

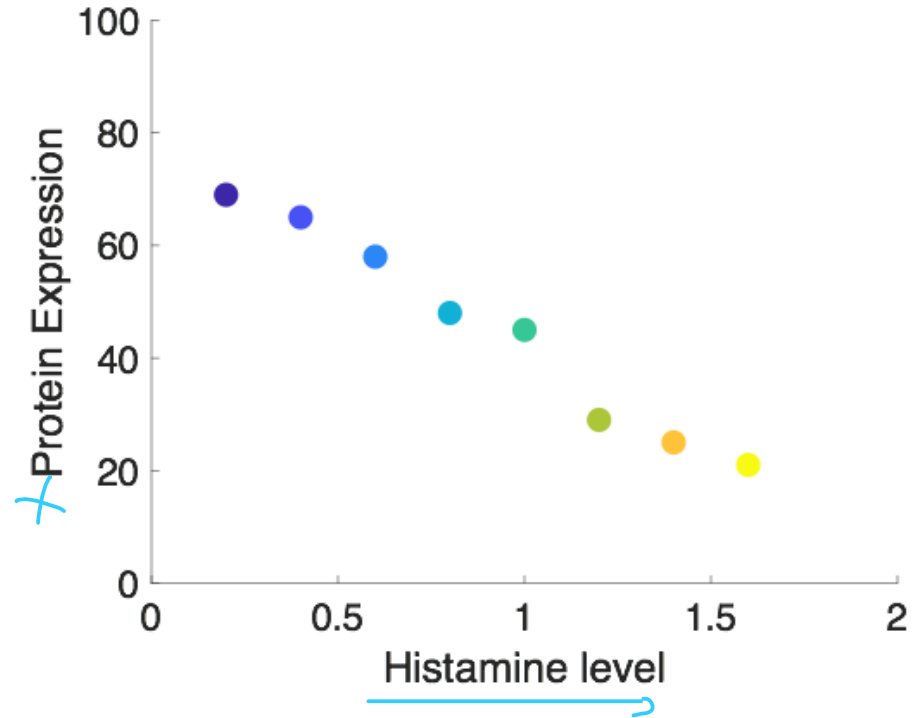
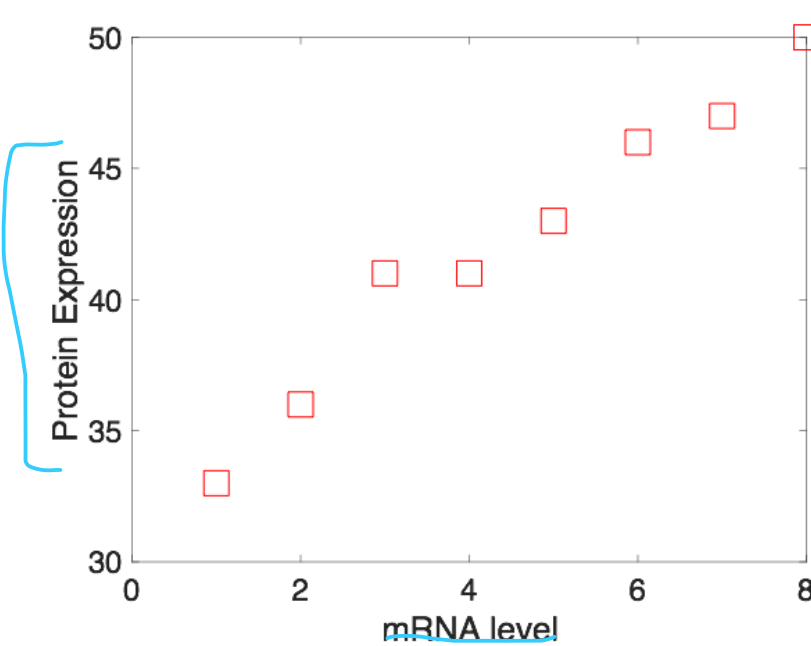
**Week 13**

# ***Regression analysis in biology***

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# Scatter plot

Shows the relation between two variables

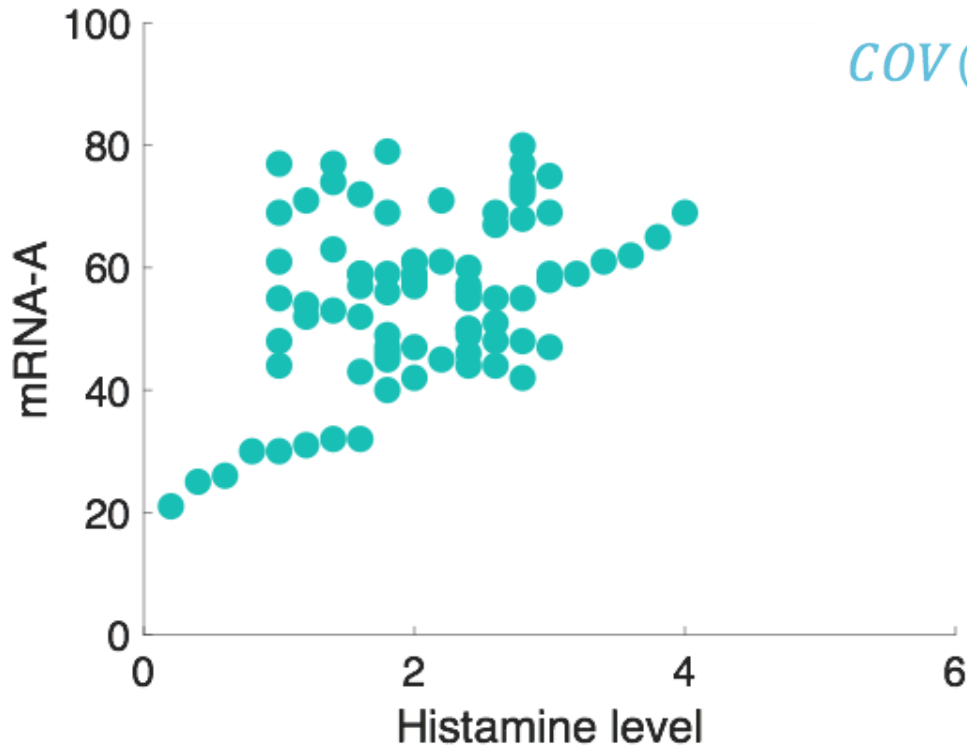


Can we quantitatively measure the strength of relationship between variables?

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

# Covariance

Does Y get larges (smalleR) as Y increase?



$$COV(x, y) = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{n - 1}$$

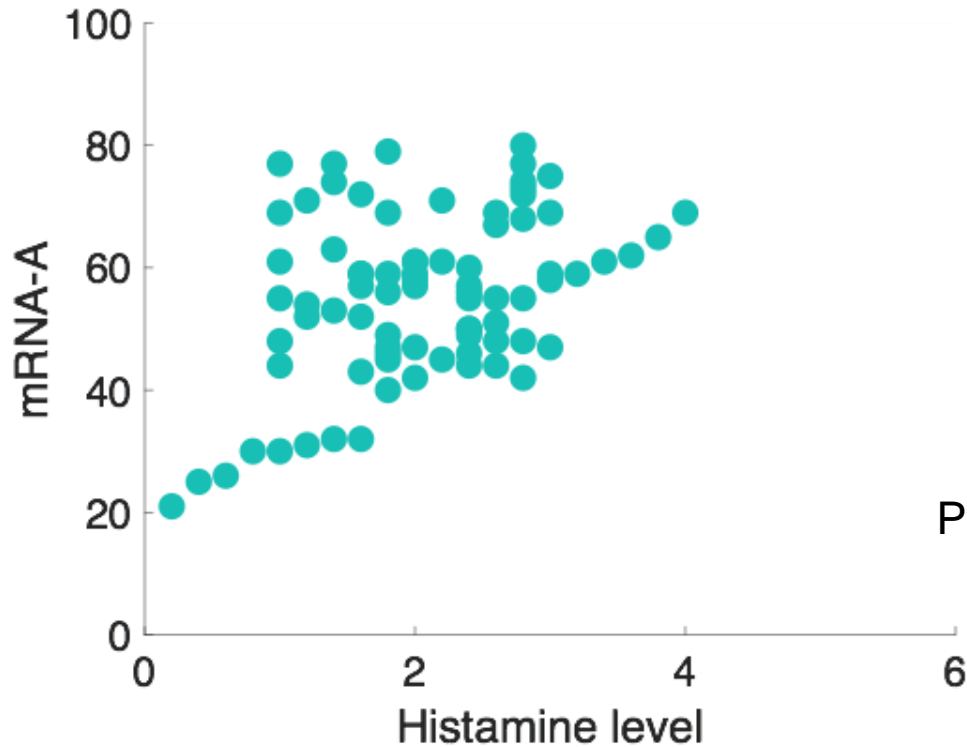
mean of x= 2.0525  
mean of y = 55.4125  
Sx = 0.7916  
Sy= 13.6537

n=80

Covariance > 0 if X and Y variables gets larger

Covariance < 0 if X and Y variables moves opposite direction

## Covariance of Histamine vs mRNA levels



$$COV(x, y) = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{n - 1}$$

Cov=1.65

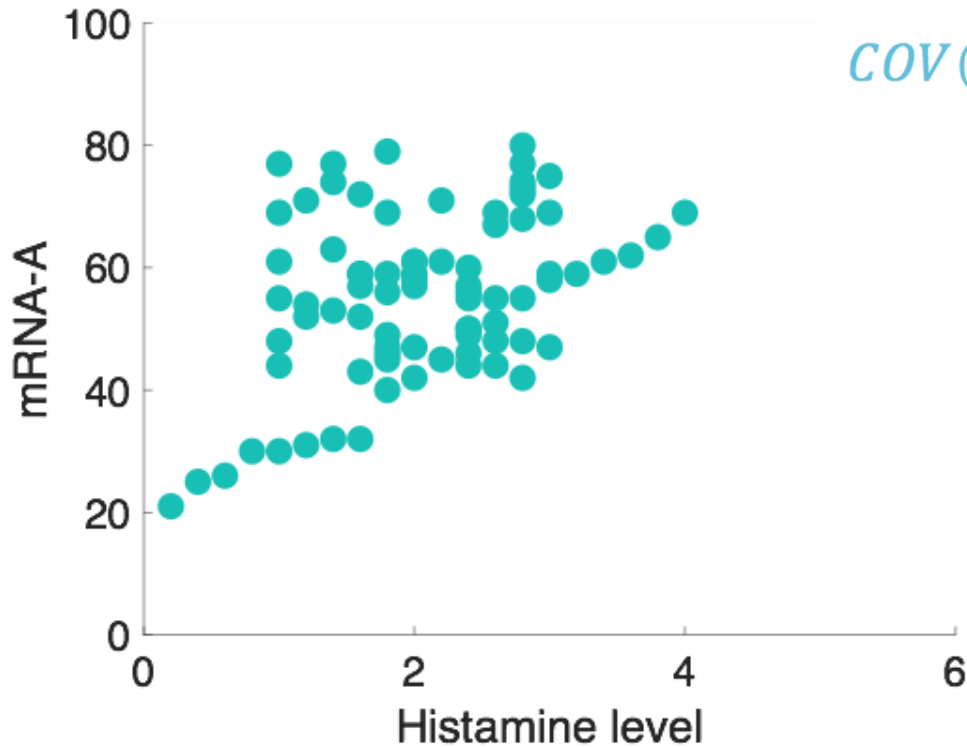
Positive correlation

Sign is a good indicator of relationship but what is the meaning of 1.65? is it a strong or weak relationship?

To determine the strength of relation, Correlation coefficient is needed?

# Covariance

Does Y get larger (smaller) as X increases?



$$COV(x, y) = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{n - 1}$$

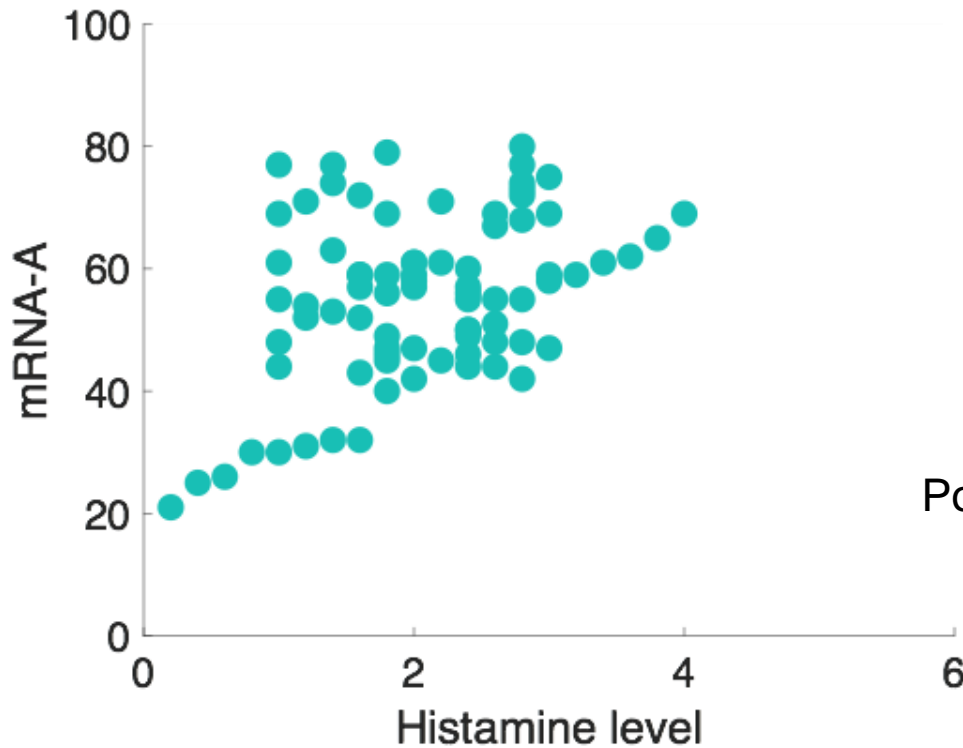
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## Covariance of Histamine vs mRNA levels



$$COV(x, y) = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{n - 1}$$

Cov=1.65

Positive correlation

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To determine the strength of relation, Correlation coefficient is needed?

# Correlation (r)

measures the direction and strength of relationship between two quantitative variable.

The correlation  $r$  measures the direction and strength of the linear (straight line) association between two quantitative variables  $x$  and  $y$ .

Although you can calculate a correlation for any scatterplot,  $r$  measures only linear relationships.

$$r = \frac{1}{n-1} \sum \left( \frac{x_i - \bar{x}}{s_x} \right) \left( \frac{y_i - \bar{y}}{s_y} \right)$$

$$\begin{aligned} r &= \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{(\sum_{i=1}^n (x_i - \bar{x})^2)(\sum_{i=1}^n (y_i - \bar{y})^2)}} \\ &= \frac{1}{n-1} \cdot \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{s_x s_y} \end{aligned}$$

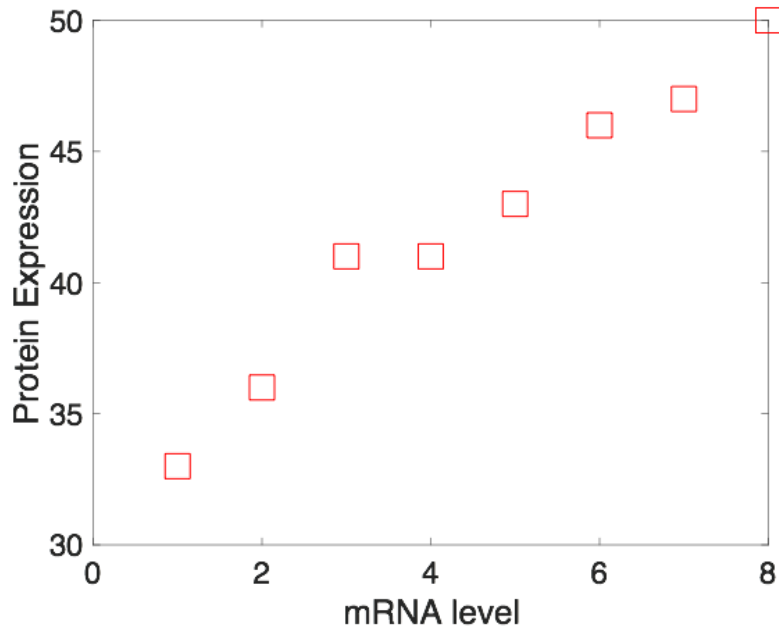
close to  $n-1$  if  $x$  and  $y$  have

$\bar{x}$  = the sample mean of  $x_1, \dots, x_n$ ,

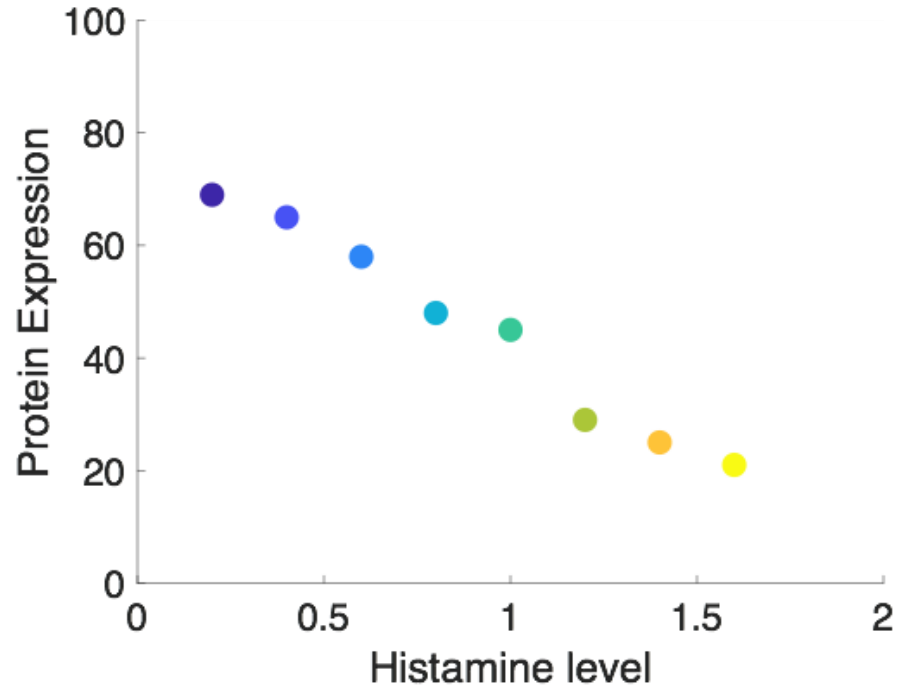
$\bar{y}$  = the sample mean of  $y_1, \dots, y_n$ ,

$s_x$  = the standard deviation of  $x_1, \dots, x_n$ ,

$s_y$  = the standard deviation of  $y_1, \dots, y_n$ .



$r=+0.9538$



$r=-0.987$

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 ~ 1 + x1
```

Estimated Coefficients:

|                    | <u>Estimate</u> | <u>SE</u> | <u>tStat</u> | <u>pValue</u> |
|--------------------|-----------------|-----------|--------------|---------------|
| <b>(Intercept)</b> | 42.933          | 2.1767    | 19.724       | 4.544e-08     |
| <b>x1</b>          | 3.2303          | 0.35081   | 9.2082       | 1.5659e-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 = 1.57e-05

```
fx >>
```

```
[co,S]=polyfit(hist,genetrial,1)
```

```
co =
```

```
3.2303 42.9333
```

```
S =
```

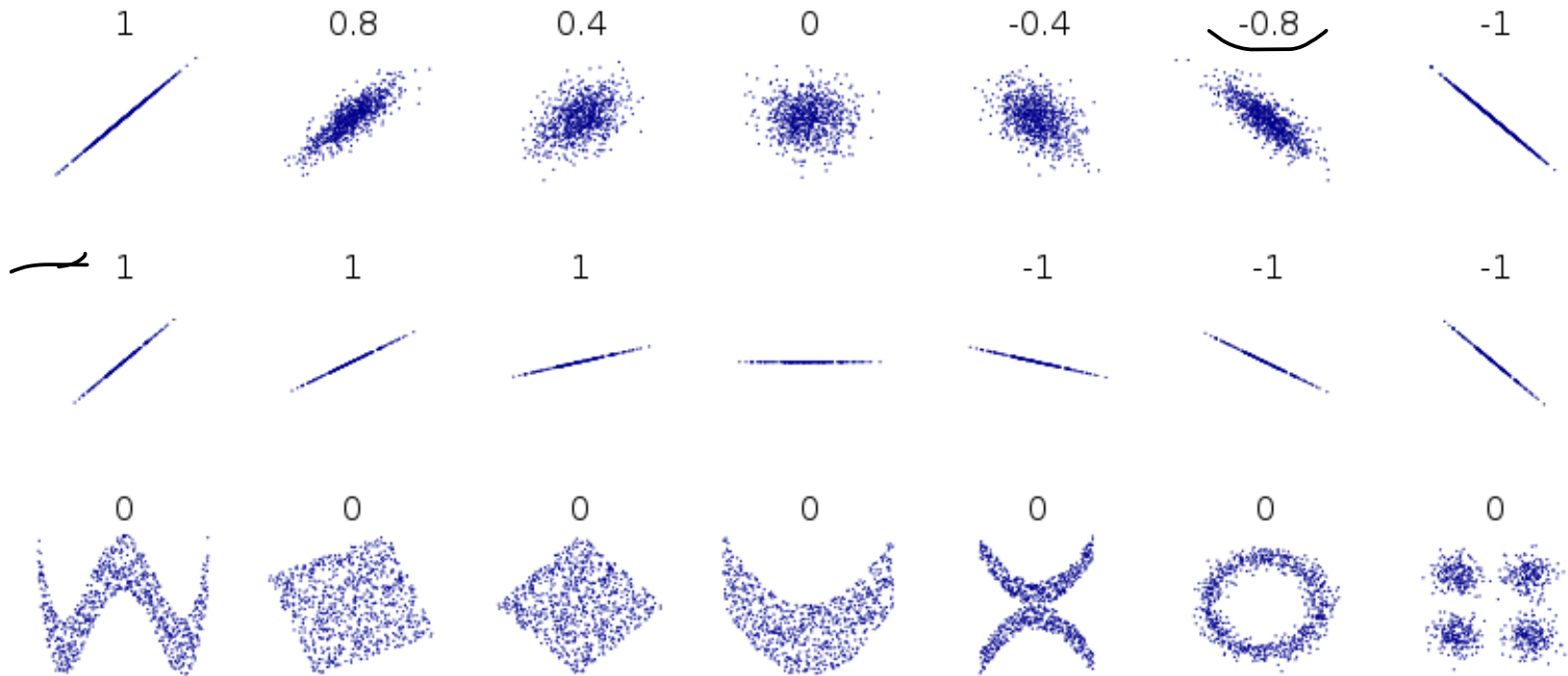
```
struct with fields:
```

```
R: [2x2 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

## Summary of Correlation between two variables

- $-1 \leq r \leq 1$  always
- $r = 1$  when all the points  $(x_i, y_i)$  lie on a line with positive slope
- $r = -1$  when all the points  $(x_i, y_i)$  lie on a line with negative slope
- When  $r = 0$ , then there is no positive or negative linear association between the two variables (though the two variables may have a non-linear relationship).

How to find a best fit line? how do you know if these coefficients are right? What does software magically return the coefficients?

Data parameters

Equation

$$y=ax+b+e$$

x = independent variable

y = dependent variable (maybe not dependent who knows)

b = intercept

a = slope

e = error

## $r^2$ 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  $x$ .

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

### Properties of $r^2$

$$0 \leq r^2 \leq 1$$

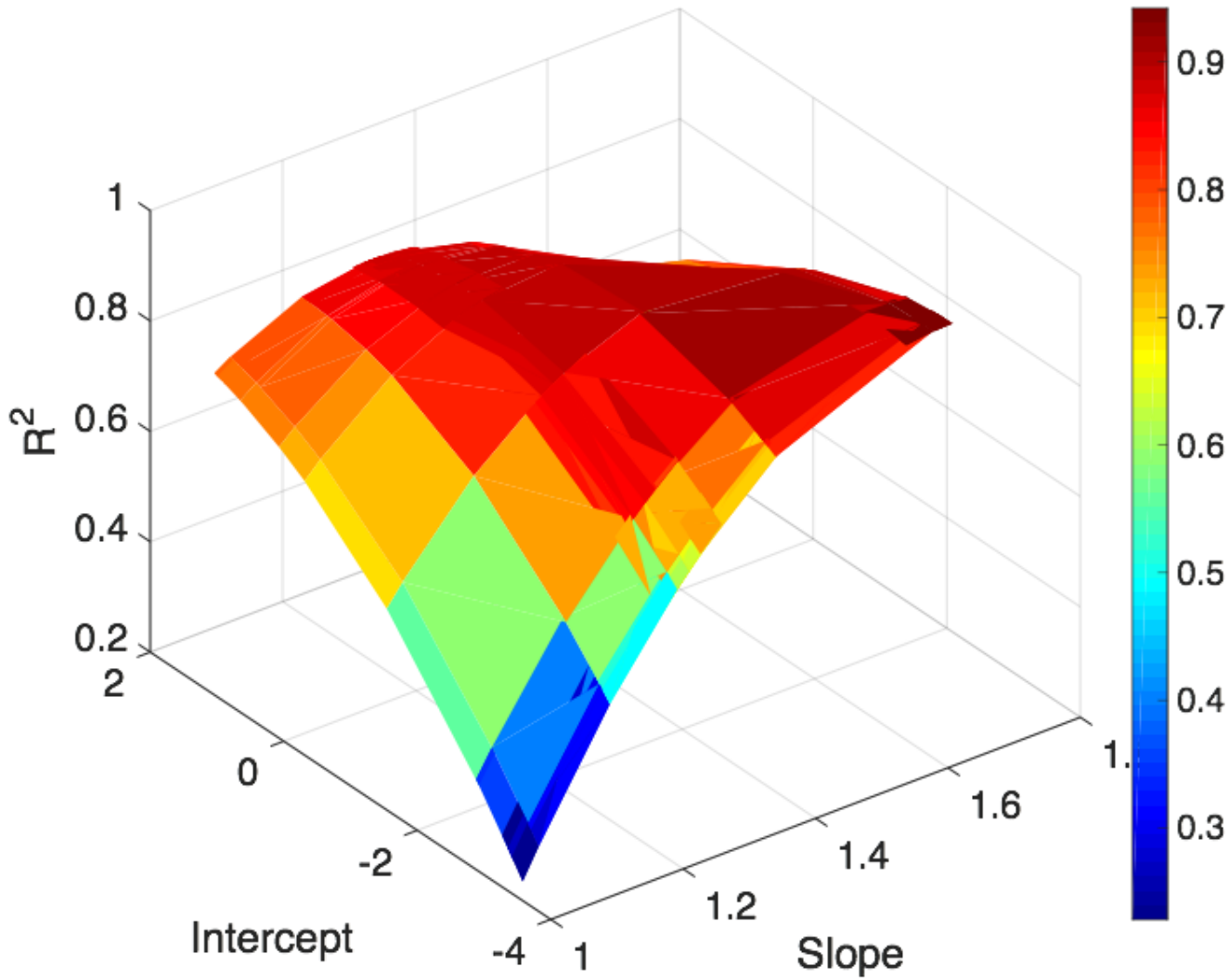
if  $r^2 = 1$ , it represents a straight line

if  $r^2 = 0$ , it indicates no correlation between  $y$  and  $x$

Larger the  $r^2$  means higher correlation, but not always

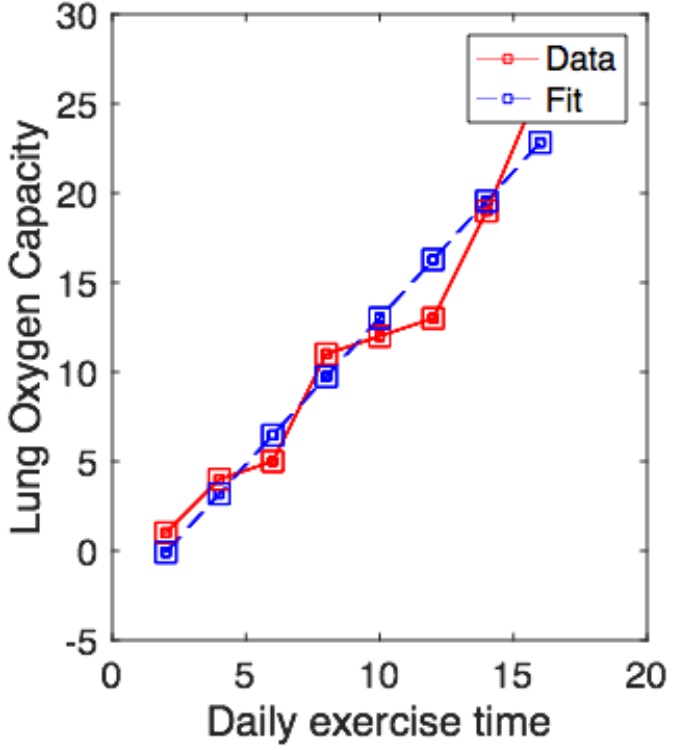
R2 gets smaller by the size of

Slope = 1.63  
Intercept = -3.35



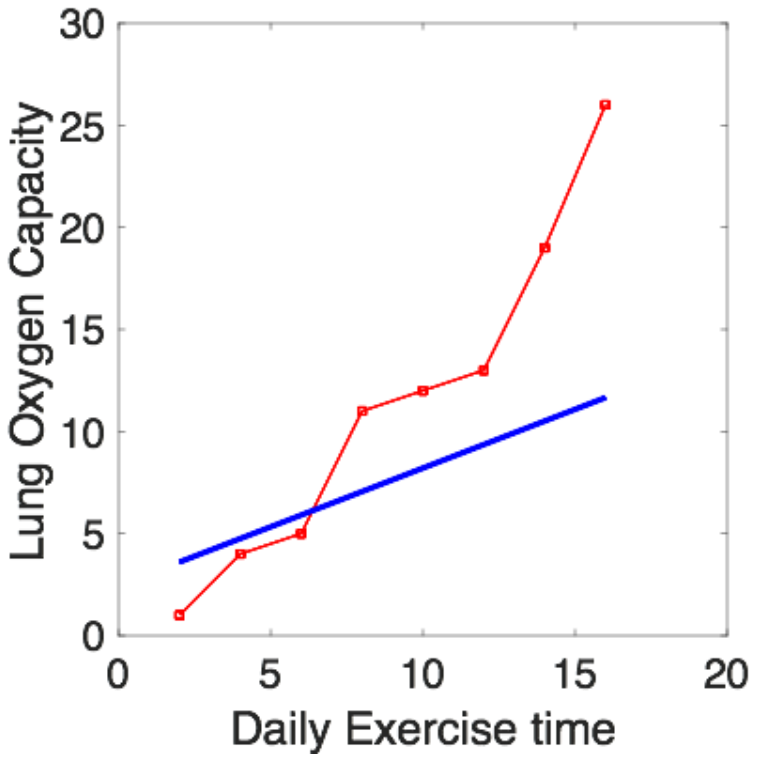
# Compare data fittings

## Perfect Fit



$R^2=0.94$

Slope = 1.63  
Intercept = -3.35

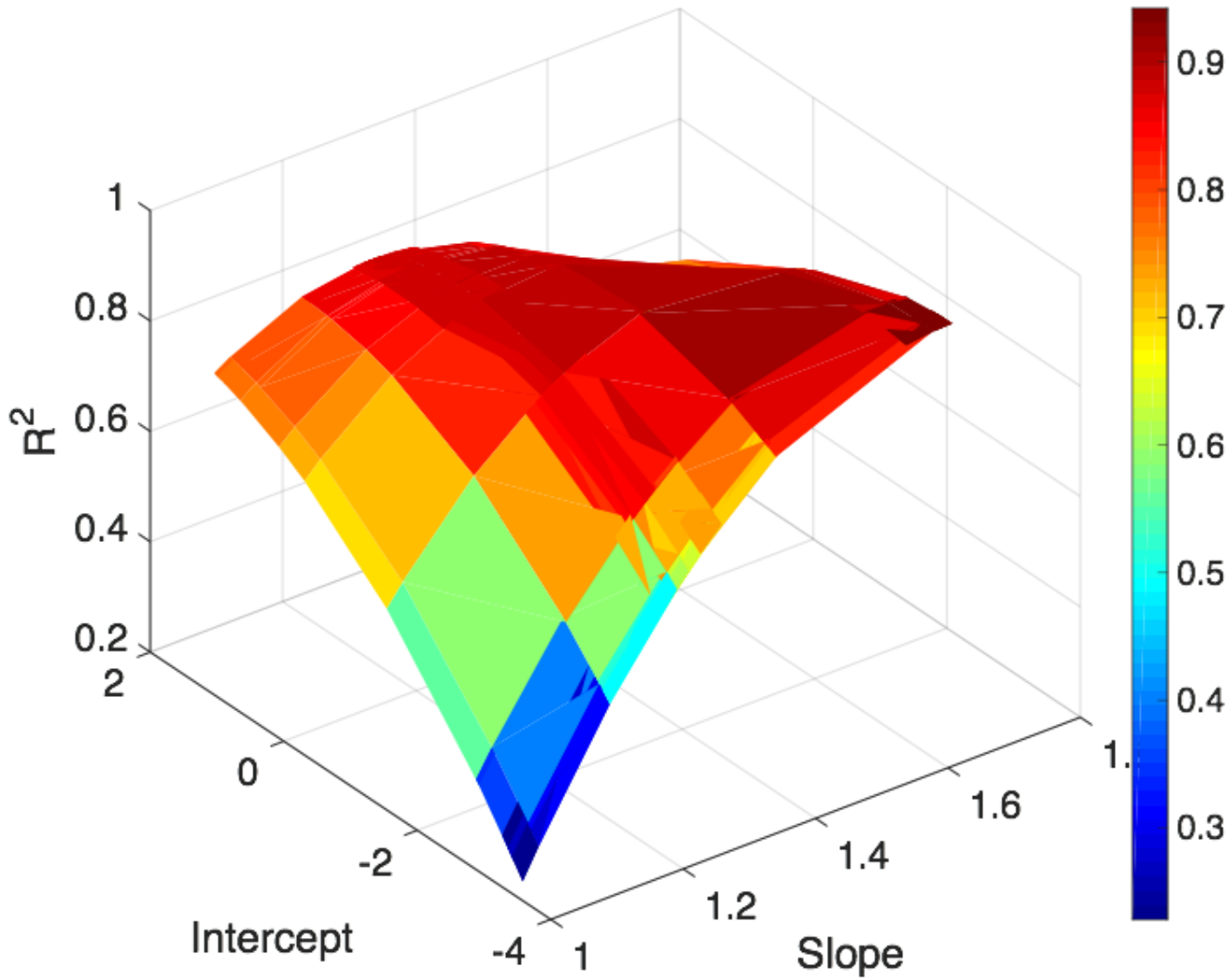


$R^2=0.77$

Slope = 0.57  
Intercept = 2.45

R2 gets smaller by the size of

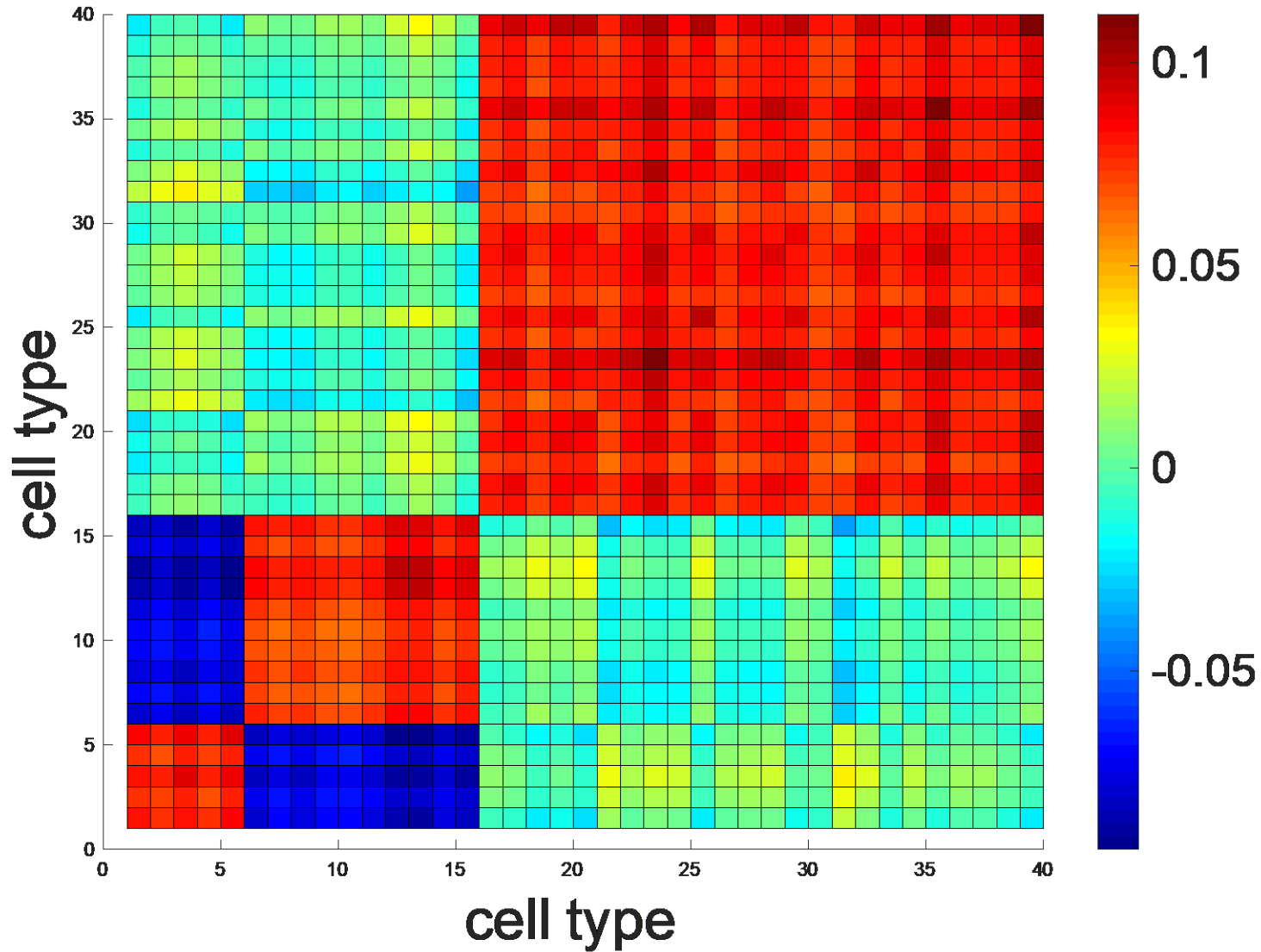
Slope = 1.63  
Intercept = -3.35



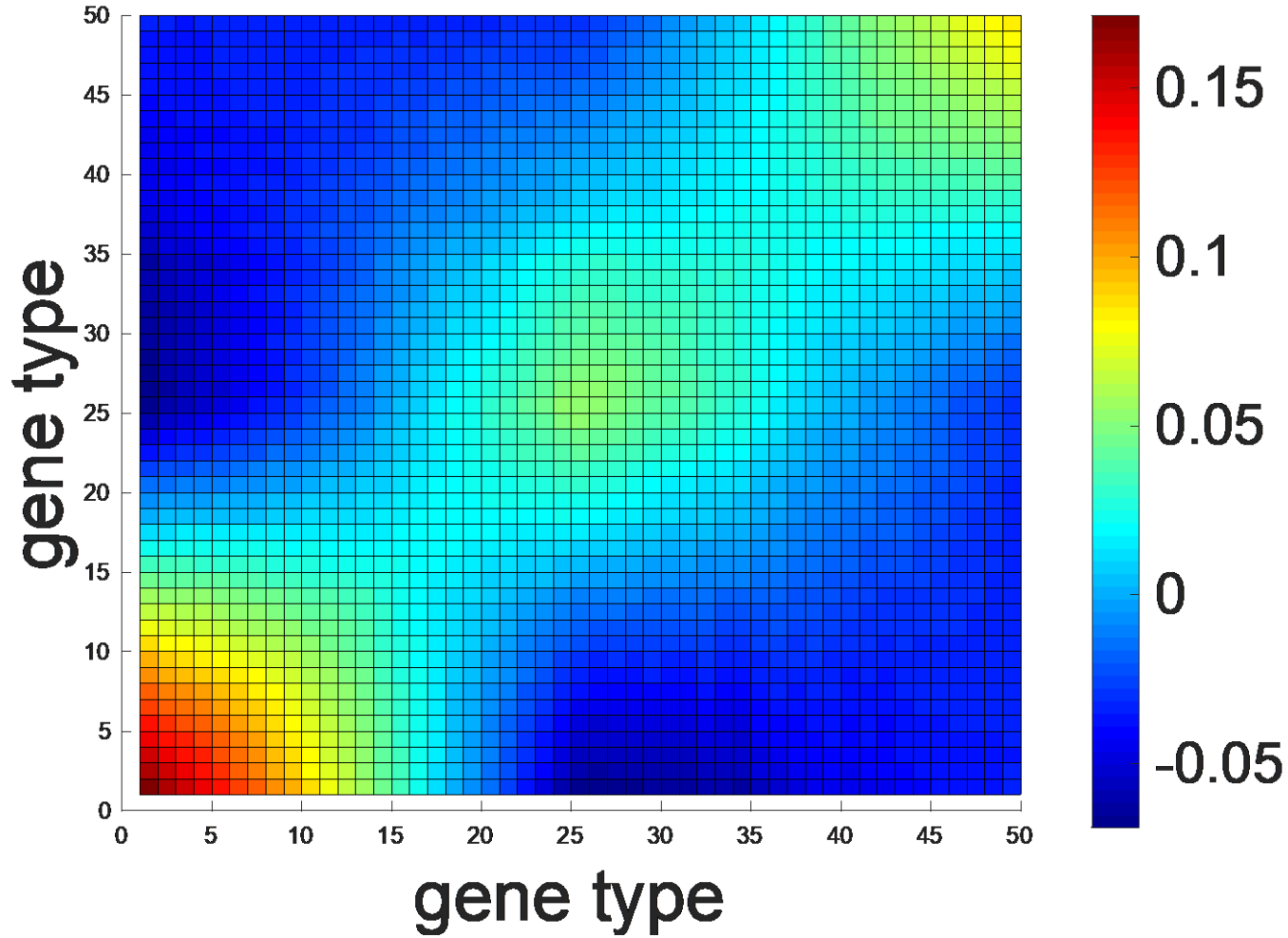




What is the covariance between different cell types?

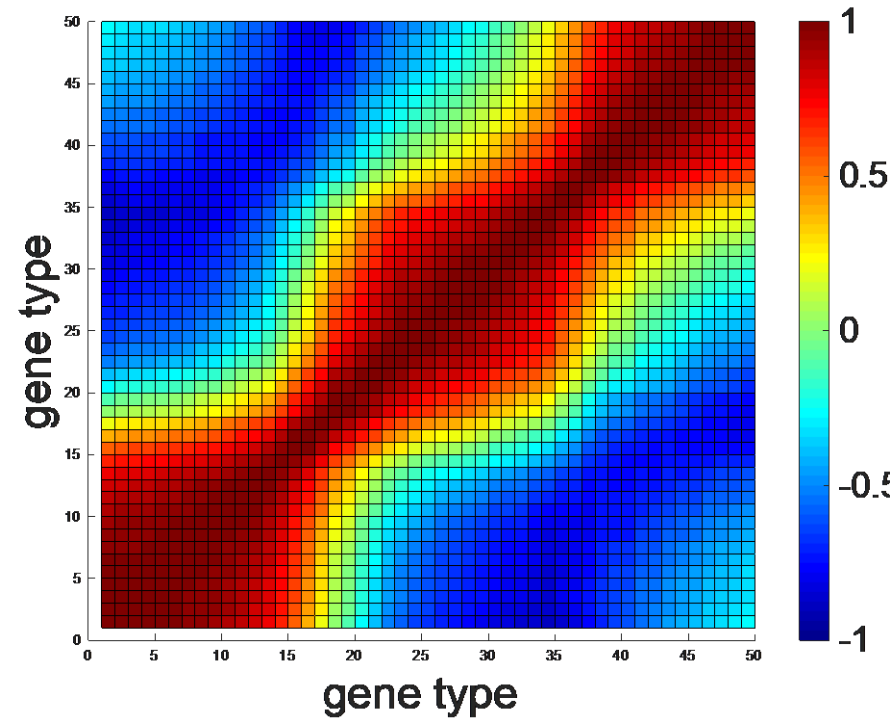
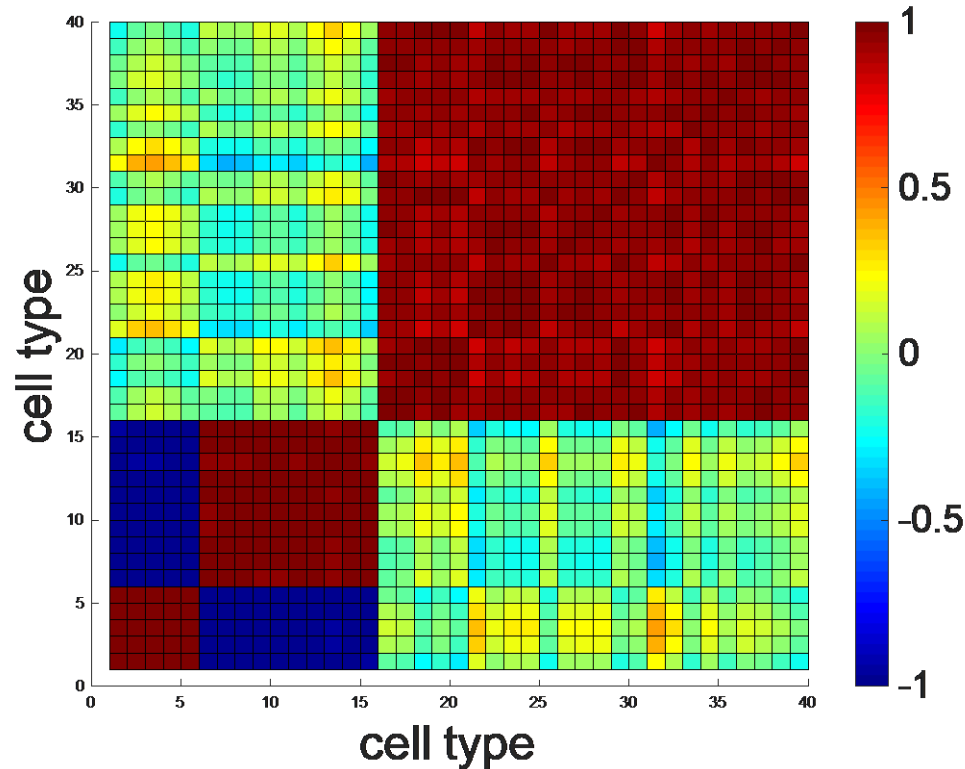


What is the covariance between different genes?



## Correlation of difference cell types

Liver cells, kidney cells and neurons



Correlation ranges from -1 to 1  
Covariance can be any number

Covariance returns the direction of relation while the correlation returns the strength of relationship

## 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

$$Y = \text{constant } (a) + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \dots + \beta_k x_n$$

It is also called as population regression equation.

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

## MULTIVARIATE REGRESSION

- $y$  - dependent variable or also called response variable
- $x_1, x_2, x_3 \dots, x_n$  are called independent variables

or explanatory variables.

- $X$  values can either quantitative or categorical.

$$Y = \text{constant (a)} + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \dots + \beta_k x_n$$

**The statistical model for multiple linear regression is**

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i$$

for  $i = 1, 2, \dots, n$ .

∪

Parameter coefficients of the model are  $\beta_0, \beta_1, \beta_2, \dots, \beta_p$ , and  $\sigma$ .

For the  $i$ th observation, the predicted response is

$$\hat{y}_i = b_0 + b_1 x_{i1} + b_2 x_{i2} + \cdots + b_p x_{ip}$$

$e_i = \text{observed response} - \text{predicted response} = y_i - \hat{y}_i$

$$= y_i - b_0 - b_1 x_{i1} - b_2 x_{i2} - \cdots - b_p x_{ip}$$

# Examples of multivariate regression

1. Dependence of fuel consumption in cars to horsepower, acceleration and weight (engineering)
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 education, age, gender, family income etc. (social science)

In Matlab

```
mdl = fitlm(X,Y)
```



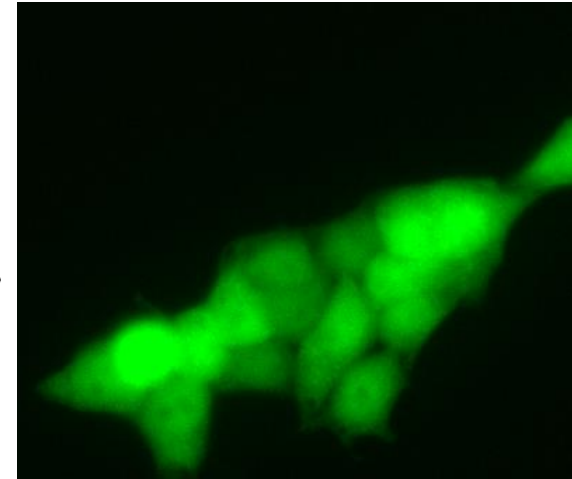
# Dependence of cell growth to expression of geneX, geneY and geneZ

Linear regression model:

$$\underline{y} \sim 1 + x1 + x2 + x3$$

Estimated Coefficients:

|                    | <u>Estimate</u> | <u>SE</u> | <u>tStat</u> | <u>pValue</u> |
|--------------------|-----------------|-----------|--------------|---------------|
| <b>(Intercept)</b> | 47.153          | 26.499    | 1.7794       | 0.078342      |
| <b>x1</b>          | 0.28602         | 0.069679  | 4.1048       | 8.4971e-05    |
| <b>x2</b>          | -0.0033967      | 0.0047938 | -0.70856     | 0.48031       |
| <b>x3</b>          | -0.3098         | 0.071258  | -4.3476      | 3.4254e-05    |



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 = 4.52e-105

>>

$$\text{Cell growth} = 47 + 0.28\text{geneX} - 0.003\text{geneY} - 0.30\text{geneZ}$$

# 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 |   |
| 20 | 147 | 148 | 221 |   |
| 21 | 147 | 167 | 221 |   |
| 22 | 148 | 209 | 221 |   |
| 23 | 153 | 221 | 220 |   |
| 24 | 154 | 164 | 218 |   |
| 25 | 155 | 122 | 216 |   |
| 26 | 155 | 140 | 215 |   |
| 27 | 156 | 157 | 215 |   |

|    | 1  | 2 |
|----|----|---|
| 1  | 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

$$\text{Cell growth} = 47 + 0.28\text{geneX} - 0.003\text{geneY} - 0.30\text{geneZ}$$

$$\text{Cell growth} = 47 + 0.28\text{gene} - 0.3\text{geneZ}$$

$$\text{Cell growth} = 47 + 0.28(0.3) - 0.30(0.6)$$

# Logistic Regression

**NATIONAL CANCER INSTITUTE**

## GENETIC CHANGES AND CANCER

### HOW GENETIC INFORMATION CREATES PROTEINS

**DNA**  
DNA is a molecule in the cell nucleus that contains instructions for making proteins. It is made of four different bases: adenine (A), thymine (T), guanine (G), and cytosine (C). A segment of DNA that contains the information for making a protein is called a gene. In the process of **transcription**, DNA that makes up a gene is copied into a complementary molecule called messenger RNA (mRNA).

**RNA**  
mRNA is also made of four bases: adenine (A), uracil (U), guanine (G), and cytosine (C). mRNA moves from the nucleus to the cytoplasm where it interacts with ribosomes, the protein factories of the cell. There, through a process called **translation**, mRNA is translated into amino acids. A sequence of three mRNA bases is called a **codon**, and each codon is translated into a specific amino acid. There are 20 different kinds of amino acids in humans.

**PROTEIN**  
As an mRNA molecule is translated, a chain of amino acids is formed. The chain eventually folds into a three-dimensional protein. The shape of a protein determines its function. Proteins have millions of functions in cells.

**Types of Genetic Mutations in Cancer**

DNA alterations can affect the structure, function, and amount of the corresponding proteins. All of these effects can change a cell's behavior from normal to cancerous. For example, a genetic alteration can intensify or eliminate the protein's function, which could make cells divide uncontrollably. Many different kinds of genetic mutations are found in cancer cells, including missense, nonsense, and frameshift mutations and chromosome rearrangements.

**MISSENSE MUTATION**

|          |           |             |          |             |
|----------|-----------|-------------|----------|-------------|
| Original | C T A     | D C G       | G P A    | DNA         |
|          | (Leucine) | (Threonine) | (Valine) | Amino Acids |
| Mutation | C T A     | D C G       | G P A    | DNA         |
|          | (Leucine) | (Cysteine)  | (Valine) | Amino Acids |

A missense mutation is a change of a single DNA base that results in a change in the amino acid sequence. Sometimes a single amino acid change can greatly alter the protein's function.

**NONSENSE MUTATION**

|          |           |             |          |             |
|----------|-----------|-------------|----------|-------------|
| Original | C T A     | D C G       | G P A    | DNA         |
|          | (Leucine) | (Threonine) | (Valine) | Amino Acids |
| Mutation | C T A     | D C G       | G P A    | DNA         |
|          | (Leucine) | (Stop)      | (Valine) | Amino Acids |

A nonsense mutation is a change of a single DNA base that creates a "stop" codon, which terminates translation. The result is a shortened protein that may not function or that may have an abnormal function.

**FRAMESHIFT MUTATION**

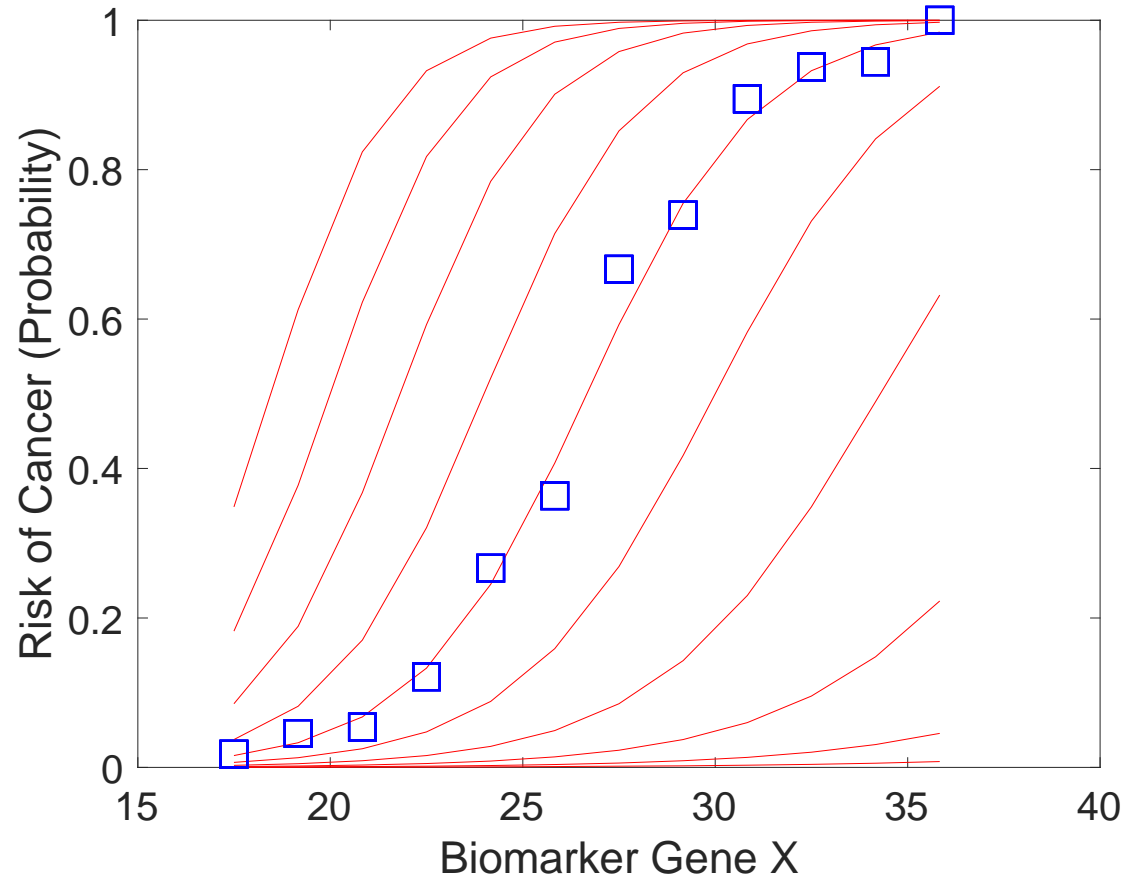
|          |           |             |          |             |
|----------|-----------|-------------|----------|-------------|
| Original | C T A     | D C G       | G P A    | DNA         |
|          | (Leucine) | (Threonine) | (Valine) | Amino Acids |
| Mutation | C T A     | A T C       | G P A    | DNA         |
|          | (Leucine) | (Istop)     | (Valine) | Amino Acids |

A frameshift mutation results from the addition or removal of DNA bases that shifts the DNA sequence and the corresponding amino acid sequence. The result is a protein whose sequence, structure, and function are very different from those of the original protein.

**CHROMOSOME REARRANGEMENTS**

DNA is wound tightly into structures called chromosomes. Chromosome rearrangements can occur when a piece of a chromosome breaks and is lost entirely (deletion), moves to a different chromosomal location (translocation), flips directions (inversions), or is repeated (duplication). These rearrangements can alter several genes at once. For example, they can generate fusion genes, in which parts of two separate genes are joined together. Proteins made from fusion genes sometimes cause cancer.

[cancer.gov/genetics](http://cancer.gov/genetics)



## What is 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**

## Logistic Regression

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.

$$P(Y=1|\beta) = \frac{\exp(b(1)+b(2)x)}{1+\exp(b(1)+b(2)x)}$$

x= binary or cont

y= binary

b(1) and b(2) are coefficients

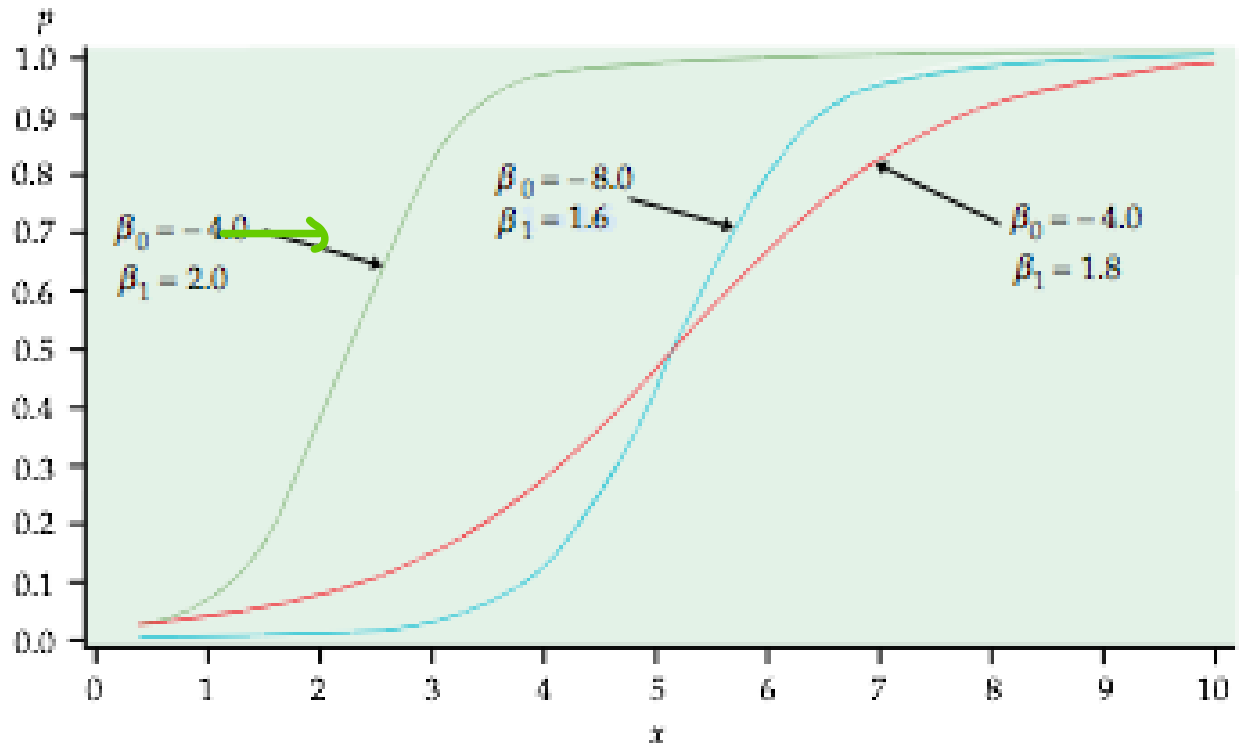
if y response variable is discrete

Y = P(Y=0) + P(Y=1)

Logistic function

it can be defined as

$f(x) = \frac{\exp(x)}{1 + \exp(x)}$

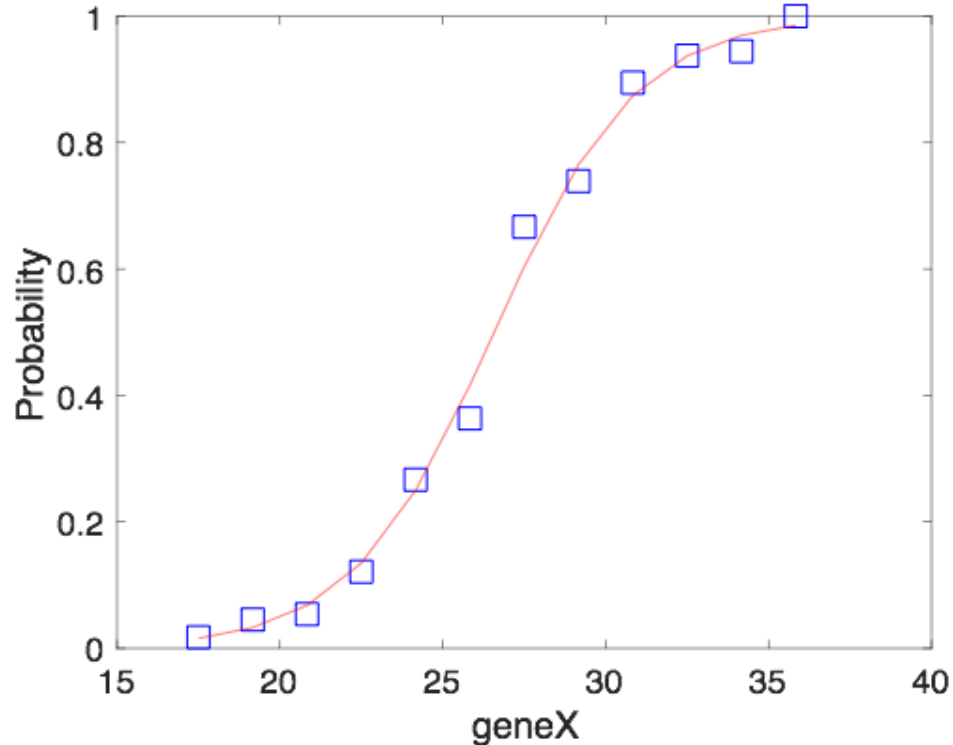


f(x) or y values always falls in range between 0 and 1

## 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 = [2180 2450 2640 2730 3100 3120 3320 3610 3800
% The number of patients tested at each levels (intervals)
tested = [57 44 37 33 30 22 21 23 19 16 18 21]';
% The number of cancer patients at each test
cancer = [1 2 2 4 8 8 14 17 17 15 17 21]';

```

|   | 1        | 2 | 3 | 4 | 5 |
|---|----------|---|---|---|---|
| 1 | -12.6748 |   |   |   |   |
| 2 | 0.3867   |   |   |   |   |
| 3 |          |   |   |   |   |
| 4 |          |   |   |   |   |

```
%logistic regression
```

```

[logitCoef,dev,stats] = glmfit(geneX,[cancer tested],'binomial','logit');
logitFit = glmval(logitCoef,geneX,'logit');

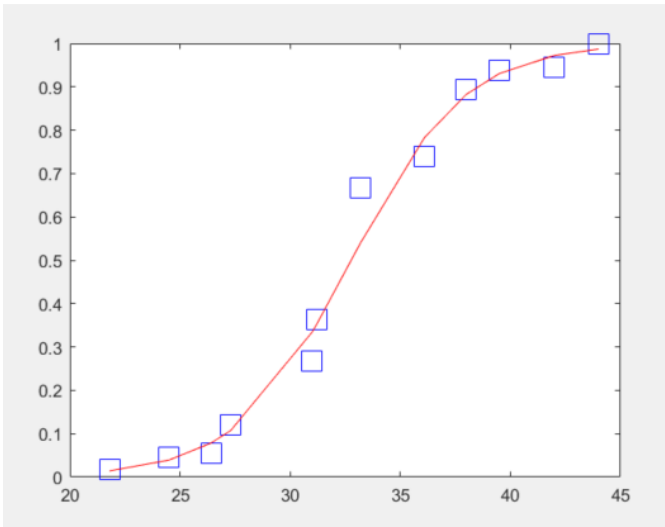
```

```

figure(3)
plot(geneX,proportion,'bs', geneX,logitFit,'r-','markersize',16);

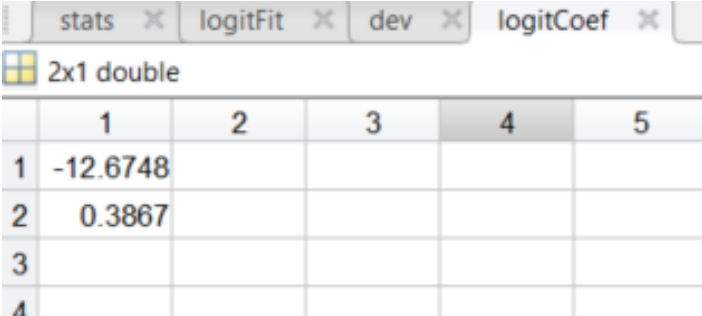
```

Glmval is uses to compute the predicted values for the model



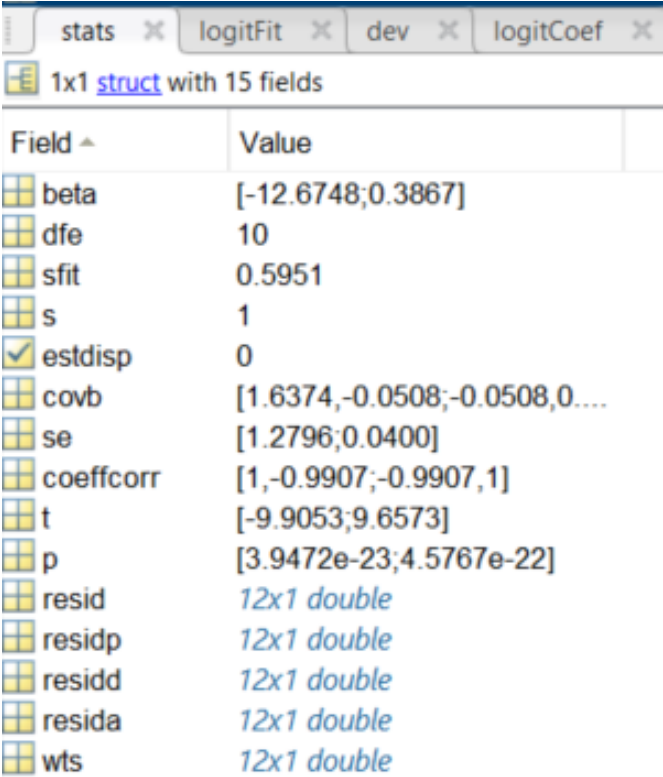
|    | 1      | 2 | 3 |
|----|--------|---|---|
| 1  | 0.0141 |   |   |
| 2  | 0.0391 |   |   |
| 3  | 0.0782 |   |   |
| 4  | 0.1073 |   |   |
| 5  | 0.3345 |   |   |
| 6  | 0.3519 |   |   |
| 7  | 0.5406 |   |   |
| 8  | 0.7831 |   |   |
| 9  | 0.8827 |   |   |
| 10 | 0.9308 |   |   |
| 11 | 0.9725 |   |   |
| 12 | 0.9871 |   |   |
| 13 |        |   |   |
| 14 |        |   |   |

# glmfit: Logistic model coefficients



A MATLAB window titled 'logitCoef' showing a 2x1 double matrix. The matrix has 4 rows and 5 columns. The first row contains the values -12.6748, 0.3867, and three empty cells. The second row contains three empty cells. The third and fourth rows are empty.

|   | 1        | 2 | 3 | 4 | 5 |
|---|----------|---|---|---|---|
| 1 | -12.6748 |   |   |   |   |
| 2 | 0.3867   |   |   |   |   |
| 3 |          |   |   |   |   |
| 4 |          |   |   |   |   |



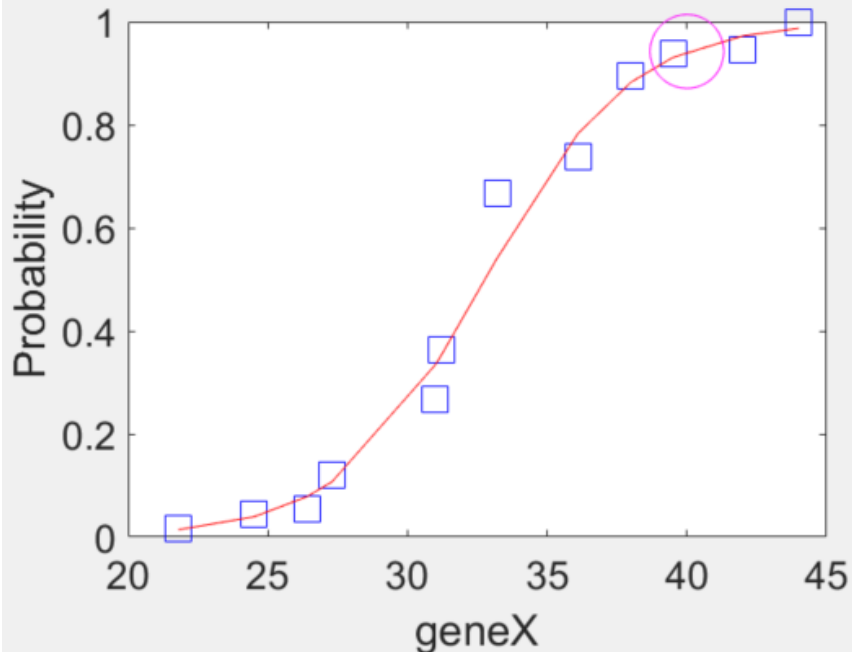
A MATLAB window titled 'logitFit' showing a 1x1 struct with 15 fields. The fields and their values are listed in a table below.

| Field ^                                     | Value                         |
|---|-------------------------------|
| beta  | [-12.6748;0.3867]             |
| dfc   | 10                            |
| sfit  | 0.5951                        |
| s   | 1                             |
| <input checked="" type="checkbox"/> estdisp | 0                             |
| covb  | [1.6374,-0.0508;-0.0508,0.... |
| se  | [1.2796;0.0400]               |
| coeffcorr                                   | [1,-0.9907;-0.9907,1]         |
| t   | [-9.9053;9.6573]              |
| p   | [3.9472e-23;4.5767e-22]       |
| resid                                       | 12x1 double                   |
| residp                                      | 12x1 double                   |
| residd                                      | 12x1 double                   |
| resida                                      | 12x1 double                   |
| wts   | 12x1 double                   |

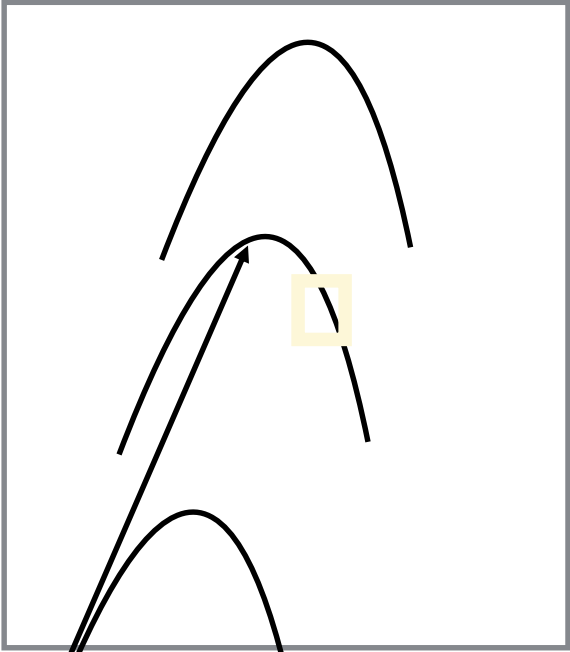
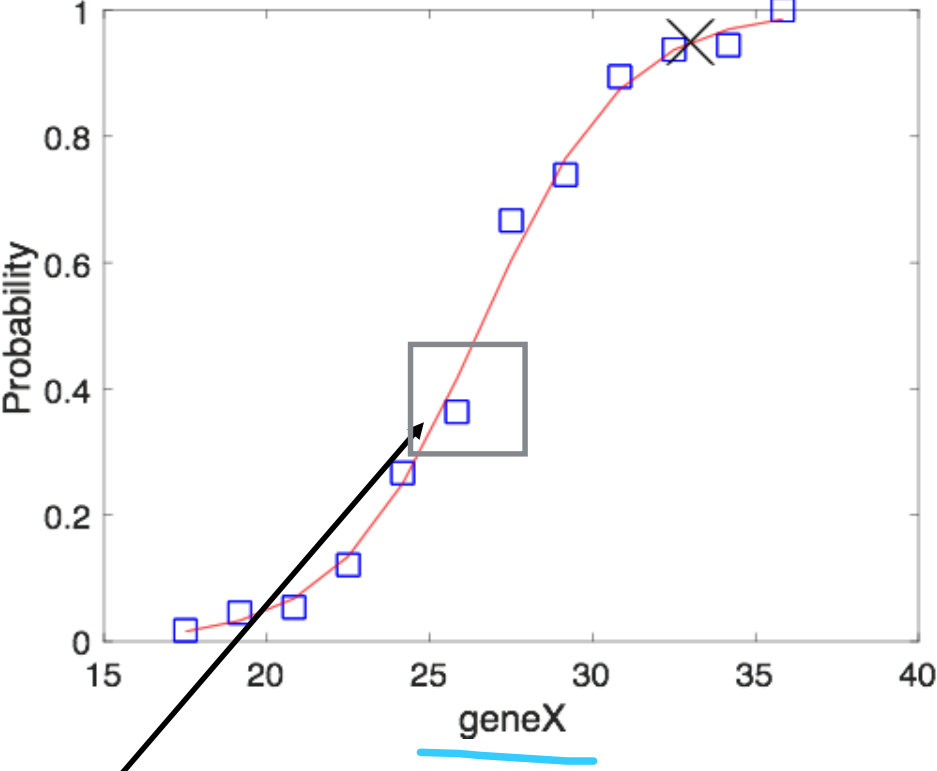
$$P(Y=1|\beta)= \exp(b(1)+b(2)x) / 1+\exp(b(1)+b(2)x)$$

```
% 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)+genepredict*logitCoef(2)))
% 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

$$\log(\text{odds}) = b_0 + b_1x = -12.12 + 0.45x$$

# The effect of coefficients on the shape of logistic model

