

# One-Hot Encoding

MACHINE LEARNING WITH PYSPARK



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# The problem with indexed values

```
# Counts for 'type' category
```

```
+-----+-----+
|  type|count|
+-----+-----+
|Midsize|  22|
|  Small|  21|
|Compact|  16|
| Sporty|  14|
|  Large|  11|
|   Van|   9|
+-----+-----+
```

```
# Numerical indices for 'type' category
```

```
+-----+-----+
|  type|type_idx|
+-----+-----+
|Midsize|    0.0|
|  Small|    1.0|
|Compact|    2.0|
| Sporty|    3.0|
|  Large|    4.0|
|   Van|    5.0|
+-----+-----+
```

# Dummy variables

+-----+		+-----+	+-----+	+-----+	+-----+	+-----+	+-----+
type		Midsize	Small	Compact	Sporty	Large	Van
+-----+		+-----+	+-----+	+-----+	+-----+	+-----+	+-----+
Midsize		X					
Small			X				
Compact	==>			X			
Sporty					X		
Large						X	
Van							X
+-----+		+-----+	+-----+	+-----+	+-----+	+-----+	+-----+

Each categorical level becomes a column.

# Dummy variables: binary encoding

type	Midsize	Small	Compact	Sporty	Large	Van
Midsize	1	0	0	0	0	0
Small	0	1	0	0	0	0
Compact	0	0	1	0	0	0
Sporty	0	0	0	1	0	0
Large	0	0	0	0	1	0
Van	0	0	0	0	0	1

Binary values indicate the presence (1) or absence (0) of the corresponding level.

# Dummy variables: sparse representation

+-----+	+-----+-----+-----+-----+-----+-----+	+-----+-----+
type	Midsize   Small   Compact   Sporty   Large   Van	Column   Value
+-----+	+-----+-----+-----+-----+-----+-----+	+-----+-----+
Midsize	1     0     0     0     0     0	0   1
Small	0     1     0     0     0     0	1   1
Compact   ==>	0     0     1     0     0     0	2   1
Sporty	0     0     0     1     0     0	3   1
Large	0     0     0     0     1     0	4   1
Van	0     0     0     0     0     1	5   1
+-----+	+-----+-----+-----+-----+-----+-----+	+-----+-----+

Sparse representation: store column index and value.

# Dummy variables: redundant column

+-----+		+-----+-----+-----+-----+-----+		+-----+-----+
type		Midsize   Small   Compact   Sporty   Large		Column   Value
+-----+		+-----+-----+-----+-----+-----+		+-----+-----+
Midsize		1     0     0     0     0		0   1
Small		0     1     0     0     0		1   1
Compact	==>	0     0     1     0     0	==>	2   1
Sporty		0     0     0     1     0		3   1
Large		0     0     0     0     1		4   1
Van		0     0     0     0     0		
+-----+		+-----+-----+-----+-----+-----+		+-----+-----+

Levels are mutually exclusive, so drop one.

# One-hot encoding

```
from pyspark.ml.feature import OneHotEncoder

onehot = OneHotEncoder(inputCols=['type_idx'], outputCols=['type_dummy'])
```

Fit the encoder to the data.

```
onehot = onehot.fit(cars)
```

```
# How many category levels?
onehot.categorySizes
```

```
[6]
```

# One-hot encoding

```
cars = onehot.transform(cars)
cars.select('type', 'type_idx', 'type_dummy').distinct().sort('type_idx').show()
```

```
+-----+-----+-----+
|  type|type_idx|  type_dummy|
+-----+-----+-----+
|Midsize|    0.0|(5,[0],[1.0])|
|  Small|    1.0|(5,[1],[1.0])|
|Compact|    2.0|(5,[2],[1.0])|
| Sporty|    3.0|(5,[3],[1.0])|
|  Large|    4.0|(5,[4],[1.0])|
|   Van|    5.0|(5,[],[])|
+-----+-----+-----+
```



# Dense versus sparse

```
from pyspark.mllib.linalg import DenseVector, SparseVector
```

Store this vector: [1, 0, 0, 0, 0, 7, 0, 0].

```
DenseVector([1, 0, 0, 0, 0, 7, 0, 0])
```

```
DenseVector([1.0, 0.0, 0.0, 0.0, 0.0, 7.0, 0.0, 0.0])
```

```
SparseVector(8, [0, 5], [1, 7])
```

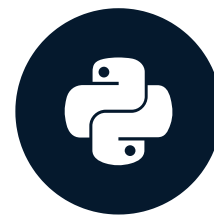
```
SparseVector(8, {0: 1.0, 5: 7.0})
```

# One-Hot Encode categoricals

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# Regression

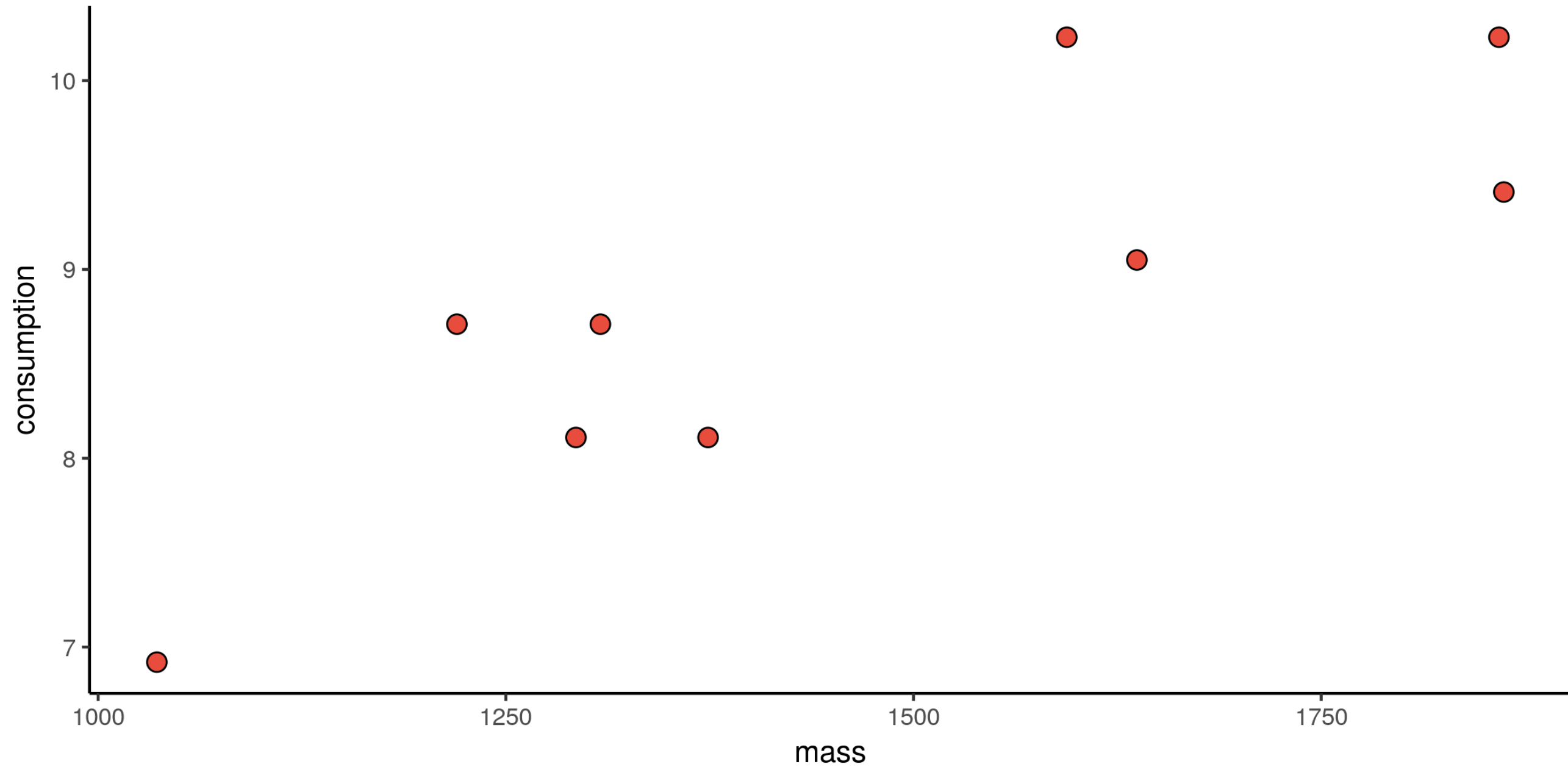
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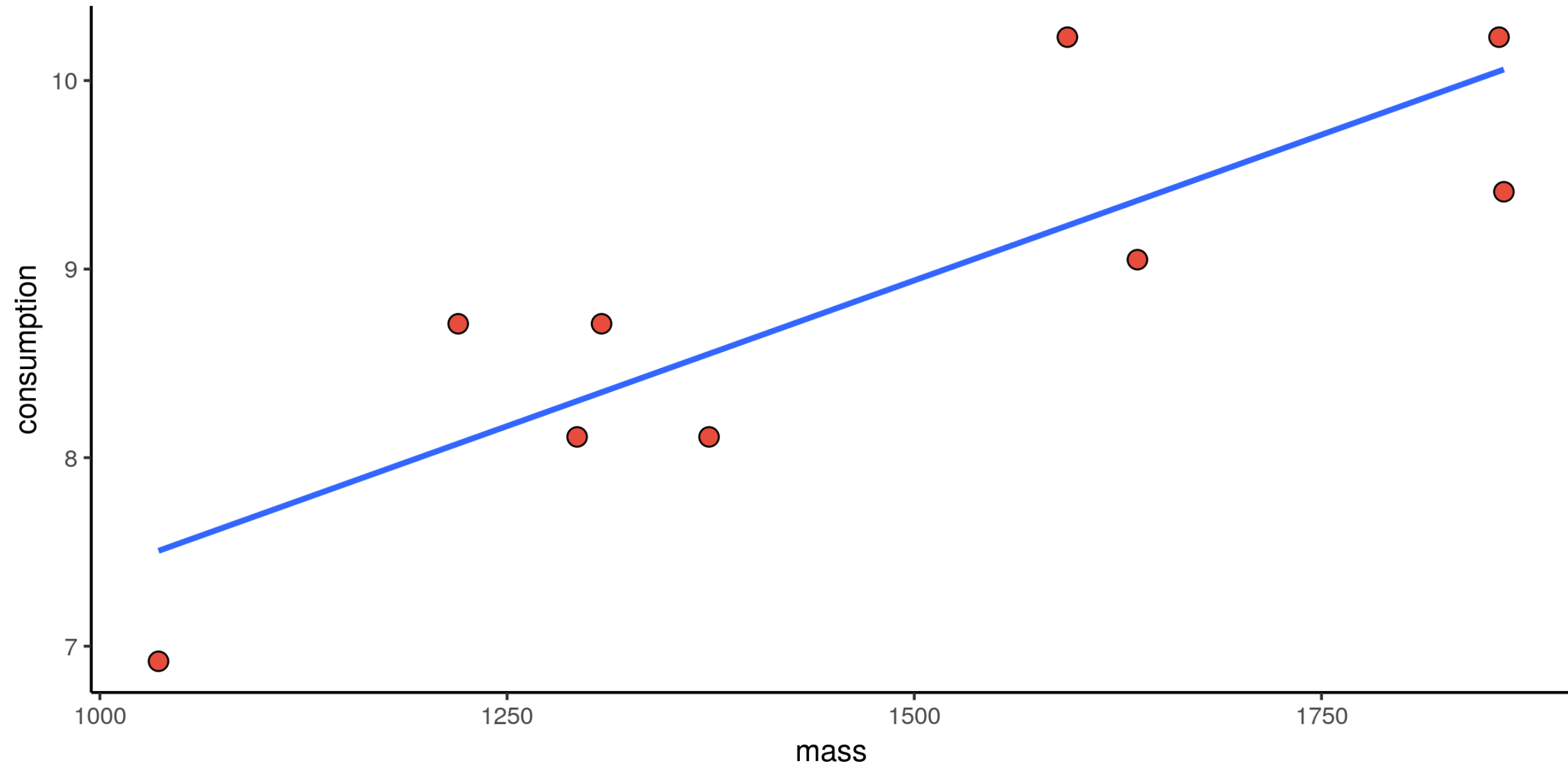
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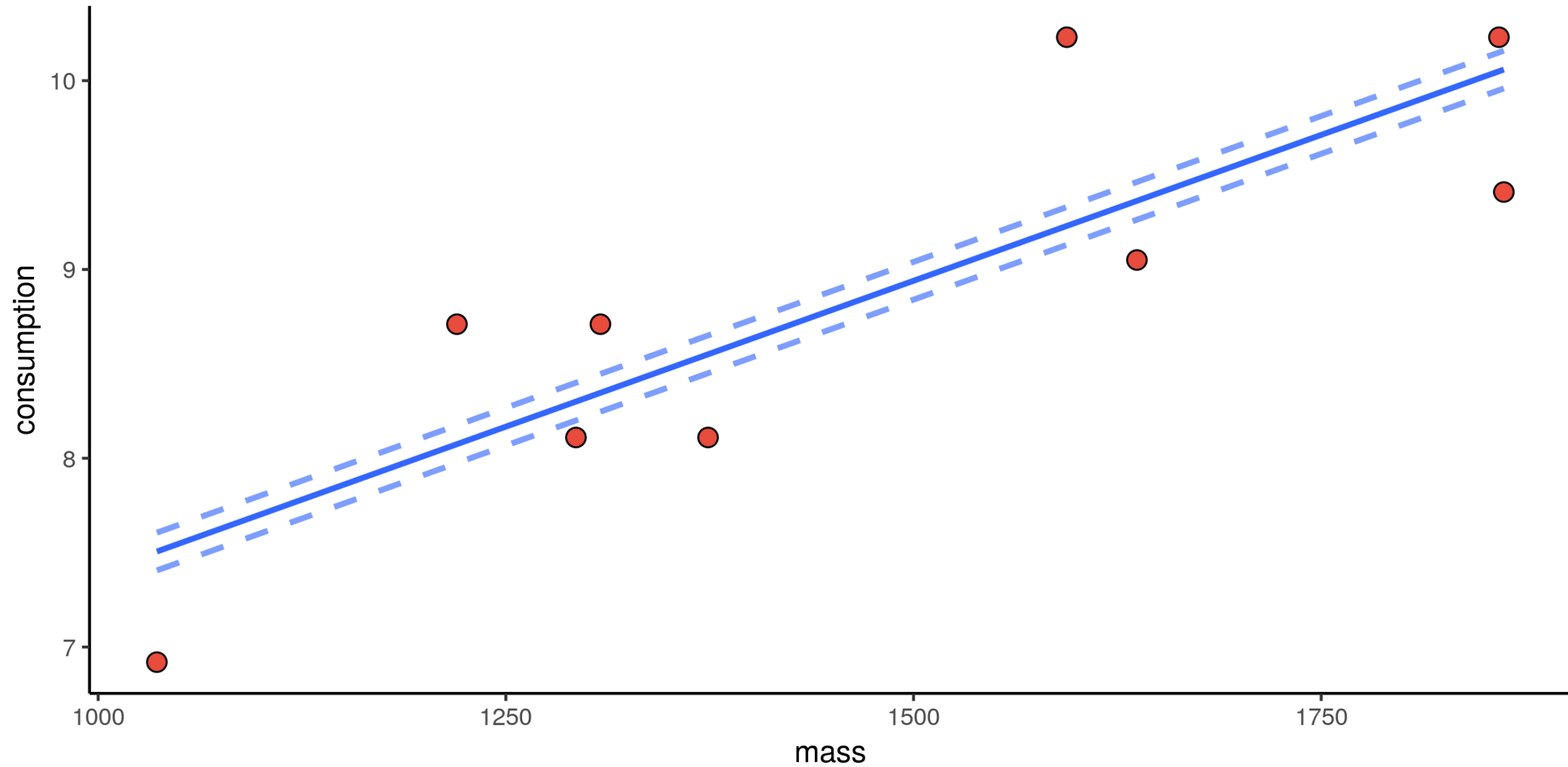
# Consumption versus mass: scatter



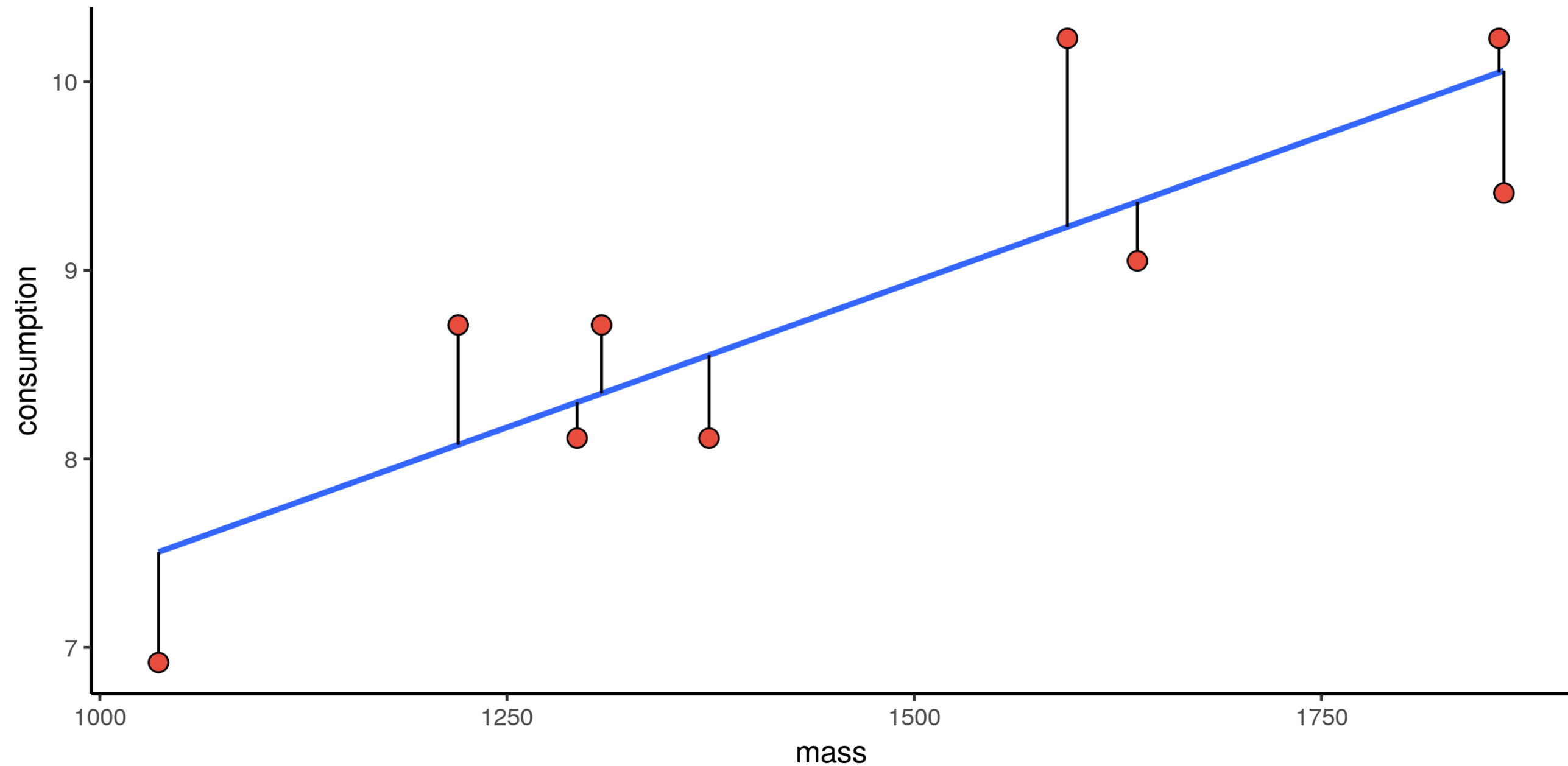
# Consumption versus mass: fit



# Consumption versus mass: alternative fits



# Consumption versus mass: residuals



# Loss function

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

MSE = "Mean Squared Error"



# Loss function: Observed values

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

$y_i$  — observed values

# Loss function: Model values

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

$y_i$  — observed values

$\hat{y}_i$  — model values

# Loss function: Mean

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

$y_i$  — observed values

$\hat{y}_i$  — model values

# Assemble predictors

Predict `consumption` using `mass`, `cyl` and `type_dummy`.

Consolidate predictors into a single column.

```
+-----+---+-----+-----+-----+
|mass  |cyl|type_dummy  |features                                |consumption|
+-----+---+-----+-----+-----+
|1451.0|6  |(5,[0],[1.0])|(7,[0,1,2],[1451.0,6.0,1.0])|9.05      |
|1129.0|4  |(5,[2],[1.0])|(7,[0,1,4],[1129.0,4.0,1.0])|6.53      |
|1399.0|4  |(5,[2],[1.0])|(7,[0,1,4],[1399.0,4.0,1.0])|7.84      |
|1147.0|4  |(5,[1],[1.0])|(7,[0,1,3],[1147.0,4.0,1.0])|7.84      |
|1111.0|4  |(5,[3],[1.0])|(7,[0,1,5],[1111.0,4.0,1.0])|9.05      |
+-----+---+-----+-----+-----+
```

# Build regression model

```
from pyspark.ml.regression import LinearRegression  
  
regression = LinearRegression(labelCol='consumption')
```

Fit to `cars_train` (training data).

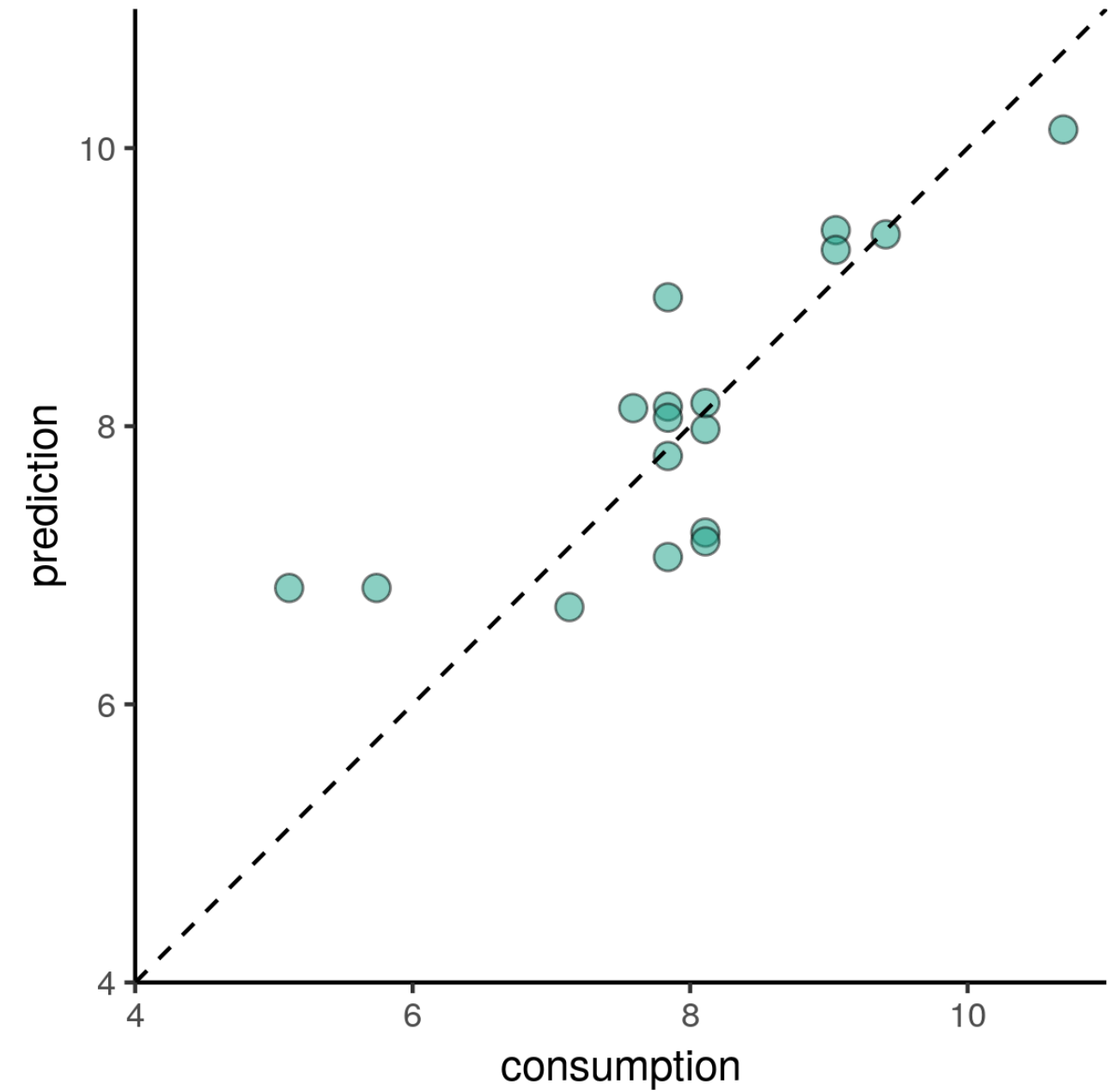
```
regression = regression.fit(cars_train)
```

Predict on `cars_test` (testing data).

```
predictions = regression.transform(cars_test)
```

# Examine predictions

```
+-----+-----+
|consumption|prediction      |
+-----+-----+
|7.84       |8.92699470743403  |
|9.41       |9.379295891451353 |
|8.11       |7.23487264538364  |
|9.05       |9.409860194333735 |
|7.84       |7.059190923328711 |
|7.84       |7.785909738591766 |
|7.59       |8.129959405168547 |
|5.11       |6.836843743852942 |
|8.11       |7.17173702652015  |
+-----+-----+
```



# Calculate RMSE

```
from pyspark.ml.evaluation import RegressionEvaluator

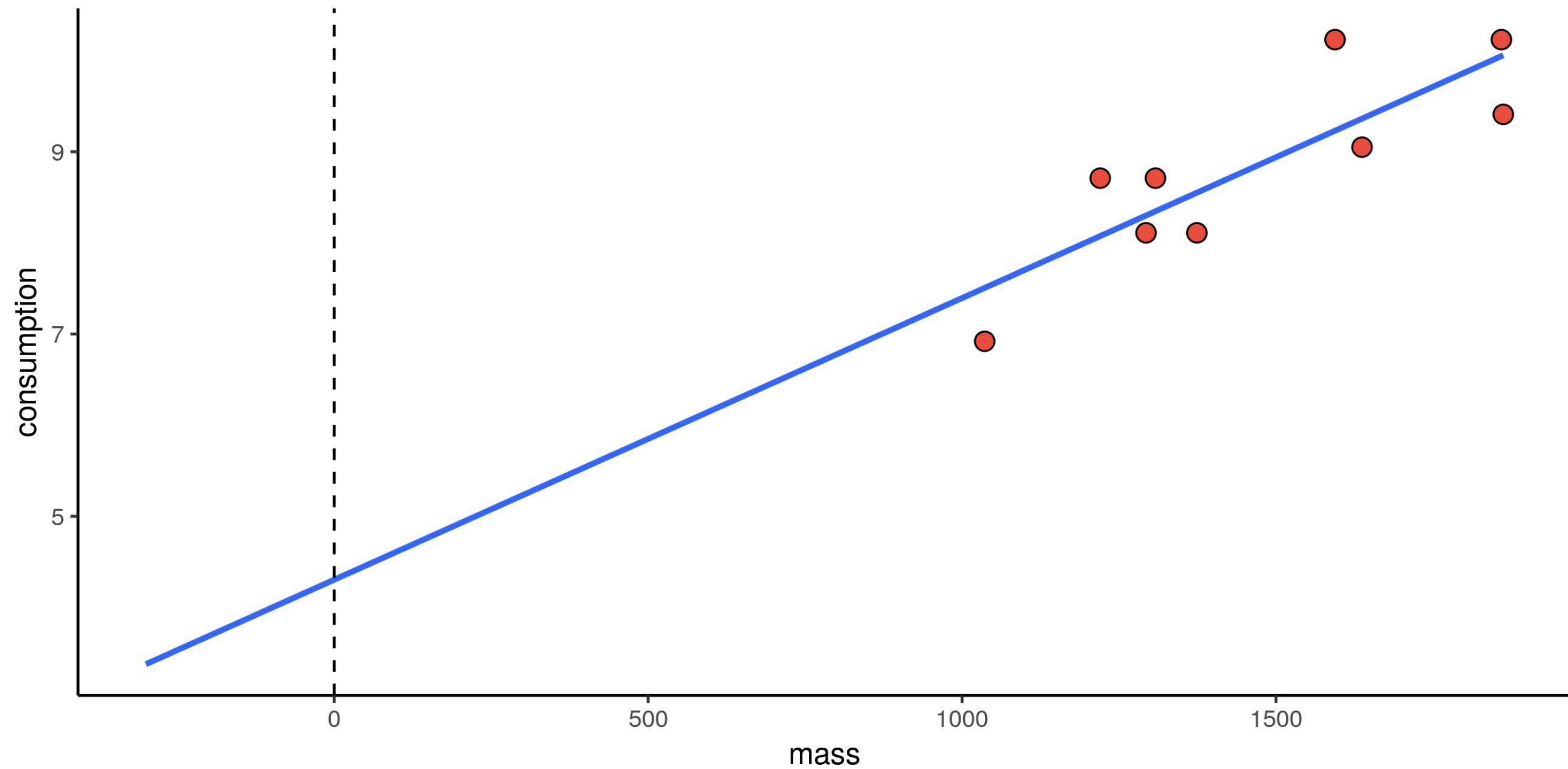
# Find RMSE (Root Mean Squared Error)
RegressionEvaluator(labelCol='consumption').evaluate(predictions)
```

```
0.708699086182001
```

A `RegressionEvaluator` can also calculate the following metrics:

- `mae` (Mean Absolute Error)
- `r2` ( $R^2$ )
- `mse` (Mean Squared Error).

# Consumption versus mass: intercept





# Examine intercept

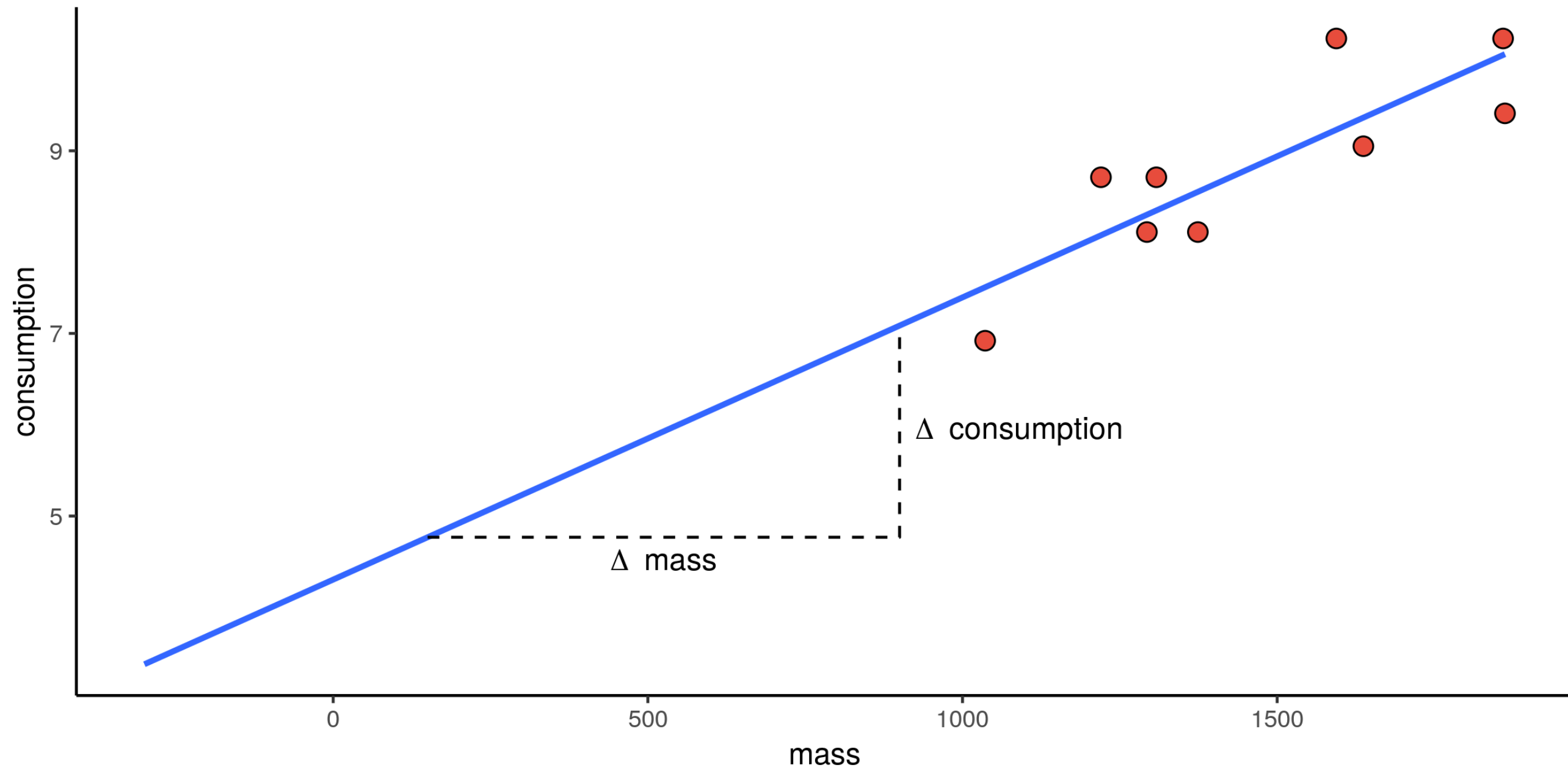
```
regression.intercept
```

```
4.9450616833727095
```

This is the fuel consumption in the (hypothetical) case that:

- `mass` = 0
- `cyl` = 0 and
- vehicle type is 'Van'.

# Consumption versus mass: slope



# Examine Coefficients

```
regression.coefficients
```

```
DenseVector([0.0027, 0.1897, -1.309, -1.7933, -1.3594, -1.2917, -1.9693])
```

mass	0.0027
cyl	0.1897
Midsize	-1.3090
Small	-1.7933
Compact	-1.3594
Sporty	-1.2917
Large	-1.9693

# Regression for numeric predictions

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# Bucketing & Engineering

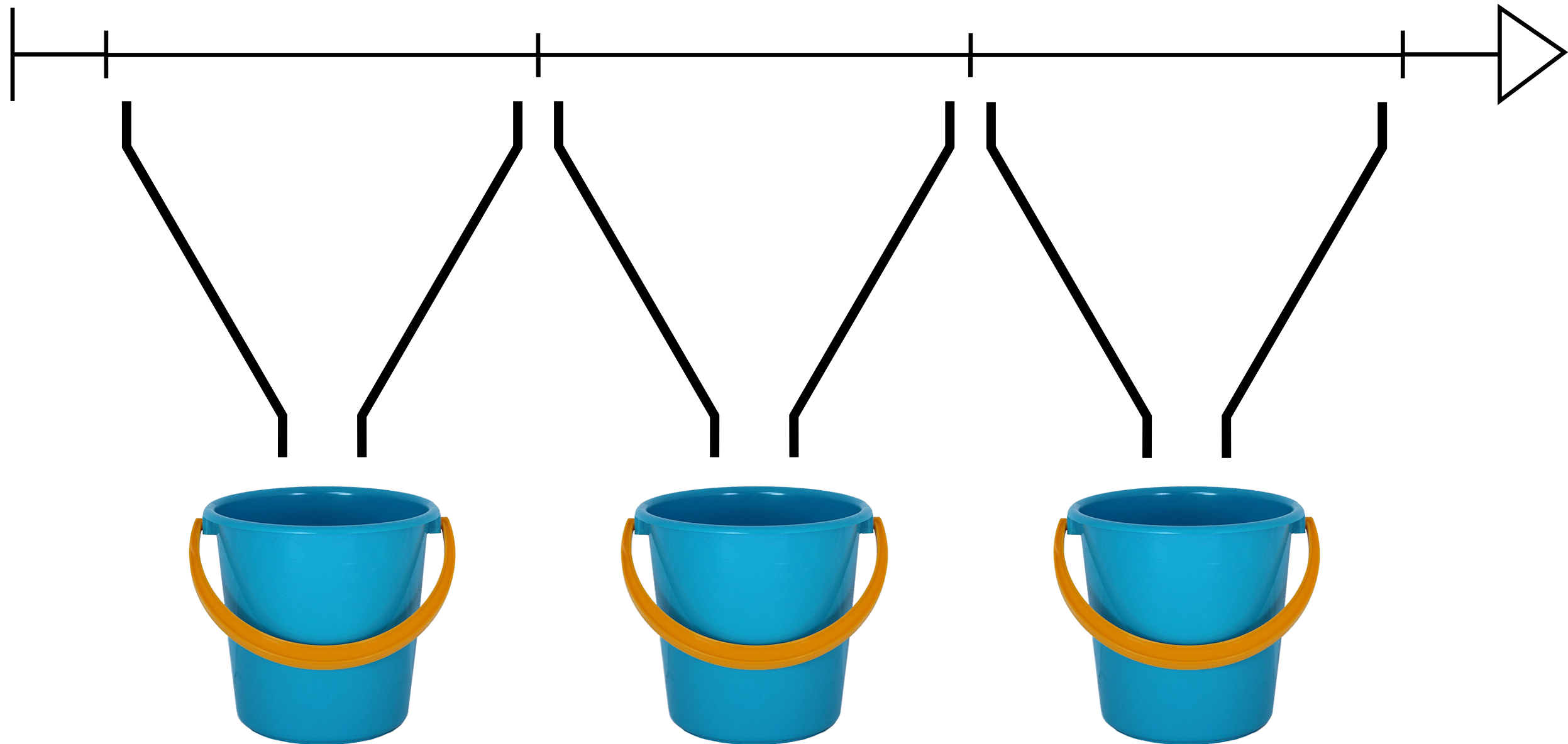
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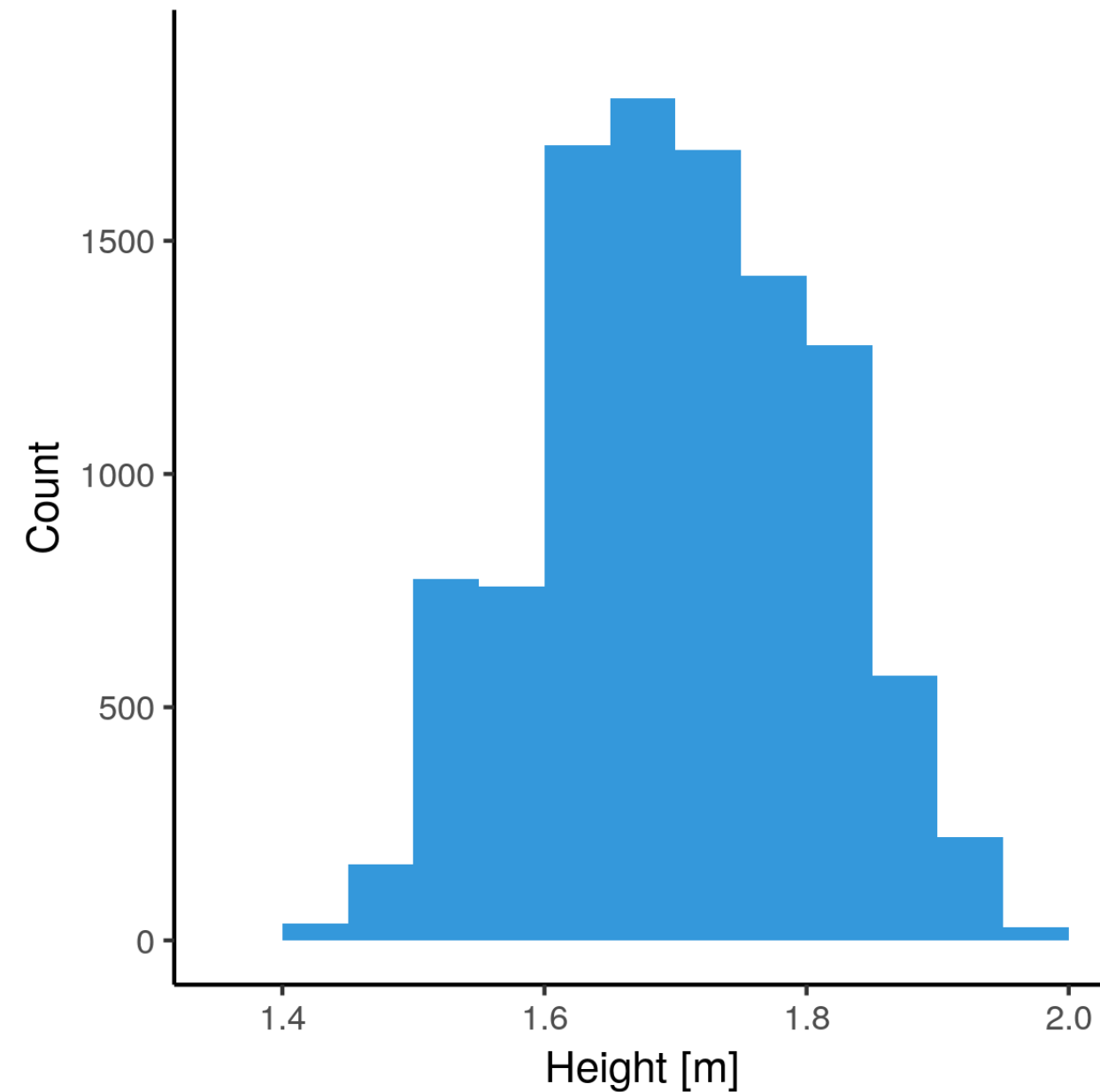
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# Bucketing

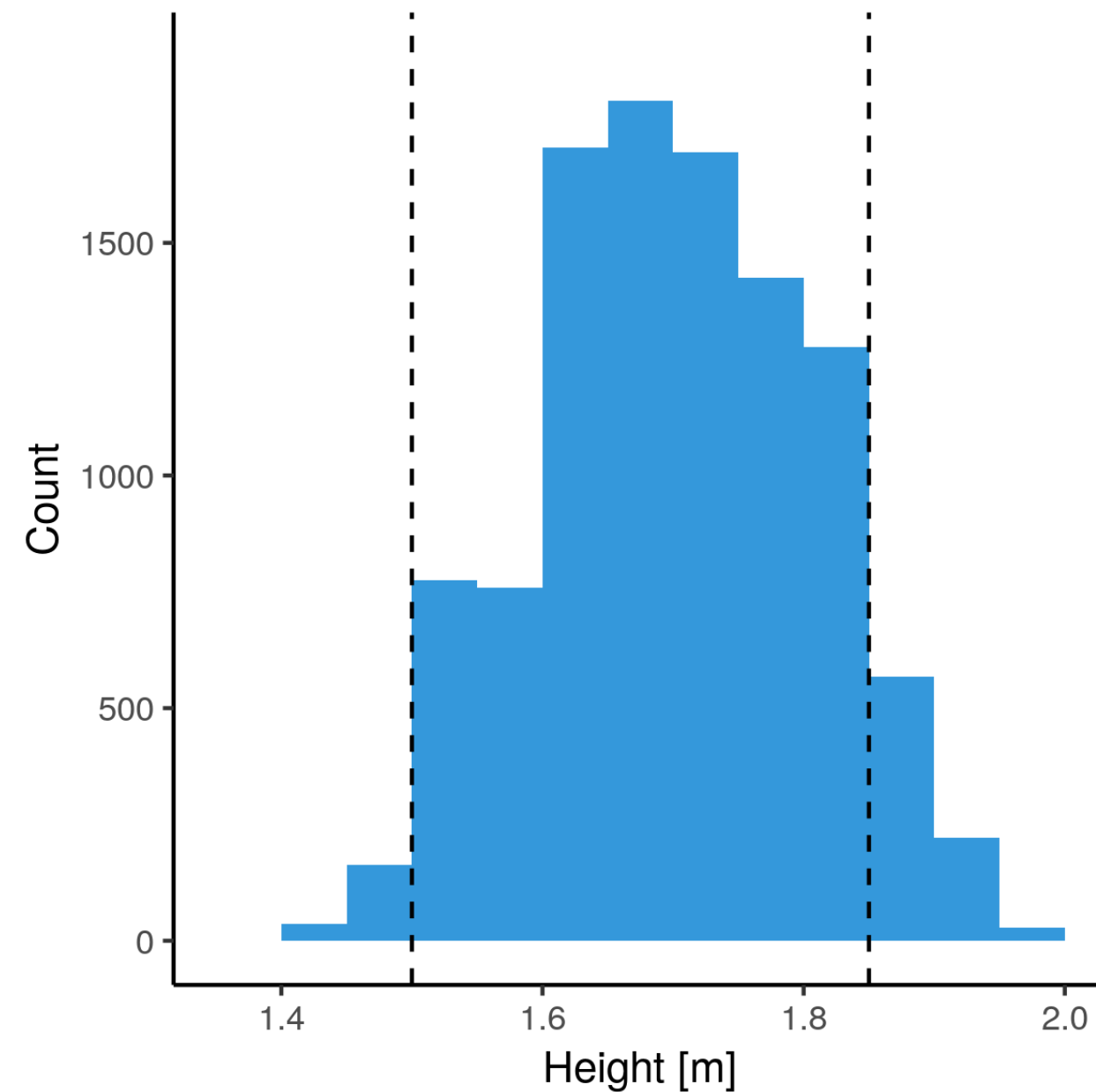


# Bucketing heights



```
+-----+
|height|
+-----+
|  1.42|
|  1.45|
|  1.47|
|  1.50|
|  1.52|
|  1.57|
|  1.60|
|  1.75|
|  1.85|
|  1.88|
+-----+
```

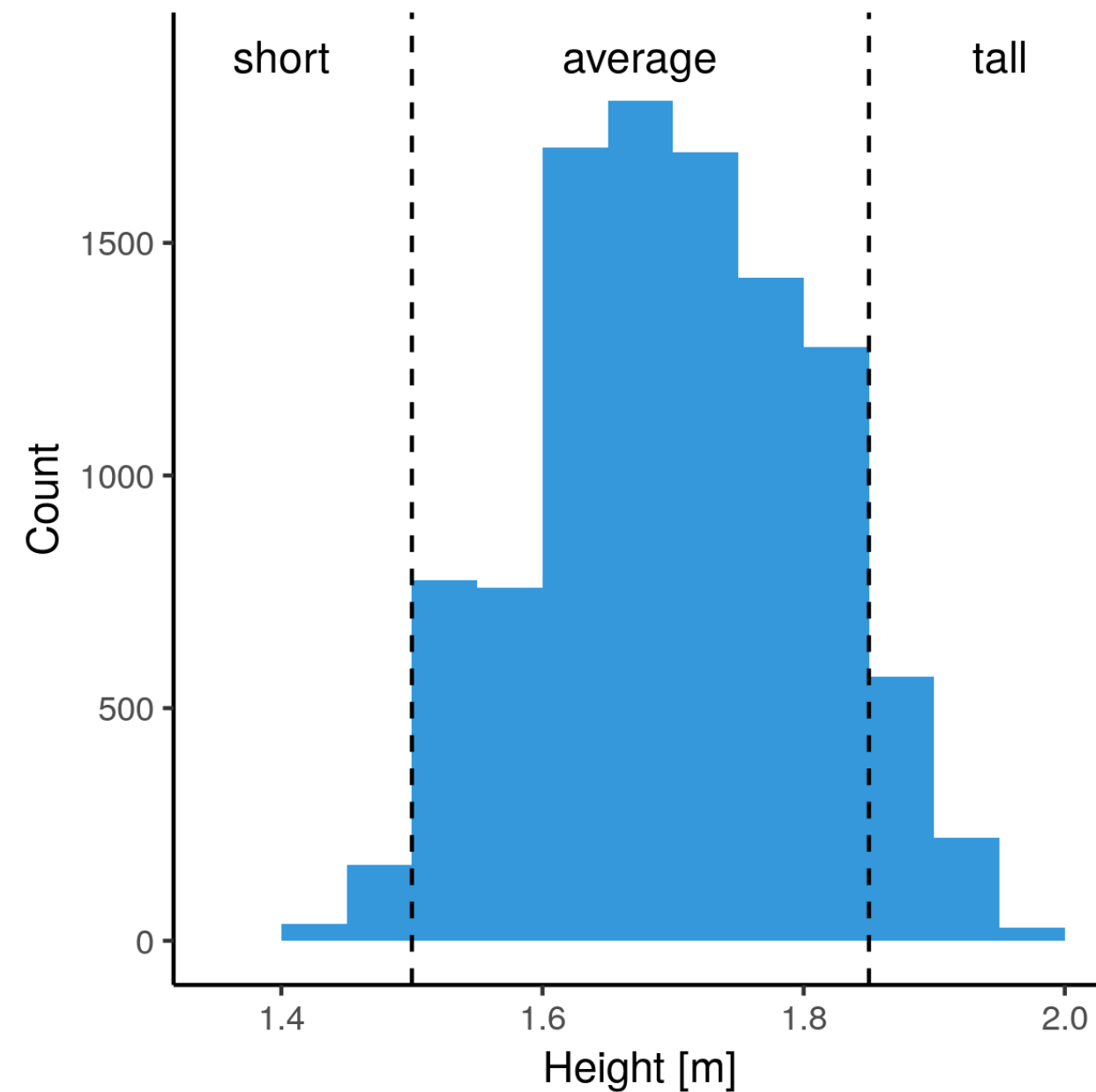
# Bucketing heights



```
+-----+
|height|
+-----+
|  1.42|
|  1.45|
|  1.47|
|  1.50|
|  1.52|
|  1.57|
|  1.60|
|  1.75|
|  1.85|
|  1.88|
+-----+
```

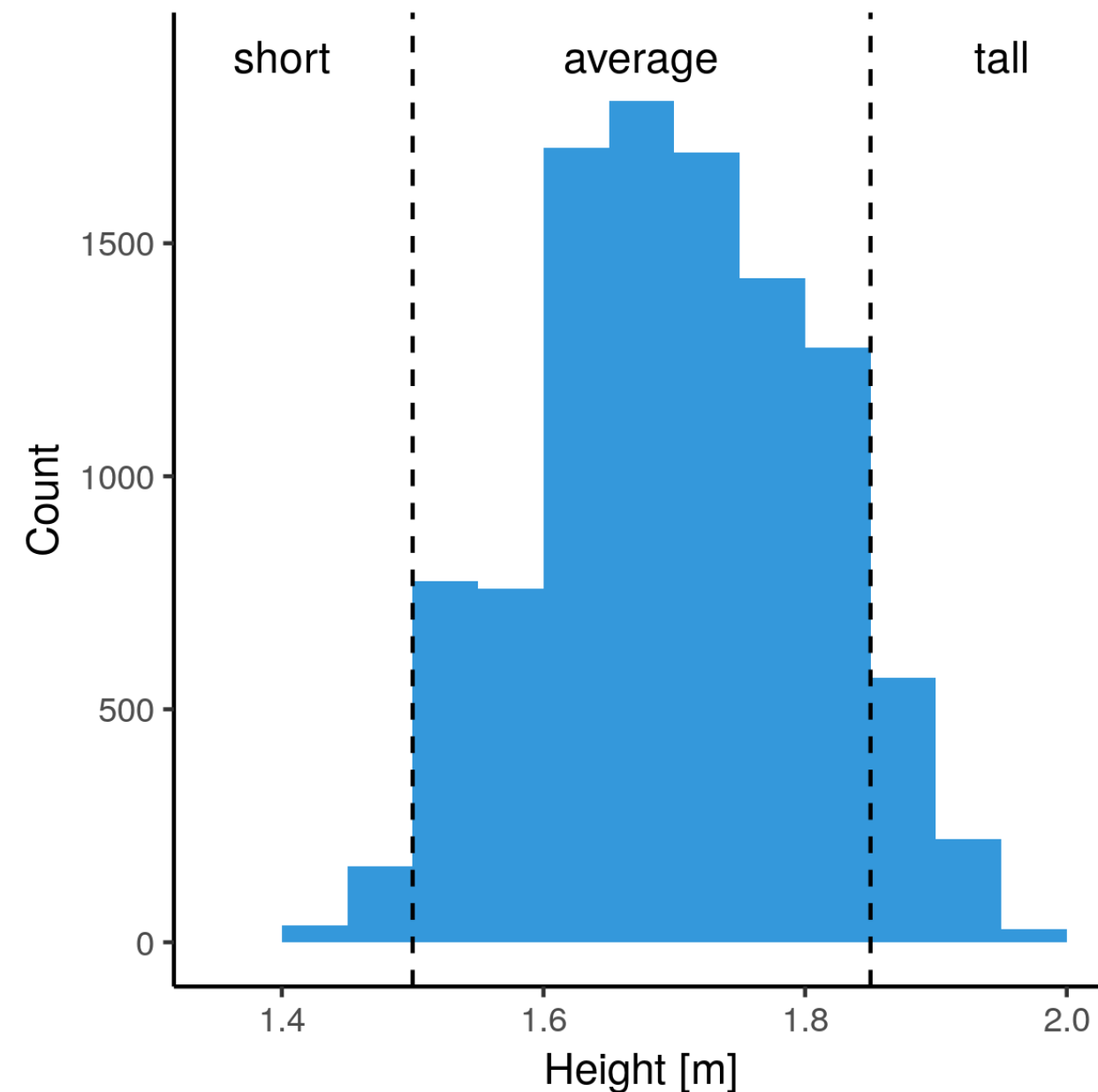


# Bucketing heights



```
+-----+
|height|
+-----+
|  1.42|
|  1.45|
|  1.47|
|  1.50|
|  1.52|
|  1.57|
|  1.60|
|  1.75|
|  1.85|
|  1.88|
+-----+
```

# Bucketing heights

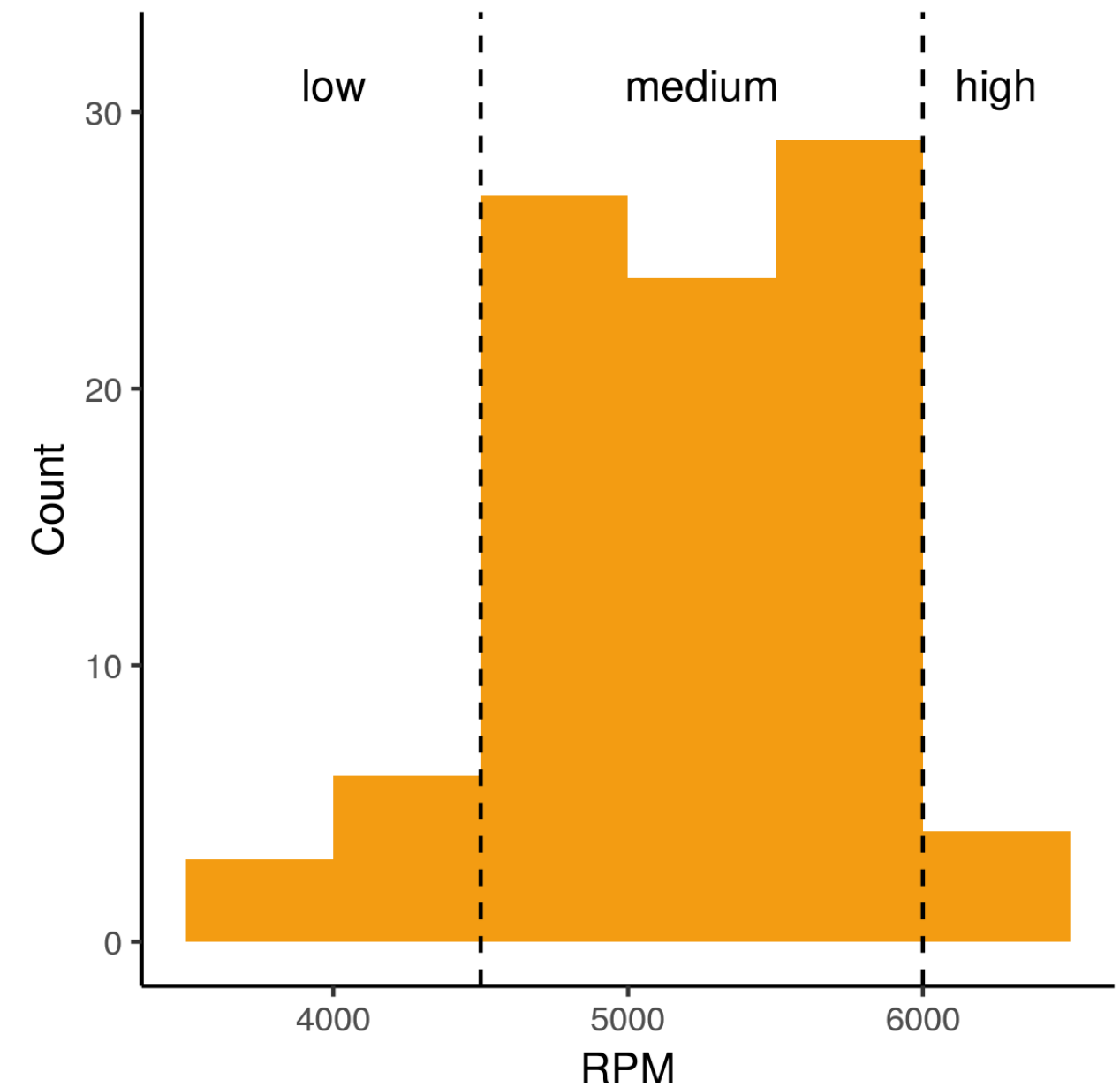


```
+-----+-----+
|height|height_bin|
+-----+-----+
|  1.42|    short|
|  1.45|    short|
|  1.47|    short|
|  1.50|    short|
|  1.52|  average|
|  1.57|  average|
|  1.60|  average|
|  1.75|  average|
|  1.85|    tall|
|  1.88|    tall|
+-----+-----+
```

# RPM histogram

Car RPM has "natural" breaks:

- $\text{RPM} < 4500$  — low
- $\text{RPM} > 6000$  — high
- otherwise — medium.



# RPM buckets

```
from pyspark.ml.feature import Bucketizer

bucketizer = Bucketizer(splits=[3500, 4500, 6000, 6500],
                        inputCol="rpm",
                        outputCol="rpm_bin")
```

Apply buckets to `rpm` column.

```
bucketed = bucketizer.transform(cars)
```

# RPM buckets

```
bucketed.select('rpm', 'rpm_bin').show(5)
```

```
+-----+-----+
| rpm|rpm_bin|
+-----+-----+
| 3800|    0.0|
| 4500|    1.0|
| 5750|    1.0|
| 5300|    1.0|
| 6200|    2.0|
+-----+-----+
```

```
bucketed.groupBy('rpm_bin').count().show()
```

```
+-----+-----+
|rpm_bin|count|
+-----+-----+
|    0.0|    8| <- low
|    1.0|   67| <- medium
|    2.0|   17| <- high
+-----+-----+
```

# One-hot encoded RPM buckets

The RPM buckets are one-hot encoded to dummy variables.

```
+-----+-----+
|rpm_bin| rpm_dummy|
+-----+-----+
|    0.0|(2,[0],[1.0])| <- low
|    1.0|(2,[1],[1.0])| <- medium
|    2.0|  (2,[],[]) | <- high
+-----+-----+
```

The 'high' RPM bucket is the reference level and doesn't get a dummy variable.

# Model with bucketed RPM

```
regression.coefficients
```

```
DenseVector([1.3814, 0.1433])
```

```
+-----+-----+
|rpm_bin| rpm_dummy|
+-----+-----+
|  0.0|(2,[0],[1.0])| <- low
|  1.0|(2,[1],[1.0])| <- medium
|  2.0|  (2,[],[])| <- high
+-----+-----+
```

```
regression.intercept
```

```
8.1835
```

Consumption for 'low' RPM:

```
8.1835 + 1.3814 = 9.5649
```

Consumption for 'medium' RPM:

```
8.1835 + 0.1433 = 8.3268
```

# More feature engineering

Operations on a single column:

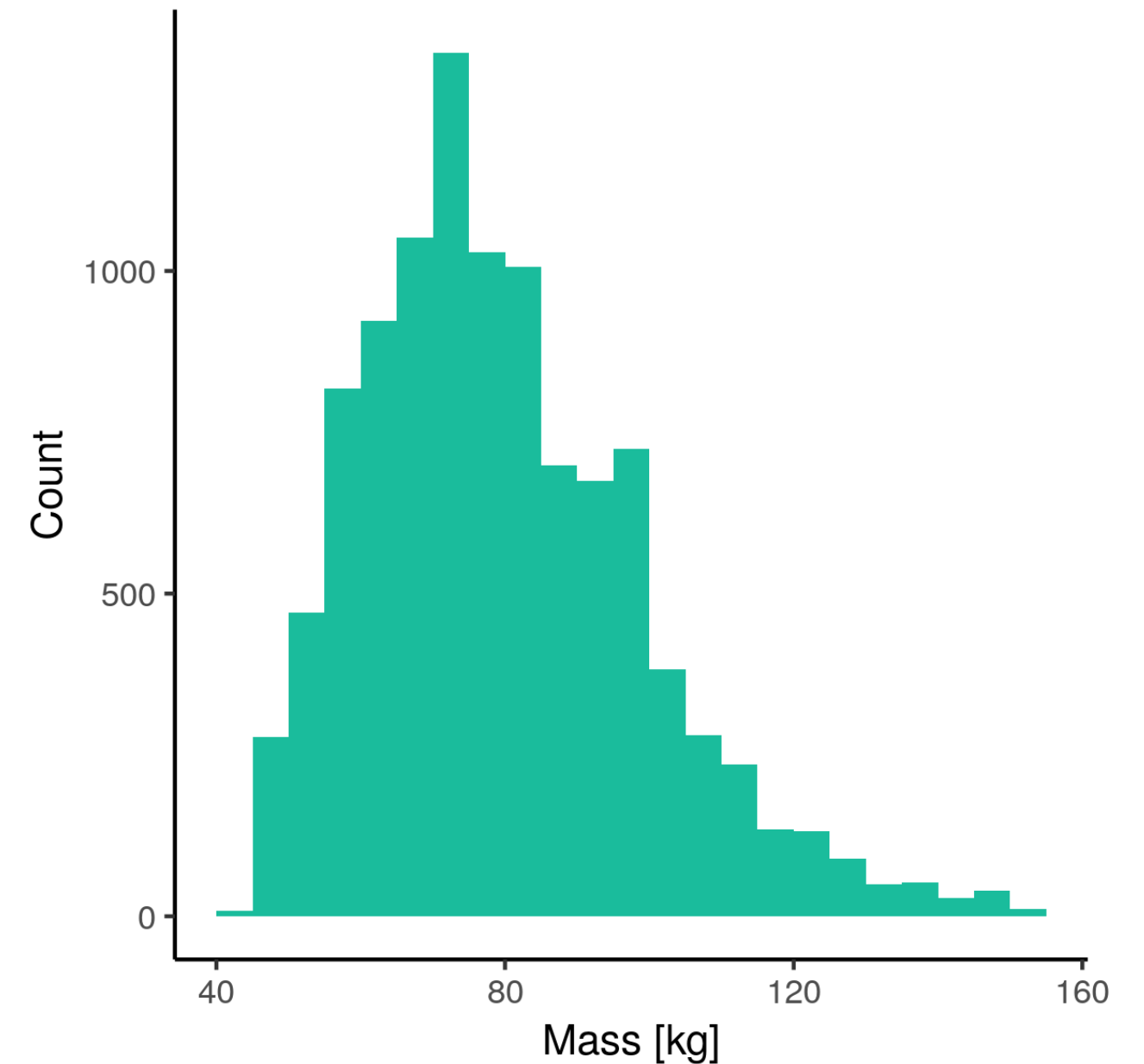
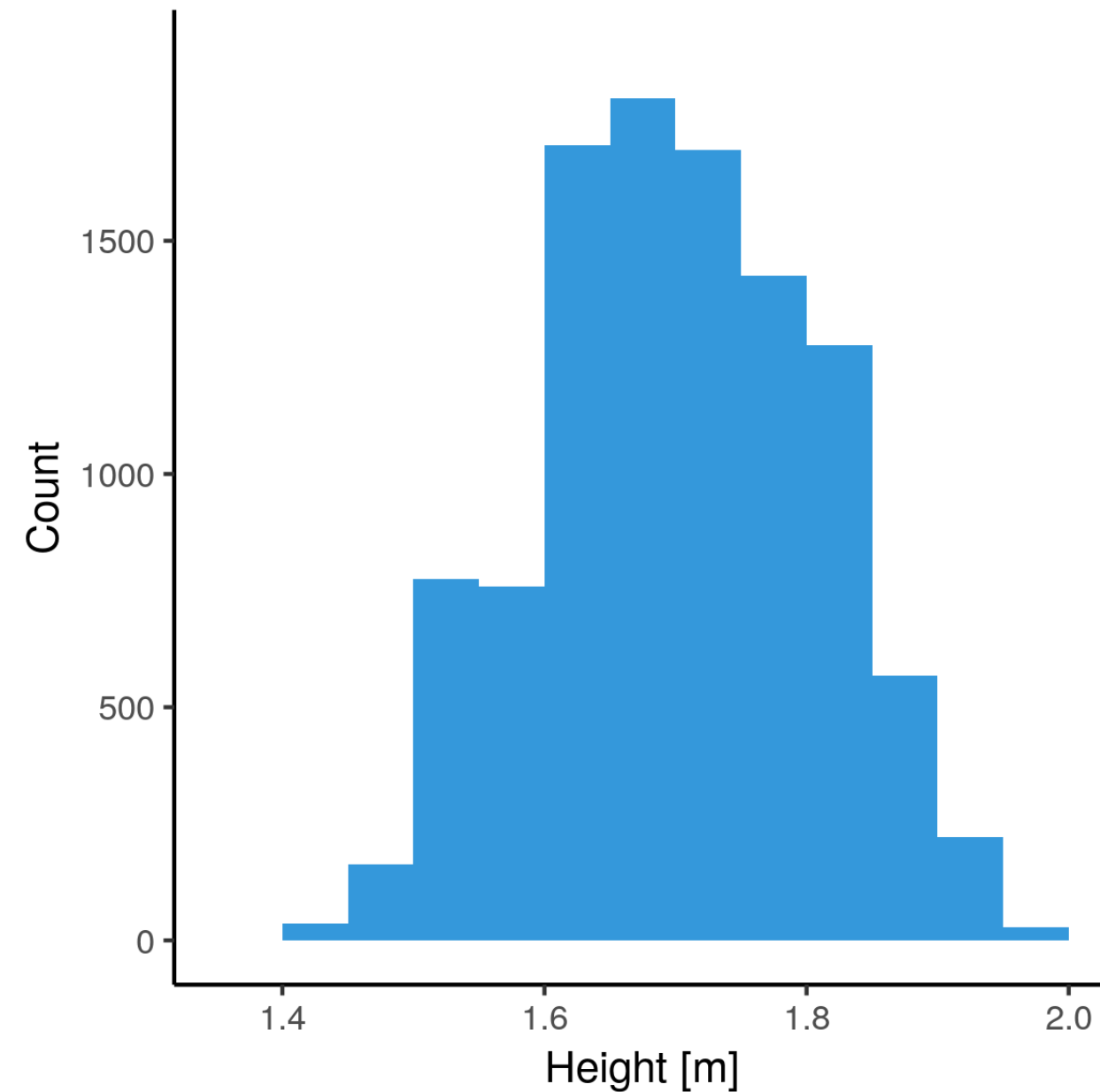
- `log()`
- `sqrt()`
- `pow()`

Operations on two columns:

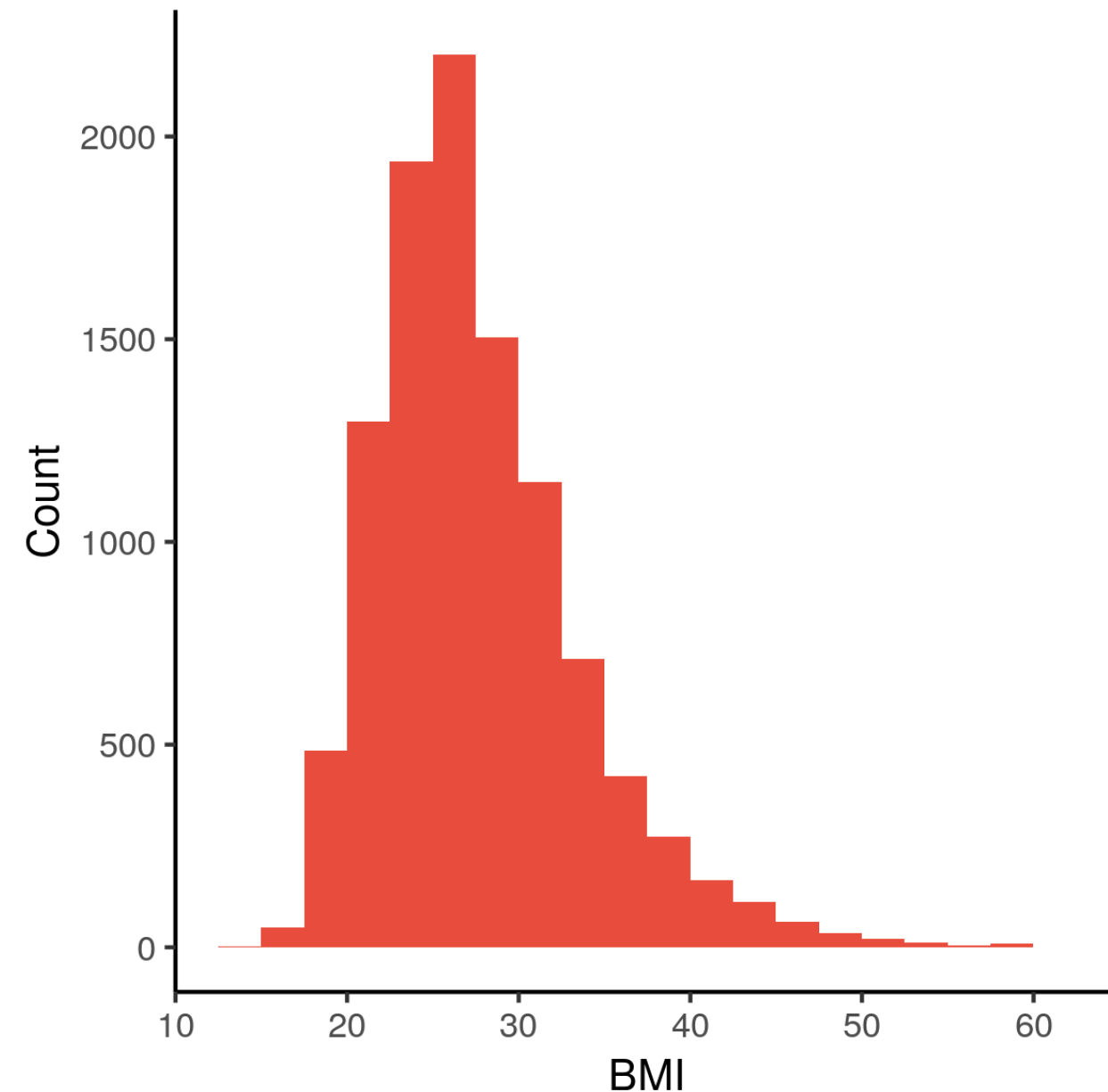
- `product`
- `ratio`.



# Mass & Height to BMI



# Mass & Height to BMI



```
+-----+-----+-----+
|height| mass| bmi|      bmi = mass / height^2
+-----+-----+-----+
|  1.52|  77.1|33.2|
|  1.60|  58.1|22.7|
|  1.57|122.0|49.4|
|  1.75|  95.3|31.0|
|  1.80|  99.8|30.7|
|  1.65|  90.7|33.3|
|  1.60|  70.3|27.5|
|  1.78|  81.6|25.8|
|  1.65|  77.1|28.3|
|  1.78|128.0|40.5|
+-----+-----+-----+
```

# Engineering density

```
cars = cars.withColumn('density_line', cars.mass / cars.length)      # Linear density
cars = cars.withColumn('density_quad', cars.mass / cars.length**2)    # Area density
cars = cars.withColumn('density_cube', cars.mass / cars.length**3)    # Volume density
```

```
+-----+-----+-----+-----+-----+
|  mass|length|density_line|density_quad|density_cube|
+-----+-----+-----+-----+-----+
|1451.0|  4.775|303.87434554|63.638606397|13.327456837|
|1129.0|  4.623|244.21371403|52.825808790|11.426737787|
|1399.0|  4.547|307.67539036|67.665579583|14.881367843|
+-----+-----+-----+-----+-----+
```

# Let's engineer some features!

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# Regularization

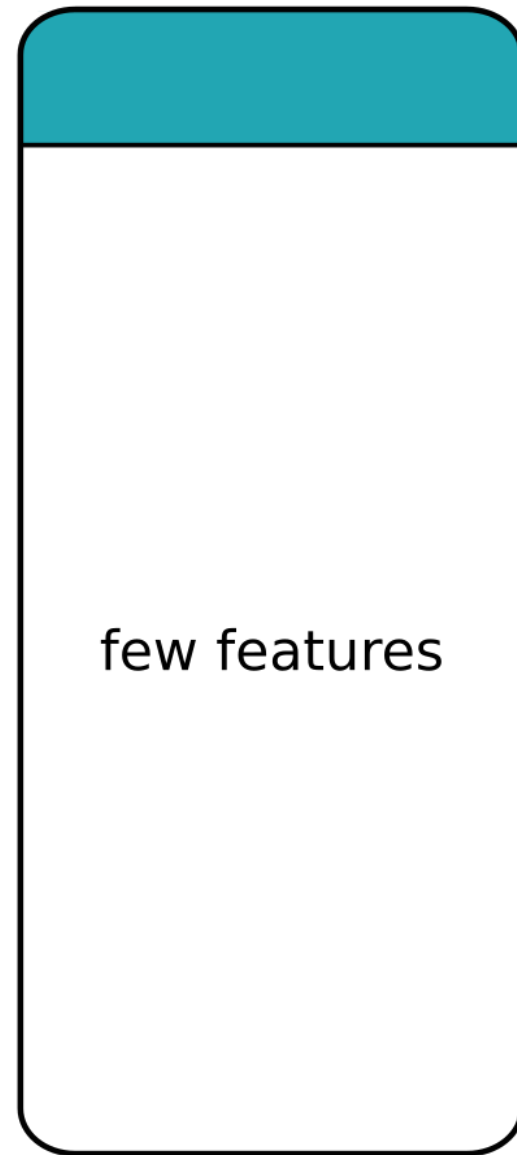
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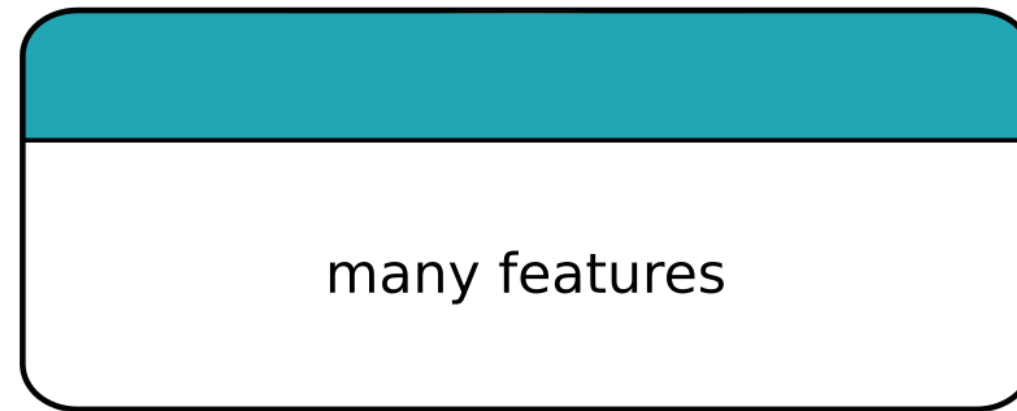
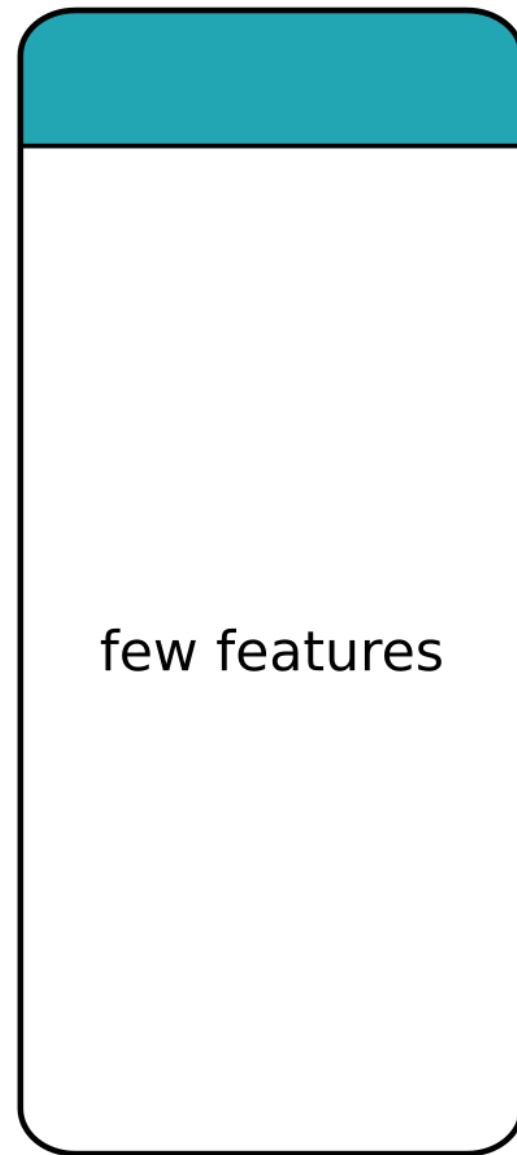
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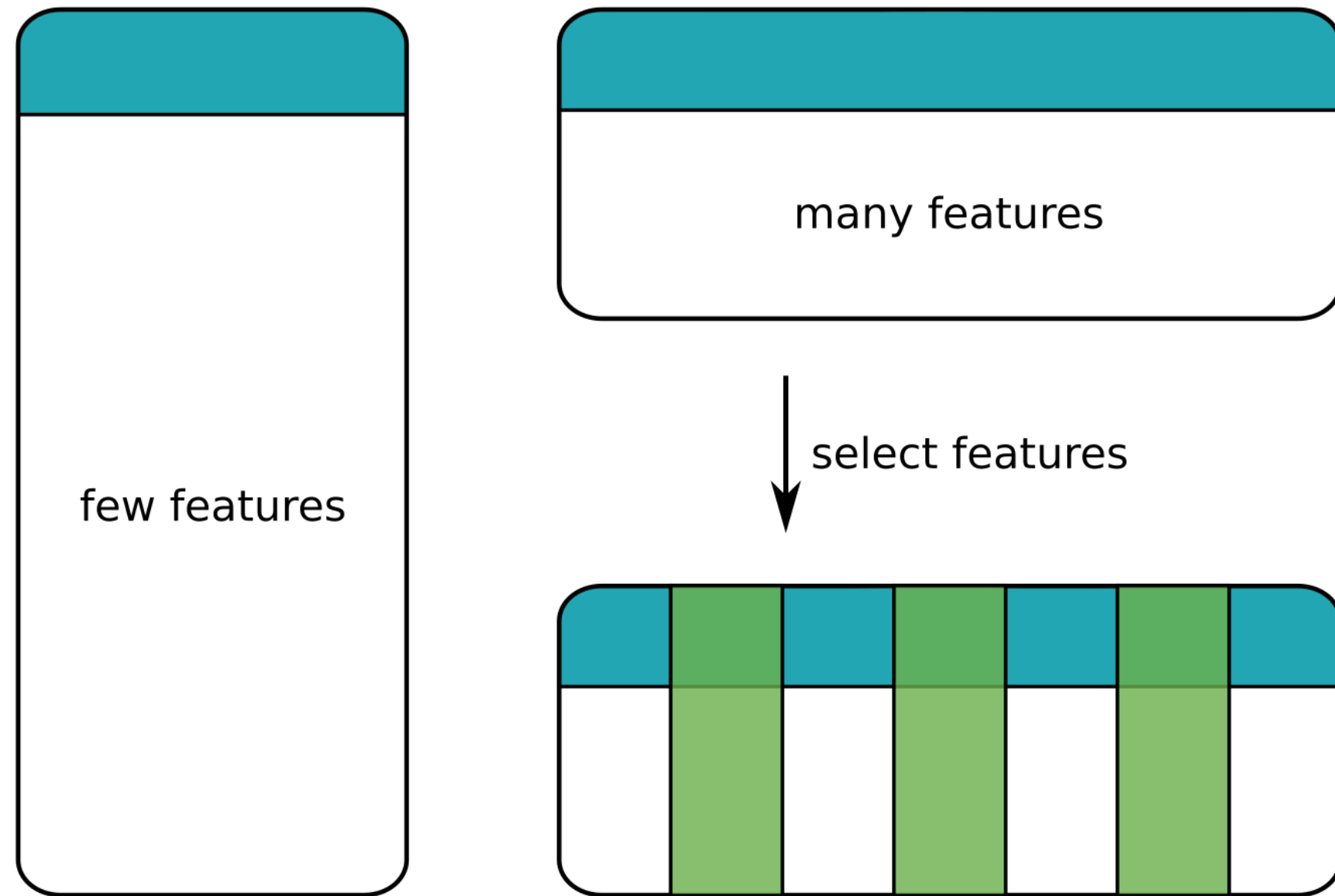
# Features: Only a few



# Features: Too many



# Features: Selected





# Loss function (revisited)

Linear regression aims to minimise the MSE.

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

# Loss function with regularization

Linear regression aims to minimise the MSE.

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 + \lambda f(\beta)$$

Add a *regularization* term which depends on coefficients.

# Regularization term

An extra *regularization* term is added to the loss function.

The regularization term can be either

- *Lasso* — absolute value of the coefficients
- *Ridge* — square of the coefficients

It's also possible to have a blend of Lasso and Ridge regression.

Strength of regularization determined by parameter  $\lambda$ :

- $\lambda = 0$  — no regularization (standard regression)
- $\lambda = \infty$  — complete regularization (all coefficients zero)

# Cars again

```
assembler = VectorAssembler(inputCols=[
    'mass', 'cyl', 'type_dummy', 'density_line', 'density_quad', 'density_cube'
], outputCol='features')
cars = assembler.transform(cars)
```

```
+-----+-----+
|features|consumption|
+-----+-----+
|[1451.0,6.0,1.0,0.0,0.0,0.0,0.0,303.8743455497,63.63860639785,13.32745683724]|9.05|
|[1129.0,4.0,0.0,0.0,1.0,0.0,0.0,244.2137140385,52.82580879050,11.42673778726]|6.53|
|[1399.0,4.0,0.0,0.0,1.0,0.0,0.0,307.6753903672,67.66557958374,14.88136784335]|7.84|
|[1147.0,4.0,0.0,1.0,0.0,0.0,0.0,264.1031545014,60.81122599620,14.00212433714]|7.84|
+-----+-----+
```

# Cars: Linear regression

Fit a (standard) Linear Regression model to the training data.

```
regression = LinearRegression(labelCol='consumption').fit(cars_train)
```

```
# RMSE on testing data  
0.708699086182001
```

Examine the coefficients:

```
regression.coefficients
```

```
DenseVector([-0.012, 0.174, -0.897, -1.445, -0.985, -1.071, -1.335, 0.189, -0.780, 1.160])
```

# Cars: Ridge regression

```
# alpha = 0 | lambda = 0.1 -> Ridge
ridge = LinearRegression(labelCol='consumption', elasticNetParam=0, regParam=0.1)
ridge.fit(cars_train)
```

```
# RMSE
0.724535609745491
```

```
# Ridge coefficients
DenseVector([ 0.001, 0.137, -0.395, -0.822, -0.450, -0.582, -0.806, 0.008, 0.029, 0.001])
# Linear Regression coefficients
DenseVector([-0.012, 0.174, -0.897, -1.445, -0.985, -1.071, -1.335, 0.189, -0.780, 1.160])
```

# Cars: Lasso regression

```
# alpha = 1 | lambda = 0.1 -> Lasso
```

```
lasso = LinearRegression(labelCol='consumption', elasticNetParam=1, regParam=0.1)
```

```
lasso.fit(cars_train)
```

```
# RMSE
```

```
0.771988667026998
```

```
# Lasso coefficients
```

```
DenseVector([ 0.0, 0.0, 0.0, -0.056, 0.0, 0.0, 0.0, 0.026, 0.0, 0.0])
```

```
# Ridge coefficients
```

```
DenseVector([ 0.001, 0.137, -0.395, -0.822, -0.450, -0.582, -0.806, 0.008, 0.029, 0.001])
```

```
# Linear Regression coefficients
```

```
DenseVector([-0.012, 0.174, -0.897, -1.445, -0.985, -1.071, -1.335, 0.189, -0.780, 1.160])
```

# Regularization ? simple model

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