

One-Hot Encoding

MACHINE LEARNING WITH APACHE SPARK



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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 OneHotEncoderEstimator

onehot = OneHotEncoderEstimator(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

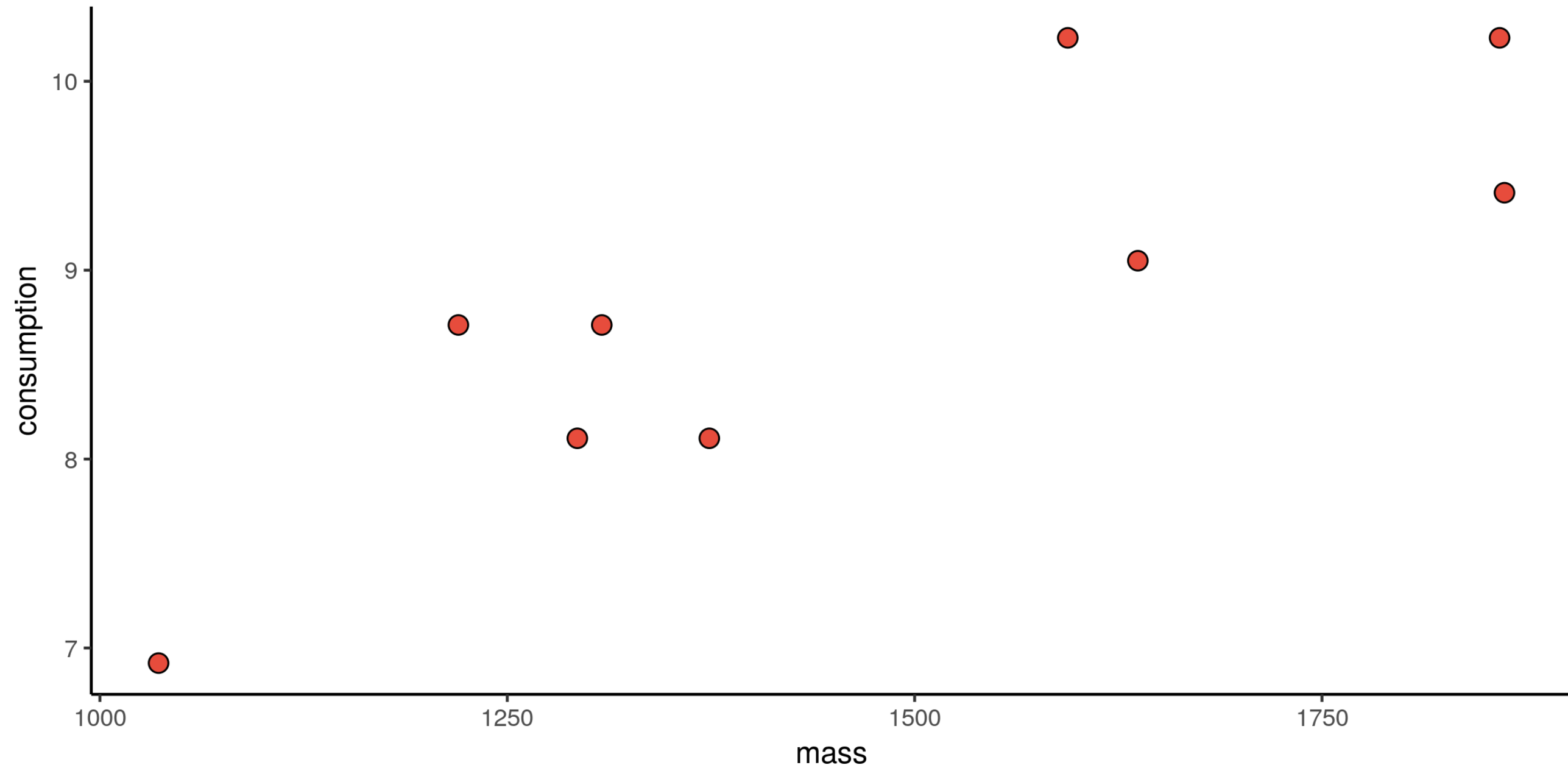
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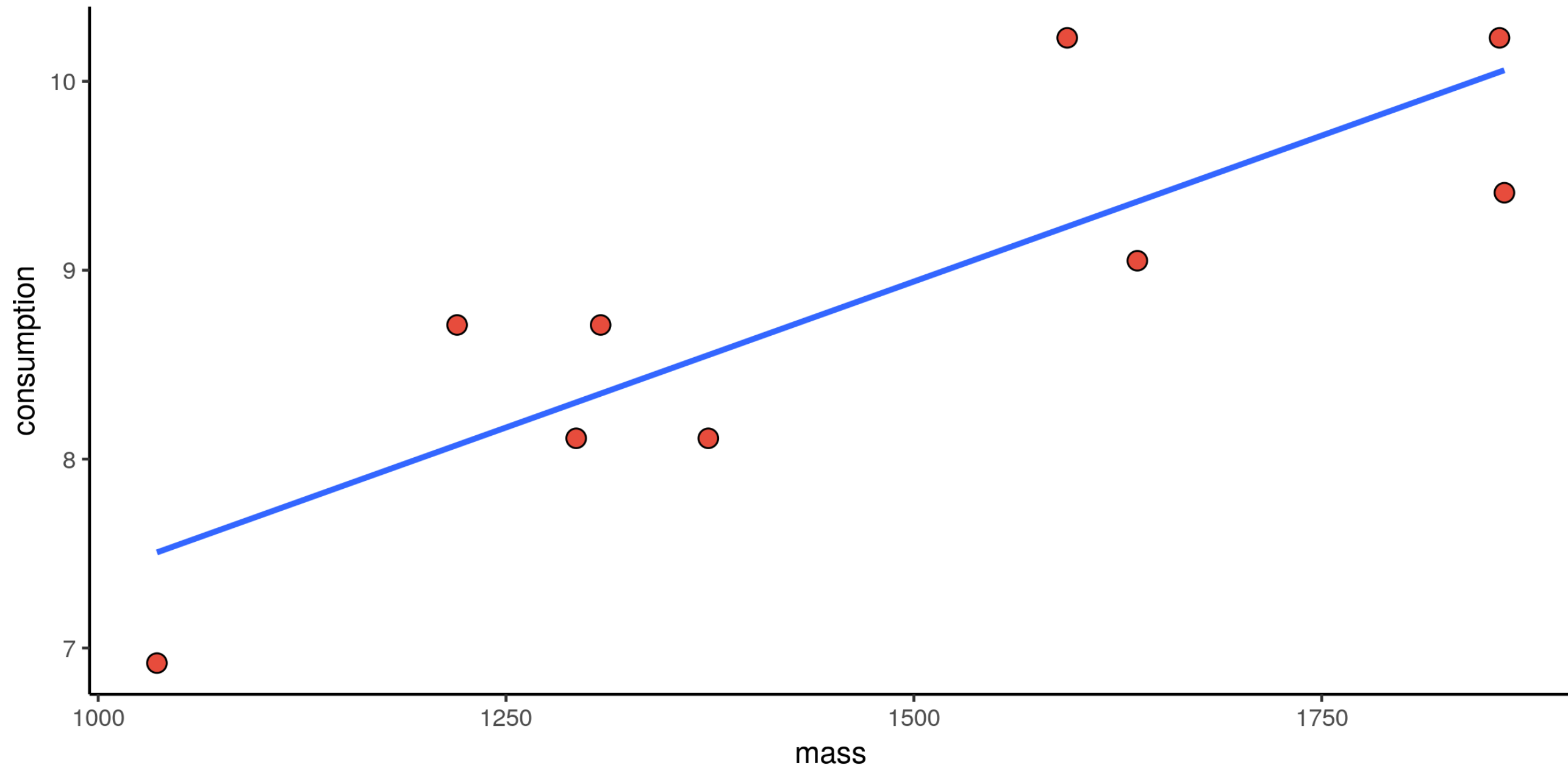
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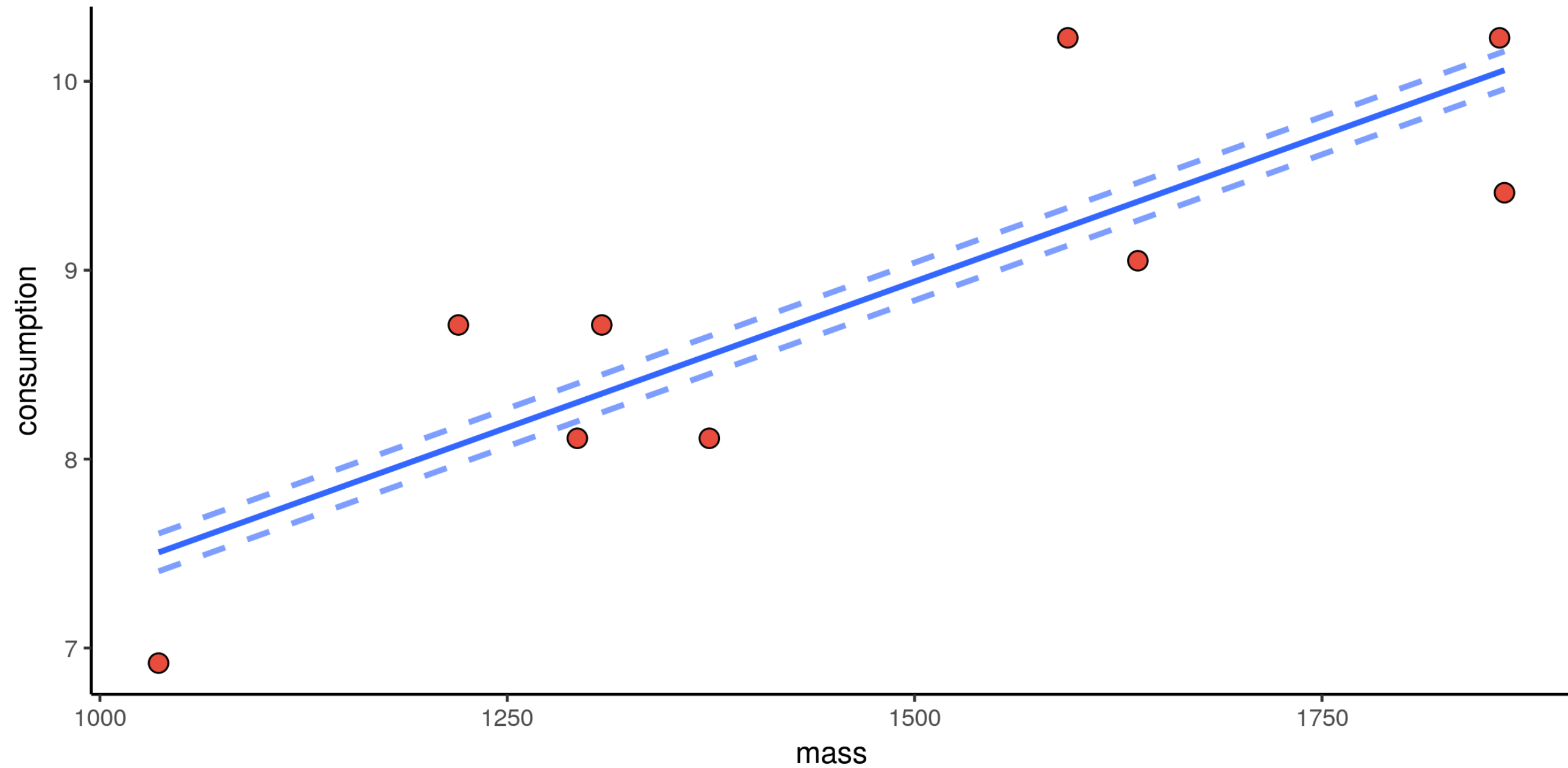
Consumption versus mass: scatter



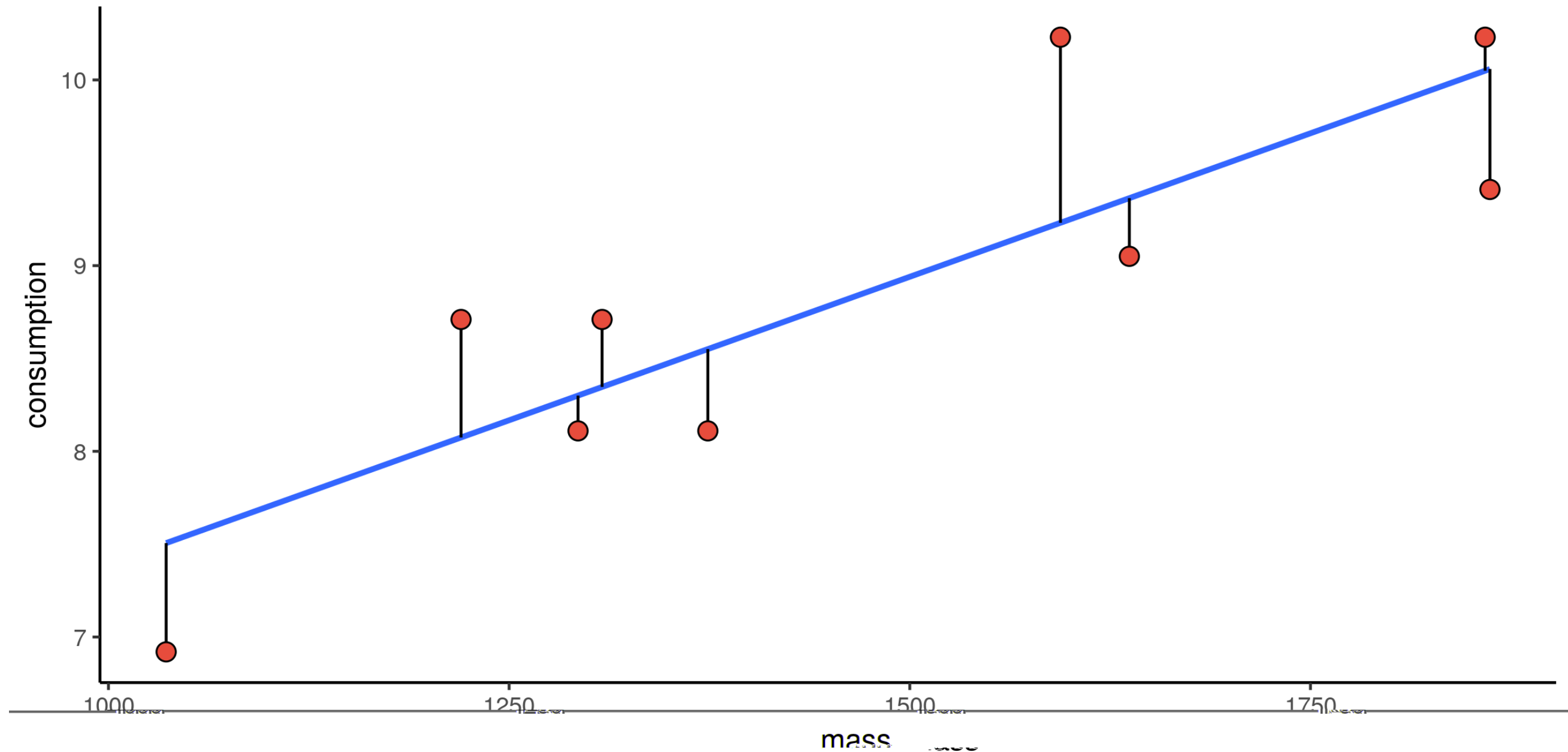
Consumption versus mass: fit



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).

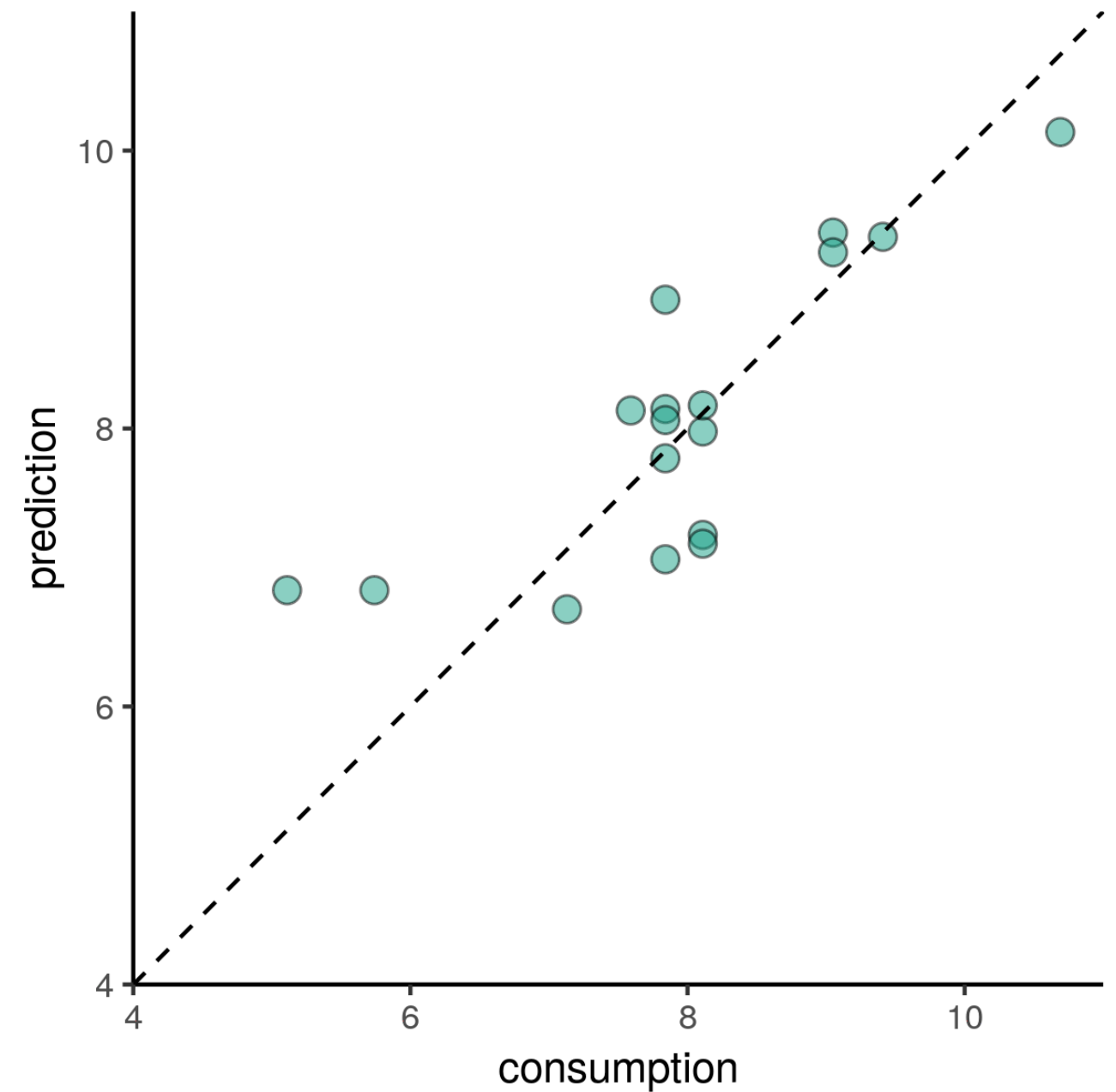
```
regression = regression.fit(cars_train)
```

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

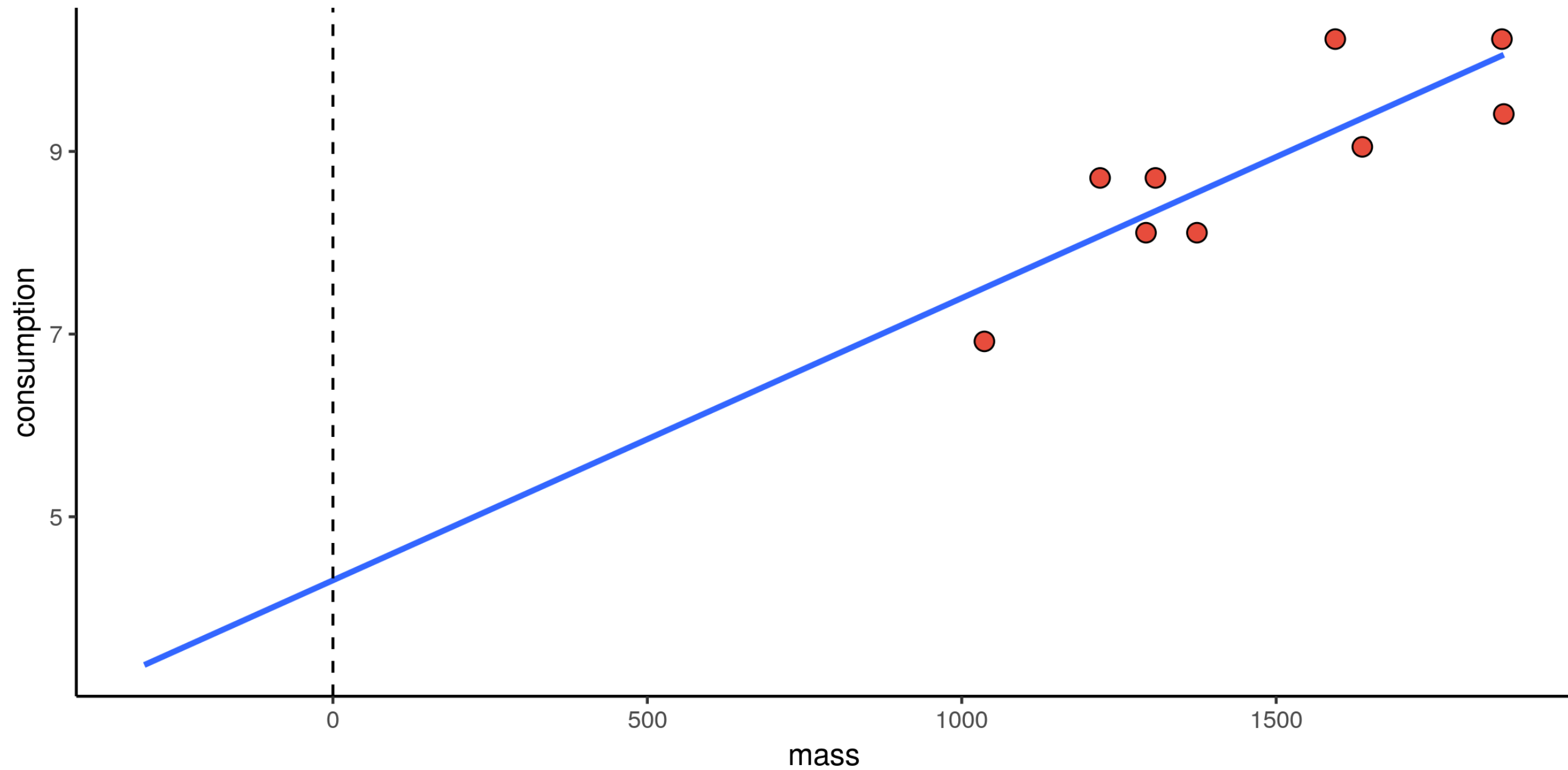
# Find RMSE (Root Mean Squared Error)
RegressionEvaluator(labelCol='consumption').evaluate(predictions)
```

```
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

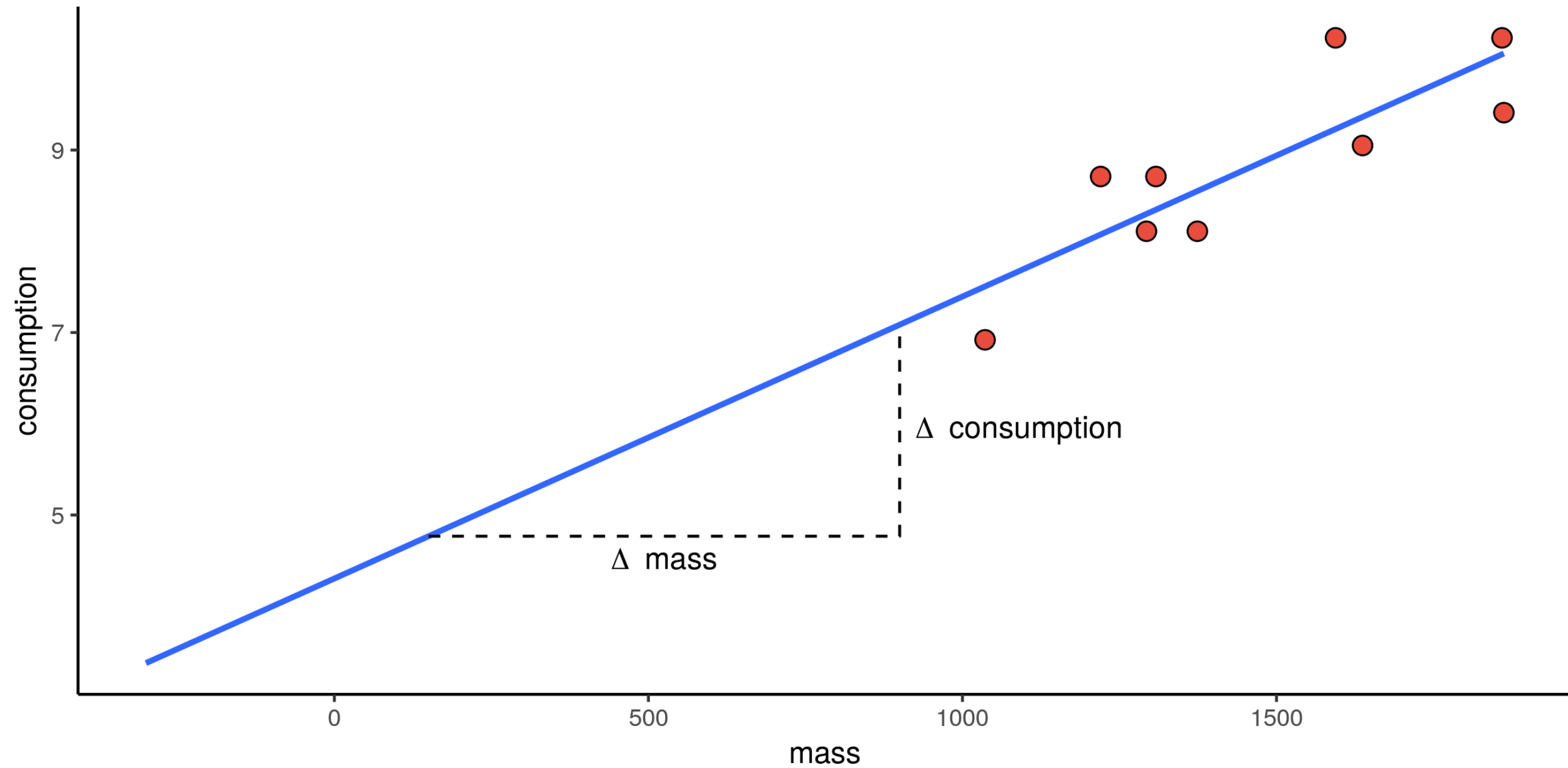
```
regression.intercept
```

```
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

MACHINE LEARNING WITH APACHE SPARK

Bucketing & Engineering

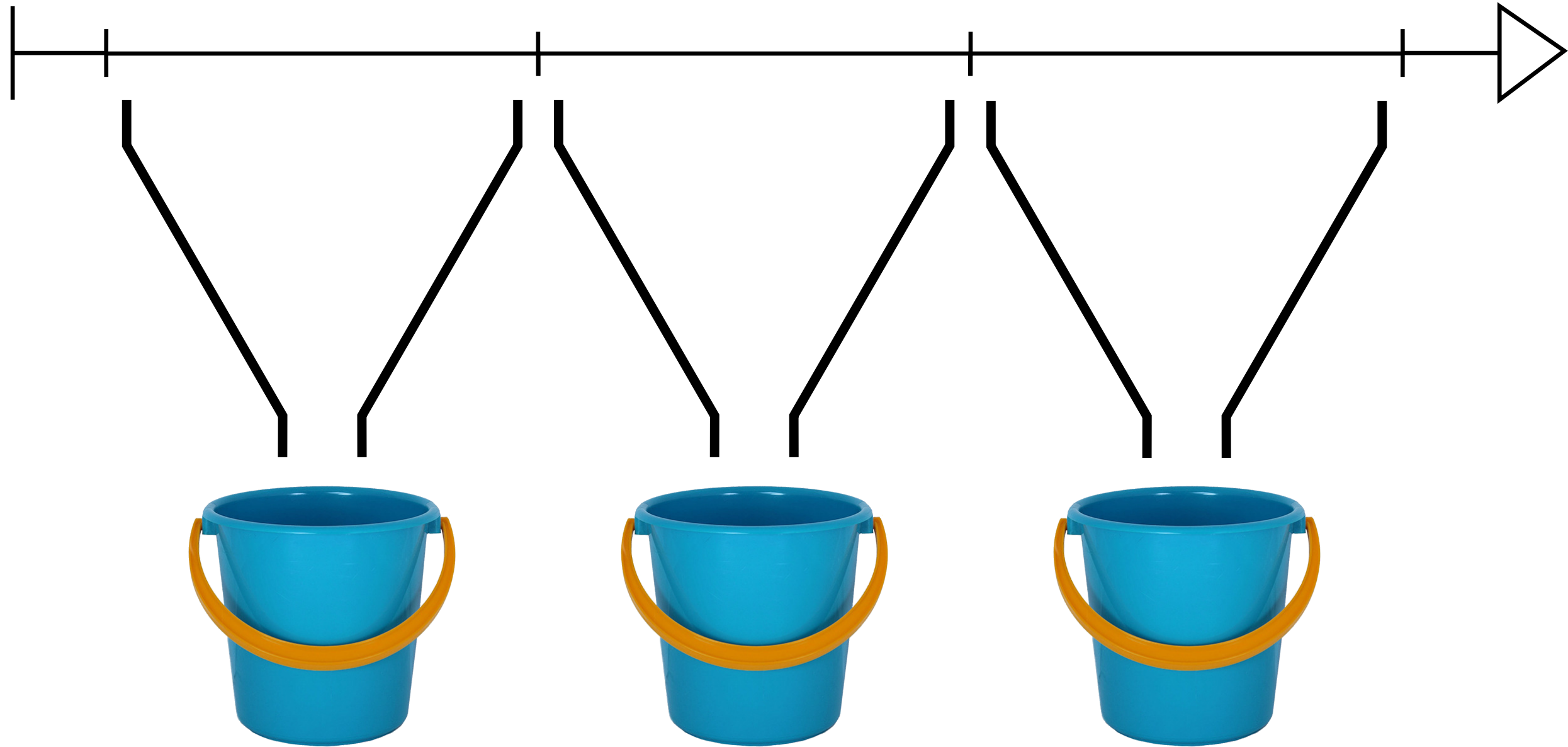
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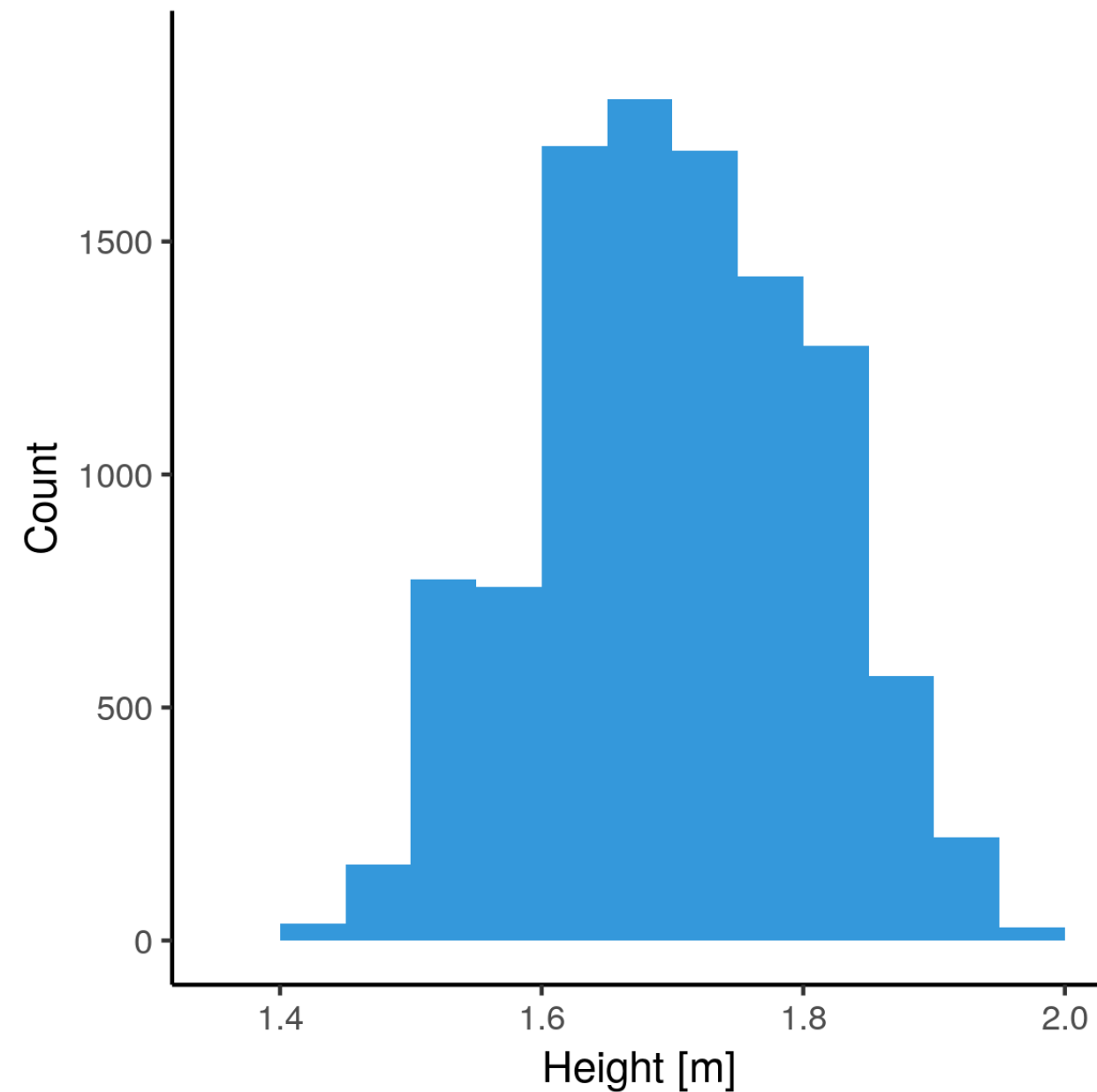
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Bucketing

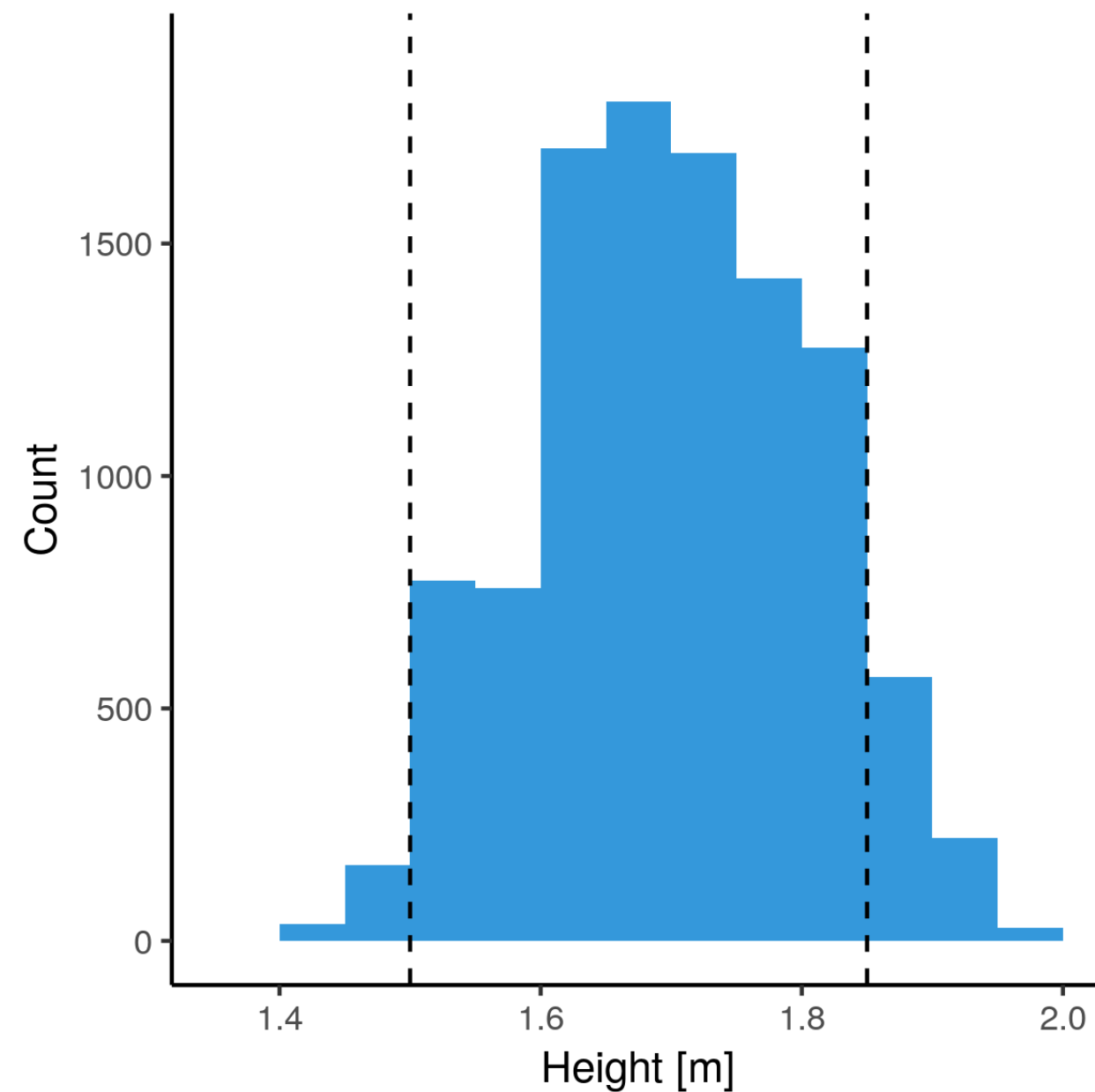


Bucketing heights



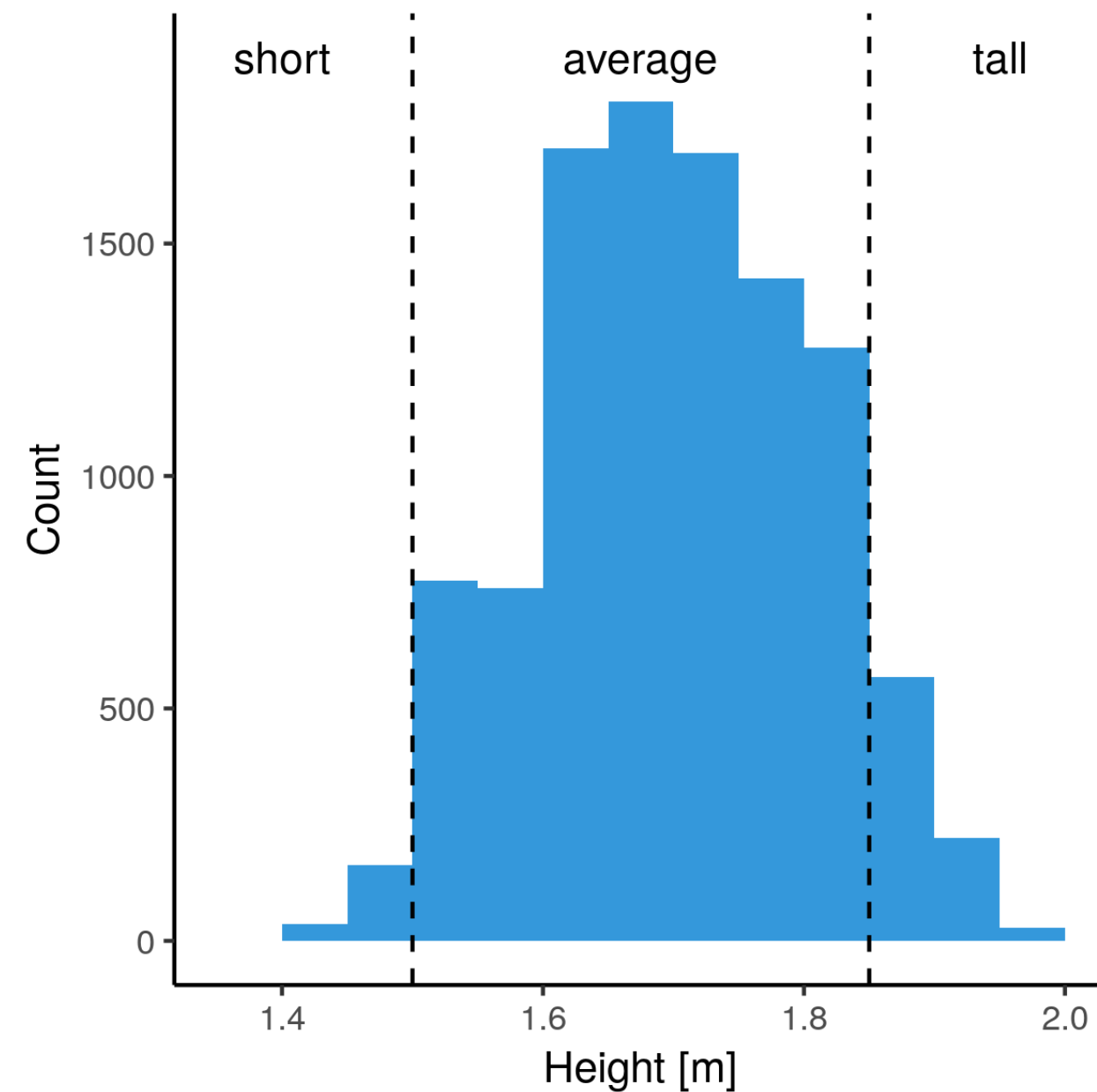
```
+-----+
|height|
+-----+
|  1.42|
|  1.45|
|  1.47|
|  1.50|
|  1.52|
|  1.57|
|  1.60|
|  1.75|
|  1.85|
|  1.88|
+-----+
```

Bucketing heights



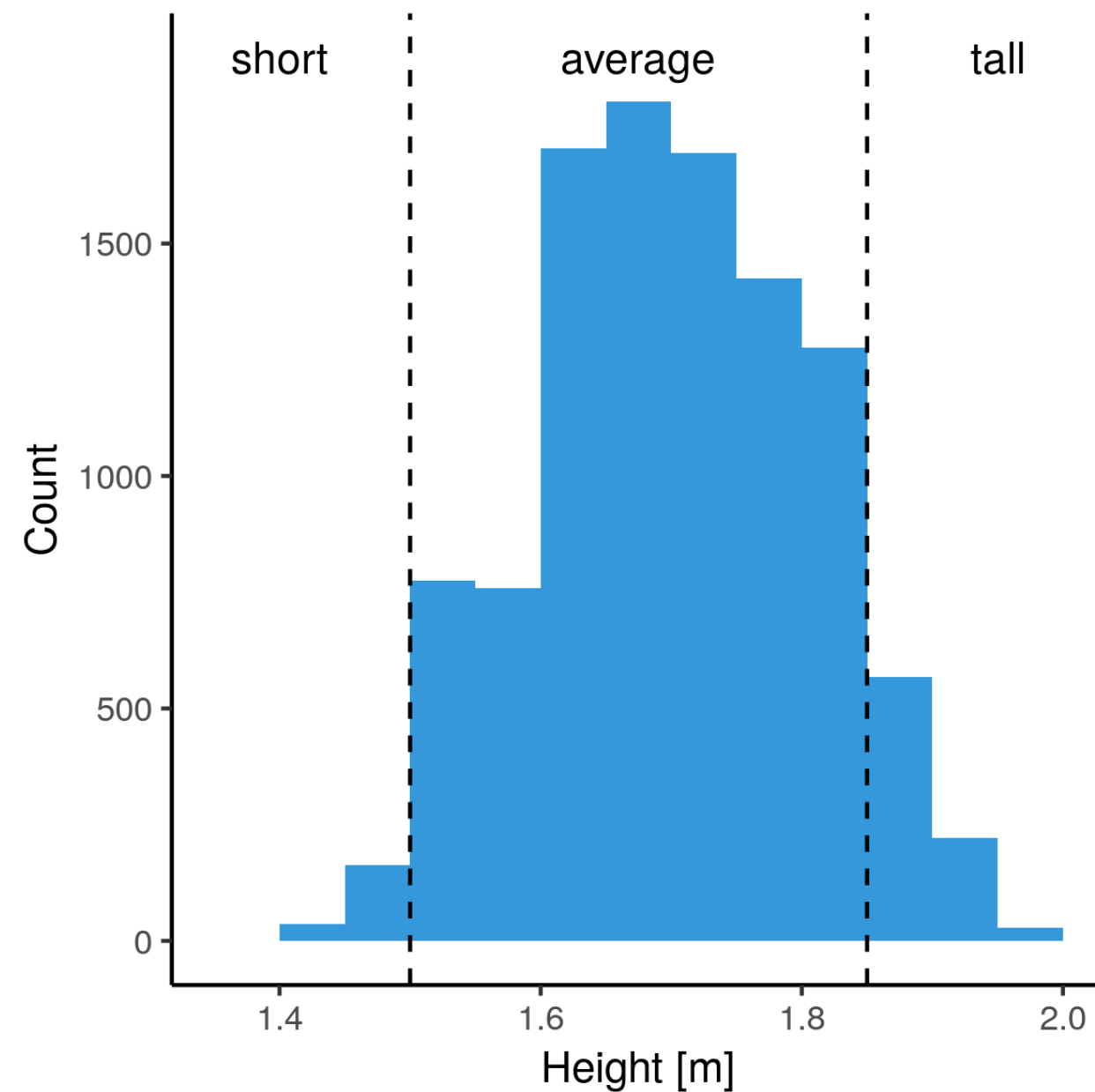
```
+-----+
|height|
+-----+
|  1.42|
|  1.45|
|  1.47|
|  1.50|
|  1.52|
|  1.57|
|  1.60|
|  1.75|
|  1.85|
|  1.88|
+-----+
```


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

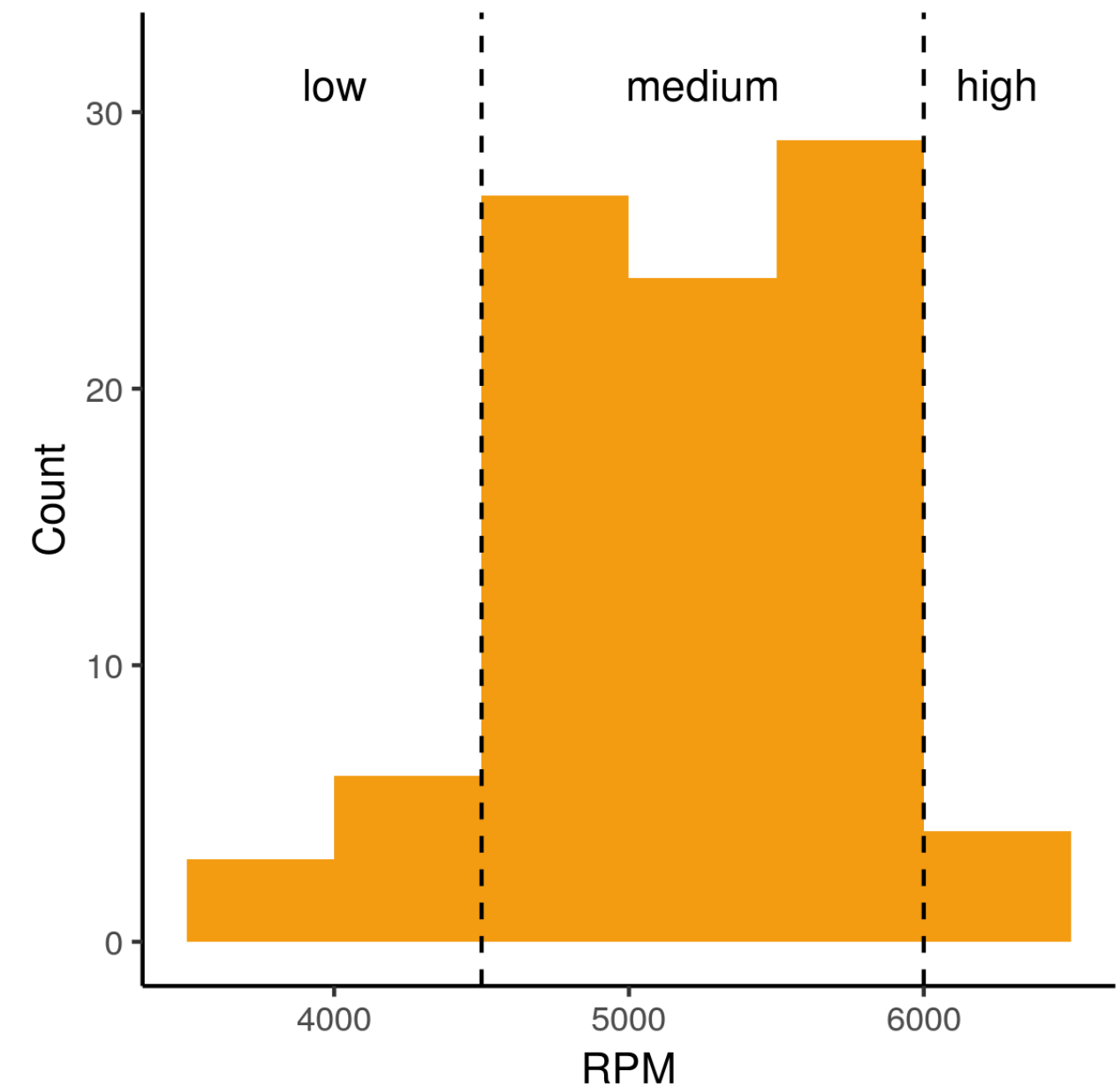


```
+-----+-----+
|height|height_bin|
+-----+-----+
|  1.42|    short|
|  1.45|    short|
|  1.47|    short|
|  1.50|    short|
|  1.52|  average|
|  1.57|  average|
|  1.60|  average|
|  1.75|  average|
|  1.85|    tall|
|  1.88|    tall|
+-----+-----+
```

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.

```
cars = 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|
+-----+-----+
```

```
cars.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

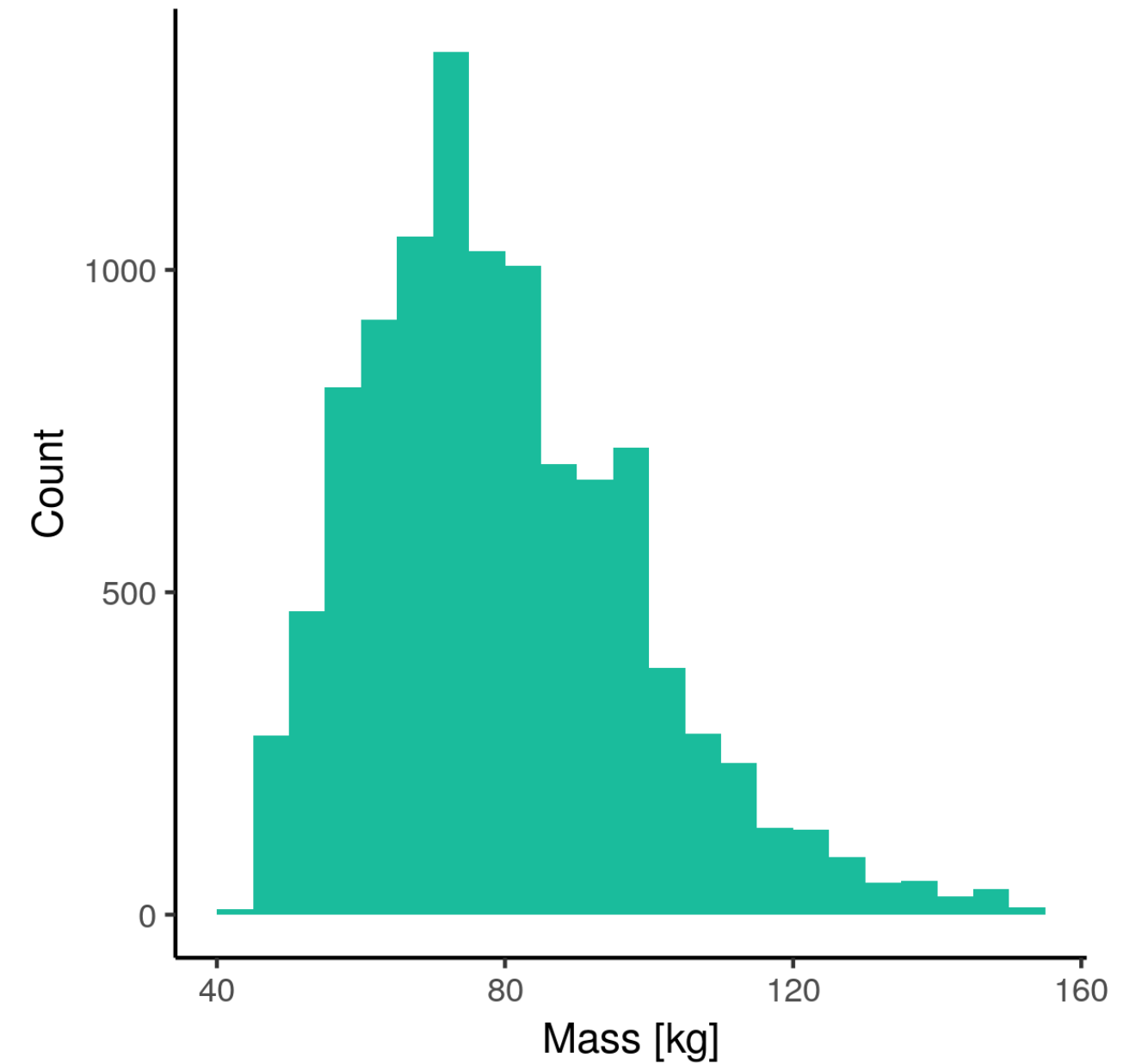
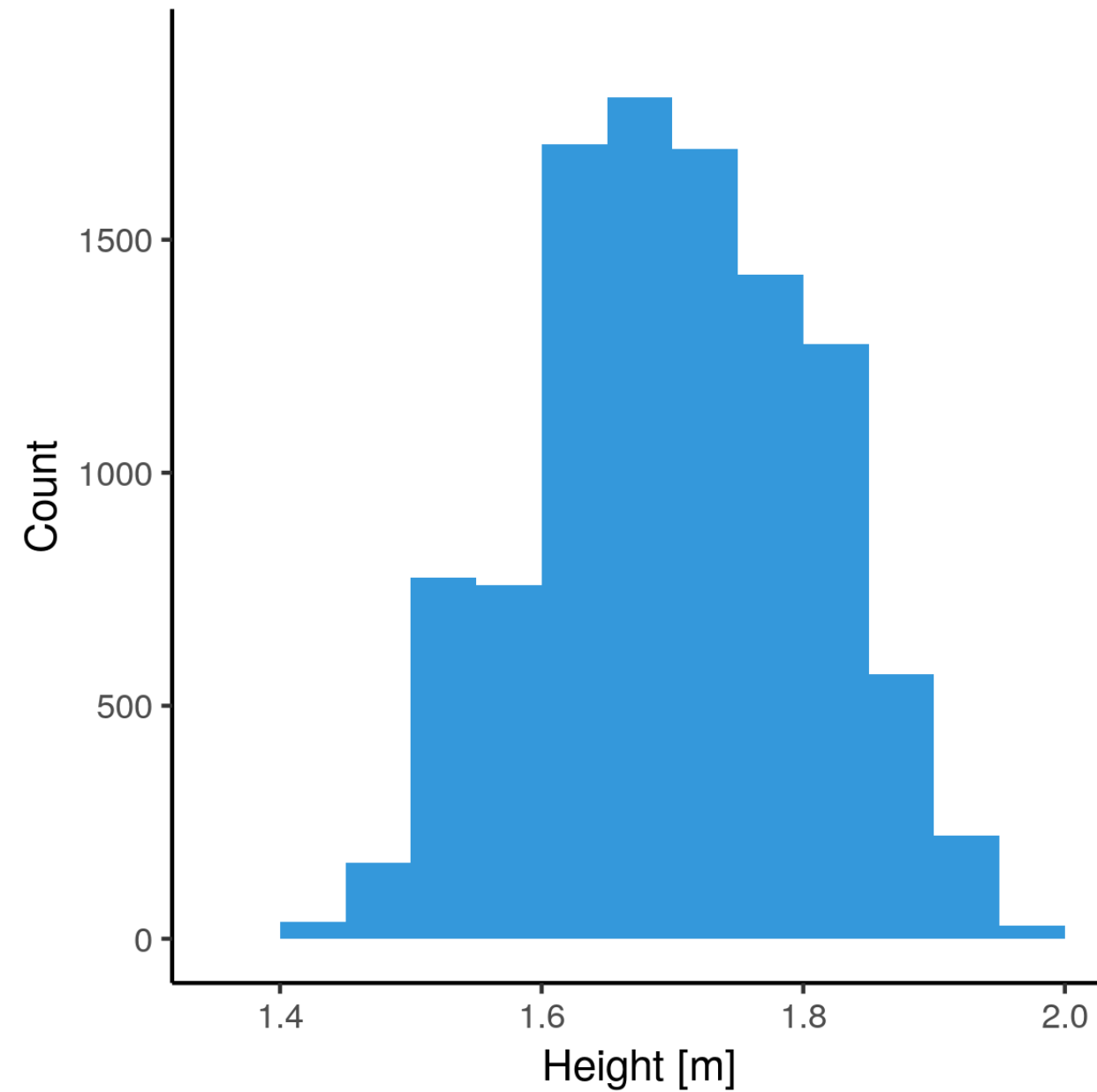
Operations on a single column:

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

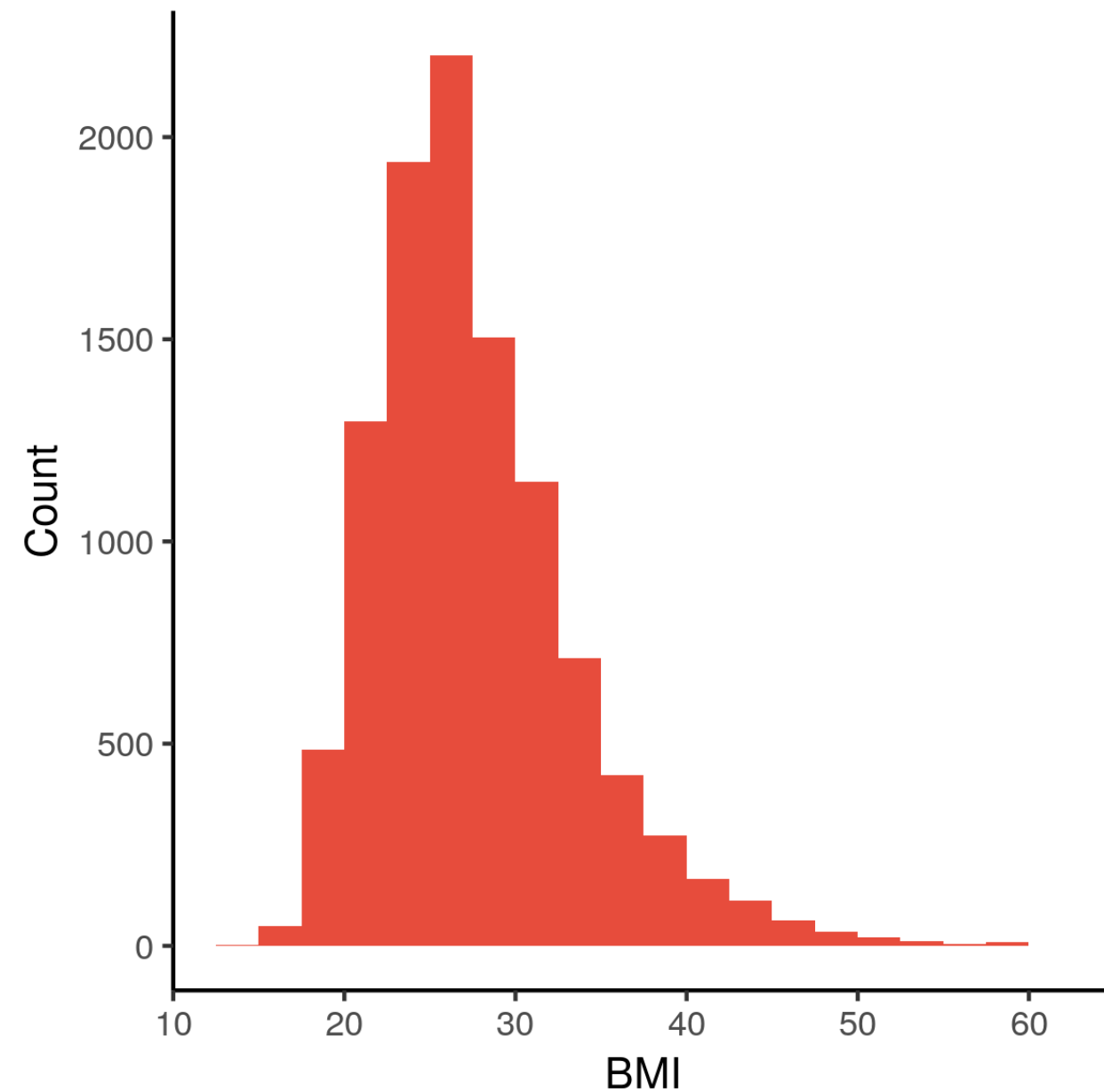
Operations on two columns:

- `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!

MACHINE LEARNING WITH APACHE SPARK

Regularization

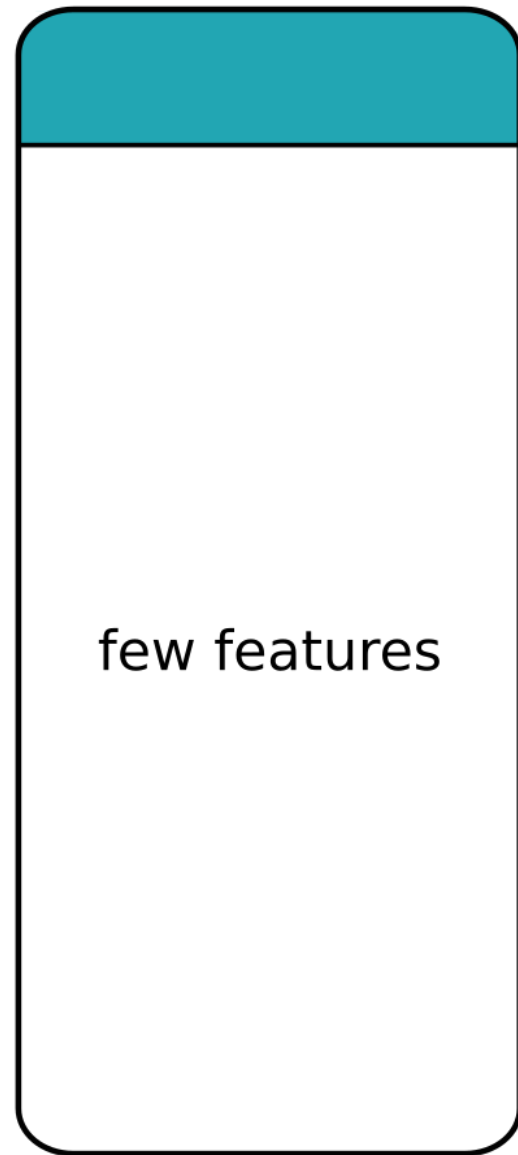
MACHINE LEARNING WITH APACHE SPARK



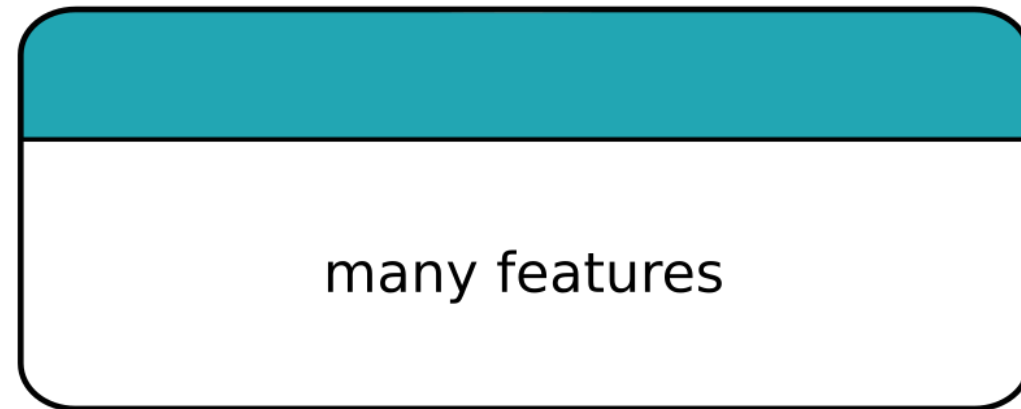
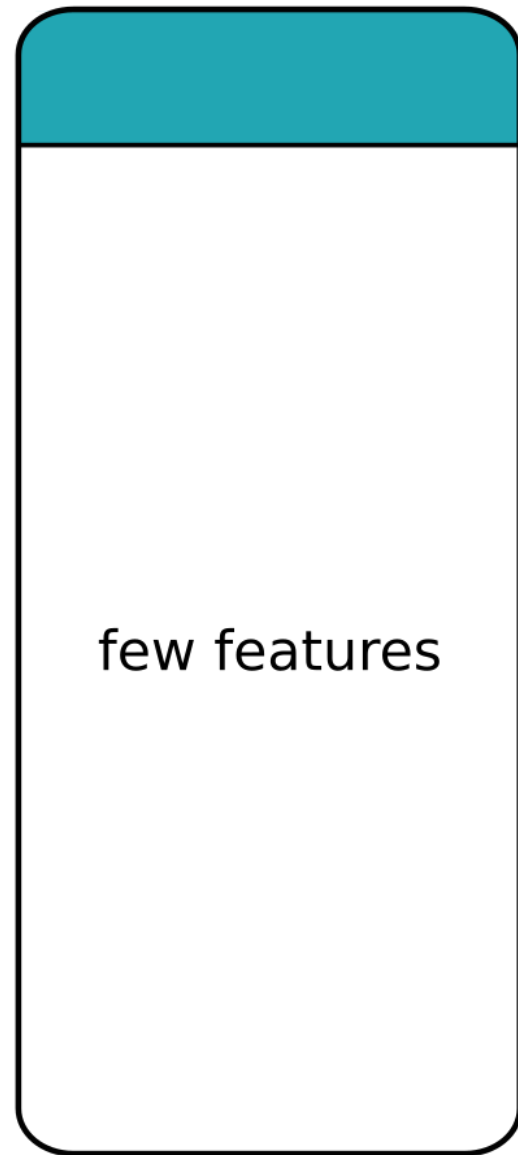
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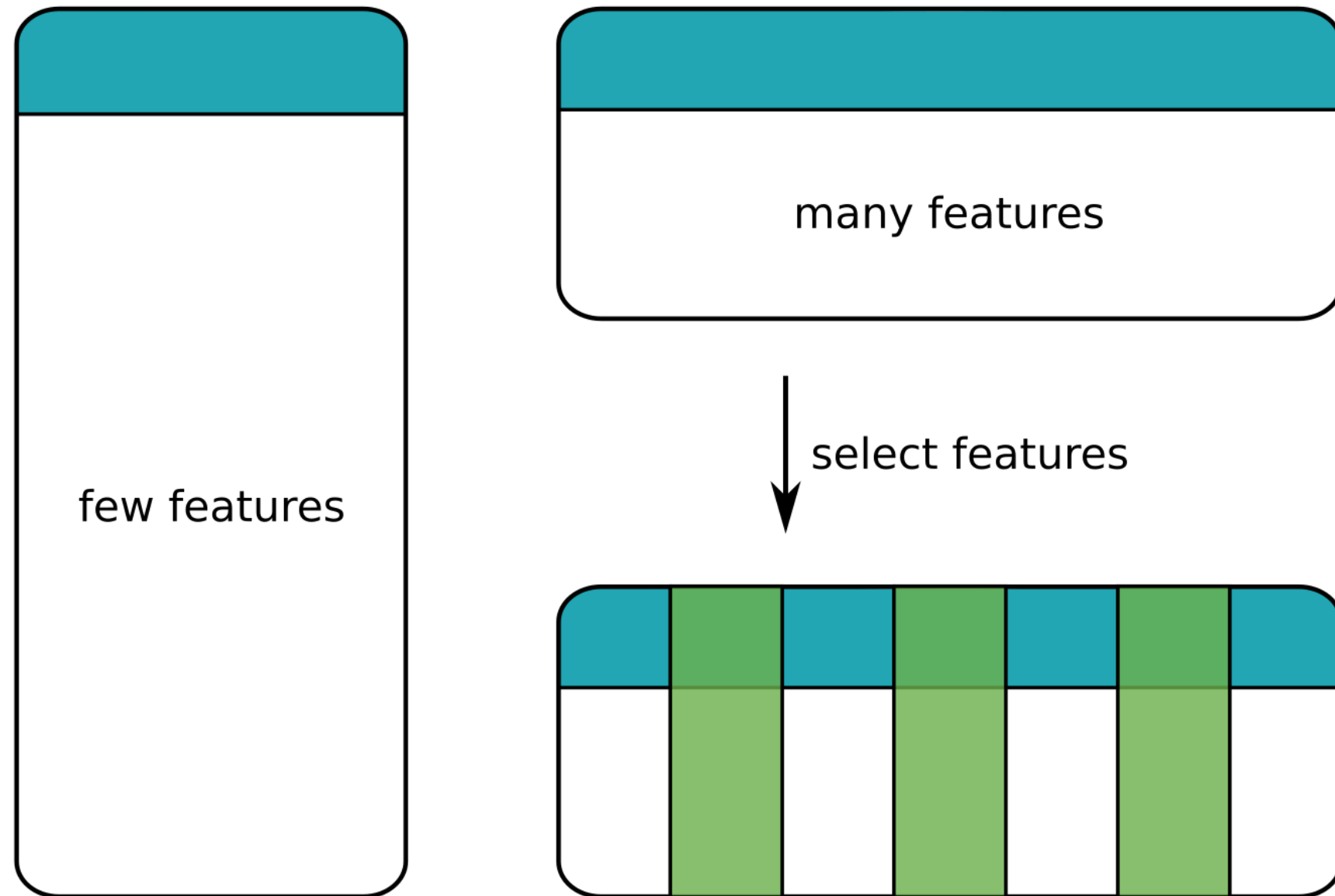
Features: Only a few



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 λ :

- $\lambda = 0$ — 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

```
# ? = 0.1 | ? = 0 -> 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

```
# ? = 0.1 | ? = 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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