Data Preparation

MACHINE LEARNING WITH PYSPARK

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Do you need all of those columns?

```
+-----+-------+-------+------+----+----+------+------+----+-----------+
|maker|  model| origin|  type| cyl|size|weight|length| rpm|consumption|
+-----+-------+-------+------+----+----+------+------+----+-----------+
|Mazda|   RX-7|non-USA|Sporty|null| 1.3|  2895| 169.0|6500|       9.41|
|  Geo|  Metro|non-USA| Small|   3| 1.0|  1695| 151.0|5700|        4.7|
| Ford|Festiva|    USA| Small|   4| 1.3|  1845| 141.0|5000|       7.13|
+-----+-------+-------+------+----+----+------+------+----+-----------+
```

Remove the `maker` and `model` fields.

Dropping columns

```
# Either drop the columns you don't want...
cars = cars.drop('maker', 'model')

# ... or select the columns you want to retain.
cars = cars.select('origin', 'type', 'cyl', 'size', 'weight', 'length', 'rpm', 'consumption')
```

```
+-------+------+----+----+------+------+----+-----------+
| origin|  type| cyl|size|weight|length| rpm|consumption|
+-------+------+----+----+------+------+----+-----------+
|non-USA|Sporty|null| 1.3|  2895| 169.0|6500|       9.41|
|non-USA| Small|   3| 1.0|  1695| 151.0|5700|        4.7|
|    USA| Small|   4| 1.3|  1845| 141.0|5000|       7.13|
+-------+------+----+----+------+------+----+-----------+
```

Filtering out missing data

```
# How many missing values?
cars.filter('cyl IS NULL').count()
```

```
1
```

Drop records with missing values in the `cylinders` column.

```
cars = cars.filter('cyl IS NOT NULL')
```

Drop records with missing values in *any* column.

```
cars = cars.dropna()
```

Mutating columns

```
from pyspark.sql.functions import round

# Create a new 'mass' column
cars = cars.withColumn('mass', round(cars.weight / 2.205, 0))
# Convert length to metres
cars = cars.withColumn('length', round(cars.length * 0.0254, 3))
```

```
+-------+-----+---+----+------+------+----+-----------+-----+
| origin| type|cyl|size|weight|length| rpm|consumption| mass|
+-------+-----+---+----+------+------+----+-----------+-----+
|non-USA|Small|  3| 1.0|  1695| 3.835|5700|        4.7|769.0|
|    USA|Small|  4| 1.3|  1845| 3.581|5000|       7.13|837.0|
|non-USA|Small|  3| 1.3|  1965| 4.089|6000|       5.47|891.0|
+-------+-----+---+----+------+------+----+-----------+-----+
```

Indexing categorical data

```
from pyspark.ml.feature import StringIndexer

indexer = StringIndexer(inputCol='type',
                        outputCol='type_idx')


# Assign index values to strings
indexer = indexer.fit(cars)


# Create column with index values
cars = indexer.transform(cars)
```

```
+-------+--------+
|   type|type_idx|
+-------+--------+
|Midsize|     0.0| <- most frequent value
|  Small|     1.0|
|Compact|     2.0|
| Sporty|     3.0|
|  Large|     4.0|
|    Van|     5.0| <- least frequent value
+-------+--------+
```

Use `stringOrderType` to change order.

Indexing country of origin

```
# Index country of origin:
#
# USA     -> 0
# non-USA -> 1
#
cars = StringIndexer(
  inputCol="origin",
  outputCol="label"
).fit(cars).transform(cars)
```

```
+-------+-----+
| origin|label|
+-------+-----+
|    USA|  0.0|
|non-USA|  1.0|
+-------+-----+
```

Assembling columns

Use a vector assembler to transform the data.

```
from pyspark.ml.feature import VectorAssembler

assembler = VectorAssembler(inputCols=['cyl', 'size'], outputCol='features')
assembler.transform(cars)
```

```
+---+----+---------+
|cyl|size| features|
+---+----+---------+
|  3| 1.0|[3.0,1.0]|
|  4| 1.3|[4.0,1.3]|
|  3| 1.3|[3.0,1.3]|
+---+----+---------+
```

Let's practice!

MACHINE LEARNING WITH PYSPARK

Decision Tree

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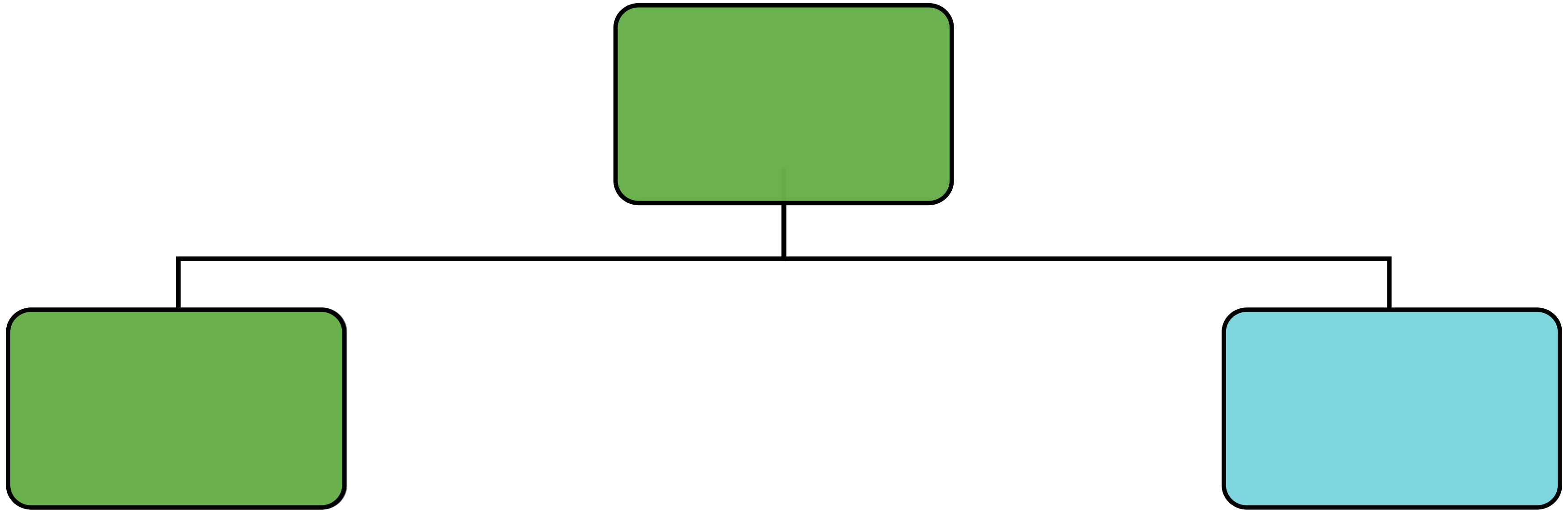
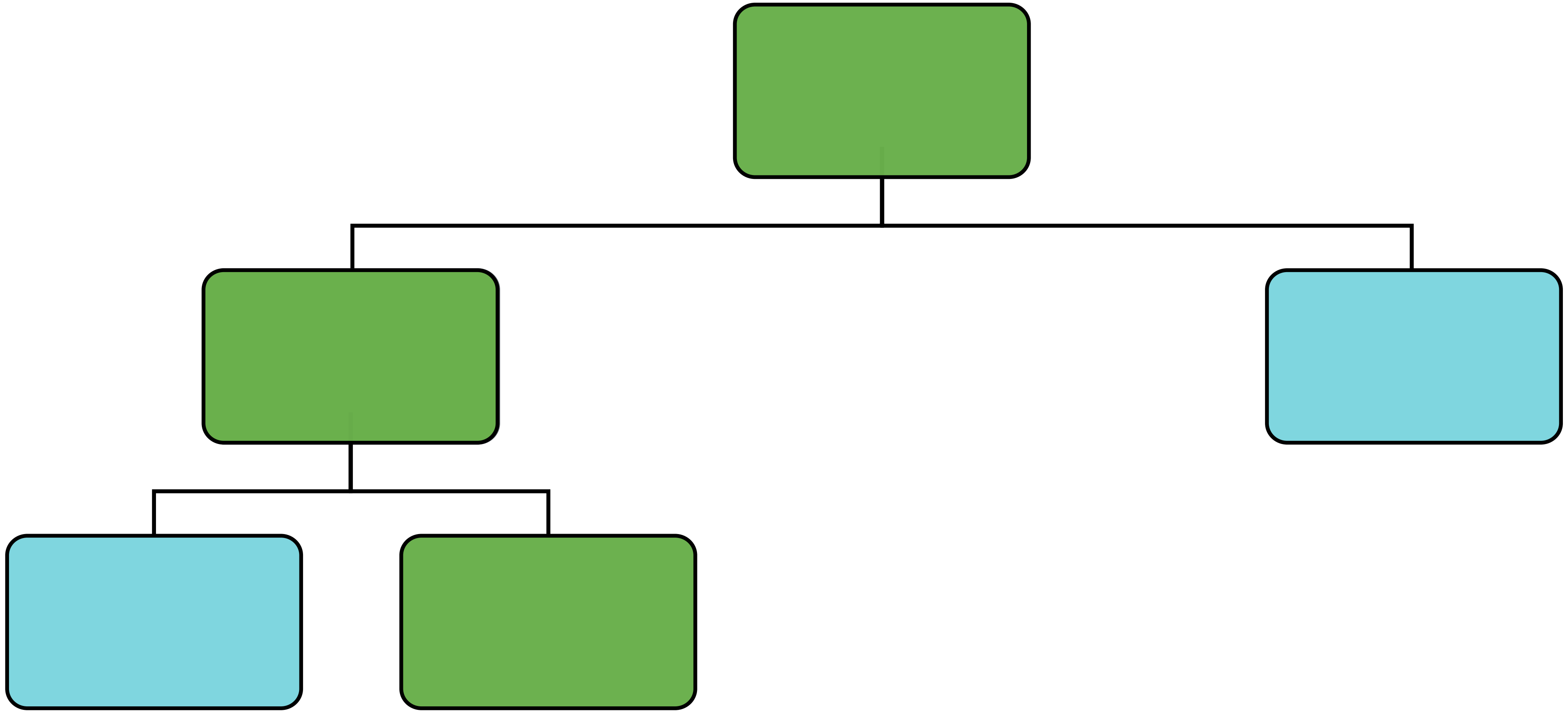
Anatomy of a Decision Tree: Root node

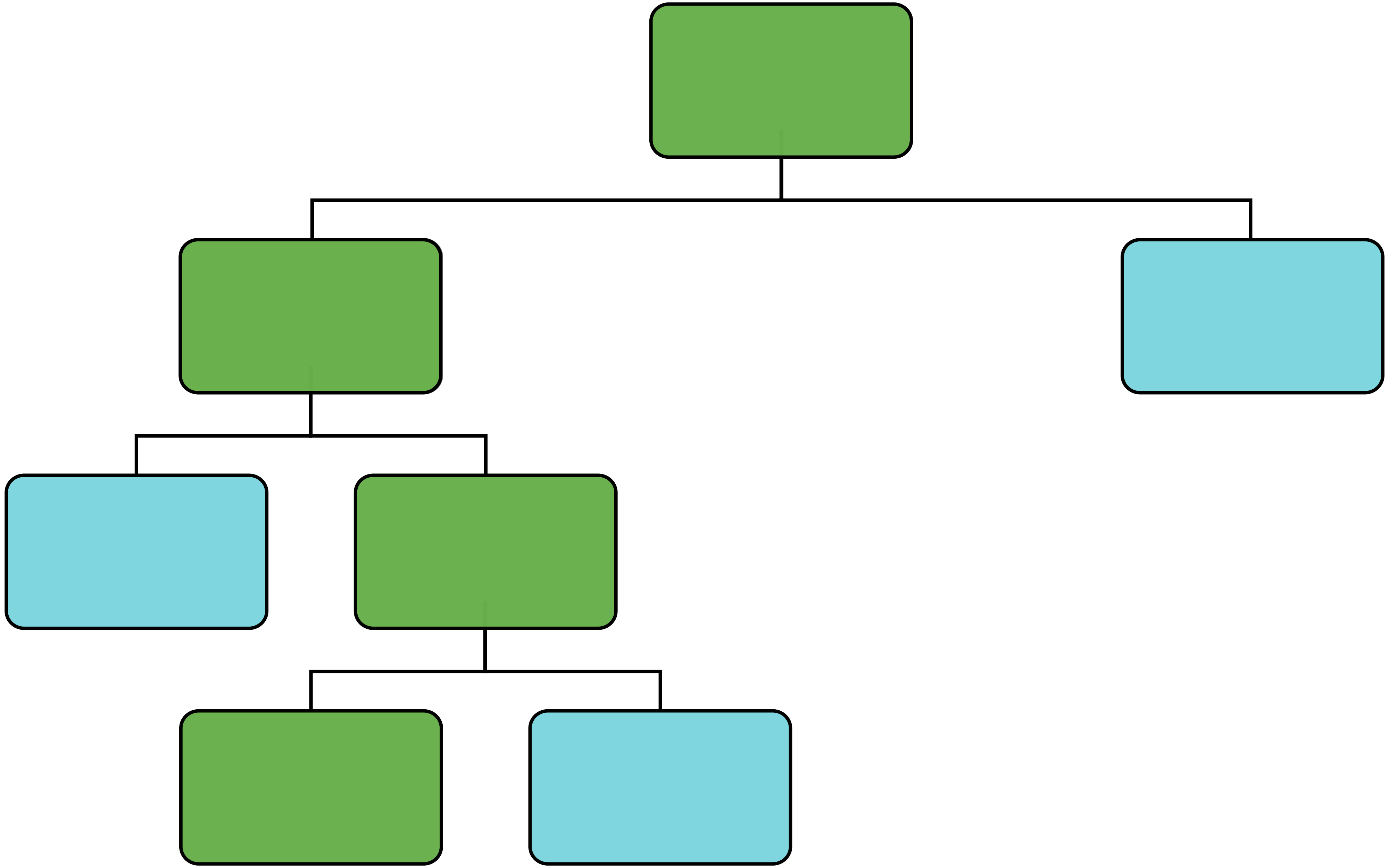
Anatomy of a Decision Tree: First split



Anatomy of a Decision Tree: Second split



Anatomy of a Decision Tree: Third split



Classifying cars

Classify cars according to country of manufacture.

```
+---+----+------+------+----+-----------+----------------------------------+-----+
|cyl|size|mass  |length|rpm |consumption|features                          |label|
+---+----+------+------+----+-----------+----------------------------------+-----+
|6  |3.0 |1451.0|4.775 |5200|9.05       |[6.0,3.0,1451.0,4.775,5200.0,9.05]|1.0  |
|4  |2.2 |1129.0|4.623 |5200|6.53       |[4.0,2.2,1129.0,4.623,5200.0,6.53]|0.0  |
|4  |2.2 |1399.0|4.547 |5600|7.84       |[4.0,2.2,1399.0,4.547,5600.0,7.84]|1.0  |
|4  |1.8 |1147.0|4.343 |6500|7.84       |[4.0,1.8,1147.0,4.343,6500.0,7.84]|0.0  |
|4  |1.6 |1111.0|4.216 |5750|9.05       |[4.0,1.6,1111.0,4.216,5750.0,9.05]|0.0  |
+---+----+------+------+----+-----------+----------------------------------+-----+

label = 0 -> manufactured in the USA
      = 1 -> manufactured elsewhere
```

Split train/test

Split data into training and testing sets.

```
# Specify a seed for reproducibility
cars_train, cars_test = cars.randomSplit([0.8, 0.2], seed=23)
```

Two DataFrames: `cars_train` and `cars_test` .

```
[cars_train.count(), cars_test.count()]
```

```
[79, 13]
```

Build a Decision Tree model

```
from pyspark.ml.classification import DecisionTreeClassifier
```

Create a Decision Tree classifier.

```
tree = DecisionTreeClassifier()
```

Learn from the training data.

```
tree_model = tree.fit(cars_train)
```

Evaluating

Make predictions on the testing data and compare to known values.

```
prediction = tree_model.transform(cars_test)
```

```
+-----+----------+----------------------------------------+
|label|prediction|probability                             |
+-----+----------+----------------------------------------+
|1.0  |0.0       |[0.9615384615384616,0.0384615384615385]|
|1.0  |1.0       |[0.2222222222222222,0.7777777777777778]|
|1.0  |1.0       |[0.2222222222222222,0.7777777777777778]|
|0.0  |0.0       |[0.9615384615384616,0.0384615384615385]|
|1.0  |1.0       |[0.2222222222222222,0.7777777777777778]|
+-----+----------+----------------------------------------+
```

Confusion matrix

A confusion matrix is a table which describes performance of a model on testing data.

```
prediction.groupBy("label", "prediction").count().show()
```

```
+-----+----------+-----+
|label|prediction|count|
+-----+----------+-----+
|  1.0|       1.0|    8| <- True positive  (TP)
|  0.0|       1.0|    2| <- False positive (FP)
|  1.0|       0.0|    3| <- False negative (FN)
|  0.0|       0.0|    6| <- True negative  (TN)
+-----+----------+-----+
```

Accuracy = (TN + TP) / (TN + TP + FN + FP) — proportion of correct predictions.

Let's build Decision Trees!

MACHINE LEARNING WITH PYSPARK

Logistic Regression

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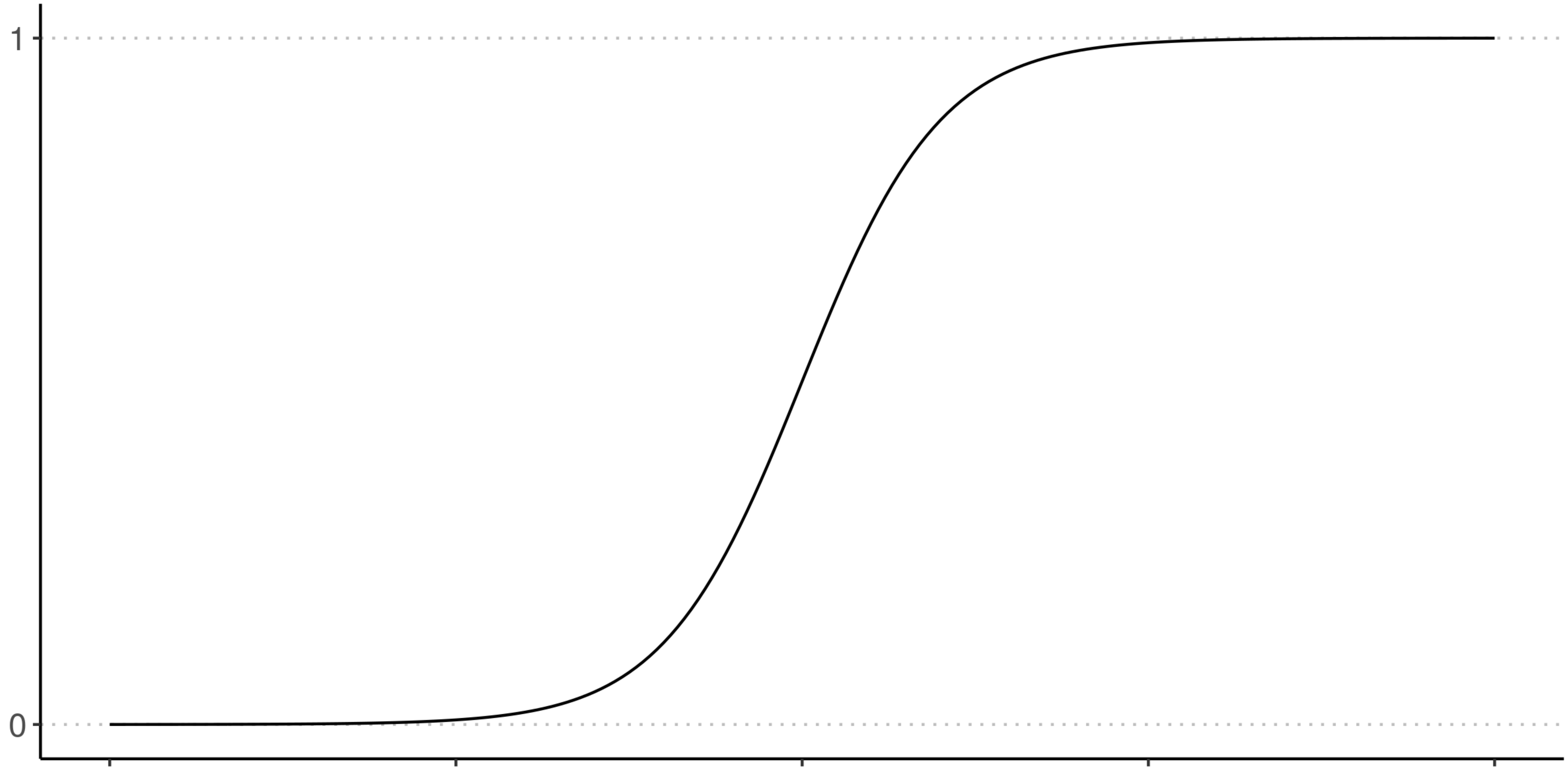
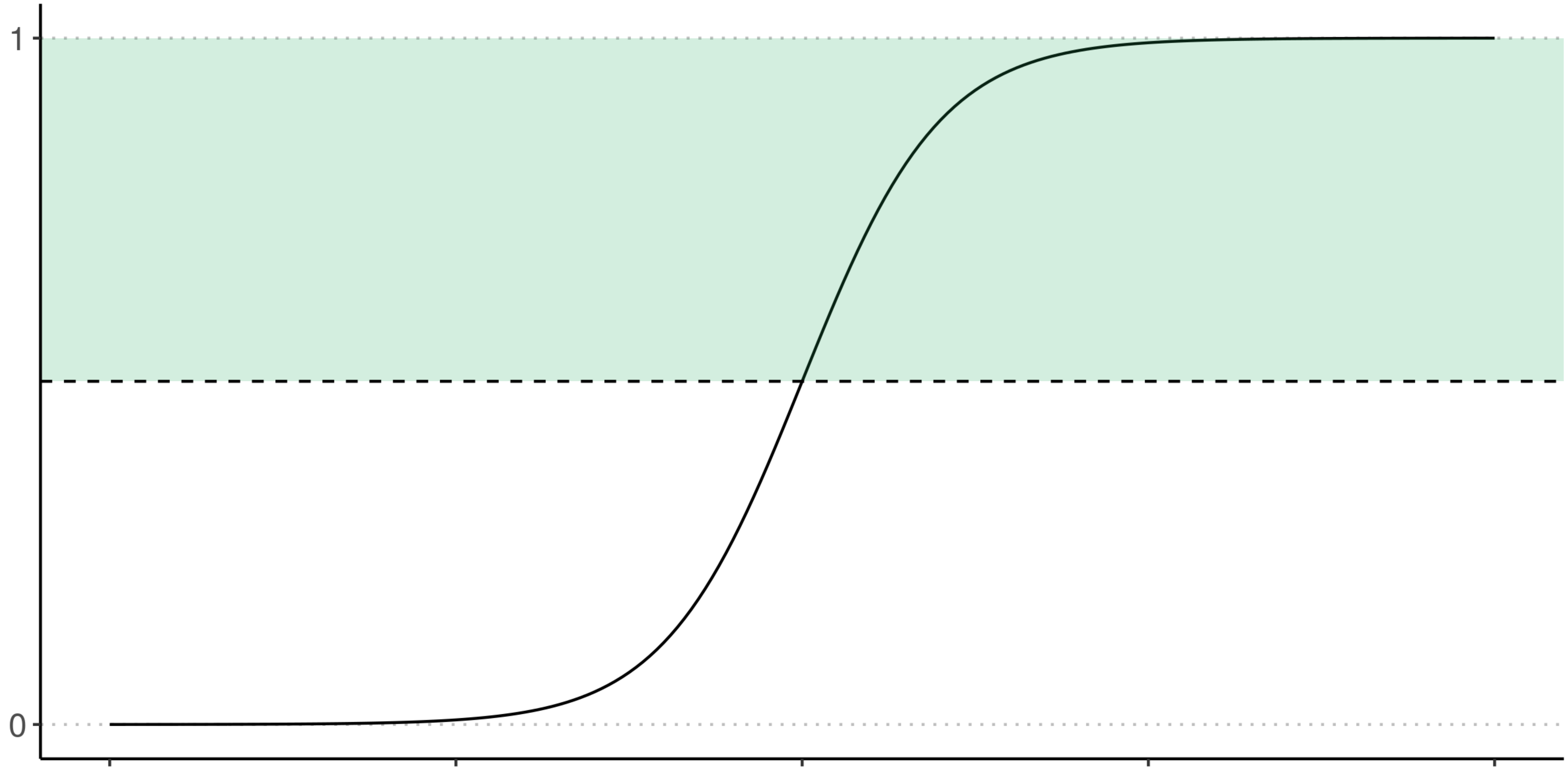
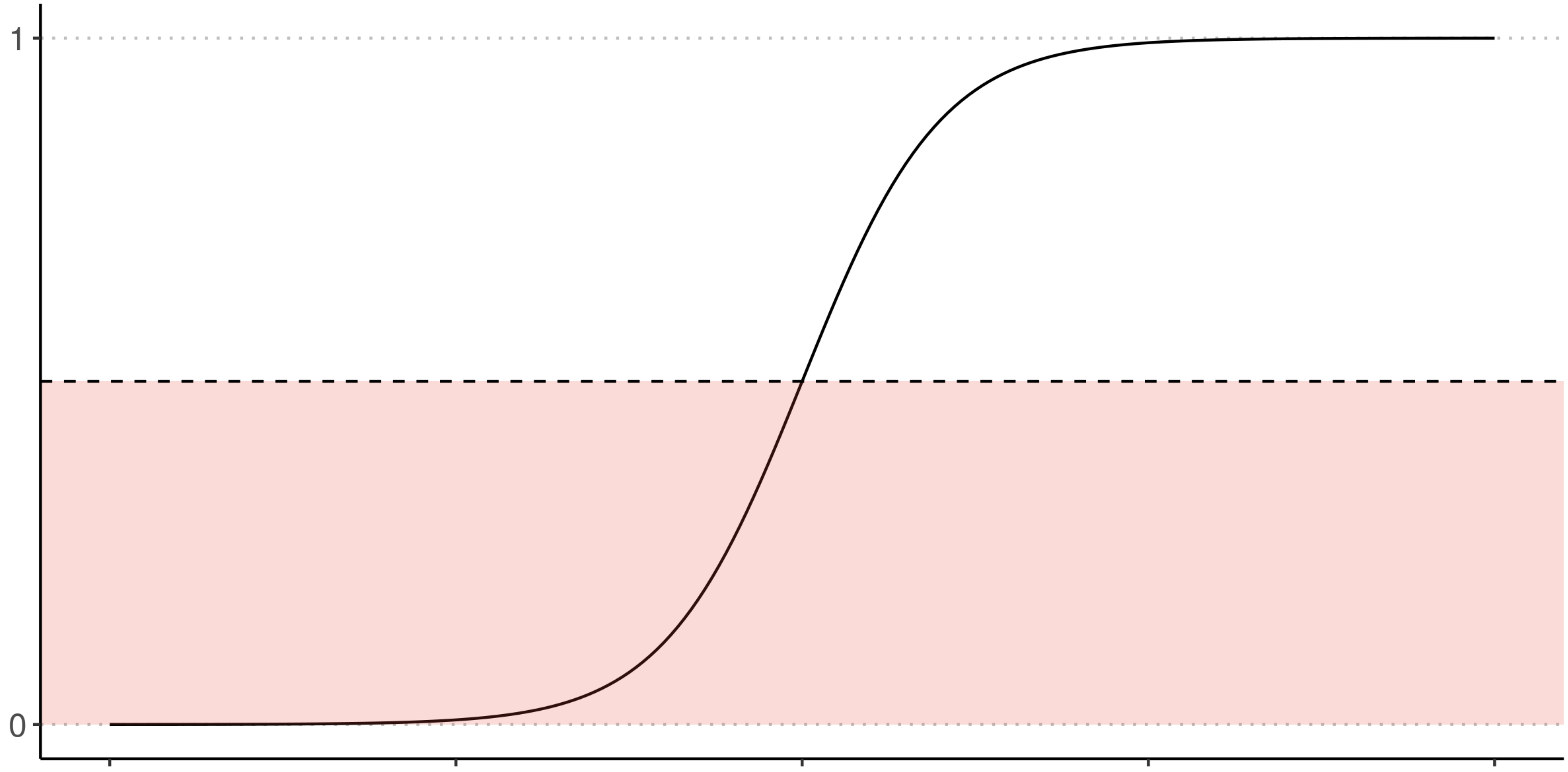
Logistic Curve



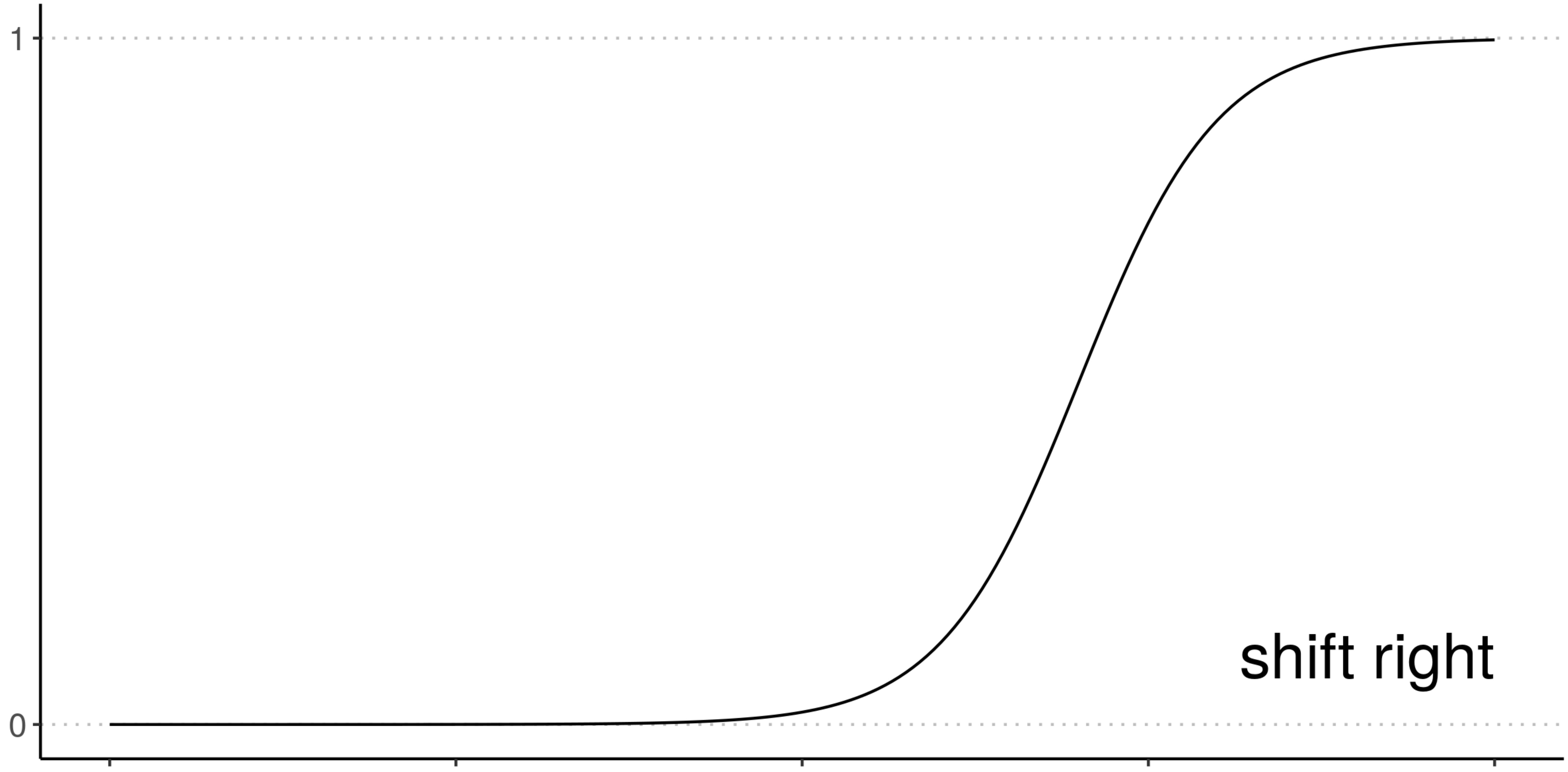
Logistic Curve



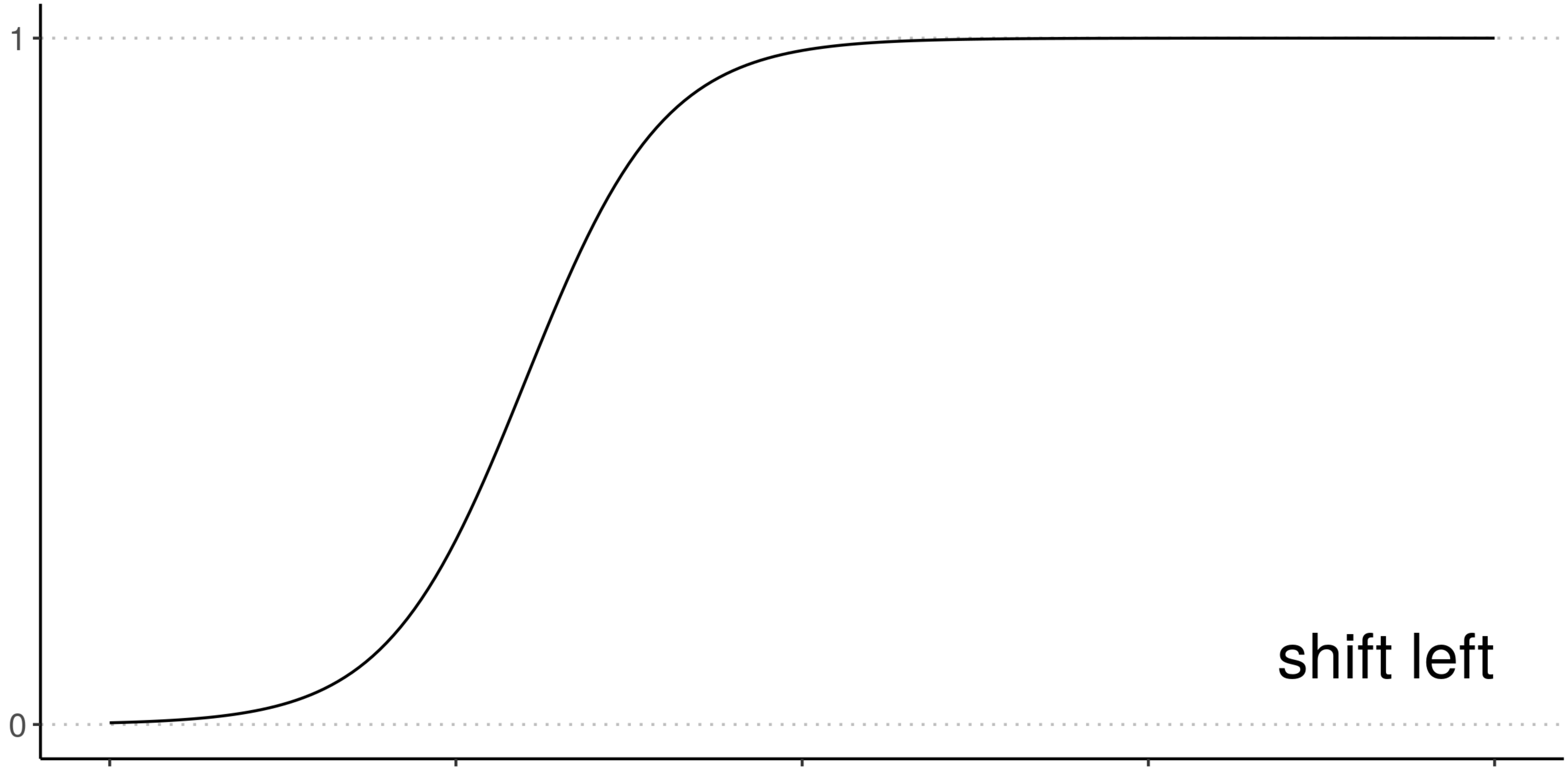
Logistic Curve



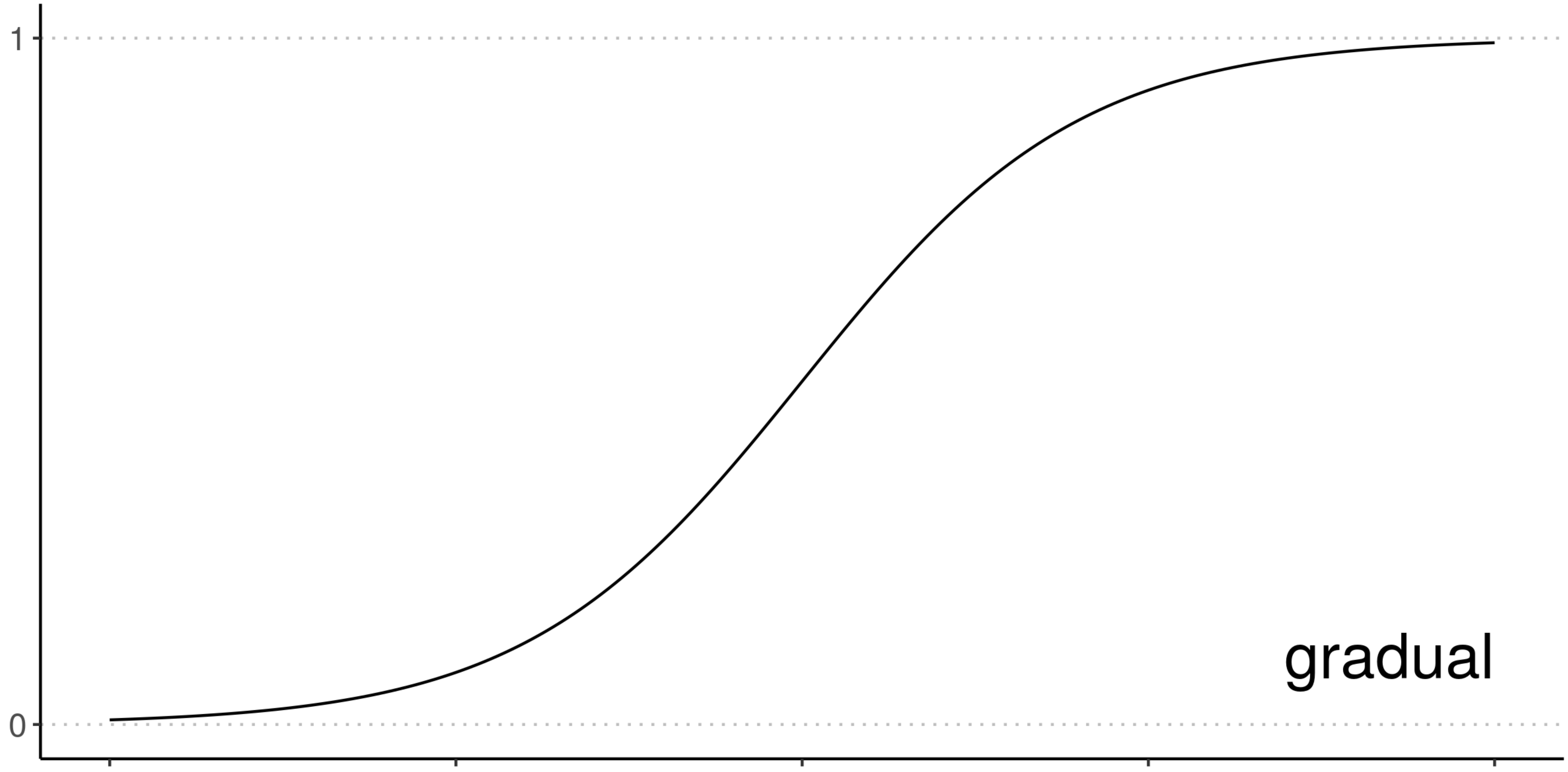
Logistic Curve



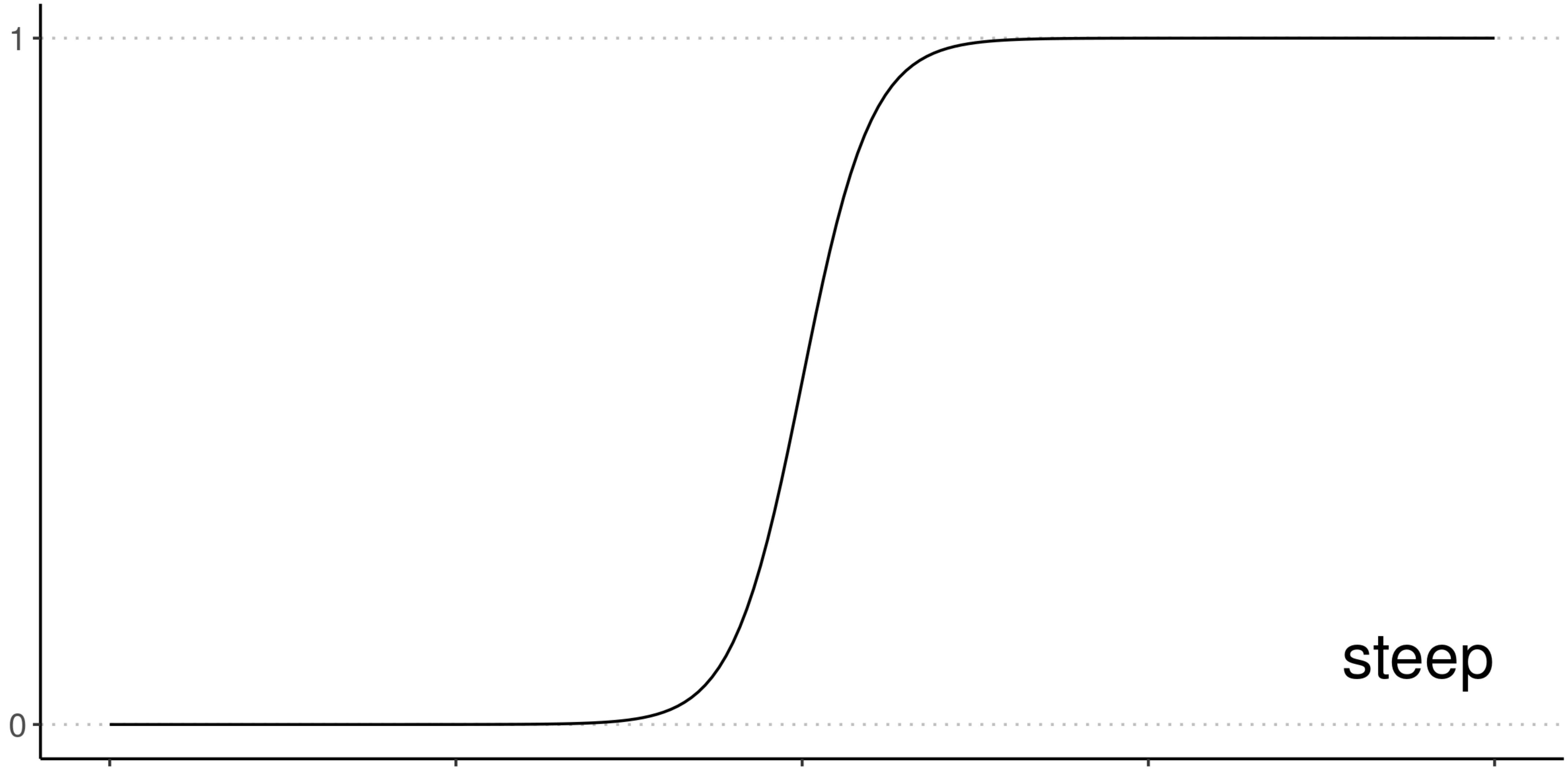
Logistic Curve



Logistic Curve



Logistic Curve



Cars revisited

Prepare for modeling:

- assemble the predictors into a single column (called `features`) and
- split data into training and testing sets.

```
+---+----+------+------+----+-----------+----------------------------------+-----+
|cyl|size|mass  |length|rpm |consumption|features                          |label|
+---+----+------+------+----+-----------+----------------------------------+-----+
|6  |3.0 |1451.0|4.775 |5200|9.05       |[6.0,3.0,1451.0,4.775,5200.0,9.05]|1.0  |
|4  |2.2 |1129.0|4.623 |5200|6.53       |[4.0,2.2,1129.0,4.623,5200.0,6.53]|0.0  |
|4  |2.2 |1399.0|4.547 |5600|7.84       |[4.0,2.2,1399.0,4.547,5600.0,7.84]|1.0  |
|4  |1.8 |1147.0|4.343 |6500|7.84       |[4.0,1.8,1147.0,4.343,6500.0,7.84]|0.0  |
|4  |1.6 |1111.0|4.216 |5750|9.05       |[4.0,1.6,1111.0,4.216,5750.0,9.05]|0.0  |
+---+----+------+------+----+-----------+----------------------------------+-----+
```

Build a Logistic Regression model

```
from pyspark.ml.classification import LogisticRegression
```

Create a Logistic Regression classifier.

```
logistic = LogisticRegression()
```

Learn from the training data.

```
logistic = logistic.fit(cars_train)
```

Predictions

```
prediction = logistic.transform(cars_test)
```

```
+-----+----------+---------------------------------------+
|label|prediction|probability                            |
+-----+----------+---------------------------------------+
|0.0  |0.0       |[0.8683802216422138,0.1316197783577862]|
|0.0  |1.0       |[0.1343792056399585,0.8656207943600416]|
|0.0  |0.0       |[0.9773546766387631,0.0226453233612368]|
|1.0  |1.0       |[0.0170508265586195,0.9829491734413806]|
|1.0  |0.0       |[0.6122241729292978,0.3877758270707023]|
+-----+----------+---------------------------------------+
```

Precision and recall

How well does model work on testing data?

Consult the confusion matrix.

```
+-----+----------+-----+
|label|prediction|count|
+-----+----------+-----+
|  1.0|       1.0|    8| - TP (true positive)
|  0.0|       1.0|    4| - FP (false positive)
|  1.0|       0.0|    2| - FN (false negative)
|  0.0|       0.0|   10| - TN (true negative)
+-----+----------+-----+
```

```
# Precision (positive)
TP / (TP + FP)
```

```
0.6666666666666666
```

```
# Recall (positive)
TP / (TP + FN)
```

```
0.8
```

Weighted metrics

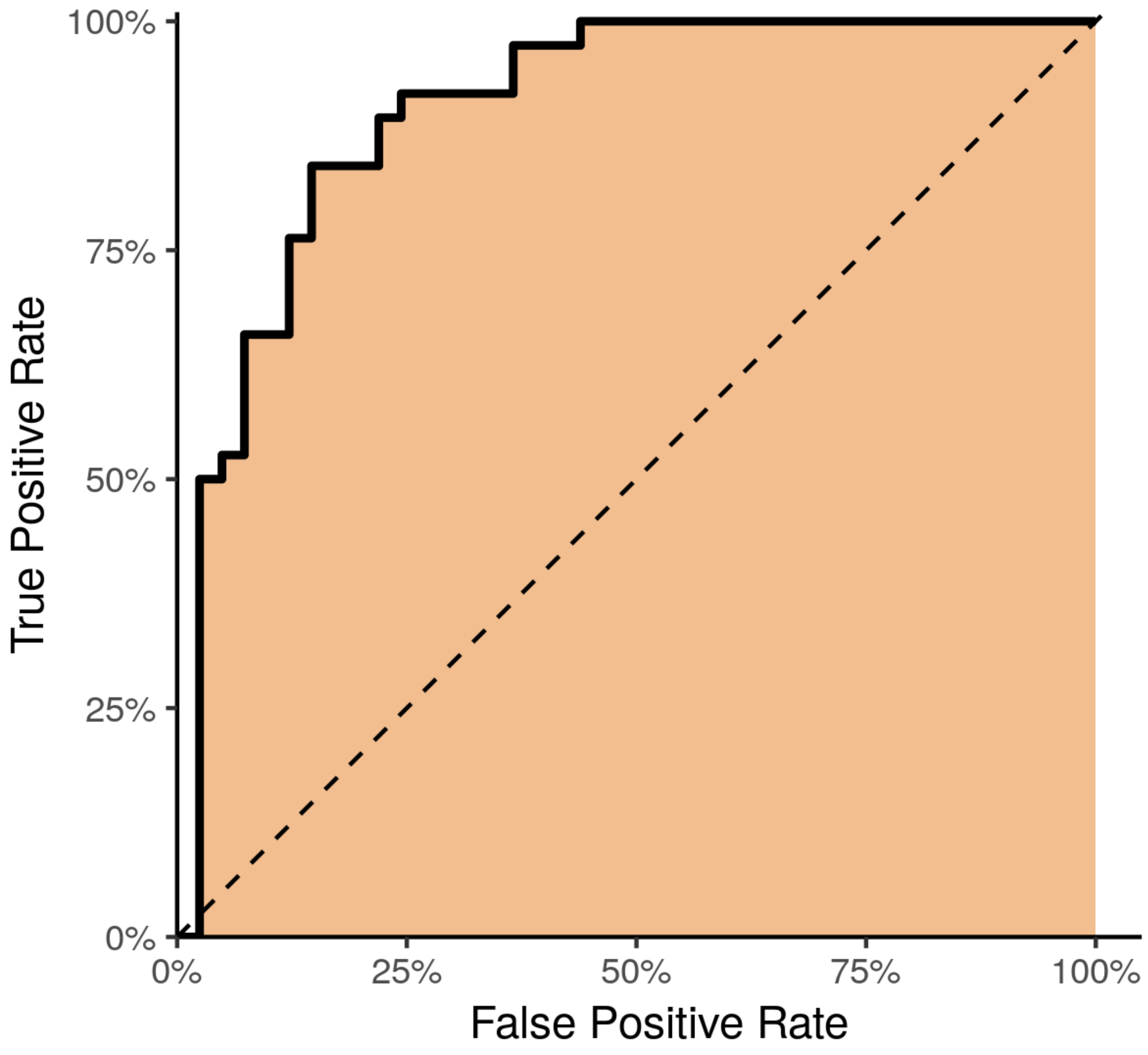
```
from pyspark.ml.evaluation import MulticlassClassificationEvaluator

evaluator = MulticlassClassificationEvaluator()
evaluator.evaluate(prediction, {evaluator.metricName: 'weightedPrecision'})
```

```
0.7638888888888888
```

Other metrics:

- `weightedRecall`
- `accuracy`
- `f1`

ROC and AUC



ROC = "Receiver Operating Characteristic"

- TP versus FP
- threshold = 0 (top right)
- threshold = 1 (bottom left)

AUC = "Area under the curve"

- ideally AUC = 1

Let's do Logistic Regression!

MACHINE LEARNING WITH PYSPARK

Turning Text into Tables

MACHINE LEARNING WITH PYSPARK

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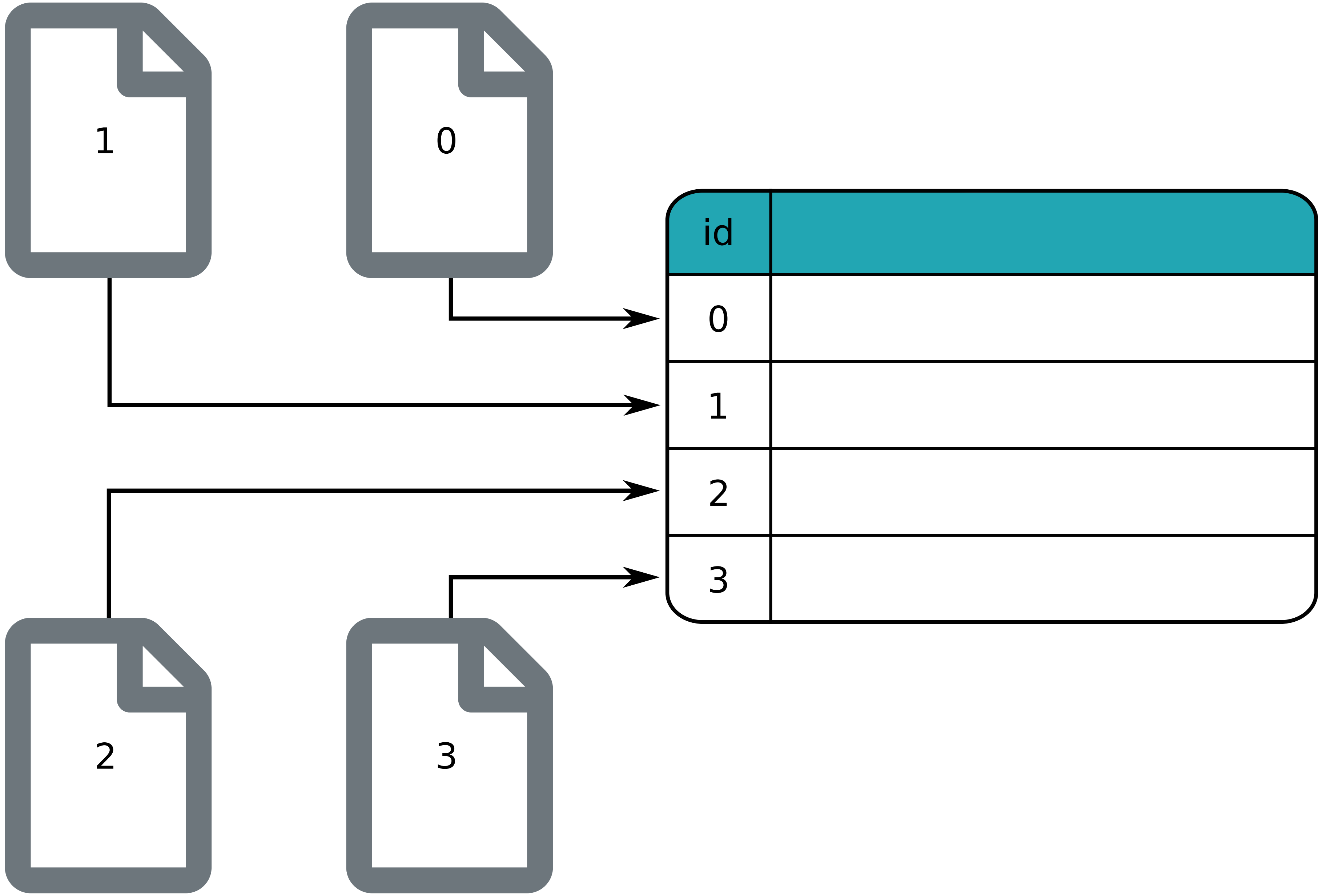
One record per document



One document, many columns

Ten Little Fingers and Ten Little Toes

Tokenize

Ten | Little | Fingers | and | Ten | Little | Toes

Remove stop words

Ten | Little | Fingers | Ten | Little | Toes

Ten	Little	Fingers	Toes
2	2	1	1

A selection of children's books

```
books.show(truncate=False)
```

```
+---+------------------------------------+
|id |text                                |
+---+------------------------------------+
|0  |Forever, or a Long, Long Time       | ---> 'Long' is only present in this title
|1  |Winnie-the-Pooh                     |
|2  |Ten Little Fingers and Ten Little Toes|
|3  |Five Get into Trouble               | -+-> 'Five' is present in all of these titles
|4  |Five Have a Wonderful Time          |  |
|5  |Five Get into a Fix                 |  |
|6  |Five Have Plenty of Fun             | -+
+---+------------------------------------+
```

Removing punctuation

```
from pyspark.sql.functions import regexp_replace

# Regular expression (REGEX) to match commas and hyphens
REGEX = '[,\\-]'

books = books.withColumn('text', regexp_replace(books.text, REGEX, ' '))
```

```
Before                                    ->    After
+---+------------------------------+            +---+------------------------------+
|id |text                          |            |id |text                          |
+---+------------------------------+            +---+------------------------------+
|0  |Forever, or a Long, Long Time|             |0  |Forever  or a Long  Long Time|
|1  |Winnie-the-Pooh               |            |1  |Winnie the Pooh               |
+---+------------------------------+            +---+------------------------------+
```

Text to tokens

```
from pyspark.ml.feature import Tokenizer

books = Tokenizer(inputCol="text", outputCol="tokens").transform(books)
```

```
+---------------------------------------+---------------------------------------------+
|text                                   |tokens                                       |
+---------------------------------------+---------------------------------------------+
|Forever or a Long Long Time            |[forever, or, a, long, long, time]           |
|Winnie the Pooh                        |[winnie, the, pooh]                          |
|Ten Little Fingers and Ten Little Toes|[ten, little, fingers, and, ten, little, toes]|
|Five Get into Trouble                  |[five, get, into, trouble]                   |
|Five Have a Wonderful Time             |[five, have, a, wonderful, time]             |
+---------------------------------------+---------------------------------------------+
```

What are stop words?

```
from pyspark.ml.feature import StopWordsRemover

stopwords = StopWordsRemover()

# Take a look at the list of stop words
stopwords.getStopWords()
```

```
['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', 'your', 'yours',
'yourself', 'yourselves', 'he', 'him', 'his', 'himself', 'she', 'her', 'hers', 'herself',
'it', 'its', 'itself', 'they', 'them', 'their', 'theirs', 'themselves', 'what', 'which',
'who', 'whom', 'this', 'that', 'these', 'those', 'am', 'is', 'are', 'was', 'were', 'be',
'been', 'being', 'have', 'has', 'had', 'having', 'do', 'does', 'did', 'doing', ...]
```

Removing stop words

```
# Specify the input and output column names
stopwords = stopwords.setInputCol('tokens').setOutputCol('words')

books = stopwords.transform(books)
```

```
+----------------------------------------------+------------------------------------------+
|tokens                                        |words                                     |
+----------------------------------------------+------------------------------------------+
|[forever, or, a, long, long, time]            |[forever, long, long, time]               |
|[winnie, the, pooh]                           |[winnie, pooh]                            |
|[ten, little, fingers, and, ten, little, toes]|[ten, little, fingers, ten, little, toes]|
|[five, get, into, trouble]                    |[five, get, trouble]                      |
|[five, have, a, wonderful, time]              |[five, wonderful, time]                   |
+----------------------------------------------+------------------------------------------+
```

Feature hashing

```
from pyspark.ml.feature import HashingTF

hasher = HashingTF(inputCol="words", outputCol="hash", numFeatures=32)
books = hasher.transform(books)
```

```
+---+--------------------------------------+------------------------------------+
|id |words                                 |hash                                |
+---+--------------------------------------+------------------------------------+
|0  |[forever, long, long, time]           |(32,[8,13,14],[2.0,1.0,1.0])        |
|1  |[winnie, pooh]                        |(32,[1,31],[1.0,1.0])               |
|2  |[ten, little, fingers, ten, little, toes]|(32,[1,15,25,30],[2.0,2.0,1.0,1.0])|
|3  |[five, get, trouble]                  |(32,[6,7,23],[1.0,1.0,1.0])         |
|4  |[five, wonderful, time]               |(32,[6,13,25],[1.0,1.0,1.0])        |
+---+--------------------------------------+------------------------------------+
```

Dealing with common words

```
from pyspark.ml.feature import IDF

books = IDF(inputCol="hash", outputCol="features").fit(books).transform(books)
```

```
+--------------------------------------+--------------------------------------+
|words                                 |features                              |
+--------------------------------------+--------------------------------------+
|[forever, long, long, time]           |(32,[8,13,14],[2.598,1.299,1.704])    |
|[winnie, pooh]                        |(32,[1,31],[1.299,1.704])             |
|[ten, little, fingers, ten, little, toes]|(32,[1,15,25,30],[2.598,3.409,1.011,1.704])|
|[five, get, trouble]                  |(32,[6,7,23],[0.788,1.704,1.299])     |
|[five, wonderful, time]               |(32,[6,13,25],[0.788,1.299,1.011])    |
+--------------------------------------+--------------------------------------+
```

Text ready for Machine Learning!

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