

2021

Basic statistical concepts for modelling

David Makowski

Key concepts

- Population
- Sample
- Estimator, estimate
- Bias and variance of an estimator
- Test
- Confidence interval
- Model

Population

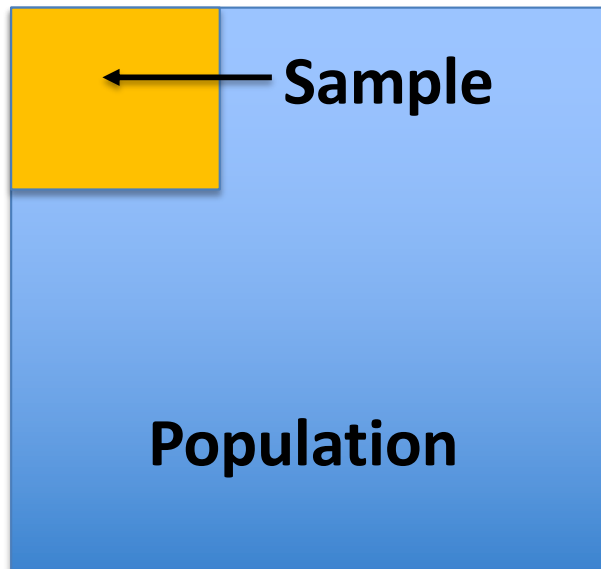
In statistics, a population is the entire pool from which a statistical sample is drawn.

A population may refer to an entire group of people, objects, events, hospital visits, or measurements.

www.investopedia.com/terms/p/population.asp

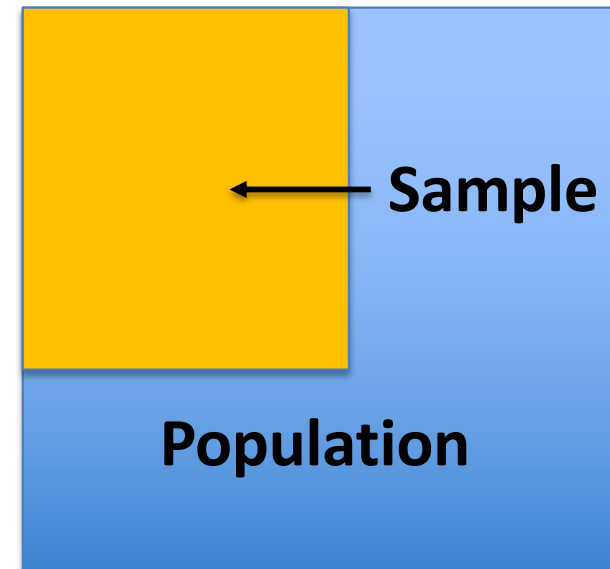
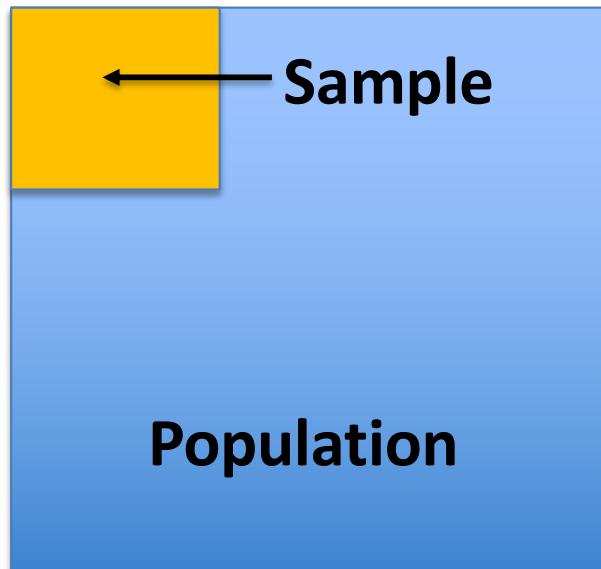
Sample

A part of a population used to estimate a characteristic of the population.



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Random sample

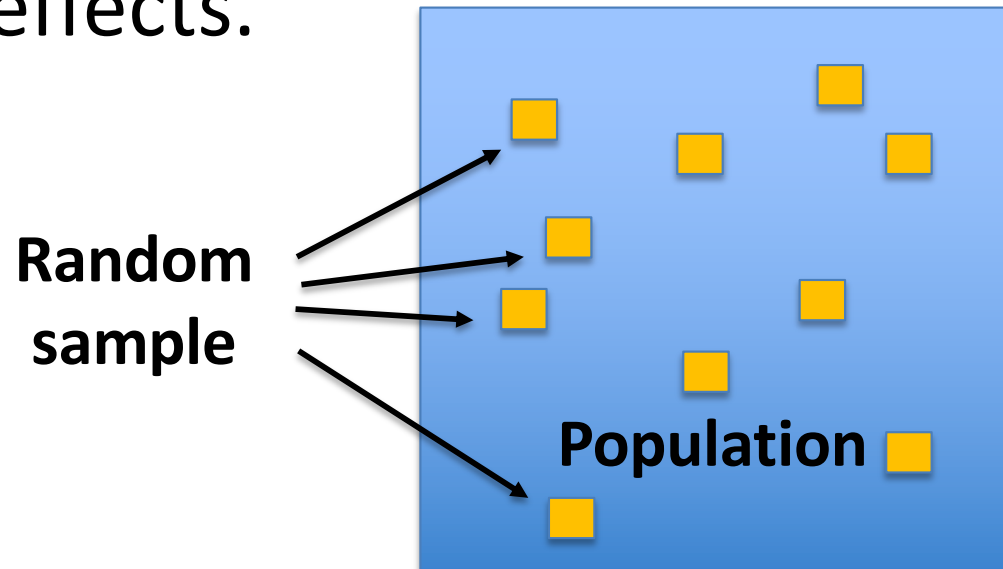
A random sample is a sample that is chosen randomly.

Random samples are used to avoid bias and other unwanted effects.

Random sample

A random sample is a sample that is chosen randomly.

Random samples are used to avoid bias and other unwanted effects.



Exercise

Consider the following series of numbers
1, 2, 3, 4,...,100

Generate 10 random samples of size 5 with the
R function `sample()`

Why a random sample?

Central Limit theorem

Abraham de Moivre (18th century)

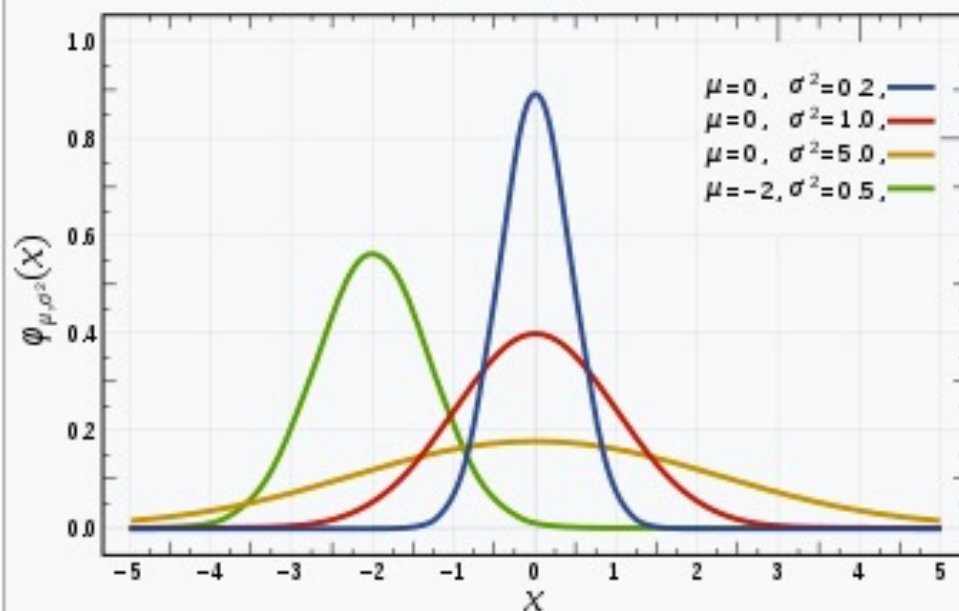
Pierre Simon Marquis de Laplace (19th century)

The distributions of the average of randomly chosen observations is closely approximated by a **normal distribution**

...even if the original observations themselves are not normally distributed.

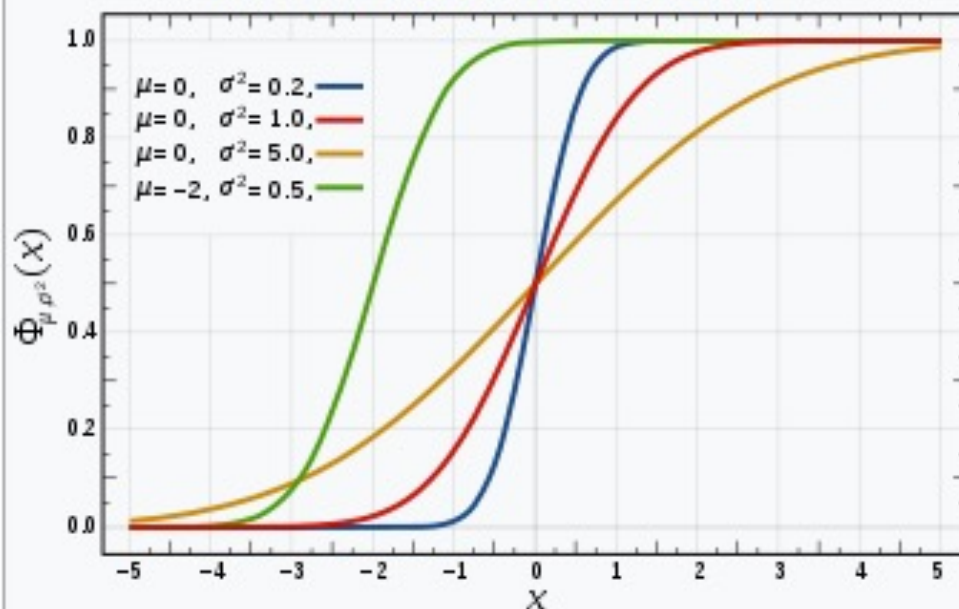
Normal Distribution

Probability density function



The red curve is the standard normal distribution

Cumulative distribution function



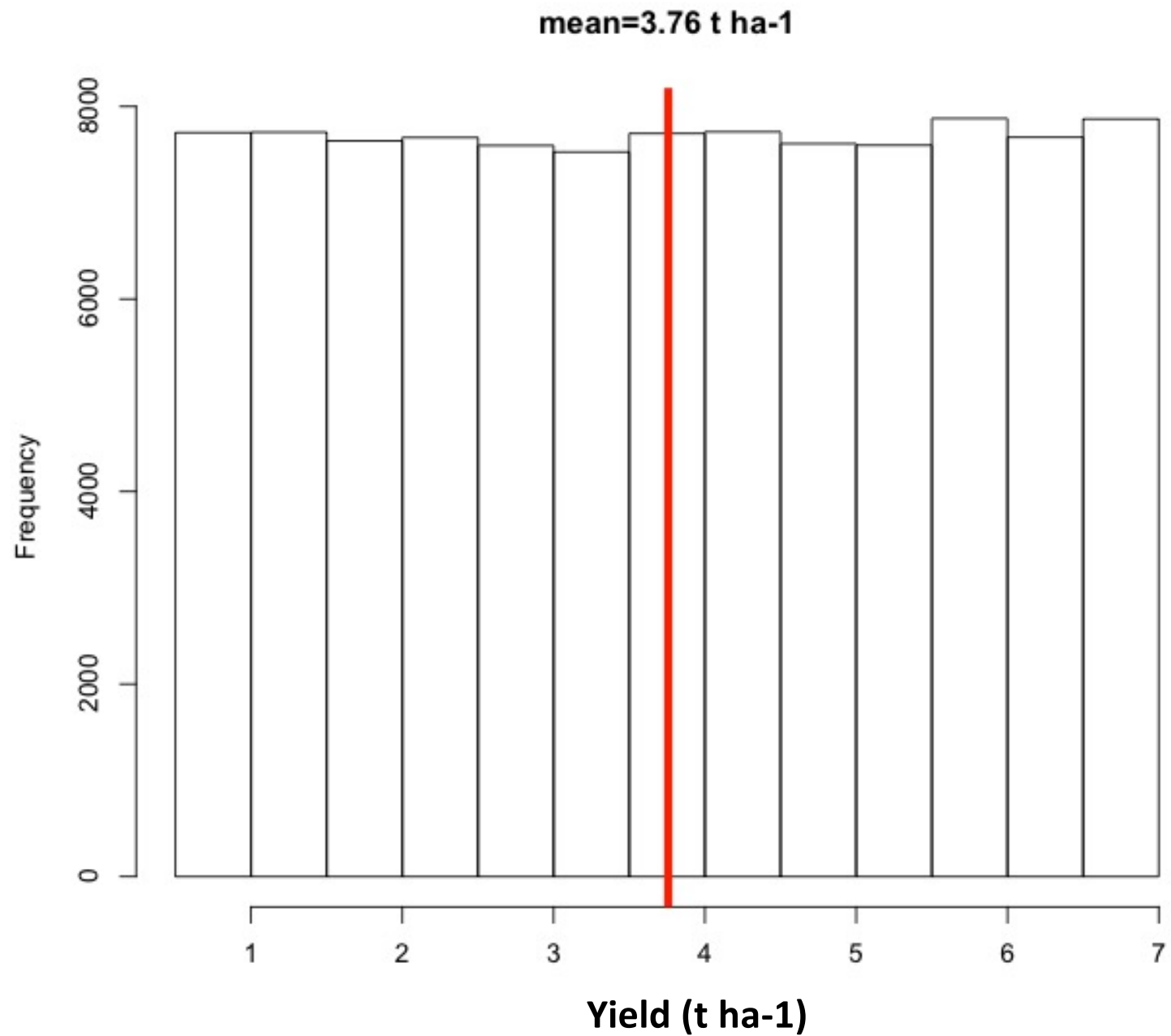
Notation	$\mathcal{N}(\mu, \sigma^2)$
Parameters	$\mu \in \mathbb{R}$ = mean (location) $\sigma^2 > 0$ = variance (squared scale)
Support	$x \in \mathbb{R}$
PDF	$\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

Central Limit theorem

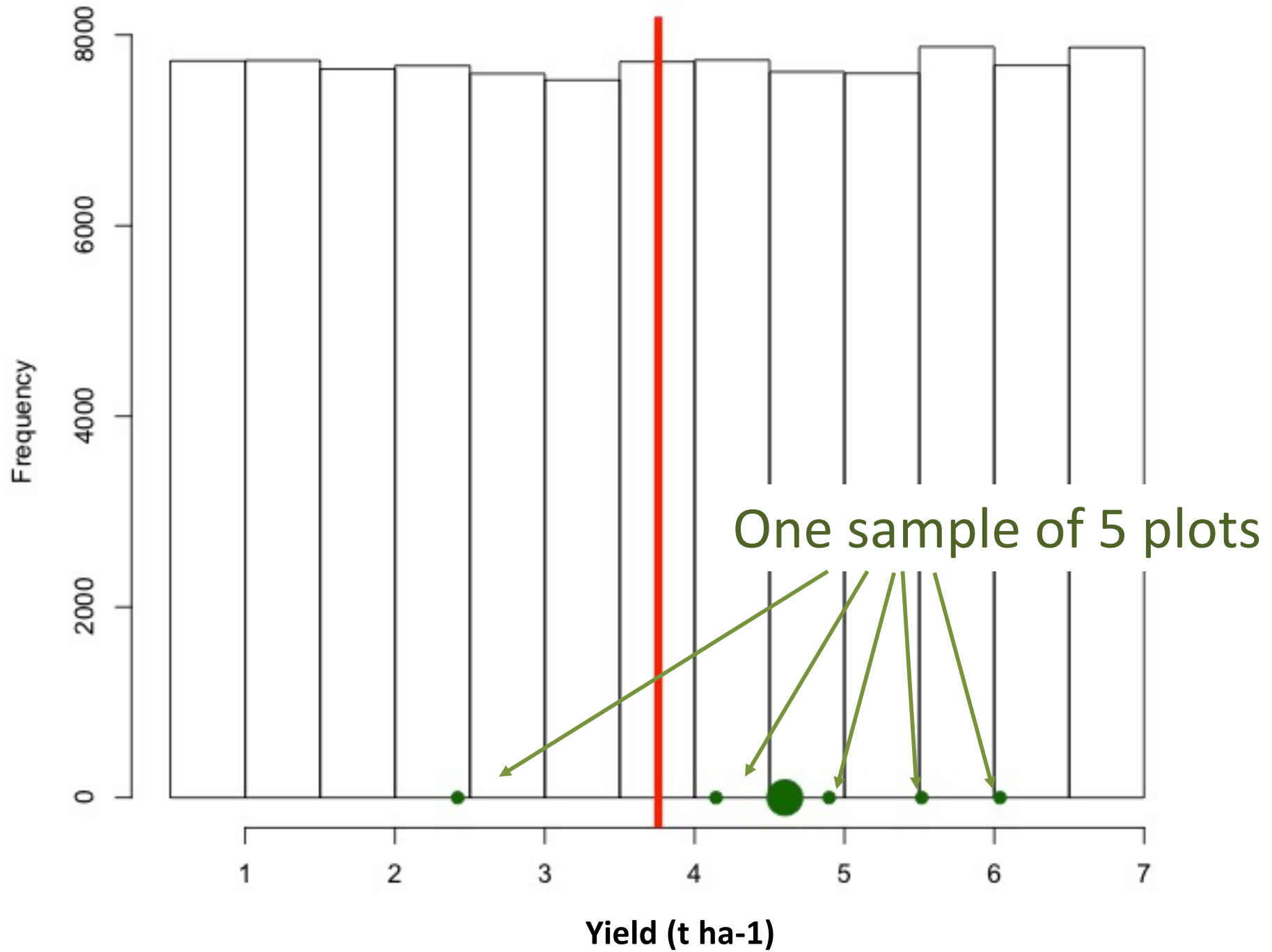
The distributions of the average of randomly chosen observations is closely approximated by a **normal distribution**

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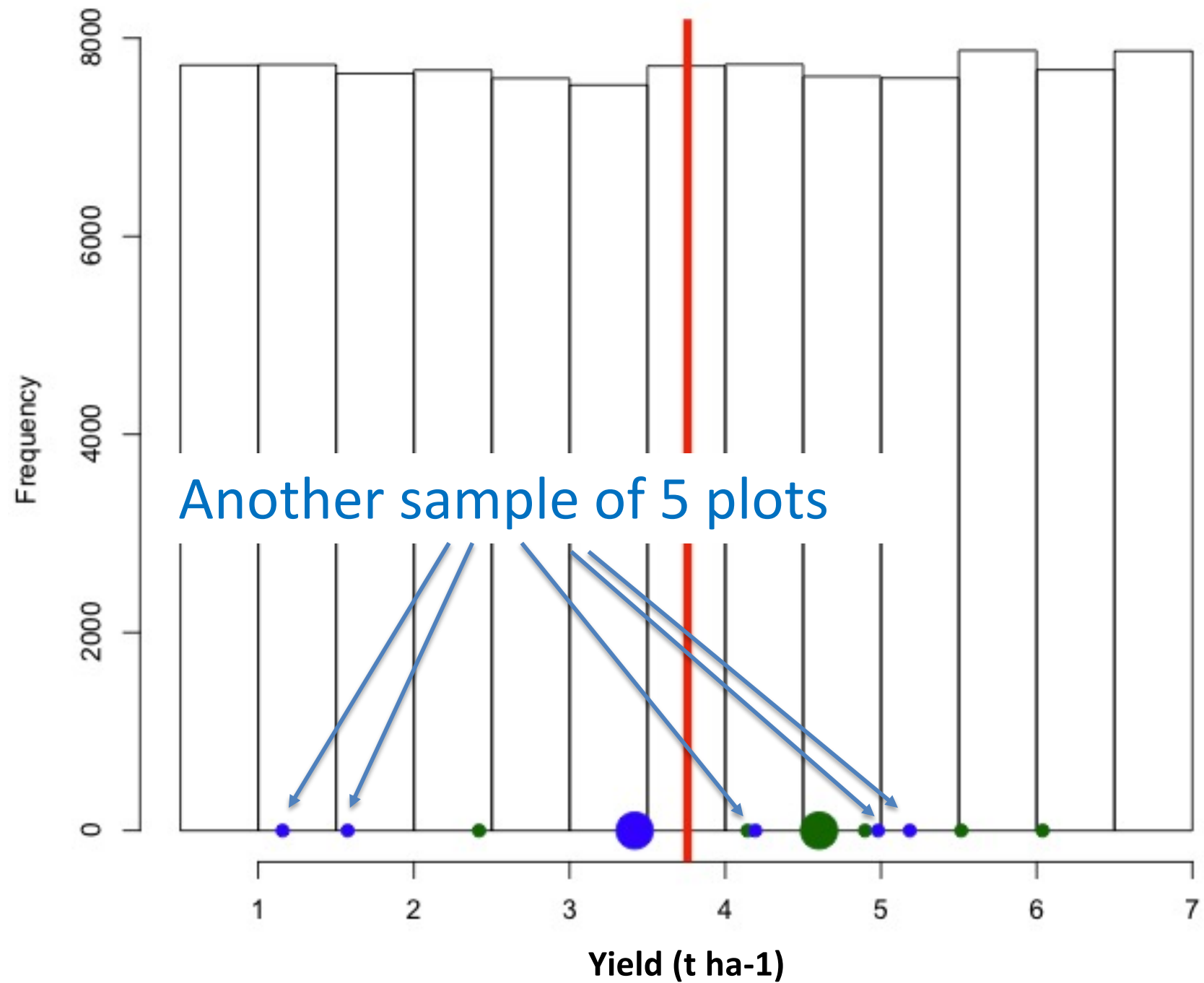
Population = 100,000 wheat plots

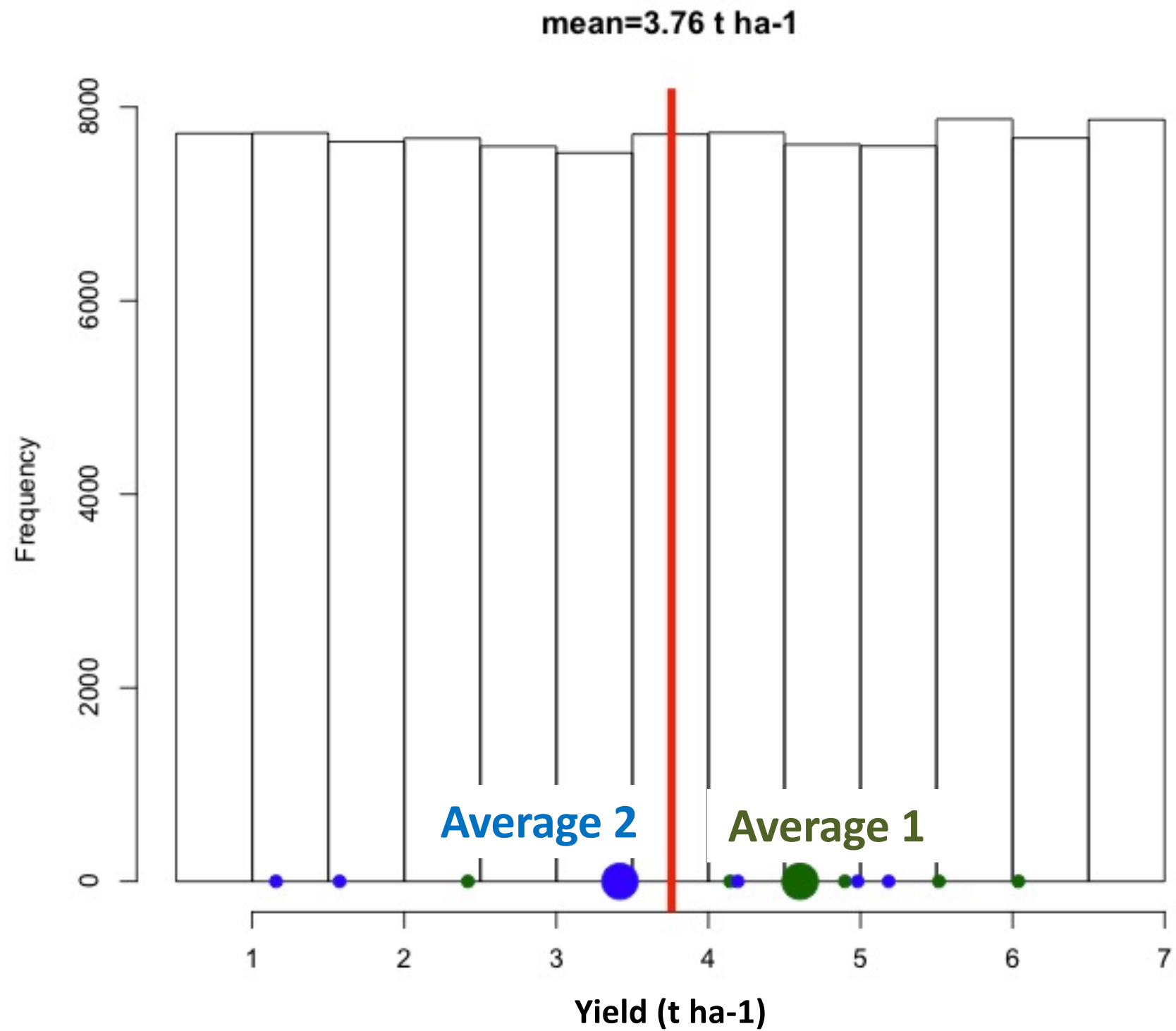


mean=3.76 t ha⁻¹

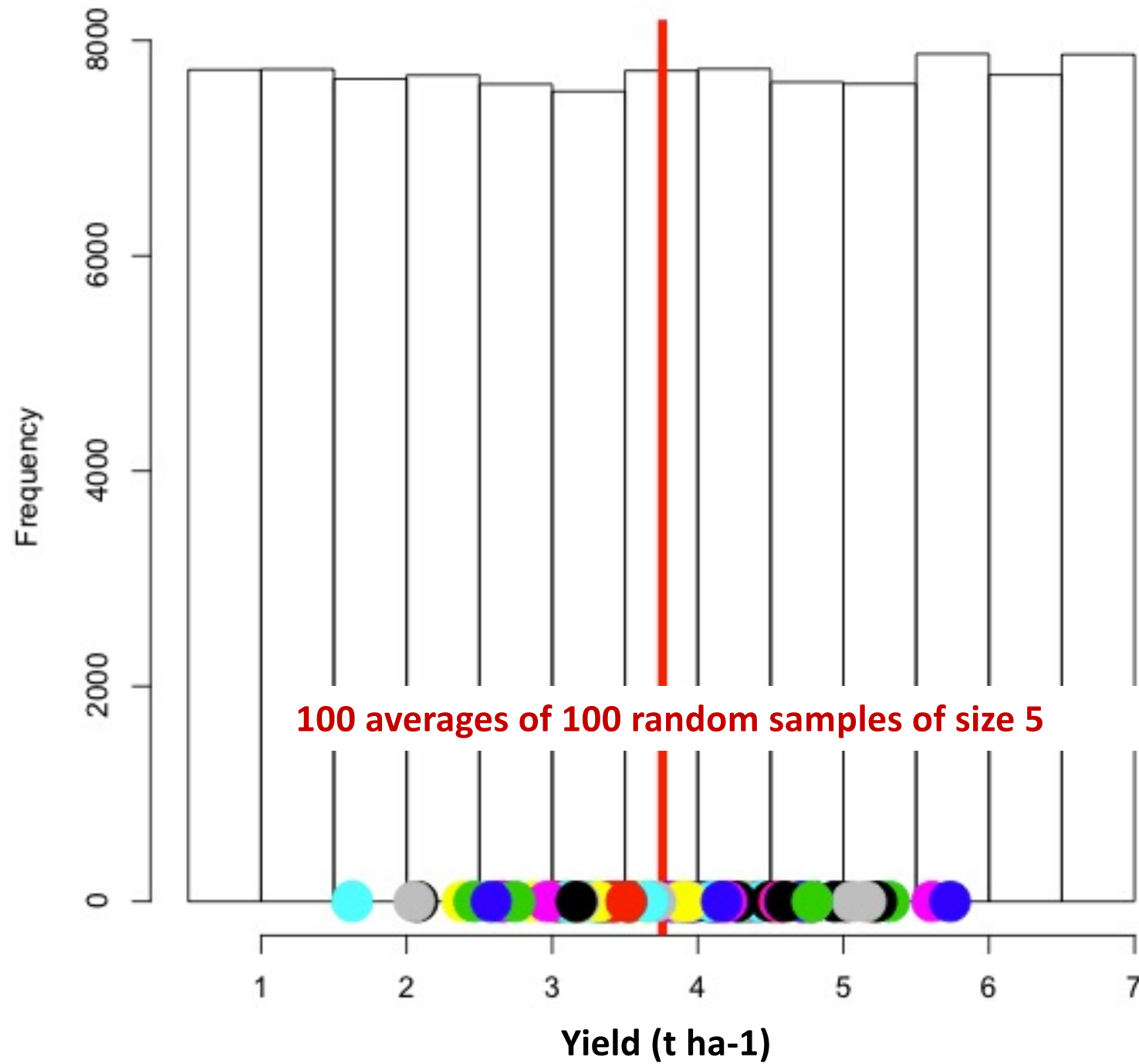


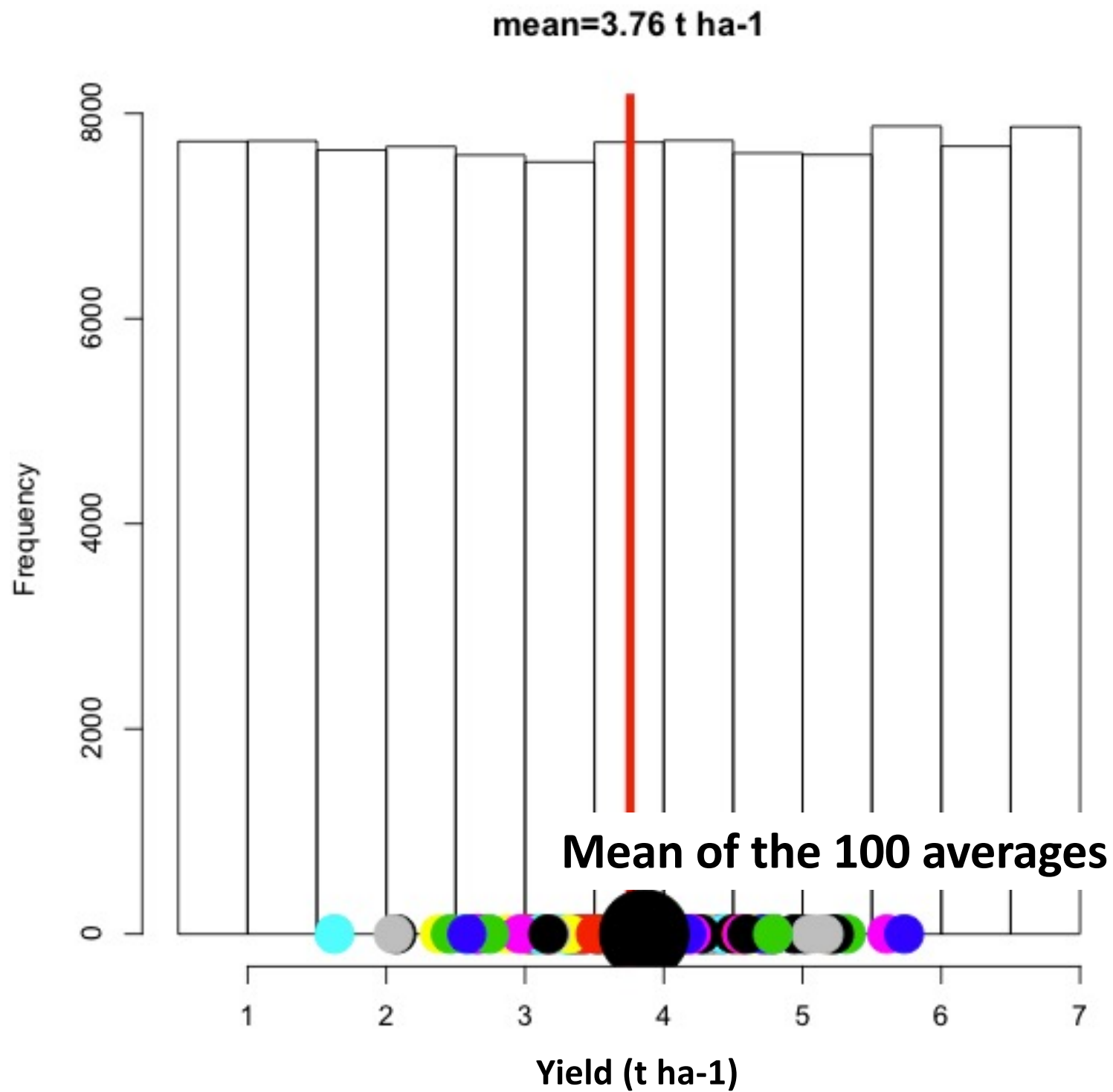
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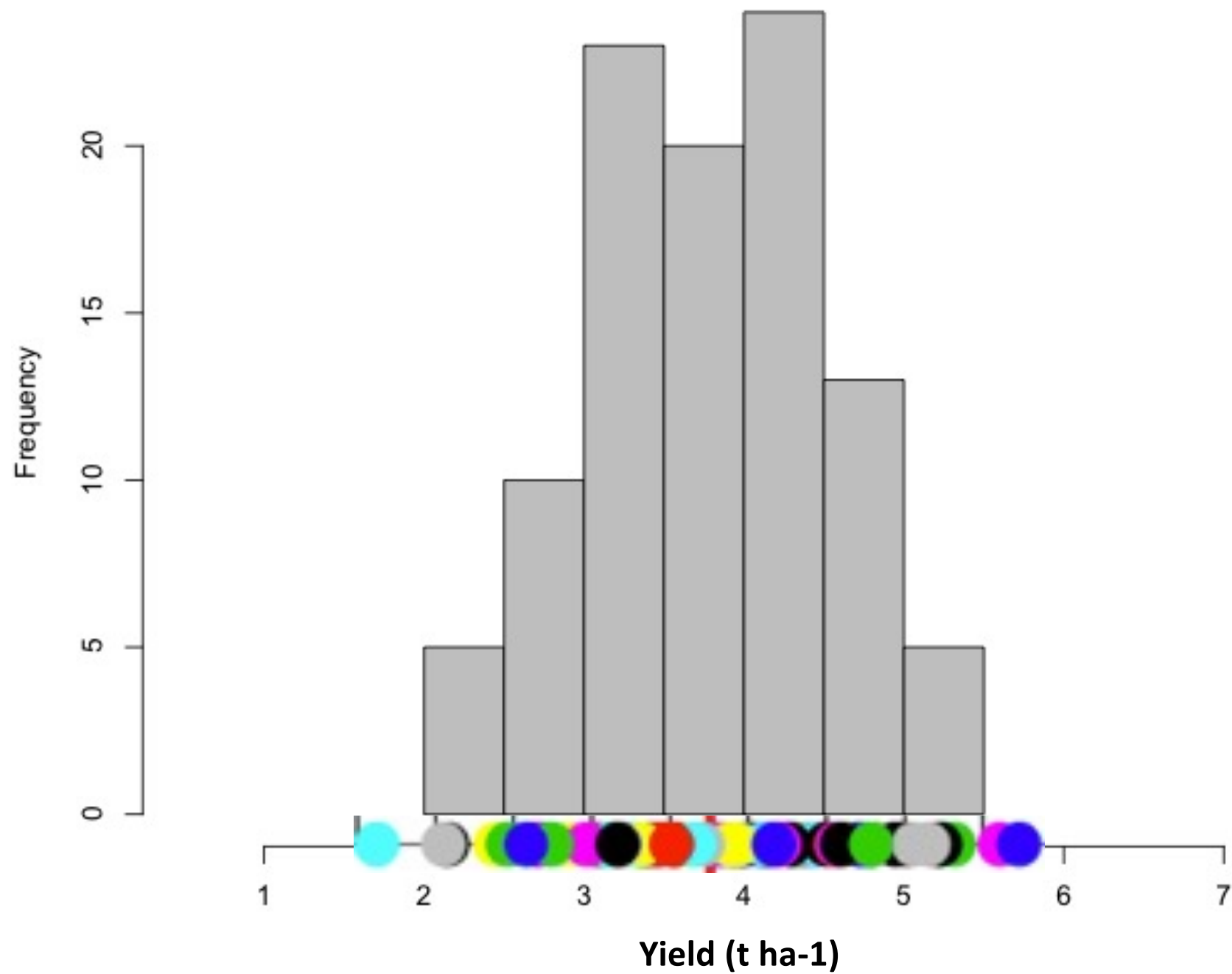


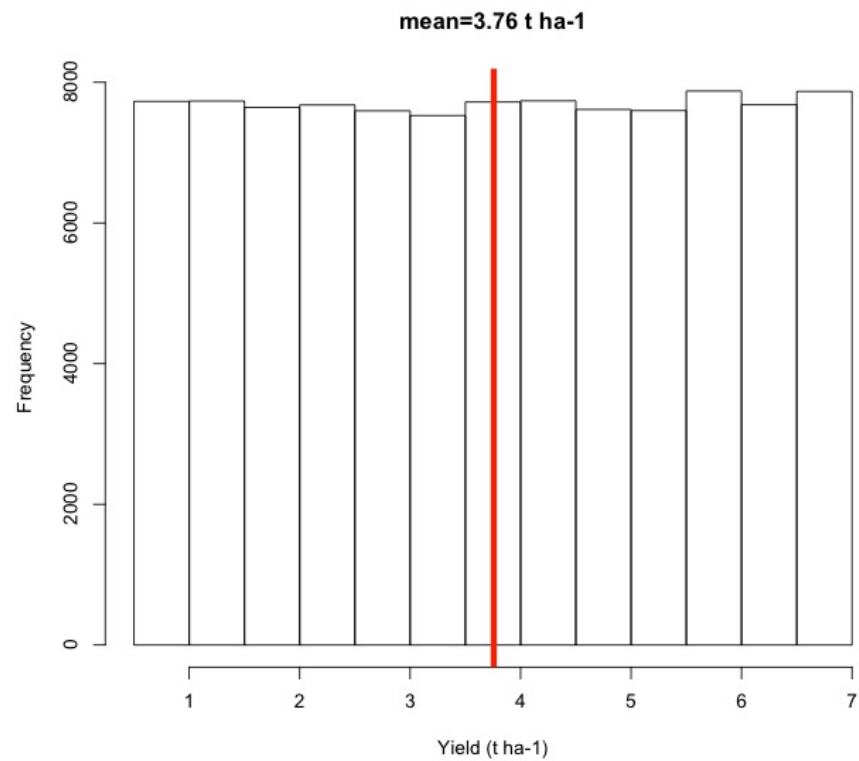
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100 averages of 100 samples of size 5

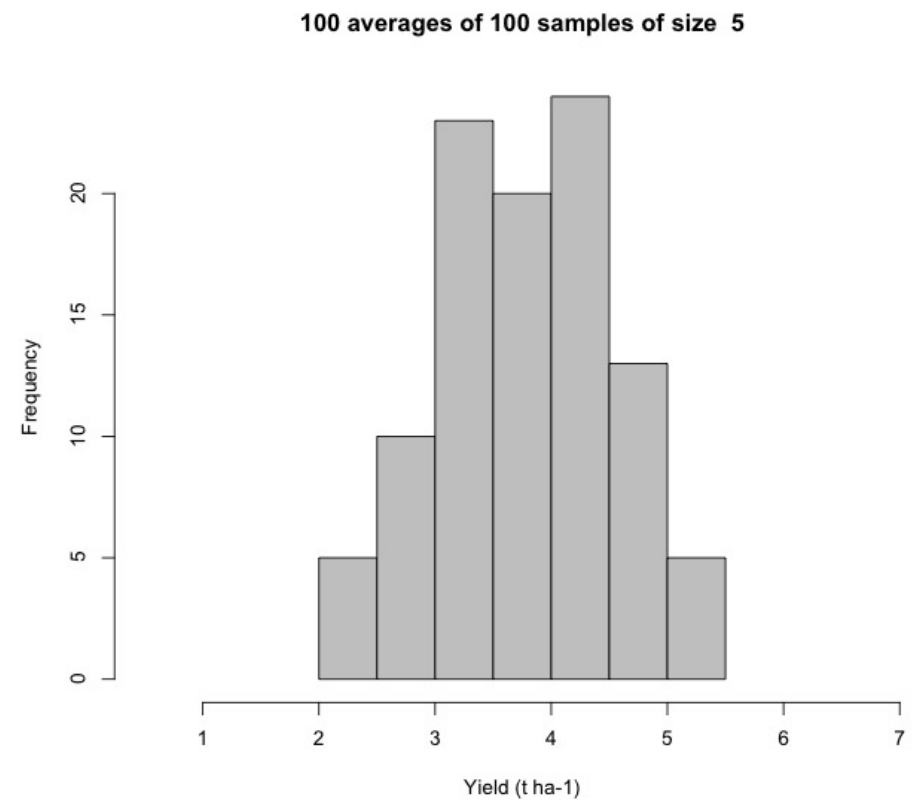




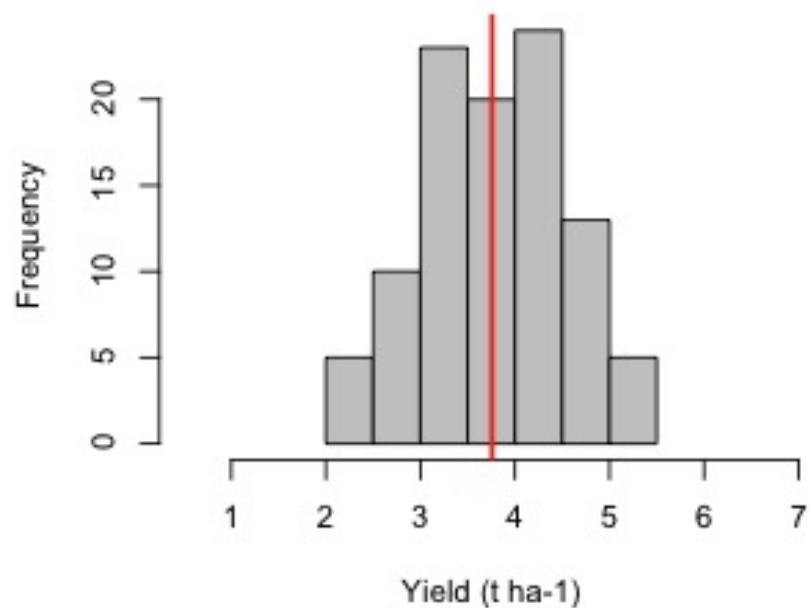
100 samples of 5 yield data



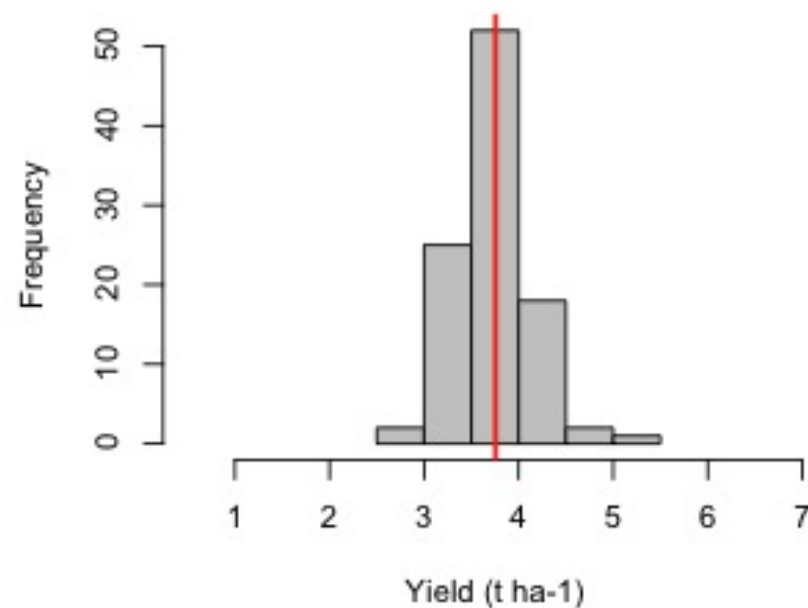
100 average values



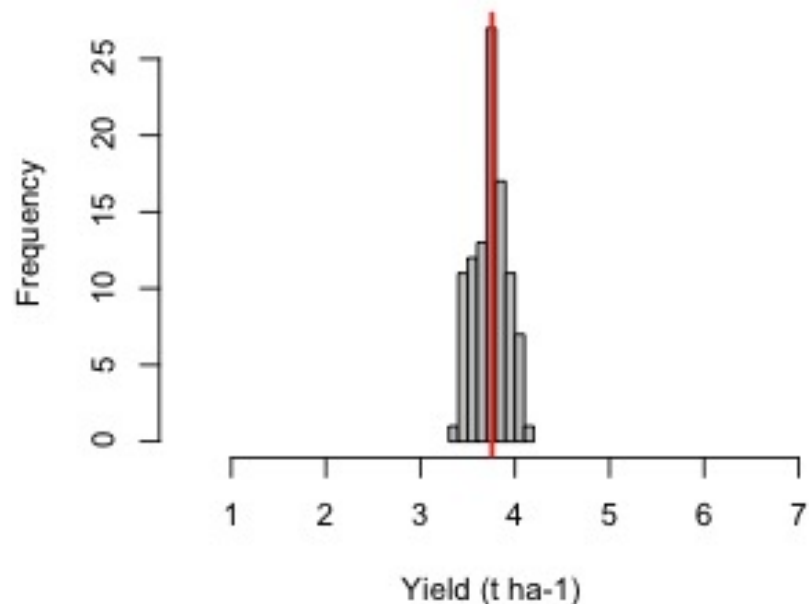
100 averages of 100 samples of size 5



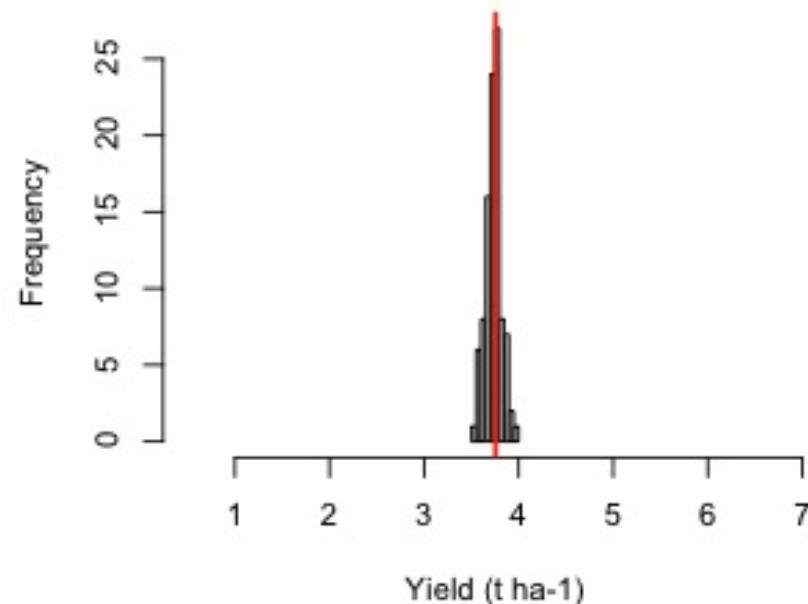
100 averages of 100 samples of size 20



100 averages of 100 samples of size 100



100 averages of 100 samples of size 500



Key concepts

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Estimator

A function of random variables that can be used in estimating unknown parameters of a theoretical probability distribution.

https://www.encyclopediaofmath.org/index.php/Statistical_estimator

Estimator

A rule used to calculate a quantity of interest from data

Estimator

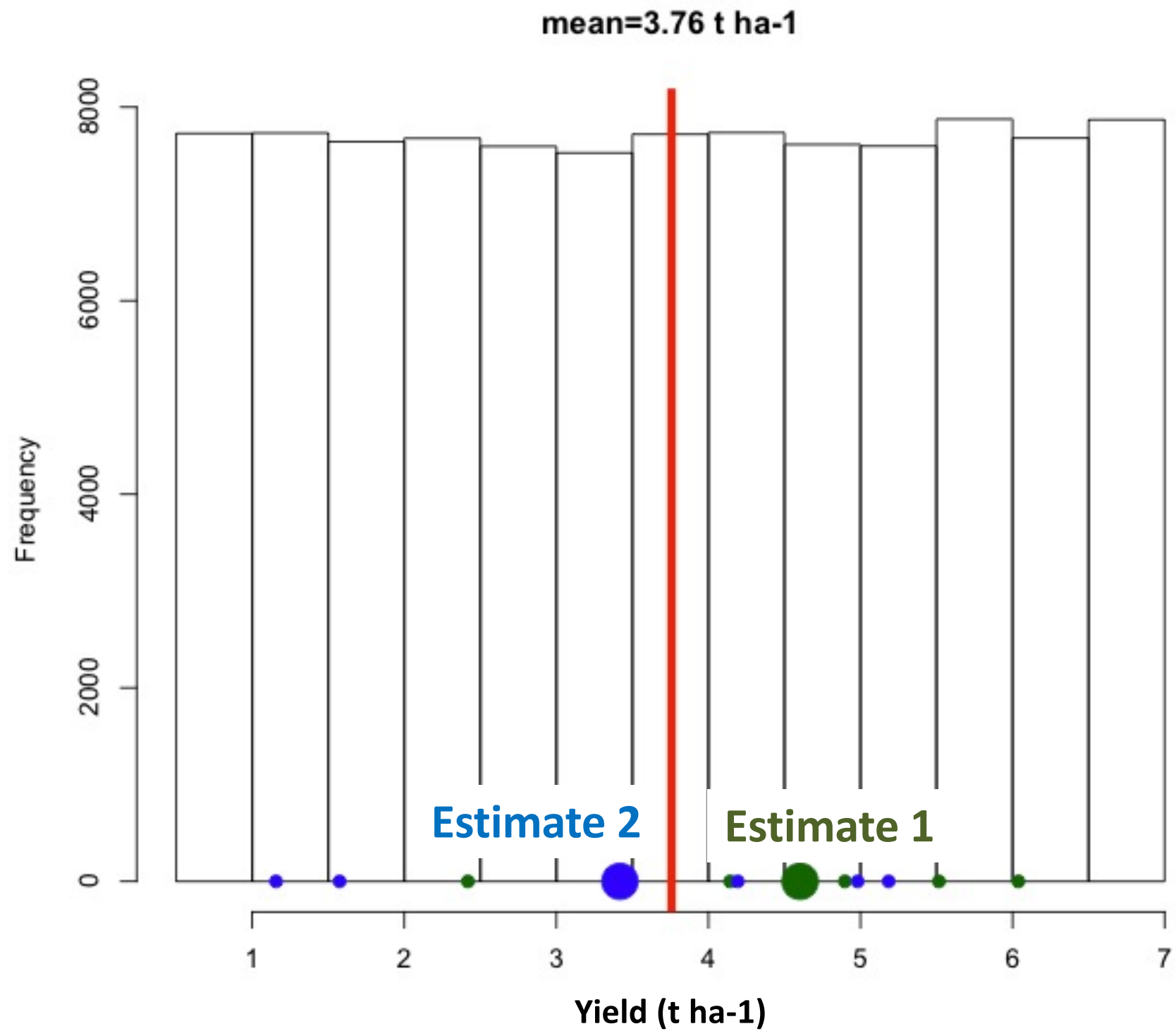
Example:

$$\bar{X} = \frac{X_1 + X_2 + X_3 + X_4 + X_5}{5}$$

Estimate

One value of an estimator calculated from one sample of data

$$\frac{1.1 + 2.8 + 5.8 + 6.1 + 0.8}{5}$$



Bias and variance of an estimator

Bias = difference between the true value and the mean value of the estimator

Variance = measure of the dispersion of the estimator around its mean value

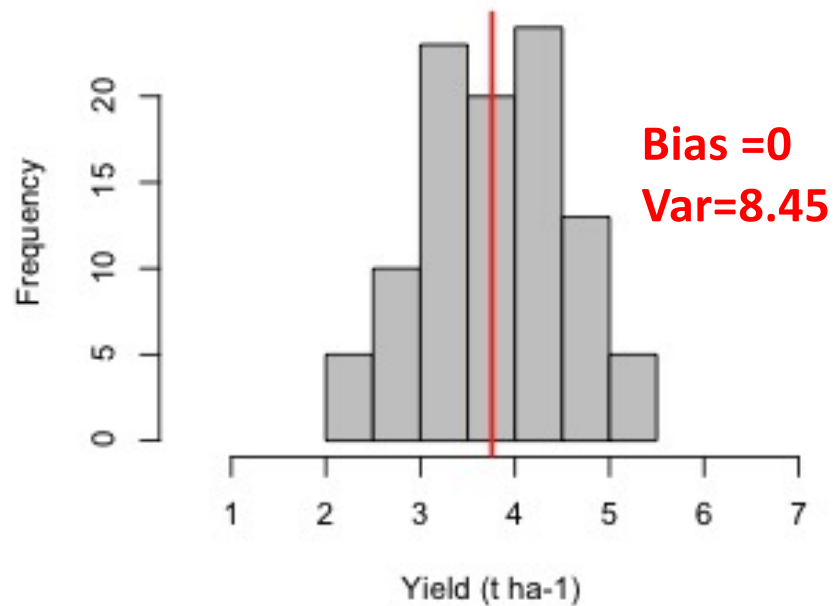
Standard deviation = $\sqrt{\text{Variance}}$

$$\bar{X} = \frac{X_1 + X_2 + X_3 + X_4 + X_5}{5}$$

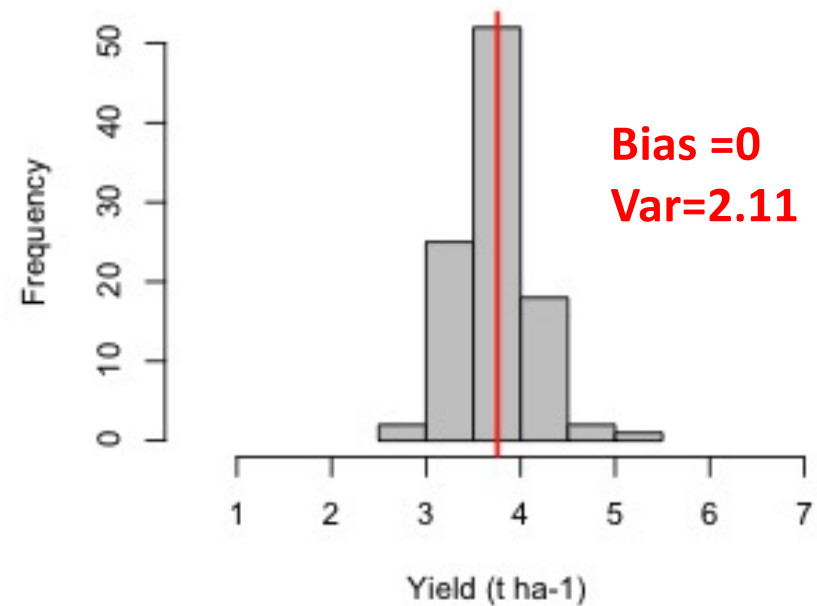
$$E(\bar{X}) = \frac{E(X_1) + E(X_2) + E(X_3) + E(X_4) + E(X_5)}{5} = E(X) = 3.76$$

$$V(\bar{X}) = \frac{1}{5} V(X) = 8.45$$

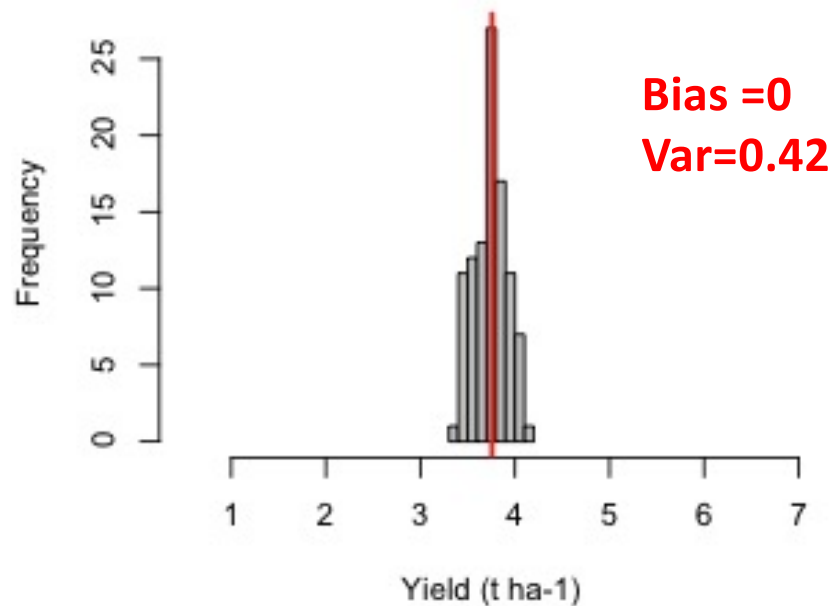
100 averages of 100 samples of size 5



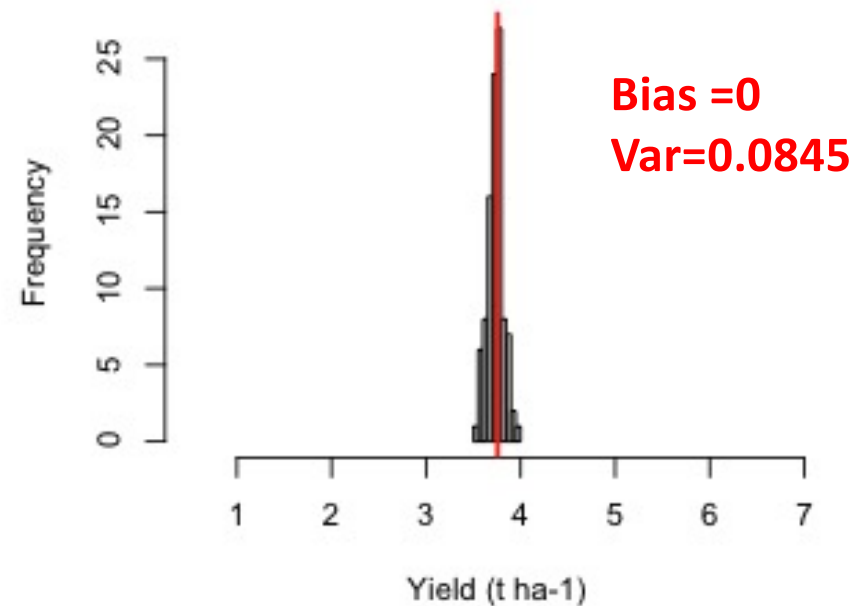
100 averages of 100 samples of size 20



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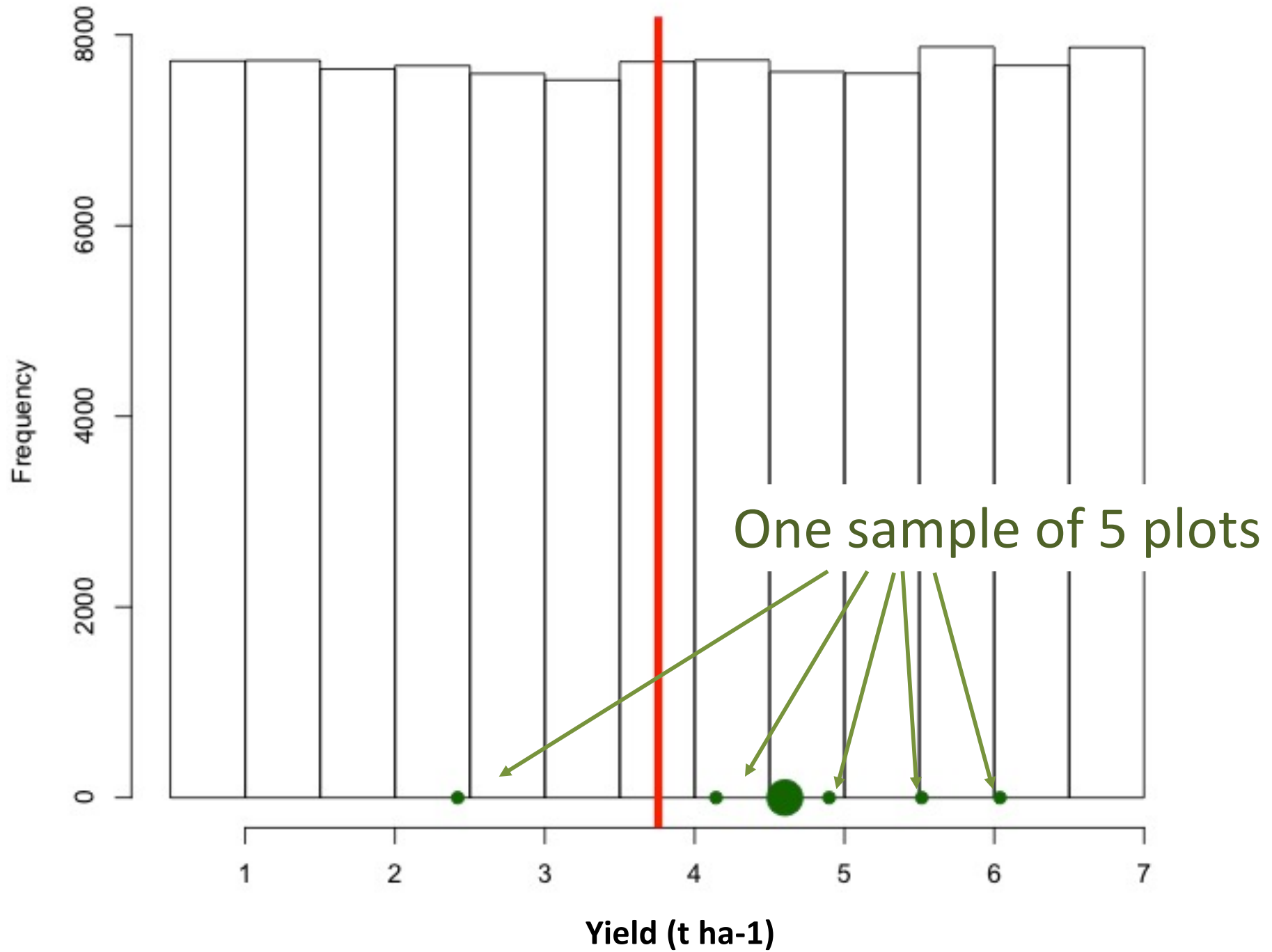
Key concepts

- **Population**
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Test

Choose between two hypotheses based on a sample of observations

mean=3.76 t ha⁻¹



A first example

H_0 : true mean < 4

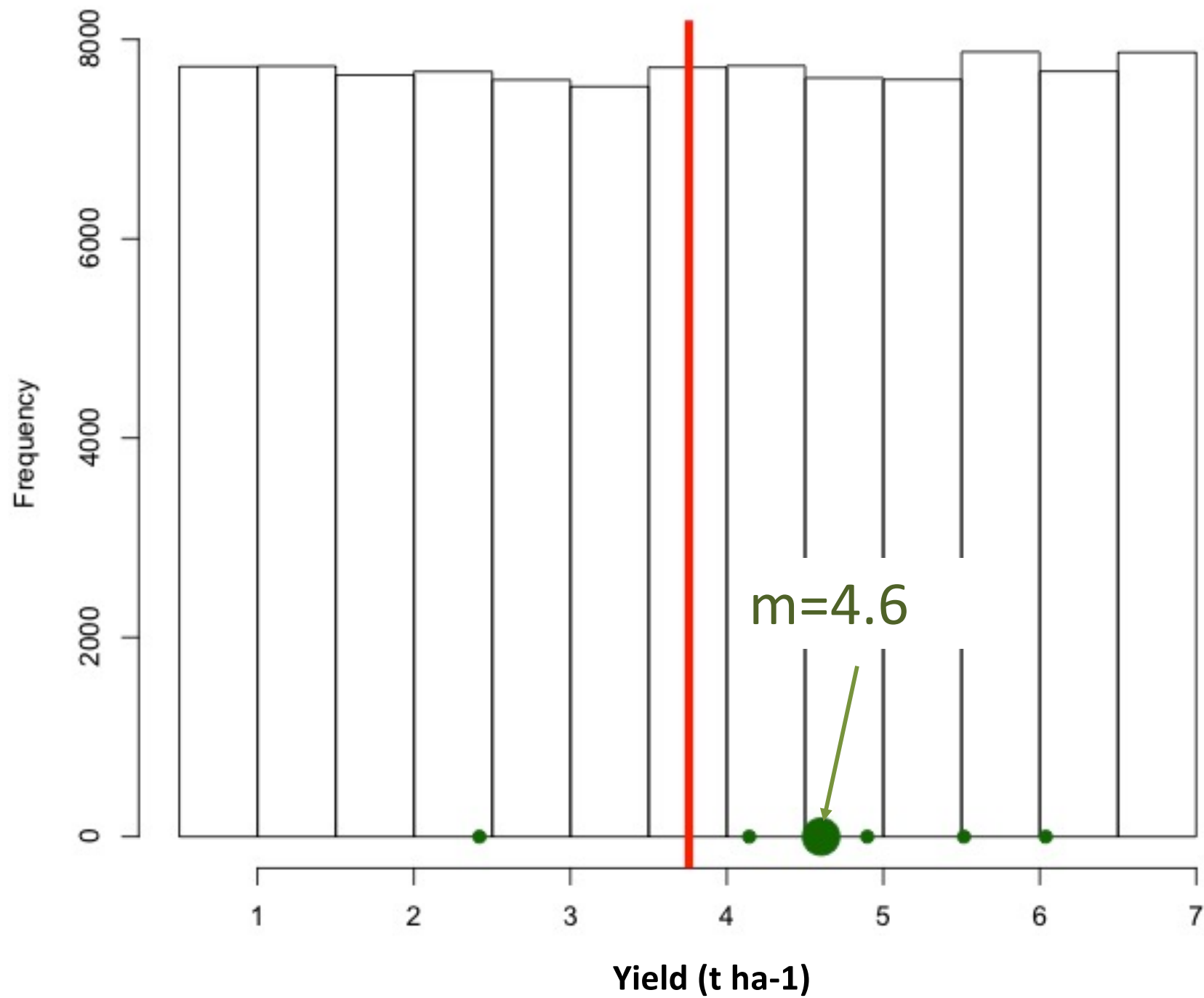
H_1 : true mean > 4

How to choose?

A naive test

If the sample mean $\bar{m} > 4$, reject H_0

mean=3.76 t ha⁻¹



A naive test

If the sample mean $\bar{m} > 4$, reject H_0

H_0 rejected

Error of decision

A naive test

If the sample mean $m > 4$, reject H_0

H_0 rejected

Error of decision: we reject H_0 while H_0 is true

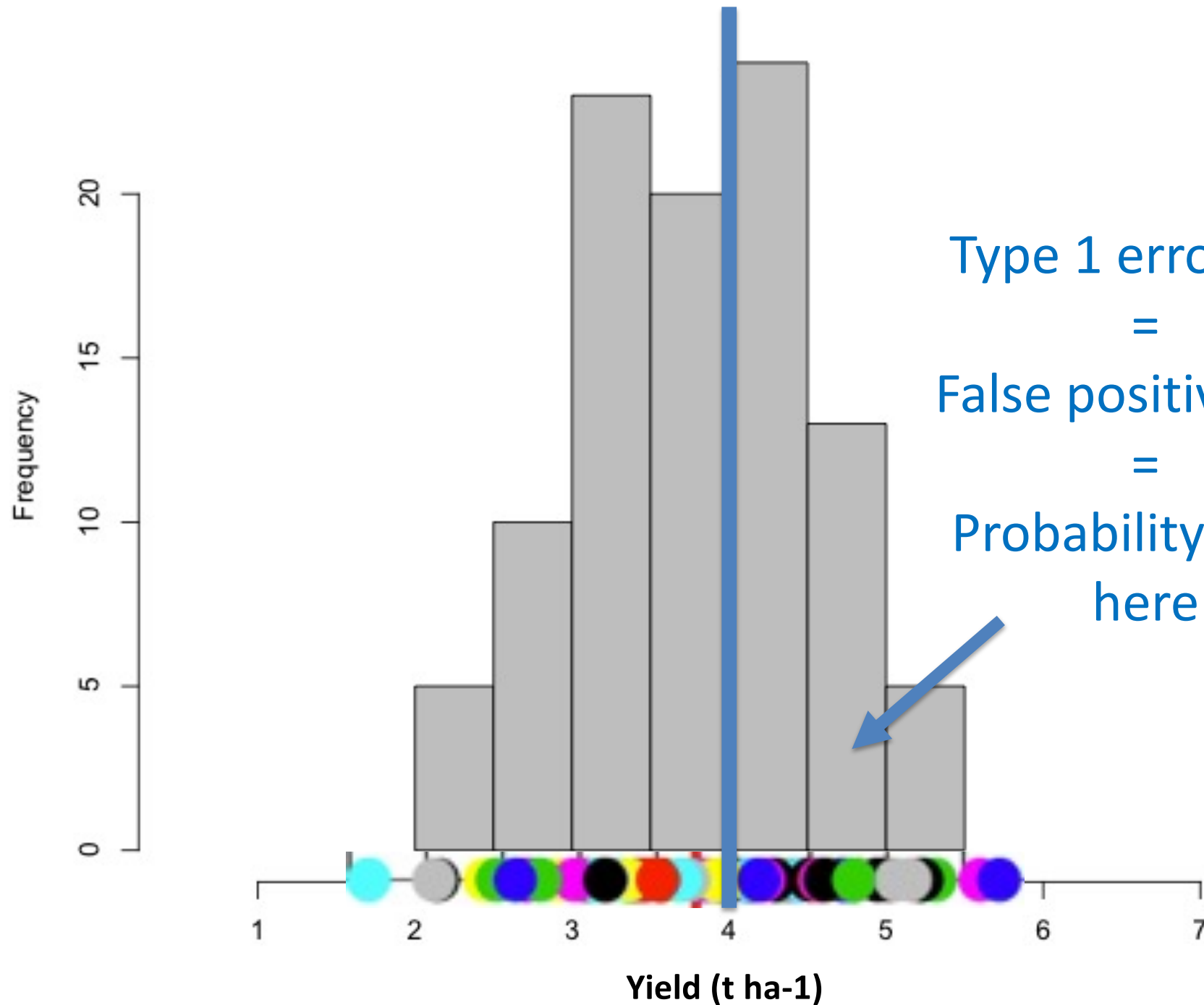
-> False positive

-> Type 1 error

What is the false positive rate of
our naive test?

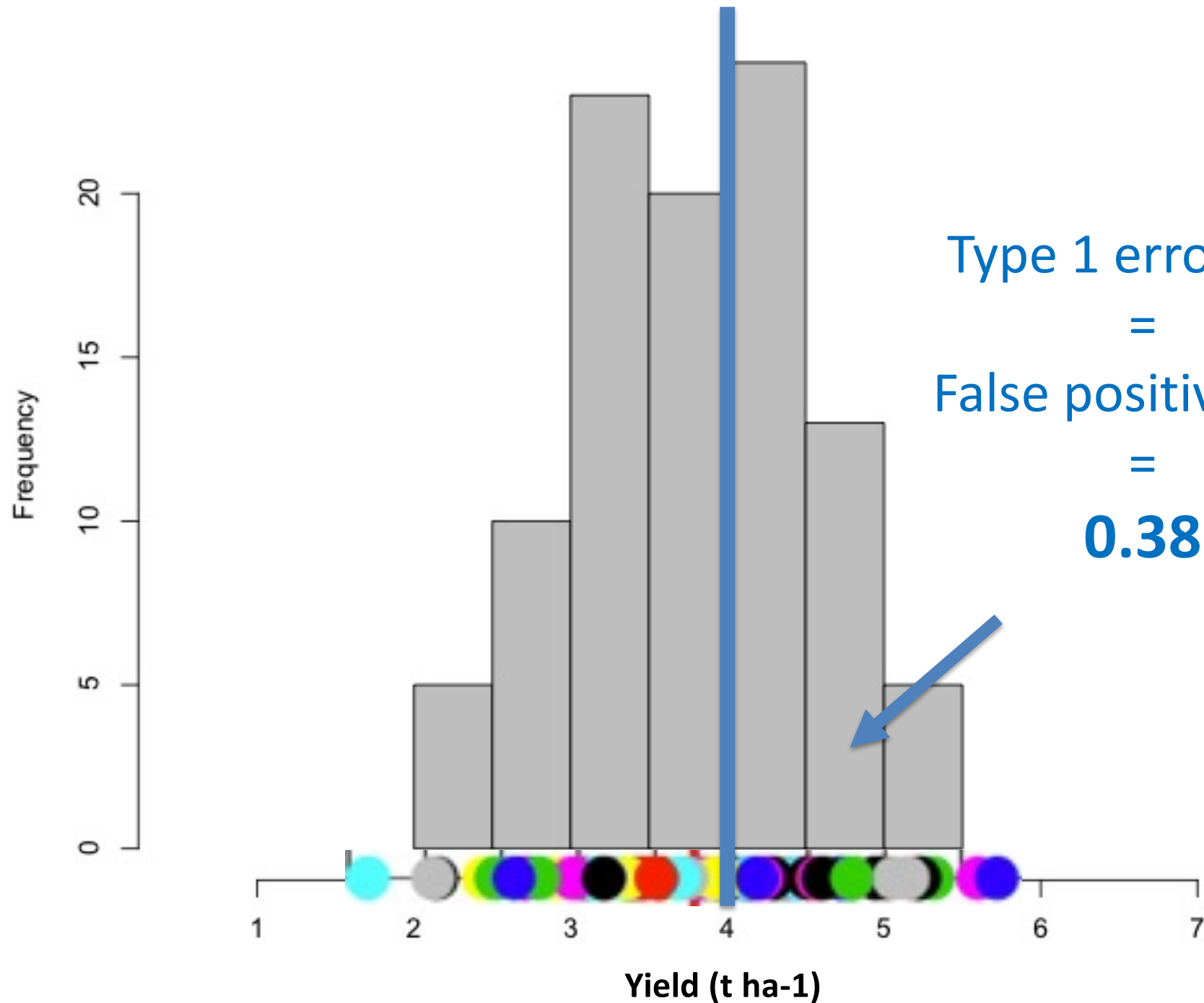
If the sample mean $m > 4$, reject H_0

100 averages of 100 samples of size 5



Type 1 error rate
=
False positive rate
=
Probability to be
here

100 averages of 100 samples of size 5



A second example

H_0 : true mean < 5

H_1 : true mean > 5

How to choose?

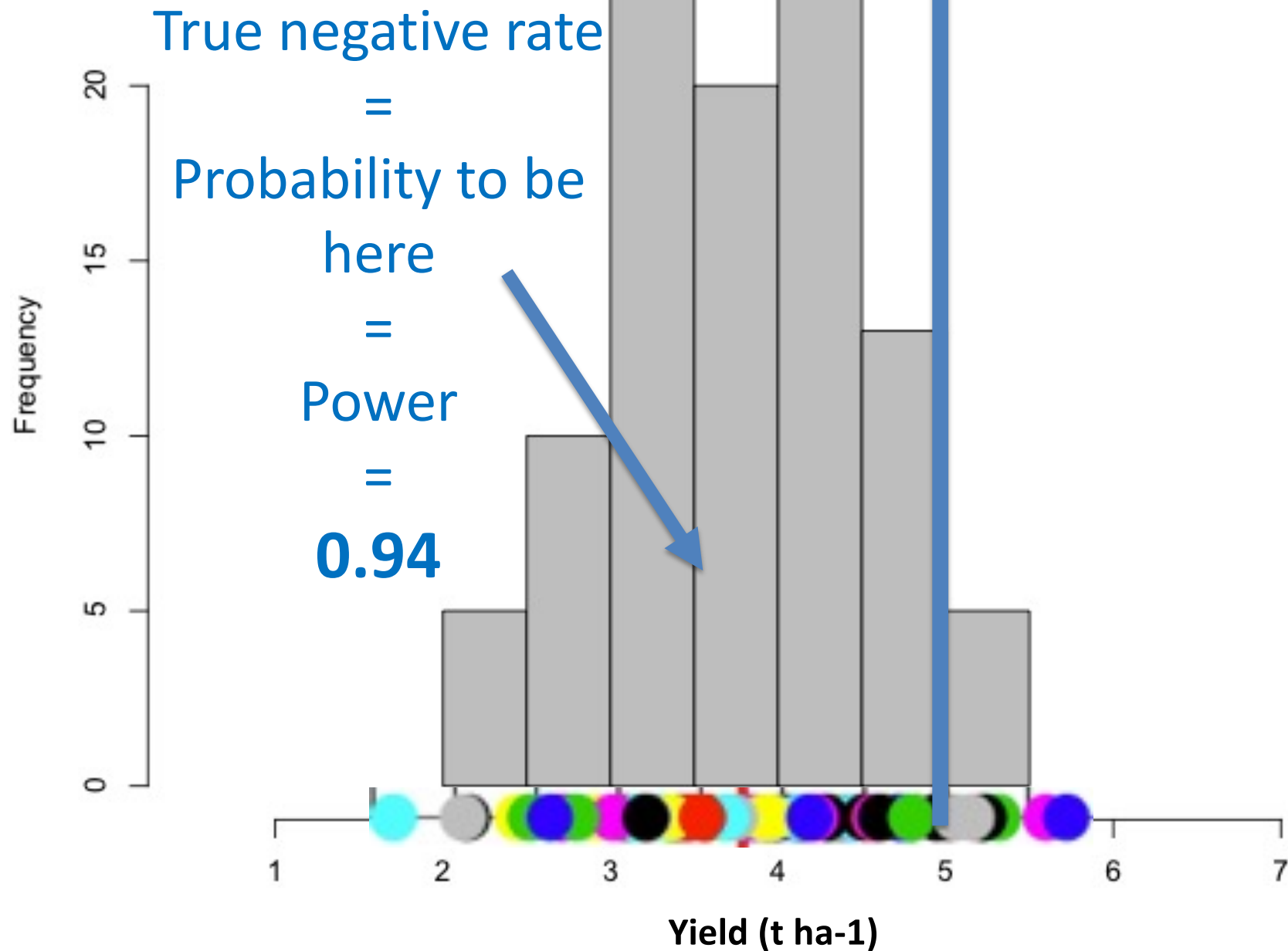
A naive test

If the sample mean $m > 5$, reject H_0

As here $m=4.6$, we accept H_0

No error of decision here: True negative

100 averages of 100 samples of size 5



Two types of error

- Type 1: Reject H_0 while H_0 true
 - False positive rate
 - Alpha risk
- Type 2: Accept H_0 while H_0 wrong
 - False negative rate
 - Beta risk
 - Equal to $1 - \text{Power}$

Two types of error

A good test is a test with

- A small type 1 error rate
- A small type 2 error rate (i.e., a high power)

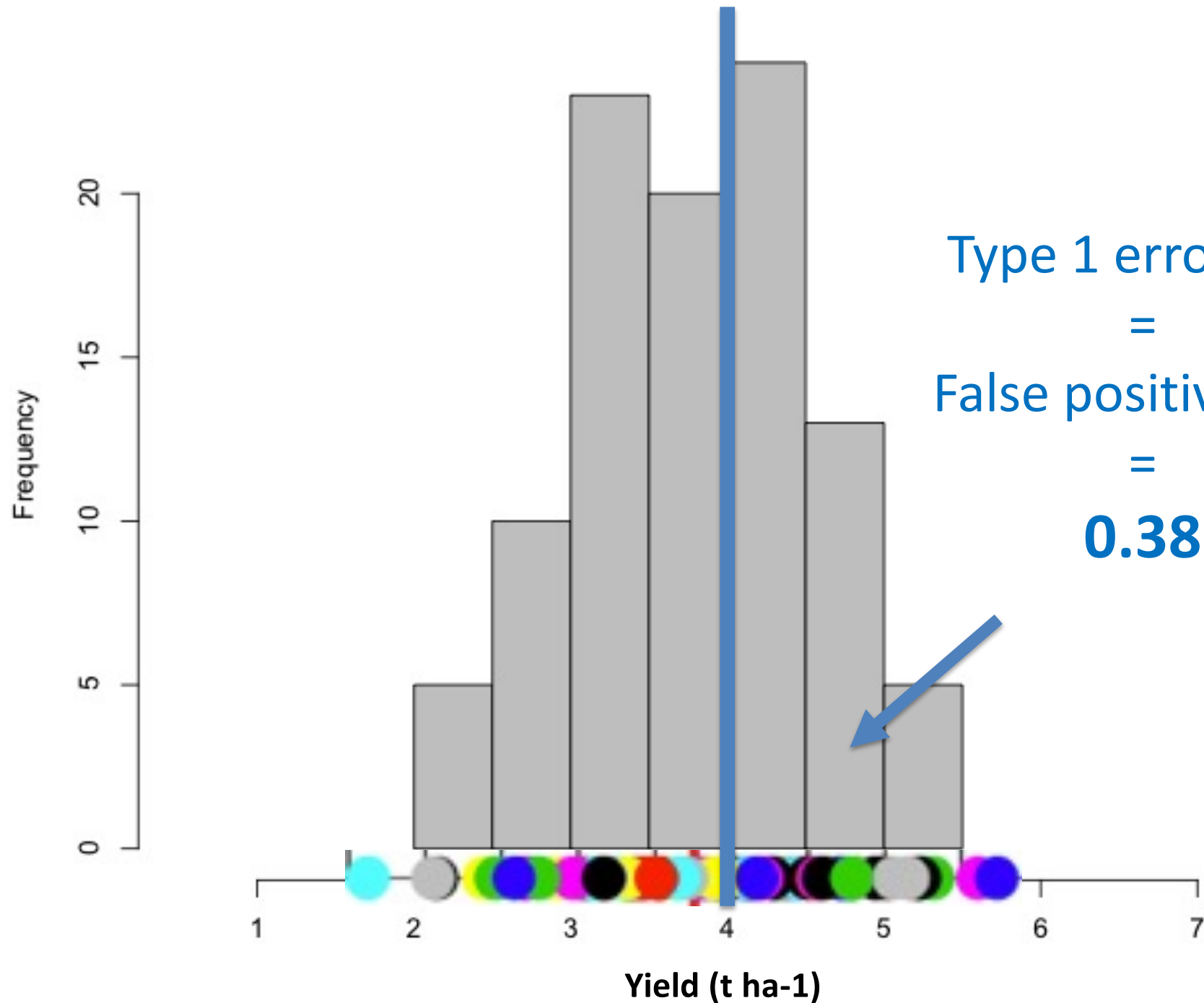
First example

H_0 : true mean < 4

H_1 : true mean > 4

How to choose?

100 averages of 100 samples of size 5



100 averages of 100 samples of size 5



Type 1 error rate too high
Very risky to reject H0

Type 1 error rate
=
False positive rate
=
0.38

First example

H_0 : true mean < 4

H_1 : true mean > 4

How to choose?

A better test

Define $T = (m-4)/s$

m = sample mean

s = standard error

T measures how far the value of m is from 4

If T is large enough, we reject H_0

A better test

Define $T = (m-4)/s$

m = sample mean

s = standard error

A better test

Define $T = (m-4)/s$

m = sample mean

s = standard error

= standard deviation/sqrt(sample size)

A better test

Define $T = (m-4)/s$

m = sample mean

s = standard error

= standard deviation/sqrt(sample size)

$$m = \frac{X1 + X2 + X3 + X4 + X5}{5}$$

$$s = \sqrt{\frac{1}{5} \frac{(X1-m)^2 + (X2-m)^2 + (X3-m)^2 + (X4-m)^2 + (X5-m)^2}{5-1}}$$

A better test

Define $T = (m-4)/s$

m = sample mean

s = standard error

= standard deviation/sqrt(sample size)

$$m = \frac{X1 + X2 + X3 + X4 + X5}{5}$$

$$s = \sqrt{\frac{1}{5} \frac{(X1-m)^2 + (X2-m)^2 + (X3-m)^2 + (X4-m)^2 + (X5-m)^2}{5-1}}$$

If $T > K$, reject H_0

How to choose K?

- Set a max acceptable value for the type 1 error rate
Ex: 0.05 i.e., 5%
- Choose K in order to stay below this value according to some probability distribution, here, the *student distribution*

t test

Define $T = (m-4)/s$

m = sample mean

s = standard error

If $T > 95\%$ quantile of a student distribution, reject H_0

t test with R

```
> Y=c(4.9,4.15,6.3,2.4,5.5)
> Y
[1] 4.90 4.15 6.30 2.40 5.50
> t.test(x=Y,mu=4,alternative="greater")
```

One Sample t-test

```
data: Y
t = 0.9788, df = 4, p-value = 0.1915
alternative hypothesis: true mean is greater than 4
95 percent confidence interval:
 3.234287      Inf
sample estimates:
mean of x
 4.65
```

t test with R

```
> Y=c(4.9,4.15,6.3,2.4,5.5)
> Y
[1] 4.90 4.15 6.30 2.40 5.50
> t.test(x=Y,mu=4,alternative="greater")
```

One Sample t-test

```
data: Y (mean(Y)-4)/(sd(Y)/sqrt(5))
t = 0.9788, df = 4, p-value = 0.1915
alternative hypothesis: true mean is greater than 4
95 percent confidence interval:
 3.234287      Inf
sample estimates:
mean of x
 4.65 mean(Y)
```

t test with R

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One Sample t-test

Type 1 error rate

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alternative hypothesis: true mean is greater than 4
95 percent confidence interval:
 3.234287      Inf
sample estimates:
mean of x
 4.65
```

p value >5%

Too risky to reject H0

Exercise

Five yield data: 1.2, 4.2, 5.0, 5.2, 1.6

H0: True mean $< 1 \text{ t ha}^{-1}$

H1: True mean $> 1 \text{ t ha}^{-1}$

Use a t test to test this hypothesis

Exercise

Five yield data: 1.2, 4.2, 5.0, 5.2, 1.6

H0: True mean $< 2 \text{ t ha}^{-1}$

H1: True mean $> 2 \text{ t ha}^{-1}$

Use a t test to test this hypothesis

Exercise

Five yield data: 1.2, 4.2, 5.0, 5.2, 1.6

H0: True mean > 6 t ha⁻¹

H1: True mean < 6 t ha⁻¹

Use a t test to test this hypothesis

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Confidence interval

Range of values that contains the true value
with a certain probability

95% confidence interval of a mean

$$IC_{95} = [L, U]$$

$$P(L < \text{True mean} < U) = 0.95$$

L and U are calculated from the sample of data

Example

```
> Y  
[1] 4.90 4.15 6.30 2.40 5.50  
> t.test(Y, conf.level=0.95)
```

One Sample t-test

```
data: Y  
t = 7.0022, df = 4, p-value = 0.00219  
alternative hypothesis: true mean is not equal to 0  
95 percent confidence interval:  
2.806223 6.493777 L U  
sample estimates:  
mean of x  
4.65
```

Exercise

Five yield data: 1.2, 4.2, 5.0, 5.2, 1.6

Ten yield data: 1.2, 4.2, 5.0, 5.2, 1.6, 2.8, 3.4, 6.1, 4.1, 3.2

Calculate

- 95% confidence interval with 5 and 10 data
- 90% confidence interval with 5 and 10 data

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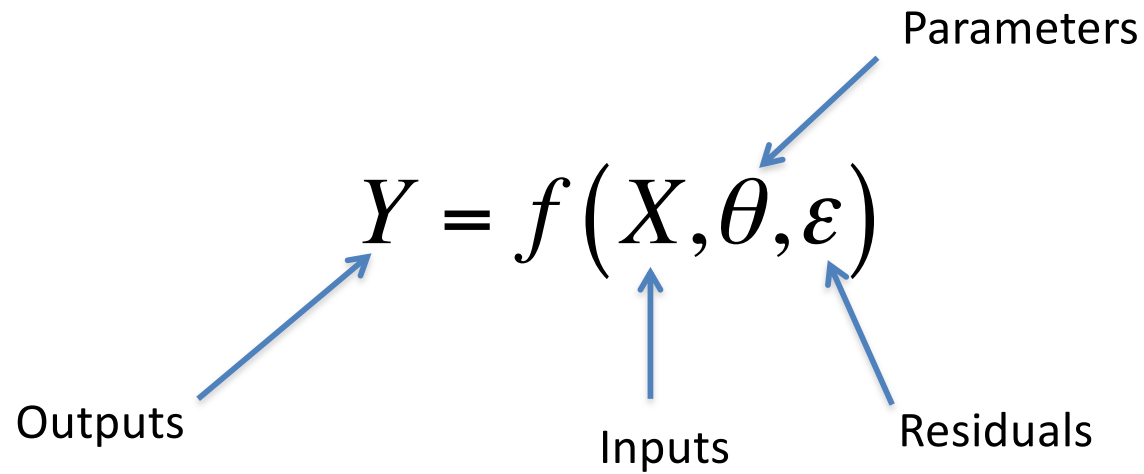
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What is a statistical model?

- A particular type of mathematical model
- A model including measurable components
... and unmeasurable components
- Some of the model components are defined as random variables

What is a statistical model?



What is a **linear** statistical model?

The diagram illustrates the linear statistical model equation $Y = X\theta + \varepsilon$. Four blue arrows point from descriptive labels to the components of the equation: 'Outputs' points to Y , 'Inputs' points to X , 'Parameters' points to θ , and 'Residuals' points to ε .

$$Y = X\theta + \varepsilon$$

Outputs

Inputs

Parameters

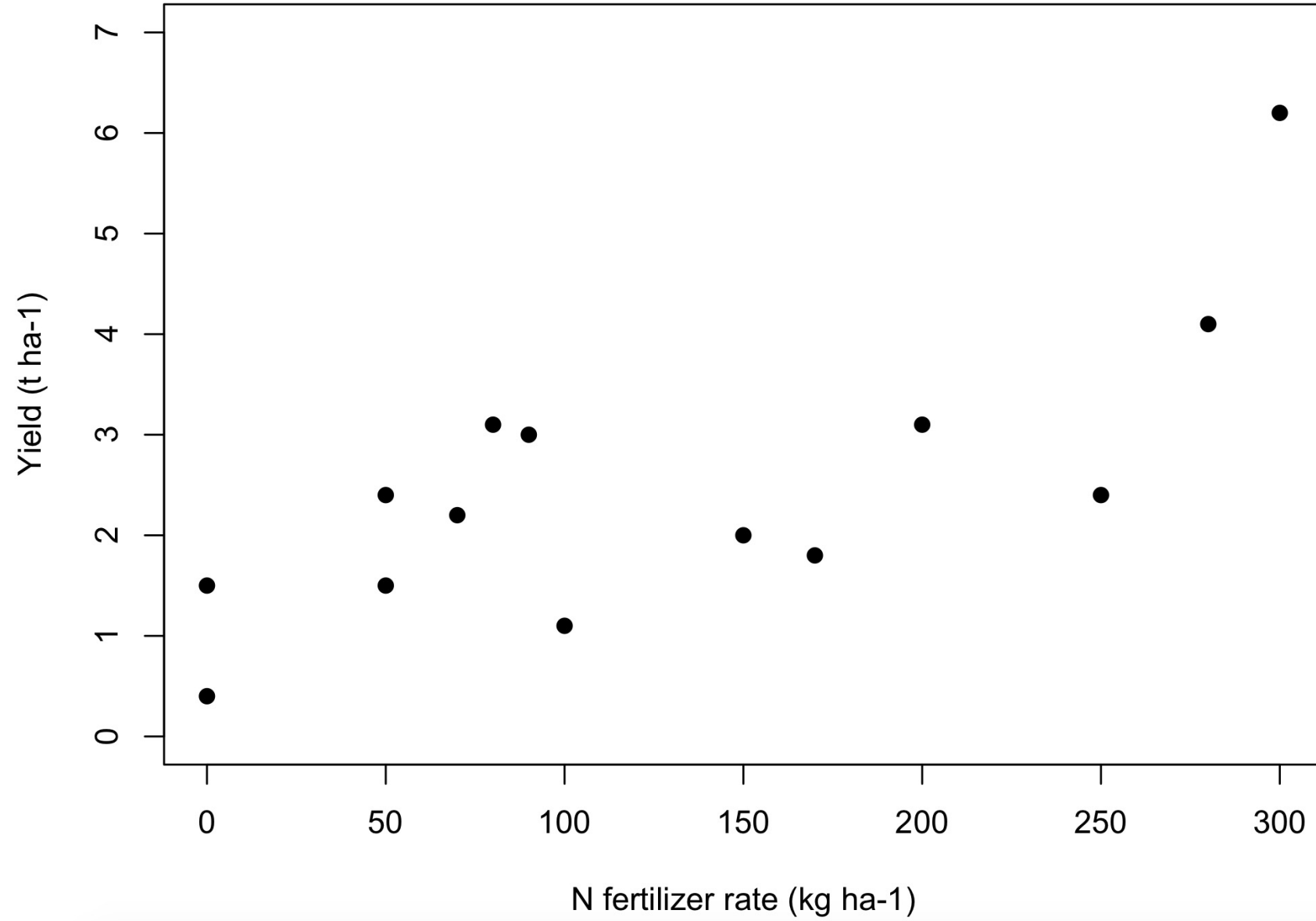
Residuals

$$\begin{pmatrix} y_1 \\ y_2 \\ \dots \\ y_N \end{pmatrix} = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1P} \\ x_{21} & x_{22} & \dots & x_{2P} \\ \dots & \dots & \dots & \dots \\ x_{N1} & x_{N2} & \dots & x_{NP} \end{pmatrix} \begin{pmatrix} \theta_1 \\ \theta_2 \\ \dots \\ \theta_P \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \dots \\ \varepsilon_N \end{pmatrix}$$

$$y_2 = x_{21}\theta_1 + x_{22}\theta_2 + \dots + x_{2P}\theta_P + \varepsilon_2$$

Applications

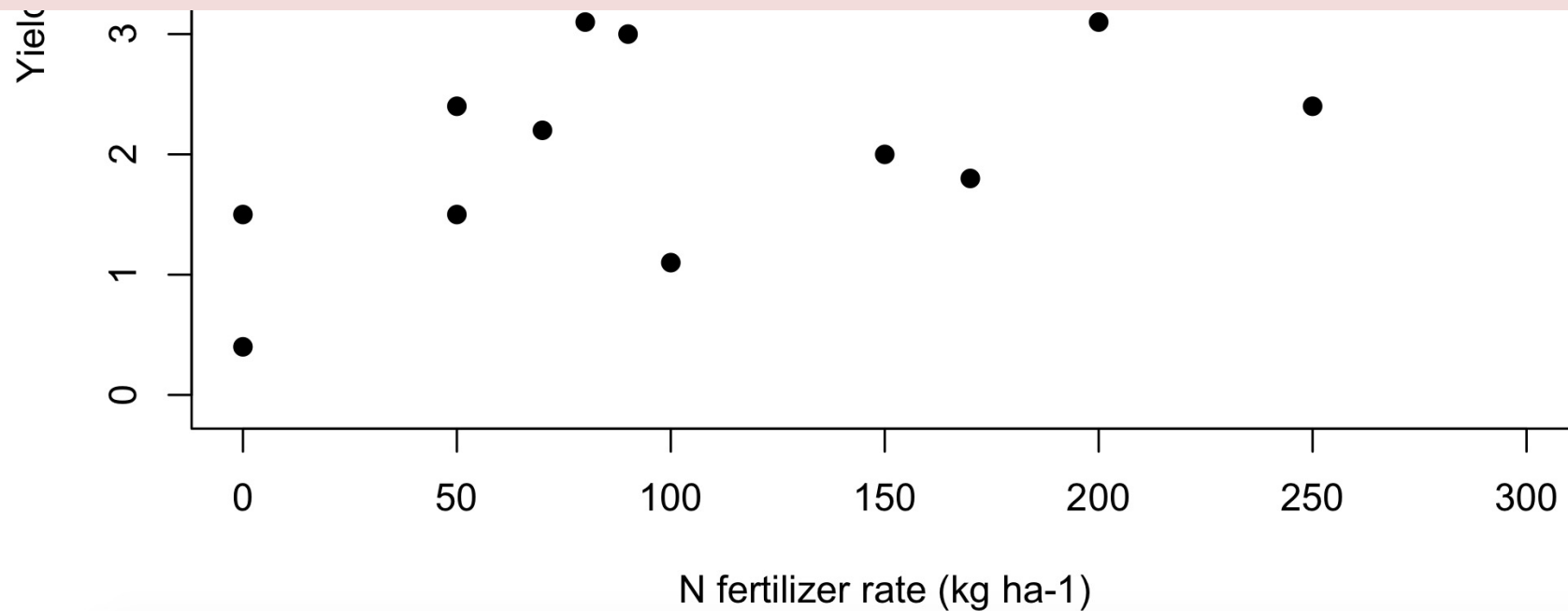
- Test whether an output (Y) is related to one or several inputs (X)
 - Statistical test
- Quantify effect of input X on output Y
 - Estimation and confidence interval
- Predict Y as a function of X
 - Prediction



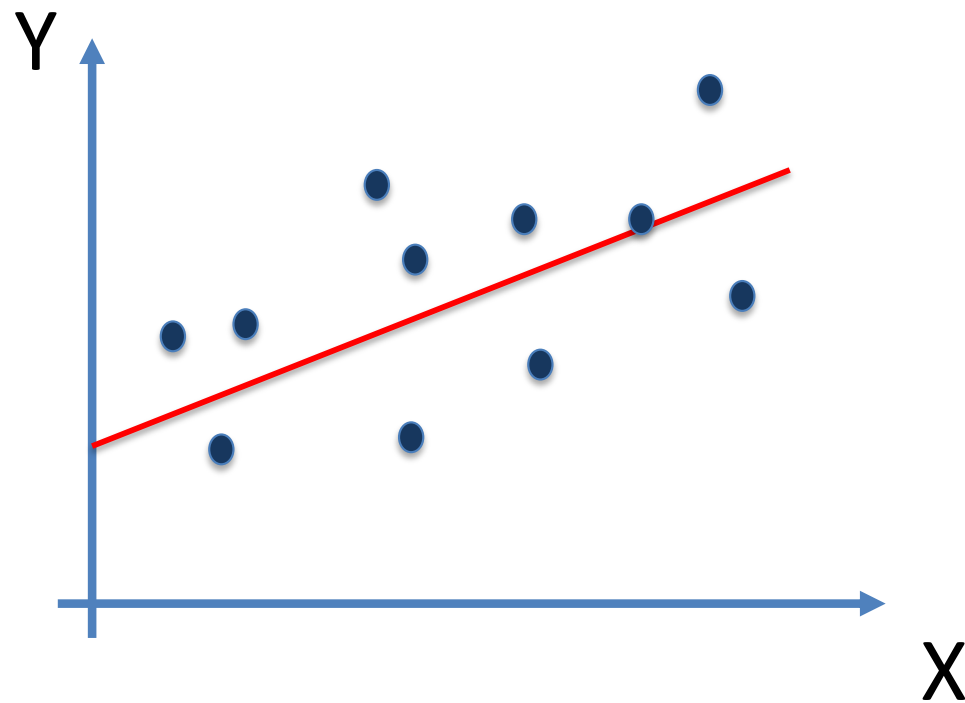
Is yield influenced by N fertilizer rate?

By how much is yield increased if we add $+1 \text{ kg ha}^{-1}$ of N fertilizer ?

Can we predict yield from N fertilizer rate?



$$Y = \alpha + \beta X + \varepsilon$$



Estimation

Use estimators to compute parameter values from a sample of data

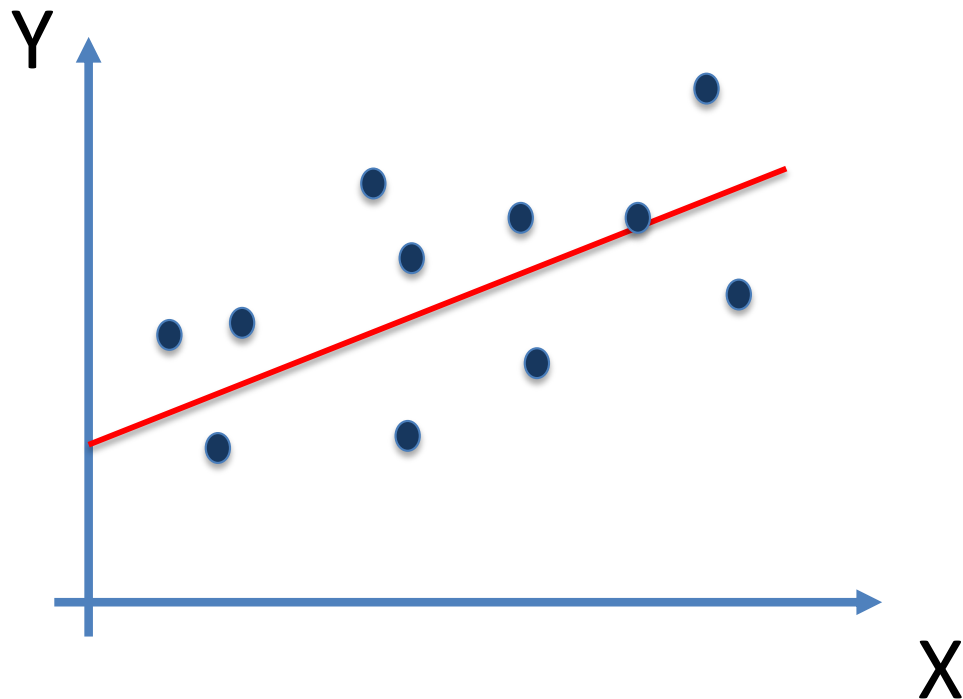
Classic estimators: Ordinary least squares

- Unbiased
- With small variances (under some assumptions)

Ordinary least squares

Estimate the parameters by minimizing

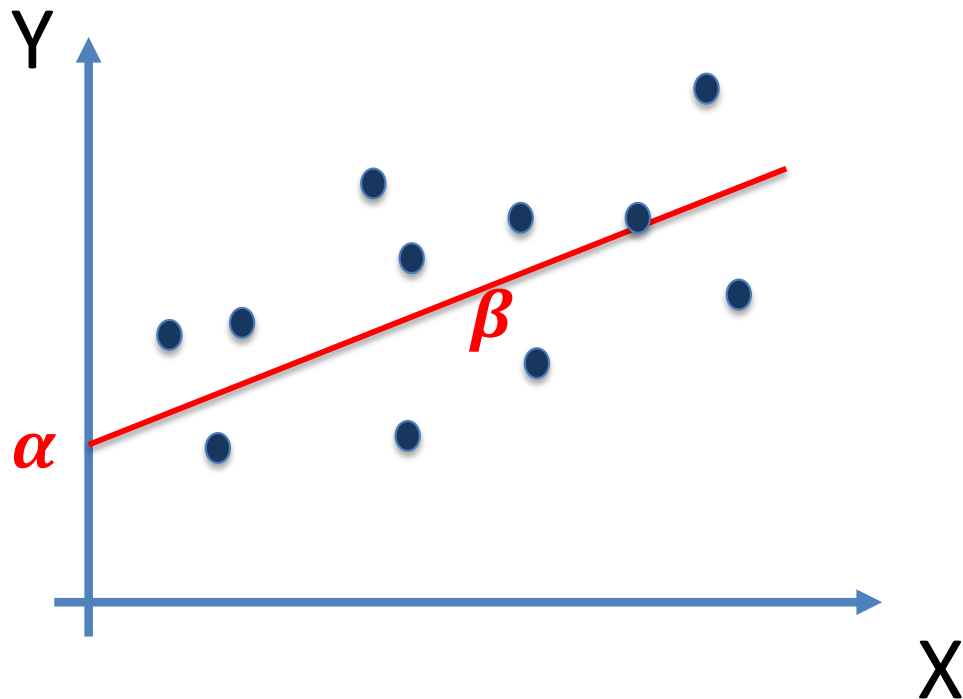
$$OLS = \sum_{i=1}^N [y_i - (\alpha + \beta x_i)]^2$$



Ordinary least squares

Estimate the parameters by minimizing

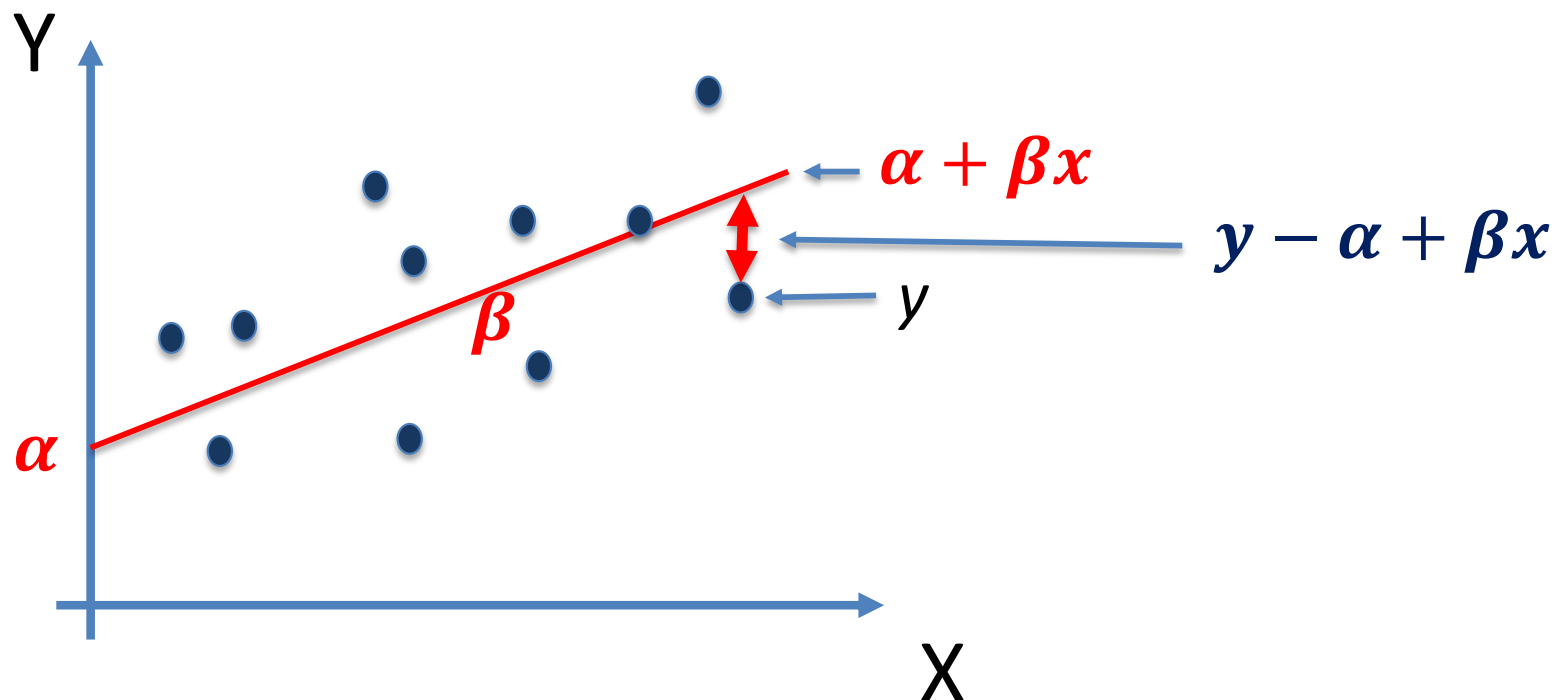
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Ordinary least squares

Estimate the parameters by minimizing

$$OLS = \sum_{i=1}^N [y_i - (\alpha + \beta x_i)]^2$$



Function « lm() » de R

```
Dose<-c(0,250,100,50,70,170,300,50,80,90,0,280,200,150)
Obs<-c(1.5,2.4,1.1,1.5,2.2,1.8,6.2,2.4,3.1,3.0,0.4,4.1,3.1,2)

plot(Dose,Obs, xlab="N fertilizer rate (kg ha-1)", ylab="Yield (t ha-1)", ylim=c(0,7),pch=19)

Mod<-lm(Obs~Dose)
summary(Mod)
```

```
> summary(Mod)
```

Call:

```
lm(formula = Obs ~ Dose)
```

Residuals:

Min	1Q	Median	3Q	Max
-1.38665	-0.72333	-0.08014	0.65167	1.88080

Coefficients:

α
 β

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	1.123915	0.445230	2.524	0.02670	*
Dose	0.010651	0.002789	3.818	0.00245	**

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9973 on 12 degrees of freedom

Multiple R-squared: 0.5485, Adjusted R-squared: 0.5109

F-statistic: 14.58 on 1 and 12 DF, p-value: 0.002446

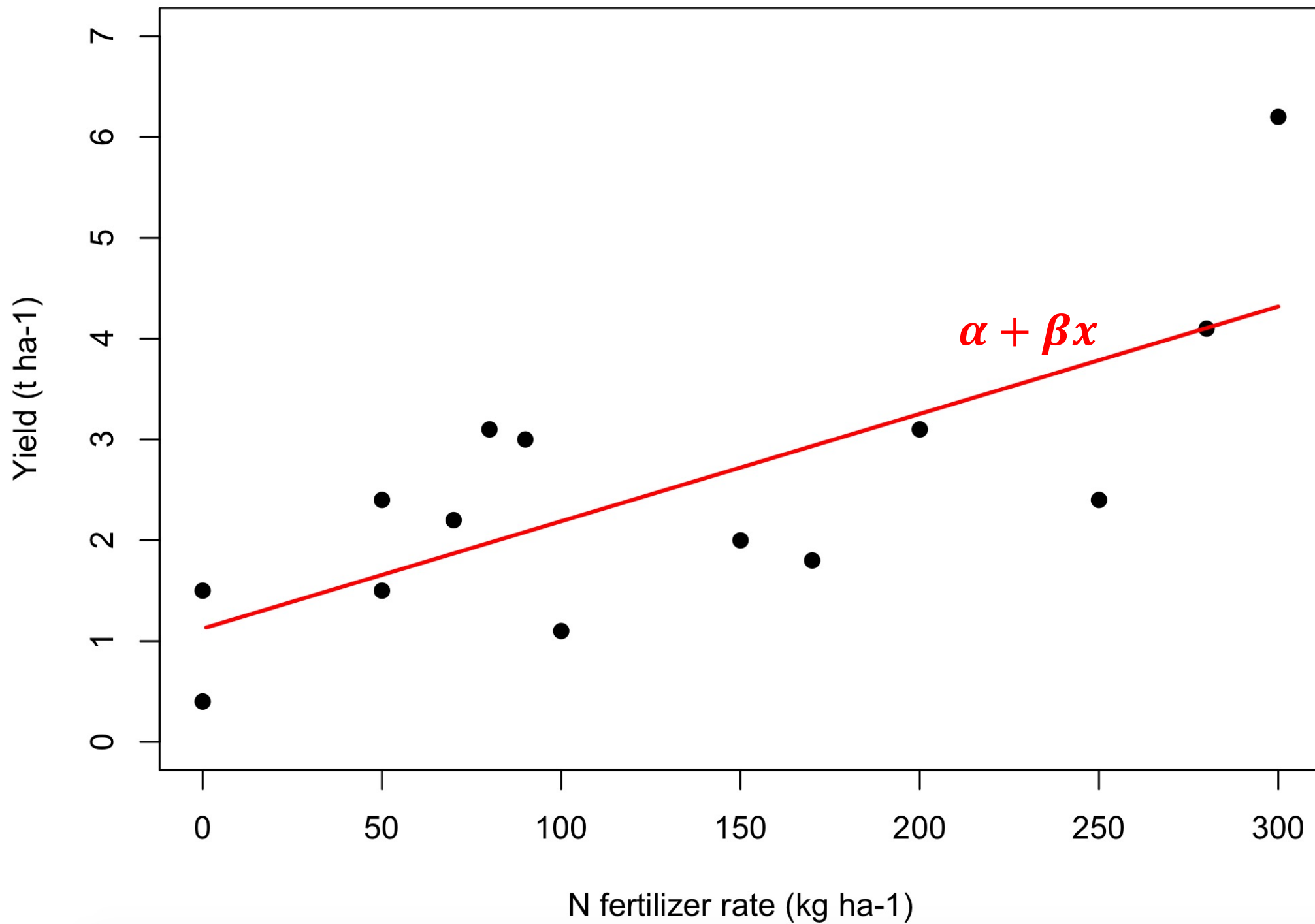

```
plot(Dose,Obs, xlab="N fertilizer rate (kg ha-1)", ylab="Yield (t ha-1)", ylim=c(0,7),pch=19)
```

```
Mod<-lm(Obs~Dose)  
summary(Mod)
```

```
D<-1:300
```

```
pred<-coef(Mod)[1]+coef(Mod)[2]*D
```

```
lines(D,pred,col="red",lwd=2)
```



Test on the effect of N fertilizer

$H_0 : \ll \beta = 0 \gg$ against $H_1 : \ll \beta \neq 0 \gg$

Test on the effect of N fertilizer

$H_0 : \ll \beta = 0 \gg$ against $H_1 : \ll \beta \neq 0 \gg$

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Call:

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	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.123915	0.445230	2.524	0.02670 *
Dose	0.010651	0.002789	3.818	0.00245 **

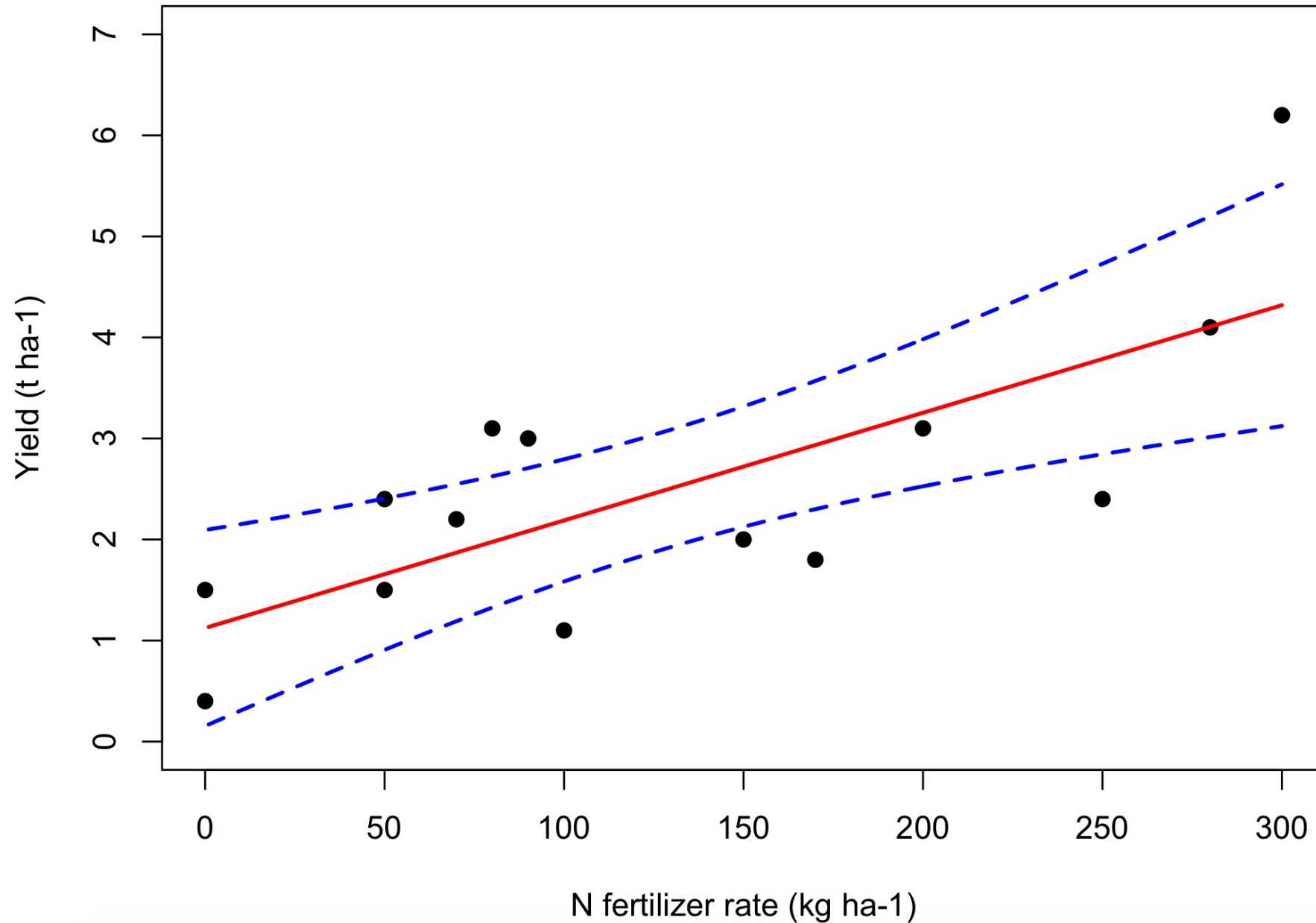
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9973 on 12 degrees of freedom

Multiple R-squared: 0.5485, Adjusted R-squared: 0.5109

F-statistic: 14.58 on 1 and 12 DF, p-value: 0.002446

Confidence intervals



```
Dose<-c(0,250,100,50,70,170,300,50,80,90,0,280,200,150)
Obs<-c(1.5,2.4,1.1,1.5,2.2,1.8,6.2,2.4,3.1,3.0,0.4,4.1,3.1,2)

plot(Dose,Obs, xlab="N fertilizer rate (kg ha-1)", ylab="Yield (t ha-1)", ylim=c(0,7),pch=19)

Mod<-lm(Obs~Dose)
summary(Mod)

D<-1:300

pred<-coef(Mod)[1]+coef(Mod)[2]*D

lines(D,pred,col="red",lwd=2)

predIC<-predict(Mod,newdata=data.frame(Dose=D),interval="confidence",level=0.95)

predIC

lines(D,predIC[,2],lty=2,lwd=2, col="blue")
lines(D,predIC[,3],lty=2,lwd=2, col="blue")
```

Model evaluation

```
> summary(Mod)
```

Call:

```
lm(formula = Obs ~ Dose)
```

Residuals:

Min	1Q	Median	3Q	Max
-1.38665	-0.72333	-0.08014	0.65167	1.88080

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	1.123915	0.445230	2.524	0.02670	*
Dose	0.010651	0.002789	3.818	0.00245	**

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9973 on 12 degrees of freedom

Multiple R-squared: 0.5485. Adjusted R-squared: 0.5109

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Efficiency

RMSE

Conclusion

Main steps for the development of a model

- Definition of inputs X and outputs Y
- Definition of equations f
- Estimation of parameters θ
- Tests and model assessment
- Practical use