



BeginneR Session

-- Regression analysis --

@kilometer00

Who ! ?

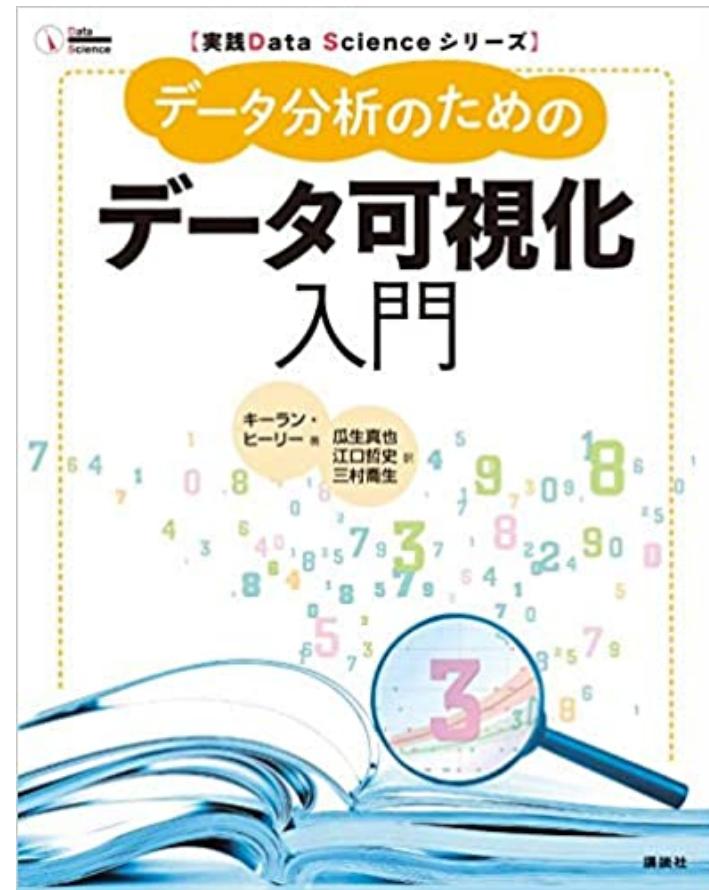
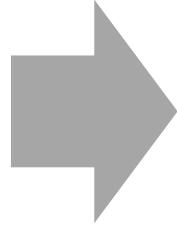
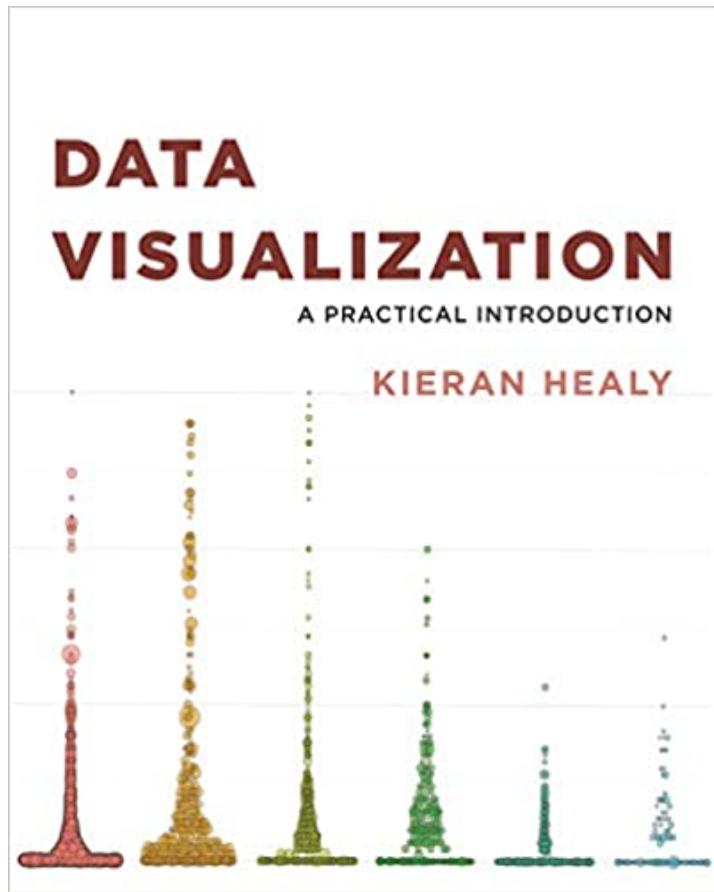


Who ! ?

- @kilometer
- Postdoc Researcher (Ph.D. Eng.)
- Neuroscience
- Computational Behavior
- Functional brain imaging
- R : ~ 10 years



宣伝!! (書籍の翻訳に参加しました。)



絶賛販売中！



BeginneR Session



BeginneR



BeginneR



Advanced



Hoxo_m



If I have seen further it is by standing on the shoulders of Giants.

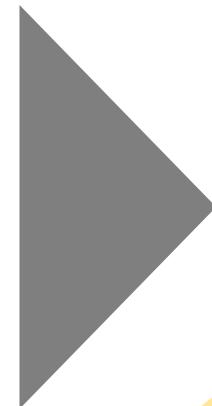
-- Sir Isaac Newton, 1676

BeginneR Session



BeginneR

Before

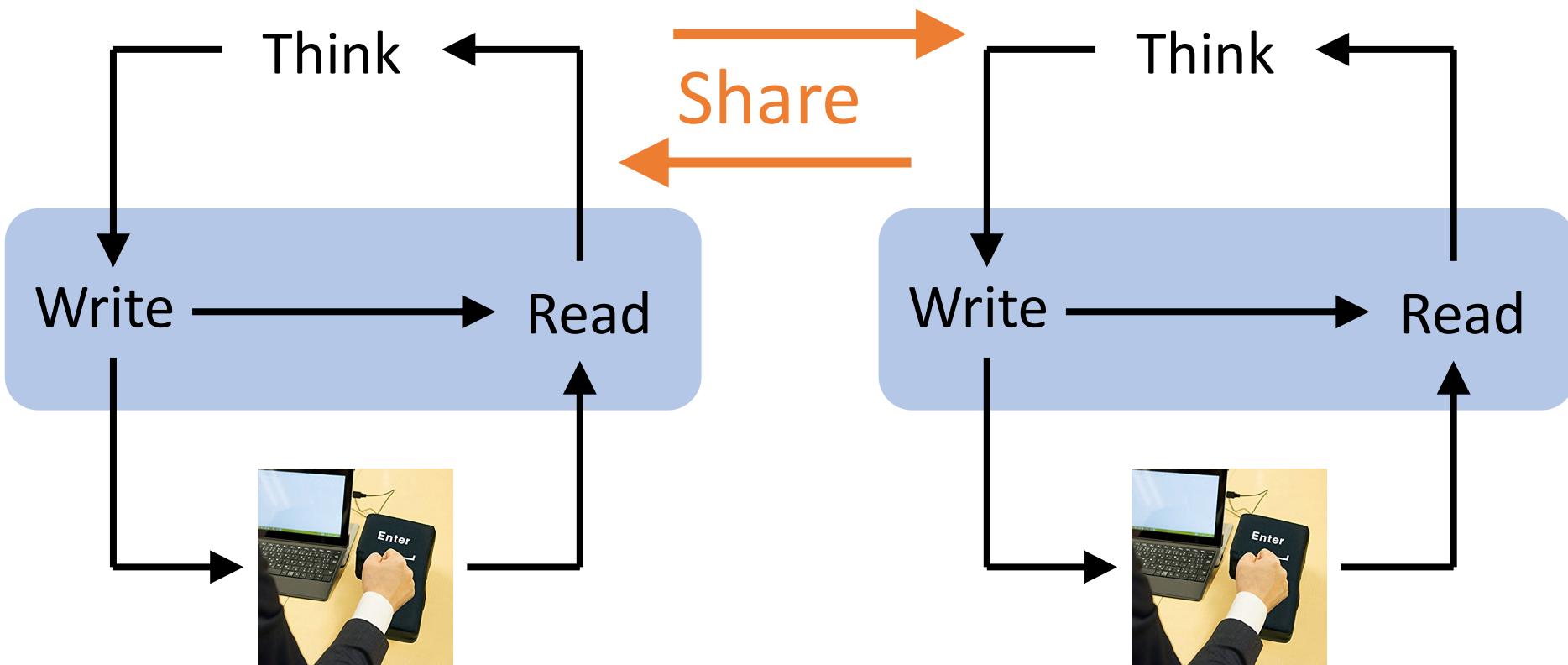


BeginneR

After

Programming

Communicate





BeginneR Session

-- Regression analysis --

@kilometer00



Install

```
install.packages("tidyverse")
```

Attach

```
library("tidyverse")
```



attach



Pipe algebra %>%

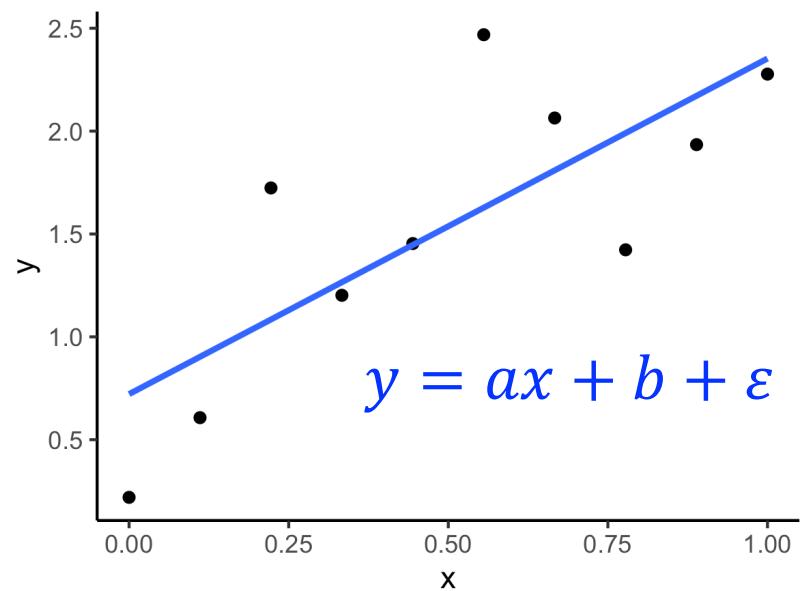
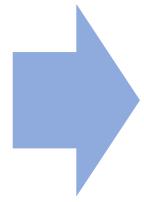
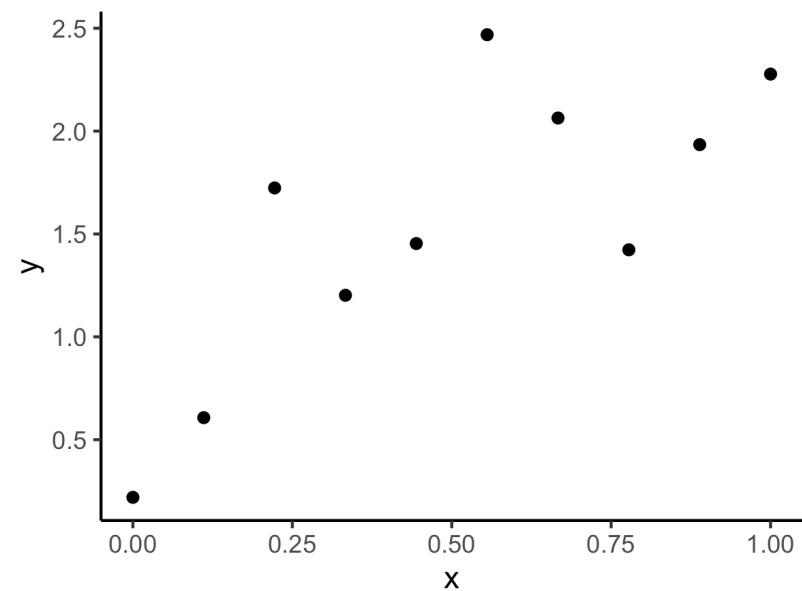
{magrittr}

$X \text{ %}>\% f$	\longleftrightarrow	$f(X)$
$X \text{ %}>\% f(y)$	\longleftrightarrow	$f(X, y)$
$X \text{ %}>\% f \text{ %}>\% g$	\longleftrightarrow	$g(f(X))$
$X \text{ %}>\% f(y, .)$	\longleftrightarrow	$f(y, X)$

線形回帰分析

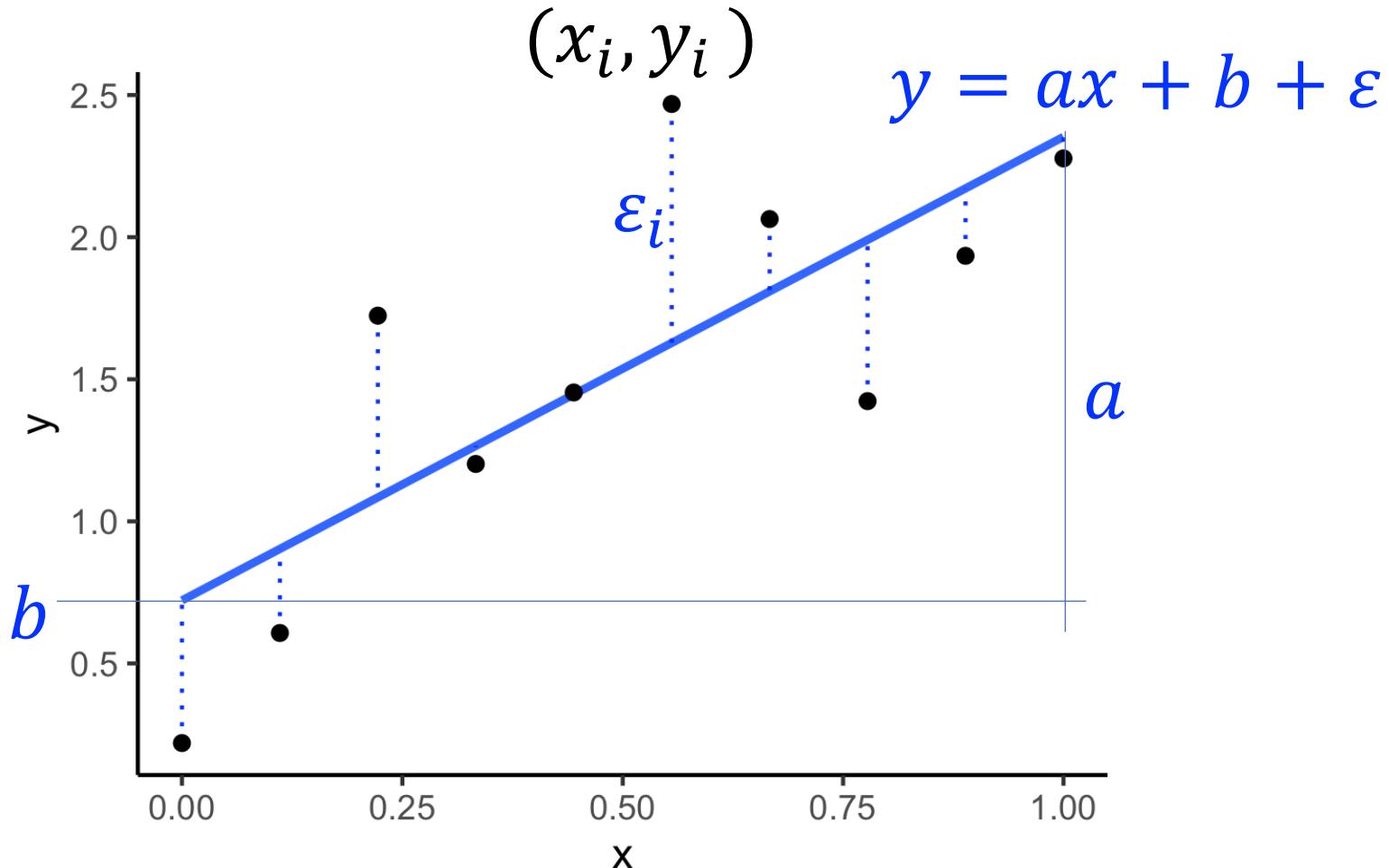
- ・回帰直線(最小二乗法)
- ・誤差の確率モデル
- ・決定係数と相関係数
- ・回帰モデルの仮説検定

線形回帰 (Linear Regression)



線形回帰 (Linear Regression)

$$\operatorname{argmin}_{(a,b)} \sum_{i=1}^n \varepsilon^2 \quad \rightarrow \quad \hat{a} = \frac{S_{xy}}{S_{xx}}, \quad \hat{b} = \bar{y} - \frac{S_{xy}}{S_{xx}} \bar{x}$$



線形回歸 (Linear Regression)

$$\operatorname{argmin}_{(a,b)} \sum_{i=1}^n \varepsilon^2 \quad \rightarrow \quad \hat{a} = \frac{S_{xy}}{S_{xx}}, \quad \hat{b} = \bar{y} - \frac{S_{xy}}{S_{xx}} \bar{x}$$

$$S_{xx} = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$$

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

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i, \quad \bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$$

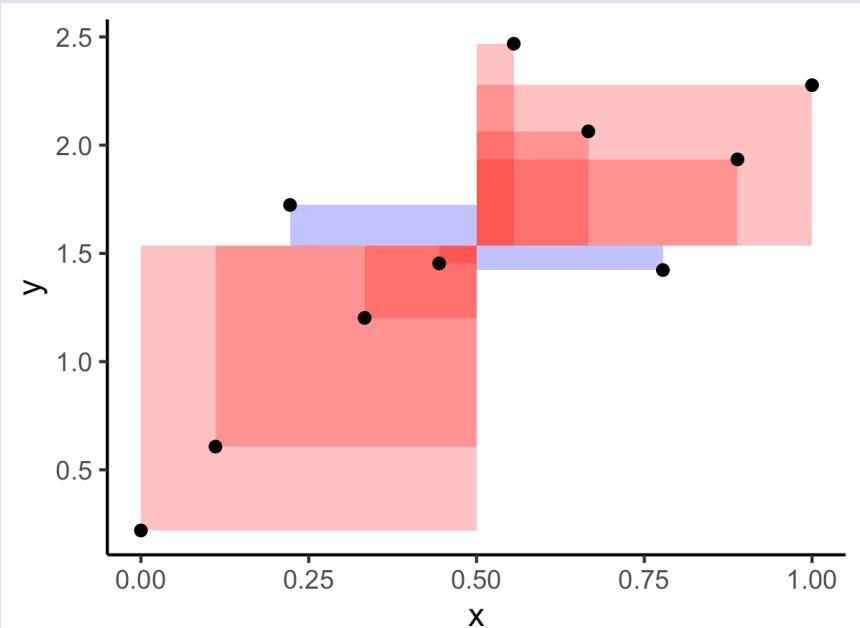
線形回歸 (Linear Regression)

$$\operatorname{argmin}_{(a,b)} \sum_{i=1}^n \varepsilon^2 \rightarrow \hat{a} = \frac{S_{xy}}{S_{xx}}, \quad \hat{b} = \bar{y} - \frac{S_{xy}}{S_{xx}} \bar{x}$$

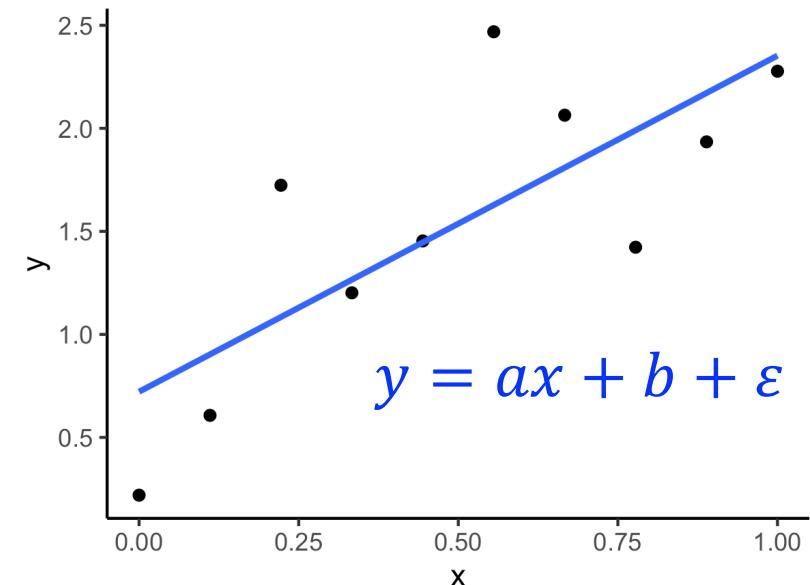
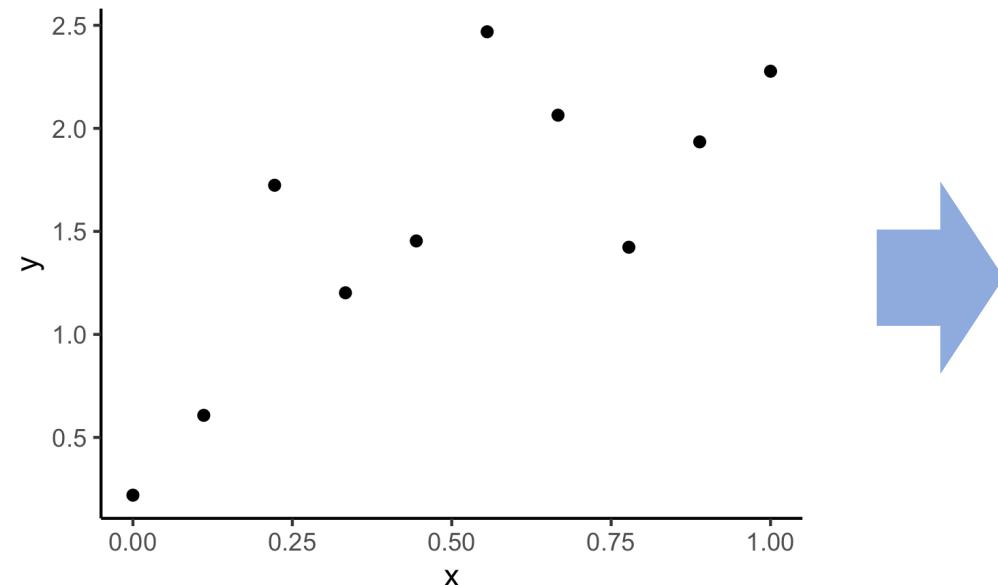
$$S_{xx} = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$$

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

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i, \quad \bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$$



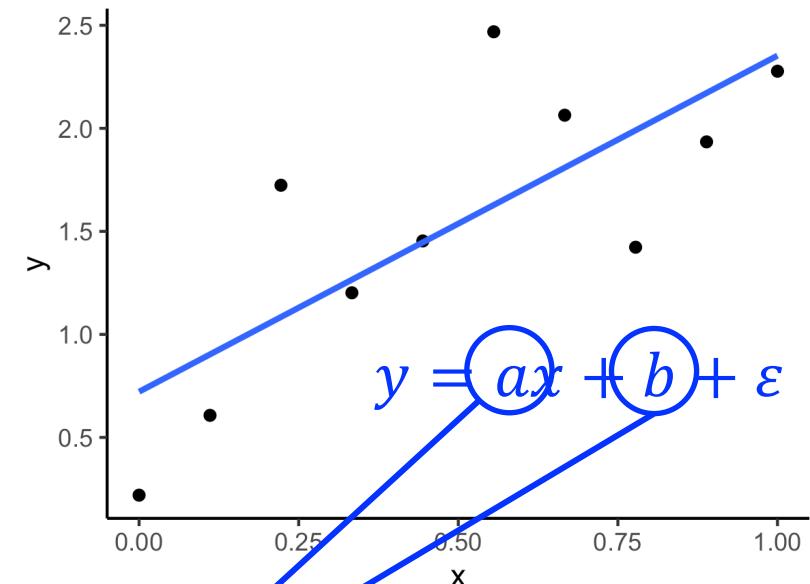
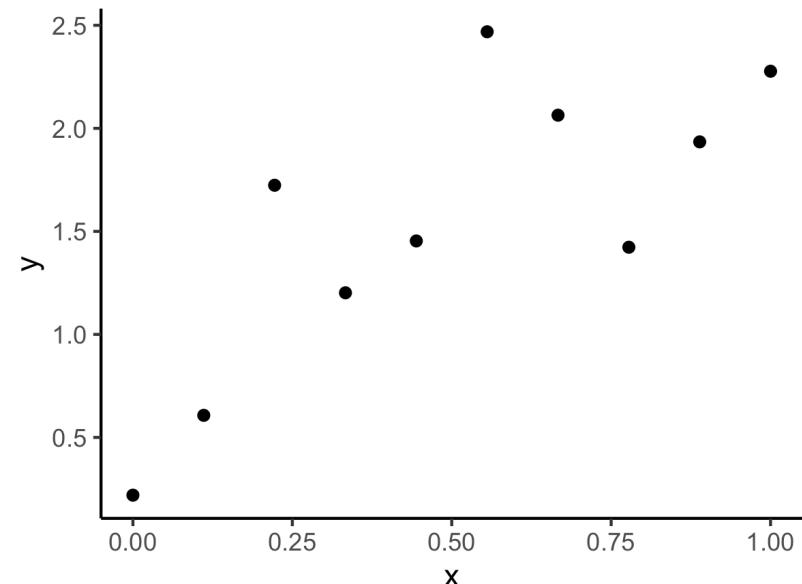
線形回帰 (Linear Regression)



```
dat_lm <- dat %>% lm(y ~ x, data = .)
```

```
## lm(formula = y ~ x, data = .)  
##  
## Coefficients:  
## (Intercept)      x  
##       0.7217  1.6311
```

線形回帰 (Linear Regression)



```
dat_lm <- dat %>% lm(y ~ x, data = .)
```

```
## lm(formula = y ~ x, data = .)
```

```
##
```

```
## Coefficients:
```

```
## (Intercept)
```

```
##      0.7217  1.6311
```

x

線形回帰 (Linear Regression)

```
dat %>% lm(y ~ x, data = .) %>% summary()  
##  
## Call:  
## lm(formula = y ~ x, data = .)  
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)  
## (Intercept)  0.7217   0.2871   2.514  0.03613 *  
## x           1.6311   0.4839   3.371  0.00978 **  
## ---  
## Residual standard error: 0.4884 on 8 degrees of freedom  
## Multiple R-squared: 0.5868, Adjusted R-squared: 0.5351  
## F-statistic: 11.36 on 1 and 8 DF, p-value: 0.009778
```

線形回帰モデル (Linear Regression Model)

回帰直線

$$\hat{y}_i = ax_i + b, \quad \underset{\arg\min_{(a,b)} \sum_{i=1}^n \varepsilon^2}{\longrightarrow} \quad \hat{a} = \frac{S_{xy}}{S_{xx}},$$
$$\varepsilon_i = y_i - \hat{y}_i \quad \longrightarrow \quad \hat{b} = \bar{y} - \frac{S_{xy}}{S_{xx}} \bar{x}$$

線形回帰モデル (Linear Regression Model)

回帰直線

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$$\varepsilon_i = y_i - \hat{y}_i \quad \longrightarrow \quad \hat{b} = \bar{y} - \frac{S_{xy}}{S_{xx}} \bar{x}$$

線形回帰モデル

$$Y_i = \alpha X_i + \beta + u_i,$$

$$u_i \sim N(0, \sigma^2)$$

線形回帰モデル (Linear Regression Model)

回帰直線

$$\hat{y}_i = ax_i + b, \quad \underset{\arg\min_{(a,b)} \sum_{i=1}^n \varepsilon^2}{\hat{a}} = \frac{S_{xy}}{S_{xx}},$$
$$\varepsilon_i = y_i - \hat{y}_i \quad \longrightarrow \quad \hat{b} = \bar{y} - \frac{S_{xy}}{S_{xx}} \bar{x}$$

線形回帰モデル

$$Y_i = \alpha X_i + \beta + u_i, \quad E[\hat{a}] = \alpha,$$
$$u_i \sim N(0, \sigma^2) \quad E[\hat{b}] = \beta$$

線形回帰 (Linear Regression Model)

```
dat %>% lm(y ~ x, data = .) %>% summary()  
##  
## Call:  
## lm(formula = y ~ x, data = .)  
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)  
## (Intercept)  0.7217    0.2871   2.514  0.03613 *  
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```

線形回帰モデル (Linear Regression Model)

決定係数R2と相関係数r

$$R^2 := \frac{\sum_i (\hat{y}_i - \bar{y})^2}{\sum_i (y_i - \bar{y})^2}$$

$$= \dots$$

$$= \left(\frac{\text{Cov}[x,y]}{\sigma_x \sigma_y} \right)^2$$

$$= r^2$$

$$\text{Cov}[x,y] := \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$$

$$S_{xy} := \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$$

線形回帰モデル (Linear Regression Model)

決定係数R2と相関係数r

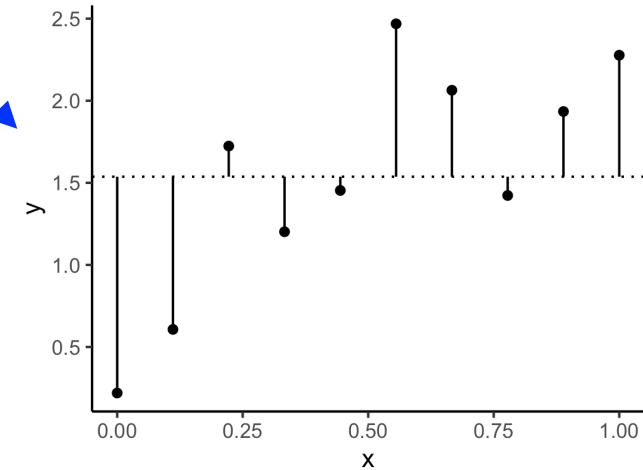
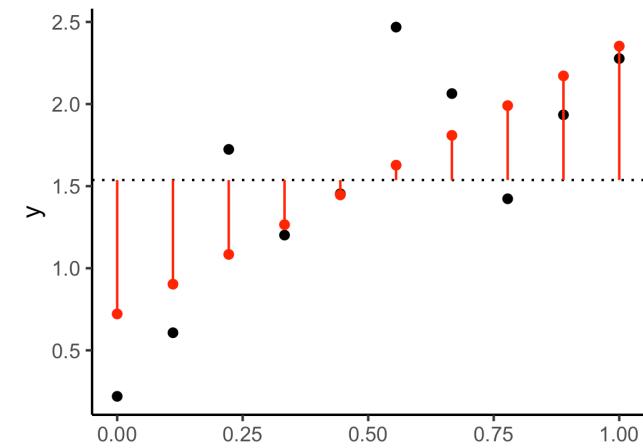
$$R^2 := \frac{\sum_i (\hat{y}_i - \bar{y})^2}{\sum_i (y_i - \bar{y})^2}$$

$$= \left(\frac{\text{Cov}[x,y]}{\sigma_x \sigma_y} \right)^2$$

$$= r^2$$

$$\text{Cov}[x,y] := \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$$

$$S_{xy} := \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$$



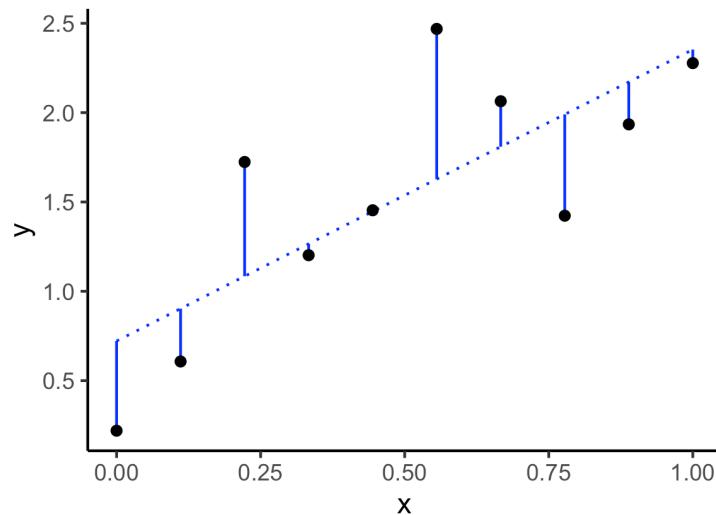
線形回帰 (Linear Regression Model)

```
dat %>% lm(y ~ x, data = .) %>% summary()  
##  
## Call:  
## lm(formula = y ~ x, data = .)  
##  
## Coefficients:  
##             Estimate Std. Error t value Pr(>|t|)  
## (Intercept) 0.7217    0.2871   2.514  0.03613 *  
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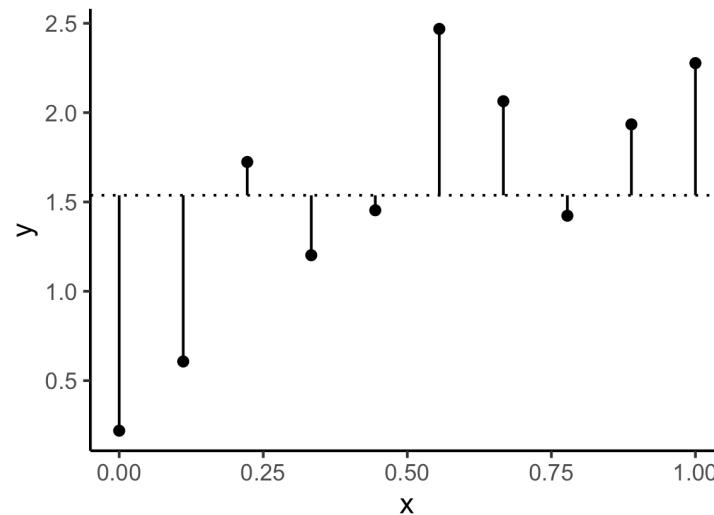
線形回帰モデル (Linear Regression Model)

F検定

$$H_1: a = \hat{a}$$



$$H_0: a = 0$$



残差平方和

$$RSS_1 = \sum_i (y_i - \hat{y})^2$$

$$RSS_0 = \sum_i (y_i - \bar{y})^2$$



$$\frac{RSS_0 - RSS_1}{RSS_1}$$

が十分にゼロから離れているかを検討する。

線形回帰モデル (Linear Regression Model)

F検定

$$x \sim N(0,1) \rightarrow \sum_{i=1}^n x^2 \sim \chi^2(n)$$

(標準)正規分布 → カイ二乗分布 → F分布

$$N(0,1) \quad \chi^2(n) \quad F(n_1, n_2)$$

$$x_1 \sim \chi^2(n_1) \quad x_2 \sim \chi^2(n_2) \rightarrow \frac{x_1/n_1}{x_2/n_2} \sim F(n_1, n_2)$$

線形回帰モデル (Linear Regression Model)

F検定

$$x \sim N(0,1) \rightarrow \sum_{i=1}^n x^2 \sim \chi^2(n)$$

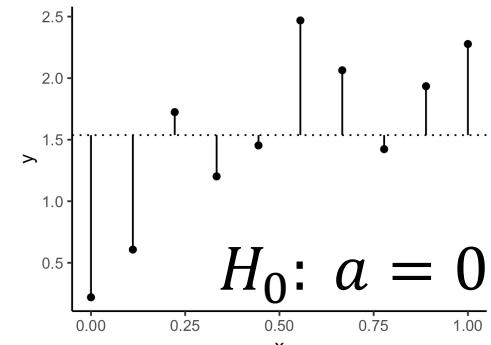
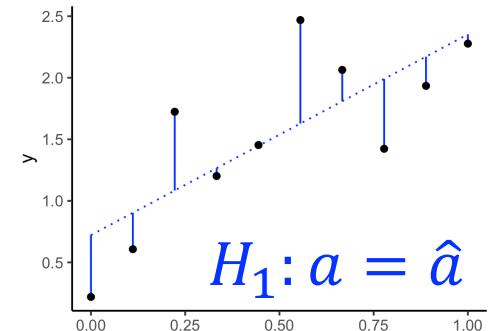
$$RSS_1 = \sum_i (y_i - \hat{y})^2$$

$$\sim \chi^2(n - k - 1)$$

$$RSS_0 - RSS_1 = \sum_i (y_i - \bar{y})^2 - \sum_i (y_i - \hat{y})^2$$

$$\sim \chi^2(k)$$

k , number of estimated parameters in the model



線形回帰モデル (Linear Regression Model)

F検定

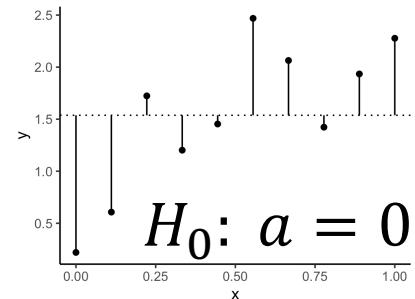
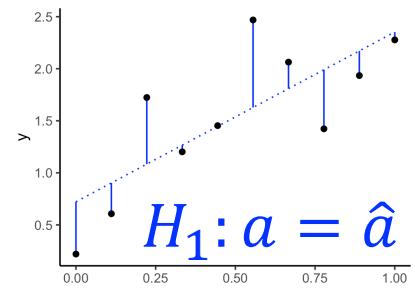
$$RSS_0 - RSS_1 \sim \chi^2(k)$$

$$RSS_1 \sim \chi^2(n - k - 1)$$

(標準)正規分布 → カイ二乗分布 → F分布

$$\chi^2(n) \quad F(n_1, n_2)$$

$$x_1 \sim \chi^2(n_1) \quad x_2 \sim \chi^2(n_2) \rightarrow \frac{x_1/n_1}{x_2/n_2} \sim F(n_1, n_2)$$



線形回帰モデル (Linear Regression Model)

F検定

$$RSS_0 - RSS_1 \sim \chi^2(k)$$

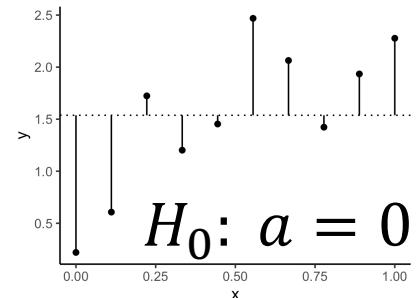
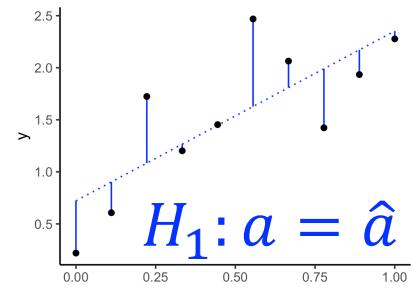
$$RSS_1 \sim \chi^2(n - k - 1)$$

(標準)正規分布 → カイ二乗分布 → F分布

$$\chi^2(n) \quad F(n_1, n_2)$$

$$\frac{(RSS_0 - RSS_1)/k}{RSS_1/(n - k - 1)} \sim F(k, n - k - 1)$$

f-statistic



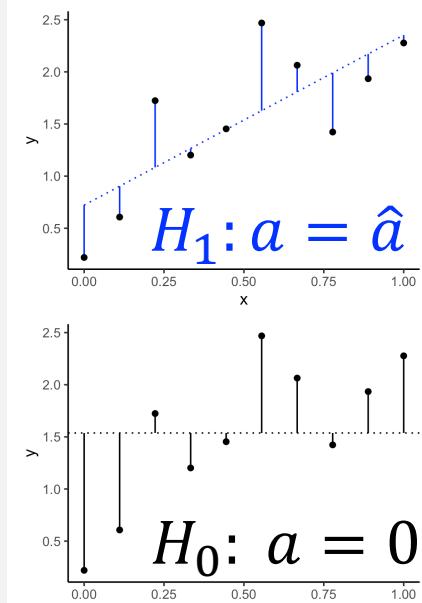
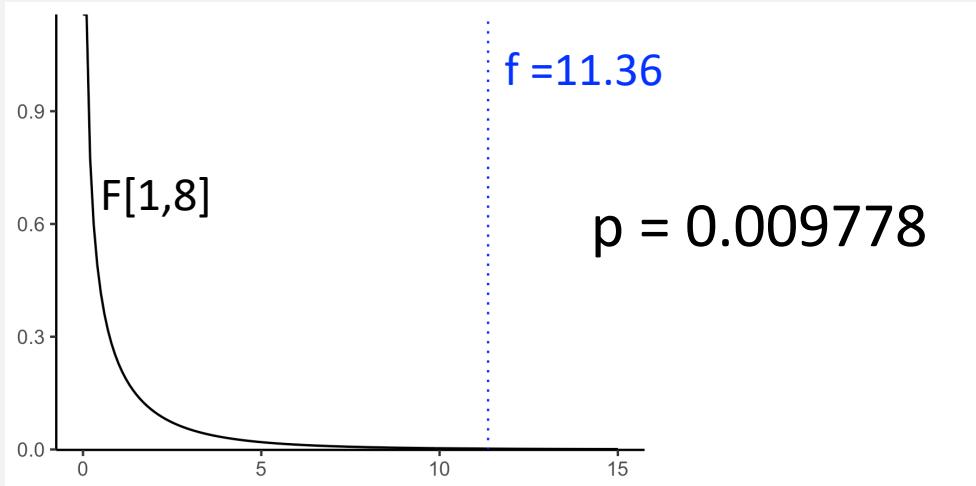
線形回帰 (Linear Regression Model)

```
dat %>% lm(y ~ x, data = .) %>% summary()
```

F-statistic: 11.36 on 1 and 8 DF, p-value: 0.009778

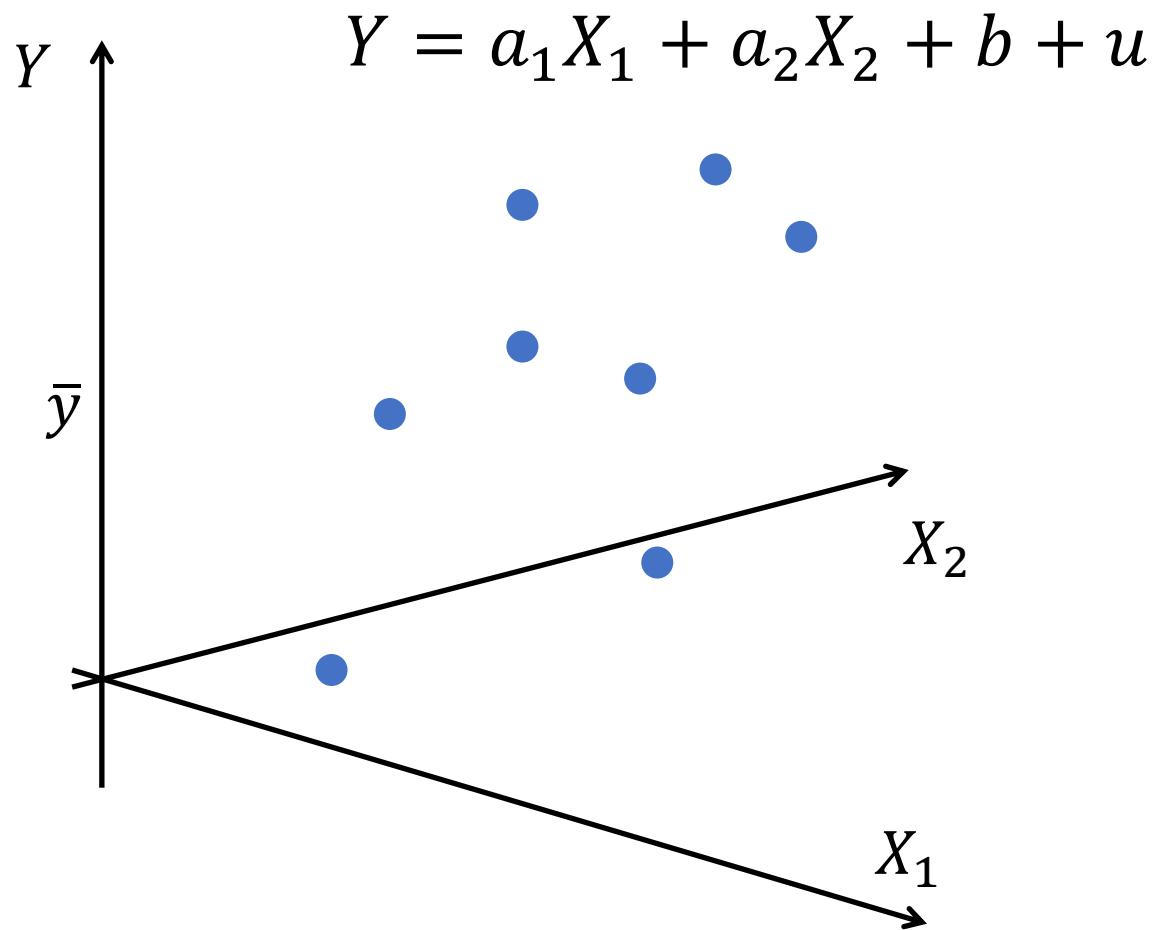
f-statistic

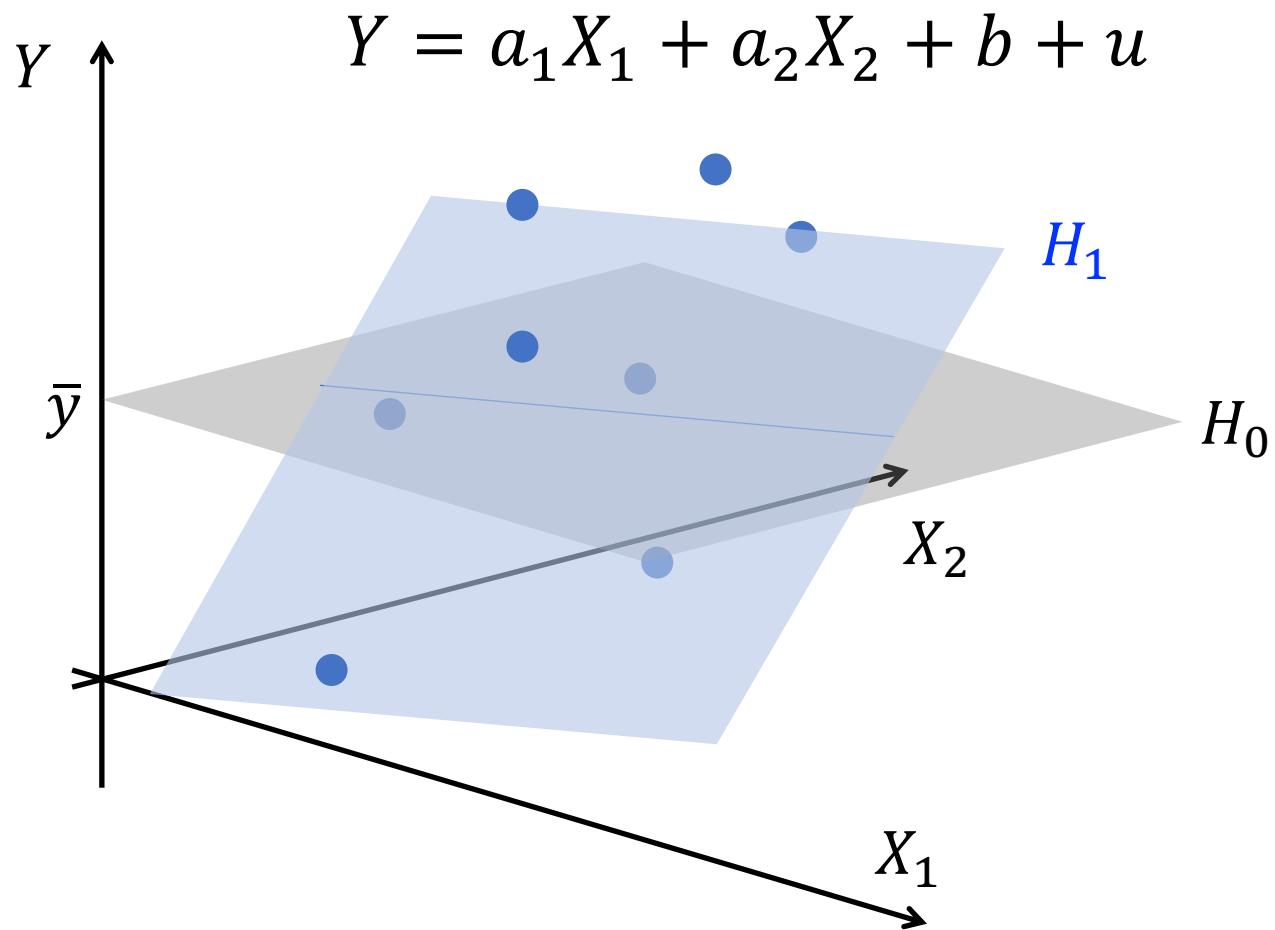
$$\frac{(RSS_0 - RSS_1)/k}{RSS_1/(n - k - 1)} \sim F(k, n - k - 1)$$



線形回帰 (Linear Regression Model)

```
dat %>% lm(y ~ x, data = .) %>% summary()  
##  
## Call:  
## lm(formula = y ~ x, data = .)  
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## (Intercept)  0.7217   0.2871   2.514  0.03613 *  
## x           1.6311   0.4839   3.371  0.00978 **  
## ---  
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## Multiple R-squared: 0.5868, Adjusted R-squared: 0.5351  
## F-statistic: 11.36 on 1 and 8 DF, p-value: 0.009778
```





線形回帰 (Linear Regression Model)

```
dat_lm <-  
  dat %>% lm(y ~ x, data = .)  
  
extract_rsq <- function(lm_model){  
  lm_model %>% .$r.squared  
}  
  
dat_lm %>% extract_rsq()  
## [1] 0.5867894
```

線形回帰 (Linear Regression Model)

```
dat_lm <-
  dat %>% lm(y ~ x, data = .)

extract_p <- function(lm_model){
  f <-
    lm_model %>%
    summary() %>%
    .$fstatistic

  pf(f[1], f[2], f[3], lower.tail = F)
}

dat_lm %>% extract_p()

##          value
## 0.009777651
```

線形回帰 (Linear Regression Model)

```
dat_lm_nest <-
  dat %>%
  group_nest() %>%
  mutate(lm = map(data,
                  ~ lm(y ~ x, data = .)))
```

A tibble: 1 x 2

	data	lm
1 <df[,2] [10 × 2]>	<list>	<list>
		<lm>



線形回帰 (Linear Regression Model)

```
dat_lm_nest <-  
  dat %>%  
  group_nest() %>%  
  mutate(lm = map(data, ~ lm(y ~ x, data = .)))  
  
dat_lm_nest %>%  
  mutate(a = map dbl(lm, ~ .$coefficients[1]),  
         b = map dbl(lm, ~ .$coefficients[2]),  
         rsq = map dbl(lm, extract_rsq),  
         pval = map dbl(lm, extract_p))
```

A tibble: 1 x 6

	data	lm	a	b	rsq	pval
1	<list>	<lis>	<dbl>	<dbl>	<dbl>	<dbl>
	1 <df[,2] [10 ...	<lm>	0.722	1.63	0.587	0.00978

線形回帰分析

- ・回帰直線(最小二乗法)
- ・誤差の確率モデル
- ・決定係数と相関係数
- ・回帰モデルの仮説検定

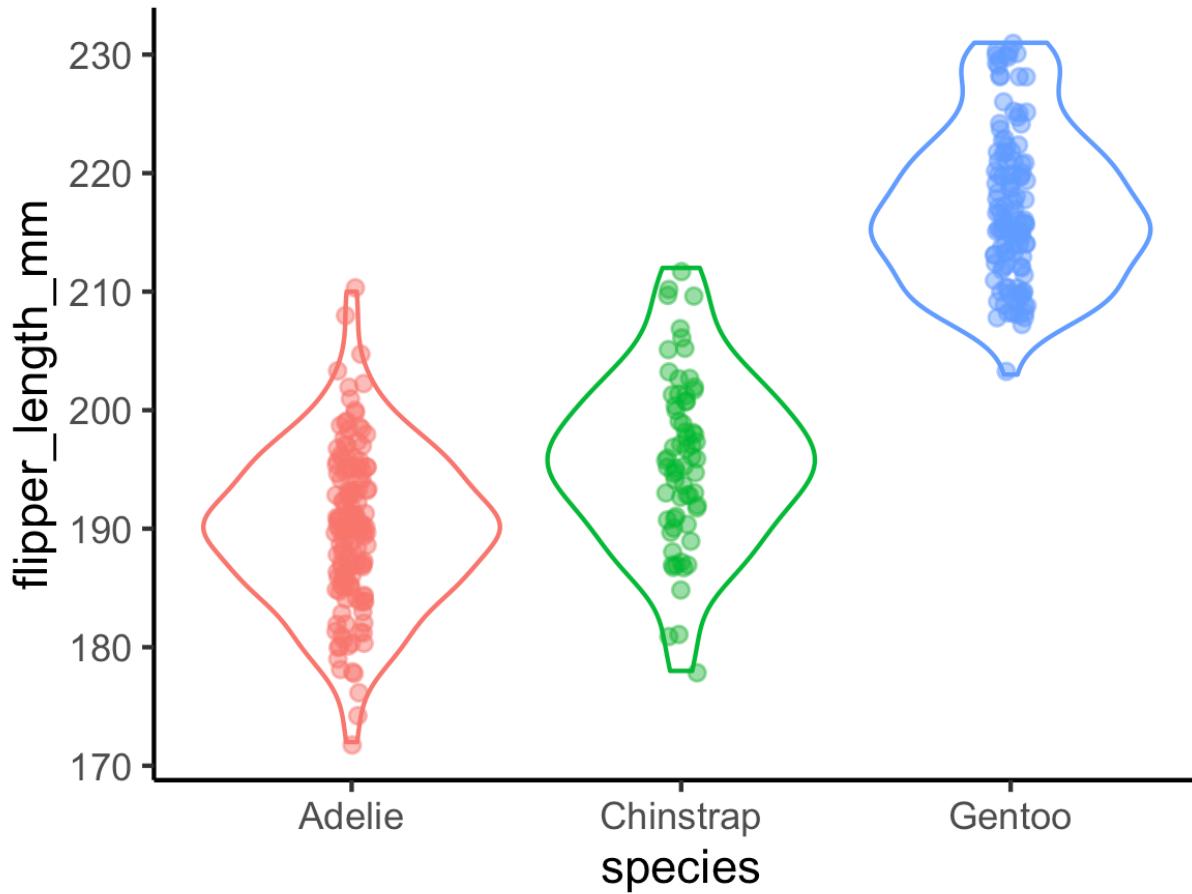
分散分析

- ・回帰モデルとの接続性
- ・One-way ANOVA
- ・Two-way ANOVA
- ・Tukey HSD Test

```
library(palmerpenguins)

penguins %>% head( )

# A tibble: 6 x 8
  species island bill_length_mm bill_depth_mm flipper_length...
  <fct>   <fct>        <dbl>        <dbl>        <dbl> ...
1 Adelie  Torg...       39.1         18.7        181
2 Adelie  Torg...       39.5         17.4        186
3 Adelie  Torg...       40.3         18          195
4 Adelie  Torg...        NA           NA          NA
5 Adelie  Torg...       36.7         19.3        193
6 Adelie  Torg...       39.3         20.6        190
# ... with 3 more variables: body_mass_g <int>, sex <fct>, year <int>
```



```
penguins %>%
  ggplot() +
  aes(species, flipper_length_mm, color = species) +
  geom_violin() +
  geom_jitter(alpha = 0.5, width = 0.05) +
  theme(legend.position = "none")
```

分散分析 (ANOVA)

```
penguins_aov <-
  penguins %>%
  aov(flipper_length_mm ~ species, data = .)
```

```
penguins_aov <-
  penguins %>%
  lm(flipper_length_mm ~ species, data = .) %>%
  aov()
```

分散分析 (ANOVA)

```
penguins_aov <-
  penguins %>%
  lm(flipper_length_mm ~ species, data = .) %>%
  aov()
```

```
penguins_aov %>%
  summary()
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
species	2	52473	26237	594.8	<2e-16
Residuals	339	14953	44		

species ***
Residuals

分散分析 (ANOVA)

```
penguins %>%
```

```
  lm(flipper_length_mm ~ species, data = .) %>%  
  summary()
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	189.9536	0.5405	351.454	< 2e-16 ***
speciesChinstrap	5.8699	0.9699	6.052	3.79e-09 ***
speciesGentoo	27.2333	0.8067	33.760	< 2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.642 on 339 degrees of freedom
(2 observations deleted due to missingness)

Multiple R-squared: 0.7782, Adjusted R-squared: 0.7769
F-statistic: 594.8 on 2 and 339 DF, p-value: < 2.2e-16

分散分析 (ANOVA)

```
penguins_species <-
  penguins %>%
  select(flipper_length_mm, species) %>%
  mutate(isAdelie = if_else(species == "Adelie", 1, 0),
         isChinstrap = if_else(species == "Chinstrap", 1, 0),
         isGentoo = if_else(species == "Gentoo", 1, 0))

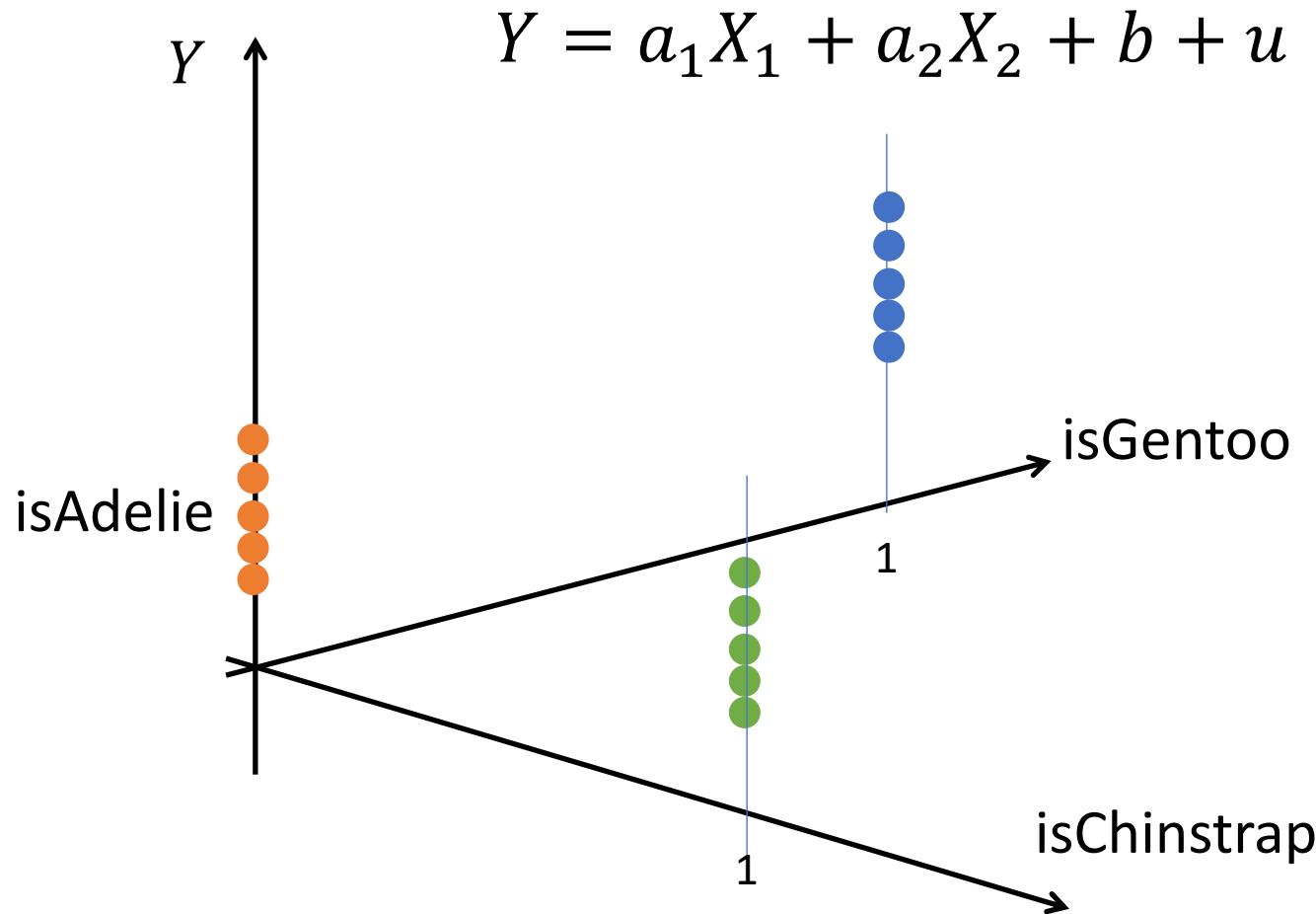
penguins_species %>%
  lm(flipper_length_mm ~ isChinstrap + isGentoo, data = .)
```

Call:

```
lm(formula = flipper_length_mm ~ isGentoo + isChinstrap, data = .)
```

Coefficients:

(Intercept)	isChinstrap	isGentoo
189.95	5.87	27.23



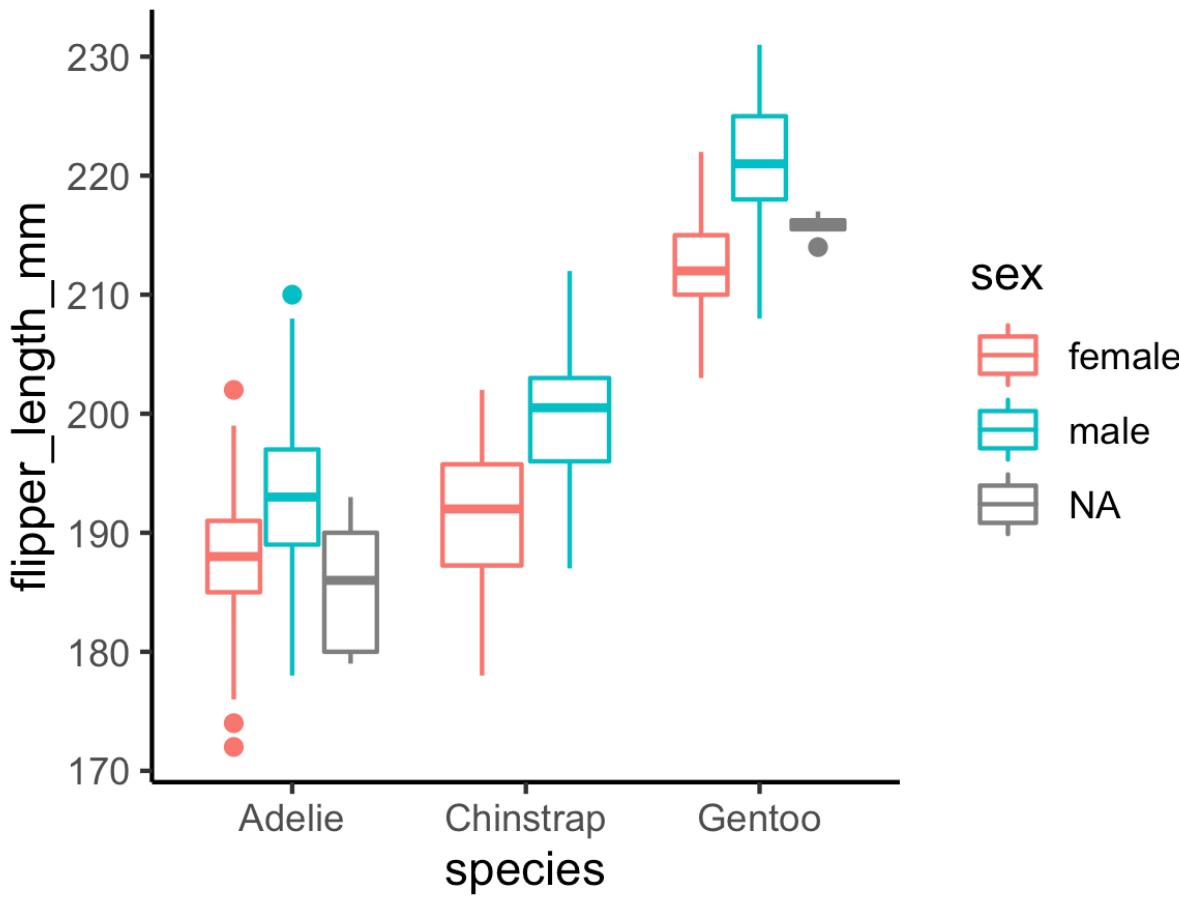
分散分析 (ANOVA)

```
penguins_aov <-
  penguins %>%
  lm(flipper_length_mm ~ species, data = .) %>%
  aov()
```

```
penguins_aov %>%
  summary()
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
species	2	52473	26237	594.8	<2e-16
Residuals	339	14953	44		

species ***
Residuals



```
penguins %>%
  ggplot() +
  aes(species, flipper_length_mm, color = sex) +
  geom_boxplot()
```

分散分析 (Two-way ANOVA)

```
penguins %>%
  lm(flipper_length_mm ~
    species + sex + species * sex,
    data = .) %>%
  aov() %>%
  summary()
```

Tukey HSD test

```
penguins %>%
  lm(flipper_length_mm ~
    species + sex + species * sex,
    data = .) %>%
aov() %>%
TukeyHSD()
```

Tukey multiple comparisons of means
95% family-wise confidence level

Fit: aov(formula = .)

\$species

	diff	lwr	upr	p	adj
Chinstrap-Adelie	5.72079	3.76593	7.675649		0
Gentoo-Adelie	27.13255	25.48814	28.776974		0
Gentoo-Chinstrap	21.41176	19.38766	23.435867		0
...					

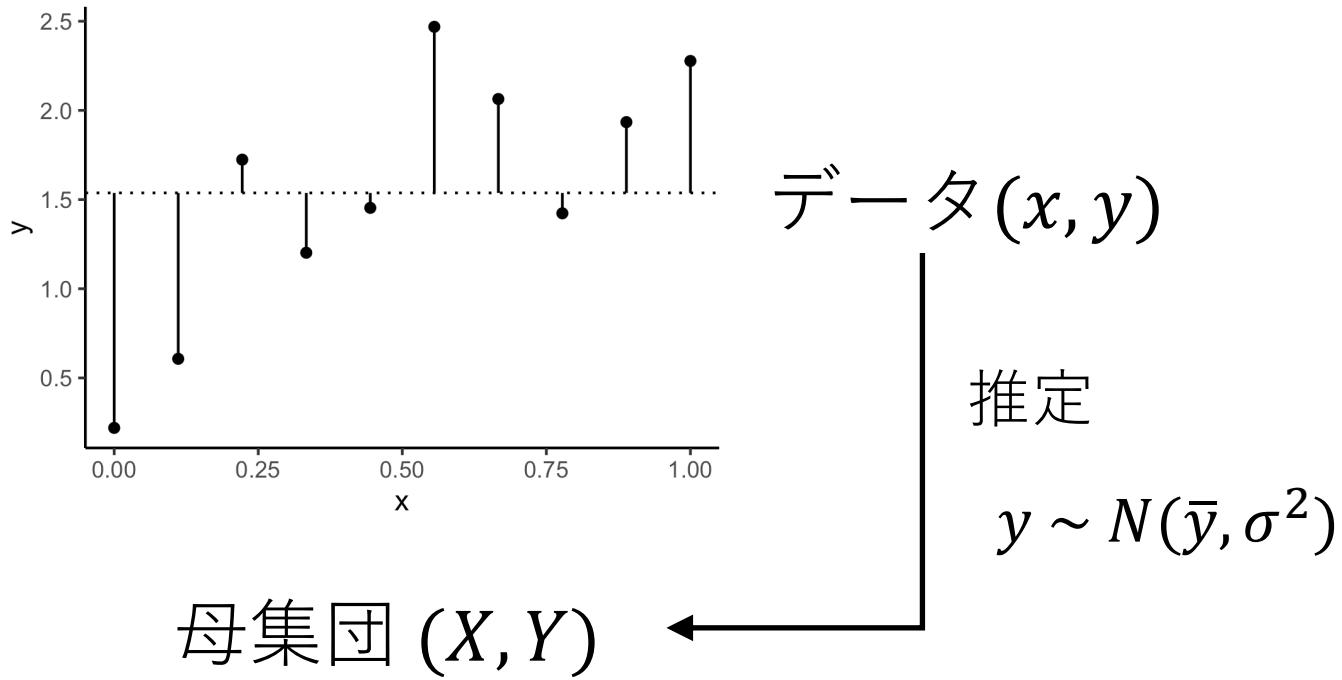
線形回帰分析

- ・回帰直線(最小二乗法)
- ・誤差の確率モデル
- ・決定係数と相関係数
- ・回帰モデルの仮説検定
- ・ブートストラップ法

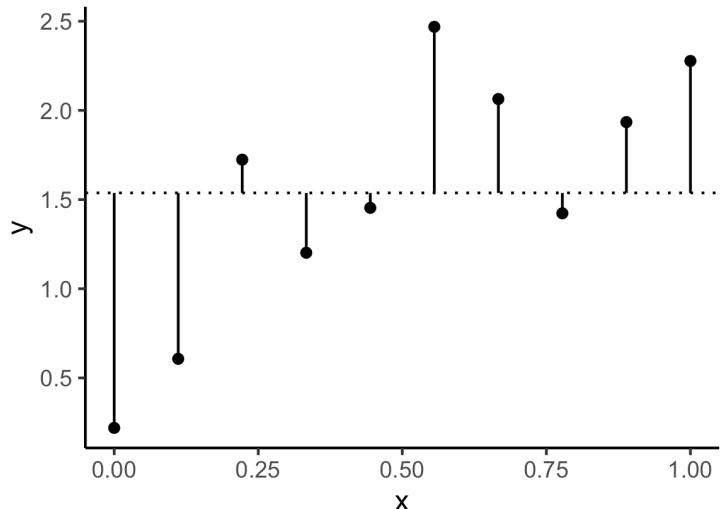
分散分析

- ・回帰モデルとの接続性
- ・One-way ANOVA
- ・Two-way ANOVA
- ・Tukey HSD Test

$H_0: a = 0$ のもとで



$H_0: a = 0$ のもとで



データ (x, y)

推定

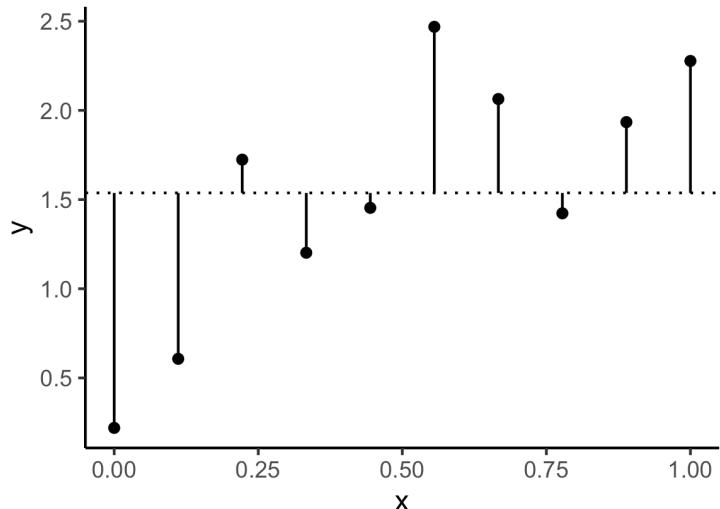
$$y \sim N(\bar{y}, \sigma^2)$$

母集団 (X, Y)

標本 (x', y')

回帰パラメータ a', b'

$H_0: a = 0$ のもとで



データ (x, y)

推定

$$y \sim N(\bar{y}, \sigma^2)$$

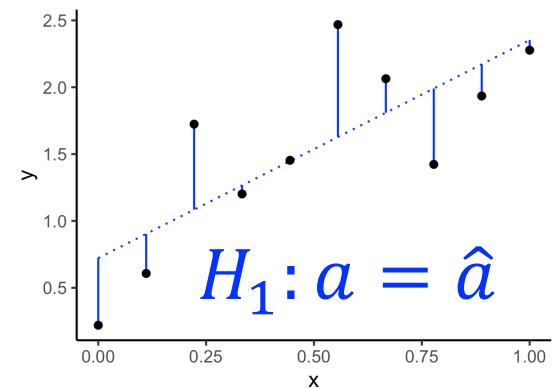
母集団 (X, Y)

標本 (x', y')

検証

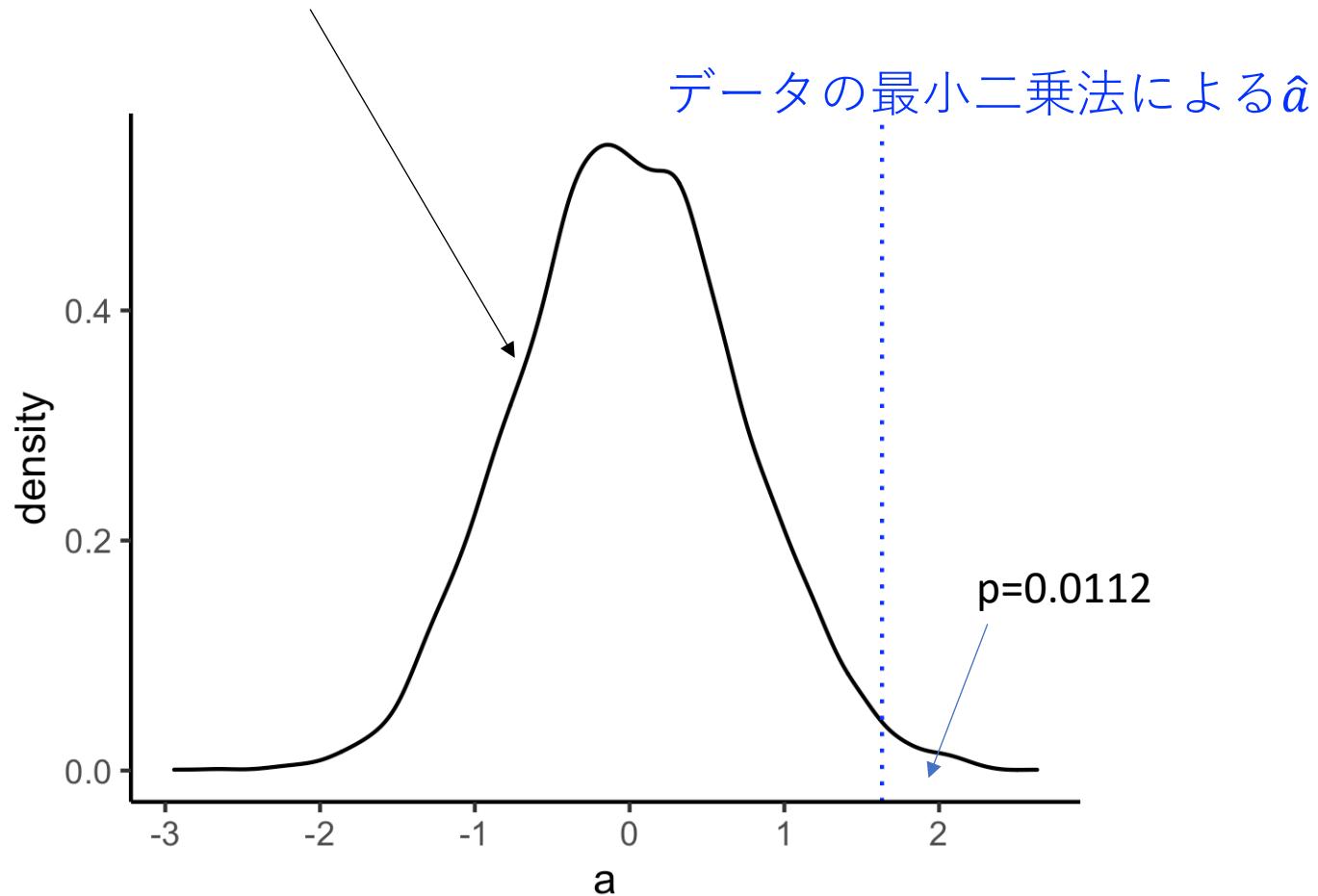
回帰パラメータ a', b'

リサンプリング

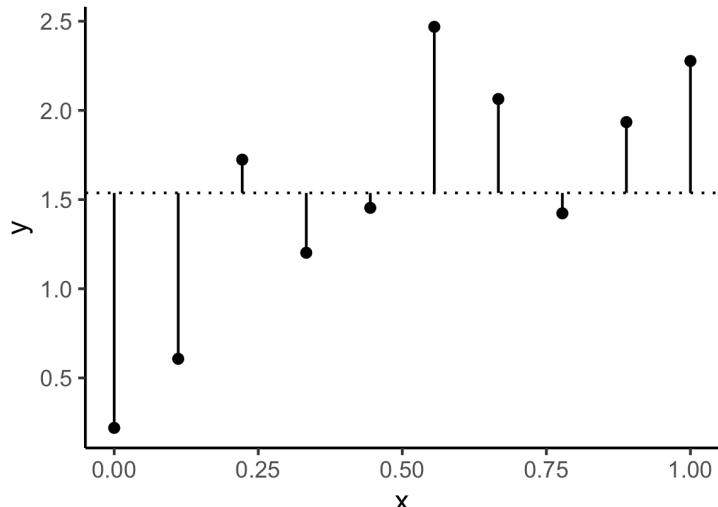


$$H_1: a = \hat{a}$$

$H_0: a = 0$ のもとで5000回リサンプルされた a' の確率密度関数



$H_0: a = 0$ のもとで



データ (x, y)

推定

$$y \sim N(\bar{y}, \sigma^2)$$

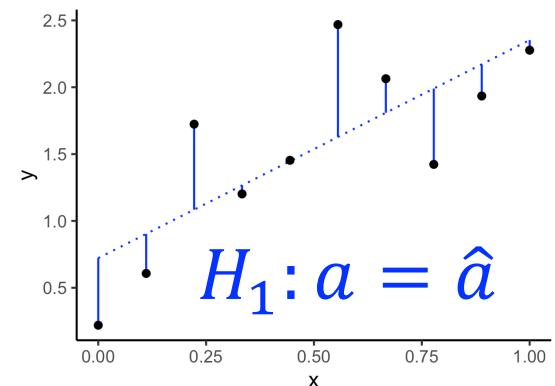
母集団 (X, Y)

標本 (x', y')

検証

回帰パラメータ a', b'

リサンプリング



$$H_1: a = \hat{a}$$

線形回帰分析

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Enjoy!!