct with 15 fields |  |  |  |  |
| Field - | Value |  |  |  |
| B beta | [-12.6748 | ;0.3867] |  |  |
| \#dfe | 10 |  |  |  |
| \#sit | 0.5951 |  |  |  |
| Bs | 1 |  |  |  |
| $\checkmark$ estdisp | 0 |  |  |  |
| \#covb | [1.6374,- | 0.0508;-0 | 0508,0.... |  |
| Bse | [1.2796;0.0 | .0400] |  |  |
| B coeffcorr | [1,-0.990 | 7;-0.9907 |  |  |
| \#t | [-9.9053; | 9.6573] |  |  |
| 回 | [3.9472e | 23;4.576 | e-22] |  |
| \#resid | $12 \times 1$ dou |  |  |  |
| \#residp | $12 \times 1$ dou |  |  |  |
| \# residd | $12 \times 1$ dou |  |  |  |
| \#resida | $12 \times 1$ dou |  |  |  |
| \# wts | $12 \times 1$ dou |  |  |  |

## $P(Y=1 \mid b e t a)=\exp (b(1)+b(2) x) / 1+\exp (b(1)+b(2) x)$

\% prediction by using logistic model
\% given that patient has an average RNA level from isolated cells genepredict=40
$\%$ what is the risk of having cancer?
\% model equation
cancerriskpro=exp(logitCoef(1)+genepredict*logitCoef(2))/(1+exp(logitCoef(1)+genepredi
\% probability
disp(cancerriskpro)
figure(3)
plot(geneX, proportion,'bs', geneX,logitFit,'r-','markersize',16);
hold on
plot(genepredict,cancerriskpro,'mo','markersize',34);
xlabel('geneX');
ylabel('Probability');
set(gca,'fontsize',18)


Coefficients are estimated by using a maximum likelihood estimation method where coefficients maximizes the prediction of observed values in the data

points on a line represents the highest points in the probability distribution

$$
\log (\text { odds })=b_{0}+b_{1} x=-12.12+0.45 x
$$

## Machine learning and Deep learning with Python




- There are many different machine learning models Including
Random Forest
Logistic Regression
Decision trees
Support Vector



## Machine Learning

It is the learning process for understanding the data sets and use this knowledge to answer the questions.
Can be used to discover for new knowledge.

The goals are

- To improve the learning system and apply learning systems
- To perform the learning with these systems and train your model
- To apply the model and answer the questions

Our goal is to help you to understand the model selection within the machine learning that can be used to solve the real world problems

## Machine Learning Types

Supervised learning
Unsupervised learning
Semi-supervised learning
Reinforcement learning
Supervised learning Unsupervised learning

supervised learning require supervision to train the model. This supervision is necessary for classification where we have labeled data on which we train the model to predict the labels of the unseen data.

## Scikit_learn library

$\qquad$

## scikit-learn

Machine Learning in Python
Getting Started Release Highlights for 1.3 GitHub

- Simple and efficient tools for predictive data analysis
- Accessible to everybody, and reusable in various contexts
- Built on NumPy, SciPy, and matplotlib
- Open source, commercially usable - BSD license


## Classification

Identifying which category an object belongs to.
CApplications: Spam detection, image recognition. Algorithme: Gradiont beosting, nearest neighbors, random forest, logistic regression, and more...


## Examples

## Dimensionality reduction

Reducing the number of random variables to consider.

## Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices.
Algorithms: Gradient boosting, nearest neighbors, random forest, ridge, and more...


Examples

## Model selection

Comparing, validating and choosing parameters and models.

## Clustering

Automatic grouping of similar objects into sets.
Applications: Customer segmentation, Grouping experiment outcomes
Algorithms: k-Means, HDBSCAN, hierarchical clustering, and more...


Examples

## Preprocessing

Feature extraction and normalization.

## Scikit_learn library

(3) https://scikit-learn.org/stable/index.html


Examples

## Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency Algorithms: PCA, feature selection, non-negative matrix factorization, and more..


Examples


Examples

## Model selection

Comparing, validating and choosing parameters and models.

Applications: Improved accuracy via parameter tuning

Algorithms: grid search, cross validation, metrics, and more...


Examples


Examples

## Preprocessing

Feature extraction and normalization.
Applications: Transforming input data such as text for use with machine learning algorithms.
Algorithms: preprocessing, feature extraction, and more...


Examples

Who uses scikit-learn?

## Example 1: Reading handwritten digits with deep learning



## Deep learning with python

Hidden


Forward Propagation
We find the most
optimum weights for each output

The value of each output neuron can be calculated as the following :
$y_{j}=b_{j}+\sum_{i} x_{i} w_{i j}$
$b$ is the bias


## Training the data with a known

 valuesoutput1, output2, output3, output42=trainingdata(X_train, Y_train, 0.10, 500)



In [164]:
for $i$ in range(80): test_prediction(i, W1, b1, W2, b2)

[^0]
## Example 2: Inhibitors to control cell motility

$N \leftarrow \rightarrow$ 中
















notorn







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## Unsupervised machine learning methods Example: Principal component analysis

## Principal Component Analysis :

It is an example of unsupervised machine learning


## Principal Component Analysis :

It is a geometry based transformation of the numerical data
Mainly used
Dimensionality reduction
Higher dimensional data plotting in lower dimensional space
Data classification for machine learning algorithms
Unsupervised Learning
no supervision from the data are used while training the model.
We check if any clusters are present
The discovered labels (for example with kmeans method)
then become the basis for classifying any new unseen data.

Principal Component Analysis :
It is an example of unsupervised machine learnign

- PCA is a mathematical method to analyze complex and large data sets.
- Covariance can be considered to be a measure of how well correlated two variables are.


## Lets start with a simple example:



Can we transform the coordinate system?

## Statistics review

Mean

$$
\bar{x}=\frac{1}{n} \sum_{i=1}^{n} x_{i}
$$

Variance : Determines the spread of only one variable. It measure 1 dimension and independent of other dimension.
$\sigma^{2}=\frac{1}{n} \sum_{i=1}^{n}\left(x_{i}-\bar{x}\right)^{2} \quad \operatorname{var}(X)=\frac{\sum_{i=1}^{n}\left(X_{i}-\bar{X}\right)\left(X_{i}-\bar{X}\right)}{(n-1)}$
Covariance: Determines how two variables are related. It is always the measured between 2 dimensions.

$$
\operatorname{cov}(x, y)=\frac{1}{n-1} \sum_{i=1}^{n}\left(x_{i}-\bar{x}\right)\left(y_{i}-\bar{y}\right)
$$

Is there any other way to represent the data?


Find the regression line by linear fitting. It represents the largest variance in the data.
$X^{\prime}$ is the measure of the size.
$Y^{\prime}$

We can also determine the signal to noise ratio qualitatively by changing the coordinate system

$X^{\prime}$ is an indication of variance of signal $\sigma^{2}{ }_{\text {signal }}$ Along the $Y^{\prime}$ axis, we observe the variance of noise $\sigma^{2}{ }_{\text {noise }}$

Signal-to-noise ratio $(\mathrm{SNR})=\sigma_{\text {signal }}^{2} / \sigma^{2}{ }_{\text {noise }}$


What if we are interested in many drugs? How to find the new basis?

PCA is a tool that helps to find the relation of variables.
Which of the drugs are related?
What are the drugs that are active for target proteins but not for others?


Colors define the intensity


## PCA for drug discovery

```
#%%
pca = PCA(n_components=3)
components = pca.fit_transform(arrselected)
X=components
fig = plt.figure(8)
ax = fig.add_subplot(projection='3d')
co=10
ax.scatter(co*X[:1800,0], co*\chi[:1800,1], co*X[:1800,2])
ax.set_xlabel('\chi Label')
ax.set_ylabel('Y Label')
ax.set_zlabel('Z Label')
plt.show()
```



Silhouette score is used to determine the optimum number of clusters


$N \leftarrow \rightarrow$ 中 $\ddagger \boldsymbol{\sim}$



Random state $=0$

Finding the class of each compounds and compare it with inhibitor/inactive map



$$
\begin{aligned}
& \text { Now } \\
& \text { Kon } 245 \\
& 10005 \\
& \text { traigy } \\
& +17008 \\
& \text { + } 4005 \\
& \text { inoong } \\
& \text { ratio } \\
& x \\
& \text { x00 }
\end{aligned}
$$



```
#%%
model = KMeans(n_clusters = 6, init = "k-means++")
label = model.fit_predict(X)
plt.figure(figsize=(10,10))
uniq = np.unique(label)
for i in uniq:
    plt.scatter(components[label == i , 0] , components[label == i ,
#plt.scatter(1*X[:1800,0], 1*X[:1800,1], marker="x", color='k')
#This is done to find the centroid for each clusters.
I
```




## Is there any clustering of drug molecules?

```
\[
N \leftarrow \rightarrow \pm Q \equiv \omega \text { 回 }
\]
```



Transforming information in multivariable data set

What information can be obtained in computational study of drug molecules?

1. Prediction of the class of drugs: The key drugs can be identified. The effectiveness of these drugs can be predicted.

2. Building large network of drugs: construct a graph that show the dependency of these drug molecules

## Lets start with a simple example:



Can we transform the coordinate system?

## Statistics review

Mean

$$
\bar{x}=\frac{1}{n} \sum_{i=1}^{n} x_{i}
$$

Variance : Determines the spread of only one variable. It measure 1 dimension and independent of other dimension.
$\sigma^{2}=\frac{1}{n} \sum_{i=1}^{n}\left(x_{i}-\bar{x}\right)^{2} \quad \operatorname{var}(X)=\frac{\sum_{i=1}^{n}\left(X_{i}-\bar{X}\right)\left(X_{i}-\bar{X}\right)}{(n-1)}$
Covariance: Determines how two variables are related. It is always the measured between 2 dimensions.

$$
\operatorname{cov}(x, y)=\frac{1}{n-1} \sum_{i=1}^{n}\left(x_{i}-\bar{x}\right)\left(y_{i}-\bar{y}\right)
$$

Is there any other way to represent the data?


Find the regression line by linear fitting. It represents the largest variance in the data.
$X^{\prime}$ is the measure of the size.
$Y^{\prime}$ is the ratio of cell survival to gene expression

We can also determine the signal to noise ratio qualitatively by changing the coordinate system

$X^{\prime}$ is an indication of variance of signal $\sigma^{2}{ }_{\text {signal }}$ Along the $Y^{\prime}$ axis, we observe the variance of noise $\sigma^{2}{ }_{\text {noise }}$

Signal-to-noise ratio $(\mathrm{SNR})=\sigma_{\text {signal }}^{2} / \sigma^{2}{ }_{\text {noise }}$


What if we are interested in many genes? How to find the new basis?

PCA is a tool that helps to find the relation of variables.
Which of the genes are expressed at the same time in cancer vs normal cells?
What are the genes that are expressed in cancer cells but not normal cells?
How the expression changes over time?


## Is there any clustering of these genes?



$$
\mathrm{Y}=\mathrm{PA}
$$



> Transforming information in multivariable data set

What information can be obtained in computational genetics?

1. Prediction of the class of these gene: The key genes can be identified. The expression of these genes can be used to predict the type (cancer or normal) of cell sample.

2. Building large network of genes: Complex data analysis is performed to learn the gene expression and construct a graph that show the dependency of expressed genes

Gene expression can also be probed for effect of toxic compounds, ions, different peptides etc.

## Time

Toxic compoynds
Intensity

Different lops
Small molêcules
Different Peptides
Cell types
Etc.
What genes are most important? So the largest eigenvalues?
What is relative significance of these genes?
Can we identify the function of unknown genes?

## Prove of Y (transformed matrix) solution by SVD

$$
\begin{array}{ll}
\mathbf{Y}=\mathbf{P X} \quad & \mathrm{Y}=\text { transformed matrix. } \\
& \mathrm{P}=\text { Principal Component } \\
& X=\text { Data Set or Covariance of } X
\end{array}
$$

$$
\begin{gathered}
\mathbf{C}_{\mathbf{Y}}=\frac{1}{n-1} \mathbf{Y} \mathbf{Y}^{T}=\frac{1}{n-1}(\mathbf{P X})(\mathbf{P X})^{T}=\frac{1}{n-1}(\mathbf{P X})\left(\mathbf{X}^{T} \mathbf{P}^{T}\right)=\frac{1}{n-1} \mathbf{P}\left(\mathbf{X} \mathbf{X}^{T}\right) \mathbf{P}^{T} \\
\text { i.e. } \quad \mathbf{C}_{\mathbf{Y}}=\frac{1}{n-1} \mathbf{P S P}^{T} \quad \text { where } \quad \mathbf{S}=\mathbf{X} \mathbf{X}^{T}
\end{gathered}
$$

Many iterations are needed to find S.


Covariance matrix of multiple variables
Diagonal indicates the variance of a variable by itself


## 100 by 100 covariance

 matrix.It is a symmetric
matrix

$$
\begin{aligned}
& \operatorname{co}(1,1) \quad \operatorname{co}(1,2) \quad \operatorname{co}(1,3) \quad \operatorname{co}(1,4) \\
& \operatorname{co}(1,1) \quad \operatorname{co}(1,2) \quad \operatorname{co}(1,3) \quad \operatorname{co}(1,4) \\
& \operatorname{Cov}(\text { gene })=\operatorname{co}(2,1 \quad \operatorname{co}(2,2) \quad \operatorname{co}(2,3) \quad \operatorname{co}(2,4) \\
& \text { 4by4 } \operatorname{co}(3,1) \quad \operatorname{co}(3,2) \quad \operatorname{co}(3,3) \quad \operatorname{co}(3,4) \\
& \operatorname{co}(4,1) \quad \operatorname{co}(4,2) \quad \operatorname{co}(4,3) \quad \operatorname{co}(4,4)
\end{aligned}
$$

## Covariance Matrix of 100 by 100 genes



We need a mathematical tool to find he vectors that demonstrates the largest variance in the covariance matrix.

Remember many principal axis (number of variables) are present, but only a few of them describe the largest variance.

## PCA by SVD

We can use SVD to perform PCA. We decompose A using SVD. PCA seeks a linear combination of variables such that the maximum variance is extracted from the variables.

## A = USV

It approximates a high-dimensional data set with a lower-dimensional linear small set. It still contains most of the information in the large set.


Singular Value Decomposition (SVD analysis)
It is a mathematical matrix decomposition method or tool to analyze complex data and answer important questions. It is used extensively for

It is very easy to use it and rich information can be obtained from data.

The main idea in PCA is to reduce the dimensionality of our data $A$ by approximating $A$ as a sum of rank matrices.

$$
A_{n}={ }_{i=1}^{n} u_{i} i_{i} v_{i}^{T} \quad \begin{aligned}
& \text { Rank } \\
& \text { matrix }
\end{aligned}
$$



Singula value decomposition to calculate eigenvalue

$$
\begin{aligned}
& A b_{i}={ }_{i} x_{i} \\
& b_{i}, x_{i}=\text { Eigenvector (principalcomponents) } \\
& { }_{i}=\text { Eigenvalue }
\end{aligned}
$$

The columns $b_{i}$ and $x_{i}$ of $B$ and $X$ are called the left and right eigenvectors respectively, and the diagonal elements $\lambda_{i}$ of $\lambda$ are called the singular values (eigenvalues).
$A b_{i}$ is in the direction of $x_{i}$

$$
A b_{i}={ }_{i} x_{i}
$$

$A V=U S$

Singular Value Decomposition (SVD) of a rectangular matrix $A$ is a decomposition of the form
$A=U S V^{\top}$
$U$ and $V$ are orthogonal matrices, and $S$ is a diagonal matrix.
$A V=U S$
$A V V^{T}=U S V^{T}$ $A=U S V^{T}$
$\mathbf{U}$ is $m \times n$ and orthonormal
$\mathbf{S}$ is $n \times n$ and diagonal
$\mathbf{V}$ is $n \times n$ and orthonormal

Singular value decomposition of A. SVD can be written always for $A$.

$$
V V^{T}=1 \quad S=\operatorname{DIA} G(1,2, \ldots \ldots \ldots . ., m)
$$

$$
1=\sqrt{i}
$$

Eigenvalues of $\mathrm{AA}^{\top}$ or $\mathrm{A}^{\top} \mathrm{A}$

## PCA uses the SVD in its calculation



Eigengene

$n \times n$
$\boldsymbol{a}_{j}=\sum_{k=1}^{r} \nu_{j k} s_{k} \mathbf{u}_{k}, \quad j: 1, \ldots, n$
In PCA, we basically find eigenvalues and eigenvectors of covariance matrix.

$$
\begin{array}{lll}
C=A A^{\top} / N & \sigma_{a} \sigma_{b}=0 & \text { highly uncorr. } \\
& \sigma_{a} \sigma_{b}=\sigma_{a}^{2} & \text { correlated }
\end{array}
$$

## IMPORTANT:

$s_{i}$ on the diagonal are called the singular values (eigenvalues) of $A$.

The columns of U represents the principal components (eigenvectors) of matrix A .

## EIGENVALUES

Why eigenvalues are important?
Considered as characteristic tool of the matrix.
For example you tell if a large sets of genes are expressed at certain time but not the other

Briefly, the eigenvalue for a given factor measures the variance in all the variables which is accounted by that factor. Largest eigenvalues gives the principal axis where the variance is largest along the corresponding principal axis.

The ratio of eigenvalues:
It is extremely important. If a factor has a low eigenvalue, the variance in the variables can be explained less significantly by the eigenvalues.

Eigenvalues of Covariance Matrix





Classify Cells using only PC1


## How many principal components do we need?




PC5
And
PC6


Principal Component Scatter Plot with Colored Clusters


## Genes 73,214, 258



Genes 68, 182, 132


Genes might change the function of cells.
Or we may say that genes with same pattern may have a link in cells

Gene Expression of Gene \#106 306 and 68


Clustering genes with cells


Change the perspective (plane) helps visually finding relations between cells and genes

PC with Colored Clusters


PC Scatter Plot with Colored Clusters


Cell relation using dendrogram

1. Cells 6 and 7 are related
2. Cells 1 and 2 are related
3. Cell 6-7 and cells 1-2 are inversely proportional or they have a different levels of gene expression.

Are they different cells?
Can we say that
6 and 7 are abnormal cells?
Or
They may have a different function?

Their function can be addressed by looking what genes are expressed


1. Eigenvectors and eigenvalues always come in pairs.
2. Eigenvalues is the scaling factor of the vector.
3. Every matrix has SVD.
4. The eigenvalues can be determined and those values can be $S_{1} \geq S_{2} \geq S_{3} \geq \ldots . . S_{n}>0$

[^0]:    $\square$ Console $1 / \mathrm{A} \times$

    Predicted number by the model: [3]
    True value of the digit:
    Predicted number by the model: [2] True value of the digit:
    [8]

    True value of the digit:

    Predicted number by the model:
    [6]
    True value of the digit:
    Predicted number by the model: [6]
    True value of the digit: 6
    Predicted number by the model:
    True value of the digit: 8
    [9]
    Predicted number by the model: [2]
    True value of the digit:

